UNIVERSIDAD DE CANTABRIA

E.T.S. INGENIEROS DE CAMINOS, CANALES Y PUERTOS

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TESIS DOCTORAL

METODOLOGÍAS PARA EL ANÁLISIS DE RIESGO DE INUNDACIÓN EN ZONAS COSTERAS

PhD DISSERTATION

METHODOLOGIES FOR COASTAL FLOODING RISK ANALYSIS

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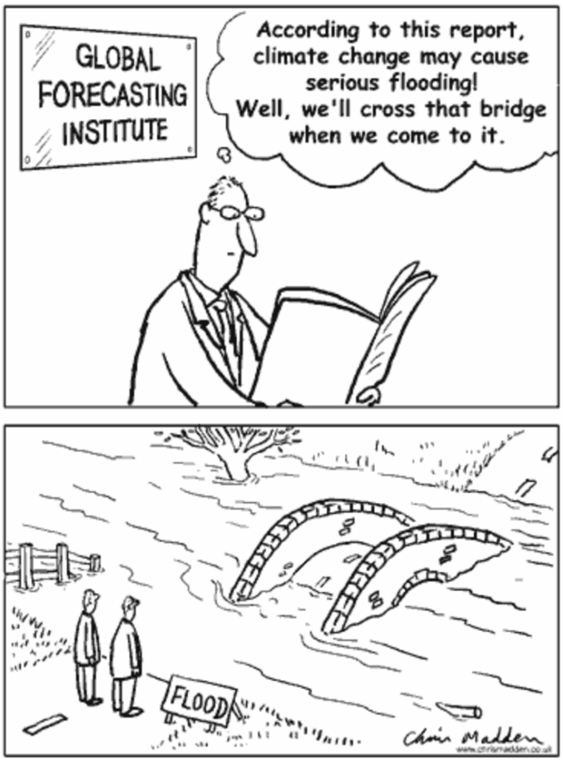
To my masters



Chris Madden

Il est impossible que
l'improbable n'arrive jamais

Emil Gumbel

Acknowledgements

It has been five years since I arrived to Cantabria University willing to keep learning about coastal processes and wave climate, motivated by the ocean waves and the fun and enriching shared moments at the beach. I acknowledge this time of continuous learning and growth. I feel really grateful to have had the opportunity to do this thesis, and even more to have had the scientific guide of Fernando Méndez, Paula Camus and Antonio Tomás. This work would not have been possible without the brilliant ideas and motivation of Fernando, the help and support of Paula and the presence and comments of Antonio. I have no words to thank the trust placed in me to perform this work, and the personal relationships that have germinated between us within the years. It has been a pleasure and an honour to work and learn with this exceptional team. Yes, a team, because I have not felt alone at any moment during this journey. Thank you.

This team grows at IHCantabria, for this reason, I would like to express my sincere thanks to Raul Medina and Iñigo Losada for giving me the opportunity to work with them in different coastal flooding projects and to start this thesis on a dynamic, young and motivating environment as IHCantabria. This institute is hold by really clever, curious and passionate people from who I have learned about science and about life. I feel lucky for every moment shared and the good friends made on the way. Thanks to all of you.

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0 Resumen en castellano

Con el objetivo lograr una mayor difusión dentro de la comunidad científica, esta tesis doctoral ha sido redactada en inglés. Sin embargo, de acuerdo con la normativa de estudios de doctorado de la Universidad de Cantabria en relación a los requerimientos exigidos para aquellas tesis redactadas en un idioma diferente al español, aprobada por Junta de Gobierno de 12 de marzo de 1999 y actualizada a 18 de diciembre de 2013, exige que aquellas tesis redactadas en un idioma diferente al español incluyan un resumen de la misma en español. A continuación se presenta un resumen de la tesis manteniendo una estructura similar a la del documento en inglés.

0.1 Motivación

Las costas de todo el mundo están densamente pobladas, se estima que más de mil millones de personas viven a unos 100 km de una costa oceánica, y alrededor de 800 millones habitan en zonas potencialmente inundables (por debajo de la cota 10 m respecto al nivel del mar medio actual), (Small and Nicholls 2003; McGranahan et al., 2007). Por tanto, dada su importancia, nuestra capacidad para predecir el impacto de tormentas extremas en nuestras costas es crucial para una gestión eficiente de las mismas, y minimizar las posibles pérdidas económicas, ecológicas y humanas futuras.

Las zonas costeras, son zonas de transición entre la tierra y la plataforma continental, siendo zonas muy dinámicas, ricas, y llenas de interacciones y efectos no lineales. A pesar de los importantes avances en el entendimiento del funcionamiento de este complejo sistema durante las últimas décadas (Holman et al. 2015), nuestro conocimiento del mismo y nuestra capacidad para predecir su comportamiento es aún limitado. Sin embargo, la gran presión social, con el aumento de población y bienes en esta franja, y la presión ambiental, con posibles cambios en los patrones atmosféricos y subida del nivel del mar por efecto del calentamiento global, requieren una estimación robusta del riesgo que ayude en la toma de decisiones.

Esta tesis se ha centrado en la caracterización del riesgo por inundación costera teniendo en cuenta la variabilidad climática. En común con otros riesgos naturales, el riesgo por inundación costera se suele cuantificar en términos económicos como el producto de la probabilidad de cada evento por sus posibles consecuencias (Gouldby and Samuels, 2005). Por tanto, habrá dos términos importantes a estudiar. Por un lado, la caracterización estadística de los eventos extremos y por otro la modelización de las consecuencias asociadas.

Para la caracterización estadística del riesgo, es necesario integrar la función de distribución conjunta de las variables que condicionan la inundación sobre una función objetivo, normalmente costes económicos. Los eventos de inundación son eventos extremos y por tanto, los registros históricos para caracterizar su distribución son limitados, teniendo por ejemplo 30 años de datos para estimar el evento de 100 años de periodo de retorno, por lo que se han desarrollado diferentes métodos estadísticos para extrapolar los datos históricos a valores extremos. Debido a que la inundación costera se produce por la combinación de distintas variables: nivel medio del mar, marea astronómica, marea meteorológica, altura de ola significante, periodo de ola medio, viento, etc., el problema estadístico al que nos enfrentamos es multivariado. Normalmente, se recurre al uso de técnicas de Monte Carlo para la extrapolación de la función de densidad conjunta, pero estas técnicas probabilísticas introducen un coste computacional extra en el modelado de los consiguientes aspectos del riesgo. Por tanto, tradicionalmente se han hecho hipótesis en las relaciones de dependencia entre las variables a analizar para simplificar el número de casos a simular, con sus asociadas limitaciones.

La selección de los modelos a utilizar para representar el sistema, dependerá de la resolución, dominio y procesos asociados. Sin embargo, las diferentes escalas temporales y espaciales están interconectadas, ya que por ejemplo, el proceso de inundación en un determinado lugar, no se puede separar de los procesos de mayor escala como los frentes de tormenta o la interacción atmósfera océano que los ocasiona. Una aproximación eficiente a este problema es mediante el uso de técnicas de downscaling estadístico. Para la caracterización extremal de nuestras variables locales y analizar los posibles eventos extremos, que no tenemos registro que hayan ocurrido, pero estadísticamente son posibles, se deben utilizar estados de mar en aguas profundas o suficientemente alejados de la costa, antes de que el oleaje se vea afectado por los procesos costeros (Bruun and Tawn, 1998). Posteriormente, estos eventos han de ser transferidos a costa con diversos modelos (propagación del oleaje, inundación, daños económicos) para tener una estimación de las consecuencias asociadas. La selección de los modelos a utilizar debe basarse en un equilibrio entre la representación física del sistema y el gasto computacional requerido para el modelado del mismo. Hoy en día, hay una alta variedad en los modelos disponibles, siendo la selección de los mismos una parte importante y no trivial en la caracterización del riesgo. Es relevante comentar, que cada uno de los engranajes del modelado debe estar tratado con similar rigor ya que el resultado final se verá condicionado por la pieza más débil del engranaje.

Una complejidad adicional en el modelado del riesgo de inundación, es la no estacionariedad de los procesos asociados, tanto en la amenaza (variabilidad interanual, tendencias o cambio climático) como en la exposición y vulnerabilidad de los sistemas a analizar.

Del amplio problema descrito, esta tesis se ha centrado en el desarrollo de una novedosa metodología, poniendo mayor hincapié en la caracterización estadística de eventos extremos multivariados pero sin olvidar el resto de engranajes necesarios para la caracterización del riesgo por inundación costera teniendo en cuenta variabilidad climática.

0.2 Estado del conocimiento

Esta sección recoge el estado de conocimiento actual en los tres aspectos fundamentales que aborda la tesis: (1) análisis extremal de eventos multivariados en aguas profundas para definir las condiciones de contorno hidráulicas; (2) desarrollo de un marco metodológico para incluir variabilidad climática y cambio climático en el análisis; (3) cuantificación del riesgo.

0.2.1 Teoría de valores extremos

La teoría de valores extremos tiene como objetivo último la estimación de probabilidades de ocurrencia para eventos de mayor magnitud que ninguno registrado (Coles, 2001). Es pieza clave para el análisis de riesgos naturales o diseño probabilístico de estructuras.

Tradicionalmente, la teoría de valores extremos, define la distribución de los máximos de un proceso estacionario, sin embargo, al trabajar con variables ambientales, la no-estacionariedad está presente en diferentes escalas temporales (estacionalidad, variabilidad interanual, tendencias...) siendo por tanto necesario el desarrollo de métodos estadísticos que sean capaces de modelarlo (Parey et al. 2010; Cooley, 2013; Salas and Obeysekera, 2013).

Existen métodos estadísticos que introducen la no estacionariedad mediante covariables en uno o varios de los parámetros de la distribución (Katz et al., 2002, Méndez et al., 2006) o mediante el uso de redes neuronales para el modelado no-lineal del comportamiento de las covariables (Cannon, 2010). El problema se complica al tratar con eventos multivariados, donde hay variación temporal de las marginales y de la estructura de dependencia entre ellas. Esto ha limitado el uso de modelos que, o bien modelan la dependencia entre las variables sin tener en consideración el clima (Hawkes et al. 2002, Wahl et al. 2012, Corbella and Strech 2013), o introducen el clima como una covariable, lo que normalmente limita el problema al caso univariado dada su complejidad (Mendez et al., 2006, Callaghan et al., 2008, Menéndez et al., 2009, Cannon 2010). Sin embargo, el problema de inundación costera es multivariado y no-estacionario, por tanto, es necesario un marco conceptual donde tenga cabida el modelado de ambos procesos.

0.2.2 Varibilidad climática – Downscaling estadístico

Los modelos de downscaling estadístico (SD) se utilizan para encontrar relaciones estadísticas entre un predictor de gran escala y un predictando local. Estos son una alternativa eficiente y de menor coste computacional al downscaling dinámico. Se ha demostrado que son una herramienta muy útil para analizar variables meteorológicas en diferentes escalas temporales (Giorgi et. al., 2001, Gutierrez et al., 2013, Camus et al. 2014).

La selección del tipo de método de downscaling estadístico a utilizar dependerá del problema en concreto, ya que cada método presenta sus particularidades. Camus et al., (2014) comprobó con éxito la eficacia del uso de una clasificación basada en tipos de tiempo de un predictor, en este caso SLP, para definir la distribución estadística de un predictando multivariado local, en este caso, altura de ola significante, periodo de ola medio y dirección de oleaje medio. Por tanto, a partir de este trabajo inicial, se plantea su extrapolación para analizar la distribución de los valores extremos.

0.2.3 Modelado del riesgo de inundación costera

El riesgo se define como el producto de la probabilidad de una amenaza por sus posibles consecuencias, y este debe tener en cuenta todos los posibles eventos que pueden ocurrir en el sistema. En el modelado de las consecuencias será necesario acoplar diferentes modelos para tener en cuenta los distintos procesos que tienen lugar.

A pesar del incremento en capacidad computacional, el modelado de cientos de eventos para una caracterización robusta del riesgo, puede resultar impracticable en términos prácticos. Es por ello, que han surgido técnicas más eficientes, como por ejemplo técnicas para seleccionar los casos a simular basadas en el riesgo (Dawson et al. 2005), el uso de downscaling híbrido (combinando downscaling estadístico y dinámico) (Camus et al. 2011a) o el uso de modelos simplificados (Jamieson et al. 2012). Todos ellos con el fin de aumentar la eficiencia computacional y permitir el análisis probabilístico del riesgo mientras se preserva precisión en el modelado.

Finalmente, para obtener la cuantificación económica, la información de la amenaza (mapas de inundación) debe ser combinada con el valor de los bienes que se han visto afectados, mediante el uso de curvas de daño. Multi Coloured Manual (UK) (Penning-Rowsell et al. 2003), HAZUSMH multi-hazard software (United States) (FEMA, 2009) e el modelo del Joint Reasearch Center (European Commission/HKV)(Huizinga, 2007) entre otros.

0.3 Objetivos

El objetivo general de la tesis es el desarrollo de un marco conceptual y metodológico para la estimación del riesgo por inundación costera teniendo en cuenta la variabilidad climática. Tras la revisión del estado del arte, los objetivos específicos de la tesis son:

1) Desarrollar un marco para el "downscaling" de la distribución multivariada de las dinámicas marinas para obtener la extensión de la inundación asociada, para finalmente calcular la distribución estadística del riesgo. (Trabajo recogido en el Capítulo II. y artículo publicado en Journal of Flood Risk Management, Rueda et al. 2015).

2) Desarrollar un modelo estadístico de extremos que tenga en cuenta la variabilidad climática a escala diaria. (Trabajo recogido en el Capítulo III, y artículo publicado en Journal of Geophysical Research-Oceans).

3) Desarrollar un modelo estadístico no estacionario de eventos multivariados. (Trabajo recogido en el Capítulo IV y artículo en revisión en Ocean Modeling).

0.4 Organización de la tesis

Esta tesis está organizada en cinco capítulos, todos ellos sintetizados en este resumen en español, que ocupa el capítulo 0.
En el capítulo I, en primer lugar, se recoge la motivación y el estado de conocimiento de la investigación. Seguidamente se presentan los objetivos y estructura de la tesis.
Los siguientes tres capítulos (II, III, IV) dan respuesta a los tres objetivos fundamentales de la tesis y cada uno de ellos corresponde con un artículo científico publicado (o en revisión). La doctoranda es la autora principal de todos ellos.

- Capítulo II "El uso de downscaling híbrido y modelos simplificados de inundación para la estimación del riesgo por inundación costera" presenta una aplicación de los últimos modelos y técnicas estadísticas para la caracterización del riesgo en una determinada zona. Este trabajo revela la necesidad de desarrollar un modelo estadístico de extremos que tenga en cuenta la variabilidad climática.

- Capítulo III "Un modelo de análisis extremal de altura de ola significante basada en tipos de tiempo" desarrolla un modelo univariado para estimar la distribución estadística de altura de ola significante máxima basada en un predictor atmosférico de gran escala. El modelo introduce la no estacionariedad mediante cambios en las probabilidades de ocurrencia de las diferentes situaciones sinópticas, denominadas, tipos de tiempo (weather types).

- Capítulo IV "Un emulador multivariado de olas y marea meteorológica basado en tipos de tiempo" desarrolla un modelo multivariado, basado en el caso univariado, donde la estructura de dependencia de las variables que condicionan la inundación es analizada para la extrapolación de su función de densidad conjunta a eventos extremos.

Finalmente, el capítulo V "Resumen y Conclusiones" recoge las principales contribuciones de la tesis y sugiere futuras líneas de investigación.

0.5 Contribuciones de la tesis

0.5.1 Proyectos científicos

Esta tesis se ha desarrollado parcialmente durante el proyecto de investigación MUSCLE-BEACH financiado por el Ministerio de Economía y Competitividad Español a través de la beca BIA2014-59643-R. Esta tesis ha sido también parcialmente financiada mediante el Proyecto "2013/S 122-208379 - Assessment of climate impacts on coastal systems in Europe" de la comisión europea, JRC Institute for prospective Technological Studies (IPTS) y el Acuerdo

de cooperación G15AC00426 con el U.S. Geological Survey.

0.5.2 Producción científica

Esta tesis ha dado lugar a tres publicaciones en diferentes revistas científicas:

1 Rueda, A., Gouldby, B., Méndez, F., Tomás, A., Lara, J., Losada, I., Díaz-Simal, P. (2015). The use of wave propagation and reduce complexity inundation models and meta-models for coastal flood risk assessment. Journal of Flood Risk Management. DOI: 10.1111/jfr3.12204

2 Rueda, A., Camus, P., Tomás, A., Méndez, F. (2016). An extreme value model for maximum wave heights based on weather types. J. Geophys. Res. Oceans, 10.1002/2015JC010952

3 Rueda, A., Camus., P., Tomás, A., Vitousek, S., Méndez, F.J (En revisión en Ocean Modelling). A multivariate extreme wave and storm surge climate emulator based on weather patterns.

Durante el desarrollo de la tesis, la doctoranda ha contribuido en diferentes artículos publicados en revistas científicas:

1 Gouldby, B., Méndez, F., Guanche, Y., Rueda, A., Mínguez, R. (2014). A methodology for deriving extreme nearshore sea conditions for structural design and flood risk analysis. Coastal Engineering. 88, 15-26

2 Camus, P., Méndez, F.J., Losada, I.J., Menéndez, M., Espejo, A., Pérez, A., Rueda, A., Guanche, Y. (2014a). A method for finding the optimal predictor indices for local wave climate conditions. Ocean Dynamics, 64 (7), 1025-1038.

3 Camus, P., Menéndez, M., Méndez, F.J., Izaguirre, C., Espejo, A., Cánovas, V., Pérez, J., Rueda, A., Losada, I.J., Medina, R. (2014b). A weather-type statistical downscaling framework for ocean wave climate. Journal of Geophysical Research, DOI: 10.1002/2014JC010141.

4 Camus, P., Rueda, A., Méndez, F., Losada, I. (En revisión en Ocean Dynamics). An atmospheric-to-marine synoptic classification for statistical

downscaling marine climate.

5 Rueda, A., Hegermiller, C., A., Antolinez, J.A.A., Camus, P., Vitousek, S., Ruggiero, P., Barnard, P., L., Erikson, L., H., Tomas, A., Mendez, F.J. (En revisión en Journal of Geophysical Research-Oceans). Multi-scale climate emulator of multimodal wave spectra: MUSCLE-spectra.

6 Rueda, A., Vitousek, S., Camus, P., Tomás, A., Espejo, A., Losada, I., Barnard, P., L., Erikson, L., H., Ruggiero, P., Reguero, B., Méndez, F.J. (Enviado a PNAS). "Global Classification of Coastal Flooding Climates"

Además el trabajo de esta tesis ha sido presentado por la doctoranda en diferentes congresos científicos:

1 Rueda, A., Camus, P., Méndez, F., Sano, M., Strauss, D., Hemer, M. 2013. Wave climate projections using statistical downscaling for the Gold Coast, Australia. EGU2013-670. Viena (Austria)

2 Rueda, A., Gouldby, B., Méndez, F.J., Tomás, A., Lara, J. Computationally efficient, yet robust, coastal flood risk analysis using a reduced complexity inundation model and meta model. Proceedings of the 6th International Conference on Flood Management (ICFM6). 17-19 Sept, 2014. Sao Paulo (Brazil).

3 Rueda, A., Méndez, F., Tomás, A., Espejo, A., Cid, A., Castanedo, S., del Jesus, M., Díaz, G., Toimil, A., Silio, A., Diez, J., Medina, R., Gouldby, B. A Practical multi-model approach for coastal flooding due to tropical cyclones. Proceedings of the 6th International Conference on Flood Management (ICFM6). 17-19 Sept, 2014. Sao Paulo (Brazil).

4 Rueda, A., Camus, P., Tomás, A., Méndez, F. Un emulador de inundación costera basado en variabilidad climática. XII Jornadas Españolas de Ingeniería de Costas y Puertos, Avilés, 24-25 Jun, 2015.

5 Rueda, A., Camus, P., Tomás, A., Méndez, F. A Monte Carlo multivariate climate emulator for coastal flooding. EVAN 2015. Santander, 16-18, Sept. 2015

6 Rueda, A., Camus, P., Méndez, F., Tomás, A., Luceño, A. An extreme value model for maximum wave heights based on weather types. 14th

International Workshop on Wave Hindcasting and Forecasting. Key West, Florida, USA, Nov 10, 2015.

7 Rueda, A., Camus, P., Méndez, F., Tomás, A., Luceño, A. Monte Carlo climate based emulator for coastal flooding. 14th International Workshop on Wave Hindcasting and Forecasting. Key West, Florida, USA, Nov 10, 2015.

8 Rueda, A., Hegermiller, C., Antolinez, J. A.A, Serafin, K. A., Anderson, D., Ruggiero, P., Vitousek, S., Barnard, P., Erikson, L., Camus, P., Tomás, A., González, M., Mendez, F. J. Towards a Multi-scale Monte Carlo Climate Emulator for Coastal Flooding and Long-Term Coastal Change Modeling: The Beautiful Problem. Ocean Sciences, New Orleans, USA, Feb. 2016

0.6 Capítulo II: El uso de downscaling híbrido y modelos simplificados de inundación para la estimación del riesgo por inundación costera.

Este apartado constituye un resumen del capítulo II de esta tesis el cual recoge el artículo de investigación publicado en la revista Journal of Flood Risk Management por Rueda, A., Gouldby, B., Méndez, F., Tomás, A., Lara, J., Losada, I., Díaz-Simal, P. en 2015 y titulado "The use of wave propagation and reduce complexity inundation models and meta-models for coastal flood risk assessment." DOI: 10.1111/jfr3.12204

0.6.1 Introducción

El riesgo se suele cuantificar en términos económicos como el producto de la probabilidad de cada evento por sus posibles consecuencias (Gouldby and Samuels, 2005). En el caso de riesgo por inundación costera, es la interacción de diferentes variables océano-meteorológicas (nivel del mar, marea astronómica, marea meteorológica, altura de ola, periodo de ola, viento…) junto con los activos presentes en la costa los que finalmente condicionarán el daño.

Los registros históricos de variables oceánicas son limitados, por tanto se han desarrollado técnicas estadísticas, normalmente basadas en métodos de Monte Carlo, para extrapolar la función de densidad conjunta de las variables oceánicas que condicionan el riesgo a valores extremos. Debido al coste computacional asociado en el modelado de las consecuencias, es decir el modelado de los procesos físicos, como propagación de ondas en aguas someras, interacción ola estructura, y corrientes en la zona inundable, se suele recurrir a una simplificación en la estructura de dependencia de las variables involucradas al extrapolar a valores extremos (Hawkes et al 2002, Defra 2005, Gouldby et al 2008) para reducir el número de casos a simular, con sus asociadas limitaciones.

Este trabajo presenta, por tanto, una metodología capaz de reducir el coste computacional asociado al modelado numérico y permitiendo una exploración robusta de los posibles eventos que pueden ocurrir en el sistema. Para ello, se recurre al downscaling hibrido (Camus et al. (2011b), Gouldby et al. (2014)) en este caso, haciendo uso del modelo de propagación de oleaje SWAN (Simulating WAves Nearshore) (Booij et al., 1999), formulaciones empíricas para estimar caudales de overtopping (Pullen et al. 2007) y un modelo simplificado de inundación (RFSM-EDA, Jamieson et al., (2012)). Como modelo estadístico de extremos multivariados se ha utilizado el método de Heffernan and Tawn (2004), de aquí en adelante, HT04.

Finalmente, la información de la amenaza se debe combinar con la estimación económica asociada a cada uso de suelo para obtener una cuantificación económica de cada evento simulado, agregando todos ellos para obtener el riesgo asociado. La metodología definida se ha aplicado a un caso de estudio en la costa norte española, en la playa del sardinero en Santander.

0.6.2 Metodología

La metodología seguida está representada en la Figura 1.

En primer lugar es necesario extrapolar la función de densidad conjunta de las variables oceánicas que condicionan la inundación a valores extremos. Este análisis se ha de realizar en aguas profundas, antes de que el oleaje se vea afectado por procesos costeros, lo que permitirá replicar los siguientes pasos de la metodología en diferentes puntos a lo largo de la costa. El método estadístico de extremos utilizado está definido por Heffernan & Tawn (2004). Mediante este análisis se obtienen cientos de eventos sintéticos multivariados, incluidos valores extremos y que preservan la estructura de dependencia de las variables originales. Este método ha sido empleado previamente en diferentes estudios (Keef et al. (2009), Keef et al., (2012), Lamb et al. (2010) and Wyncoll and Gouldby (2013), Jonathan et al. 2013a, Ewans and Jonathan, 2013, Jonathan et al. 2013 and Gouldby et al. 2014).

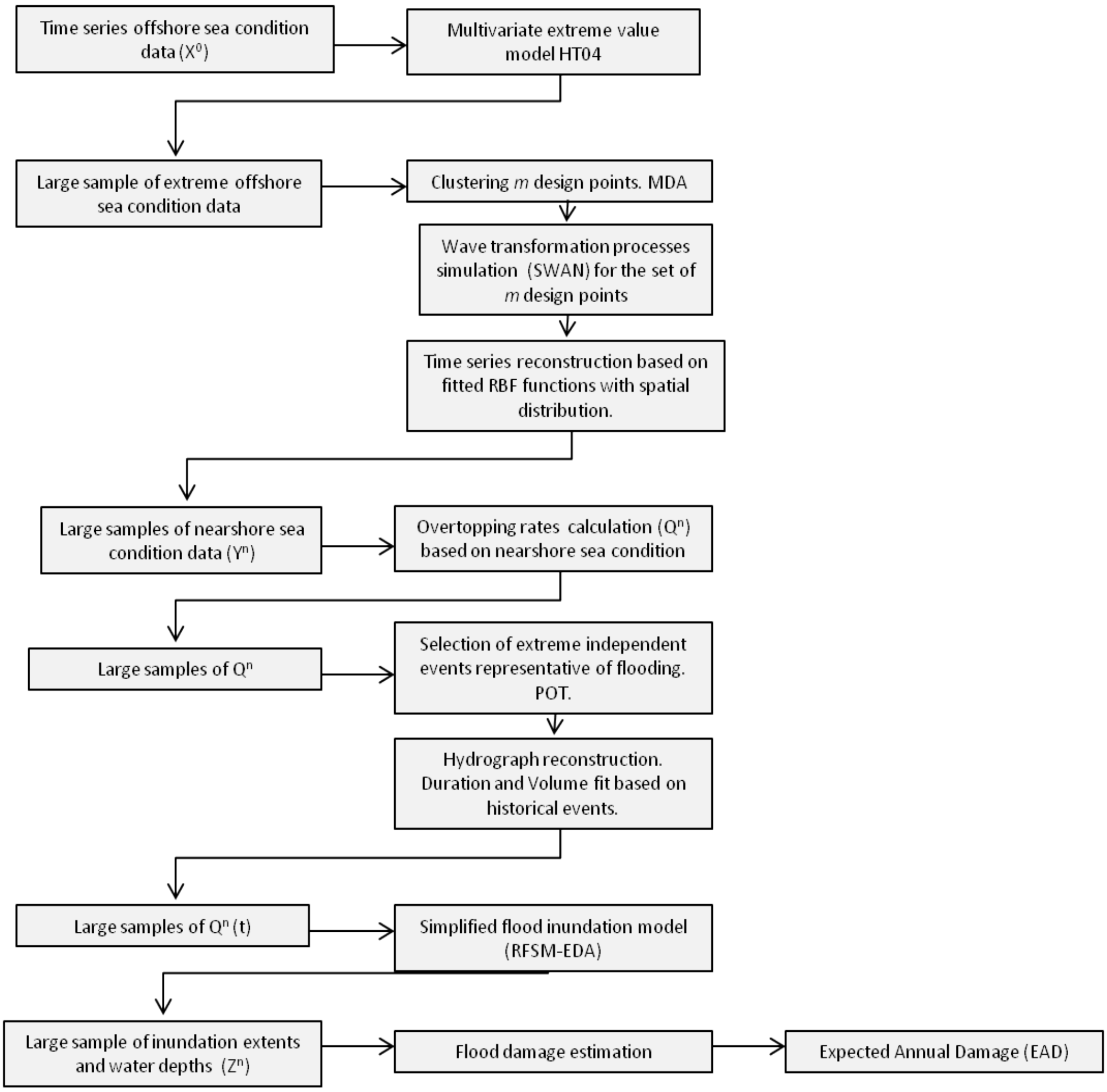


Figura 1. Diagrama de flujo de la metodología seguida.

Una vez que tenemos un conjunto amplio de eventos sintéticos, incluidos extremos, en aguas profundas estos deben ser transformados a costa. Para ello, se ha aplicado una técnica de downscaling híbrido basado en el modelo de transformación del oleaje SWAN, siguiendo la metodología definida en Camus et al. (2011a). El downscaling híbrido, consiste en seleccionar un número de casos representativos del conjunto total, éstos son simulados y posteriormente gracias a técnicas de interpolación, en este caso la técnica utilizada son las funciones de base radial, Radial Basis Fuction (RBF), el conjunto total es reconstruido en diferentes puntos en aguas someras a lo largo de la costa(Figura 2).

A continuación se ha de estimar el caudal de rebase, duración y volumen asociado con cada evento simulado. Para obtener el caudal de rebase se ha utilizado las formulaciones empíricas del manual Eurotop (Pullen et al. 2007), que relacionan estados de mar y caudal de rebase para diferentes tipologías de defensas costeras. Para estimar la duración y volumen asociado con cada evento simulado, se ha recurrido a ajustar los eventos históricos y utilizar esta información para extrapolar a los eventos sintéticos.

Los hidrogramas de caudal de rebase a lo largo de la costa para cada evento simulado son las condiciones de contorno del modelo de inundación. En este caso el modelo elegido es Rapid Flood Spreading Method – Explicit Diffusion wave with Acceleration term, RFSM-EDA(Jamieson et al., 2012). Las ecuaciones que resuelve, basadas en la formulación de Bates et al. (2010), son una simplificación de las ecuaciones de Saint-Venant considerando el término advectivo despreciable. Esta simplificación supone un gran ahorro computacional, permitiendo la simulación de un gran número de eventos. Una ventaja adicional del RFSM-EDA, es la malla de cálculo empleada, la cual es una malla irregular, basada en la topografía, lo que permite la utilización de modelos del terreno de alta resolución sin condicionar el tamaño de celda.

Cada uno de los eventos simulados tendrá asociado un daño, con una distribución espacial. Para estimar el valor económico, hemos recurrido al uso de curvas de daño (Penning-Rowsell et al. 2003, FEMA, 2009, Huizinga, 2007), las cuales se han definido para cada uso del suelo de la zona de estudio por un experto economista. Estas curvas informan del valor, o daño, asociado a cada uso del suelo para distintas profundidades de agua. La integración de los daños asociados en nuestro periodo de tiempo simulado nos da una estimación del riesgo por inundación costera en la zona.

0.6.3 Caso de estudio

Esta metodología ha sido aplicada a una playa urbana en la ciudad de Santander (Figura 2). Los datos de oleaje provienen del reanálisis local Downscaled Ocean Waves DOW (Camus et al. 2013), los cuales presentan datos horarios desde 1948 a 2013. Los datos del nivel del mar provienen de dos mareógrafos del Instituto Español de Oceanografía (1940-2005) y Puertos del Estado (1995-presente).

Los datos topográficos han sido obtenido de un mapa nacional 1:25000 (MTN25) del Instituto Geográfico Nacional con el cual se ha obtenido un mapa digital del terreno de 5 metros de resolución horizontal. Para la batimetría se ha utilizado "General Bathymetric Chart of the Ocean" GEBCO (Becker et al. 2009) y cartas náuticas de la zona.

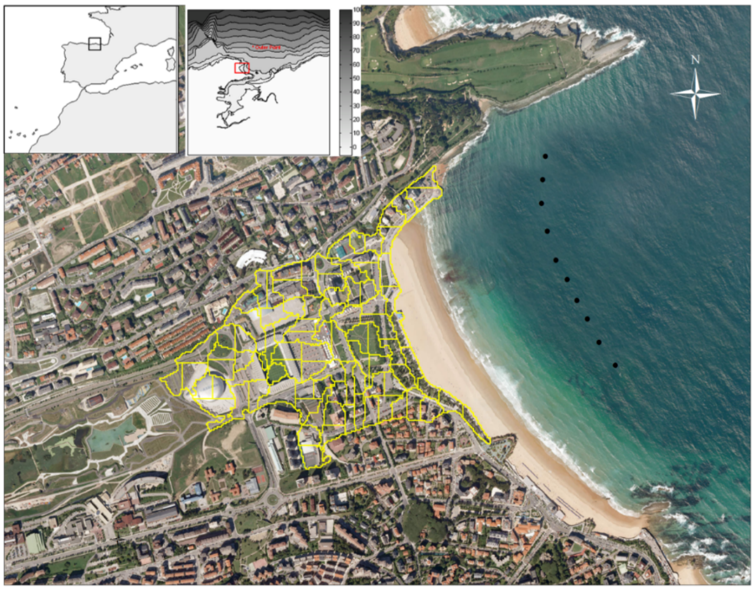


Figura 2. Mapa de la zona de estudio. Puntos en aguas someras (negro) y malla computacional RFSM-EDA (amarillo)

La Figura 3 muestra un evento de inundación extrema ocurrido durante el invierno del 2014. La agregación del daño asociado a cada evento simulado nos permite obtener una estimación del riesgo; así pues la estimación del daño esperado anual (expected anual damage, EAD) será la agregación de los daños anuales entre el número de años simulados. La Figura 4 representa el evento de 100 años de periodo de retorno (por celdas) y su daño asociado en el área de estudio.

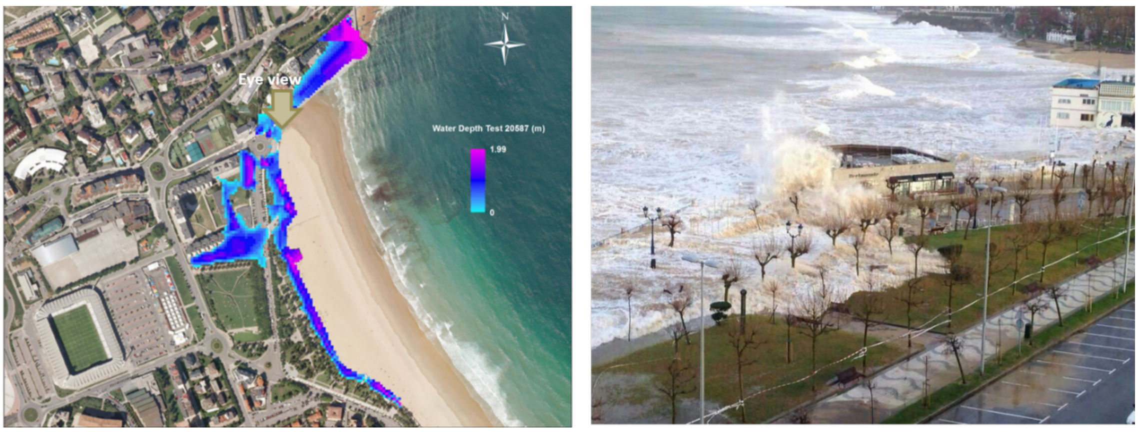


Figura 3. (Izq) Extensión de la inundación y profundidad de agua (test 20587). (Derecha) Foto tomada el 1 de Marzo de 2014 durante un evento extremo.

Es importante comentar la presencia de incertidumbre en cada uno de las etapas del modelado del riesgo. Hay cierta incertidumbre relacionada con la extrapolación de la función de densidad conjunta (Neal et al. 2012). Estas incertidumbres se propagan a través y combinadas con las incertidumbres relacionadas con el modelo de propagación del oleaje (Camus et al. 2011a). Las siguientes etapas incorporan aún mayor incertidumbre en la estimación de los caudales de rebase (Smith et al. 2012), modelado de la inundación y finalmente estimación del daño asociado (Moel et al. 2011).

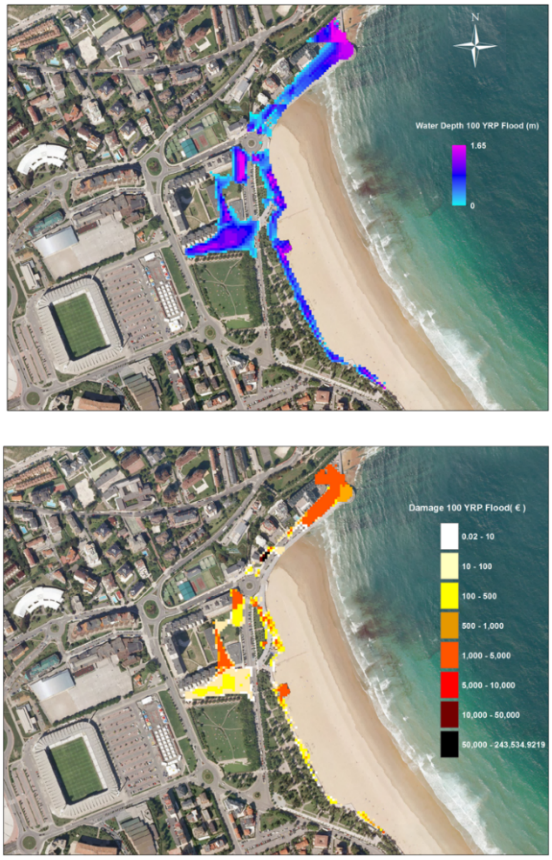


Figura 4. (Arriba) Inundación de 100 años de periodo de retorno (por celdas). (Abajo) daño asociado. Unidad espacial 5x5=25m2

0.6.4 Conclusiones

La estimación cuantitativa del riesgo por inundación costera es pieza clave para la gestión y toma de decisiones de este espacio del litoral. Para obtener una estimación cuantitativa, la información de la probabilidad de la amenaza se debe combinar con la información de las consecuencias para obtener los posibles daños asociados.

La eficacia computacional de la metodología propuesta permite simular cientos de eventos multivariados sin necesidad de asumir hipótesis en la estructura de dependencia de las variables involucradas. Esto es posible gracias al uso de un modelo de downscaling híbrido, para modelar los procesos costeros (Camus et al. 2013, Gouldby et al. 2014), y un modelo simplificado de inundación, para obtener la extensión de la inundación y profundidad de agua, conservando los principio hidráulicos básicos de conservación de masa y conectividad de flujo. Esta metodología permite la estimación de la distribución estadística del daño en tiempos computacionales reducidos.

El modelo estadístico de extremos multivariados utilizado en este capítulo es estacionario, es decir independiente del tiempo. Sin embargo, las inundaciones costeras son eventos climáticos los cuales presentan cierta variabilidad tanto estacional como interanual o por efecto del cambio climático, por tanto el desarrollo de un modelo que permita incluir esta variabilidad climática en la estimación extremal será abordado en el próximo capítulo.

0.7 Capítulo III: Un modelo de análisis extremal de altura de ola significante basado en tipos de tiempo

Este apartado constituye un resumen del capítulo III de esta tesis el cual recoge el artículo de investigación publicado en la revista Journal of Geophysical Research. Oceans por Rueda, A., Camus, P., Tomás, A. y Méndez F.J. en 2016 y titulado "An extreme value model for maximum wave heights based on weather types". doi: 10.100212015JC01952

0.7.1 Introducción

Este trabajo nace de la necesidad de incluir la no-estacionariedad de los eventos climáticos en el análisis de los eventos extremos. Tradicionalmente, la teoría de valores extremos proporciona una estimación de la distribución de los máximos para procesos estacionarios. Sin embargo, en el contexto de variables ambientales, la no-estacionariedad está presente a diferentes escalas temporales (estacionalidad, variabilidad interanual, tendencias…etc.) (Méndez et al. 2006; Holthuijsen 2007; Menéndez et al. 2009). Muchas estructuras se han diseñado basado en periodos de retorno obtenidos mediante técnicas estacionarias, (Klein et al. 2009); sin embargo la frecuencia de eventos extremos varía con el tiempo, y es probable que éstas cambien en respuesta a cambios climáticos (IPCC, 2007; Milly et al., 2008).

Este capítulo presenta un modelo de altura de ola extremal que introduce la no-estacionariedad mediante cambios en las probabilidades de ocurrencia de patrones atmosféricos. El modelo está basado en técnicas de downscaling estadístico mediante el uso de tipos de tiempo. Estas técnicas relacionan una variable local, denominada predictando (p.ej. altura de ola) con un predictor de mayor escalada (p.ej. campos de presión a nivel del mar). El modelo desarrollado en este capítulo se basa en trabajos previos (Camus et al. 2014) y su extrapolación a valores extremos. Este modelo permite el análisis de periodos de retorno de una variable local (altura de ola significante) asociados a diferentes escalas temporales, p.ej. análisis estacional e interanual así como inclusión del cambio climático. El marco estadístico desarrollado es lo suficientemente flexible para su aplicación a eventos multivariados (capítulo IV).

Las metodologías de downscaling estadístico suponen una alternativa eficiente y de bajo coste computacional al downscaling dinámico. Su eficacia para analizar variabilidad climática en diferentes escalas temporales ha sido estudiada previamente (Giorgi et al. 2001, Gutierrez et al. 2013, Camus et al. 2014). Sin embargo ejemplos de su aplicabilidad para describir eventos extremos son más escasos en la literatura (Garavaglia et al., 2010), siendo el trabajo presentado en este capítulo totalmente novedoso en el campo de estudio.

La teoría de valores extremos define la distribución generalizada de extremos (GEV) como aproximación de los máximos de un bloque de tiempo, y la distribución generalizada de Pareto (GP) como distribución de los eventos sobre un umbral, para datos independientes e idénticamente distribuidos. Aunque la independencia temporal no es una condición estrictamente necesaria, ya que ciertos grados de dependencia pueden ser igualmente válidos siempre que esta se trate debidamente (Leadbetter et al. 1983; Galambos, 1987). Aunque las distribuciones de máximos de un bloque de tiempo se suelen ajustar a máximos anuales (para asegurar la independencia), la posibilidad de utilizar datos muestreados a una mayor frecuencia temporal aumenta el tamaño de la muestra y por tanto permite ajustes más robustos, además de permitir el análisis de eventos extremos a escalas de tiempo menores. Para ello es necesario definir un índice extremal que "penaliza" la dependencia entre los datos. Este índice fue descrito por Coles (2001), y se define como la inversa de la duración media de permanencia en un cluster. En nuestro caso, cada cluster viene representado por un tipo de tiempo y, por tanto, el índice extremal es dependiente del predictor, tomando valores cercanos a uno para situaciones atmosféricas esporádicas (grandes tormentas) y cercano a cero para situaciones anticiclónicas asociadas con condiciones menos extremas y más persistentes.

0.7.2 Metodología

La metodología seguida viene representada en la Figura 5 y los pasos a seguir son:

1. Colección de datos históricos del predictor y predictando y pre-procesado del predictor.
2. Clasificación guiada en tipos de tiempo siguiendo la metodología propuesta por Cannon (2012).
3. Definición de los tipos de tiempo.
4. Ajuste del predictando asociado a cada tipo de tiempo a un modelo estacionario de extremos (p.ej. GEV).
5. Obtención del índice extremal asociado con cada tipo de tiempo.
6. Convolución de las funciones de distribución de los tipos de tiempo para obtener los periodos de retorno asociados.
7. Aplicación del modelo a diferentes periodos de tiempo.

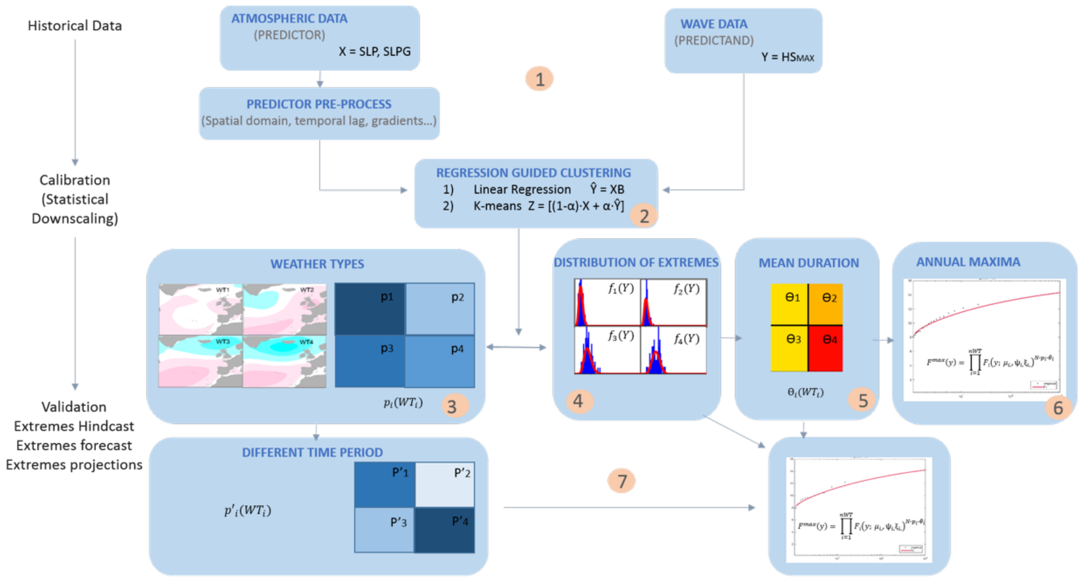


Figura 5. Metodología del modelo de extremos no estacionario

La escala temporal de interés es el día, por tanto, definimos el predictor y predictando a escala diaria. La escala temporal y espacial del predictor es uno de los mayores condicionantes de la metodología propuesta, ya que hemos de tener en cuenta las zonas de generación del oleaje y el tiempo que este tarda hasta llegar a la costa. Para ello, utilizamos la información proporcionada por la herramienta ESTELA (Perez et al., 2014) para elegir nuestra área de influencia y el tiempo medio de viaje del oleaje en su propagación hasta costa (*n* días). El predictor diario, por tanto, se define como la media *n*-diaria de los campos de presiones (SLP) y gradientes de presiones (SLPG) a nivel del mar en la zona de influencia. El predictando diario viene dado por los máximos de altura de ola significante diaria en el punto de estudio.

Para la clasificación en tipos de tiempo se ha empleado una clasificación guiada (Camus et al. en revisión), la cual proporciona subconjuntos homogéneos del predictando agrupados en función de patrones atmosféricos similares. El siguiente paso de la metodología es ajustar las distribuciones del predictando asociado a cada tipo de tiempo a una GEV, la cual viene definida por:

$$F(y) = \exp\left\{-\left[1 + \xi\left(\frac{y-\mu}{\psi}\right)\right]^{\frac{-1}{\xi}}\right\} \qquad [0.1]$$

donde, μ es el parámetro de localización, ψ es el parámetro de escala y ξ es el parámetro de forma. Cada tipo de tiempo tiene asociado también una duración media la cual condicionará el valor del índice extremal.

La agregación de la función de distribución del predictando a una escala temporal mayor, por ejemplo el mes o el año, se realiza mediante la convolución de las funciones de distribución asociadas a cada tipo de tiempo.

$$F^{max}(y) = \prod_{i=1}^{N_{WT}} F_i(y;\mu_i,\psi_i,\xi_i)^{N\cdot p_i\cdot\theta_i}, \qquad [0.2]$$

donde $F_i(y;\mu_i,\psi_i,\xi_i)$ es la función de distribución del predictando asociada con el tiempo de tiempo i WT_i, p_i es la probabilidad de ocurrencia (mensual o anual) del cluster *i*, *N* es el número de bloque de máximos (N=30dias/mes o N=365días/año) *y* θ_i es el índice extremal asociado con cada tipo de tiempo.

La estimación de la función de distribución de altura de ola máxima en periodos fuera del periodo de estudio es posible simplemente actualizando las probabilidades de ocurrencia de los distintos tipos de tiempo para el nuevo periodo.

0.7.3 Aplicación

La metodología descrita se ha aplicado a tres localizaciones del Atlántico norte con diferentes climas marítimos: Coruña, España [9° W, 43.5°N], La Palma, Canarias, España [18° W, 29° N], y Mayo, Irlanda [10.5°W, 54.5° N]. (Figura 6)

Los datos de presiones a nivel del mar provienen del Climate Forecast System Reanalysis (CFSR, Saha et al. 2010) con una resolución espacial de 0.5° y disponibles desde 1979 a 2013. Los datos de oleaje, también disponibles desde 1979 a 2013 son obtenidos del reanálisis de oleaje desarrollado por Perez et al. 2015 con resolución temporal horaria y 0.125° de resolución espacial.

El predictor se ha definido a partir de los campos medios 3 diarios de SLP y SLPG en el área representada en la Figura 6. El predictando de cada punto de estudio se define como la altura de ola máxima diaria. Los 34 años históricos de datos diarios se han dividido en 100 patrones de tipos de tiempo siguiendo la metodología de Camus et al. (en revisión). Mediante el ajuste de extremos de la distribución de alturas de ola para cada uno de los subconjuntos y posterior convolución para determinados periodos temporales (modificando las probabilidades de ocurrencia de los diferentes tipos de tiempo) es posible analizar la distribución de las máximas alturas de ola asociadas a cada uno de estos periodos.

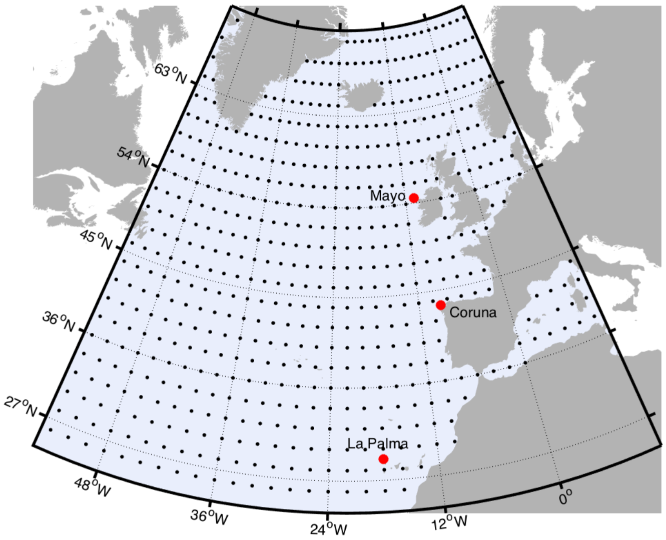


Figura 6. Dominio espacial del predictor (puntos negros). Los puntos rojos representan las zonas de estudio (predictandos locales)

Las Figura 7 y Figura 8 muestran los periodos de retorno de altura de ola máxima anual y mensual respectivamente para las tres localizaciones analizadas. Los ajustes están obtenidos mediante la ecuación 0.2, únicamente modificando el número de eventos por bloque (N = 365 eventos/año o N= 30eventos/año) y las probabilidades de ocurrencia de los tipos de tiempo (medias anuales o mensuales). Las bandas de confianza se obtienen mediante simulación de Monte Carlo basada en las probabilidades de ocurrencia de cada tipo de tiempo y en las distribuciones estadísticas de los estimadores de los parámetros en cada tipo de tiempo.

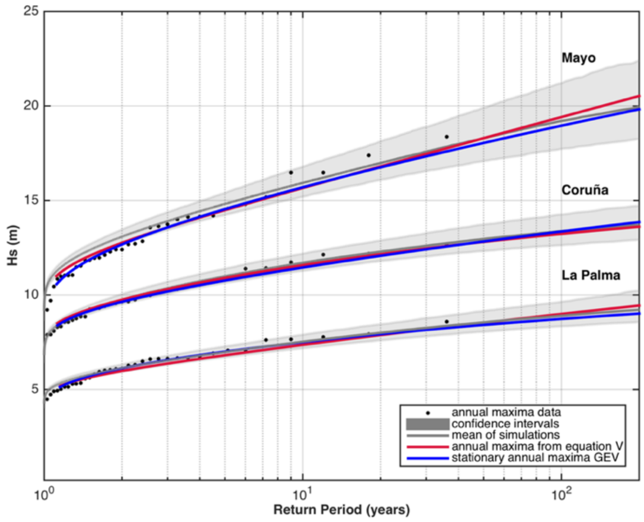


Figura 7. Periodo de retorno de altura de ola máxima anual para las tres localizaciones analizadas. Las zonas sombreadas representan los intervalos de confianza del 95 % de la altura de ola máxima anual mediante simulación de Monte Carlo basada en las probabilidades de ocurrencia anuales de los tipos de tiempo durante el periodo de calibración (1979-2013)

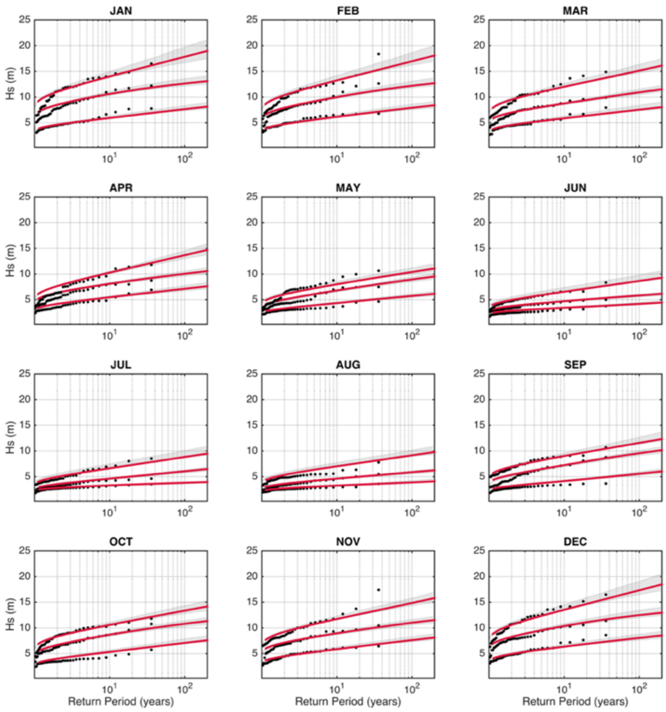


Figura 8. Periodo de retorno de altura de ola máxima mensual en las tres localizaciones analizadas. Las zonas sombreadas representan los intervalos de confianza del 95 % de la altura de ola máxima mensual mediante simulación de Monte Carlo basada en las probabilidades de ocurrencia mensuales de los tipos de tiempo durante el periodo de calibración (1979-2013)

Gracias a la relación establecida entre los patrones atmosféricos y la distribución de alturas de ola máximas, es posible inferir la distribución de alturas de ola máxima en periodos temporales diferentes al periodo de calibración del modelo, siempre y cuando se considere estacionaria la relación entre las situaciones atmosféricas y las olas que estas producen. Esto nos permite estimar la distribución de alturas de ola extremal para diferentes escenarios de cambio climático, basados en las proyecciones de modelos atmosféricos globales, o la reconstrucción de largas series temporales históricas. En este estudio se ha reconstruido la altura de ola máxima mensual durante el s.XX, basada en el reanálisis atmosférico 20CR (Compo et al. 2011). Este estudio demuestra la gran variabilidad interanual en la distribución de alturas de ola (Izaguirre et al. 2011) y la importancia de patrones atmosféricos de gran escala como la NAO (Hurrell et al., 2003).

0.7.4 Conclusiones

En este capítulo se ha presentado un modelo de downscaling estadístico capaz de modelar la distribución de altura de ola máxima para diferentes escalas temporales. El modelo se basa en el agrupamiento de los datos en base a situaciones atmosféricas similares, denominadas tipos de tiempo. La no-estacionariedad de la distribución de máximos se incluye en el análisis mediante las variaciones en las probabilidades de ocurrencia de cada tipo de tiempo.

El modelo se ha aplicado en diferentes localizaciones del Atlántico Norte, demostrando su idoneidad para simular eventos extremos a escala anual o mensual. Se ha realizado una reconstrucción de altura de ola máxima durante el siglo XX basado en los campos de presiones del reanálisis de 20 CR (Compo et al. 2011). Este trabajo refleja la influencia de patrones de gran escala, como el descrito por el índice NAO, en la variabilidad de la altura de ola extremal en el Atlántico Norte.

0.8 Capítulo IV: Un emulador multivariado de olas y marea meteorológica basado en tipos de tiempo

Este apartado constituye un resumen del capítulo IV de esta tesis el cual recoge el artículo de investigación en revisión en la revista Ocean Modeling por Rueda, A., Camus, P., Tomás, A. Vitousek, S. y Méndez F.J. y titulado "A multivariate wave and storm surge climate emulator based on weather patterns"

0.8.1 Introducción

Los eventos de inundación costera se producen por la interacción no lineal entre diferentes procesos (p.ej. marea astronómica, marea meteorológica, set-up del oleaje, lluvia..etc.). Los eventos extremos de inundación se pueden originar por la excepcionalidad de una estas variables (p.ej. marea meteorológica), pero generalmente es la combinación de valores elevados de varios de estos procesos la causa de un impacto extremo. Por tanto, para la estimación de riesgo por inundación es necesario analizar y ser capaces de extrapolar las probabilidades de ocurrencia de estos eventos multivariados.

Las valores de las variables océano-meteorológicas que condicionan la inundación (altura de ola significante Hs, periodo de ola medio Tm y marea meteorológica, SS) están todas ellas condicionadas por los patrones atmosféricos de mayor o menos escala y, por tanto, presentan gran dependencia entre ellas. En el capítulo III, se ha presentado un modelo de downscaling estadístico que relaciona patrones atmosféricos con la distribución de alturas de ola máximas en un determinado lugar. Su desarrollo para abordar el caso multivariado ocupa este capítulo.

Trabajos previos han abordado el análisis multivariado de extremos (Heffernan and Tawn,; 2004; Gouldby et al, 2014; Corbella and Strech, 2013; Ben Alaya et al, 2014) e incluyendo la no-estacionaridad de los eventos climáticos en el análisis mediante covariables en uno o más de los parámetros de la distribución (Serafin and Ruggiero, 2014; Bender et al, 2014; Masina et al, 2015). El uso de patrones de tiempo para modelar la no-estacionariedad simplifica la formulaciones matemáticas ya que los ajustes asociados a cada tipo de tiempo se consideran estacionarios, y se introduce la no-estacionariedad en el modelado mediante variaciones en las probabilidades de ocurrencia de estos tipos de tiempo.

Para analizar la distribución de los máximos de eventos multivariados, las variables involucradas se deben agregar a una función respuesta. En este caso, hemos definido como función respuesta un índice que define el nivel del mar total considerando únicamente variables océano-climáticas. Este índice, denominado de aquí en adelante TWL (Total Water Level), se define como la suma lineal de la marea meteorológica (SS) y run-up del oleaje, el cual es función de la altura de ola significante (Hs) y el periodo de ola medio (Tm). El modelado de la estructura de dependencia de estas variables se realiza mediante cópulas gaussianas.

0.8.2 Metodología

La metodología seguida para generar eventos multivariados teniendo en cuenta la variabilidad climática está recogida en la Figura 9. Los pasos a seguir son:

1. Colección y pre-proceso de datos históricos del predictor (SLP, SLPG) y predictando multivariado (Hs, Tm y SS).
2. Definición de patrones de tipos de tiempo.
3. Ajuste de las marginales del predictando asociado a cada tipo de tiempo a un modelo estacionario de extremos (p.ej. GEV).
4. Obtención del índice extremal asociado con cada tipo de tiempo.
5. Ajuste de la función de dependencia mediante una función de cópula gaussiana para cada tipo de tiempo.
6. Generación sintética de extremos multivariados considerando la probabilidad de ocurrencia de cada tipo de tiempo.

Son varios los pasos comunes con la metodología definida en el apartado anterior en el caso univariado (definición del predictor, definición de los patrones de tipos de tiempo, ajuste de las marginales y obtención del índice extremal). Sin embargo, en el caso multivariado, para definir el predictando se elegirán aquellos valores contemporáneos de Hs, Tm y SS que maximicen nuestra función respuesta (TWL) a escala diaria. Una vez que se han ajustado las marginales asociadas a cada tipo de tiempo, se ha de ajustar la estructura de dependencia. Para ello, de entre las diferentes familiar de cópulas, se ha elegido una cópula gaussiana dada su flexibilidad para modelar varias variables (Ben Alaya et al. 2014). Una cópula es una función multivariada cuyas marginales están distribuidas uniformemente en el intervalo N(0 1) y la correlación entre ellas analizada en este espacio n-dimensional. Finalmente, una vez que las marginales y la estructura de dependencia están ajustadas para cada tipo de tiempo, es posible generar realizaciones diarias de eventos multivariados basados en las probabilidades de ocurrencia anuales de los tipos de tiempo.

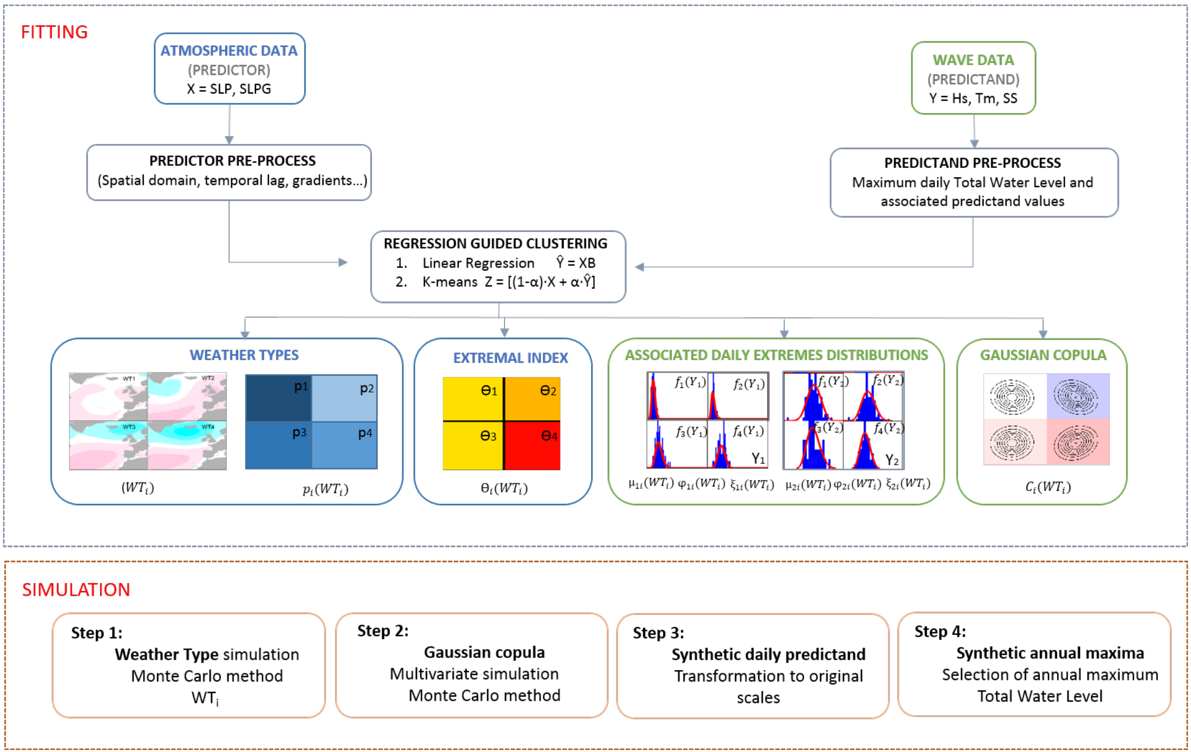


Figura 9. Metodología para generar eventos multivariados considerando la variabilidad climática

0.8.3 Aplicación

El modelo desarrollado en este apartado se ha aplicado en una localización en el norte de España, Santander. [4°W, 43.5°N]. Los datos de presiones a nivel del mar provienen de Climate Forecast System Reanalysis (CFSR, Saha et al. 2010) con una resolución espacial de 0.5° y disponibles desde 1979 a 2013. Los datos de oleaje, también disponibles desde 1979 a 2013 son obtenidos del reanálisis de oleaje desarrollado por Perez et al. 2015 con resolución temporal horaria y 0.125° de resolución espacial. Los datos de marea meteorológica provienen del reanálisis Global Ocean Surge (GOS) (Cid et al., 2014) con resolución temporal horaria y 0.125° de resolución espacial.

En este caso, al igual que en el caso univariado, se ha clasificado los 34 años de datos en 100 tipos de tiempo. La Figura 10 muestra los tipos de tiempo, representados por campos de presión a nivel del mar, así como el valor del índice extremal asociado y la probabilidad de ocurrencia media anual.

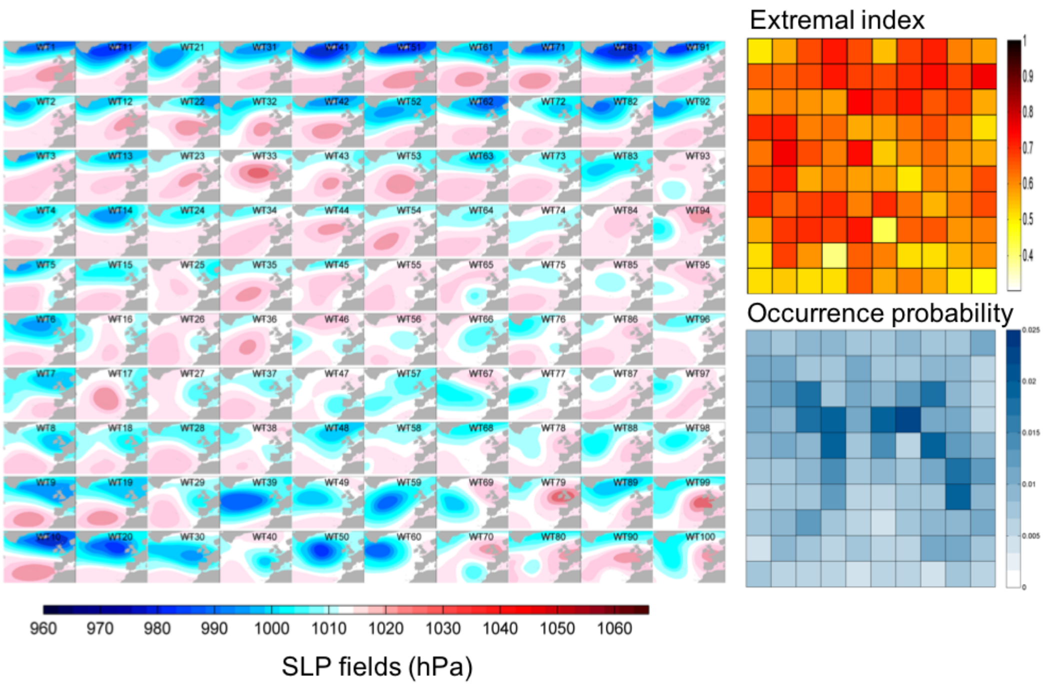


Figura 10. Clasificación en tipos de tiempo (WT). Índice extremal y probabilidad de ocurrencia asociada.

Las marginales asociadas a cada tipo de tiempo se ajustan a una GEV y posteriormente se analiza la estructura de dependencia mediante una copula gaussiana asociada a cada tipo de tiempo. Como se observa en la Figura 11, donde se muestra la correlación por pares de variables, la estructura de dependencia es altamente dependiente de la situación atmosférica que genera cada evento, existiendo una alta variabilidad entre grupos. Por tanto, al dividir nuestra muestra de datos según situaciones atmosféricas similares somos capaces de obtener mayor información de las variables involucradas permitiendo posteriormente una extrapolación más robusta.

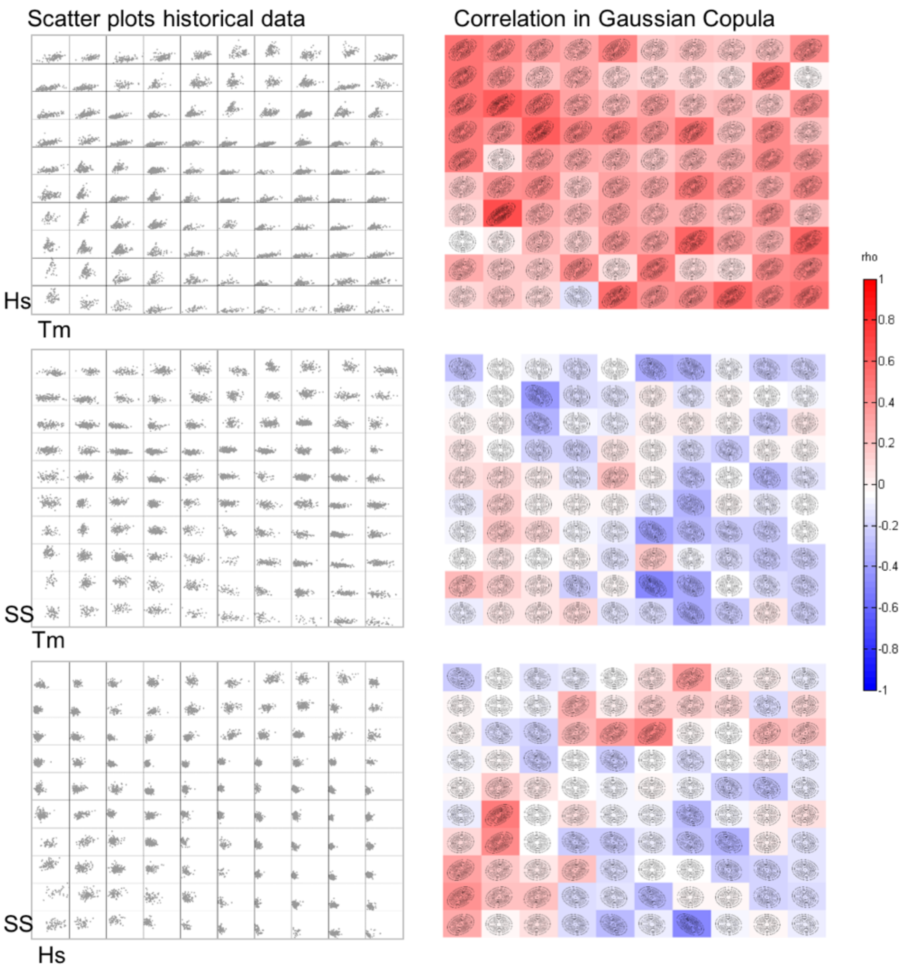


Figura 11. Los paneles de la izquierda representan los gráficos de dispersión para cada tipo de tiempo de los datos históricos representados en parejas (de arriba a abajo: Hs-Tm; SS-Tm y SS-Hs). Los paneles de la derecha representan las copulas gaussianas asociadas, el color de fondo representa el coeficiente de correlación.

Una vez que tanto las marginales como la estructura de dependencia están ajustadas para cada tipo de tiempo, es posible generar series sintéticas de eventos multivariados preservando las relaciones estadísticas pero siendo capaces de extrapolar a eventos extremos. En este caso, se han generado 300 realizaciones de 1500 años, obteniendo 164,250,000 eventos diarios.

El objetivo de esta metodología es la estimación de la probabilidad de excedencia de una función respuesta, en este caso TWL. En la parte superior de la Figura 12, el periodo de retorno de los máximos anuales obtenidos mediante la metodología propuesta (línea roja), se ha comparado con un ajuste estacionario de máximos anuales (línea azul). Se observan diferencias en la parte superior de la distribución, ya que en con el modelo multivariado de extremos propuesto se explora mejor las posibles combinaciones de las variables involucradas, como ha sido comentado por Bruun and Tawn (1998) y Gouldby et al. (2014) en trabajos previos.

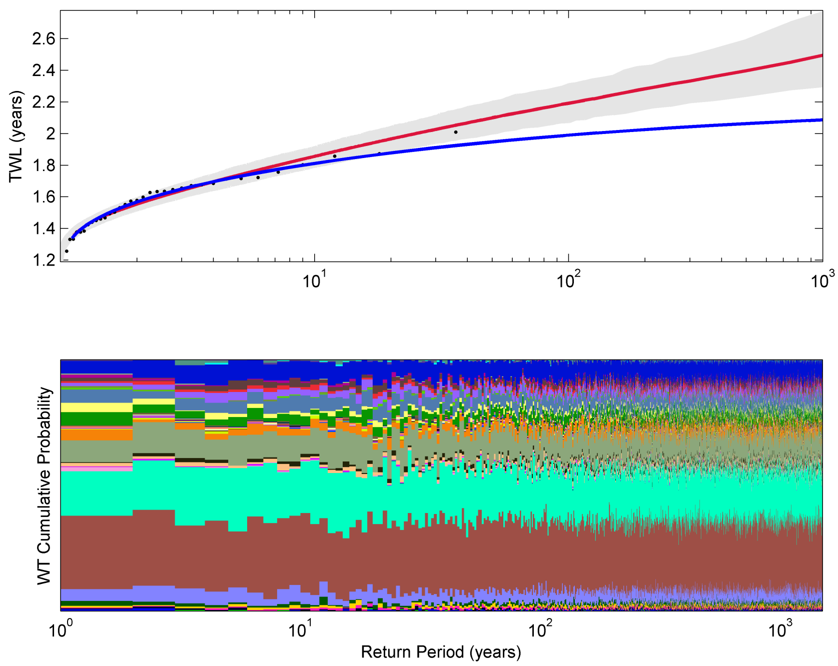


Figura 12. Panel superior: Periodo de retorno de la función respuesta, TWL. La línea roja representa la media de las simulaciones de Monte Carlo, y las bandas grises el percentil 95% de las simulaciones. La línea azul representa el ajuste GEV estacionario a los máximos anuales (puntos negros). Panel inferior: probabilidad de ocurrencia de cada tipo de tiempo de origen de los máximos auales.

0.8.4 Conclusiones

Este capítulo presenta un emulador multivariado a escala diaria, de las variables oceánicas no deterministas que condicionan la inundación costera (altura de ola, Hs, periodo medio Tm y marea meteorológica, SS). El uso de tipos de tiempo, permite introducir la no-estacionariedad mediante cambios en las probabilidades de ocurrencia de los tipos de tiempo. El uso de cópulas gaussianas para analizar la estructura de dependencia, facilita la inclusión de otras variables como precipitación, caudal fluvial, viento, etc., de una forma sencilla y escalable.

El modelo multivariado de extremos propuesto permite extrapolar la función de densidad conjunta de las variables que condicionan la inundación costera informando sobre cuáles son las situaciones atmosféricas responsables de los eventos más extremos.

En la zona de estudio la interacción entre marea astronómica y marea meteorológica se puede considerar despreciable, por tanto para obtener un emulador del nivel máximo del mar total a escala diaria, la contribución de la marea astronómica se puede incluir linealmente en la simulación de Monte Carlo.

El modelo presentado, no tiene en cuenta la cronología de los eventos, por lo tanto limita su uso a problemas donde la cronología no sea tan importante (p.ej. inundación). Sin embargo se podría expandir su aplicabilidad a problemas morfodinámicos donde la cronología de los eventos es crucial en el modelado del sistema, mediante por ejemplo, cadenas de Markov o términos autoregresivos de las probabilidades de ocurrencia de los distintos tipos de tiempo.

0.9 Capítulo IV: Conclusiones generales y futuras líneas de investigación

0.9.1 Contribuciones generales

Esta tesis ha dado lugar a varias contribuciones en forma de tres artículos científicos publicados y varias presentaciones en congresos internacionales y nacionales. Algunas investigaciones relacionadas con la tesis pero no incluidas en ésta han dado lugar a la publicación de tres artículos adicionales, en los cuales la doctoranda ha participado como co-autora. A continuación se presentan las conclusiones de los tres artículos principales.

0.9.1.1 Sumario de "El uso de downscaling híbrido y modelos simplificados de inundación para la estimación del riesgo por inundación costera"

Rueda, A., Gouldby, B., Méndez, F., Tomás, A., Lara, J., Losada, I., Díaz-Simal, P. (2015). The use of wave propagation and reduce complexity inundation models and meta-models for coastal flood risk assessment. Journal of Flood Risk Management. DOI: 10.1111/jfr3.12204

- La metodología desarrollada en este trabajo permite el análisis de la distribución estadística del daño y su distribución espacial en tiempos computacionales razonables. La eficiencia computacional se consigue gracias al uso de un modelo de downscaling híbrido (Camus et al. 2013; Gouldby et al. 2014) y un modelo de inundación simplificado (Jamieson et al. 2012).
- La estimación cuantitativa del daño es necesaria para la toma de decisiones, en el diseño de estructuras y minimización del riesgo. Para ello, la información de la probabilidad de la amenaza se debe combinar con las consecuencias asociadas para obtener las posibles pérdidas atribuidas a la inundación. Para obtener una cuantificación económica, se ha recurrido al uso de funciones de daño definidas para cada uso del suelo, y así obtener el daño económico asociado con

cada evento simulado.

- La eficiencia computacional permite no necesitar hacer hipótesis en la estructura de dependencia de las variables involucradas, por tanto, posibilita una mejor exploración de los eventos que pueden ocurrir en el sistema.
- Los eventos de inundación costera son eventos climáticos; como tales, para una estimación robusta del riesgo, es necesario el desarrollo de modelos multivariados de extremos que introduzcan la variabilidad climática en el análisis.

0.9.1.2 Sumario de "Un modelo de análisis extremal de altura de ola significante basado en tipos de tiempo"

Rueda, A., Camus, P., Tomás, A., Méndez, F. (2016). An extreme value model for maximum wave heights based on weather types. J. Geophysical. Research. Oceans, 10.1002/2015JC010952ç

- Se presenta un modelo estadístico para analizar la distribución de altura de ola máxima diaria. Este modelo se basa en la clasificación en tipos de tiempo, obteniendo grupos homogéneos del predictando agrupados en función de patrones atmosféricos similares.
- La no-estacionariedad se introduce en el modelo mediante cambios en las probabilidades de ocurrencia de cada tipo de tiempo. (p.ej. las probabilidades de ocurrencia de cada tipo de tiempo en un determinado mes, estación o año).
- Los resultados del modelo permiten identificar las situaciones atmosféricas relacionadas con los eventos más extremos. La influencia de patrones de gran escala como la NAO queda reflejada en el análisis así como la variabilidad interanual de altura de ola máxima.
- El uso de un modelo de downscaling estadístico basado en tipos de tiempo permite la reconstrucción de la altura de ola máxima diaria en diferentes periodos distintos al periodo de calibración. En este caso, se ha reconstruido la altura de ola máxima mensual a lo largo del s. XX

basado en el reanálisis atmosférico 20CR (Compo et al. 2011).

- Las proyecciones de cambio climático de la distribución de altura de ola extremal se podrían abordar con bajo coste computacional al analizar los cambios en las probabilidades de ocurrencia de los tipos de tiempo.

0.9.1.3 Sumario de "Un emulador multivariado de olas y marea meteorológica basado en tipos de tiempo"

Rueda, A., Camus., P., Tomás, A., Vitousek, S., Méndez, F.J (En revisión en Ocean Modelling). A multivariate extreme wave and storm surge climate emulator based on weather patterns

- Se ha desarrollado un nuevo modelo de downscaling estadístico para analizar la distribución extremal multivariada de olas y marea meteorológica.
- Para poder extrapolar la función de distribución conjunta de las variables que condicionan la inundación costera se han de ajustar las marginales (altura de ola significante, periodo de ola media y marea meteorológica) a un modelo de extremos (GEV) y la estructura de dependencia se analiza mediante una cópula gaussiana.
- La flexibilidad que presenta las copulas gaussianas permite escalar el problema a más variables, como la precipitación.
- La metodología propuesta permite relacionar eventos extremos de inundación con las situaciones atmosféricas que los han generado.

0.9.2 Futuras líneas de investigación

El desarrollo de esta tesis ha dado lugar a nuevos interrogantes, abriendo la posibilidad a nuevas líneas de investigación:

- La metodología a adoptar en el análisis de riesgo de inundación es muy dependiente (en el término de la amenaza) de las diferentes contribuciones de olas, marea astronómica o marea astronómica, así como presencia o no de ciclones tropicales… etc. Por tanto, establecer a escala global cuales son los condicionantes de la inundación costera puede ayudar a una mejor definición de la metodología a emplear.

- En referencia a la cascada de incertidumbre: todo modelado tiene asociado cierta incertidumbre. En el caso del sistema de modelado presentado en esta tesis para el análisis de riesgo por inundación costera igualmente hay cierta incertidumbre en cada uno de sus etapas. La cuantificación de estas incertidumbres no se han llevado a cabo durante el desarrollo de esta tesis pero, sin embargo, para ayudar en la toma de decisiones estas incertidumbres deben ser comunicadas de forma clara, y, por tanto, un estudio de las contribuciones relativas a la incertidumbre en cada etapa del modelado es aconsejable.
- En referencia a la aplicabilidad del emulador multivariado de eventos extremos a la verificación de obras marítimas: El modelo de extremos multivariado desarrollado, basado en técnicas de Monte Carlo, no asume ninguna hipótesis en la estructura de dependencia de las variables involucradas, es un generador aleatorio de eventos multivariado basado en la probabilidad de ocurrencia de determinadas situaciones atmosféricas, por tanto, su aplicabilidad para el análisis de verificación de Nivel III de obras marítimas puede ser relativamente sencilla al incluir los modos de fallo y parámetros del dique en la simulación, con la ventaja de la trazabilidad de los tipos de tiempo que originan el fallo en la estructura.
- En referencia a los procesos costeros: por un lado, en esta tesis se han empleado formulaciones empíricas por su bajo coste computacional. Sin embargo, existen modelos basados en procesos, (p.ej. tipo boussinesq) más sofisticados y, por tanto, con mayor coste computacional, que hoy en día no son viables para análisis probabilísticos de riesgo. Introducir técnicas para mejorar la eficiencia computacional e introducir más procesos físicos en el modelado es, por tanto, otra futura línea de investigación. Por otro lado, aunque en la literatura la calidad del modelado del oleaje bajo condiciones

moderadas se considera bastante aceptable (Ardhuin and Herbers 2002; Thomson et al. 2006; Ardhuin et al. 2007; Smit et al. 2014); no es así para el caso de eventos extremos, donde nuestro conocimiento es aún limitado. La observación de los procesos costeros en condiciones extremas, nos ayudaría a nuestro entendimiento de los procesos en estas condiciones extremas y, por tanto, ayudaría mejorar la parametrización en los modelos y finalmente, una mayor precisión en la estimación del riesgo.

- En referencia a la influencia de la lluvia y la descarga fluvial en la inundación costera: las tormentas responsables de la inundación en la costa pueden ocasionar no únicamente niveles del mar elevados sino también venir acompañadas de precipitación, por tanto la inclusión de esta en el análisis tanto estadístico como en el modelado numérico es esencial en determinadas localizaciones. Las metodologías y herramientas desarrolladas y/o usadas en esta tesis pueden simplificar su inclusión en el análisis.
- En referencia al análisis del riesgo: Esta tesis se ha desarrollado en el ámbito académico, introduciendo las más novedosas metodologías, sin embargo a expensas de la inclusión de información de los gestores costeros en la definición del problema. En un estudio aplicado, estas metodologías se vería altamente beneficiada al definir el problema desde la base, entendiendo cuales son las decisiones que se han de tomar, la naturaleza de la decisión y escalas temporales y espaciales de los procesos involucrados.
- En referencia a la interacción de la erosión e inundación costera: el marco metodológico desarrollado en esta tesis no tiene en cuenta la cronología de los eventos y, por tanto, no puede introducir cambios morfológicos en la simulación, a pesar que, en la realidad, los procesos de erosión e inundación están completamente acoplados. Para poder modelarlos conjuntamente se ha desarrollado un emulador climático que tiene en cuenta la cronología entre eventos (Rueda et al. (en revisión en JGR-Oceans). Sin embargo, hoy en día el modelado

acoplado de los procesos morfológicos e hidráulicos especialmente en periodos de recuperación está en continuo desarrollo.

Chapter I

Introduction and background to the research

1 Chapter I. Introduction and background to the research

1.1 Motivation

Over a billion people reside within 100km of an ocean coast, with an estimated 800 million living within 10 m of current sea level (Small and Nicholls 2003; McGranahan et al. 2007). Our ability to accurately predict the impact of storm related events on the coastal environment will be critical for coastal planners and managers to minimise the loss of life and economic losses in the future.

Coastal areas are dynamic, rich and complex, and full of interactions and nonlinearities. Over the past four decades, significant progress has been made in the understanding of the complex interaction between hydrodynamic, sediment transport, and morphological processes (Holman et al., 2015). However, our understanding of these processes and our ability to predict their behavior are still limited. Nevertheless, the increased coastal urbanization and threats of future climate change and sea level rise require to accurately establish future risks associated to different socioeconomic development scenarios. By doing so, decision makers can be provided with vital information for a best management of our coasts. This is to say that choices must be made, despite our limited understanding. As such, it would be crucial that risk assessments that contribute to decision-making or the formation of policy account for the uncertainty involved.

In common with other natural hazards, coastal flood risk may be quantified as the probabilities of flood events and their potential consequences (Gouldby and Samuels, 2005) and is usually expressed in monetary terms. The consequences of a particular climate-related event might not be directly proportional to its extremeness, since the final consequences are a function of all contributing factors whether they arise from the hazard, the exposure or the vulnerability, as it has been previously commented in the SREX report, acknowledging the role of 'human systems where vulnerability and exposure are high'. Based on the SREX report the definition of each component of risk is:

- Hazard: climate-related drivers, where the physical characteristics of each unit are taken into consideration.
- Exposure: the presence of people, livelihood, species or ecosystems, environmental services and resources, infrastructure, or economic, social, or cultural assets in places that could be adversely affected.
- Vulnerability: the propensity or predisposition to be adversely affected.

The hazard component is more related with the probabilities and the exposure and vulnerability condition the consequences for a given hazard. Therefore, to properly characterize the risk it is necessary a robust estimation of the probabilities and an accurate downscaling to get the associated consequences.

Coastal flooding events often arise as the combination of different variables such as mean sea level, astronomical tide, storm surge, significant wave height, mean period, sea level pressure, wind speed and/or wind direction. These variables, more often than not, contain some dependence between them that need to be considered on the statistical analysis of a coastal flood risk assessment. To this end, it is necessary to integrate the joint probability density function, including extremes, of the condition variables over a function that defines the consequences, typically economic damage. Historical records of sea conditions responsible for flooding are limited, therefore different statistical methods have been developed to extrapolate these historic data to extreme values. The use of Monte Carlo methods is a common practice to undertake this extrapolation, however, it can introduce a high computational burden for use in practical applications in the assessment of the subsequent components of the risk analysis. Hence, a simplifying assumption of full dependence between the sea condition variables is often made. This is not because robust methods are not available, it is due to the additional complexity and high computational effort they may require (Hawkes et al 2002, Defra 2005, Gouldby et al 2008).

To estimate the consequences, it is necessary to not only identify the system boundaries (multivariate extreme analysis) but also to select models that represent the relevant physical processes and variables. The selection of models for the appropriate representation of the system would depend on the resolution and domain of applicability of the model and the processes that it is able to represent. Usually, to obtain the final impact, different numerical models would need to be coupled. For example, the quantification of coastal flood risk in a particular location cannot be divorced from the longer-scale processes of storm fronts and ocean-atmosphere interaction. The natural boundary conditions for undertaking multivariate extreme value analysis should be defined off-shore to account for the sample of space of possible events that could occur in the system, prior to the complex nearshore wind wave and infragravity wave transformation processes of refraction, shoaling, breaking, etc. (Bruun and Tawn, 1998). Different local models are afterwards needed to consider the wave propagation processes, water levels and inundation extents. The selection of the appropriate numerical models is a trade off between the physical representation of the system and the computational expenses that it requires, as well as, the number of cases that need to be simulated, being the model selection not an easy task. To reduce the computational demand associated with complex numerical models, the use of hybrid emulators (Sacks et al. (1989), Kingston et al. (2011), Camus et al., (2011a)) is becoming a common practice (Gouldby et al. 2014).

An additional complication for coastal flood risk estimation is that, costal floods as climate-related events, are non-stationary (they change in space and/or time), not only the hazard component might change in time but also the exposure and vulnerability of the system and the dependences between them, increasing the complexity of the problem. There is little doubt about the influence of human policies in the evolution of our system. Although its quantification it is not an easy task, it might be an opportunity to improve our understanding of it by improving the representation of the processes, accessing to high resolution observational data and also developing methodologies that help to estimate the changes in our exposure to risk minimizing the cascade of uncertainty.

This thesis has been focused on the development of a novel, robust and statistically rigorous coastal flooding risk assessment in a changing climate. The developed statistical models might also help in the probabilistic design of coastal structures incorporating non-stationarity in the simulation of extreme nearshore sea conditions.

1.2 State of knowledge

This section provides a brief description of the context that involves the three main aspect addressed in this thesis: (1) analysis of multivariate extremes at an offshore location to define the hydraulic boundary conditions; (2) introduction of climate variability and climate change in the framework; (3) risk quantification (direct damage associated to wave and storm surge-induced flooding events).

1.2.1 Extreme Value Theory

The need to understand the frequency of natural hazards and develop resilient, long-term structures has promoted extreme value theory as a relevant discipline for engineering and applied science over the last century. The ultimate goal of this theory is the estimation of the probability of events larger than any on record (Coles, 2001).

Traditionally, extreme value theory, typically provides a statistical description of the maxima of a stationary process, where stochastic properties are considered constant in time. However, in the context of environmental variables, non-stationarity (e.g. seasonality, interannual variability, long-term trends, etc) is often found at different time scales (e.g Méndez et al., 2006; Holthuijsen, 2007;

Menéndez et al., 2009). Many structures have been designed on return levels derived from stationary methods, which assume no change in the frequency of extremes over time (Klein et al., 2009). However, the frequency of extremes is likely to change in response to changes in climate (IPCC, 2007; Milly et al., 2008). Therefore, statistical methods that account for the non-stationary behavior of the climate system are needed (e.g. Parey et al., 2010; Cooley 2013; Salas and Obeysekera 2013).

Typically, non-stationary behavior is introduced as a covariate in one or more of the parameters of the extreme value distribution, which are estimated by maximizing the likelihood function. The parameters of an extreme distribution are varied to represent non-stationary processes such as seasonal effects (modelled with harmonic functions, e.g. sine waves), long-term trends (linear and/or exponential terms) and climatic influence (covariates) such as the ENSO variability (Katz et al., 2002, Méndez et al., 2006). Other non-stationary methods use neural networks to model the non-linear behavior of covariates (Cannon, 2010). Changes in the covariates produce changes in the distribution of extremes and thus allow analysis of projected climate variability.

In addition, coastal flooding results from non-linear interactions of multiple oceanographic, hydrological, geological and meteorological processes (e.g., astronomical tide, monthly sea-level anomalies, storm surge, wave set-up, wind set-up, fluvial discharges, precipitation and land subsidence). Extreme coastal flooding can result from an exceptional intensity of a single process (e.g. storm surge), but more often results from the combination of elevated values of more than one of the aforementioned processes, namely a compound event (Leonard et al., 2014). Statistically, longer records result in smaller errors, and furthermore, the record should be long enough to encompass the range of variability in extremes (Serafin and Ruggiero, 2014). This has prompted the development of probabilistic methods to simulate thousands of years of estimates of multivariate parameters (Hawkes et al. 2002, Wahl et al. 2012, Corbella and Strech 2013). Most probabilistic methods analyse the dependence between variables of interest without taking into consideration the climate (Hawkes et al. 2002, Wahl et al. 2012, Corbella and Strech 2013) or introduce the climate as a covariate which usually impose the use of a single variable as main driver due to the complexity involved (Mendez et al., 2006, Callaghan et al., 2008, Menéndez et al., 2009, Cannon 2010). Therefore, a flexible framework able of dealing with multivariate extremes is required.

1.2.2 Climate variability – Statistical downscaling

Statistical downscaling (SD) approaches are used to relate large scale predictors to regional-to-local predictands. SD provides a cheap and efficient alternate to dynamical downscaling (i.e. performing a series of nested simulations). SD has proven to be a useful tool to analyze meteorological variables at a variety of time scales (Giorgi et. al., 2001, Gutierrez et al., 2013, Camus et al. 2014). Giorgi et al., (2001), classifies the SD methods into: i) transfer functions, ii) weather type approaches and iii) stochastic weather generators. Each method has its own strengths and weaknesses, reproducing certain local weather statistical characteristics with more or less accuracy, being difficult to select one against other and always depending on each particular case. Other relevant aspect that determines the skills of the SD is the predictor choice, in terms of variables and spatial domain (Fowler et al., 2007). In the case of sea surface waves, sea level pressure (SLP) fields and the squared SLP fields have been demonstrated to be a good predictor (Wang et al., 2012 and Casas-Prat et al., 2014). Among the available SD methods, weather-types approaches allow to downscale multiple sea-state parameters thanks to the non-linear relationships established. The use of weather-types approaches to successfully downscale the mean (Camus et al., 2014) or extremes (Garavaglia et al., 2010) of a local variable of interest via large-scale predictors such as sea-level pressure fields (SLP) has been already performed. However, its applicability to estimate return values of a variable of interest and to analyse the extreme wave climate variability (Izaguirre et al. 2011) at different time scales such as seasons or years has not been explored previously.

1.2.3 Coastal flood risk modeling

Risk is defined as the product of the probability of a hazard event and the consequences, and they must account for the sample of space of possible events that can occur in the system. The estimation of the impact of a simulated coastal flood event may require the coupling of different hydrodinamic models to account for the different physical processes, such as wave propagation processes, wave overtopping or water flow over the floodplain. There are numerous numerical models used for simulating the propagation of waves from offshore to nearshore. Perhaps the most widely used model is SWAN (Booij et al., 1999). Even with increases in computational resources, these numerical models can be impractical to run dynamically for large data sets. In recognition of these practical limitations, methods comprising the application of meta-models to the wave transformation process (Camus et al., 2011a), have been developed. There are also a wide variety of numerical models available for simulating flood events. These range in complexity from simplified sea level projection (bathtub) methods, to volume spreading methods (Gouldby et al., 2008a), diffusion wave methods (Bates and De Roo, 2000) and models that solve the full shallow water equations (L'homme et al. 2010), for example. The simplified models have been widely applied in probabilistic analyses due to their computational efficiency. This efficiency is however, often obtained at the expense of accuracy of the predicted flooding scenario. More recently, new hybrid diffusion wave/full shallow water equation (SWE) models have emerged (Bates et al., 2010, Jamieson et al., 2012).

Finally, the information of the hazard must be combined with the exposure and vulnerability to estimate the consequences. To that end, the asset value and the flood damage functions have to be assigned to the different land-use units. Different databases can be consulted such as the Multi Coloured Manual (UK) (Penning-Rowsell et al. 2003), HAZUSMH multi-hazard software (United States) (FEMA, 2009) or the JRC Model (European Commission/HKV)(Huizinga, 2007) where general damage functions are defined.

A methodology that overcomes the computational constraints while preserving the accuracy in the simulations is therefore required for a probabilistic risk assessment.

1.3 Objectives of the thesis

The general objective of this thesis is to develop a novel, robust and statistically rigorous coastal flooding risk assessment for a changing climate. After the review of the state of knowledge in the different aspects involved, the specific objectives of this thesis are focused on:

1) To develop a framework to downscale the multivariate extreme value distribution of marine dynamics to flooding extent and calculate the statistical distribution of damage. (Chapter II Rueda et al. 2015, paper published in Journal of Flood Risk Management).
2) To develop an extreme value model able of dealing with climate variability and intramonthly variability (daily maxima). (Chapter III, Rueda et al. 2016, paper published in Journal of Geophysical Research-Oceans).
3) To develop a framework for a time-dependent multivariate extreme value model. (Chapter IV, Rueda et al. 2016, paper under review in Ocean Modelling).

1.4 Layout of the thesis

The structure of the thesis is organized as follows:

In this Chapter I, the motivations for the research and the background to the research of the studied aspects are presented first. At the end of this chapter the specific objectives designed to answer the questions raised are outlined and the structure of the thesis is described.

The following three chapters (II, III and IV) address the specific objectives of the thesis. Each of the chapters corresponds to a paper published (or accepted) in peer-review journals. The PhD candidate is the lead author on all of them. Each paper retains its original content, but its format has been adapted to this thesis.

- Chapter II "The use of wave propagation and reduced complexity inundation models and metamodels for coastal flood risk assessment" presents a novel application of state-of-the-art statistical and numerical models to assess coastal flood risk in a local area. This work reveals the necessity to introduce a framework where climate variability is considered in the multivariate extreme analysis.
- Chapter III "An extreme value model for maximum wave heights based on weather types" develops a univariate model to estimate the statistical distribution of significant wave height maxima based on a large-scale atmospheric predictor. The model introduces the non-stationarity by changes in the occurrence probabilities of the synoptic situations, namely, weather types.
- Chapter IV "A multivariate extreme wave and storm surge climate emulator based on weather patterns" develops a multivariate model, based on the univariate case, where the dependence structure associated with the marine variables responsible of coastal flooding is taken into consideration for the extrapolation of their joint density function.

Finally, Chapter V "Summary and future research" reviews the main results of the thesis and suggests priority areas to be developed in the future.

1.5 Thesis contribution

1.5.1 Scientific projects

This thesis has been partially developed under the MUSCLE-BEACH project, founded by the Spanish 'Ministerio de Economia y Competitividad' under Grant BIA2014-59643-R. The thesis has also been partially funded by project "2013/S 122-208379 - Assessment of climate impacts on coastal systems in Europe" from the European Commission, JRC, Institute for prospective Technological Studies (IPTS) and under the Grant/Cooperative Agreement G15AC00426 by the U.S. Geological Survey.

1.5.2 Scientific production

The work in this thesis has yielded to 3 scientific papers published and/or accepted to several scientific journals:

1 Rueda, A., Gouldby, B., Méndez, F., Tomás, A., Lara, J., Losada, I., Díaz-Simal, P. (2015). The use of wave propagation and reduce complexity inundation models and meta-models for coastal flood risk assessment. Journal of Flood Risk Management. DOI: 10.1111/jfr3.12204

2 Rueda, A., Camus, P., Tomás, A., Méndez, F. (2016). An extreme value model for maximum wave heights based on weather types. J. Geophys. Res. Oceans, 10.1002/2015JC010952

3 Rueda, A., Camus., P., Tomás, A., Vitousek, S., Méndez, F.J (Under review at Ocean Modelling). A multivariate extreme wave and storm surge climate emulator based on weather patterns.

During the progress of the thesis the PhD candidate has also contributed in several papers published in peer-review scientific journals:

1 Gouldby, B., Méndez, F., Guanche, Y., Rueda, A., Mínguez, R. (2014). A methodology for deriving extreme nearshore sea conditions for structural design and flood risk analysis. Coastal Engineering. 88, 15-26

2 Camus, P., Méndez, F.J., Losada, I.J., Menéndez, M., Espejo, A., Pérez, A., Rueda, A., Guanche, Y. (2014a). A method for finding the optimal predictor indices for local wave climate conditions. Ocean Dynamics, 64 (7), 1025-1038.

3 Camus, P., Menéndez, M., Méndez, F.J., Izaguirre, C., Espejo, A., Cánovas, V., Pérez, J., Rueda, A., Losada, I.J., Medina, R. (2014b). A weather-type statistical downscaling framework for ocean wave climate. Journal of Geophysical Research, DOI: 10.1002/2014JC010141.

4 Camus, P., Rueda, A., Méndez, F., Losada, I. (Under review – Ocean Dynamics). An atmospheric-to-marine synoptic classification for statistical downscaling marine climate.

5 Rueda, A., Hegermiller, C., A., Antolinez, J.A.A., Camus, P., Vitousek, S., Ruggiero, P., Barnard, P., L., Erikson, L., H., Tomas, A., Mendez, F.J. (Under review - Journal of Geophysical Research-Oceans). Multi-scale climate emulator of multimodal wave spectra: MUSCLE-spectra.

6 Rueda, A., Vitousek, S., Camus, P., Tomás, A. Espejo, A., Losada, I., Barnard, P., L., Erikson, L., H., Ruggiero, P., Reguero, B., Méndez, F.J. (submitted to PNAS). “Global classification of Coastal Flooding Climates”

Besides, the work presented in this thesis has been presented by the PhD candidate in several scientific congresses and conferences:

1 Rueda, A., Camus, P., Méndez, F., Sano, M., Strauss, D., Hemer, M. 2013. Wave climate projections using statistical downscaling for the Gold Coast, Australia. EGU2013-670. Viena (Austria)

2 Rueda, A., Gouldby, B., Méndez, F.J., Tomás, A., Lara, J. Computationally efficient, yet robust, coastal flood risk analysis using a reduced complexity inundation model and meta model. Proceedings of the 6th International Conference on Flood Management (ICFM6). 17-19 Sept, 2014. Sao Paulo (Brazil).

3 Rueda, A., Méndez, F., Tomás, A., Espejo, A., Cid, A., Castanedo, S., del Jesus, M., Díaz, G., Toimil, A., Silio, A., Diez, J., Medina, R., Gouldby, B. A Practical multi-model approach for coastal flooding due to tropical

cyclones. Proceedings of the 6th International Conference on Flood Management (ICFM6). 17-19 Sept, 2014. Sao Paulo (Brazil).

4 Rueda, A., Camus, P., Tomás, A., Méndez, F. Un emulador de inundación costera basado en variabilidad climática. XII Jornadas Españolas de Ingeniería de Costas y Puertos, Avilés, 24-25 Jun, 2015.

5 Rueda, A., Camus, P., Tomás, A., Méndez, F. A Monte Carlo multivariate climate emulator for coastal flooding. EVAN 2015. Santander, 16-18, Sept. 2015

6 Rueda, A., Camus, P., Méndez, F., Tomás, A., Luceño, A. An extreme value model for maximum wave heights based on weather types. 14th International Workshop on Wave Hindcasting and Forecasting. Key West, Florida, USA, Nov 10, 2015.

7 Rueda, A., Camus, P., Méndez, F., Tomás, A., Luceño, A. Monte Carlo climate based emulator for coastal flooding. 14th International Workshop on Wave Hindcasting and Forecasting. Key West, Florida, USA, Nov 10, 2015.

8 Rueda, A., Hegermiller, C., Antolinez, J. A.A, Serafin, K. A., Anderson, D., Ruggiero, P., Vitousek, S., Barnard, P., Erikson, L., Camus, P., Tomás, A., González, M., Mendez, F. J. Towards a Multi-scale Monte Carlo Climate Emulator for Coastal Flooding and Long-Term Coastal Change Modeling: The Beautiful Problem. Ocean Sciences, New Orleans, USA, Feb. 2016

Chapter II

The use of wave propagation and reduce complexity inundation models and meta-models for coastal flood risk assessment

2 Chapter II. The use of wave propagation and reduce complexity inundation models and meta-models for coastal flood risk assessment.

Abstract

To estimate coastal risk, it is necessary to integrate the joint probability density function, including extremes, of the sea condition variables over a function that defines the consequences, typically economic damage. The use of Monte Carlo methods is common practice to undertake this integration, however, it can introduce a high computational burden for use in practical applications. Hence, a simplifying assumption of full dependence between the sea condition variables is often made. This chapter describes a method that overcomes this simplifying assumption through the use of two techniques. A hybrid emulator of the SWAN wave model is used to increase the computational efficiency associated with the wave transformations. In addition, a computationally efficient dynamic inundation model has been incorporated to further reduce the computational burden. To demonstrate the system, it has been applied to an urban coastal area located in Northern Spain.

This chapter is based on: Rueda, A., Gouldby, B., Méndez, F., Tomás, A., Lara, J., Losada, I., Díaz-Simal, P. (2015). The use of wave propagation and reduce complexity inundation models and meta-models for coastal flood risk assessment. Journal of Flood Risk Management. DOI: 10.1111/jfr3.12204

2.1 Introduction

Flood risk may be quantified as the probabilities of flood events and their potential consequences (Samuels et al., 2005) and is usually expressed in monetary terms (e.g. €/year). Historical records of sea conditions responsible for flooding are limited, therefore some statistical methods have been developed to extrapolate these historic data to extreme values. Extreme coastal flooding events often arise as the combination of different variables: mean sea level, astronomical tide, storm surge, significant wave height, and mean period, wind speed, wind direction. These variables, more often than not, contain some dependence between them that requires consideration when defining statistical models that simulate extreme events. When undertaking coastal flood risk analysis in practice, these dependencies are not generally considered in a robust manner and simplifying assumptions are made. This is not because robust methods are not available, it is due to the additional complexity and computational burden they require (Hawkes et al 2002, Defra 2005, Gouldby et al 2008).

The methodology described in this chapter overcomes simplifying assumptions regarding the handling of dependence within the sea condition variables by using a robust multivariate extreme value model. This requires the use of a Monte Carlo method that outputs a large set of sea condition events that imposes a high computational demand in the subsequent components of the risk analysis. This demand is significantly reduced by the use of an emulator of two specific techniques. A hybrid emulator of the SWAN wave model has been applied. Emulators are well-established as methods for reducing the computational demand associated with complex numerical models (Sacks et al. (1989), Kingston et al. (2011), Camus et al., (2011a)). The design points used to construct the emulator are obtained using a selection method applied to the Monte Carlo output (Camus et al. (2011b), Gouldby et al. (2014)). Additional computational efficiencies are made through the use of a reduced complexity flood inundation model. Reduced complexity inundation models are well-established in current practice. The particular inundation model used in this work, described by Jamieson et al (2012), uses a meshing system that comprises sub-cell topographical aspects and uses an inertial formulation of the shallow water equations developed by Bates et al (2010).

This methodology could be applied to small or large spatial scales without using excessive computational resources. It thus offers significant improvements to approaches applied in current practice. A case study on the north coast of Spain mainly affected by overtopping events is used to show the ability and flexibility of the proposed methodology.

2.2 Overview of the methodology

In common with other natural hazard analysis, flood risk (R) is typically defined as probability of consequence (C) and is typically expressed in terms of Expected Annual Damage (EAD), USACE (1996). In the context here, the probability component comprises multiple sea condition variables and hence can be written as:

$$R = E[C] = \int_{0}^{\infty} f_{\mathbf{X^0}}(\mathbf{X^0})\, g(\mathbf{X^0})\, d\mathbf{X^0} \qquad [1]$$

where $\mathbf{X^0}$ is a vector comprising the offshore sea condition variables (wave height, wave period, wave direction, wind intensity and direction, astronomical tide, storm surge level, mean sea level) and fx0(X0) is the joint probability density function of these sea-conditions. The consequences of flooding are a function, g, of these sea conditions. Within the method described here, the joint probability density function of offshore sea conditions is extrapolated to extreme values using the method of Heffernan and Tawn (2004), hereinafter referred to as HT04. This overcomes limitations of existing simplified methods applied in practice (Defra 2005). The HT04 method has been applied in the context of fluvial flood risk analysis by Keef et al. (2009), Keef et al., (2012), Lamb et al. (2010) and Wyncoll and Gouldby (2013). It has also been applied to offshore wave conditions (Jonathan et al. 2013a, Ewans and Jonathan, 2013, Jonathan et al.

2013) and nearshore environment (Gouldby et al. (2014)).

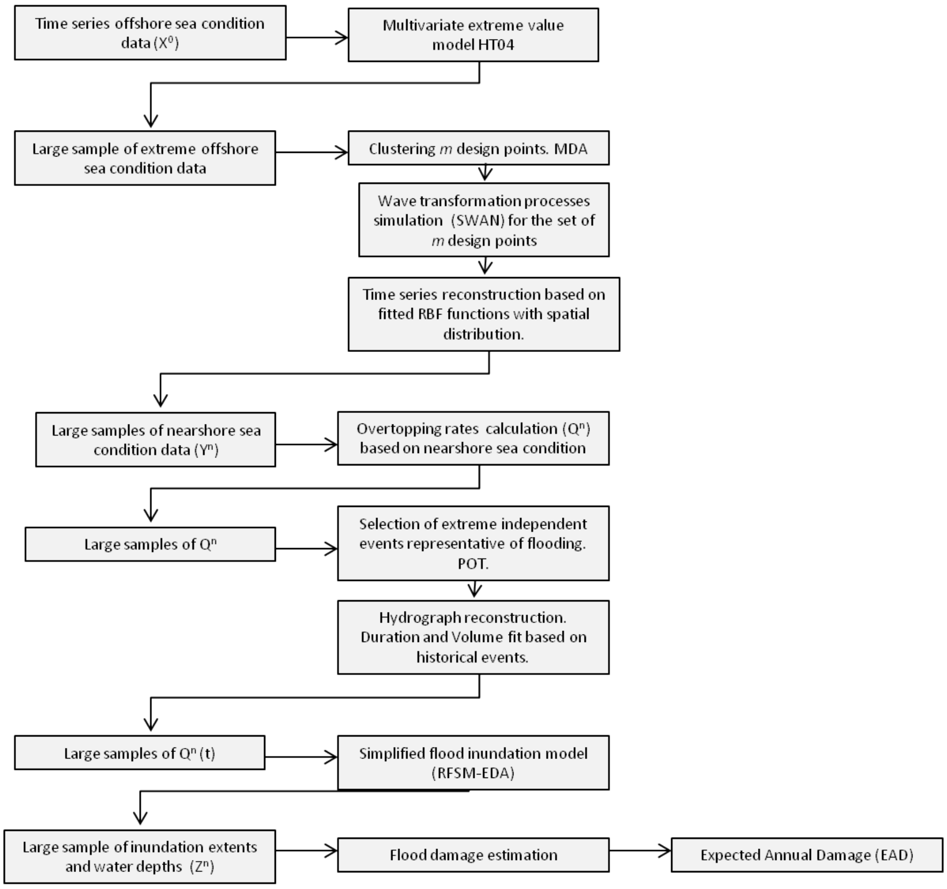


Figure 1. Methodology Flow Chart

The multivariate analysis applied provides a stochastically generated set of peak values of sea-conditions, which includes extremes and preserves the dependence characteristics of the original data. This set of events are transformed to nearshore using a hybrid emulator of the SWAN (Simulating WAves Nearshore) (Booij et al., 1999) wave transformation model. The design points for the emulator are selected using a selection algorithm using the approach described by Camus et al (2011a). The transformed nearshore peak sea-condition events are then used to calculate overtopping rates based on empirical methods from the EurOtop manual (Pullen et al. 2007) for each coastal defense section. The corresponding overtopping rates form the boundary conditions for flood inundation simulations performed using RFSM-EDA, (Jamieson et al., 2012). The resulting outputs are aggregated to determine risk. The different steps of the methodology are summarized in Figure 1 and described in detail throughout the case study.

2.3 Case study

The location chosen for the case study site is Sardinero Beach in the coastal town of Santander on the Cantabrian Coast in northern Spain. This coastal area is sporadically affected by large swells generated in the North Atlantic basin (significant wave height up to 10m, storm surge level up to 1m and spring tidal range up to 5m) producing wave-induced overtopping events. Sardinero is an urban sandy beach very popular due to the recreation amenities throughout the year. The beach and the city are separated by a promenade of varying height (Figure 2). The promenade serves as coastal defence for a residential area.

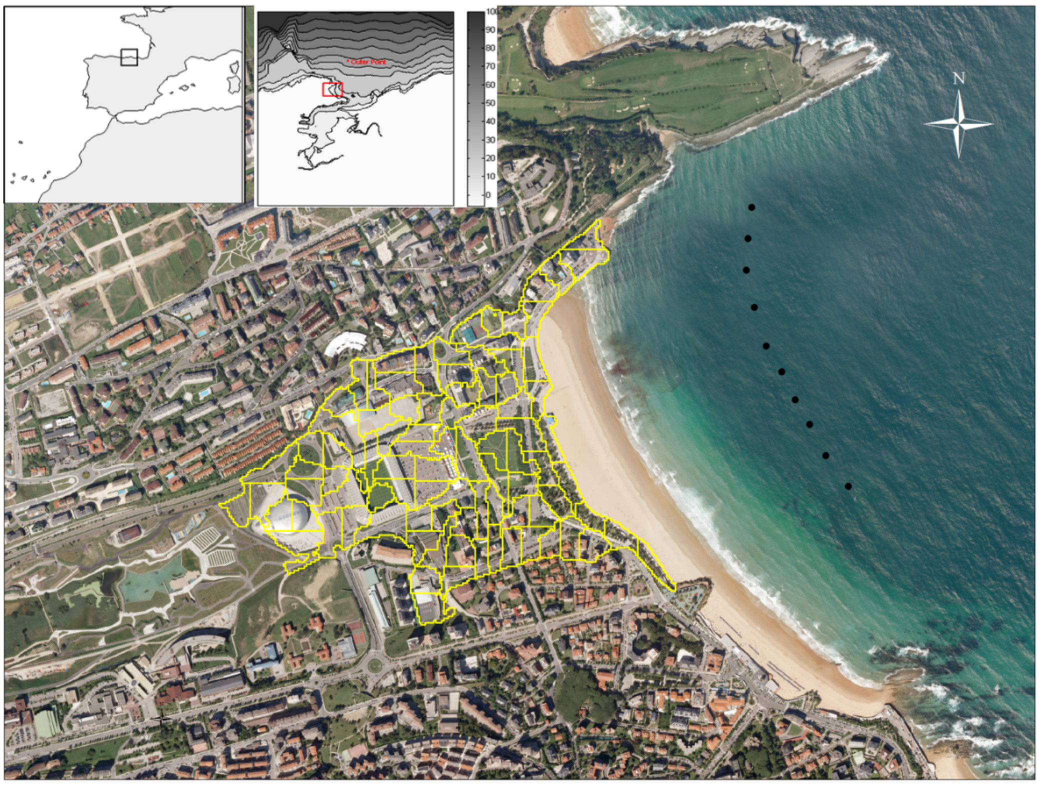


Figure 2. Map of the study location, nearshore points (black) and RFSM-EDA computational mesh (yellow).

2.3.1 Data

The Global Ocean Waves (GOW) calibrated hindcast, (Reguero et al., 2012, Mínguez et al., 2011), has been used as the primary source of offshore wave data for this study. This reanalysis data set uses the Wave Watch III numerical model forced by 6-hourly wind fields from the atmosphere model NCEP/NCAR. The reanalysis GOW spans from 1948 to 2013 with hourly resolution. It has been further downscaled to regional scale to obtain a Downscaled Ocean Waves (DOW) database, (Camus et al., 2013). The DOW data comprises hourly data for the period 1948-2013 with a spatial resolution of approximately 200 m, which has been extensively validated with nearshore buoys throughout the Spanish coast.

Sea level data (astronomical tide and surge residuals due to pressure and wind) in the form of hourly time series from two different tide gauges, the Spanish Institution of Oceanography (1940-2005) (IEO) and from Puertos del Estado (1995-present), were used in the analysis. The gaps in the time series were filled using a regional storm surge reanalysis of southern Europe, Global Ocean Surge (GOS) (Cid et al., 2014).

The topographic data has been obtained from a national topographic map 1:25000 (MTN25) from the National Geographic Institute, which has been resampled to a 5 meters horizontal resolution Digital Terrain Model (DTM). The bathymetry used has been defined by means of: (a) the global bathymetry "General Bathymetric Chart of the Oceans" (GEBCO), (Becker et al. 2009). It has a spatial resolution of 1' from a combination of sounding waves and satellite data. It is available at the British Oceanographic Data Centre (BDOC) and; (b) the Spanish coastal charts, providing a detailed representation of the shallow water areas.

2.3.2 Multivariate Extreme Value Method

A joint probability method, based on HT04, is adopted to obtain the large sample of offshore multivariate extreme dataset necessary to characterize risk.

The methodology and data used is described in detail in Gouldby et al. (2014) and is summarized briefly here.

The offshore variables considered within the case study site include: wave height (*Hs*), mean period (*Tm*) and direction (θ_{Hs})), winds (speed (*U*) and direction (θ_U)), sea level (surge (*S*) and astronomical tide (*AT*)) that can combine to induce flooding.

The problem then is to determine the probability of exceeding specified levels of the flood consequence, which is directly conditioned by the combination of the offshore variables. To define the flood consequences, variables related with the impact like the number of injuries or fatalities, for example, or alternatively economic damage can be used. Often intermediate variables such as depth or velocity of flooding are required for mapping purposes. In this case study, economic damage has been defined as the variable of interest denoting it as *C* (see equation 1).

Whilst there are alternatives, there are significant benefits in employing joint probability methods (JPM), (Bruun and Tawn 1998, Hawkes et al. 2002 and Gouldby et al. 2014). These JPM methods require extrapolation of the joint density of $\boldsymbol{X}^{o}$ to extremes and then integration over the region $\Delta(\boldsymbol{X}^{o})>c$

$$\Pr(C > c) = \int_{C>c} f_{\mathbf{X}^{o}}(\mathbf{X}^{o})\, d\mathbf{X}^{o} \qquad [2]$$

The HT04 approach evolves by first specifying semi-parametric marginal distributions, with the extremes defined by Generalised Pareto Distributions (GPD´s) which are transformed onto Gumbel scales. If $\boldsymbol{X'}_i$ denotes the vector of all transformed variables $\boldsymbol{X'}_j$ excluding X'_i, the method is typically applied using the multivariate non-linear regression model

$$\boldsymbol{X'}_{-i}|X'_i = \boldsymbol{a}X'_i + {X'_i}^{\boldsymbol{b}}\,\boldsymbol{W} \;\; for\; X'_i > v \qquad [3]$$

where ***a*** and ***b*** are vectors of the parameters from the fitted pair-wise regression model, *v* is a specified threshold and ***W*** is a vector of the regression residuals. The model is fitted using maximum likelihood where the residuals are assumed to be normally distributed. Once fitted, a Monte Carlo simulation procedure is used whereby samples from the residuals are used to generate realisations of $\boldsymbol{X}'_i$. These are then transformed back to the original scales. The result is a large (in this case approximately 314,000 realisations, representative of 10,000 years) set of offshore sea condition events.

2.3.3 Nearshore Data

To proceed with the analysis, it is necessary to transform the stochastically generated set of offshore conditions to the nearshore. Transformation of the large set of offshore sea conditions may often not be practical due to computational resource constraints. To overcome this constraint, a meta-model of SWAN has been developed. Whilst there are a wide variety of meta-modelling methods, Camus et al. (2011a), has used Radial Basis Functions (RBF´s) to replicate the SWAN wave model and hence that method is chosen here. The RBF has the following form:

$$\mathbf{Y}^{\mathbf{N}} = p(\mathbf{X}^o) + \sum_{i=1}^{m} a_i \Phi(\left\| \mathbf{X}^o - \mathbf{D} \right\|) \qquad [4]$$

Here, $\boldsymbol{Y}^{\boldsymbol{N}}$ is the vector of the *n* near-shore sea conditions (ie the output of the meta-model) and:

$$p(\boldsymbol{X}^{\boldsymbol{o}}) = b_0 + b_1 X_1^o + b_2 X_2^o ...... + b_n X_n^o \qquad [5]$$

$b_0, b_1 ... b_n$ are coefficients to be found by fitting the RBF to the known points and Φ is a Gaussian function defined as:

$$\Phi(\left\| \mathbf{X^o} - \mathbf{D} \right\|) = \exp(-\frac{\left\| \mathbf{X^o} - \mathbf{D} \right\|^2}{2c^2}) \qquad [6]$$

where c is a shape parameter, ***D*** is a vector comprising the *m* "known" near-shore wave conditions derived from the SWAN model design point simulations. Once fitted, the RBF´s are used in place of the SWAN model to transfer the offshore data to a series of nearshore locations (Figure 2). The number of design points (m) used to construct the meta-model was *m*=500. The Max-Diss Algorithm (MDA) was run to define these design points. These points are shown, together with the simulated and historical data, in Figure 3.

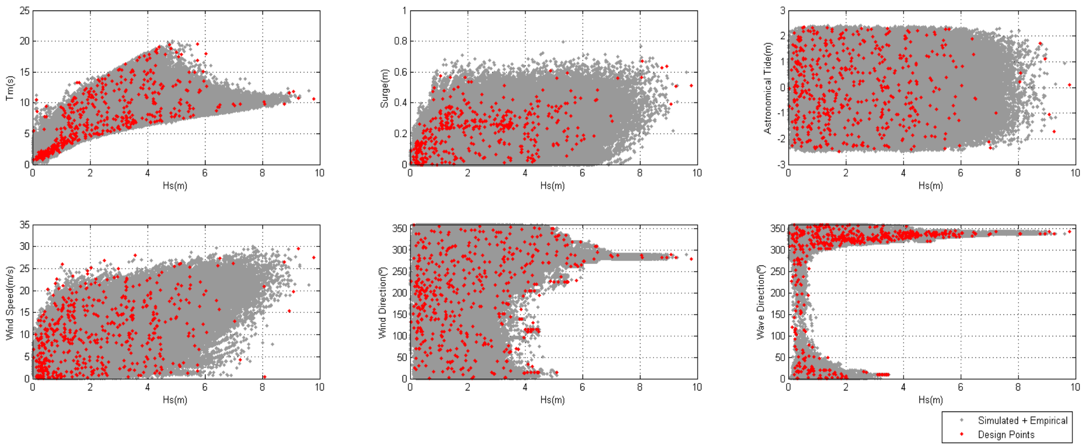


Figure 3.Simulated offshore data and design points output from the MDA algorithm

2.3.4 Overtopping Rates

The estimation of the floodplain inflow will depend on the typology of the defense structure. The most recent manual to predict wave overtopping of sea defense and related coastal or shoreline structures is EurOtop (Pullen et al. 2007). Based on the formulae presented in EurOtop for the positive, zero and negative freeboard situations, overtopping rates are calculated at each defense section for every simulated sea state at the toe of the structure, obtaining a series of peak overtopping rates, Q^N. As an example, the formulae to obtain overtopping rates for smooth sloping and bermed seawalls is given by eq.7.

$$\frac{q}{gT_m H_s} = Q_0 \exp\left(-b\frac{R_c}{T_m\sqrt{gH_s}}\right) \qquad [7]$$

Some of the defenses have a berm, which can reduce the overtopping rate by a factor up to 0.6. Figure 4 shows the historical time series reconstruction of the offshore point (X_0), a local point (Y_6) and the associated hourly averaged overtopping rates (Q_6) in section number "6".

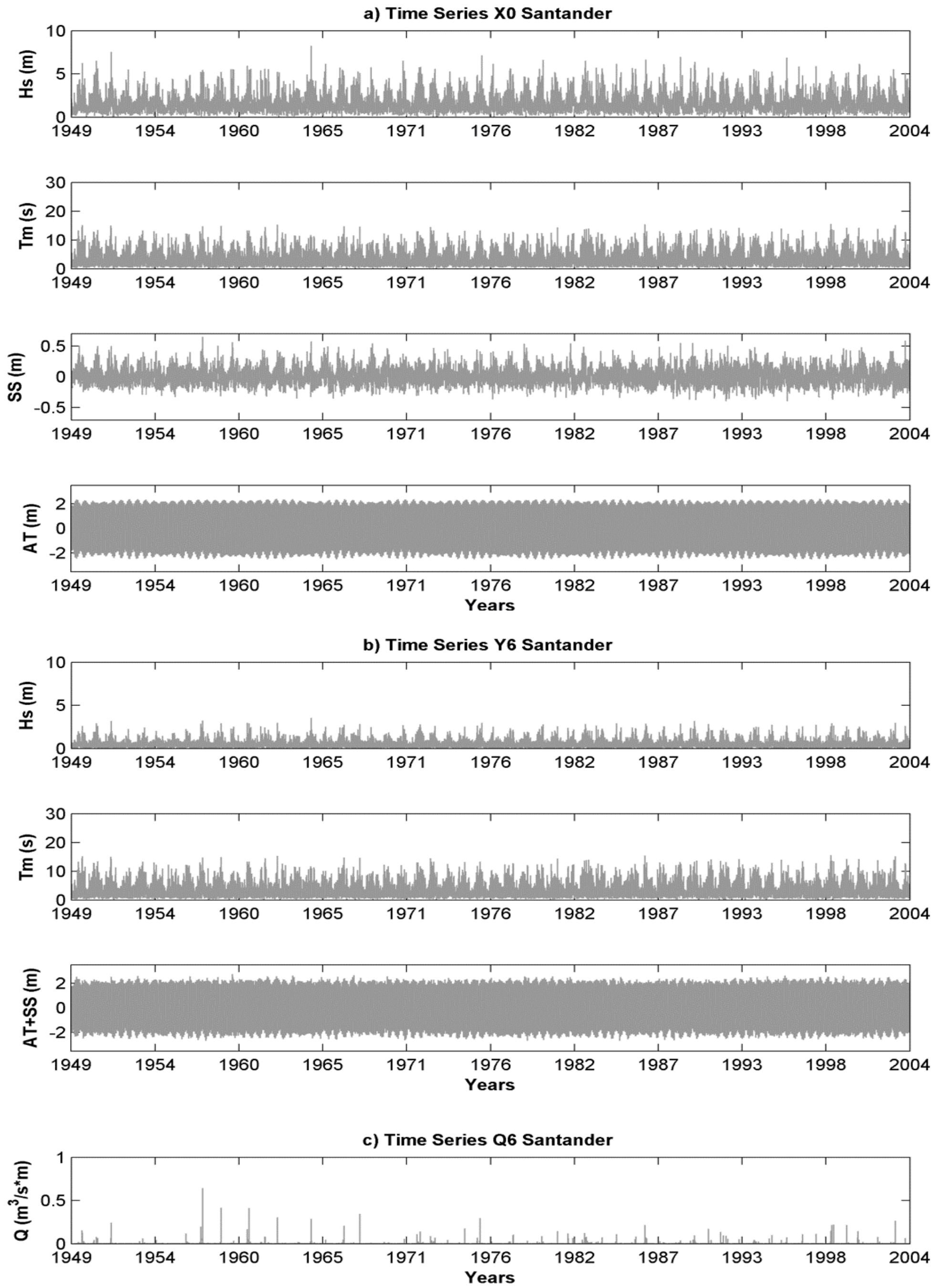


Figure 4.Historical time series reconstruction from (a)offshore reanalysis wave data to (b)nearshore wave data and finally (c)overtopping rates in section 6.

The next step in the analysis is to define the hydraulic boundary conditions used as input to the inundation model. These are specified in terms of a hydrograph *$Q_n(t)$* for each of the stochastically simulated peak events. For practical purposes, the design hydrographs have been kept simple while synthesizing and preserving some physical properties (such as peak overtopping discharge *P*, volume *V*, duration *d*, and hydrograph shape) (Serinaldi, et al., 2011). In this study, a triangular hydrograph shape has been assumed based on these three parameters. The physical properties of each simulated hydrograph are based on historical information where the events chosen are those with an overtopping rate representative of flooding (>0.1m3/s), this threshold value was set empirically since the inundation extent produced by lower values of overtopping rate were found insignificant for this modelling configuration. The historical data used is selected with the standard peaks-over-threshold approach and the corresponding duration, and total volume of each event has been calculated.

With these examples of observed hydrographs a relationship has been established between peak overtopping rate and its corresponding duration (Figure 5). Using this relationship a synthetic hydrograph for each stochastically simulated sea-state can be defined and used as input for the inundation model.

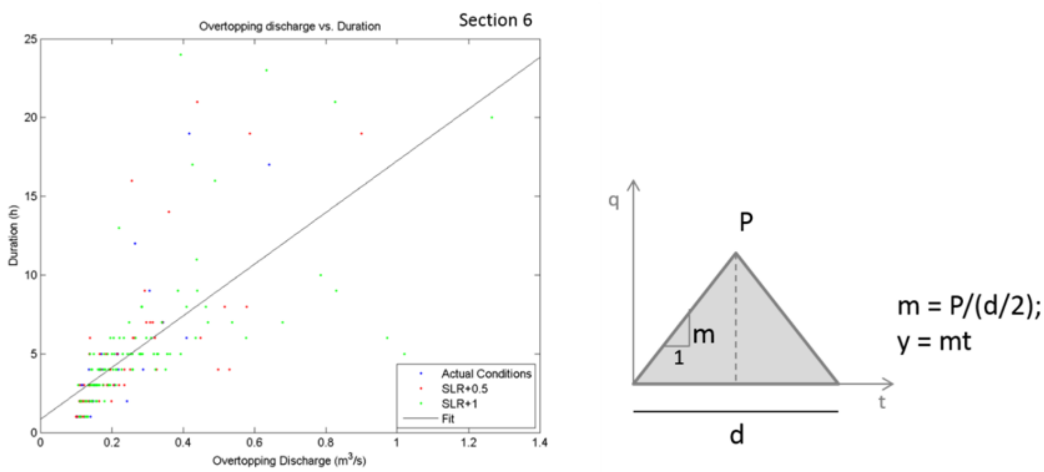


Figure 5.: Example of a Duration Fit (section 6) (left) and Synthetic Hydrograph scheme (right)

2.3.5 Flooding Model

There are a wide variety of numerical models available for simulating flood events. These range in complexity from simplified sea level projection methods, to volume spreading methods (Gouldby et al., 2008a), diffusion wave methods (Bates and De Roo, 2000) and models that solve the full shallow water equations (L'homme et al. 2010), for example. The simplified models have been widely applied in probabilistic analyses due to their computational efficiency. This efficiency is however, often obtained at the expense of accuracy of the predicted flooding scenario. More recently, new hybrid diffusion wave/full Shallow Water Equation (SWE) models have emerged, (Bates et al., 2010). In this approach, a local acceleration term is included with only the advection term of the full shallow water equations excluded. This additional term enables stable solutions at much larger time steps, thereby significantly increasing computational efficiency when compared to standard diffusion wave models. High-resolution (1-2m horizontal) LIDAR data is increasingly being used for flood inundation simulations. Running numerical models at this resolution can, depending on the size of the study area and model formulation, be exceptionally computationally demanding. To make use of this detailed information, whilst still achieving practical simulation times, a new model has been developed. This model, Rapid Flood Spreading Method – Explicit Diffusion wave with Acceleration term, RFSM-EDA, (Jamieson et al., 2012) stems from earlier modelling systems used for national and regional flood risk analysis in England and Wales, (Gouldby et al. 2008a).

The RFSM-EDA model operates on a topographically based mesh enabling model simulations to be undertaken at coarse resolution, offering significant increases in computational efficiency when compared with traditional (flat cell) models (Jamieson et al., 2012, Jamieson et al. 2013). This meshing system requires the analysis of the floodplain topography using a pre-processing algorithm to develop an irregular mesh of so-called Impact Zones (Figure 2). The resolution of the Impact Zones mesh is not dependant on the DTM resolution as the user can control the size range of the Impact Zones. Therefore, a fine resolution DTM can be used to produce the mesh of Impact Zones without effect on the number of

Impact Zones (and the model runtime). The flow calculations that are performed on the coarse mesh are defined using the set of equations proposed by Bates et al. (2010).

The topographically based nature of the mesh requires a slightly different approach than that applied by Bates et al. (2010). The flow across each cell interface, Q_f, is given by

$$Q_f^{t+\Delta t} = \frac{\left(Q_f^t - g\Delta t A_f^t S_f^t\right)}{1 + g\Delta t n^2 \left|Q_f^t\right| \Big/ A_f^t \left(R_f^t\right)^{4/3}} \qquad [8]$$

Where Q_f is the interface flow, t is time, A_f is interface area, R_f is hydraulic radius of the interface, n is Manning's coefficient and S_f is the water surface slope across the interface. Conservation of mass is ensured through the implementation of Eqn. 9.

$$V_i^{t+\Delta t} = V_i^t + \Delta t \sum_j Q_f^{t+\Delta t} \qquad [9]$$

where V_i is the volume in Impact Zone i, and j is a neighbouring cell. The volume within each Impact Zone (V_i) is a function of the water level. These relationships are defined during the pre-processing stage. This stage is computationally efficient and it, later on, enables efficient computations during the simulation. The equations are solved using an adaptive time-step. Numerical stability is ensured through implementation of a CFL criterion developed by Guinot and Soares-Frazão (2006). Overall the RFSM-EDA results have proved to be closely comparable to those from full SWE models (Environment Agency 2013, Jamieson et al., 2012).

The study area is 401735.5 m^2 with only 89 cells or Impact Zones (IZ) defining the computational mesh with an average IZs size of 4410.11 m^2. The reduced number of cells helps to the fast simulation run times of the inundation model. These efficient run times allow choosing a large number of simulation events for a better representation of risk, with no need to limit the number of simulations to the annual maxima or any other higher threshold. For this particular study case and mesh configuration, one simulation takes less than 10 seconds on a standard desktop computer. Therefore, we can choose a simulation dataset composed of all those events that result in significant economic damage (overtopping rate higher than 0.1 m^3/s in any of the defined sections). The total number of RFSM-EDA simulations undertaken for the case study analysis was 69926. Figure 6 shows an example of the simulations performed associated with an extreme event that recently occurred. On the right hand side, a picture taken on March, 1st, 2014 reveals a dramatic storm event that recently affected the study area.

Figure 6. (Left) Inundation extent and water depth (test 20587).(Right) Picture taken on March 1st, 2014 during an extreme event.

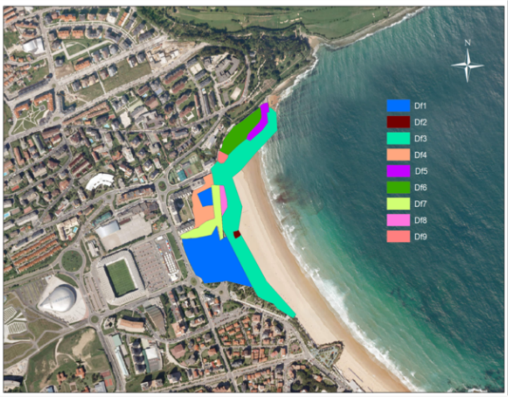
2.3.6 Damage Model

The last step is to calculate the associated damage for every scenario simulated. To that end, the asset value and the flood damage functions have to be assigned to the different land-use units. Different databases can be consulted such as the Multi Coloured Manual (UK) (Penning-Rowsell et al. 2003), HAZUSMH multi-hazard software (United States) (FEMA, 2009) or the JRC Model (European Commission/HKV)(Huizinga, 2007) where general damage functions are defined. However, this study has a specific definition of the damage functions based on local data and expert judgment, which is recommended for micro-studies to reduce uncertainties (Buck 2004). For example, it could include additional benefits such as reflecting local building construction or deterioration for example. In the case study nine different land uses have been defined (Figure 7). One of the land uses is an electrical facility (land use 9) that provides services to a broad area that may suffer indirect damages if the facility is disconnected. The inclusion of this land use shows the possible global effects of flooding events.

Based on the properties from the table in Figure 7, a Beta Cumulative Distribution Function CDF-type damage curve has been assigned to each land use class. Therefore, the estimated damage can be described as follow:

$$DamageUnit_i = AssetValue_i \times H\left(\frac{z - z_{min_i}}{z_{max_i} - z_{min_i}}\right) \qquad [10]$$

where the cumulative distribution function H is defined by a Beta distribution family of Beta(2,2), z_{min} is the threshold where damage starts and z_{max}, the water depth at which damage stops increasing.



Code	Description	Uses	Thresholds (cm)	Maximum depth (cm)	Damage waves/depth	Indirect Damage	Asset Value (€/m2)
001	Urban Park-Garden	Recreational	5	150	(W) (D)	No	20
002	Business/Commercial	Economics/consumer Supply	20	100	(D)	Yes	150
003	Urbanized pedestrian walk	Recreational	30	150	(W)	No	60
004	Residential areas	Residence	10	100	(D)/(W)	Yes	180
005	Residential areas	Parking	10	50	D	Yes	70
006	Hotels	Touristic	20	100	D	Yes	150
007	Parking	Services	30	180	D	Yes	20
008	Sporting activities	Services	5	50	D	Yes	110
009	Electric infrastructure	Infrastructure	20	100	(D)	Yes	20.000

Figure 7.Land Uses Units

To calculate the total damage of each stochastic realisation the damage of each cell within the flood plain must be summed up.

The last step to calculate flood risk or the expected annual damage (EAD) is the integration of the total risk over the 10000 simulated years, *EAD* = ΣC_k/*years*; where *k* represents each of the simulated events. In the example, the EAD for

Sardinero beach is 0.8M€. With the large set of simulated events it is possible to obtain different statistical outputs such as the inundation map and spatial expected damage conditional on certain return period. As an example in Figure 8, based on the water depth probability at each cell, the 100 year return period event and its corresponding damage are presented.

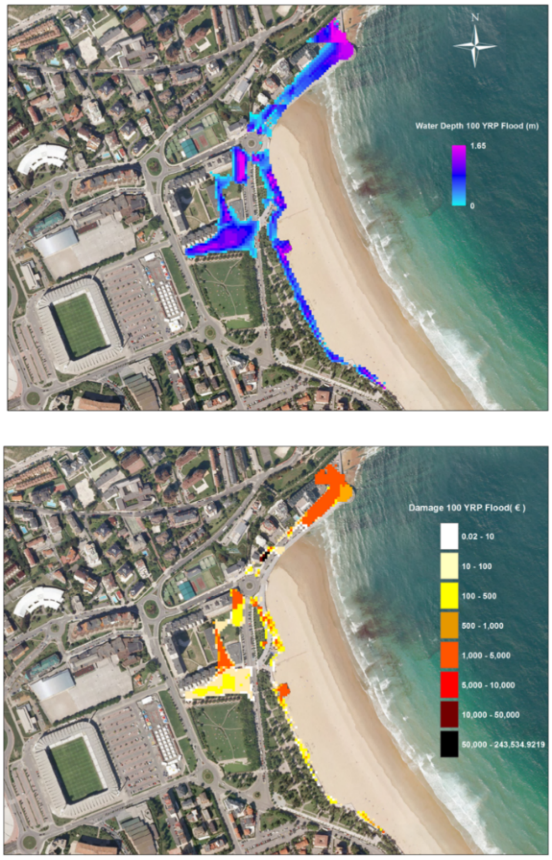


Figure 8.100 year return period flood depth in the floodplain (top) and its associated damage (bottom).Spatial units are 5x5=25m2

As with all coastal flood risk modelling systems, there are uncertainties associated with the different components. There are significant uncertainties relating to the extrapolation of the joint probability density. This form of uncertainty has been explored, to a certain extent, by Neal et al. (2012) in the context of fluvial flooding. These uncertainties propagate through and combine with the model structural error introduced by the use of the meta-model and the SWAN model itself. The influence of the number of design points in the meta-model structural error was analysed by Camus et al., (2011a). The subsequent analysis has associated larger uncertainties, such as the well known model structural errors associated with empirical wave overtopping estimation (Smith et al. (2012)) and hydrograph shape estimation. Uncertainty is also associated with the inundation model, land uses and damage models (Moel et al. (2011)). The quantification of these uncertainties has not been undertaken here. It is however, envisaged that future work will analyse and explore the relative importance of these uncertainties.

2.4 Conclusions

Quantitative flood risk analysis methods are increasingly being used around the world to support flood risk management decisions at various spatial scales. Risk assessments allow local, regional and national governments to estimate the consequences of flooding to their communities rather than just to point where the hazard zones are. Information of the probability of the hazard must be combined with the consequence information in order to obtain the potential losses due to flooding. Existing analyses often make simplistic assumptions regarding the joint probability density functions due to computational limitations. The methodology detailed here makes use of an emulator and reduced complexity inundation model, to overcome these computational constraints.

Although the methodology has been applied to a small urban area in northern Spain, one of its advantages is that it could be extended to larger spatial scales. This scalability arises from the computational efficiency afforded by the wave transformation metamodel (Camus et al. 2013, Goudlby et al. 2014) and the reduced complexity inundation model. The Monte Carlo simulation of the fitted multivariate extreme value model represents the overtopping rates along the coastal boundary more realistically than simplified methods that assume full-dependence. The use of a validated simplified inundation model to compute the inundation extents and water depth allows the simulation of the large sample of extreme independent events preserving the key hydraulic principles of mass conservation and flow connectivity. This methodology enables the determination of the statistical distribution of damage and its spatial distribution in practical computational timescales.

Coastal floods are climate-related events, therefore future work is required to define a multivariate extreme value model that incorporates climate variability into the Monte Carlo simulation (Serafin and Ruggiero, 2014).

Chapter III

An extreme value model for maximum wave heights based on weather types

3 Chapter III. An extreme value model for maximum wave heights based on weather types.

Abstract

Extreme wave heights are climate-related events. Therefore, special attention should be given to the large-scale weather patterns responsible for wave generation in order to properly understand wave climate variability. We propose a classification of weather patterns to statistically downscale daily significant wave height maxima at arbitrary, local areas of interest. The time-dependent statistical model obtained here is based on the convolution of the stationary extreme value model associated to each weather type. The inter-daily dependence is treated by a climate-related extremal index. The model´s ability to reproduce different time scales (daily, seasonal and interanual) is presented by means of its application to three locations in the North Atlantic: Mayo (Ireland), La Palma island and Coruña (Spain).

This chapter is based on: Rueda, A., Camus, P., Tomás, A., Méndez, F. (2016). An extreme value model for maximum wave heights based on weather types. J. Geophys. Res. Oceans, 10.1002/2015JC010952

3.1 Introduction

The need to understand the frequency of natural hazards and develop resilient, long-term structures has promoted extreme value theory as a relevant discipline for engineering and applied science over the last century. The ultimate goal of this theory is the estimation of the probability of events larger than any on record. (Coles, 2001).

Traditionally, extreme value theory, typically provides a statistical description of the maxima of a stationary process, where stochastic properties are considered constant in time. However, in the context of environmental variables, non-stationarity (e.g. seasonality, interannual variability, long-term trends, etc) is often found at different time scales (e.g Méndez et al., 2006; Holthuijsen, 2007; Menéndez et al., 2009). Many structures have been designed on return levels derived from stationary methods, which assume no change to the frequency of extremes over time (Klein et al., 2009). However, the frequency of extremes is likely to change in response to changes in climate (IPCC, 2007; Milly et al., 2008). Therefore, statistical methods that account for the non-stationary behavior of the climate system are needed (e.g. Parey et al., 2010; Cooley 2013; Salas and Obeysekera 2013).

Typically, non-stationary behavior is introduced as a covariate in one or more of the parameters of the extreme value distribution, which are estimated by maximizing the likelihood function. The parameters of an extreme distribution are varied to represent non-stationary processes such as seasonal effects (modeled with harmonic functions, e.g. sine waves), long-term trends (linear and/or exponential terms) and climatic influence (covariates) such as the ENSO variability (Katz et al., 2002, Méndez et al., 2006). Other non-stationary methods use neural networks to model the non-linear behavior of covariates (Cannon, 2010). Changes in the covariates produce changes in the distribution of extremes and thus allow analysis of projected climate variability.

Extreme events can result from the combination of high values of different components. Statistically longer records result in smaller errors, and furthermore, the record should be long enough to encompass the range of variability in extremes (Serafin et al., 2014). This has prompted the development of probabilistic methods to simulate thousands of estimates of wave climates (Hawkes et al. 2002, Mendez et al., 2006, Callaghan et al., 2008, Menéndez et al., 2009, Cannon 2010, Wahl et al. 2012, Corbella and Strech 2013). Most probabilistic methods analyze the dependence between variables of interest without taking into consideration the climate (Hawkes et al. 2002, Wahl et al. 2012, Corbella and Strech 2013) or introduce the climate as a covariate which impose, normally, the use of a single variable as main driver due to the complexity involved (Mendez et al., 2006, Callaghan et al., 2008, Menéndez et al., 2009, Cannon 2010).

This work introduces an extreme value model that relates the non-stationary behavior of extremes to the occurrence probability of associated daily weather patterns. The proposed method is based on the availability of weather-types approaches to successfully downscale the mean (Camus et al., 2014) or extremes (Garavaglia et al., 2010) of a local variable of interest via large-scale predictors such as sea-level pressure fields (SLP). The use of a weather type approach to estimate return values of a variable of interest, in this case significant wave height, allow analysis of extreme wave climate variability at different time scales such as seasons or years and it may open the possibility to explore a multivariate analysis.

This chapter is organized as follows: Section 2 provides a background on weather-typing approaches and extreme value theory. Section 3 describes the methodology. Section 4 presents the application of the method to three study sites and analyzes the extreme significant wave height distribution at different time scales (annual and monthly maxima). Wave climate variability is also characterized at one of the locations by using a 20th century hindcast of monthly significant wave height maxima. Finally, section 5 contains the summary and the conclusions.

3.2 Background

3.2.1 Weather-type statistical downscaling

Statistical downscaling (SD) approaches are used to relate large scale predictors to regional-to-local predictands. SD provides a cheap and efficient alternate to dynamical downscaling (i.e. performing a series of nested simulations). SD has proven to be a useful tool to analyze wave climate at a variety of time scales (Giorgi et. al., 2001). Among several SD methods described in Camus et al., 2014, we have chosen a weather-type approach, where a discrete number of weather patterns are classified according to synoptic similarity. To our knowledge, SD estimation of daily extremes wave events based on weather types has not been previously explored.

3.2.2 Extreme value theory

Basic extreme value theory assumes that realization of a random variable are independent and identically distributed (i.i.d). Under the assumptions of independence and stationarity, the Generalized Extreme Value (GEV) and Generalized Pareto (GP) distributions arise as approximations for block maxima (e.g. annual maximum) and for excesses over a high threshold, respectively (Katz, 2013). For the GEV and GP to hold as asymptotic approximations to the distribution of extremes, temporal independence is not strictly necessary, since a wide range of middle dependence conditions could be equally valid (Leadbetter et al., 1983; Galambos, 1987).

In studies of wave climate, GEV models are typically based on annual maxima (Coles, 2001, Beirlant et al., 2004). However, employing higher sampling frequencies, allows larger sample sizes and thus improved accuracy of the model as long as appropriate treatment of the dependence structure is maintained. Based on this, we analyze the feasibility of sampling daily and correcting the dependence between consecutive days by the use of extremal indices. The extremal index is defined as the inverse of the mean cluster duration (Coles, 2001). Here, each cluster is defined as a weather-type (WT). The WT classification which groups the data according to similar wave-generating meteorological processes, improves the homogeneity of sub-samples and, therefore, the hypothesis of "identically distributed" samples. This approach permits the downscaling of non-stationary processes taking into consideration non-linear relationships by means of changes in the probability of occurrence of the WTs.

3.3 Methodology

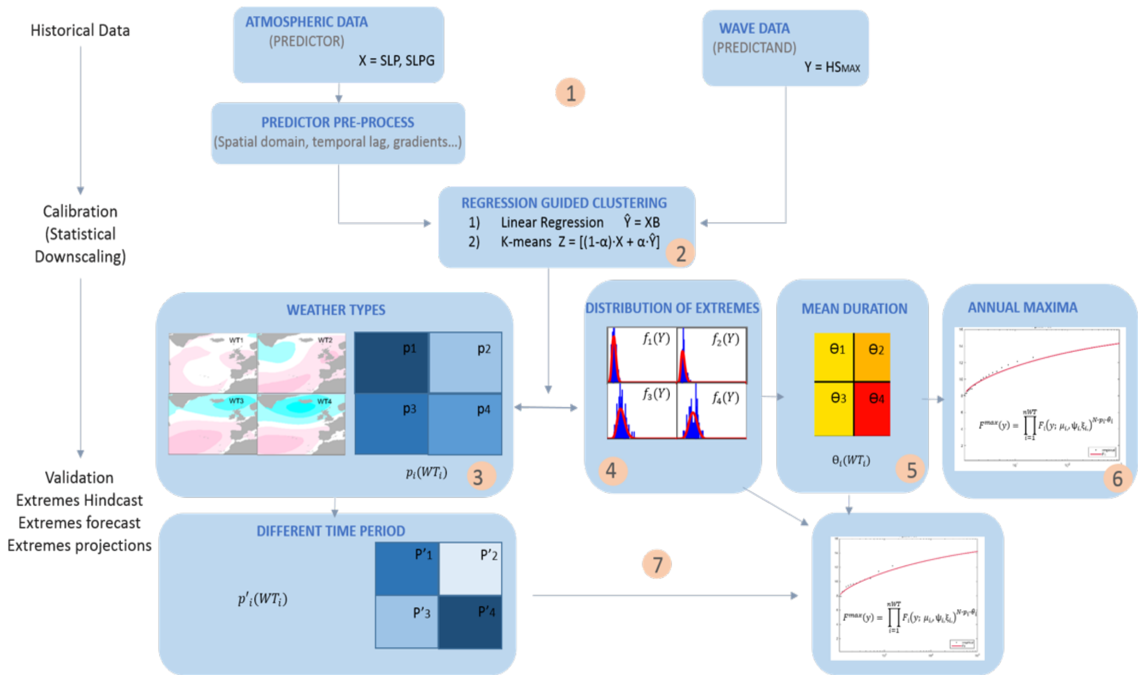


Figure 9. The proposed methodology to obtain a climate-dependent extreme model

Figure 9 summarizes the daily extreme SD method. The steps of the methodology are:

1. Collecting historical data of predictor and predictand and pre-processing the predictor.
2. Performing a regression-guided classification following Cannon (2012).
3. Defining weather types of the synoptic circulation conditions.
4. Fitting a stationary extreme model (e.g. GEV) on the predictand associated to each weather type.
5. Obtaining the extremal index associated to each weather type.

6. Performing the convolution of the distribution functions of the weather types to obtain associated return periods.
7. Applying the model to different temporal periods.

3.3.1 Predictor and predictand definition

The first step is to obtain historical data of both the atmospheric predictor and predictand needed to ascertain the statistical model that relates them. The spatial and temporal coverage of the predictor is one of the most important consideration of the proposed methodology. Based on previous works (Camus et al., 2014; Perez et al., 2014) the predictor data must fulfill two main characteristics: (1) the spatial domain should cover the oceanic region responsible for generation of waves arriving at a location of interest, and (2) the temporal coverage (recent history) should account for the wave travel time from generation to the target location. The daily predictor is defined as the sea level pressure (SLP) and the square SLP gradients (SLPG), the latter representing the geostrophic wind conditions that are derived from the SLP fields. To account for recent atmospheric conditions, responsible of the swell component, the daily predictor is defined as the mean condition of each day and the *n* previous days.

3.3.2 Regression-guided classification

A higher skill of the statistical downscaling method for multivariate wave climate has been achieved using a semi-supervised clustering algorithm (Camus et al., submitted), following the regression-guided approach proposed by Cannon (2012). A better grouping of the predictand is obtained due to a stronger relation of the WTs with the local wave climate. This approach has helped to improve the classification performance also when the predictand is associated with extreme values. The classification is performed as follows: First, the dimensionality of the data is reduced by applying Principal Component Analysis (PCA). Next, a multiple linear regression linking the predictand *Y* (defined by the sea-state parameter of analysis, the daily maximum significant wave height, *Hs*) and the predictor *X* (defined by the PCs that explain 95% of the variance of daily

SLP and SLPG fields) is performed. The linear regression is formulated as

$$Y = X \cdot B + E, \quad [11]$$

where *B* is the matrix of the regression coefficient to be estimated and *E* is the residual error matrix. The predictions from the fitted model are given by

$$\hat{Y} = X \cdot B \quad [12]$$

Once the regression model is fitted, the atmospheric data (*X*) and the predictions of the local waves from the regression model ($\hat{Y}$) are concatenated and weighted using the parameter α. Next, a K-means algorithm is applied to the combined dataset

$$Z = \left[(1-\alpha) \cdot X \; + \; \alpha \cdot \hat{Y}\right]; \quad [13]$$

where $0 \leq \alpha \leq 1$. The two end-members are $\alpha=0$, where only the predictor is classified corresponding to unsupervised clustering and $\alpha=1$, where the method is driven exclusively by the prediction of the predictand, equivalent to fully-supervised clustering. A random initialization of the K-means algorithm is used, but in order to ensure enough data to compute the extreme analysis, a minimum number of data points are required in each cluster to accept the classification.

3.3.3 Weather types

In the third step, the number of weather types N_{WT} are calculated as the mean of the synoptic circulation conditions included in each cluster of the regression-guided classification (Camus et. al., submitted). Each cluster of the classification will have an associated empirical probability of occurrence for the period of study.

3.3.4 Fitting a GEV for each WT

In the fourth step, a stationary extreme value model is fit to the sample associated with each WT. GEV theory provides a description of the probability distribution of block maxima of a sample. Although the GEV distribution is typically fit to annual maxima, in this case the application is still appropriate as input data (or local predictand) represent maxima of daily blocks associated with each particular WT. Thus, a stationary GEV is fit for each cluster. The GEV distribution is given by

$$F(y) = \exp\left\{-\left[1 + \xi\left(\frac{y-\mu}{\psi}\right)\right]^{\frac{-1}{\xi}}\right\} \qquad [14]$$

The model has three parameters: the location parameter, μ; the scale parameter, ψ; and the shape parameter, ξ. The GEV distribution includes three family-types corresponding to the different types of the tail behaviour. When $\xi>0$, corresponds to the Frechet distribution that has a heavy tail decaying polynomially; when $\xi<0$, the GEV corresponds to the Weibull family that is characterized by a bounded tail; and when $\xi=0$, the GEV is a Gumbel distribution having an exponentially decaying tail (Coles, 2001).

Special consideration is required in the estimation of the shape parameter both because it is usually correlated with the location and scale estimations and because it exhibits a strong influence on the estimate of large (return period) quantiles. Therefore, some analysis is performed to provide a more reliable fit of the distribution. The first step is to determine the suitability of the fitted distribution based on a Chi-squared test and finally a weighted average of the shape parameter with the four immediate neighbours in the PCs space is performed. Therefore, the GEV parameters obtained to each WT are based on the associated historical data, only a smoothing of the shape parameter is performed via its average within similar WTs.

3.3.5 Climate-based extremal index

The extremal index θ (Coles et al., 2001) is used to approximately account for the dependence between records of the same sample. In this approach, we have defined a finite number of samples corresponding with the number of WTs. Persistent circulation patterns or WTs may have an interdaily dependence which can be overcome with the climate-based extremal index $\{\theta_i, i= 1,..,N_{WT}\}$. The extremal index is estimated by calculating the mean duration $\bar{d_i}$ of persistent conditions at each WT, so that the larger the duration of the WT, the larger the dependence among successive observations and smaller the extremal index.

3.3.6 Monthly and annual distributions

The statistical relationship between the predictor and the predictand is established in the sixth step. The cumulative distribution function (CDF) at a monthly or annual scale of the peak sea-state parameter, *y*, for the whole study period can be inferred as

$$F^{max}(y) = \prod_{i=1}^{N_{WT}} F_i(y; \mu_i, \psi_i, \xi_i)^{N \cdot p_i \cdot \theta_i}, \qquad [15]$$

where $F_i(y;\mu_i,\psi_i,\xi_i)$ is the cumulative distribution function for the corresponding predictand of WT_i, p_i is the probability (monthly or annual) of the *ith* cluster in the studied period, *N* is the number of block maxima per month (N=30days/month) or per year (N=365days/year), and θ_i is the extremal index associated to WT_i. Assuming a constant extremal index associated to each WT imposes a mean persistence of each WT. Although with this simplification, certain natural variability is probably not being modeled, it simplifies the simulation and still provides accurate estimates. This methodology bears similarities to the procedure proposed by Challenor (1982) using twelve distributions for monthly maxima and by Morton et al. (1997) using four seasonal distributions. However, in our method, each weather type has its own occurrence probability p_i, which must be considered when combining the corresponding distributions.

3.3.7 Using the model in different time periods

Extreme wave height distributions for different time periods are estimated based on the new probabilities of the clusters $\{p'_i, i = 1, \dots, N_{WT}\}$ and the corresponding distribution function of the predictand obtained previously with eq. IV for each weather type (or cluster). The model is presented by calculating return levels for annual and monthly maxima and a reconstruction of significant wave maxima over the twentieth century. Since the method presented here is a non-stationary model, the quantiles are time dependent.

3.4 Application

The methodology is applied to three regions of the North Atlantic with different wave climates: Coruña, Spain [9° W, 43.5°N], La Palma, Canary island, Spain [18° W, 29° N], and Mayo, Ireland [10.5°W, 54.5° N]. Large different wave climates are found among these sites despite their common location in the North Atlantic. The northern locations (Mayo and Coruña) are more exposed to Atlantic storms, thus receiving higher energetic conditions. In addition, the bathymetry and coastline configuration varies at each location, for example the Canary Islands rise from very deep waters where as Ireland has a shallow continental shelf. (see Table 1 and Figure 10 for more information of each site).

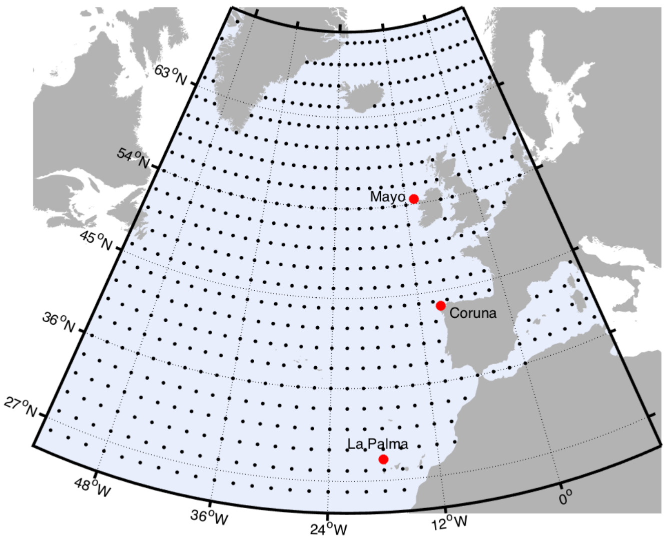


Figure 10. Selected spatial domain of SLP predictor (black points). Red points show study locations (analyzed predictands)

3.4.1 Data

3.4.1.1 Predictor

The global SLP fields of the Climate Forecast System Reanalysis (CFSR, Saha et al., 2010) are used to define the predictor of the SD model. The temporal coverage spans from 1979 to 2013 with hourly temporal resolution and 0.5° spatial resolution.

3.4.1.2 Predictand

Long-term, continuous and spatially-resolved records of data are needed in the construction of SD models. Therefore, wave reanalyses often provide the preferred data source due to their homogeneity and temporal coverage. In this work, the wave hindcast of 1979 to 2013 by Perez et al. (2015) with hourly resolution and 0.125° spatial resolution in the continental shelf provides the historical significant wave height (*Hs*) data.

Location	Lon (º)	Lat (º)	Water depth (m)	Distance from coastline (km)
Mayo	-10.5	54.5	179.08	35
Coruña	-9	43.5	204.24	21
La Palma	-18	29	2707	25

Table 1. Geographical characteristics of each study site

3.4.2 Statistical downscaling method for daily maxima

Based on the method for "Evaluating the Source and Travel time of the wave Energy reaching a local Area ", namely ESTELA (Perez et al., 2014), a common generation area for all the locations is selected. Figure 10 shows the area selected in the North Atlantic basin 24°N to 70°N and 54°W to 10°E as the spatial domain of the predictor. In order to account for the wave propagation time from generation to destination, the predictor is defined as the 3-daily mean SLP and 3-daily mean SLPG. PCA reduces the data redundancy and keeps 95% of the data variance using 95 PCs. The predictand *y* is the maximum significant wave height (Hs_{max}) every 24 hours at the target location.

The weather type classification is performed at each location. As in Camus et al. (2014) a number of N_{WT}=100 synoptic WTs are used. A lesser number of WTs was tested with poorer results and a larger number of WTs diminishes the number of data points at each WT. Although individual classification is obtained at each study site, only the classification at Mayo on the Northwest Irish coast is shown. However, the results for each site are discussed in the text.

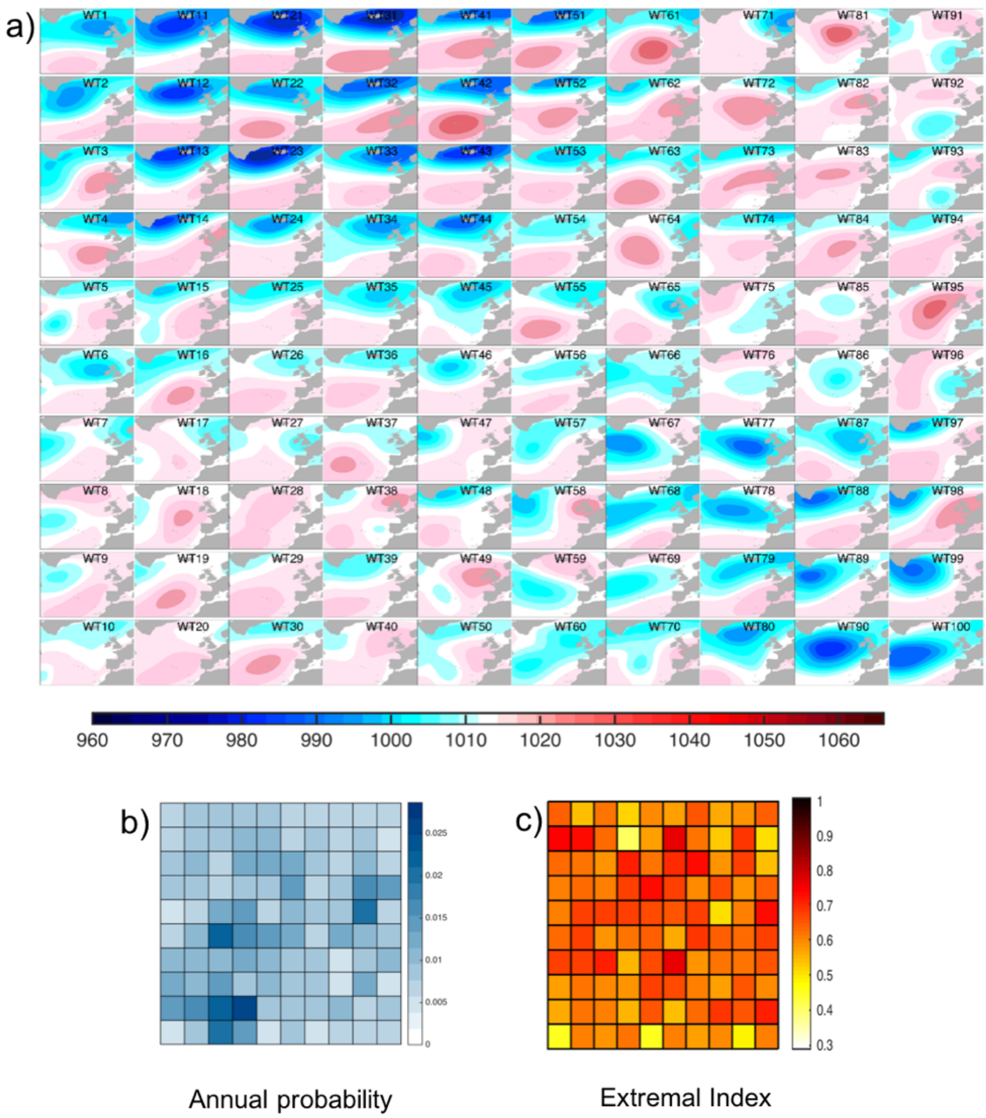


Figure 11.(a) Weather-types (WT) classifications represented by SLP fields (hPa) corresponding to the predictor-to-predictand classification obtained for Mayo, Ireland. (b) Occurrence probability (pi, in blue scale) and (c) Associated extremal index (ϑi, in red scale).

In Figure 11a, the WTs corresponding to Mayo location are illustrated in a 2-D lattice using a similarity criterion to provide an intuitive visualization of the classification. Low-pressure systems (below an averaged sea-level pressure of 1013hPa) are displayed on blue colour scale and high pressure systems on a red colour scale. Two different groups of low pressure systems are found. The first group, associated with the WTs located on the upper left corner of the lattice is related to the positive phase of the North Atlantic Oscillation (NAO), which is characterized by intense low pressure system located over Greenland and the high over the Azores islands. The second group, located on the bottom right corner, exhibit a similar dipole but displaced south-eastward and can be associated with the East Atlantic (EA) positive phase. Figure 11b shows the occurrence probability of the WTs during the historical period (1979-2010) in a blue colour scale, and Figure 11c the associated extremal index in a red colour scale. Lower values of the extremal index are found for the WTs representing anticyclonic situations over the study site, since their mean persistence is usually larger than in storms conditions. Similar weather patterns are found in the other locations, however, different optimal factors (α) for the classification are chosen at each site to obtain the most accurate extreme analysis. The final optimal factors chosen at each site were: α = 0.6 for Coruña, α = 0.3 for Mayo and α = 0.2 for La Palma. The differences between optimal factors are attributable to the geographic location of each study site. In particular, because only one parameter (*Hs*) is used in the regression guided algorithm the predictand does not provide enough information to infer the origin of the waves. Notably, this effect and the lower values of the optimal factor are found for the Mayo and La Palma sites.

Figure 12 shows the histogram of daily significant wave height maxima, the fitted GEV distribution and the parameter estimates for each WT. In Figure 12, weather types with more intense low-pressure systems, responsible for wave generation in the Atlantic basin correspond to larger values of the location parameter. This pattern is observed for all the locations. The shape estimate parameter in Mayo takes slightly positive values (Frechet family-type), at some WTs that represent high pressure systems possibly due to the rare occurrence of large waves associated to these WTs. This effect is consistent with typical behaviour of summer season (Menéndez et al. 2009). No positive values of the shape parameter are found at La Palma or Coruña sites for any of the WTs.

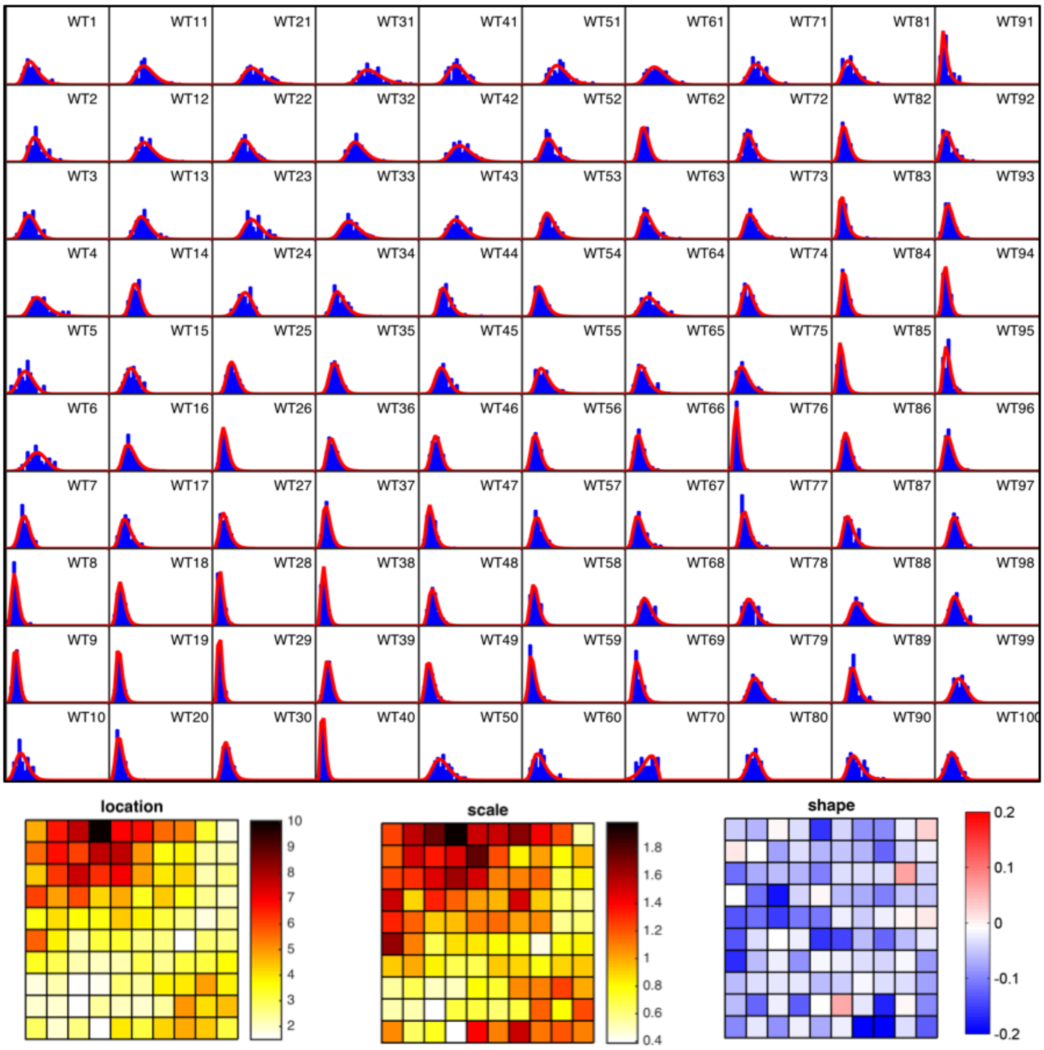


Figure 12.Associated histogram and GEV fitted probability distributions for daily maxima significant wave height in meters at each WT at Mayo, Ireland. The corresponding parameter estimates of each distribution are illustrated in the lower panels

Figure 13 shows the annual return period significant wave height for the three study sites including 95% confidence intervals (shaded areas) obtained via a

Monte Carlo simulation. One thousand realizations of 3,000 years at daily scale are used to calculate the confidence intervals. In each realization, different values $\{\mu_i, \psi_i, \xi_i, i = 1, \ldots, N_{WT}\}$ are employed considering the statistical distribution of the parameter estimates. In order to account for the inter-daily dependence in the Monte Carlo simulation, the parameter estimates associated to each WT are modified according to the associated extremal index (Coles et al., 2001). Different behavior is observed at the different locations: Coruña and La Palma have bounded tails (Weibull-family behavior) while Mayo has a heavy tail (Frechet-family behavior) and wider confidence intervals. Therefore, for example, the estimates of the 100-year event for the different locations are: Mayo 19.2 (± 1.9) m, Coruña 13.37 (± 0.9) m and La Palma 8.9 (± 0.7) m. For comparison purposes, a stationary GEV fit is also show in Figure 13. The stationary GEV provides similar results to the current WTs method, however, the stationary method is constrained to the available historical data, and thus is limited in its application to longer time periods.

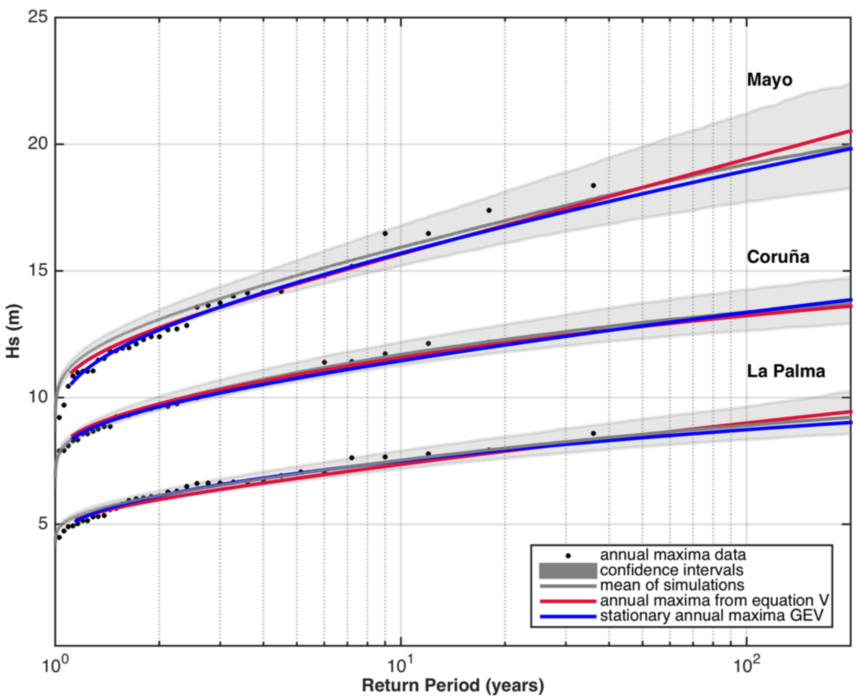


Figure 13. Annual return period significant wave height for the three study sites. The shaded areas represent the 95% confidence intervals of the annual significant wave heights obtained via Monte Carlo simulation based on WTs annual occurrence probabilities during the calibration period (1979-2013)

The monthly GEV distributions of significant wave height are shown in Figure 14. Larger waves occur at Mayo for every month, and decreasing for Coruña and La Palma. To obtain the annual maxima distribution associated to each month, the monthly WTs occurrence probabilities are used, for both the annual return period estimation based on eq. 15 (red line) as well as for the Monte Carlo simulation. The most severe conditions, with the largest monthly quantiles, occur during the winter months (Dec, Jan, Feb) for the three locations. The statistical model is able to reproduce the extreme monthly behavior with a few exceptions at Mayo in February or November, where it does not replicate two exceptionally large wave events. In general, poorer skills of the model are found to reproduce the lower values of the distribution, however on average the larger values are well represented.

3.4.3 Assessing climate variability

The statistical model developed here, is able to reproduce extreme wave heights at different time periods outside the calibration period, owing to the statistical relationships established between the local extreme conditions and the atmospheric forcings. As an example a reconstruction of monthly significant wave height maxima for the whole twentieth century is presented in Figure 15.

The long-term reconstruction of maxima significant wave height is derived from SLP data from the twentieth century atmospheric reanalysis (20CR) (Compo et al. 2011), spanning from 1871 to 2010. The use of 20CR reanalysis as a predictor is validated with the comparison of the occurrence rates of the defined WTs for the two reanalysis (20CR and CFSR) for the common period (1979-2010) (Figure 15b). On the upper panel of Figure 15, the historical monthly maxima significant wave height is shown for the wave reanalysis time period (blue), as well as, the reconstruction of 95% intervals of simulated monthly maxima based on WTs probabilities obtained with SLP fields from 20CR. Figure 15b show good agreement between hindcasts and high skill of the model to reproduce wave height maxima outside of the calibration period. Application of the current method to Global Climate Models (GCMs) under different climate scenarios to estimate future extreme events is straightforward. However, due to the large uncertainty associated with GCMs we have focused the current study on the twentieth century.

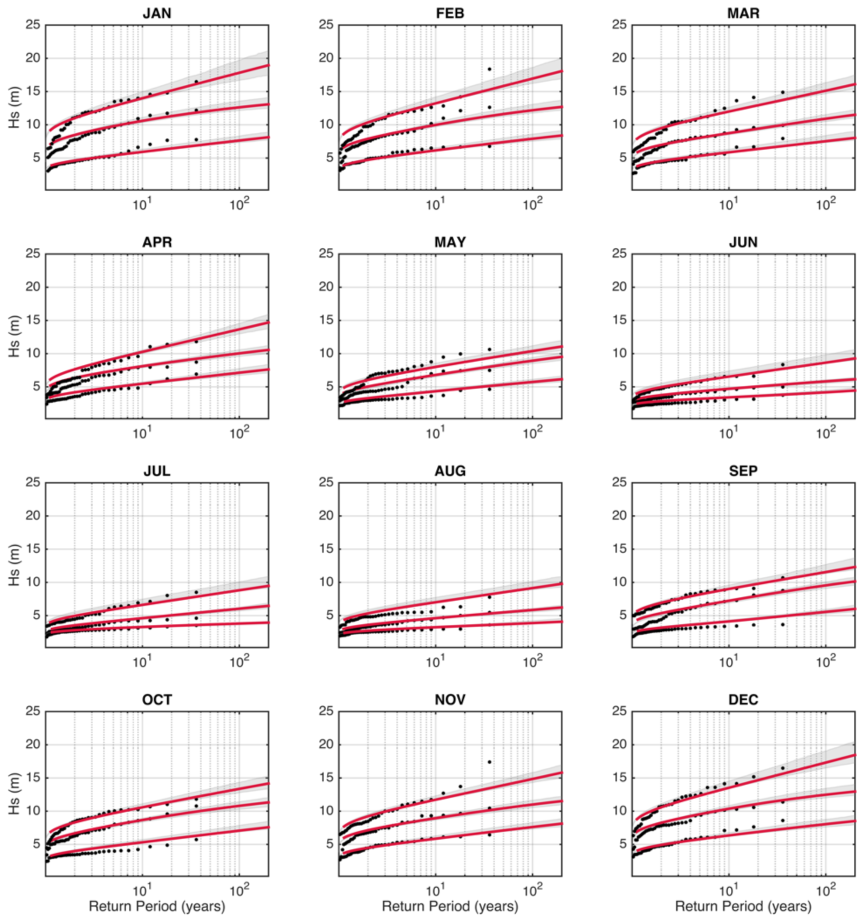


Figure 14. Monthly return period significant wave heights for the three study sites. The shaded area represents the 95% confidence intervals for the annual significant wave heights obtained via Monte Carlo simulation based on WTs monthly occurrence probabilities during the calibration period (1979-2013).

Variability in atmospheric patterns characterized by the NAO index may have a large influence in wave extremes (Izaguirre et. al., 2010). Therefore, in order to test how the model is able to reproduce climate variability, we have analyzed the evolution of the occurrence probability of WTs that are related to the positive phase of NAO (Hurrell et al., 2003) at the Mayo location. The selected WTs correspond with those located on the upper left corner of the mesh of Figure

11, which as mentioned in section 4.2 have higher probability of occurrence with positive values of NAO (Figure 15c). The second and third panels of Figure 15a demonstrate a clear correlation between the occurrence probability of these WTs and the NAO index (0.67 Pearson correlation). Large values of NAO index were found during the late 1980s and early 1990s which correspond to larger probabilities of occurrence of the selected WTs and therefore larger values of wave height maxima (first panel Figure 15a). Similarly, when lower values of the NAO index are record, the probability of occurrence of the selected WTs diminish and with it, the associated significant wave height maxima. This pattern is easily perceptible by the simulated mean annual maxima, the orange line of first panel Figure 15a. These results are in agreement with previous works (Bertin et al., 2013, Camus et al., 2014), where the influence of the NAO pattern on mean wave height in northern Europe was investigated.

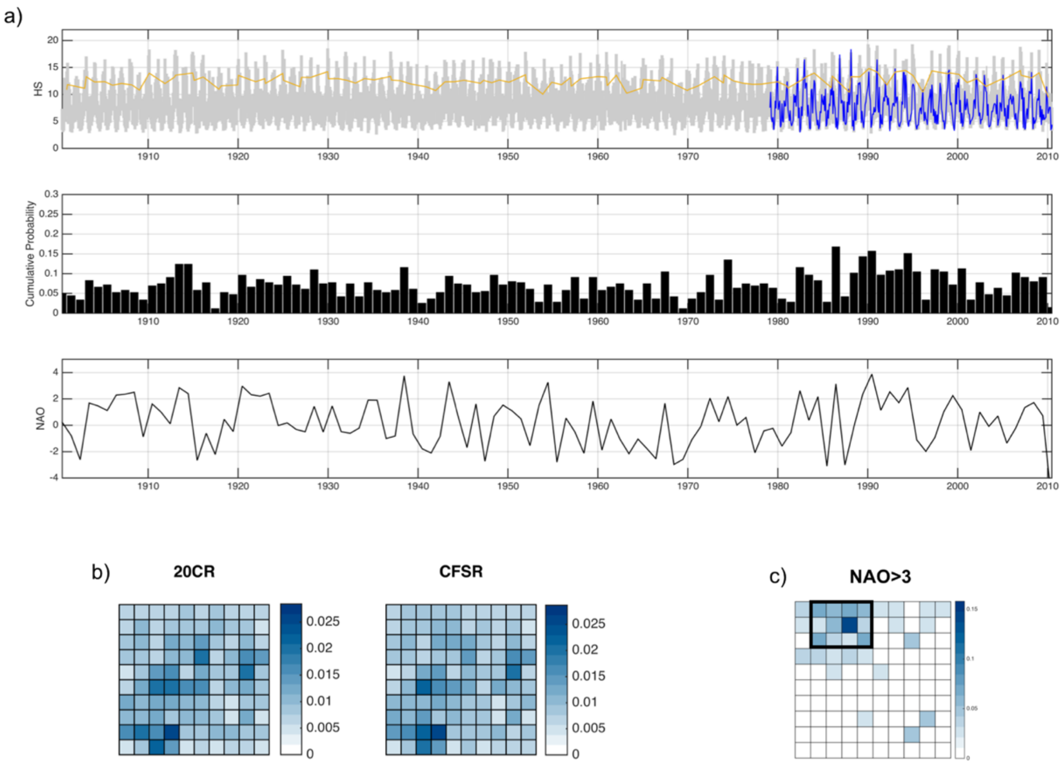


Figure 15(a) Upper panel, Monthly maxima temporal evolution at Mayo, Ireland (blue line) from GOW reanalysis (1979-2013), and 2.5 and 97.5 quantiles of simulated Hs (shaded area) based on monthly WTs occurrence probabilities from 20CR (1950-2010), orange line corresponds to the mean annual simulated maxima. Middle panel, WTs annual occurrence probability of those WT associated with large values of NAO index (≥3). Lower panel, annual NAO index (Hurrell,2003). b) Probabilities of occurrence for the present conditions (1979-2010) of the WTs (classification shown in figure 3) from CFSR reanalysis, and 20CR reanalysis (c) WTs occurrence probabilities *associated with NAO index ≥3.*

The analysis performed here reveals the importance of large-scale climatic patterns in the behavior of extreme significant wave heights. In addition, if we calculate the 100-year return period event in the Irish location estimated using the whole 20th century and only the last thirty-four years of wave reanalysis data it is found that they differ by almost one meter (not shown). This difference may be due to the persistence of positive phase of NAO during most of the wave reanalysis time period which coincides with the occurrence of larger wave events. Therefore, it is possible that the largest recorded event at the Mayo location (18.37 m) had a much longer return period that would be expected to occur during the observed record.

3.5 Summary and conclusions

A statistical model to downscale and analyze the variability of daily maxima of significant wave height is presented. The model is based on the ability of a predictor-to-predictand synoptic classification model to group observations according to similar generating meteorological processes, namely WTs. A stationary extreme value model is fit to each WT. The associated distribution for a certain period of time is obtained via a combination of the GEV distributions of the 100 WTs used here to classify the whole population. Non-stationarity is introduced in the model through the occurrence probability of each WT as a function of time. The inter-daily dependence is treated by a climate-based extremal index.

The model is applied to three locations in the Atlantic basin with different wave climates. Differences were found in the optimal regression-guided classification, mainly in the factor α, that defines the relative influence of the predictor and predictand in the classification. Some differences were also found in the parameter estimates of the extreme value distributions of each WT, reflecting the particularities of the extreme distributions for each site. The results of the model provide useful information to identify which WTs are related to the more extreme events and to explain the interannual variability. The influence of large-scale patterns, such as those described by the NAO index, has been explored by analyzing the time evolution of the occurrence probabilities of certain WTs. A reconstruction of monthly maxima estimates for the 20th century has been performed using the 20CR atmospheric reanalysis (Compo et al., 2011). Although it is beyond the scope of this work the importance of understanding large-scale patterns such as NAO is highlighted due to its influence on extreme wave height variability.

The model provides new ways to gain insights about climate variability of extreme events. This work has focused on a univariate model given the complexity and novelty introduced. However, future research will focus on modeling the daily-to-interannual sequence of weather patterns and the extension to multivariate extreme analysis by considering other sea-state parameters such as wave period, direction or 10-m wind intensity.

Chapter IV

A multivariate extreme wave and storm surge emulator based on weather patterns

4 Chapter IV. A multivariate extreme wave and storm surge climate emulator based on weather patterns

Abstract

Coastal floods often coincide with large waves, storm surge and tides. Thus, joint probability methods are needed to properly characterize extreme sea levels. This work introduces a statistical downscaling framework for multivariate extremes that relates the non-stationary behavior of coastal flooding events to the occurrence probability of daily weather patterns. The proposed method is based on recently-developed weather-type methods to predict extreme events (e.g., significant wave height, mean wave period, surge level) from large-scale sea-level pressure fields. For each weather type, variables of interest are modeled using Generalized Extreme Value (GEV) distributions and a Gaussian copula for modelling the interdependence between variables. The statistical dependence between consecutive days is addressed by defining a climate-based extremal index for each weather type. This work allows attribution of extreme events to specific weather conditions, enhancing the knowledge of climate-driven coastal flooding.

This chapter is based on: Rueda, A., Camus., P., Tomás, A., Vitousek, S., Méndez, F.J (Submitted to Ocean Modelling). A multivariate extreme wave and storm surge climate emulator based on weather patterns.

4.1 Introduction

Coastal flooding results from non-linear interactions of multiple oceanographic, hydrological, geological and meteorological processes (e.g., astronomical tide, monthly sea-level anomalies, storm surge, wave set-up, wind set-up, fluvial discharges, precipitation and land subsidence). Coastal flooding can result from an exceptional intensity of a single process (e.g. storm surge), but more often results from the combination of elevated values of more than one of the aforementioned processes, namely a compound event. As defined by the IPCC SREX report (Seneviratne et al., 2012) and Leonard et al. (2013), the main characteristics of a compound events are: (1) the extremeness of the impact rather than the individual components, (2) the multivariate nature of the impact and (3) the components statistical dependence. In this chapter, we examine extreme non-tidal total water level (TWL) defined as the linear summation of storm surge (SS) and wave run-up, which is functionally related to significant wave height, Hs, and mean period, Tm (Stockdon et al., 2006). Because synoptic atmospheric circulation patterns control the magnitude of SS, Hs and Tm, all three variables show strong statistical dependence.

The processes responsible for extreme waves and storm surge are non-stationary. They vary seasonally, interannually and on longer time scales, possibly due to climate change (Milly et al, 2008). Recently, many extreme value models were developed to deal with non-stationarity (Katz et al, 2002; Mendez et al, 2006) and conditional multivariate extremes (Heffernan and Tawn, 2004; Gouldby et al, 2014), including bivariate copula-based methods (Wahl et al, 2012), non-stationary bivariate copulas (Bender et al, 2014; Masina et al, 2015), multivariate copulas (Corbella and Strech, 2013) and multivariate Gaussian copulas (Ben Alaya et al, 2014). Despite its predictability, the astronomical tide is also a component that adds non-stationarity to the estimation of TWL (Dixon and Tawn, 1999; Coles and Tawn, 2005), and often requires dependency correction between consecutive events using an extremal index (Leadbetter, 1983; Tawn 1992; Coles, 2001; Batstone et al, 2013).

Statistical models of extreme coastal flooding have been developed by combining highly energetic wave conditions (defined by large values of Hs and Tm) and high water levels (high tides and storm surge), with a time-dependent peak over threshold extreme value model (Serafin and Ruggiero, 2014) that accounts for seasonal and interanual variability based on sea-level pressure (SLP) and sea-surface temperature (SST) indices.

Recently, Camus et al (2014a) developed a method to obtain daily SLP-based predictors that explain the inter-daily variability of wave climate. Based on these daily predictors, Camus et al. (2014b) presented a weather-type statistical downscaling framework for wave climate at daily scale. Statistical-downscaling methods based on weather types typically apply regional-scale predictors such as a collection of SLP patterns to estimate the local predictand, e.g. wave height, mean period and/or wave direction. Other applications of weather-types methods allow downscaling of multivariate directional spectra (Espejo et al, 2014) and precipitation extremes (Garavaglia et al, 2010).

In this chapter, we propose a weather-types framework (Camus et al, 2014b) to model daily multivariate events using Generalized Extreme Value (GEV) marginal distributions for each predictand variable and Gaussian copulas for the correlation between variables. The statistical dependence between consecutive days is addressed by defining a climate-based extremal index for each weather type. We use the coastal flooding index, TWL, to characterize the extremeness of the compound events.

A benefit of the weather-type framework is the ability to trace back weather patterns responsible for large local flooding events. The water level contribution from the astronomical tide is deterministic, and the surge-tide interaction practically negligible in the area of study, therefore it is not considered in this chapter. However, the framework could be easily extended to consider time scales of variability of the astronomical tide (e.g. seasonal, spring-neap, 4.4-yr, 8.85-yr and 18.6-yr cycles) and its inclusion in the Monte Carlo simulation of the hydraulic boundary conditions.

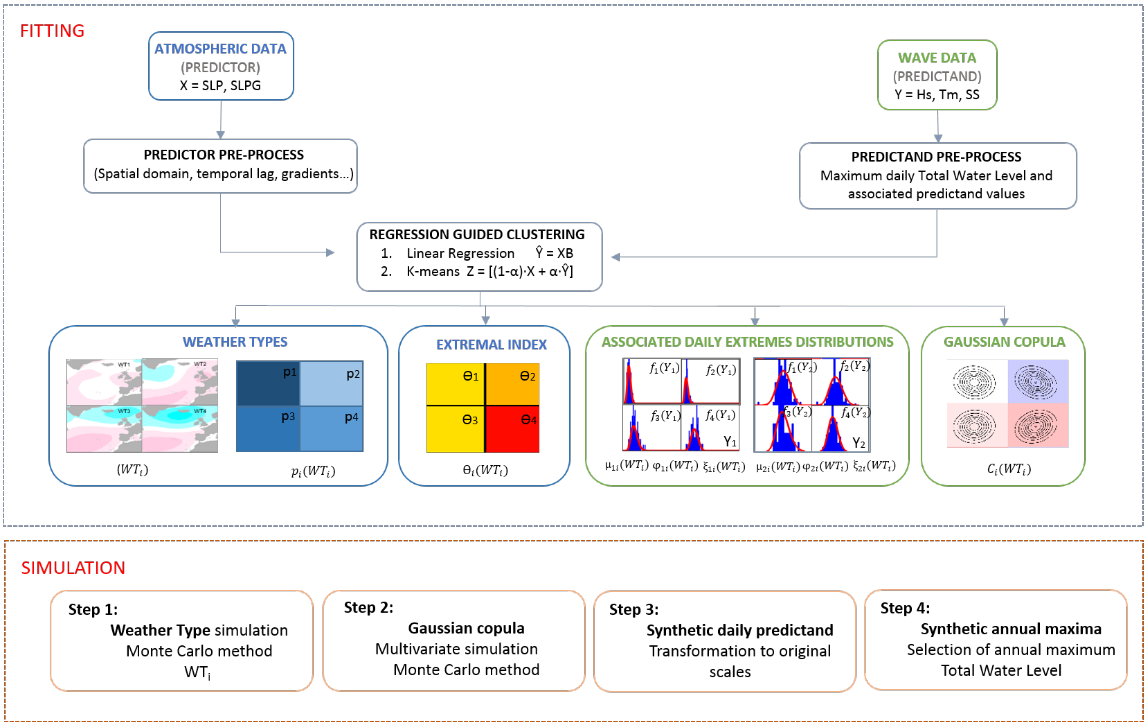


Figure 16. Proposed methodology to obtain a multivariate climate-dependent extreme model.

4.2 Methodology

The proposed methodology is an extension of Rueda et al. (2016) to multivariate analysis. The methodology is composed of several steps:

1. Collect and pre-process historical data of predictor (SLP) and predictands (Hs, Tm, and SS).
2. Define weather types from synoptic SLP patterns.
3. Fit a stationary extreme value models (e.g. GEV) to the multivariate predictand (Hs, Tm, SS) associated with each weather type.
4. Obtain an extremal index to account for the mean duration of each weather type.
5. Model the dependence between predictand variables for each weather type using a Gaussian copula function.
6. Generate synthetic multivariate extremes taking into consideration the occurrence probability and dependence structure associated with each weather type.

A summary of the methodology is illustrated in Figure 16. Each step is described in detail below.

4.2.1 Predictor and predictand definition

The first step is to obtain historical data of both the atmospheric predictor and predictand and construct the statistical model that relates them. In this work, the predictand is defined as the climate-related drivers (significant wave height (Hs), mean period (Tm) and storm surge (SS)) of elevated TWL during storm events. Based on previous works (Camus et al., 2014a, Perez et al., 2014), the daily predictor is defined as the sea-level pressure (SLP) and squared SLP gradients (SLPG), representing the geostrophic wind conditions, in a spatial domain that covers the corresponding wave-generation area. The daily SLP and SLPG fields are averaged over the *n* previous days in order to account for the recent atmospheric conditions over time scales of the wave generation and propagation.

The daily predictands (Hs, Tm, and SS) are selected based on a coastal flooding response function, in this case defined as the daily maximum TWL, which is the summation of surge level and an empirical estimate of wave run-up on dissipative beaches (Stockdon et al., 2006). The hourly values of Hs, Tm, and SS are used to compute the daily maximum TWL according to the formula (eq. 16).

$$\mathrm{TWL} = \mathrm{SS} + 0.043 \cdot \sqrt{\mathrm{Hs} \cdot L_0} \; , \qquad [16]$$

where $L_0 = \frac{g}{2\pi} {T_m}^2$.

4.2.2 Weather types

A regression-guided clustering improves the wave and storm surge downscaling based on weather types (WTs) (Camus et al., submitted). The regression-guided clustering is performed on an augmented dataset (Z) which appends the weighted predictor (X) and predictand estimations *($\hat{Y}$)* from a linear regression model ($\hat{Y} = B \cdot X$) between predictand (Y) and predictor (X):

$$Z = \left[(1-\alpha)\cdot X\,;\ \alpha\cdot\hat{Y}\right], \qquad [17]$$

where α is a weighting factor which varies from 0 (unsupervised classification) to 1 (fully supervised classification).

In this work, a multivariate regression between the predictand Y (defined by the sea-state parameters: daily Hs, Tm and SS) and the predictor X (defined by the number of principal components (PCs) that explain 95% of the variance of daily SLP and SLPG fields) is fitted. The K-means algorithm (Hastie et al. 2001) is applied to the combined dataset Z, which includes the regression-guided predictions, to obtain N_{WT} clusters. The optimal α is obtained by minimizing the intra-cluster dispersion following the method of Camus et al. (submitted). Increasing cluster homogeneity improves the fit of the extreme value models for annual maxima univariate predictand (Hs, Tm, and SS) and therefore provides a better extrapolation of their joint density function.

Finally, each weather type (WT_i) is calculated as the mean of the synoptic circulation patterns included in each cluster of the regression-guided classification, and the probability of each cluster (p_i) is calculated from the number of SLP fields belonging to each cluster.

4.2.3 Fitting the marginal extreme distribution

The marginal distributions of the predictands (Hs, Tm, and SS) for each weather type is fit to a generalized extreme value (GEV) distribution. The GEV distribution describes the probability distribution of block maxima of a sample (Fisher & Tippett 1928). In this case, the daily block maxima is selected from the hourly predictand data and each sample is defined by those days belonging to a particular WT. The GEV cumulative distribution function (CDF) is given by:

$$F(y) = exp\left\{-\left[1+\ \xi\left(\frac{y-\mu}{\psi}\right)\right]^{\frac{-1}{\xi}}\right\}, \qquad [18]$$

where μ is the location parameter, ψ is the scale parameter and ξ is the shape parameter (Coles et. al, 2001). The parameter estimates are calculated using a chi-square test and a weighted average of the shape parameter (with the four immediate neighbors in the PCs space) is performed in order to avoid anomalous values.

4.2.4 Climate-based extremal index

The statistical dependence between daily data belonging to the same WT is modeled using an extremal index θ (Coles et al. 2001). Without applying the extremal index, the frequency of extreme values of the predictand is overestimated. In this work, the extremal index is defined as the inverse of the mean persistence on each weather type. Therefore, increasing the duration of a specific WT, increases the dependence between the associated data of the predictand. For those WTs associated with extreme conditions the value of the extremal index is expected to be close to 1. The dependence estimated using the extremal index influences the GEV parameter estimates. Following Leadbetter (1983), the distribution of the maximum considering the dependence of a stationary process satisfies:

$$H(y) = \{F(y)\}^{\theta} , \qquad [19]$$

where $\theta(0 \leq \theta \leq 1)$ is the extremal index and F(y) is the GEV(μ, ψ, ξ) given by Eq.3 and G(y) is a GEV(μ_θ, ψ_θ, ξ_θ) distribution with

$$\mu_\theta = \mu + \frac{\psi(\theta^{\xi}-1)}{\xi}, \psi_\theta = \psi\theta^{\xi} \; and \; \xi_\theta = \xi \qquad [20]$$

thus, the statistical dependence influences only the location and scale parameters via the extremal index θ. The parameter estimates obtained via Eq. [20] are used during the simulation procedure (section 4.2.6).

4.2.5 Statistical dependence structure

The statistical correlation between environmental variables is a non-stationary process (Wahl et al., 2015). However, few statistical methods resolve the non-stationary related with the dependence structure. An example can be found in Bender et al. (2014), who introduced a non-stationary copula model to extrapolate joint density functions. However, since variables describing coastal hazards such as Hs, Tm, and SS are often strongly correlated to each other and to the weather pattern leading to their generation. We propose, the use of a weather-type classification that leverages the statistical dependence of weather and storm-related events (e.g. coastal flooding), since each WT has associated a particular dependence structure. The non-stationarity is introduced in the model by means of the time-dependent behavior of the occurrence probabilities of the daily weather types at seasonal and interanual time scales.

Copula functions are useful tools to model the dependence between variables with different marginal distributions. The use of copulas in multivariate problems, mainly in hydrology, has become popular in recent years (see for example, Nelsen (2006) and Salvadori et al. (2007)). Many different families of copulas are available and we have selected a Gaussian copula approach due to its flexibility to model several variables (Ben Alaya et al. 2014). A copula is a multivariate distribution whose marginals are uniformily distributed in the interval [0, 1]. The marginal functions of each variable are transformed to a normal distribution N(0,1). The dependence between variables is modeled by their correlation in the Gaussian space, defined by a symmetric, positive-definite matrix whose elements represent Spearman´s correlation coefficients. Vogl et al. (2012) and Laux et al. (2011) demonstrate that the marginals of a Gaussian copula must be independent and identically distributed. In this case, grouping predictand variables according to weather types (WTs) satisfies this requirement. The adequacy of the Gaussian copulas to model the dependence structure of the analyzed variables associated to each WT has been tested by a standard model diagnosis following Renard et al. (2007) (not shown).

4.2.6 Monte Carlo climate-based simulation

Once the marginal distributions and the dependence structure between variables are fit for each weather type, it is possible to generate a synthetic extreme wave climate based on the weather type occurrence probabilities.

The simulation procedure establishes a daily-scale model of extreme wave climate based on the annual occurrence {p_i, i=1, ..., N_{WT}} of the weather types. In order to construct a synthetic wave climate, the first step is to obtain a random weather type for each day of simulation, which is modeled assuming a Generalized Bernoulli distribution due to the categorical choice of one of the N_{WT}. Then, based on the marginal fits and Gaussian copula associated to the daily simulated WT, random daily synthetic Hs, Tm, and SS are obtained. Finally, the process is repeat thousands of times to obtain a large synthetically-generated sample of daily multivariate extreme events, identifying the annual maxima of TWL and recorded the associated values of Hs, Tm, and SS.

4.3 Application

4.3.1 Study location and data

The proposed methodology is applied to Santander bay in northern Spain [4°W, 43.5°N] (see Figure 17). The data used to establish the statistical downscaling (SD) model is described below.

4.3.2 Predictor

The global SLP fields of the Climate Forecast System Reanalysis (CFSR) (Saha et al. 2010) are used to define the predictor of the SD model. The temporal coverage of CFSR spans 1979 to 2013 with hourly time resolution and 0.5° spatial resolution.

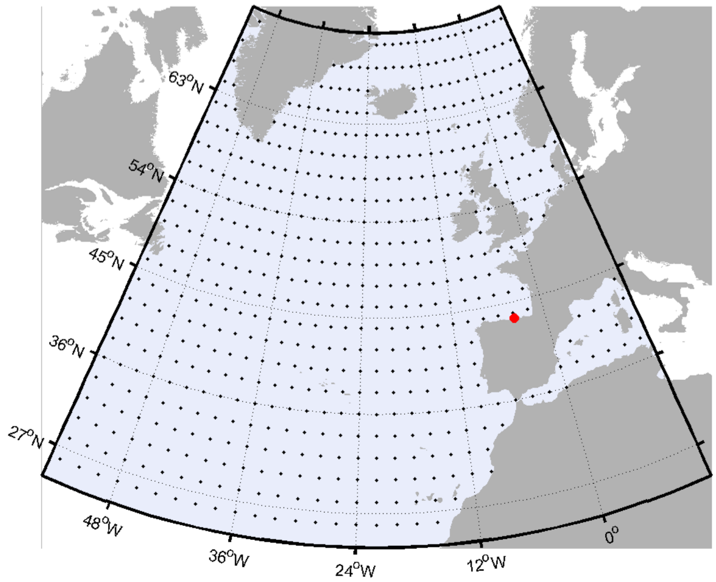


Figure 17.Selected spatial domain of SLP predictor (black points). The red point shows the study site at Santander (Spain)

4.3.3 Predictand

Long-term records of historical data are needed to construct SD models. Reanalysis models often represent the preferred data source due to their spatial and temporal coverage. In this work, we utilize the wave hindcast (of Hs and Tm) from 1979 to 2013 developed by Perez et al., (2015) with hourly temporal resolution and 0.125° spatial resolution. Storm surge data comes from the Global Ocean Surge (GOS) reanalysis (Cid et al., 2014) with hourly temporal resolution and 0.125° spatial resolution.

4.3.4 Method implementation

The wave climate in Santander is mainly influenced by extratropical storms generated in the north and northwest Atlantic. Figure 17, shows the spatial domain of the predictor from 24°N to 70°N and 54°W to 10°E. The predictor is defined as the three-day mean SLP and mean SLPG, calculated for each day of the study period. Principal component analysis (PCA) is applied to reduce the data dimensionality. In this particular case, the first 95 PCs were used in the classification algorithm, keeping 95% of the data variance.

A regression-guided classification on 100 WTs is implemented based on the daily PCs of the predictor and the daily multivariate predictand. An optimal factor (α) of 0.6 is used in this study case. Figure 18 shows the WTs classification, as well as the associated extremal index and average annual occurrence probability. In Figure 18, the WTs are organized in a bidimensional lattice, where similar weather patterns are located together.

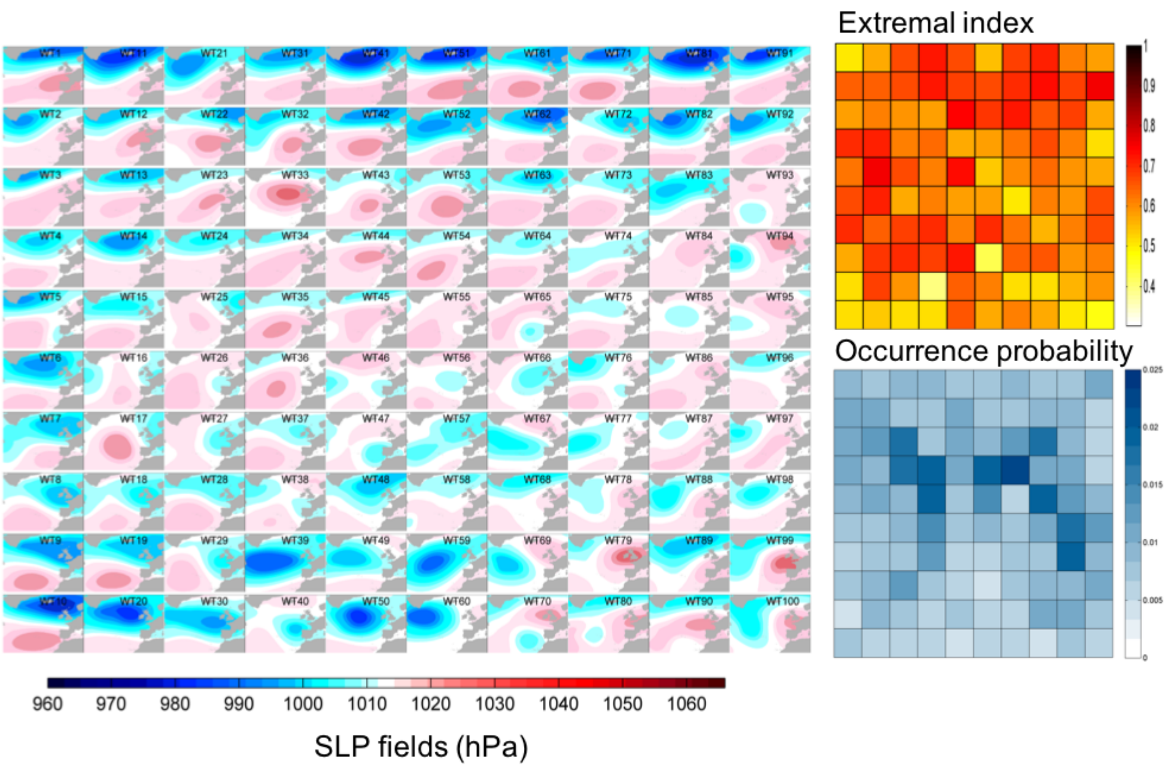


Figure 18. The regressione guided weathere types (WT) classification represented by SLP fields (hPa) corresponding to the predictore toe predictand classification obtained for a factor α=0.6. The associated extremal index (ϑi, in red scale) and occurrence probability (pi, in blue scale) are also represented (right side panels).

The daily multivariate predictand (Hs, Tm, and SS) is associated to each particular WT, obtaining stationary, identically-distributed samples of each variable. Any remaining time-dependence between samples is overcome by introducing the extremal index associated to each WT.

Figure 19, Figure 20, and Figure 21 show Hs, Tm, and SS distributions, respectively, for each weather type and the best fit GEV distribution and parameter estimates. Low pressure systems centered over the British Isles (WT8, WT9) produce large combined significant wave heights, wave periods, and storm surge in the study location. However, the largest storm surges, accompanied with low wave energy, occur when low pressure systems are located over the study site (WT29, WT30, WT40). On the other hand, the largest wave periods occur when low pressure systems are located in northern Atlantic Ocean over Iceland (WT1, WT11). The variation in the intensity of each variable according to weather types reflects the importance of modeling wave climate according to large-scale atmospheric predictors.

The dependence structure associated to each weather type is modeled using a multivariate Gaussian copula as described in section 4.2.5. The correlation between variables (Hs, Tm, and SS) is illustrated by a 2D comparison in Figure 22. As expected, the significant wave height and mean period are positively correlated for most weather types. Only one WT (WT40) has a negative correlation between Hs and Tm which corresponds to a low-pressure system close to the study site. Correlations between SS-Tm, and SS-Hs vary significantly between WTs. Generally, positive correlations correspond to low pressure systems and negative correlations to high pressure systems, although each pattern presents particularities. Note that large correlations are found for many WTs, reinforcing the advantage of splitting up the multivariate analysis in independent distributions based on coherent weather types.

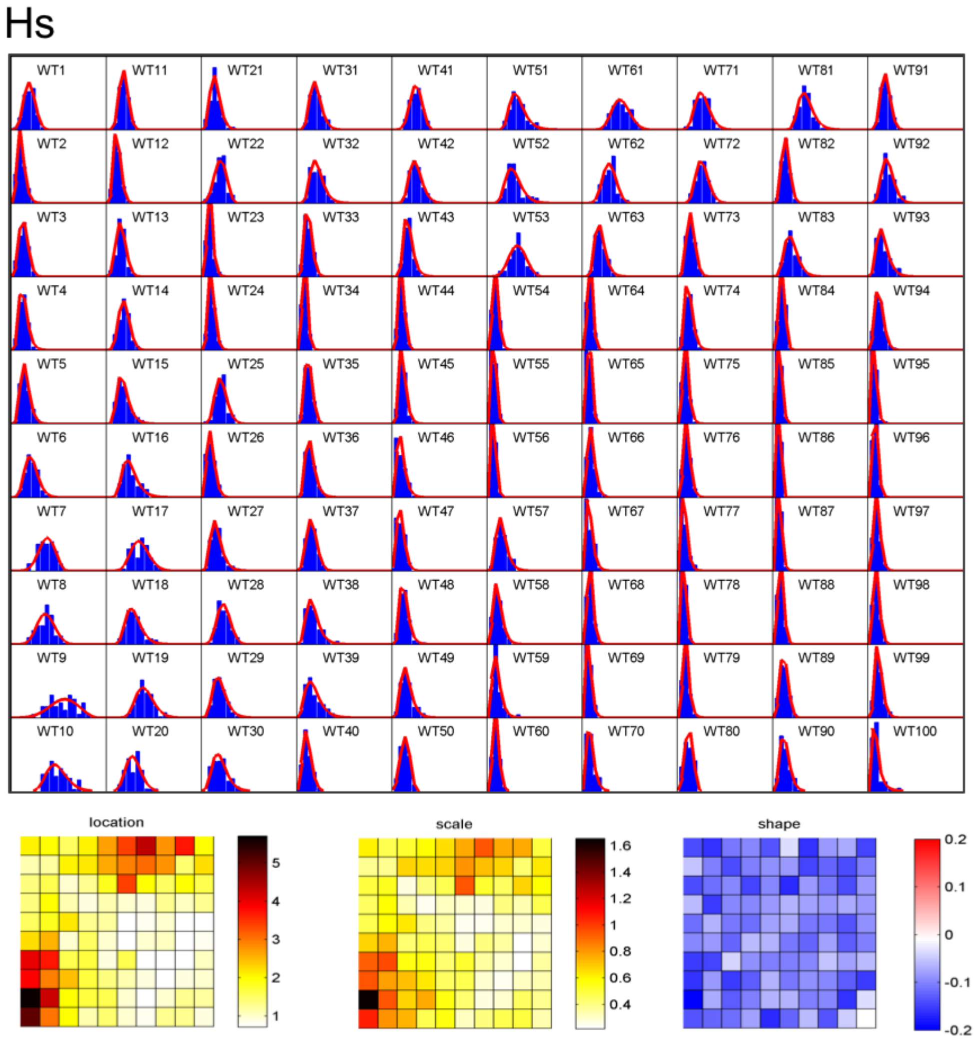


Figure 19.The associated histogram and GEV probability density function for daily significant wave height (in meters) associated to the maximum TWL at each WT. X-axis [0 11] , Y-axis [0 0.95] The corresponding parameter estimates of each distribution are illustrated in the lower panels.

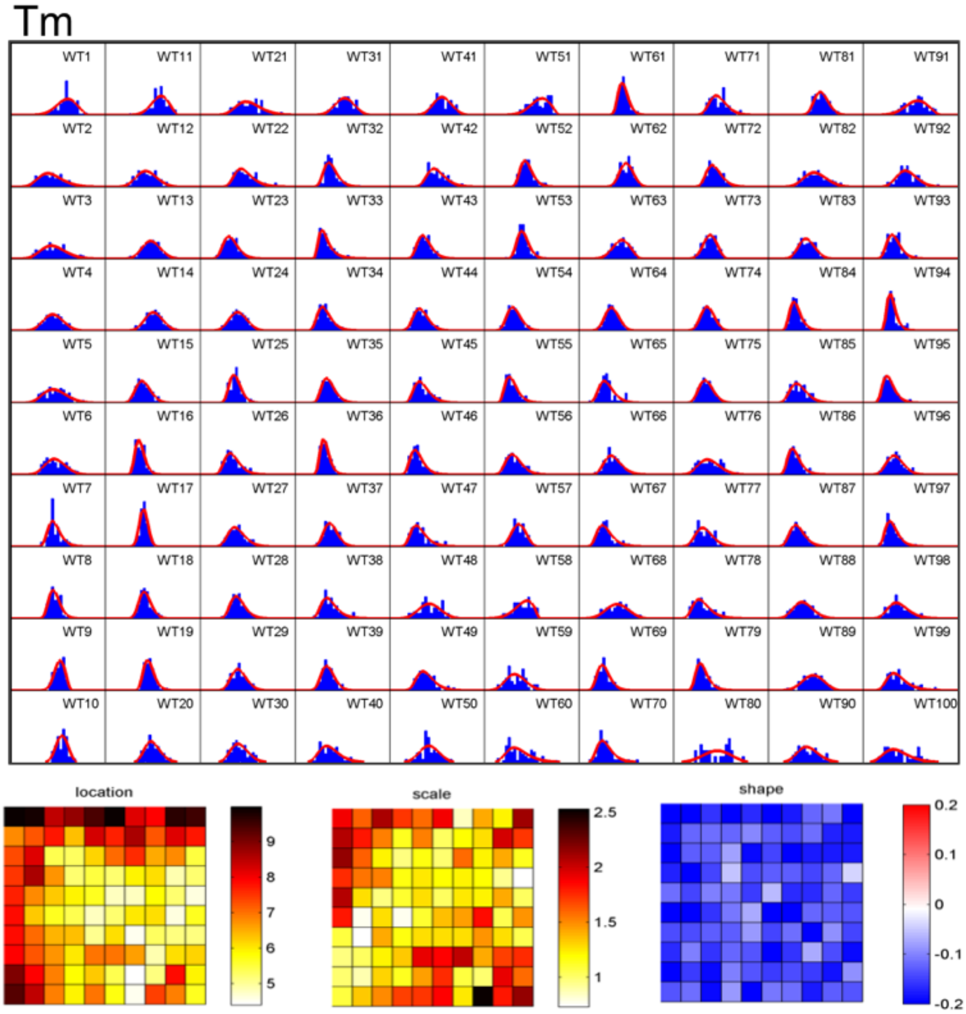


Figure 20. The associated histogram and GEV probability density function for daily mean period (in seconds) associated to the maximum TWL at each WT. X-axis [0 18] , Y-axis [0 0.95] The corresponding parameter estimates of each distribution are illustrated in the lower panels.

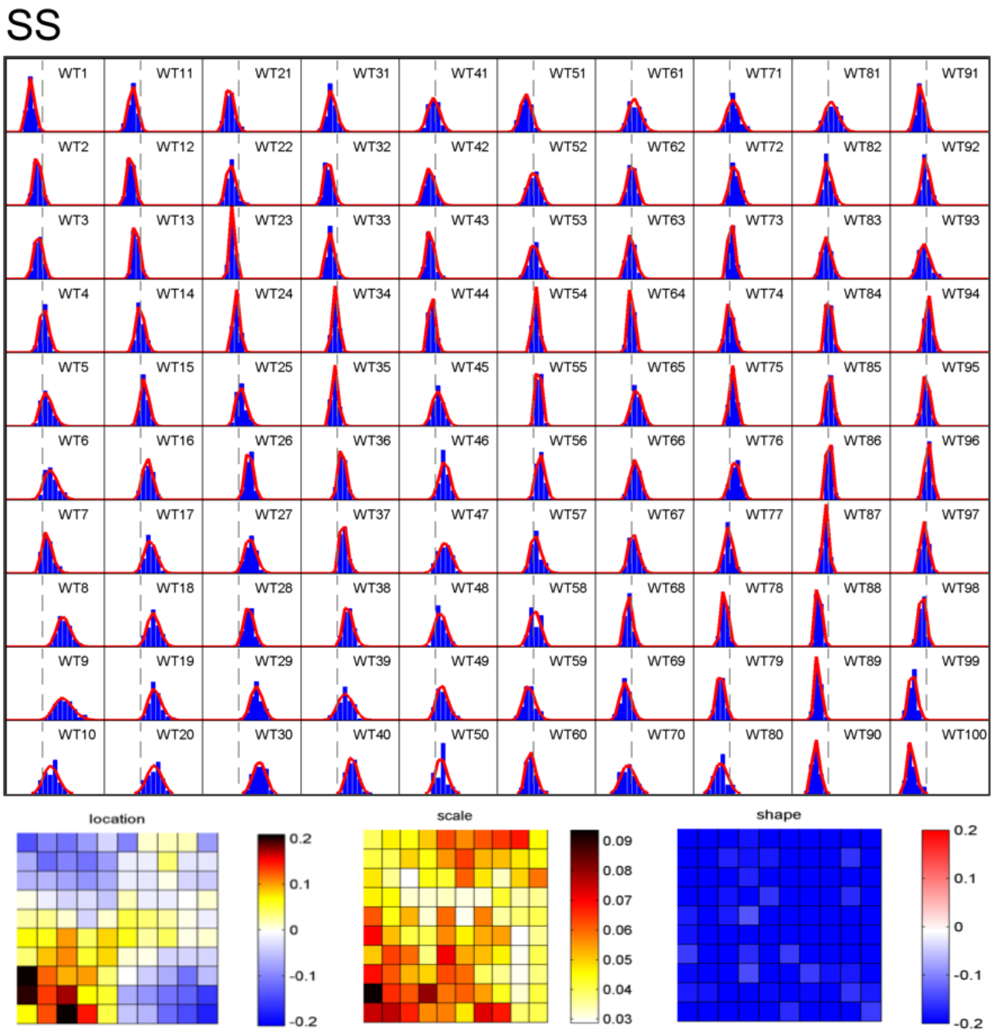


Figure 21. The associated histogram and GEV probability density function for daily storm surge (in meters) associated to the maximum TWL at each WT. X-axis [-0.4 0.6], Y-axis [0 0.7]. The corresponding parameter estimates of each distribution are illustrated in the lower panels.

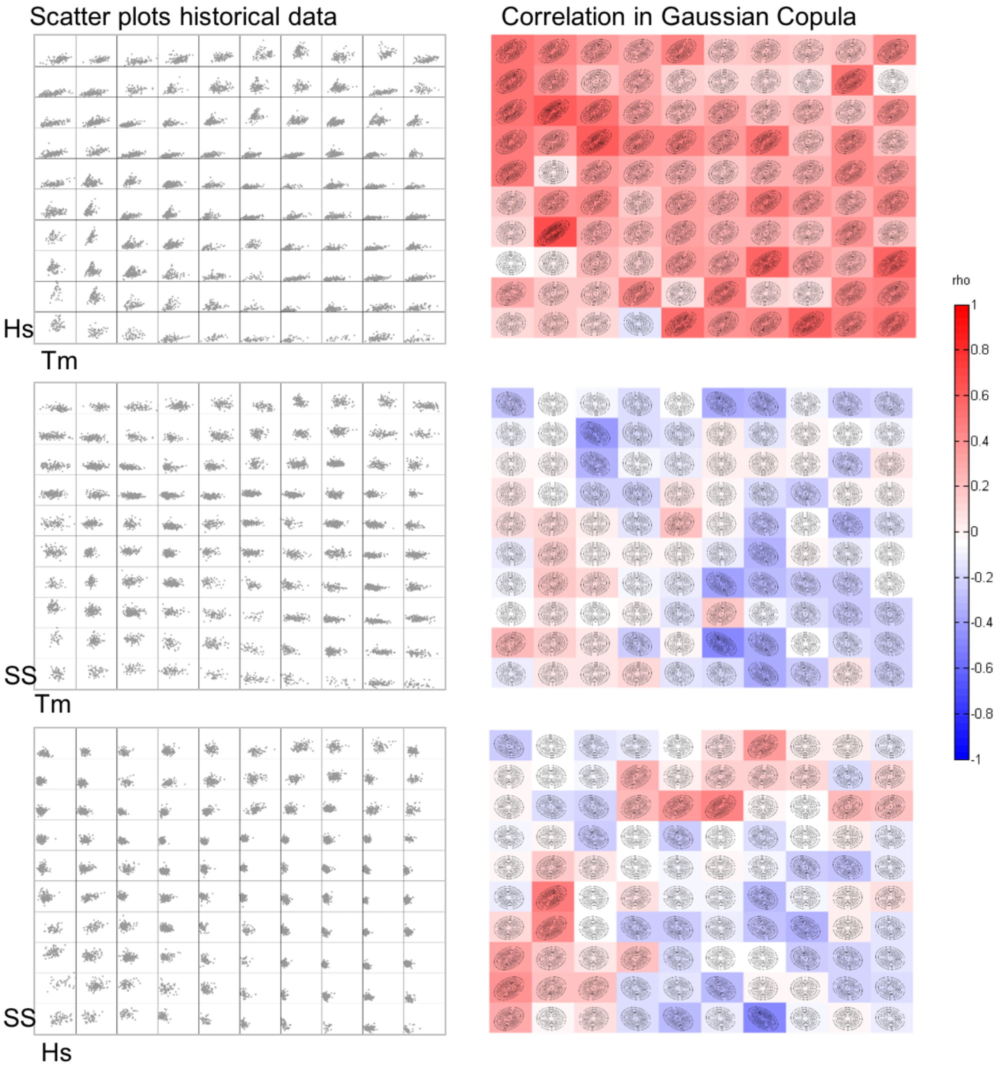


Figure 22. The left panels represent the scatter plots for each WT of the historical data represented in groups of pairs (from top to down: Hs---Tm; SS---Tm; and SS---Hs). The right panels represent the associated Gaussian copulas, where the background color shows the the corresponding correlation coefficient.

Once the marginal distributions and dependence structure between variables are fit and verified (not shown) for each WT, it is possible to generate synthetic time series of extreme events responsible for coastal flooding. To this end, a Monte Carlo simulation is performed where 300 realizations of 1500 years are simulated, obtaining 164,250,000 daily events. The daily realizations of Hs, Tm, and SS that produce the TWL annual maxima from the Monte Carlo simulation are illustrated in the upper panel of Figure 23 (colored dots). The color represents the WT of origin, which are illustrated in the lower panel of the same figure.

Different families of multivariate events can be found on the simulated sample. For example, WT9 (clear green) and WT10 (brown), on Figure 24 share large probabilities of producing an annual maximum of TWL. Although WT9 and WT10 have similar synoptic weather patterns (Figure 18), and therefore exhibit similar ranges of Hs and Tm, anticyclonic circulation over the study area (WT10) reduces the values of the associated SS of the simulated events.

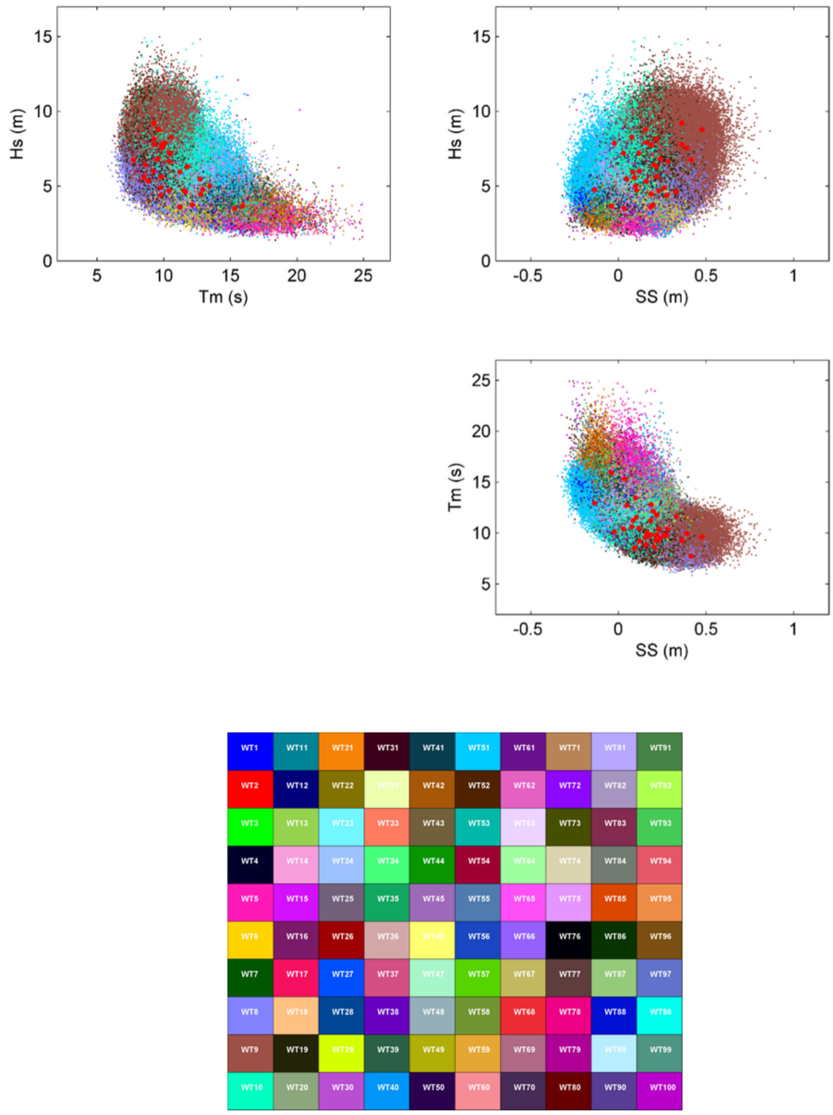


Figure 23. Historical annual maxima (red dots) and annual maxima of Monte Carlo simulated events based on weather type probabilities and TWL definition. The colors of the simulated events correspond with the WT of origin (represented in the lower panel)

The ultimate goal of the proposed methodology is to estimate the exceedance probability of a response function, in this case TWL. In the upper panel of Figure 24, the return period of annual maxima TWL obtained using the proposed methodology is compared to historical data. The red line is the mean of the Monte Carlo simulations and grey shaded areas represents the 95% confidence intervals. This result is compared to a standard univariate extreme value method, in this case a GEV of the annual maxima of the historical TWL (blue line). The multivariate approach provides a better fit to the historical data. The differences between the two methods in the upper tail of the distribution are consistent with the findings of Bruun and Tawn (1998) and Gouldby et al. (2014) who proposed that potential erroneous extrapolation can arise in multivariate problems when not using a joint probability method.

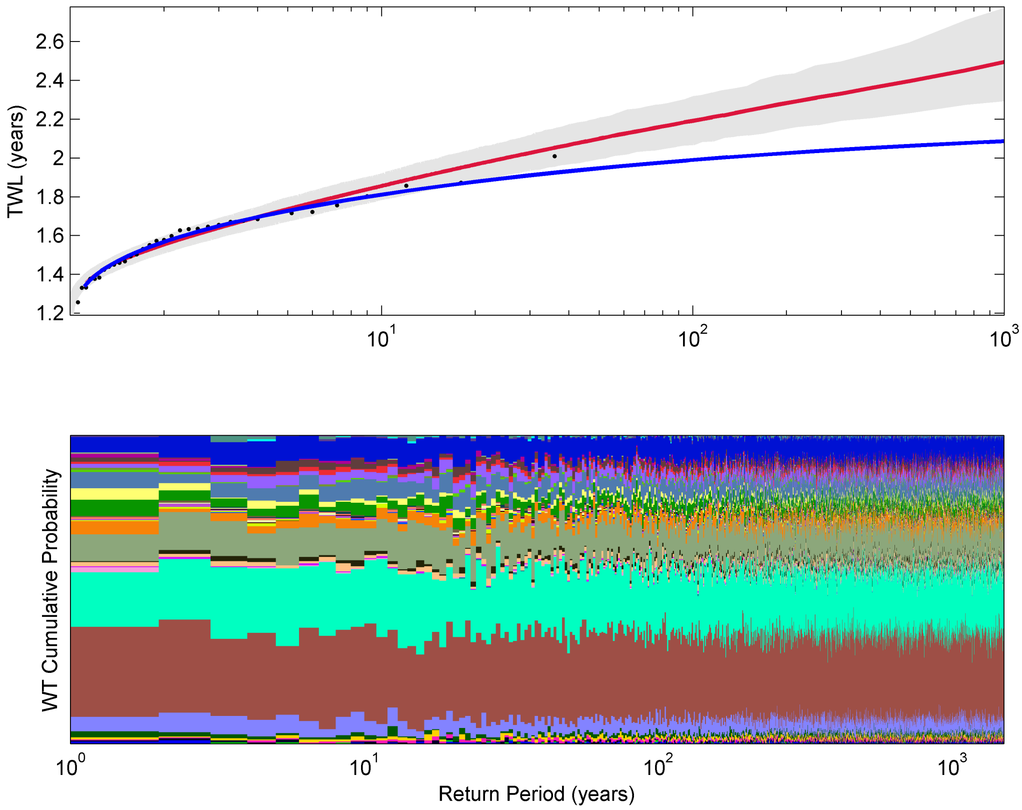


Figure 24. Upper panel: extreme TWL vs. return period plot. Red line represents the mean of the climate-based simulations and grey shaded area are the 95% confidence intervals. Blue line shows the stationary GEV fit for the historical annual maxima (black dots). Lower panel: WT of origin of the annual maxima simulated events.

The proposed method captures the non-stationary behaviour of climate by accounting for the variability of weather patterns over time. In the current Monte Carlo method, the occurrence probability of each weather type is fixed. However, the change in occurrence probability of weather types, as suggested by GCMs may be easily integrated into the proposed method. In the lower panel of Figure 24, the WTs responsible for the annual maxima TWL are illustrated. Generally, only 10 individual WTs are responsible for the highest annual TWL and the highest probabilities of producing an annual maximum are shared between WT9, WT10, WT20 and WT1. Thus, the proposed method allows the trace back from extreme flooding events to the weather conditions responsible for their genesis.

4.4 Summary and conclusions

In this chapter, a new climate-based approach to analyze and reconstruct extreme waves and storm surges is presented. The model is based on a predictor-to-predictand synoptic regression-guided classification model that groups extreme events according to similar generating meteorological processes, namely, weather types. Stationary extreme value models for the marginals, significant wave height, mean period, and storm surge are fit to each weather type and a Gaussian copula is used to account for the statistical dependence between the variables. The inter-daily data dependence is modeled with a climate-based extremal index. In this chapter, we have focused on a trivariate problem (significant wave height, mean period, storm surge level) but the method is scalable to more variables due to the flexibility of the multivariate Gaussian copula. Non-stationarity (seasonality, interannual variability, and climate change) can be introduced in the model through the occurrence probability of each weather type as a function of time as predicted by global climate models.

The model is applied to the northern coast of Spain and the analysis of the results allows the identification of the weather types responsible for extreme coastal flooding events. In our particular application, the tide-surge interaction is practically negligible. If included, the tidal elevation could be added linearly in a Monte Carlo simulation.

In summary, the proposed multivariate extreme value model is able to extrapolate the joint density function of the variables that influence coastal flooding, providing insight into the connection between weather patterns and multivariate extreme wave climate.

Chapter V

Summary and future research

5 Chapter V. Summary and future research

5.1 Summary of contributions

This thesis has yielded several contributions in the form of three papers and several conference presentations. Some research related to the thesis but not included in it yielded to three additional published papers co-authored by the PhD candidate. The summary of the three main chapters of the thesis as well as other scientific contributions are shown below.

5.1.1 Summary of "The use of wave propagation and reduced complexity inundation models and metamodels for coastal flood risk assessment".

Rueda, A., Gouldby, B., Méndez, F., Tomás, A., Lara, J., Losada, I., Díaz-Simal, P. (2015). The use of wave propagation and reduce complexity inundation models and meta-models for coastal flood risk assessment. Journal of Flood Risk Management. DOI: 10.1111/jfr3.12204

- The methodology developed in this work enables the determination of the statistical distribution of damage and its spatial distribution in practical computational timescales. The computational efficiency is afforded by the wave transformation metamodel (Camus et al., 2013; Gouldby et al., 2014) and the reduce complexity inundation model (Jamieson et al., 2012).
- Quantitative flood risk assessments are often essential for decisions based on design, risk minimization and event attribution. To that end, information of the probability of the hazard must be combined with the consequence information in order to obtain the potential losses due to flooding. To that end, local damage functions associated with the different land used have been used to estimate the economic damage associated with each simulated event.
- The computational efficiency of the developed framework allows no

simplistic assumptions regarding the joint probability density function of the variables that condition coastal flooding. Therefore, the sample of space of possible events that could occur in the system is better explored.

- The Monte Carlo simulation of the fitted multivariate extreme value model represents the overtopping rates along the coastal boundary more realistically than simplified methods that assume full dependence.
- Coastal floods are climate-related events; therefore, future work was required to define a multivariate extreme value model that incorporates climate variability into the Monte Carlo simulation.

5.1.2 Summary of “An extreme value model for maximum wave heights based on weather types”.

Rueda, A., Camus, P., Tomás, A., Méndez, F. (2016). An extreme value model for maximum wave heights based on weather types. J. Geophysical. Research. Oceans, 10.1002/2015JC010952

- A statistical model to downscale and analyse the variability of daily maxima of significant wave height is presented. The model is based on the ability of a predictor-to-predictand synoptic classification model to group observations according to similar generating meteorological processes, namely Weather Types (WTs).
- Non-stationarity is introduced in the model through the occurrence probability of each WT as a function of time, i.e., probabilities of each WT at a particular month, season or year.
- The results of the model provide useful information to identify which WTs are related to the more extreme events and to explain the interannual variability. The influence of large-scale patterns, such as those described by the NAO index, has been explored by analyzing the time evolution of the occurrence probabilities of certain WTs.
- The use of a statistical-downscaling weather type framework allows the reconstruction of daily maxima wave height in different time period outside the calibration one. In this case, a reconstruction of monthly

maxima estimates for the 20th century has been performed using the 20CR atmospheric reanalysis (Compo et al., 2011).

- The model provides new ways to gain insights about climate variability of extreme events. The importance of large-scale patterns such as NAO is highlighted due to its influence on extreme wave height variability.
- Climate change problems could be address with low computational effort by analysing the changes in the occurrence probabilities of the different WTs.

5.1.3 Summary of "A multivariate extreme wave and storm surge climate emulator based on weather patterns".

Rueda, A., Camus., P., Tomás, A., Vitousek, S., Méndez, F.J (Under review at Ocean Modelling). A multivariate extreme wave and storm surge climate emulator based on weather patterns

- A new climate-based approach to analyze and reconstruct extreme waves and storm surges is presented. The model is based, as in the univariate case, on a predictor-to-predictand synoptic regression-guided classification model that groups extreme events according to similar meteorological processes, namely, weather types.
- In order to be able to extrapolate the joint density function of the marine variables that condition coastal flooding, stationary extreme value models for the marginals, (significant wave height, mean period, and storm surge) are fit to each weather type and a Gaussian copula is used to account for the statistical dependence between the variables.
- The flexibility of the Gaussian copula allows the scalability of the method to more variables than the three ones presented.
- The analysis of the results allows the identification of the weather types responsible for extreme coastal flooding events.
- The proposed multivariate extreme value model is able to extrapolate the joint density function of the variables that influence coastal flooding, providing insight into the connection between weather patterns and

multivariate extreme wave climate.

5.1.4 Summary of other contributions as co-author.

- Gouldby, B., Méndez, F., Guanche, Y., Rueda, A., Mínguez, R. (2014). A methodology for deriving extreme nearshore sea conditions for structural design and flood risk analysis. Coastal Engineering. 88, 15-26. This paper introduces a methodology to derive extreme nearshore conditions for flood risk analysis.
- Camus, P., Méndez, F.J., Losada, I.J., Menéndez, M., Espejo, A., Pérez, A., Rueda, A., Guanche, Y. (2014a). A method for finding the optimal predictor indices for local wave climate conditions. Ocean Dynamics, 64 (7), 1025-1038. This paper looks for optimal predictor indices for local wave conditions.
- Camus, P., Menéndez, M., Méndez, F.J., Izaguirre, C., Espejo, A., Cánovas, V., Pérez, J., Rueda, A., Losada, I.J., Medina, R. (2014b). A weather-type statistical downscaling framework for ocean wave climate. Journal of Geophysical Research, DOI: 10.1002/2014JC010141. This paper proposes a weather-type statistical downscaling framework for ocean wave climate.

5.2 Future research

The development of this thesis has lead to further investigation, opening some new research topics:

- The definition of a methodology for coastal flooding risk assessment is highly dependent (in terms of the hazard) of the relative contribution of waves, surge and tide. Therefore, it would be desirable to establish homogenous areas at global scale to select the best methodology in each particular case.
- Regarding the uncertainty cascade: Any modelling system has inherent some uncertainties. In the case of the coastal flood risk modelling system

proposed in this thesis there are uncertainties associated with any of its different components. There are significant uncertainties relating to the extrapolation of the joint probability density function, (although they are treated to some extent with the Monte Carlo method), these uncertainties propagate through and combine with the hydrodynamic models structural errors. Uncertainty is also associated with the land uses and damage models (Moel and de Aerts, 2011). The quantification of these uncertainties has not been undertaken here. However, the estimation and communication of the uncertainties involved in the risk assessment should be honestly translated to the interested parties.

- Regarding the applicability of the multivariate extreme climate emulator on the verification of marine structures: the multivariate climate emulator developed, based on Monte Carlo methods, does not assume any hypothesis on the dependence structure of the variable involved. It is a random generator of multivariate extremes based on the occurrence probability of certain weather types, therefore its applicability to Level III structure verification is pretty straight forward by including the failure modes and dike parameters on the simulation. With the advantage to be able to trace back the synoptic atmospheric situation responsible for structure failure.
- Regarding the near-shore processes: The modelling of the near-shore processes (wave breaking, wave runup, wave overtopping, etc., …) are analysed in the thesis using simple empirical formulations. On the state of the art, wave transformation during moderate wave and wind conditions is simulated reasonably well (Ardhuin and Herbers 2002; Thomson et al. 2006; Ardhuin et al. 2007; Smit et al. 2014); however, present knowledge regarding wave transformation during extreme events is limited. The observations of near-shore processes during extreme storms would help in our understanding of wave evolution during these extreme events and therefore will lead to improved parameterization in models that finally will help in risk quantification. In the particular case of beaches, the modelling of infragravity waves is essential for a correct estimation of

wave run-up and overtopping (Gallien, 2016). More sophisticated numerical models that account for these processes are available, such as the Navier-Storkes-type models or Boussinesq-type models, however the computational times involved made them still unfeasible for risk assessments.

- Regarding the influence of rain and river discharge in coastal flooding events: coastal storms responsible for flooding might bring not only elevated ocean water levels but also considerable rainfall. The final impact, therefore, would be caused by their combine effect, and if that is the case, it needs to be included in the analysis. During the progress of this thesis different tools have been developed and/or used that might facilitate its inclusion. Firstly, the use of an inundation model such as RFSM-EDA (chapter I) allows to use ocean water levels, river discharge and/or rainfall as boundary conditions simultaneously. Secondly, the multivariate framework developed in chapter IV, allows the inclusion of rainfall in the statistical analysis thanks to the use of statistical downscaling techniques and the flexibility of Gaussian copulas to model several variables. However, although some tests have been made for each particular component (numerical and statistical modeling), no real application combining these tools has been performed yet.
- Regarding the risk assessment: The methodology developed in this thesis could be defined as an "academic approach", where no third parties are involved in the definition of the problem. However, real life applications would benefit from a stakeholder-centered approach, or what is collectively referred as a "bottom-up" approach. These approaches begin by understanding the information needed by the stakeholder, the key decision that need to be made, the nature of the decision variable and the spatial and temporal scale of the climate and meteorological processes involved. It would be interesting to adapt the developed methodologies to help on decision-making process of particular stakeholders.
- Regarding the interaction between coastal erosion and coastal flood

events: The methodological framework developed in this thesis does not account for the event chronology and therefore no changes in beach morphology are considered. However, coastal erosion and flood events are completely coupled processes. To be able to include them on the simulation, a climate emulator that account for event chronology at a daily scale has been recently developed (Rueda et al. (submitted to JGR-Oceans)). This modelling framework at a daily scale might allow the analysis of morphological changes and the inclusion of the tide on the simulation. Nevertheless, the coupling of morphology and hydraulic simulations throughout storm and specially recovery periods is a topic of ongoing research on the scientific community.

6 References

Ardhuin, F.,and T.H.C. Herbers. (2002). Bragg scattering of random surface gravity waves by irregular seabed topography. Journal of Fluid Mechanics, 451 1-33. doi:10.1017/S0022112001006218

Ardhuin, F., T.H.C. Herbers, K.P. Watts, G.P van Vledder, R. Jensen, and H.C. Graber (2007). Swell and slanting-fetch effects on wind wave growth. Journal of Physical Oceanography, 37,908-931

Bates, P. D. and De Roo, A. P. J. (2000). A simple raster-based model for flood inundation simulation. Journal of Hydrology 236: 54-77.

Bates, P. D., Horritt, M. S. and Fewtrell, T. J. (2010). A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. Journal of Hydrology 387(12): 33-4

Batstone, C., Lawless, M., Tawn, J., Horsburgh, K., Blackman, D., McMillan, A., Worth, D., Laeger, S., Hunt, T. (2013). A UK best-practice approach for extreme sea-level analysis along complex topographic coastlines. *Ocean Engineering*, 71. 28-39. 10.1016/j.oceaneng.2013.02.003

Becker, J. J., D. T. Sandwell, W. H. F. Smith, J. Braud, B. Binder, J. Depner, D. Fabre, J. Factor, S. Ingalls, S-H. Kim, R. Ladner, K. Marks, S. Nelson, A. Pharaoh, R. Trimmer, J. Von Rosenberg, G. Wallace, P. Weatherall., (2009). Global Bathymetry and Elevation Data at 30 Arc Seconds Resolution: SRTM30_PLUS, Marine Geodesy, 32:4, 355-371, DOI: 10.1080/01490410903297766

Ben Alaya, M.A., Chebana, F., Ouarda, T.B.M.J., (2014), Probabilistic Gaussian Copula Regression Model for Multisite and Multivariable Downscaling, *J. Climate,* DOI: 10.1175/JCLI-D-13-00333.1

Bender, J., Wahl, T., Jensen, J. (2014). Multivariate design in the presence of non-stationarity, *J. of Hydrology*, 514, 123-130.

Beirlant J, Geogebeur Y, Segers J, Teugels J. (2004). Statistics of extremes. Theory and applications. John Wiley & Sons, Chichester

Bertin, X., E. Prouteau, and C. Letetrel, (2013). A significant increase in wave height in the North Atlantic Ocean over the 20th century. Global and Planetary Change, 106, 77- 83.

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

Bruun, J. T. and Tawn, J. A. (1998). Comparison of approaches for estimating the probability of coastal flooding. *Journal of the Royal Statistical Society: Series C* (Applied Statistics) 47(3): 405-423.

Buck W. (2004). Monetary evaluation of flood damages, In D. Mahlzahn, T. Plapp. (ed) Disasters and Society, From Hazard Assessment to Risk Reduction, Int. Conf. July 2004, Karlsruhe, Berlin: Logos Verl. 2004, p. 123 - 127

Callaghan, D., P. Nielsen, A. Short, and R. Ranasinghe, (2008). Statistical simulation of wave climate and extreme beach erosion, *Coastal Eng.,* 55(5), 375–390

Cannon, A.J., (2010). A flexible nonlinear modelling framework for nonstationary generalized extreme value analysis in hydroclimatology. Hydrological Processes, 24: 673-685. doi: 10.1002/hyp.7506

Cannon, A.J., (2012). Regression-guided clustering: a semi-supervised method for circulation-to-environment synoptic classification, *Journal of Applied*

Meteorology and Climatology, 51,185-190.

Camus, P., Mendez, F.J., Medina, R., Cofiño, A.S. (2011b). Analysis of clustering and selection algorithms for the study of multivariate wave climate. Coast. Eng. 58 (6), 453-462

Camus, P., Mendez, F.J., Medina, R., Tomás, A., Izaguirre, C. (2013). High resolution downscaled ocean waves (DOW) reanalysis in coastal areas, Coastal Engineering, 72, 56-68.

Camus, P., Mendez, F.J., Medina, R., (2011a). A hybrid efficient method to downscale wave climate to coastal areas. Coast. Eng. 58 (9), 851–862.

Camus, P., Méndez, F.J., Losada, I.J., Menéndez, M., Espejo, A., Pérez, J., Rueda, A., Guanche, Y., (2014a). A method for finding the optimal predictor indices for local wave climate conditions. *Ocean Dynamics*, 64(7), 1025-1038. doi:10.1007/s10236-014-0737-2

Camus, P., Menéndez, M., Méndez, F.J. , Izaguirre, C. , Espejo, A., Cánovas, V. , Pérez, J., Rueda, A., Losada, I. J., Medina R., (2014b), A weather-type statistical downscaling framework for ocean wave climate, *J. Geophys. Res. Oceans*, 119, 7389–7405, doi:10.1002/2014JC010141.

Casas-Prat, M., Wang, X.L., Sierra, J.P. (2014). A physical-based statistical method for modeling ocean wave heights. Ocean Modelling, 73, 59-75.

Castelletti, A., Galelli, S., Ratto, M., Soncini-Sessa, R., Young, P.C., (2012). A general framework for dynamic emulation modelling in environmental problems. Environ. Mode Softw. 34, 5–18.

Challenor PG. (1982). A new distribution for annual extremes of environmental variables, Quarterly Journal - Royal Meteorological Society, volume 108, no. 458, pages 975-980.

Cid A., Castanedo S., Abascal A.J., Menéndez M. & Medina R. (2014). A high resolution hindcast of the meteorological sea level com- ponent for Southern Europe: the GOS dataset. *Clim Dyn*, 43, 2167–2184. doi: 10.1007/s00382-013-2041-0.

Coles, S. (2001). An introduction to statistical modeling of extreme values, London, U.K.:*Springer Verlag*, 208 pp

Coles, S., Tawn, J. (2005), Seasonal effects of extreme surges, Stoch Environ Res Risk Assess (2005) 19: 417–427.

Compo GP, Whitaker JS, Sardeshmukh PD, Matsui N, Allan RJ, Yin X, Gleason BE et al., (2011). The twentieth century reanalysis project. Q J Roy Meteor Soc 37(654):1–28.

Cooley, D. (2013). Return periods and return levels under climate change. Chapter 4, Extremes in a changing climate: Detection, analysis and uncertainty, A. AghaKouchak, D. Easterling, and K. Hsu, eds., Vol. 65, Springer, New York

Corbella, A., Stretch, D.D., (2013). Simulating a multivariate sea storm using Archimedean copulas. *Coast. Eng*. 76, 68–78.

Davison, A. C. and Smith, R. L. (1990). Models for exceedances over high thresholds. Journal of the Royal Statistical Society, Series B (Statistical Methodology) 52(3): 393-442.

Dawson, R., Sayers, P., Hall, J., Hassan, M. & Bates, P. (2005) Efficient broad scale coastal flood risk assessment. In Coastal Engineering 2004, Proc. 29th Int. Conf., Lisbon, Portugal, ed. J. McKee Smith. New Jersey: World Scientific, 2005. Vol.3, pp.3061-3073

Defra / Environment Agency (2005). Use of joint probability methods in flood management: A guide to best practice. Defra / Environment Agency R&D Technical Report FD2308/TR2

Dixon, M.J., Tawn, J.A. (1999), The effect of non-stationarity on extreme sea-level estimation. *J. Roy. Stat. Soc.,* 48C, 135–151.

Environment Agency (2010) Benchmarking of 2D Hydraulic Modelling Packages, Environment Agency Report SC080035/SR2, Bristol

Environment Agency, (2013). Prototype wave overtopping tool for mdsf2, Bristol.

Espejo, A., Camus, P., Mendez, F.J., Losada, I.J. (2014) Spectral ocean wave climate variability based on circulation patterns, *J. Phys. Oceanography*, doi: 10.1175/JPO-D-13-0276.1

Ewans, K. and Jonathan, P., (2013). Evaluating environmental joint extremes for the offshore industry using the conditional extremes model. Journal of Marine Systems. 130,124-130. http://dx.doi.org/10.1016/j.jmarsys.2013.03.007

Federal Emergency Management Agency (FEMA). (2009) Multi-hazard loss estimation methodology. Flood Model. Technical Manual.

Fisher, R. A. and Tippett, L. H. C. (1928) Limiting forms of the frequency distribution of the largest or smallest member of a sample. Proceedings of the Cambridge Philosophical Society, vol 24, pp. 180–290.

Fowler, H.J., Blenkinsop, S., Tebaldi, C. (2007). Linking climate change modelling to impact studies: recent advances in downscaling techniques for hydrological modelling. International Journal of Climatology, 27, 1547-1578.

Galambos, J. (1987). The Asymptotic Theory of Extreme Order Statistics, 2nd edition. Kreiger, Malabar, FL.

Gallien, T.W. (2016) Validated coastal flood modeling at Imperial Beach, California: Comparing total water level, empirical and numerical overtopping methodologies, Coastal Engineering, Vol. 111, 95-104, ISSN 0378-3839, http://dx.doi.org/10.1016/j.coastaleng.2016.01.014.

Garavaglia, F., Gailhard, J., Paquet, E., Lang, M., Garcon, R., Bernardara, P. (2010). Introducing a rainfall compound distribution model based on weather patterns sub-sampling. *Hydrology and Earth System Sciences Discussions, Copernicus Publications*, 14, 951-964.

Giorgi, F., B. Hewitson, J. Christensen, M. Hulme, H. Von Storch, P. Whetton, R. Jones, L. Mearns, C. Fu, 2001. Regional Climate Information: Evaluation and Projections (Chapter 10). In Climate Change (2001): The Scientific Basis, Contribution of Working 32 Group I to the Third Assessment Report of the IPCC [Houghton, J. T., Y. Ding, D. J. Griggs, M. Noguer, P. J. van der Linden, X. Dai, K. Maskell, and C. A. Johnson (eds.)]. Cambridge U. Press: Cambridge, pp. 739-768.

Gouldby, B., Méndez, F.J., Guanche, Y., Rueda, A. and Mínguez, R. (2014). A methodology for deriving extreme nearshore sea conditions for structural design and flood risk analysis. *Coastal Engineering*. 88, 15-26.

Gouldby, B., Sayers, P., Mulet-Marti, J., Hassan, M. and Benwell, D. (2008a). A methodology for regional-scale flood risk assessment. Water Management 161(3): 169-182.

Gouldby, B., Sayers, P. and Tarrant, O. (2008b). Application of a flood risk model to the Thames Estuary for economic benefit assessment. Risk Analysis VI: Simulation and Hazard Mitigation, Caephalonia, WITpress.

Guinot, V. and Soares-Frazão, S. (2006). Flux and source term discretization in two-dimensional shallow water models with porosity on unstructured grids. International Journal for Numerical Methods in Fluids 50(3): 309-345.

Gutierrez, J. M., D. San-Martın, S. Brands, R. Manzanas, and S. Herrera (2013), Reassessing statistical downscaling techniques for their robust application under climate change conditions, J. Clim., 26(1), 171–188.

Hastie, T., Tibshirani, R., Friedman, J., (2001). The Elements of Statistical Learning. Springer, New York.

Hawkes, P. J., B. P. Gouldby, J. A. Tawn, and M. W. Owen, (2002). The joint probability of waves and water levels in coastal engineering design, J. Hydraul. Res., 40(3), 241–251.

Heffernan, J. E. and Tawn, J. A. (2004). A conditional approach for multivariate extreme values (with discussion). *Journal of the Royal Statistical Society: Series B* (Statistical Methodology) 66(3): 497-546.

Hill, W.J., Hunter,W.G., (1966). A review of response surface methodology: a literature survey. Technometrics 8 (4), 571–590.

Holman, R.A., Haller, M.C., Lippmann, T.C., Holland, K.T. and Jaffe, B.E. (2015). Advances in nearshore processes research: Four decades of progress. Coastal forum: Shore and Beach. Vol. 83, No1, 39-52.

Holthuijsen ,LH. (2007). Waves in oceanic and coastal waters. Cambridge University Press, ISBN 978-0521860284. 387 pp.

Huizinga, H., J. (2007). Flood damage functions for UE member states, HKV Consultants, Implemented in the framework of the contract #382442-F1SC awarded by the European Commision -Joint Research Center.

Hurrell, J.W., Kushnir, Y., Ottersen, G. and Visbeck, M., (2003). An overview of the North Atlantic Oscillation. Geophysical Monograph 134, 2003

IPCC, 2007: Climate Change (2007): The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M.Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 996 pp.

Izaguirre, C., F. J. Méndez, M. Menéndez, A. Luceño, and I. J. Losada, (2010). Extreme wave climate variability in southern Europe using satellite data, J. Geophys. Res., 115, C04009, doi:10.1029/2009JC005802

Izaguirre, C., Mendez, F.J., Menendez, M., Losada, I.J., (2011). Global extreme wave height variability based on satellite data, Geophysical Research Letters, 38, doi: 10.1029/2011GL047302.

Jamieson, S., Lhomme, J., Wright, G. and Gouldby, B. (2012). Highly efficient 2D inundation modelling with enhanced diffusion-wave and sub-element topography. Proc. Inst. Wat. Man. 165(10): 581-595.

Jamieson, S., Lhomme, J., Wright, G and Gouldby, B. (2013). Coarse mesh inundation modelling. Proceedings of 2013 IAHR World Congress.

Jonathan, P., Ewans, K. (2013). Statistical modelling of extreme ocean environments for marine design: a review. Ocean Engineering. 62, 91-109.

Jonathan, P., Flynn, J. and Ewans, K. (2013b). Joint modelling of wave spectral parameters for extreme sea states. Ocean Engineering 37((11)12): 1070-1080.

Katz, R.W., Parlange, M.B and Naveau, P. (2002). Statistics of extremes in hydrology, *Adv. Water Resour.*, 25, 1287–1304, doi:10.1016/S0309-1708(02)00056-8.

Katz, R.W. (2013). Statistical methods for nonstationary extremes. Extremes in a Changing Climate, Springer. Netherlands.

Keef, C., Tawn J and Svensson C (2009). Spatial risk assessment for extreme river flows. Appl Stat 58,(5): 601–618.

Keef, C. Tawn, J., Lamb R. (2012). Estimating the probability of widespread flood events. Environmetrics 24 (1),13-21

Kennedy, M.C., Anderson, C.W., Conti, S., O'Hagan, A., (2006). Case studies in gaussian process modelling of computer codes. Reliab. Eng. Syst. Saf. 91 (10), 1301–1309

Kingston, G., Robinson, D., Gouldby, B., Pullen, T., (2008). Reliable prediction of wave overtopping volumes using Bayesian neural networks. FLOODrisk 2008. Keble College, Oxford, UK (p. pp.).

Kingston, G.B., Rajabalinejad,M., Gouldby, B.P., Van Gelder, P.H.A.J.M., (2011). Computational intelligence methods for the efficient reliability analysis of complex flood defence structures. Struct. Saf. 33 (1), 64–73

Klein Tank, A.M.G., F.W. Zwiers and X. Zhang, (2009). Guidelines on Analysis of extremes in a changing climate in support of informed decisions for adaptation. WMO-TD No. 1500, 56 pp

Lamb, R., Keef, C., Tawn, J., Laeger, S., Meadowcroft, I., Surendran, S., Dunning, P. and Batstone, C. (2010). A new method to assess the risk of local and widespread flooding on rivers and coasts. Journal of Flood Risk Management

3(4): 323-336.

Laux, P., S. Vogl, W. Qiu, H. Knoche, and H. Kunstmann. (2011). Copula-based statistical refinement of precipitation in RCM simulations over complex terrain. *Hydrol. Earth Syst. Sci*., 15, 2401–2419, doi:10.5194/hess-15-2401-2011.

Leadbetter, M.R. (1983). Extremes and local dependence in stationary sequences, Z. Wahrsch. Verw. Gebiete 65. 291-306.

Leonard, M., Westra, S., Phatak, A., Lambert, M., van den Hurk, B., McInnes, K., Risbey, J., Schuster, S., Jakob, D., Stafford-Smith, M. (2014). A compound event framework for understanding extreme impacts, *WIRES Clim Change*, 5, 113-128, doi: 10.1002/wcc.252

L'homme, J., Gutierrez-Andres, J., Weisgerber, A., Davison, M., Mulet-Marti, J., Cooper, A. and Gouldby, B. (2010). Testing a new two-dimensional flood modelling system: analytical tests and application to a flood event. *Journal of Flood Risk Management* 3(1): 33-51

Masina, M., Lamberti, A., and Archetti, R. (2015). Coastal flooding: A copula based approach for estimating the joint probability of water levels and waves. *Coastal Engineering*, 10.1016/j.coastaleng.2014.12.010, 37-52.

McGranahan, G., D. Balk, and B. Anderson (2007). The rising tide: assessing the risks of climate change and human settlements in low elevation coastal zones. Environ. Urbanisation 19, 17–37, doi:10.1177/0956247807076960.

McMillan, H. K. and Brasington, J. (2007). Reduced complexity strategies for modelling urban floodplain inundation. *Geomorphology* 90(34): 226-243

Mendez, F. J., M. Menendez, A. Luceño, Losada, I.J. (2006), Estimation of the long-term variability of extreme significant wave height using a time-dependent Peak Over Threshold (POT) model, *J. Geophys. Res.*, 111, C07024, doi:10.1029/2005JC003344.

Menéndez M, Méndez FJ, Izaguirre C, Losada IJ. (2009). The influence of seasonality on estimating return values of significant wave height. Coast Engineer. 56(3):211-9

Milly, P. C. D., J. Betancourt, M. Falkenmark, R. M. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer. (2008), Climate change: Stationarity is dead: Whither water management? *Science*, 319(5863), 573, doi:10.1126/science.1151915

Mínguez, R., Espejo, A., Tomás, A., Méndez, F. J. and Losada, I. J. (2011). Directional calibration of wave reanalysis databases using instrumental data. J. Atmos. Oceanic Technol. 28: pp 1466-1485.

Moel, H. de & Aerts, J.C.J.H. (2011). Effect of uncertainty in land use, damage models and inundation depth on flood damage estimates. Natural Hazards, 58(1), 407-425.doi:10.1007/s11069-010-9675-6

Morton, I. D., Bowers, J. and Mould, G., (1997). Estimating return period wave heights and wind speeds using a seasonal point process model,Coast. Eng., 31(1): 305–326.

Neal, J., Keef, C., Bates, P., Beven, K., Leedal. D. (2012). Probabilistic flood risk mapping including spatial dependence. Hydrol. Process, 27 (9), 1349-1363

Nelsen, R.B., (2006). An Introduction to Copulas, second edition. Springer-Verlag, New York.

Penning-Rowsell, E. C., Johnson, C., Tunstall, S., Tapsell, S., Morris, J., Chatterton, J., Coker, A., Green, C. (2003). The Benefits of flood and coastal defence: techniques and data for 2003. Flood Hazard Research Centre, Middlesex

University.

Parey S. (2010). Different ways to compute temperature return levels in the climate change context.Environmetrics 21:698–718

Perez J, Menéndez M, Méndez FJ, Losada IJ. (2014). ESTELA: A method for evaluating the source and travel-time of the wave energyreaching a local area.*Ocean Dynamics* 64:1025–1038 1037.

Perez J, Menéndez M, Camus P., Méndez FJ, Losada IJ. (2015). Statistical multi-model climate projections of surface ocean waves in Europe. *Ocean Modelling*, 10.1016/j.ocemod.2015.06.001

Pullen, T., N.W.H. Allsop, T. Bruce, A. Kortenhaus, H. Schüttrumpf, and J.W. van der Meer. (2007). EurOtop – Wave Overtopping of Sea Defences and Related Structures: Assessment Manual, Die Küste, 73, 193 pp.

Reguero, B. G., Menendez, M., Mendez, F. J., Minguez, R. and Losada, I. J. (2012). A Global Ocean Wave (GOW) calibrated reanalysis from 1948 onwards. Coastal Engineering 65(0): 38-55.

Renard, B., Lang, M. (2007). Use of a Gaussian copula for multivariate extreme value analysis: some case studies in hydrology. Advances in Water Resources, Elsevier, 30, p. 897 - p. 912.

Rueda, A., Camus, P., Méndez, F. J., Tomás, A., and Luceño, A. (2016), An extreme value model for maximum wave heights based on weather types, J. Geophys. Res. Oceans, 121, doi:10.1002/2015JC010952.

Sacks, J.,Welch,W.J., Toby, J.M.,Wynn, H.P., (1989). Design and analysis of computer experiments. Stat. Sci. 4 (4), 409–423.

Saha, S., (2010). NCEP Climate Forecast System Reanalysis (CFSR) 6-hourly Products, January 1979 to December 2010. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory. http://dx.doi.org/10.5065/D69K487J.

Salas, J. and Obeysekera, J. (2014). Revisiting the Concepts of Return Period and Risk for Nonstationary Hydrologic Extreme Events. J. Hydrol. Eng., 19(3), 554–568.

Salvadori, G., De Michele, C., Kottegoda, N.T., Rosso, R., (2007). Extremes in Nature. An Approach Using Copulas, Volume 56 of Water Science and Technology Library. Springer.

Seneviratne, S.I., N. Nicholls, D. Easterling, C.M. Goodess, S. Kanae, J. Kossin, Y. Luo, J. Marengo, K. McInnes, M. Rahimi,M. Reichstein, A. Sorteberg, C. Vera, and X. Zhang, (2012): Changes in climate extremes and their impacts on the natural physical environment. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 109-230.

Serafin, K. A., and P. Ruggiero. (2014). Simulating extreme total water levels using a time-dependent, extreme value approach, *J. Geophys. Res. Oceans*, 119, 6305–6329, doi:10.1002/2014JC010093.

Serinaldi, F. (2011). Analytical confidence intervals for index flow duration curves, *Water Resour. Res.*, 47, W02542, doi:10.1029/2010WR009408

Smit, P., T. Janssen, L. Holthuijsen, and J. Smith. (2014). Non-hydrostatic modeling of surf zone wave dynamics. Coastal Engineering, 83, 36-48

Smith, R. A. E., Bates, P. D., and Hayes, C. (2012). Evaluation of coastal flood inundation model using hard and soft data, Environ. Model. Softw., 30, 35–46.

Small, C., and R.J. Nicholls. (2003). A global analysis of human settlements in coastal zones. Journal of Coastal Research. 19,584-599.

Stockdon H.F., Holman R.A., Howd P.A. & Sallenger A.H. (2006). Empirical parameterization of setup, swash, and runup. Coast Eng 53, 573–588.

Thomson, J., S. Elgar, T. Herbers, B. Raubenheimer, R. Guza. (2006). Tidal modulation of infragravity waves via nonlinear energy losses in the surfzone. Geophysical Research Letters, 33(5).

USACE (1996). Risk-based Analysis for Flood Damage Reduction studies. Engineer Manual EM 1110-2-1619

Vogl, S., P. Laux, W. Qiu, G. Mao, and H. Kunstmann, (2012). Copula-based assimilation of radar and gauge information to derive bias-corrected precipitation fields. *Hydrol. Earth Syst*. Sci., 16, 2311–2328, doi:10.5194/hess-16-2311-2012.

Wahl, T., Mudersbach, C., Jensen, J., (2012), Assessing the hydrodynamic boundary conditions for risk analyses in coastal areas: a multivariate statistical approach based on Copula functions, *Nat. Hazards Earth Syst. Sci*., 12, 495–510.

Wahl, T., Jain, S., Bender, J., Meyers, S. D., Luther, H. E. (2015). Increasing risk of compound flooding from storm surge and rainfall for major US cities. *Nature climate change*. Doi:10.1038/NCLIMATE2736

Wang, X.L., Feng, Y., Swail, V. R. (2012). North Atlantic wave height trends as reconstructed from the 20th century reanalysis. Geophysical Research Letters 39, L18705.

Wyncoll, D. and Gouldby, B. (2013). Application of a multivariate extreme value approach to system flood risk analysis. Journal of flood risk management. http://dx.doi.org/10.1111/jfr3.12069.

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