Climate Change Risk Indicators for seaports in the United Kingdom

Abstract

Climate change is the most threating environmental issue and the biggest challenge that humanity has ever faced. While acting as the key nodes of globalisation and international business, seaports are exposed to the vulnerability of climate impacts, mainly because of their locations, including low-lying areas, coastal zones, and deltas. The paper is to develop a Climate Change Risk Indicator (CCRI) framework for climate risk assessment of seaports, enabling research-informed policymaking on such a demanding topic. Due to the increasing number of extreme weather events (EWEs), climate change adaptation is becoming an essential and necessary issue to be addressed by seaport stakeholders. Climate risk analysis aids rational adaptation planning. Many climate assessments have been done for measuring climate vulnerabilities, and various climate adaptation measures have been proposed for reducing climate risks. However, few of them used quantitative approaches for climate risk evaluations in seaports and fewer on the provisions of CCRIs for comparing climate risks of different locations and timeframes to guide rational policy making. Furthermore, climate change is a dynamic issue, requiring big objective data to support the analysis (e.g. monthly climate data on CCRIs) of climate threats and vulnerabilities. In this paper, Evidence Reasoning (ER) is employed to evaluate the climate risks in seaports by tackling the incomplete data. The findings reveal the quantitative measures of climate change risks in different locations and in different months. Furthermore, the risk levels of seaports in the future are assessed for observing the changes and informing policy making. The main contributions of this study include the visualisation of the comprehensive climate risk levels and provision of a new climate risk analysis framework through the comparison of climate change risks with respect to different locations and timeframes. Suitable climate adaptation measures can be chosen to implement, and seaports can cooperate on climate resilience issues (e.g. seaport network service and pre-disaster relief logistics).

1. Introduction

Over the past few years, the focus on climate change studies has switched from mitigation only to a mixture of mitigation and adaptation (California Institute of Technology, 2018). In a maritime nation like the United Kingdom, climate change will cause sea-levels to rise continuously throughout the 21st century, and coastal and offshore infrastructure is also vulnerable to changing patterns of storm conditions. The Marine Climate Change Impacts Partnership (MCCIP) has released a report on the current and future impacts of climate change in the UK, noting that more disruptions to operations could occur in ports. The potential sensitive weather-related disruptions include wind, heat, cold and fog (The Maritime Executive, 2020). In the European Economic Area (EEA) member countries, the total reported economic losses provoked by extreme weather events (EWEs) from 1980 to 2017 added up to approximately EUR 453 billion (in 2017 Euro values) (European Environment Agency, 2020). An EWE is an event that is rare at a particular place and time of year. The definition of an EWE would normally be as rare as or rarer than the 10th or 90th percentile of a probability density function estimated from observations (IPCC, 2014b).

The Intergovernmental Panel on Climate Change (IPCC) is an international association for climate change research. Climate change adaptation is one of the critical studies by the IPCC working group II in the fifth assessment report (Field et al., 2014). They have undertaken thorough reviews on transport infrastructures and stated that transportation systems would face enormous challenges by the environment in the near future (2030-2040) and the long future (2080-2100), especially in developed cities. They have also indicated the climate-related drivers of impacts for coastal zone systems and transportation systems. Coastal cities with extensive port facilities and surrounding industries are risky to increased flood exposure. High-density cities located in low-lying coastal areas are also facing high vulnerability. There is a possibility of an unexpecting increase in coastal vulnerability in the next two decades. A challenging sector to adapt is because of large existing population and stocks, especially in developed country cities, leading to potentially significant secondary economic impacts with regional and possibly global consequences for international trade. The emergency response needs well-functioning transport infrastructures.

Field et al. (2012) find that a changing climate leads to alternation in EWEs in different sectors, including intensity, frequency, duration, spatial extent, and timing. It can result in unprecedented EWEs. For instance, in 2019, the stand-out EWEs were the many different types of floods, causing millions of pounds worth of damage and causing misery to many people. Transportation is profoundly affected by climate change. Seaports are the critical nodes of international supply chains and then be on the edge of economic and natural disasters. Beside storming and flooding, the heat wave also presents a severe climate impact. In 2003, the heat wave in Central Europe caused the death toll at more than 70,000 (Bouchama, 2004). On the other hand, extreme and continuous heat can also damage road surfaces (Wang et al., 2019b) and distort rail lines (Sieber, 2013), and it affects the land transport connectivity of seaports. Therefore, climate change adaptation planning for seaports is critical to visualise, analyse and mitigate the climate risks of passengers and goods from different EWEs.

As there are different drivers to EWEs and different adaptations for a particular EWE, it is important to develop a conceptual framework that enables to integrate all climate vulnerabilities to access the climate risks of transport infrastructures (e.g. seaports) at a whole in different seasons, and also now and in future. This paper aims to develop a Climate Change Risk Indicator (CCRI) framework to tackle this issue. The resources for climate change adaptation can be scientifically allocated for different seaports against different climate threats in different seasons. Also, it can aid to integrate all climate threats to compare the climate vulnerabilities across seaports, and to implement suitable adaptation measures to a particular seaport (Zommers and Alverson, 2018).

The reminder of this paper is organised as follows. Section 2 presents a literature review on climate change adaptation and vulnerability assessment for seaports. The CCRI assessment model by the ER approach is described gradually in Section 3. Next, twelve seaports in the UK are selected to analyse the feasibility of the CCRI framework in Section 4. It is followed by the research implications and conclusion in Section 5.

2. Literature review

The literature review is conducted from three perspectives, including climate vulnerability assessment, climate change adaptation reports, and climate data in the UK.

2.1. Climate vulnerability impact assessment for seaports

There are various studies for different climate vulnerabilities and increasing trend in climate change adaptation areas (Poo et al., 2018). We observe a growing number of climate vulnerability studies for critical transportation infrastructures and coastal regions in the past decade. These two kinds of studies are closely related to CCRI framework setup and future development. Based on the biographical review by Poo et al. (2018) and further update, eight climate vulnerability impact studies have been conducted with a focus on seaports have been undertaken with a focus on coastal regions. Table 1 presents the summary of the studies. There are different climate threats, and a risk assessment to encounter such threats is not seen in the current literature.

Table 1 Summary of climate vulnerability impact assessment for seaports

Location	Multi/ Single ports	Wind velocity/ direction	Storm surge	Wave height	Sea-level rise	Wave direction	Reference
Port Arthur, Tasmania	Single				v		(Hunter et al., 2003)
Port-aux-Francais, Kerguelen Island	Single				v		(Testut et al., 2006)
Rhine–Meuse–Scheldt delta	Multi		v	v	v		(Zhong et al., 2012)
Port Kembla, New South Wales	Single				v		(Chhetri et al., 2014)
Catalan coast, North-west Mediterranean Sea	Multi	v		v	v		(Sánchez-Arcilla et al., 2016)
Catalan coast, North-west Mediterranean Sea	Multi			v	v		(Sierra et al., 2016)
Northern Tyrrhenian Sea	Multi	v					(Repetto et al., 2017)
Port of Barcelona, Catalonia	Single			v	v	v	(Sierra et al., 2017)

Note: "v represents covered"

By analysing the previous seaport climate vulnerability studies, climate threats are deemed as critical parameters for undergoing vulnerability assessments. “Wind velocity/ direction”, “Storm surge”, “Wave Height”, “Sea-level rise”, and “Wave direction” are the critical factors influencing climate vulnerability assessments, while “Temperature” and “Precipitation” are not mentioned in these studies. “Sea-level rise” is the most altered threat as it is included in all studies except the one by Repetto et al. in 2017, which is mainly focusing on wind events. “Sea-level rise” includes the assessments of sea-level changes with different scenarios and defines the acceptable discharges of considered seaports (Repetto et al., 2017). Some common factors have been considered, but a common standard for assessing the climate vulnerabilities are not developed yet. It is necessary to create a framework for comparing the risks between different seaports for measuring the urgency of adaptation planning.

A summary of the climate impact studies on coastal regions has been shown in Table 2. The coastal region studies are expanding the vulnerability assessment to a city or a district scale. Therefore, except for assessing climate threats and coastal vulnerabilities like the seaport studies, further assessments have been done. For instance, “Landslide”, “Flooding”, “Hurricane”, “Tolerance”, and “Social-economy” are the categories of specific indicators in the coastal regional studies. “Climate exposure” is defined as the group of climate stressors. “Coastal vulnerability” considers the vulnerabilities in some coastal details. Wave exposure, Coastal erosion and characteristics of coasts are included. “Landslide” and “Flooding” are the corresponding indicators for assessing the risks of specific extreme events.

“Tolerance” is the group of indicators for assessing the relieving abilities of coastal areas. “Social-economy” means the social and economic characteristics of the regions nearby. Land use, transportation network and population are all included in these categories to measure the sensitivity and importance of the port cities. Before 2008, the studies are not comprehensive, and they are mainly focusing on climate threats. From 2008, more multi-criteria assessments have been done in different parts of the world. Furthermore, Briguglio (2010) and Hanson et al. (2011) have set up adaptation index, vulnerability index, and ranks for assessing the flooding risk to global coastal cities in 2010 and 2011 respectively. In 2019, McIntosh et al. evaluate seaport vulnerability by open-data indicators, and then they set up a comparative assessment of seaport for North Atlantic medium and high-use seaports. This study provides a solid platform to implement a CCRI assessment for the UK seaports.

Table 2 Summary of climate vulnerability impact assessment for coastal regions

Location	**Multi/ Single**	**Climate exposure**	**Coastal vulnerability**	**Land-slide**	**Flooding**	**Tolerance**	**Social-economy**	**Reference**
Australia	Multi	v			v			(Graeme and Kathleen, 1999)
Port Said Governorate, Egypt	Multi	v					v	(El-Raey, 1997, El-Raey et al., 1999)
Viti Levu, Fiji Islands	Single		v					(Gravelle and Mimura, 2008)
Andaman Islands	Multi	v						(Kumar et al., 2008)
Germany	Multi	v						(Sterr, 2008)
Worldwide selected cities	Multi	v	v			v	v	(Briguglio, 2010)
Worldwide selected cities	Multi						v	(Hanson et al., 2011)
Copenhagen, Denmark	Single	v	v				v	(Hallegatte et al., 2011)
Chennai, India	Multi		v		v			(Arun Kumar and Kunte, 2012)
Shanghai, China	Single		v					(Yin et al., 2013)
South Africa	Multi	v	v			v	v	(Musekiwa et al., 2015)
Southeast Florida, the US.	Multi	v	v			v	v	(Genovese and Green, 2015)
Port Harcourt Metropolis, Nigeria	Single				v	v	v	(Akukwe and Ogbodo, 2015)
Cayman Islands	Single	v	v					(Taramelli et al., 2015)
Sao Paulo, Brazil	Single	v	v	v	v		v	(Vitor Baccarin et al., 2016)
Greater Tokyo area, Japan	Multi	v			v	v	v	(Hoshino et al., 2016)
Kuwait	Multi		v	v	v	v	v	(Alsahli and Alhasem, 2016)
Gulf of Bejaia, Algeria	Multi	v	v	v	v		v	(Djouder and Boutiba, 2017)
Port Said Governorate, Egypt	Single		v				v	(Abou Samra, 2017)
Barcelona	Single	v	v				v	(Cortès et al., 2018)
Jamaica and Saint Lucia	Multi	v			v			(Monioudi et al., 2018)
China	Multi					v	v	(Wan et al., 2018)
North Atlantic region, the US.	Multi	v	v		v	v	v	(McIntosh and Becker, 2019, McIntosh et al., 2018)

Some common factors have been considered, but a common standard for assessing the climate vulnerabilities are not developed yet. A dynamic and seasonal indicator-based assessment is needed for the risks between different seaports for measuring the urgency of adaptation planning (Rangel-Buitrago et al., 2020). Therefore, more studies are analysed to investigate the local climate change adaptation reports for seaports in Section 2.2 and local climate data in Section 2.3 before the CCRI framework in Section 3.

2.2. Climate threats from climate change adaptation reports

Except collecting the factors from journal articles, local climate change adaptation reports provide valuable materials for understanding the climate threats. For instance, on 9th May 2011, the UK Government published “Climate Resilient Infrastructure: Preparing for a Changing Climate” (Department for Environment Food & Rural Affairs, 2011). It sets out the governmental view and planning to adapt infrastructures in transportation sectors to climate change impacts.

Table 3 Summary of climate risks influencing transport infrastructure gathered by the UK Government

Infrastructure	**Key risks**

Roads	• Flooding from increased storminess and precipitation • Bridge destruction due to increased river flow resulting from storminess and precipitation • Road embankments damage in south-east England due to drier summers and wetter winters
Railways	• Flooding from increased storminess and precipitation • Bridge damage due to increased river flow resulting from storminess and precipitation • Rail embankments damage in south-east England due to drier summers and wetter winters • Overheating of underground trains by increased temperatures
Ports	• High tides / storm surges causing increased sea level at ports • High winds at ports due to increased storminess
Airports	• High winds at airports due to increased storminess

Department for Environment, Food & Rural Affairs (DEFRA) invited nine UK seaport professional bodies, and they had submitted climate change adaptation reports about seaport risks under Climate Change Act 2008. The first-round reports are published by DEFRA in 2011, and the second-round reports are released in 2015 and 2016. The two round reports are all shown in Table 4.

Table 4 List of reporting bodies of climate change adaptation reports

Reporting bodies	**Seaports/ Docks**	**Reference**
Associated British Ports	Hull, Humber, Immingham and Southampton	(Associated British Ports, 2011, Associated British Ports, 2016)
Port of Dover	Dover	(Port of Dover, 2011, Port of Dover, 2015)
Felixstowe Dock and Railway Company	Felixstowe	(Felixstowe Dock and Railway Company, 2011, Felixstowe Dock and Railway Company, 2015)
Harwich Haven Authority	Harwich Haven	(Jan Brooke Environmental Consultant Ltd, 2011)
Mersey Docks and Harbour Company Ltd	Liverpool	(Mersey Docks and Harbour Company Ltd, 2011)
Milford Haven Port Authority	Milford Haven	(Milford Haven Port Authority, 2011, Milford Haven Port Authority, 2015)
PD Teesport Ltd	Teesport and Hartlepool	(PD Teesport Ltd, 2011, PD Teesport Ltd, 2015)
Port of London Authority	London	(Port of London Authority, 2011, Port of London Authority, 2016)
Port of Sheerness Ltd	Sheerness	(Peel Ports Group, 2011)

334 risk items have been identified and addressed with different formats and scales. Even though the risk levels of each item cannot be directly compared, some insights can still be observed by statistical analyses and by visualising the climate vulnerabilities in this country. Three sets of categories have been set up by the authors manually, including climate threat types, seasons, and operation sectors. As Port of London Authority has not associated risk items to corresponding climate threats, the 43 risk items from Port of London have been excluded from the analyses in this paper (i.e. Tables 5).

To define them on a standardised plate, different EWEs are reclassified with reference to the categories by the IPCC working group II in the Fifth Assessment Report of 2014, including "Extreme precipitation", "Heat wave/ High temperature", "Cold wave/ Increased snow events", "Sea-level rise (SLR)/ Storm surge", and "Storminess" (Intergovernmental Panel on Climate Change, 2014). More EWEs are also found in adaptation reports mentioned in Table 4, including "Drought", "Seasonal changes of fog events", "Seasonal changes of lighting events", "Seasonal changes of weather patterns", and "Seasonal changes of wind speeds and directions", "High water flow", "Low water flow", "Change in sediment", and "High water temperature". In Table 5, EWEs are considered and classified, and each reported climate risk item can consist of more than one threat. For example, Port of Dover has stated a threat, "Extreme conditions leading to staff absence, extra work and excess passengers cause staff to take time away from their core roles". This threat is double-counted and reclassified as "Extreme precipitation", and also "Cold wave/ Increase in winter precipitation". "Storminess", "Seasonal changes to wind speed and direction", and "Extreme precipitation" play the three most crucial roles in affecting the operational activities of seaports with their individual occupancy rates higher than 30%. "Heat wave/ High temperature" and "Sea-level rise (SLR)/ Storm surge" are both important as they have their individual occupancy rate higher than 20%. The remaining threats/concerns, "Cold wave/ Increase in snow events", "Drought", "Seasonal changes of fog events", "High water flow", "Low water flow", "Change in sediment", and "High water temperature", have their occupancies between 10% and 20% respectively. Occupancy is the parameter used to measure the amounts of different categories against the total. For example, 88 risk items have been categorised as "Extreme precipitation" with an occupancy rate at 30.24% (88/(334-43[1])). Alternatively, we can observe that summer poses higher risk than winter, and about 70% of EWEs are not seasonal.

Table 5 Occupancy of different extreme weather events, climate risks, operation sectors

EWEs	Occupancy	Season	Occupancy	Operation sector	Occupancy
Extreme precipitation	88 (30.24%)	Winter	29 (9.97%)	Approach routes closure	7 (2.10%)
Heat wave/ High temperature	78 (26.80%)	Summer	59 (20.27%)	Civil engineering, jetties, pontoons	5 (1.50%)
Cold wave/ Increase in snow events	51 (17.53%)	Annual	203 (69.76%)	Electrical engineering/ Power supplies	14 (4.19%)
Sea-level rise (SLR)/ Storm surge	77 (26.46%)			External reputation	6 (1.80%)
Storminess	112 (38.49%)			General	15 (4.49%)
Drought	32 (11.00%)			Hydrography and dredging	23 (6.89%)
Seasonal changes of fog events	43 (14.78%)			Increase in tourism and recreational use	7 (2.10%)
Seasonal changes to wind speed and direction	97 (33.33%)			Infrastructure and equipment	64 (19.16%)
High water flow	37 (12.71%)			Licensing and consenting	15 (4.49%)
Low water flow	33 (11.34%)			Loading and moving	29 (8.86%)
Change in sediment	32 (11.68%)			Maintenance dredging and disposal	3 (0.90%)
High water temperature	38 (13.06%)			Marine engineering	7 (2.10%)
				Navigation	17 (5.09%)
				Staff and personnel/ Business continuity	32 (9.58%)

Furthermore, operation sectors are based on the definitions from Harwich Haven Authority. "Approaching routes connectivity" describes the possibilities of road/rail closure due to adverse weather. "Snow and flooding" also affect the stability of the road and rail infrastructures. "Civil engineering, jetties, pontoons" describes the risk of poor designs, jetties submerging by extreme events, especially SLR. "Electrical engineering/ Power supplies" states the risks by flooding water to any electrical infrastructure causing power outage. "External reputation" describes the possibilities of losing the external reputation due to delay and cancellation of services. "Hydrography and dredging" describe the risk coming with the change in coastal lines and disruptions to hydrographic surveying and dredging regime. "Increase in tourism and recreational use" can cause the busy traffic and activities near ports or port routes, which can increase risks. "Infrastructure and equipment" describe the risks in adverse weathers damaging the coastal infrastructure and equipment, which include tarmac, ramps, and cranes. "Licensing and consenting" states the chance of insurance premiums rising because of the unstable services. "Freight loading and moving" means the effect and delays in cargo movements. "Marine engineering" associates with the risks inside the vessel, mainly potential reduction. "Navigation" describes the effect of navigational safety by inadequate Nav-aids, buoys, and height of beacons. "Staff and personnel/ Business continuity" are mainly about operating conditions for staff in different areas. "Statutory duties" describes the regulatory issues, such as increasing the spread of invasive alien species and sea against adverse impact. "Storage and cargos" involve a higher risk for different kinds of cargos by the increase in EWEs. "Vessel services" states the disruptions of vessel movements on the water. "General" defines risk items without specific operation sectors. "Infrastructure and equipment", "Vessel services", and "Staff and personnel/ Business continuity" are the three most affected operation sectors.

2.3. Climate data in the UK.

The data relating to CCRIs for observing and analysing climate threats are obtained from multiple data sources including the Meteorological Office (Met Office, 2018), Climate Projection (UK Climate Projection, 2018), and British Oceanographic Data Centre (BODC) (British Oceanographic Data Centre, 2018). They are all objective data available from the mentioned data sources.

[1] Here 334 is the total risk items while 43 means the number of risk items from Port of London, which have not been categorised into any climate threats as explained above.

Met Office is the UK national weather service. It is an executive agency and of the Department for Business, Energy, and Industrial Strategy. They forecast the climate change across all timescales from weather forecasts. In 2009, UK Climate Projections in 2009 (UKCP09) is released, and it provides a data assessment of how the UK climate may change in this century. UKCP09 is a gridded observation dataset. The historical dataset spans across the period of 1910 – 2016 and covers the UK at a 5 x 5 km resolution. The data from 2016 – 2019 have been checked to be consistent. Therefore, it is used to analyse the current risks and set up the grades of the CCRIs for analysis. The future dataset is presented in the same format based on the same grades, and thus it is possible to foresee the future climate risk levels using the CCRI framework. The further definitions and timeframes of climate indices are shown in Table 6.

Table 6 Definitions and timeframes of CCRIs

Climate index	**Timeframe**	**Definition**
Maximum temperature	1910 – 2016	Average daily maximum air temperature (^{o}C)
Minimum temperature	1910 – 2016	Average daily minimum air temperature (^{o}C)
Precipitation	1910 – 2016	Total precipitation amount (mm)
Mean wind speed	1969 – 2014	Average hourly mean wind speed at a height of 10 m above ground level (knots)
Mean sea level pressure	1961 – 2014	Average hourly mean sea level pressure (hPa)
Mean relative humidity	1961 – 2014	Average hourly relative humidity (%)
Mean vapour pressure	1961 – 2014	Average hourly vapour pressure (hPa)
Mean cloud cover	1961 – 2006	Average ourly total cloud cover (%)
Days of air frost	1961 – 2016	Counted days when the minimum air temperature is below 0 ^{o}C (days)
Days of ground frost	1961 – 2016	Counted days when the grass minimum temperature is below 0 ^{o}C (days)
Days of rain >= 10 mm	1961 – 2016	Counted days with >= 10mm precipitation (0900-0900 UTC) (days)
Days of sleet or snow falling	1971 – 2011	Counted days with sleet or snow falling (days)

Next, ten maximum sea-level records and ten maximum skew surge records are collected from 45 UK seaports based on the data from BODC. BODC is a national facility for collecting and releasing data about the marine environment for the UK and it is a part of the National Oceanography Centre (NOC). It is for observing the risks of flooding due to SLR. Average values of two types of the top-ten records have been calculated for each seaport. Based on the calculated rank-ordered statistics any extreme storm surge can coincide with any tide. Therefore skew surge which is the difference between the maximum observed sea level and the maximum predicted tide are used as an indicator (Williams et al., 2016). The maximum observed sea level measured by tide gauges are primarily determined by the tidal regime. The difference (residual) between the maximum observed sea level and the maximum predicted tide is governed by the wind stress and the local atmospheric pressure, roughly two thirds to one third split, respectively. UKCP09 also provides SLR and skew surge rise data in the future. Grade setting is further explained in Section 3.2.

By the above statistical analyses, climate change risks can be defined from the different perspectives of EWEs, seasons, and operation sectors. As a result, EWEs are summarized in Table 7 which are partially matched with two references, the IPCC (2014a) and Forzieri et al. (2018). It becomes a foundation of the EWEs in the CCRI framework in Section 3. Climate-related drivers of impacts to urban areas are chosen, and they consist of "Extreme temperature", Drying trend", "Warming Trend", "Snow cover", "Damaging cyclone", "Extreme precipitation", and "Sea-level rise". As "Warming Trend", "Extreme temperature", and "Drying trend" always come together in the adaptation reports. Therefore, they have been merged into "Warming trend/ Extreme temperature/ Drought".

Table 7 EWEs of corresponding climate threats

IPCC (2014a)	**Forzieri et al. (2018)**
Warming trend/ Extreme temperature/ Drought	Heat wave / Drought/ Wildfires
Extreme precipitation	Flooding
Snow cover	Cold wave/ Snow events
Damaging cyclone	Wind gust/ Storminess

Sea-level rise	Flooding

3. CCRI assessment framework by the ER approach

A comprehensive CCRI framework is critical to assess and compare the climate vulnerabilities of seaports against climate threats and EWEs between different timeframes and scales. By implementing a CCRI framework, adaptation measures can be effectively allocated, and seaports can cooperate for disaster management to enhance climate resilience, including emergency berthing. Task Team on Definitions of Extreme Weather and Climate Events (TT-DEWCE) from the World Meteorological Organization (WMO) has stated that there are fixed and well known EWEs and their thresholds differ from location to location (Task Team on Definitions of Extreme Weather and Climate Events, 2016). This section describes a six-step CCRI framework. The climate data of seaports are chosen and evaluated from the lowest level to highest level indicators in a developed CCRI hierarchy in Section 3.1. For comparing different seaports' climate characteristics, the climate data across the whole UK is collected, and then assessment grades are defined by obtaining specific percentile (Zanobetti et al., 2013) to define the risk grades of the climate indicators in section 3.2 Next, all evaluations are s synthesised using the ER algorithm in Section 3.3. When applying the ER algorithm in CCRI, two input data are required, and they associate with the actual climate risk of the investigated port against the lowest level indicator and the weight of each indicator in the hierarchy (i.e. Fig. 1). Therefore, Sections 3.4 and 3.5 are presented to describe how the two sets of input data are obtained and used to support the CCRI framework, before the final climate risk value is obtained and visualized via software in Section 3.6.

3.1. Define the CCRI hierarchy

By summarising the literature of climate threats and EWEs in Section 2, the influential climate indicators are identified from the Met Office, the UK Environment Agency, and BODC. In order to find out the most influential climate indicators for constructing seaport CCRI framework, a structured interview based on the literature review in Section 2 has been conducted and presented to environmental professions, shipping agents and seaport managers. More details about the structured interview and the relevant analysis have been presented (Poo, 2020). Based on the interview result, the purified indicators are identified and summarised to construct the CCRI hierarchy in Figure 1. 5 x 5 km monthly gridded observational datasets and 25 x 25 km monthly gridded forecasting datasets are collected from UKCP09, and we also investigate the forecasting data by Met Office to compare the existing and future risks. The future period is set to be 2050s (2040-2069), and the emission scenario is defined as medium. 50th percentile data in the 2050s with a medium emission scenario is taken as the reference for analysis and there is a probabilistic projection for every variable. 2050 is a key year recommended for reaching global net zero CO2 emissions by IPCC, and so it is commonly used as a forecasting reference (Owen et al., 2010). Heat stress is projected to increase by many climate model ensembles and generations, driven mainly by temperature increases, humidity declines and low cloud cover (Stefanon et al., 2012). Therefore, "Warming trend/ Extreme temperature/ Drought" is defined by combining the warming and drying trend, and the whole framework is shown in Figure 1.

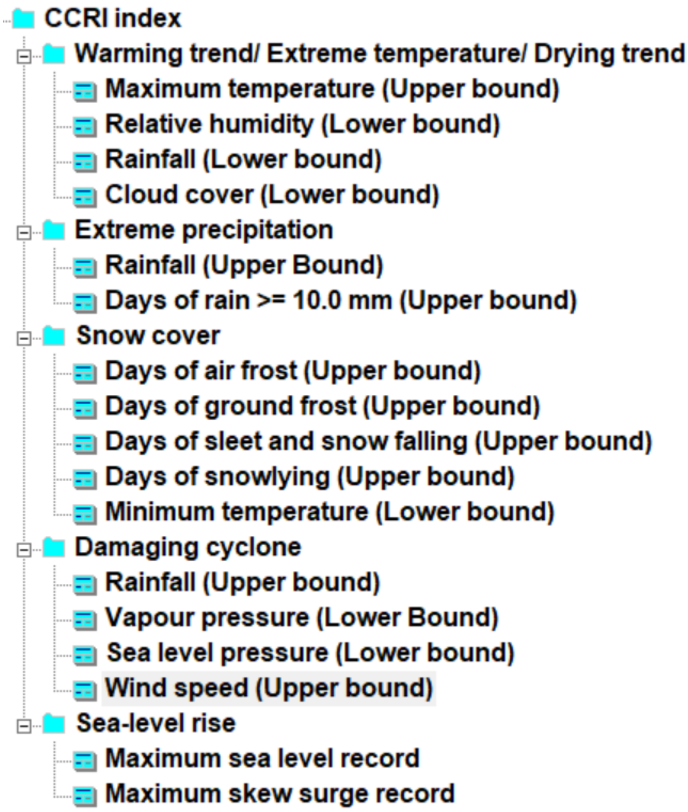


Figure 1 CCRI hierarchy

3.2. Set the evaluation grades to each indicator

As monthly average climate data represent the possibilities of EWEs, percentile values of climate data are commonly used in assessing climate vulnerability (Monahan and Fisichelli, 2014, Peterson et al., 2002). Percentile values of different CCRIs, shown in Table 8, are chosen and the dataset for the CCRI framework is set up by the reference from Task Team on Definitions of Extreme Weather and Climate Events (2016). For the CCRIs from Met Office, 60th, 70th, 80th, 90th, and 95th percentile values are used to divide the upper bound (UB) assessment grades into five categories, and 40th, 30th, 20th, 10th and 5th percentile values are used to define the five-lower bound (LB) assessment grades. It is common to reference 5th, 10th, and 20th, for both UB and LB sides, as extreme climate data (Albouy et al., 2016, Jones et al., 2019). All datasets are divided with respect to the five linguistic assessment grades {L_1 "Low risk", L_2 "Moderately low risk", L_3 "Medium risk", L_4 "Moderately high risk", L_5 "High risk"} to facilitate the climate risk value evaluation in the ER algorithm in Section 3.3. As a result, the values used to define the grades of each indicator are shown in Annex 1. Forecasting data is referred from UKCP09. There are five CCRIs without forecasting data, including "Days of rain >= 10.0 mm (days)", "Days of air frost (days)", "Days of ground frost (days)", "Days of sleet and snow falling (days)", and "Days of snowlying (days)". Those indicators are defined as unknown, and the final climate risk indexes are presented with possible ranges. The average values, best possible values and worst possible values are calculated for the evaluations reflecting the current best knowledge (i.e. uncertainty in data).

As the maximum sea level records and maximum skew surge records from the BODC are presented by extreme data from BODC. In addition, the forecasting changes are collected from UKCP09. The two records from BODC are both historical high records, which means they are extreme data. They, with reference to the recommended grades in previous studies (Zhang et al., 2013), are divided into five assessment grades by the five values at 10th, 30th, 50th, 70th and 90th percentiles of records from all 45 ports data in Annex1 (Zhang et al., 2013). For forecasting, the UKCP09 values, the long-term linear trend in skew surge (1951-2099) for the 10-year return level (mm/yr) and sea-level change (m), to foresee the sea-level and storm surge changes respectively. Table 8 summaries the evaluation grades of each indicator.

Table 8 Climate change risk indicators framework details

Climate threat	ID	CCRI	UB/ LB	Source	Monthly data	Forecast data	L1 40th/60th Low risk	L2 30th/70th Moderately low risk	L3 20th/80th Medium risk	L4 10th/90th Moderately high risk	L5 5th/95th High risk	Reference
							Grade and Percentile					
Warming trend/ Extreme temperature/ Drought/ Wildfire	1	Maximum temperature (ºC)	UB	Met Office	Yes	Yes	13.73	15.5	17.24	19.17	20.52	(Asner and Alencar, 2010)
	2	Relative humidity (%)	LB	Met Office	Yes	Yes	81.52	78.54	78.54	76.31	74.47	(Rebetez et al., 2006)
	3	Rainfall (mm)	LB	Met Office	Yes	Yes	62.22	51.09	40	27.05	18.59	(Rebetez et al., 2006)
	4	Cloud cover (%)	LB	Met Office	Yes	Yes	69.96	67.76	64.9	60.64	56.71	(Asner and Alencar, 2010)
Extreme precipitation/ Flooding	5	Rainfall (mm)	UB	Met Office	Yes	Yes	88.5	105.94	130.5	174.68	222.65	(Segond et al., 2007)
	6	Days of rain >= 10.0 mm (days)	UB	Met Office	Yes	No	2.62	3.31	4.38	6.24	8.22	(Li et al., 2019)
Snow cover/ Cold wave/ Snow events	7	Days of air frost (days)	UB	Met Office	Yes	No	3.64	6.12	9.15	13.52	17.17	(Loyola et al., 2014)
	8	Days of ground frost (days)	UB	Met Office	Yes	No	11.09	14.03	16.88	20.38	23.06	(Ballantyne et al., 1998)
	9	Days of sleet and snow falling (days)	UB	Met Office	Yes	No	0.68	1.78	3.4	6.3	9.17	(Ballantyne et al., 1998)
	10	Days of snowlying (days)	UB	Met Office	Yes	No	0.04	0.39	1.53	4.37	8.01	(Ballantyne et al., 1998)
	11	Minimum temperature (ºC)	LB	Met Office	Yes	Yes	6.22	7.75	9.2	10.59	11.48	(Dewey, 1977)
Storminess/ Wind gust	12	Rainfall (mm)	UB	Met Office	Yes	Yes	88.5	105.94	130.5	174.68	222.65	(Slingo et al., 2014)
	13	Vapour pressure (hPa)	LB	Met Office	Yes	No	8.32	7.78	7.26	6.63	6.14	(Matthews et al., 2014)
	14	Mean seal level pressure (hPa)	LB	Met Office	Yes	Yes	1012.73	1011.21	1009.21	1006.02	1003.08	(Matthews et al., 2014)
	15	Mean wind speed (knots)	UB	Met Office	Yes	Yes	9.92	10.88	12.2	14.36	16.44	(Slingo et al., 2014)
							10th	**30th**	**50th**	**70th**	**90th**	
Sea-level rise/ Flooding	16	Maximum relative sea level record (m)	N/A	BODC/ Met Office	No	Yes	2.31	3.02	3.44	4.02	6.10	(Lewis et al., 2011)
	17	Maximum skew surge record (m)	N/A	BODC/ Met Office	No	Yes	0.69	0.81	0.95	1.14	1.39	(Lewis et al., 2011)

* UB: upper bound of the data sets; LB: lower bound of the data sets.

3.3 Evidential Reasoning for CCRIs

Due to the future data unavailability of some climate indicators, it is essential to employ an advanced reasoning technique that can 1) cope with high uncertainty in climate data and 2) synthesise all the CCRIs to generate a single climate risk value to build up a comprehensive framework. A CCRI framework demands the construction of a hierarchical structure to accommodate the climate risk indicators concerning different climate threats (i.e. Figure 1). Corresponding CCRIs have been selected to assess each climate threat independently. In the hierarchical structure, it is always the case that the risk indicators at a higher level are also making use of the information from the lower levels. Therefore, it is essential to synthesise the vulnerability performance of a seaport against individual indicators from the lowest level to the highest one. In the process of assessing the climate risks, the two main uncertainties that decision-makers may encounter include multiple types of climate indices and incomplete data set. Evidential reasoning (ER) as a multi-attribute decision making (MADM) approach, shows its potential for the development of CCRI framework by meeting the above requirements (Yang and Singh, 1994). ER has been widely used for risk analysis in the maritime and transport industries with its characteristics and advantages/disadvantages found in a wealthy literature (e.g. Alyami et al., 2019, Wan et al., 2019a, Wan et al., 2019b, Wang et al., 2019a, Yang et al., 2014, Yang et al., 2018, Yang and Wang, 2015, Zhang et al., 2016). The heart of this approach is an ER algorithm developed from the concept of the Dempster–Shafer (D–S) theory, requiring modelling the hypothesis set with the requirements and limitations of the accumulation of evidence

By connecting all input information and undertaking the analysis, it is possible to convert and synthesise different types of CCRIs into a final climate risk index. The following equations have integrated the newest ER algorithm within the CCRI context. A represents the set with five linguistic assessment grades {L_1 "Low risk", L_2 "Moderately low risk", L_3 "Medium risk", L_4 "Moderately high risk", L_5 "High risk"}, which has been combined from two subsets A_1 and A_2 based on two different CCRIs in a lower level of A in the hierarchy. Let α be the degree of belief (DOB) attaching to different linguistic terms and ω_k (k = 1, 2) represents the normalised relative weights of the two CCRIs at the lower level.

$$A=\{\alpha_1 L_1,\alpha_2 L_2,\alpha_3 L_3,\alpha_4 L_4,\alpha_5 L_5\}\text{, where }\sum_{m=1}^{5}\alpha_m \le 1 \tag{1}$$

$$A_k=\{\alpha_{1,k} L_1,\alpha_{2,k} L_2,\alpha_{3,k} L_3,\alpha_{4,k} L_4,\alpha_{5,k} L_5\}\text{, where }\sum_{m=1}^{5}\alpha_{m,k} \le 1 \text{ and k = 1, 2} \tag{2}$$

$$\sum_{k=1}^{2}\omega_k = 1 \tag{3}$$

$$M_{m,k}=\omega_1 \alpha_{m,k}\text{, where m = 1, 2, 3, 4, 5 and k = 1, 2} \tag{4}$$

Equation (1) represents the set with five linguistic assessment grades and equation (2) represents the corresponding CCRIs grade sets from two subsets. By the normalised relative weights are given in equation (3), and individual relative weight is obtained, the individual degrees, M can be obtained by equation (4).

$$H_k=\bar{H}_k+\tilde{H}_k\text{, where k = 1, 2} \tag{5}$$

$$\bar{H}_k=1-\omega_k\text{, where k = 1, 2} \tag{6}$$

$$\tilde{H}_k=\omega_k\left(1-\sum_{m=1}^{5}\alpha_{m,k}\right)\text{, where k = 1, 2} \tag{7}$$

Equations (5) to (7) represent the remained belief value (H) unassigned to $M_{m,1}$ and $M_{m,2}$, where m = 1, 2, 3, 4, 5. $\bar{H}$ represents the degree to which other CCRIs can play a role in the assessment and $\tilde{H}$ is attributable to the possible incompleteness in the subsets A_1 and A_2.

$$a'_m=K\left(M_{m,1}M_{m,2}+M_{m,1}H_2+H_1M_{m,2}\right)\text{, where m = 1, 2, 3, 4, 5} \tag{8}$$

$$\bar{H}'_U = K\left(\bar{H}_1\bar{H}_2\right) \tag{9}$$

$$K = \left(1 - \sum_{T=1}^{5}\sum_{\substack{R=1\\R\neq T}}^{5} M_{T,1}M_{R,2}\right)^{-1} \tag{10}$$

Let a'_m be the non-normalised degree to which the synthesised evaluation is set to the five linguistic grades and $\bar{H}'_U$ the non-normalised remaining belief unassigned after the commitment of belief to the five grades. They work together as the result of the synthesis of the vulnerability degrees. After the above 10 equations, the final two equations below mean the calculation of the combined degrees a_m. They are generated by putting $\bar{H}'_U$ back to the five expressions using the following normalisation process and H_U means the normalised remaining belief unassigned in the synthesised set.

$$a_m = a'_m / \left(1 - \bar{H}'_U\right), \text{ where m = 1, 2, 3, 4, 5} \tag{11}$$

$$H_U = \tilde{H}_U / \left(1 - \bar{H}'_U\right) \tag{12}$$

The above equations give the process of combining two CCRIs. If three CCRIs are required to be combined, the result obtained from the combination of any two sets can be further synthesised with the third one using the above algorithm. Similarly, multiple sets from the evaluations of more sub-criteria can also be assessed in the same way. To facilitate the implementation of the ER algorithm in the CCRI of seaports, an illustrative numerical example is presented in Annex 1.

3.4 Evaluate the climate risk of seaports using climate data against the lowest level indicators

The input datasets, now and future, are used (i.e. in Eq. 2) to evaluate seaports using climate data from the lowest level indexes in the CCRI framework. For instance, , Twelve seaports, “Dover (DOV)”, “Dundee (DUN)”, “Felixstowe (FEL)”, “Grangemouth (GRA)”, “Immingham (IMM)”, “Leith (LEI)”, “Liverpool (LIV)”, “London (LON)”, “Milford Haven (MIL)”, “Sheerness (SHE)”, “Southampton (SOU)”, and “Tee (TEE)”, are chosen for a demonstration as they are near different urban areas and they are mostly assigned by the UK government to implement adaptation plans in this paper. A map showing the locations of all the studied ports is seen in Figure 2.

Figures 2 A map of the studied ports in the UK

3.5 Assign the weights to the CCRIs in the hierarchy

The CCRI framework consists of three layers: “Climate risk index”, “EWEs”, and “CCRIs”. The relative weights (i.e. in Eq. 3) are also necessary for connecting three layers as mentioned in Section 3.3. For “CCRIs”, all the lowest level CCRIs have assigned equal weights as there is no experimental evidence to support different weight assignments based on the literature and domain expert judgements in the interview survey (Poo, 2020). For “EWEs”, the weight assignment comes from a sensitivity study result for different critical infrastructures in Europe (Forzieri et al., 2018): “Warming trend/ Extreme temperature/ Drought/ Wildfire” as 29.93%; “Extreme precipitation/ Flooding” as 30.17%; “Snow cover/ Cold wave/ Snow events” as 19.70%; “Storminess/ Wind gust” as 20.20%; and “Sea-level rise” as 30.17%.

3.6 Synthesise the evaluation using the ER algorithm and its calculation software IDS

By implying ER equations in Section 3.3, the climate risk index of each investigated seaport can be evaluated from the lowest level to the top level “climate index”. ER embedded software IDS (Yang and Xu, 2002) is used for facilitating the calculation. The assessment grades of the top level attribute are given their corresponding utility values using a linear function as the set of {0, 0.25, 0.5, 0.75, 1} for {“Low risk”, “Moderately low risk”, “Medium risk”, “Moderately high risk”, “High risk”} (Yang et al., 2009). The software IDS integrates the logics of a utility interval to assess the unassigned DOB. The ER algorithm provides a utility interval, which is a boundary where the unassigned DOB is located to either the lowest utility grade “Slightly preferred with a minimum utility value” or the highest utility grade “Greatly preferred with a maximum utility value”. The average value of the two associated utility values is used for any ranking purpose under the uncertainty in data.

4 Case analysis of the UK seaport climate risk

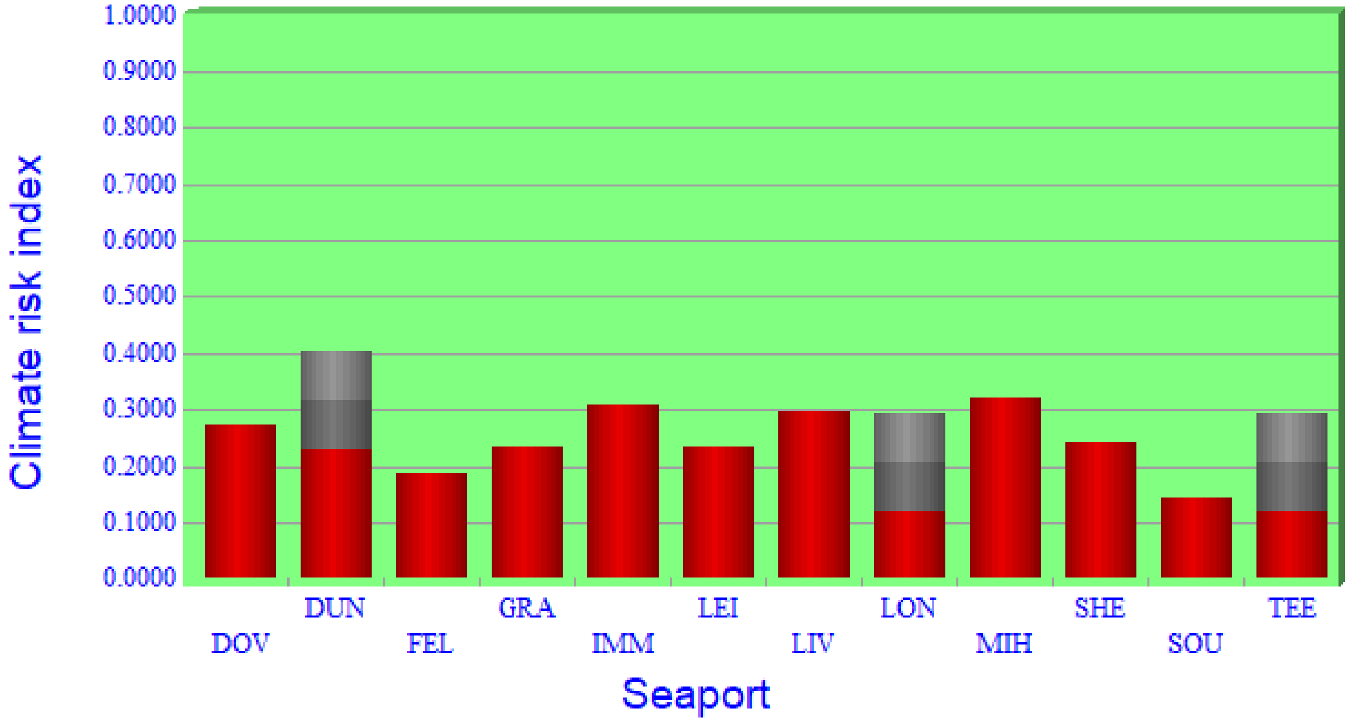
To validate the framework, twelve seaports mentioned in Section 3.4 are evaluated in terms of their CCRI index. The results are analysed directly and through a sensitivity analysis and compared with the observable facts for the validation. By assessing the climate risk indexes of twelve selected seaports, comparisons are conducted between ports and the same ports at different months. Met office defines winter from December to February, and summer from June to August. Therefore, seasonal climate datasets are compared and analysed. Also, now and future, as known as historical data and forecasting data, are compared for observing the climate change impacts through measuring climate vulnerability changes from now to 2050. The raw data and linguistic assessment grades for Felixstowe in Table 9 is shown as an example. Also, the dataset represents the two levels, the EWE level and CCRI level.

Table 9 The raw data and linguistic assessment grades for Felixstowe

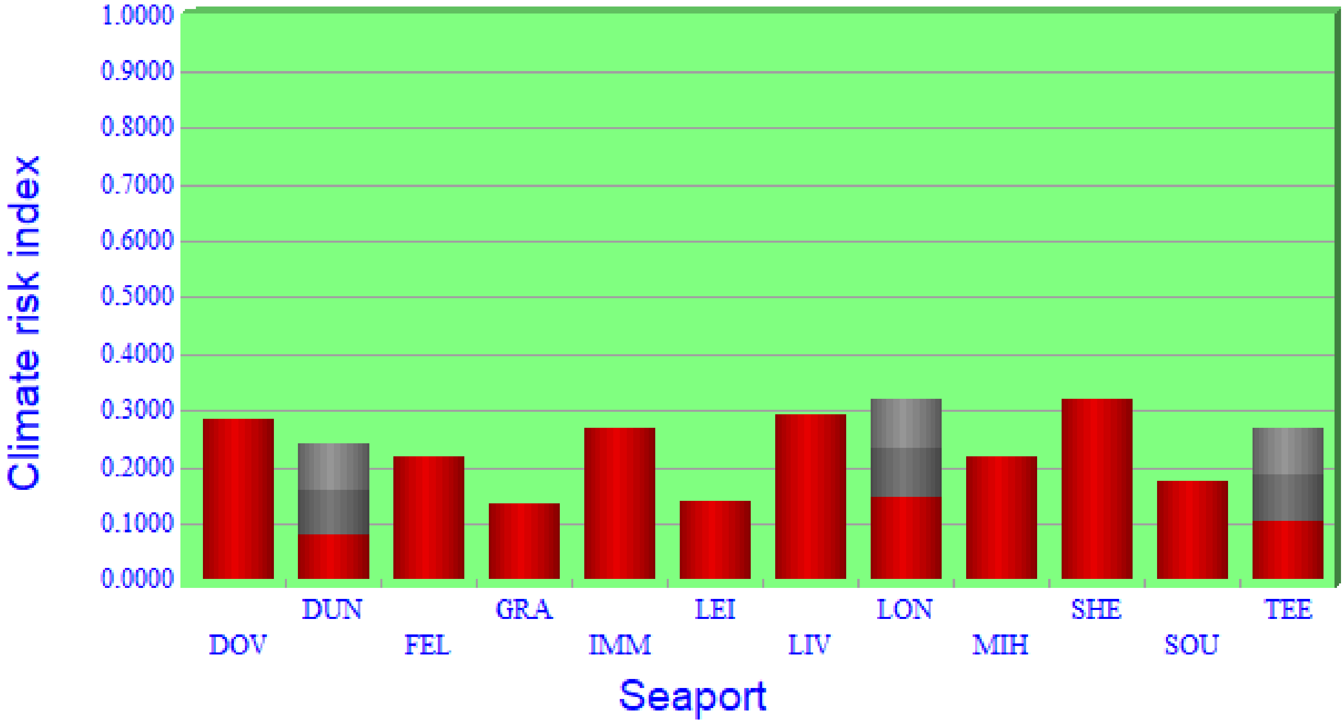
EWE	ID	CCRI	LB /UB	Winter	Value	Summer	Value
Warming trend/ Extreme temperature/ Drought/ Wildfire	1	Maximum temperature	UB	1 (100%)	7.008	4 (50%), 5 (50%)	19.823
	2	Relative humidity	LB	1 (100%)	83.906	1 (5%), 2 (95%)	79.132
	3	Rainfall	LB	2 (85%), 3 (15%)	54.769	2 (100%)	61.117
	4	Cloud cover	LB	1 (100%)	70.983	5 (100%)	63.456
Extreme precipitation/ Flooding	5	Rainfall	UB	1 (100%)	54.769	1 (100%)	61.117
	6	Days of rain >= 10.0 mm	UB	1 (100%)	0.688	1 (100%)	1.245
Snow cover/ Cold wave/ Snow events	7	Days of air frost	UB	1 (20%), 2 (80%)	5.642	1 (100%)	0.007
	8	Days of ground frost	UB	1 (85%), 2 (15%)	5.614	1 (100%)	2.498
	9	Days of sleet and snow falling	UB	2 (35%), 3 (65%)	2.870	1 (100%)	0.004
	10	Days of snowlying	UB	3 (80%), 4 (20%)	2.141	1 (100%)	0.000
	11	Minimum temperature	LB	1 (20%), 2 (80%)	2.560	1 (100%)	12.395
Storminess/ Wind gust	12	Rainfall	UB	1 (100%)	54.769	1 (100%)	61.117
	13	Vapour pressure	LB	2(85%), 3 (15%)	7.712	1 (100%)	14.289
	14	Mean seal level pressure	LB	1 (100%)	1015.046	1 (100%)	1016.009
	15	Mean wind speed	UB	5 (100%)	17.136	5 (100%)	12.333
Sea-level rise	16	Maximum sea level record	NA	1 (15%), 2 (85%)	4.862	1 (15%), 2 (85%)	4.862
	17	Maximum skew surge record	NA	3 (15%), 4 (85%)	1.116	3 (15%), 4 (85%)	1.116

4.1 Comparison between locations and seasons

By obtaining the climate risk indexes of the twelve seaports of January in Figure 2 and July in Figure 3, the climate risk indexes of months are shown. The coloured bar presents substantial climate risk, and the other two grey boxes offer possible climate risks. The sum of the coloured bar and a grey box shows the average climate risk indexes if it is with uncertainties. Taking DUN in January as example, the average score is 0.3169, and the range of possible index values is from 0.2289 to 0.4049. In Table 10, a climate risk index comparison between different locations and different months takes place. Ranks are given to the investigated seaports by comparing their climate risk indexes in the same month. "Maximum relative sea level record (m)" and "Maximum skew surge record (m)" data are missing for DUN, LON and TEE. Therefore, the relevant average values are taken for comparison, as the results are incomplete.



Figures 3 Climate risk indexes of the twelve UK seaports in January



Figures 4 Climate risk indexes of the twelve UK seaports in July

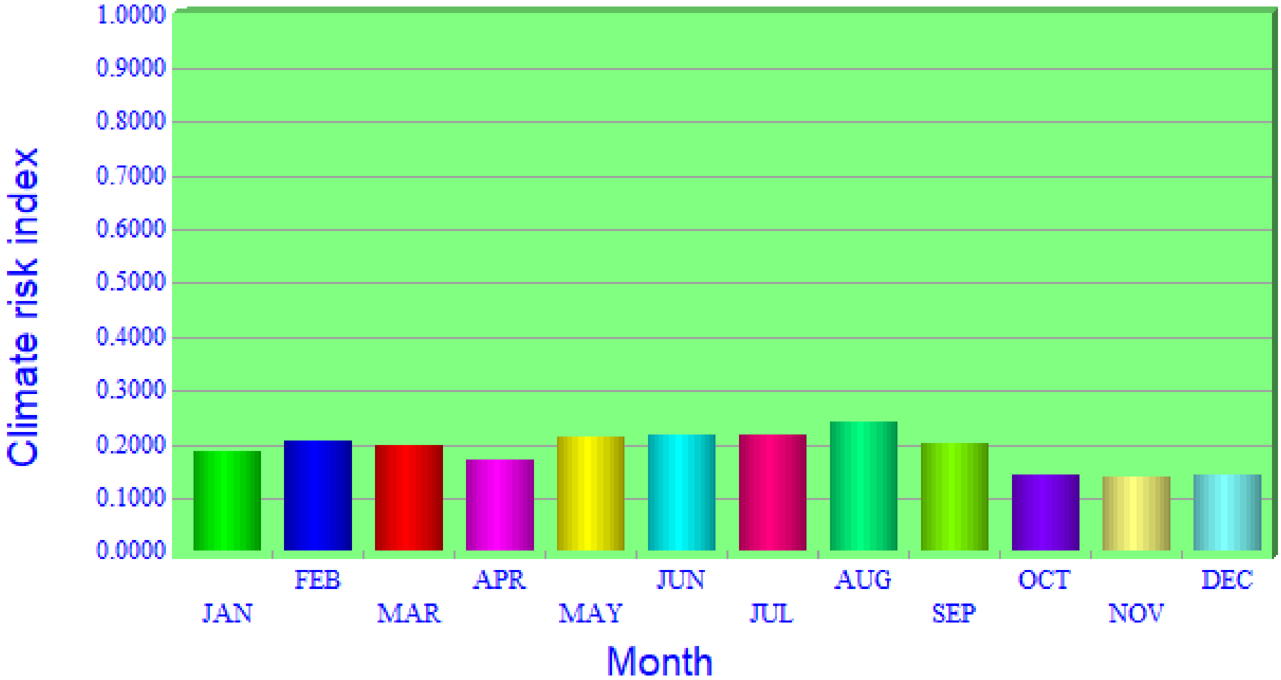
The findings from Figures 3 and 4 reveal that some south seaports, including DUN and GRA, obtain a higher risk value in January and a lower value in July, and vice versa. FEL and SOU are exposed to higher risks in July, and lower in January. For the ports in the middle of the UK such as LIV and IMM, they have a higher risk index in January than in July. It is found that the potential climate risks facing by different seaports are different among different months. Also, their ranks are different during different months. Therefore, it is necessary to observe the variation of climate risk indexes of seaports throughout a year and find the possible most threatening periods in a year.

Table 10 Climate risk indexes of the twelve UK seaports in January and July

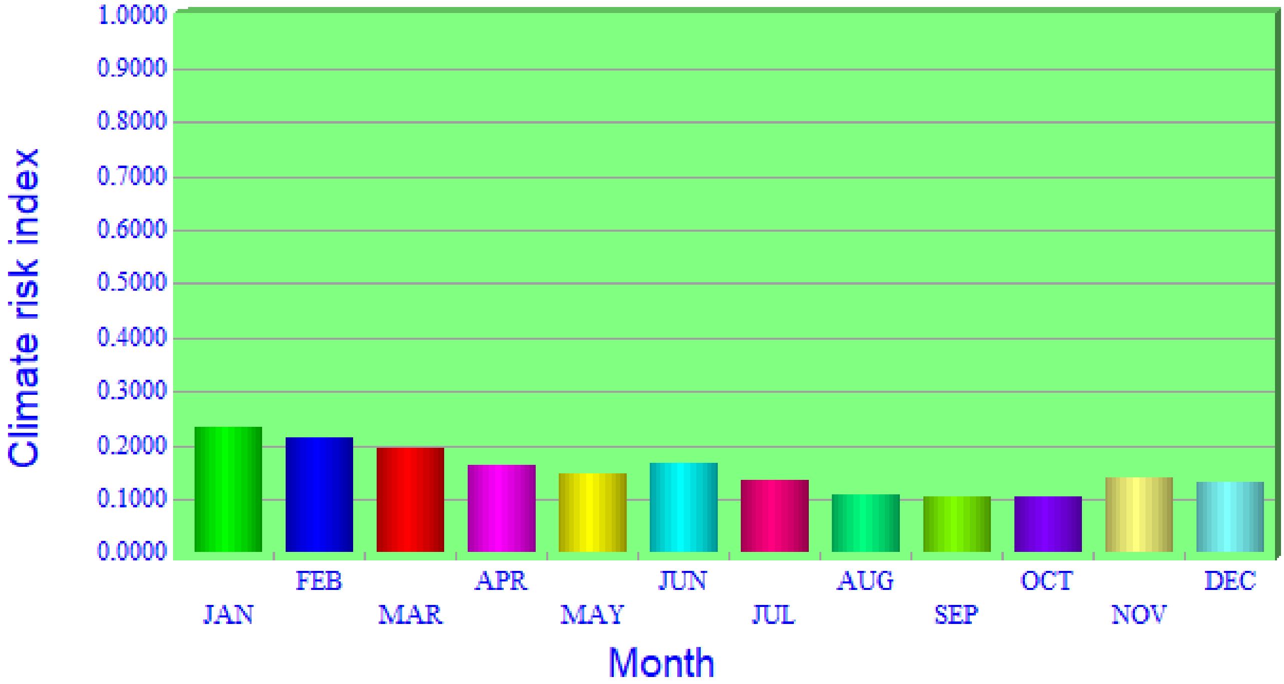
Location	DOV	DUN	FEL	GRA	IMM	LEI	LIV	LON	MIH	SHE	SOU	TEE
January	0.2726	0.3169	0.1878	0.2323	0.3083	0.2355	0.2988	0.2049	0.3225	0.2420	0.1437	0.2066
Rank	5	2	11	8	3	7	4	10	1	6	12	9
July	0.2840	0.1612	0.2193	0.1370	0.2692	0.1391	0.2930	0.2339	0.2197	0.3210	0.1768	0.1888
Rank	3	10	7	12	4	11	2	5	6	1	9	8

4.2 Comparison between months

By the comparison between different months, it is possible to spot out the dangerous seasons. FEL and GRA are taken places for a demonstration as they are both international seaports listing on sailing schedules of Maersk Line (A.P. Moller - Maersk, 2020). The result is presented in Figures 5 and 6 and Table 11. The highest indexes of the two ports are both existing in July, and FEL sustains the highest value in August. The lowest climate risk indexes of the two ports take place in November and September, respectively. 0.1384 is the minimum climate risk indexes of FEL throughout the twelve months, and that of GRA is 0.1054. By comparing indexes between the highest and lowest indexes, FEL scores 23.48% higher than the lowest index in January, and that in July is 37.53%. Then, GRA scores 38.14% higher than the lowest index in January, and it is the lowest in July. Therefore, the seasonal climate differences of two ports are at different scales. It is possible for further cooperation for climate resilience. For example, as FEL is facing a higher rise in climate risks in summer while GRA is facing higher risks in winter, relief operations or seaport network service can be planned between two seaports from a climate adaptation perspective.



Figures 5 Monthly climate risk indexes of Felixstowe



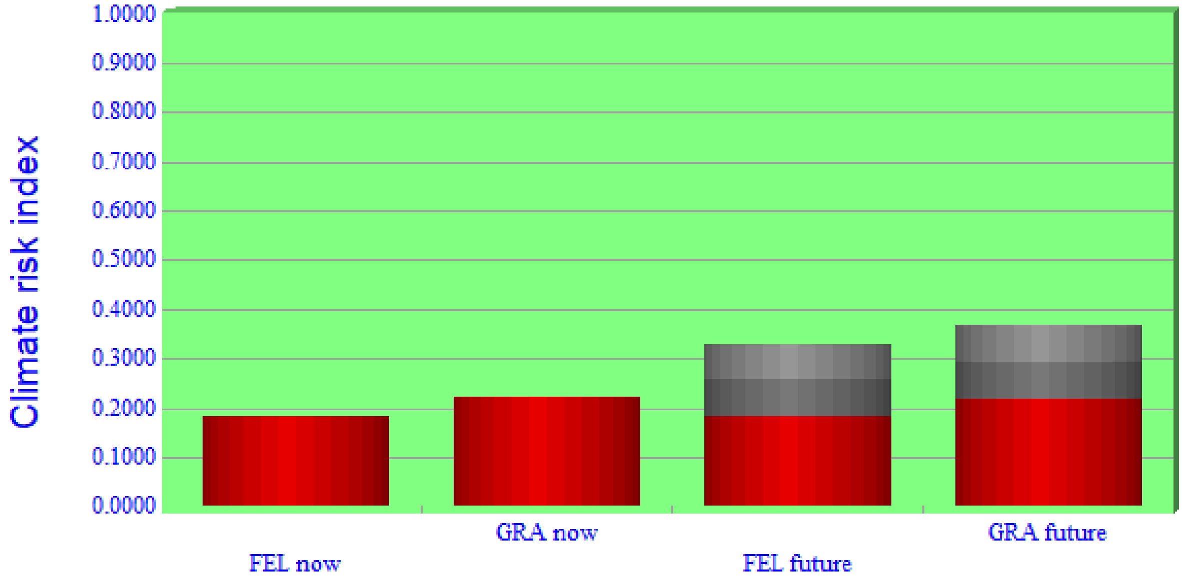
Figures 6 Monthly climate risk indexes of Grangemouth

Table 11 Climate risk indexes of Felixstowe and Grangemouth in all months

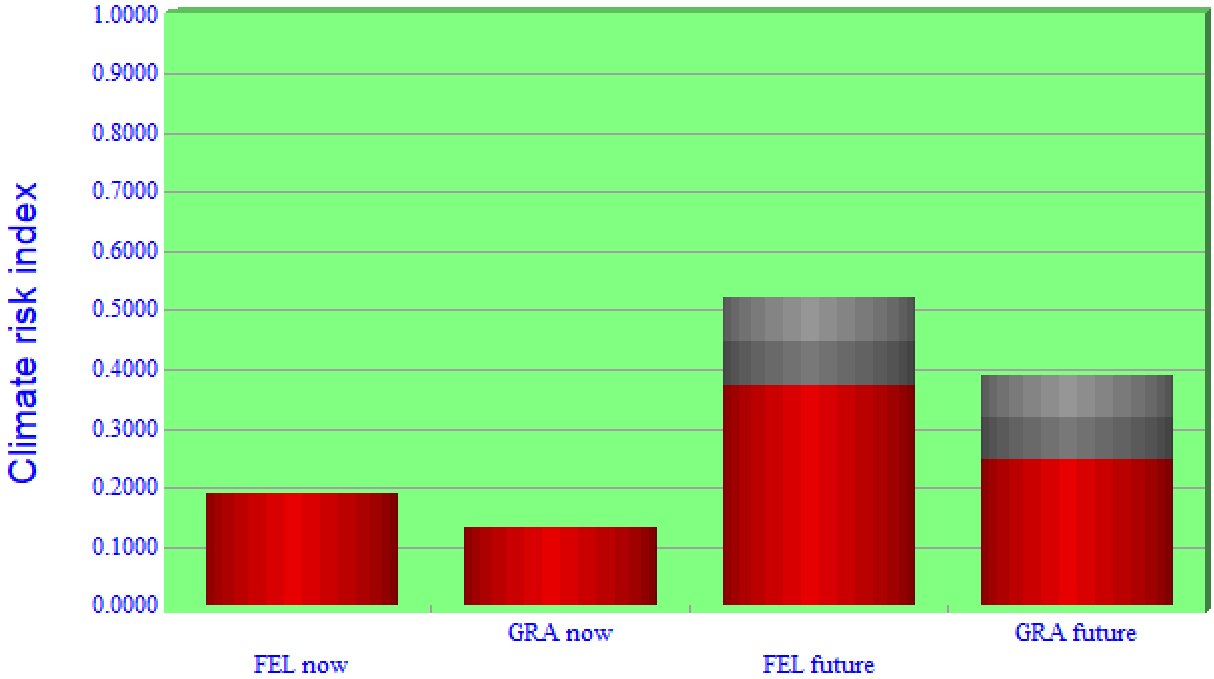
Month	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Felixstowe	0.1878	0.2059	0.200	0.1723	0.2150	0.2182	0.2186	0.2409	0.2020	0.1456	0.1384	0.1450
Rank	8	5	7	9	4	3	2	1	6	10	12	11
Grangemouth	0.2333	0.2151	0.193	0.1629	0.1487	0.1673	0.137	0.1075	0.1054	0.106	0.1384	0.1302
Rank	1	2	3	5	6	4	8	10	12	11	7	9

4.3 Comparison between now and future

The analysis in this section is to compare the now and future climate risks of the investigated ports. Figures 7 and 8 are used to observe the changes of climate risk indexes of winter and summer in the twelve seaports. Some forecasting data are missing, including “Days of air frost (days)”, “Days of ground frost (days)”, “Days of sleet and snow falling (days)”, and “Days of snowlying (days)” and the associated data is set as 100% unknown in the ER reasoning. A comprehensive comparison takes places for FEL and GRA in Table 12. Future average scores are used to compare those of now. “Best Possible Future” is classified as the lowest possible future climate risk index and “Worst Possible Future” is classified as the possible highest possible future climate risk index. For the two chosen seaports, the climate risk indexes from two locations increase more significantly in summer. FEL is increased by 135.72% and GRA is increased by 140.39%. In winter, FEL increases more significantly by 41.21%, and that of FEL increases by 32.20%. By the comparison between now and the future, the trend of climate vulnerability changes can be visualised. The results in this section alert the possible, more serious climate risks in the future. Therefore, more climate change studies are needed to be done to tackle climate change by mitigation but also adaptation for the more uncertain future. Also, the changes in climate risk indexes are different between locations and months, which can be used to rationalise the associated seaport adaptation planning.



Figures 7 Future climate risk indexes of Felixstowe and Grangemouth in winter



Figures 8 Future climate risk indexes of Felixstowe and Grangemouth in summer

Table 12 Future climate risk indexes of Felixstowe and Grangemouth

Seaport	**Felixstowe**		**Grangemouth**	
Month	**Winter**	**Summer**	**Winter**	**Summer**
Now	0.1820	0.1898	0.2211	0.1327
Best Possible Future	0.1850 (+1.65%)	0.3718 (+95.89%)	0.2181 (-1.36%)	0.2470 (+86.13%)
Average Future	0.2570 (+41.21%)	0.4474 (+135.72%)	0.2923 (+32.20%)	0.3190 (+140.39%)
Worst Possible Future	0.3290 (+80.77%)	0.5230 (+175.55%)	0.3665 (+65.76%)	0.3910 (+194.65%)

4.4 Sensitivity analysis

For validating the result, a sensitivity analysis by a one-factor-at-a-time (OAT) approach, which is the most common method in previous studies (Ferretti et al., 2016) is conducted. The mechanism of the approach is to observe how sensitive the conclusions are to minor changes in inputs. If the methodology is sound and its inference reasoning is logical, then the sensitivity analysis must at least follow the following two axioms (Yang et al., 2009):

1) A slight increment/decrement in the degrees of belief associated with any linguistic variables of the CCRIs will certainly result in the effect of a relative increment/decrement in the DOB of the linguistic variables and the values of climate risk indexes;
2) Given the same variation of DOB distributions of the lowest-level factors, its influence magnitude to the values of climate risk indexes will keep consistency with their weight distributions.

For achieving two axioms, a DOB of 0.1 is reassigned in each CCRI and moved towards the maximal decrement of the values of climate risk indexes. The dataset of FEL in October is picked for sensitivity analysis. If the model reflects the logical reasoning, the climate risk index values will increase accordingly. For example, if the DOB of "Days of rain >= 10.0 mm UB" (i.e. ID = 6) belonging to "L_5 High risk" increases by 0.1 and, correspondingly, the DOB of it belonging to "Low risk" decreases by 0.1. (If the DOB attached to "L_1 Low risk" is less than 0.1, then the remaining DOB can be taken from the one attached to "L_2 Moderately low risk," this process continues until that 0.1 DOB is consumed) Afterwards, to study such influence magnitude of CCRIs based on an interval [0, 0.1], the change of a DOB from 0 to 0.1 with a smaller step of 0.01 is used for each CCRI towards the maximal increment of the values of climate risk indexes. The analysis results are shown in Table 14.

For the first axiom, it is proved as climate risk index increases if any CCRI DOB increases as shown in Table 13. For example, when DOB of "Maximum temperature UB" (i.e. ID = 1) increases by 0.1, it is found that the climate risk index increases from 0.1461 to 0.1510, which is a positive correlation. In terms of the second Axiom, the variation of the CCRIs is different, and some CCRIs provide similar impacts to climate risk indexes. It is because all the lowest level CCRIs have assigned equal weights while the EWEs have been given different weights by literature review. For example, "Maximum sea level record" (i.e. ID = 16), and "Maximum skew surge record" (i.e. ID = 17), provide the same consistent pattern of changes as they are influencing the same EWE, "Sea-level rise" in Table 14. Also, the normalised weight of "Sea-level rise" is 23.18, and that of "Warming trend/ Extreme temperature/ Drought/ Wildfire" is 22.99%. "Maximum temperature UB" (i.e. ID = 1), "Relative humidity LB" (i.e. ID = 2), "Rainfall LB" (i.e. ID = 3and "Cloud cover LB" (i.e. ID = 4) provides smaller changes, with a range from +1.854% to +3.709%, comparing to +5.151% provide by "Maximum sea level record" (i.e. ID = 16), and "Maximum skew surge record" (i.e. ID = 17) as shown in Table 13. Also, CCRIs for "Warming trend/ Extreme temperature/ Drought/ Wildfire" (i.e. ID = 1 – 4) change in similar patterns in Table 14, and they are different from the patterns of CCRIs for Sea-level rise (i.e. ID = 16 – 17). "Cloud cover" have a less change comparing to other CCRIs for "Warming trend/ Extreme temperature/ Drought/ Wildfire because no DOB of "Cloud cover LB" (i.e. ID = 4) belong to "L_1 Low risk" and "L_2 Moderately low risk", and the DOB is taken from "L_3 Medium risk" which can only provide a less increment. On the other hand, "Days of air frost UB" (i.e. ID = 7), "Days of ground frost UB" (i.e. ID = 8), "Days of sleet and snow falling UB" (i.e. ID = 9), "Days of snowlying UB" (i.e. ID = 10), and "Minimum temperature LB" (i.e. ID =11), provide the least variation as the normalised weight is the smallest. It means that influence magnitudes to the values of climate risk indexes will keep consistency with their weight distributions. After all, CCRI framework mechanism is validated.

Table 13 Sensitivity analysis of climate risk index given the variation of the CCRIs

EWE	Weight ratio	Normalised weight	ID	CCRI	LB /UB	New climate risk index	Change
Warming trend/ Extreme temperature/ Drought/ Wildfire	29.93%	22.99%	1	Maximum temperature	UB	0.1510	+3.709%
			2	Relative humidity	LB	0.1510	+3.709%
			3	Rainfall	LB	0.1510	+3.709%
			4	Cloud cover	LB	0.1483	+1.854%
Extreme precipitation/ Flooding	30.17%	23.18%	5	Rainfall	UB	0.1531	+5.151%
			6	Days of rain >= 10.0 mm	UB	0.1531	+5.151%

Snow cover/ Cold wave/ Snow events	19.70%	15.13%	7	Days of air frost	UB	0.1472	+1.099%
			8	Days of ground frost	UB	0.1472	+1.099%
			9	Days of sleet and snow falling	UB	0.1472	+1.099%
			10	Days of snowlying	UB	0.1472	+1.099%
			11	Minimum temperature	LB	0.1472	+1.099%
Storminess/ Wind gust	20.20%	15.52%	12	Rainfall	UB	0.1472	+1.072%
			13	Vapour pressure	LB	0.1472	+1.072%
			14	Mean seal level pressure	LB	0.1472	+1.072%
			15	Mean wind speed	UB	0.1472	+1.072%
Sea-level rise	30.17%	23.18%	16	Maximum sea level record	NA	0.1531	+5.151%
			17	Maximum skew surge record	NA	0.1531	+5.151%

*New climate risk index means that a 10% DOB is reassigned in each factor and moved toward the maximal increment.

Table 14 Sensitivity analysis of climate risk index given the variation of the CCRIs in [0, 0.1] at a Step of 0.01

		Variation									
ID	**CCRI**	**0.01**	**0.02**	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**	**0.08**	**0.09**	**0.1**
1	Maximum temperature	0.0005	0.0011	0.0016	0.0022	0.0027	0.0032	0.0038	0.0043	0.0049	0.0054
2	Relative humidity	0.0005	0.0011	0.0016	0.0022	0.0027	0.0032	0.0038	0.0043	0.0049	0.0054
3	Rainfall	0.0005	0.0011	0.0016	0.0022	0.0027	0.0032	0.0038	0.0043	0.0049	0.0054
4	Cloud cover	0.0003	0.0006	0.0008	0.0011	0.0014	0.0016	0.0019	0.0022	0.0025	0.0027
5	Rainfall	0.0007	0.0015	0.0022	0.0029	0.0037	0.0044	0.0052	0.006	0.0067	0.0075
6	Days of rain >= 10.0 mm	0.0007	0.0015	0.0022	0.0029	0.0037	0.0044	0.0052	0.006	0.0067	0.0075
7	Days of air frost	0.0002	0.0003	0.0005	0.0007	0.0008	0.001	0.0011	0.0013	0.0015	0.0016
8	Days of ground frost	0.0002	0.0003	0.0005	0.0007	0.0008	0.001	0.0011	0.0013	0.0015	0.0016
9	Days of sleet and snow falling	0.0002	0.0003	0.0005	0.0007	0.0008	0.001	0.0011	0.0013	0.0015	0.0016
10	Days of snowlying	0.0002	0.0003	0.0005	0.0007	0.0008	0.001	0.0011	0.0013	0.0015	0.0016
11	Minimum temperature	0.0002	0.0003	0.0005	0.0007	0.0008	0.001	0.0011	0.0013	0.0015	0.0016
12	Rainfall	0.0002	0.0003	0.0005	0.0007	0.0008	0.0010	0.0011	0.0013	0.0015	0.0016
13	Vapour pressure	0.0002	0.0003	0.0005	0.0007	0.0008	0.0010	0.0011	0.0013	0.0015	0.0016
14	Mean seal level pressure	0.0002	0.0003	0.0005	0.0007	0.0008	0.0010	0.0011	0.0013	0.0015	0.0016
15	Mean wind speed	0.0002	0.0003	0.0005	0.0007	0.0008	0.0010	0.0011	0.0013	0.0015	0.0016
16	Maximum sea level record	0.0007	0.0015	0.0022	0.0029	0.0037	0.0044	0.0052	0.006	0.0067	0.0075
17	Maximum skew surge record	0.0007	0.0015	0.0022	0.0029	0.0037	0.0044	0.0052	0.006	0.0067	0.0075

4.5 Discussion

While the implications of the each finding presented in Sections 4.1 – 4.3 are separately presented above, their common insights are drawn in this section. By understanding the impacts of different EWEs, insights can be presented into temporal and spatial perspectives. Extreme precipitation, storminess, and sea-level rise do not have spatial patterns, but extreme hot and cold weather events. Southern seaports experience higher risks in summer, while northern seaports experience higher risks in winter. In the future, except extreme cold weather events, all other EWEs provide higher risks to the UK seaports. Therefore, the seaports in the northern part of the UK face relatively less increase in climate risks those in the south.

These findings visualise the possible climate risks in different seaports. As the percentile values of the climate data are based on the UK data, it is suitable to compare the risks temporally and geometrically. By comparing the single seaport temporally, the result can guide the seaport management sector to amend and enhance the adaptations on EWE. On the other hand, the governmental bodies, such as DEFRA, can use the geometrical finding to design the adaptation measures. For example, seaports in South England are facing a higher risk during summer, while seaports in Scotland are facing a higher risk during winter. Some seaports can be aligned for contingency routing and resource allocation. Furthermore, a more extensive regional or national assessment can be done if a larger scale dataset is input in this framework. Also, different nations can use this assessment method for measuring different climate risks.

5 Conclusion

A new CCRI framework is proposed and implemented to measure the climate risk of seaports in the UK. The development of the CCRI framework can stimulate climate risks tracking and monitoring by monthly data from a national climate dataset. It contributes to the development of a climate risk comparison platform for adaptation planning and port relief logistics operations. This conceptual framework can be tailored and implemented in other regions to improve seaport climate resilience. Its capability to compare the indexes with different locations and the forecasting datasets makes it possible to rationalise seaport climate adaptation planning in a proactive manner. Therefore, the seaport alliance can use climate risk indexes for implementing climate disaster management. Furthermore, various climate threats on different seaports are identified and assessed, and so adaptation measures on a specific threat can be rationally implemented in proportion to its quantifiable risk levels.

Concerning such changes and findings, the results can be used as a factor for warehouse locations for humanitarian relief logistics, and climate adaptation resources can be allocated in a more effectively. Pre-positioning warehouses at strategic locations is an approach commonly taken by some humanitarian relief organisations. Using risk indexes can improve their capacities to deliver sufficient relief aid within a relatively short timeframe, and to provide shelter and assistance to disaster victims. Also, the findings can be used to choose adaptation measures for seaports from a national perspective as the climate risk levels of seaports can be visualised. Therefore, a climate risk index can assist the resources pre-positioning and adaptation measures allocation by implicating a further analysis based on the finding by CCRI framework.

The study can provide different seaport stakeholders with new insights about climate vulnerabilities assessment and climate change adaptation. There are three directions for further developments. First, some climate events, such as fog and seasonal variation of wind, are not associated with small area climate data to support. Thus, interviews on seaport stakeholders are required to obtain the relevant data, and then the qualitative information can be implemented into CCRI framework. Second, adaptive capacity, sensitivity, and social-economic factors in a regional and national scale can be collected to enhance the CCRI framework development. Lastly, the CCRI framework can be implied to other kinds of transport infrastructure, such as airports and railway stations. By then, the CCRI framework can be applied to develop a decision-making model for deciding suitable adaptation measures for a dedicated region with different transportation modes.

There are a few limitations in the CCRI framework. First, the weights of the lowest level indicators are equalled at this moment. A further investigation is valuable by consulting professionals for weight assignments. Second, the CCRI framework currently focuses on climate exposure. The climate resilience includes the sensitivity of the regions and adaptation ability of seaports. Therefore, it is possible to extend it to include more parameters to understand the climate relicense index of seaports. ER has the advantage of incorporating new parameters with the need for significant alternation of the current hierarchy. Furthermore, further analysis can be conducted to investigate on how each indicator contributes to the high risk in the investigated port from the climate exposure perspective.

Acknowledgements

This work is supported by EU H2020 ERC-COG-2019 project (TRUST – 864724) and EU H2020 Marie Skłodowska-Curie project (GOLF MSCA-RISE 777742). The authors thank the Editor and the anonymous reviewers for their constructive comments which improves the quality of this paper.

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Annex 1 Illustration of the ER algorithm

The ER algorithm is illustrated by an empirical incomplete dataset for EWE "Sea-level rise".

$A_1 = (0, 0, 0{,}0.9{,}0); A_1 = (0, 0, 0{,}0.7{,}0.3);\;\; \omega_1 = 0.4;\;\; \omega_2 = 0.6$

To calculate the basic conditional probability masses $\mathrm{M}_{m,k}$ as defined by Eq. 4.

$M_{1,1} = 0.6 \times 0 = 0; M_{1,2} = 0.6 \times 0 = 0; M_{1,3} = 0.6 \times 0 = 0;$
$M_{1,4} = 0.6 \times 0.9 = 0.36; M_{1,5} = 0.6 \times 0 = 0;$
$M_{2,1} = 0.4 \times 0 = 0; M_{2,2} = 0.4 \times 0 = 0; M_{2,3} = 0.4 \times 0 = 0;$
$M_{2,4} = 0.6 \times 0.7 = 0.42; M_{2,5} = 0.6 \times 0.3 = 0.18;$

Next the remaining relative importance $\overline{H}_k$ for all $k = (1, 2)$ is obtained as follows using Eq. 6

$\overline{H}_1 = 1 - \omega_1 = 1 - 0.4 = 0.6;\; \overline{H}_2 = 1 - \omega_2 = 1 - 0.6 = 0.4$

The remaining probability mass $\widetilde{H}_k$ due to the possible incompleteness of any individual grad $\alpha_{m,k}$ is defined by Eq. 7.

$\widetilde{H}_1 = \omega_1(1 - \sum_{m=1}^{5} \alpha_{m,1}) = \omega_1 \left[1 - \left(\alpha_{1,1} + \alpha_{2,1} + \alpha_{3,1} + \alpha_{4,1} + \alpha_{5,1}\right)\right]$
$= 0.4 \;[1 - (0 + 0 + 0 + 0.9 + 0)] = 0.04$
$\widetilde{H}_2 = \omega_2(1 - \sum_{m=1}^{5} \alpha_{m,2}) = \omega_2 \left[1 - \left(\alpha_{1,2} + \alpha_{2,2} + \alpha_{3,2} + \alpha_{4,2} + \alpha_{5,2}\right)\right]$
$= 0.6 \;[1 - (0 + 0 + 0 + 0.7 + 0.3)] = 0$

By calculation $\overline{H}_k$ and $\widetilde{H}_k$, H_k can be obtained by Eq. 5.

$H_1 = \overline{H}_1 + \widetilde{H}_1 = 0.6 + 0.04 = 0.64;\;\; H_2 = \overline{H}_2 + \widetilde{H}_2 = 0.4 + 0 = 0.4$

The remaining combined probability mass $\widetilde{H'}_U$ due to the possible incomplete assessment of $\alpha_{m,k}$ by 'Maximum sea level record" and "Maximum skew surge record" is defined by Eq. 8.

$\widetilde{H'}_U = K\left(\widetilde{H}_1\widetilde{H}_2 + \widetilde{H}_1\overline{H}_2 + \overline{H}_1\widetilde{H}_2\right) = 1.069\;\;(0 \times 0 + 0.04 \times 0.4 + 0.6 \times 0) = 0.017$

The combined remaining relative importance $\overline{H'}_U$ from the two CCRIs conducted by 'Maximum sea level record" and "Maximum skew surge record" are obtained using Eq. 9.

$\overline{H'}_U = K(\overline{H}_1\overline{H}_2) = 1.069(0.6 \times 0.4) = 0.257$

The normalizing factor K for combining the two CCRIs 'Maximum sea level record" and "Maximum skew surge record" is calculated using Eq. 10.

$$K = \left[1 - \sum_{T=1}^{5} \sum_{\substack{R=1 \\ T \neq R}}^{5} M_{T,1}\, M_{R,2}\right]^{-1} = [1 - (0.18 \times 0.36)]^{-\mathbf{1}} = 1.069$$

To calculate the combined probability mass a_j, Eq. 11, along with Eq. 8, is employed as follows.

$$a_1 = \frac{\mathrm{a}'_1}{1-\overline{\mathrm{H}'}_{\mathrm{U}}} = \frac{1.069\ (0\times0+0\times0.4+0.64\times0)}{1-0.257} = 0$$

$$a_2 = \frac{a'_2}{1-\overline{H'}_U} = \frac{1.069\ (0\times0+0\times0.4+0.64\times0)}{1-0.257} = 0$$

$$a_3 = \frac{a'_3}{1-\overline{H'}_U} = \frac{1.069\ (0\times0+0\times0.4+0.64\times0)}{1-0.257} = 0$$

$$a_4 = \frac{a'_3}{1-\overline{H'}_U} = \frac{1.069\ (0.36\times0.42+0.36\times0.4+0.64\times0)}{1-0.257} = 0.812$$

$$a_5 = \frac{a'_3}{1-\overline{H'}_U} = \frac{1.069\ (0\times0.18+0\times0.4+0.64\times0.18)}{1-0.257} = 0.166$$

Finally, the remaining combined probability mass H_U due to the possible incomplete assessment of 'Maximum sea level record" and "Maximum skew surge record" is calculated by Eq. 12.

$$H_U = \frac{\widetilde{H'}_U}{1-\overline{H'}_U} = \frac{0.1032}{1-0.2669} = 0.166$$

Then the result can be described as follows

'Sea-level rise" = $\{0$ "L1 Low risk", 0 "L2 Moderately low risk", 0 "L3 Medium risk",
0.812 "L4 Moderately high risk", 0.166 "L5 High risk", 0.023 "Unknown"$\}$