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Climate change adaptation for seaports by Climate Change Risk Indicators (CCRI)

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1. Abstract

The study is to provide a Climate Change Risk Indicators (CCRI) framework for climate adaptation for seaports, to link research to policy-making process on such a demanding topic. This paper first provides a literature review with international bodies and technical bodies on climate change adaptation for seaports. Second, a Fuzzy Evidential Reasoning (FER) model is employed to evaluate the climate risks in seaports. Third, six seaports in United Kingdom (UK) are selected for examples to demonstrate the use of CCRI. Finally, a comparative analysis of Yangtze River Delta and the United Kingdom (UK) in climates and seaport industries is done to visualize the possibilities in implementing the frameworks.

2. Literature review

2.1. Review of climate vulnerabilities

Over the past few years, the focus on climate change study has switched from just mitigation to both mitigation and adaptation. As global warming is still unstoppable and it brings more extreme weather, the relevant accidents and failures become more frequent. Moreover, the losses and fatalities are more severe. In the past two decades, several weather-related severe events are causing significant economic damage. In 2018, Typhoon Mangkhut crashed Asia countries very hard by bringing high wind and storm surges to the coastal cities (Wallemacq et al., 2018). In the same year, a heatwave in United Kingdom brought provided an uncomfortable condition for travelers in railway (Baker and Grant, 2018). Appropriate climate risk control and adaptation measures become necessary.

There are various studies for different climate change vulnerabilities and increasing trend in the climate change adaptation areas (Poo et al., 2018). We can observe several risk assessment on climate for critical infrastructures, including cyclones (Lam et al., 2017, Hoshino et al., 2016) and heatwave (Schubert et al., 2014). Also, there are some data driven studies for visualizing the climate resilience (Stamos et al., 2015) and escalation of extreme climate impacts (Forzieri et al., 2018). They have built up the data model by year data. Stamos et al. have compared the climate impacts by the number of extreme weather events (EWE), wind gusts, snowfall, blizzard, heavy precipitation, heat waves, and coldwaves. Forzieri et al. also indicated sensitivity by literature reviews and expert surveys, vulnerabilities for GIS data collection, and hazard projections for hazards.

Intergovernmental Panel on Climate Change (IPCC) is the international body for assessing the science related to climate change. Climate change adaptation is one of the key studies by IPCC working group II (Field et al., 2014). They have untaken thorough reviews on transport infrastructures and stated that transportation system will face more challenges by the environment in the near future (2030-2040) and the long future (2080-2100), especially in developed cities. They have indicated climate-related drivers of impacts for coastal zone systems and transportation systems: Extreme high temperature, extreme precipitation, snow cover, damaging cyclone, sea level, and flooding. Also, they indicated the climate shift of normal weathers and extreme weathers together (Field et al., 2012).

Although showing much attractiveness in the field of climate adaptation research, the findings still reveal limited insights on the validation of the proposed adaptation measures in future. One of the reasons is that the work did not address the issue as to how to use today's objective project tomorrow's climate risks reasonably. As climate change presents different impacts across regions/cities, it is hard to judge the adequate measures for a specific port without an accurate climate forecast. It is essential to set up CCRIs to overview the climate risk assessments for transport infrastructures of different regions. Also, the number of EWEs are varying in different seasons. To further sing a different tune, some cities can be beneficial and safer by global warming, especially reduction in snow events (Ho, 2010). So, it is essential to distinguish the magnitude of different climate risks in different seasons or months. In the next section, a climate change adaptation summary from business and operation sectors of ports is done to understand the sensitivity of seaports to different climate drivers.

2.2. Review of technical reports

On 9th May 2011, the Government published Climate Resilient Infrastructure: Preparing for a Changing Climate (Defra, 2011). It sets out the Government's view on adapting infrastructures in transport sectors to the climate change impacts in Table 1:

Table 1 Summary climate change adapting infrastructures in transport sectors by government

Infrastructure	Key risks
Roads	• Flooding from increased precipitation and storminess • Bridge damage due to increased river flow resulting from precipitation and storminess • Road embankments damage in south-east England due to wetter winters and drier summers
Railways	• Flooding from increased precipitation and storminess • Bridge damage due to increased river flow resulting from precipitation and storminess • Road embankments damage in south-east England due to wetter winters and drier summers • 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

Six UK bodies were invited by Defra and they had submitted climate change adaptation reports about seaport risk under Climate Change Act 2008:

Table 2 Summary of climate change adaptation reports by UK seaports

Reporting bodies	Seaports/ Docks	Reference
Associated British Ports	Hull, Humber, Immingham and Southampton	(Associated British Ports, 2011)
Port of Dover	Dover	(Port of Dover, 2011)
Felixstowe Dock and	Felixstowe	(Felixstowe Dock and Railway

Railway Company		Company, 2011)
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)
PD Teesport Ltd	Teesport and Hartlepool	(PD Teesport Ltd, 2011)
Port of London Authority	London	(Port of London Authority, 2011)
Port of Sheerness Ltd	Sheerness	(Peel Ports Group, 2011)

Except Port of London, all seaports from Table 2 have implemented risk assessments, with 344 risk items with different formats and scales. Even though we can't assess the risk levels by directly combining the results. But still we can observe the types of disaster:

- Extreme precipitation;
- Heat wave/ High temperature;
- Increase in snow events;
- Sea-level rise (SLR)/ Storm surge; and
- Storminess.

It is well matched the finding by IPCC working group II in 2014. Also, there is one extra concerns on climate change: Fogging. It could delay the ferry timetable due to poor visibility and also the mooring/pilot transfer/vessel movements.

On the other hand, we can divided seaport into different risk sectors:

- Approaching routes connectivity
- Civil engineering, jetties, pontoons;
- Electrical engineering/ Power supplies;
- External reputation;
- Hydrography and dredging;
- Increase in tourism and recreational use;
- Infrastructure and equipment maintenance;
- Licensing and consenting;
- Freight loading and moving;
- Navigation;
- Staff and personnel/ Business continuity;
- Statutory duties;
- Cargo storage; and
- Vessel services.

Approaching routes connectivity describes the possibilities of road/rail closure due to adverse weather. Snow and flooding also affected the stability of the road and rail infrastructures. Civil engineering, jetties, pontoons describes the risk of inadequate designs, jetties submerging by extreme events, especially SLR. Electrical engineering/ Power supplies is more understandable 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. An increase in tourism and recreational use can cause the busy traffic and activities near ports or the port routes which can enhance risks. Infrastructure and equipment describe the risks in adverse weathers damaging the onshore infrastructure and equipment, which include tarmac, ramps, and cranes. Licensing and consenting stated the chance of insurance premiums rising because of the unstable services. Loading and moving talked about affection and delay in cargo movements. Marine engineering stated about the risks inside the vessel, mainly potential reduction. Navigation described the affection 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 governmental issues, such as increasing the spread of invasive alien species and sea defense adversely impact. Cargo storage may have higher risk for different kind of cargos by the increase in EWEs. Vessel services stated the disruption of vessel movements on the water.

2.3. Review of Fuzzy Evidence Reasoning (FER)

In the process of analyzing vehicles selection, the primary uncertainties that decision makers may encounter include (Wang and Yang, 2001):

- Different kinds of assessments (linguistic terms, numbers, or stochastic values) depending on the factors of the decision criteria;
- Imprecise estimation owing to insufficient data, small time intervals for evaluation, shortcomings in expertise or the inability of experts to provide a sufficiently detailed assessment;
- Proper and robust aggregation of subjective and objective assessments made on multiple decision criteria.

One possible and practical way to process the incompleteness and unavailability of data is to integrate different expert judgments based on scientific assessments. Consequently, decision criteria can have both qualitative and quantitative depending on the sources. To connect all input information and undertake analysis it is necessary to convert different types of assessments into a single qualitative or quantitative form. The final research method will be determined by the nature of the decision scenario and data forms. Multiple criteria decision-making (MCDM) method is selected to analyze it. A typical MCDM technique, also as known as ER (Jian-Bo and Singh, 1994), requires the transformation from quantitative to qualitative assessments and is appropriate for undertaking CCRI analysis. FER has been widely used in climate change assessment (Yang et al., 2018) and performance measurement (Ha et al., 2017), is applied for synthesizing the surveying results. The latest algorithm can be analyzed and it is explained by the following formulations:

A represent the set with four linguistic expressions $\left(L_1, L_2, L_3, L_4\right)$, which has been combined from two subsets A_1 and A_2 based on two different sub-criteria. Let α represents degrees of belief attaching to different linguistic terms and ω represents normalized relative weights.

$$A = \left\{\alpha_1 L_1, \alpha_2 L_2, \alpha_3 L_3, \alpha_4 L_4\right\}, \text{ where} \sum_{m=1}^{4} \alpha_m \leq 1 \tag{1}$$

$$A_m = \left\{\alpha_{\mathrm{m},1} L_1, \alpha_{\mathrm{m},1} L_m, \alpha_{\mathrm{m},1} L_3, \alpha_{\mathrm{m},1} L_4\right\}, \text{ where} \sum_{m=1}^{4} \alpha_{m,k} \leq 1 \text{ and } \; k = 1,2 \tag{2}$$

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

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

Equation (1) represents the set with four linguistic expressions and equation (2) represents the corresponding from two subsets. By the total normalized relative weights are given in equation (3) and individual relative weight is obtained, the individual degrees, M can be obtained as equation (4).

$$H_k = \bar{H}_k + \tilde{H}_k \text{, where } k = 1,2 \tag{5}$$
$$\bar{H}_k = 1 - \omega_k \text{, where } k = 1,2 \tag{6}$$
$$\tilde{H}_k = \omega_k \left(1 - \sum_{m=1}^{4} \alpha_{m,k}\right) \text{, where } k = 1,2 \tag{7}$$

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

$$a'_m = K\left(M_{m,1}M_{m,2} + M_{m,1}H_2 + H_1M_{m,2}\right) \text{, where } m = 1,2,3,4 \tag{8}$$
$$\bar{H}'_U = K\left(\bar{H}_1\bar{H}_2\right) \tag{9}$$
$$K = \left(1 - \sum_{T=1}^{4} \sum_{\substack{R=1 \\ R \neq T}}^{4} M_{T,1}M_{R,2}\right)^{-1} \tag{10}$$

Let a'_m be the non-normalized degree to which the synthesized evaluation is confirmed to the four linguistic expressions and $\bar{H}'_U$ thenon-normalized remaining belief unassigned after the commitment of belief to the four linguistic expressions. They work together as the result of the synthesis of the judgments. After the above 10 equations, the final two equations means the calculation of the combined degrees a_m. They are generated by putting $\bar{H}'_U$ back to the four expressions using the following normalization process and H_U means the normalized remaining belief unassigned in the synthesized set.

$$a_m = a'_m / \left(1 - \bar{H}'_U\right) \text{, where } m = 1,2,3,4 \tag{11}$$
$$H_U = \tilde{H}_U / \left(1 - \bar{H}'_U\right) \tag{12}$$

The above gives the process of combining two sub-criteria based on four linguistic variables. The number. If three sub-criteria with more (or less) linguistic expressions are required to be combined, the result obtained from the combination of any two sets can be further synthesized with the third one using the above algorithm. Simlarily, multiple sets from the evaluations of more sub-criteria or the judgements from multiple persons can also be combined. The application of the approach, however, requires the assumption that all evaluations are assessed or obtained by the same linguistic expressions (one common utility space), which is often not the case in decision making. Therefore, the evaluations of both upper-level criteria and lower-level sub-criteria need to be transformed before being aggregated using a belief distribution based utility mapping technique which has been widely used in linking the bottom and top attributes even they have different numbers of linguistic variables.

3. CCRI by Fuzzy ER Approach

CCRI requires the construction of a hierarchical structure accommodating many criteria and sub-criteria with the appropriate presentation of their aggregates. In such a hierarchical structure, it is usually the case that the selection analysis at a higher level is also making use of the information that produced at lower levels. It is therefore essential to synthesize the evaluations of climate risks in different ports. When the qualitative assessment using linguistic terms is involved in the analysis, however, it is complicated to use normal mathematically logical operations to conduct the synthesis.

An ER method is well matched to undertake modeling subjective credibility which is induced by partial evidence. The kernel of this approach is an ER algorithm developed on the concept of the Dempster–Shafer (D–S) theory, which requires modeling the hypothesis set with the requirements and limitations of the accumulation of evidence. Eventually, it was successfully applied to vessel selection by ER algorithm (Yang et al., 2009). The most substantial strength of ER is its ability to deal with vague and incomplete and data, as well as precise and complete. It is also useful for enabling the experts to involve in a decision-making problem to make their decisions either subjectively or quantitatively. It inherently means that both specific numbers and verbal descriptors can make judgments.

1. Defining the problem

By the literature review on technical reports and IPCC findings, we can observe EWEs can be a reference for observation the climate risks for seaports. So, we list out the matching of IPCC findings and EWEs mentioned in seaport technical reports.

Climate parameters for observation and analysis are selected from MET Office (Met Office, 2018), Climate Projection (UK Climate Projection, 2018), EU Floods Directive (Environment Agency, 2018) and British Oceanographic Data Centre (BODC) (British Oceanographic Data Centre, 2018). All monthly variables are selected MET Office and then some of the risks without monthly data are further chosen from other sources.

Met Office data is collected from UK Climate Projections in 2009 (UKCP09) gridded observation datasets. The historical dataset spans the period 1910–2016 and covers the UK at 5 × 5 km resolution. It will be used to observe the existing risks. Also, by the UKCP09, we can find some forecasting data to compare the existing risks and future risks. The time period is set to 2050s (2040-2069) and the emission scenario is medium. 50th percentile data in 2050s with medium emission scenario is taken as the reference for analysis as they had done a probabilistic projections for every variables. The definition and time zone of climate variables are shown below:

Table 3 Definition and time zone of climate variables

Climate variables	Definition	Time zone
Maximum temperature	Average of daily maximum air temperature (°C)	1910 – 2016
Minimum temperature	Average of daily minimum air temperature (°C)	1910 – 2016
Mean temperature	Average of daily mean air temperature (°C)	1910 – 2016
Precipitation	Total precipitation amount (mm)	1910 – 2016
Mean wind speed	Average of hourly mean wind speed at a height of 10 m above ground level (knots)	1969 – 2014
Mean sea level pressure	Average of hourly mean sea level pressure (hPa)	1961 – 2014
Mean relative humidity	Average of hourly relative humidity (%)	1961 – 2014
Mean vapour pressure	Average of hourly vapour pressure (hPa)	1961 – 2014
Mean cloud cover	Average of hourly total cloud cover (%)	1961 – 2006
Days of air frost	Count of days when the minimum air temperature is below 0 °C (days)	1961 – 2016
Days of ground frost	Count of days when the grass minimum temperature is below 0 °C (days)	1961 – 2016
Days of rain >= 1 mm	Count of days with >= 1mm precipitation (0900-0900 UTC) (days)	1961 – 2016

Days of rain >= 10 mm	Count of days with >= 10mm precipitation (0900-0900 UTC) (days)	1961 – 2016
Days of sleet or snow falling	Count of days with sleet or snow falling (days)	1971 – 2011
Days of snow lying	Count of days with greater than 50% of the ground covered by snow at 0900 UTC (days)	1971 – 2011

Task Team on Definitions of Extreme Weather and Climate Events (TT-DEWCE) from World Meteorological Organization (WMO) has stated that there are fixed and well known the extreme events and their threshold differ from location to location. So, 80th, 90th, 95th and 99th percentile values are used to divide the upper bound (UB) grades in five and 20th, 10th, 5th and 1st percentile values are used to divide the lower bound (LB) grades in five. The values used as defining grades are shown below:

Table 4 Marginal values of climate variables from Met Office for defining grades

Types of disasters	Climate variables	UB/LB	Percentile 20th/80th	10th/90th	5th/95th	1st/99th
Warming trend/ Extreme temperature/ Drying Trend	Maximum temperature	UB	17.24	19.17	20.52	22.91
	Mean temperature	UB	13.19	14.78	15.86	17.64
	Minimum temperature	UB	9.2	10.59	11.48	12.86
	Relative humidity	LB	78.54	76.31	74.47	70.7
	Rainfall	LB	40	27.05	18.59	7.44
	Cloud cover	LB	64.9	60.64	56.71	48.57
Extreme precipitation	Rainfall	UB	130.5	174.68	222.65	346.63
	Days of rain >= 1.0 mm	UB	17.66	20.54	23.04	27.24
	Days of rain >= 10.0 mm	UB	4.38	6.24	8.22	12.78
Snow cover	Days of air frost	UB	9.15	13.52	17.17	24.23
	Days of ground frost	UB	16.88	20.38	23.06	27.68
	Days of sleet and snow falling	UB	3.4	6.3	9.17	15.18
	Days of snowlying	UB	1.53	4.37	8.01	18.35
	Maximum temperature	LB	2.02	4.37	5.63	7.22
	Mean temperature	LB	-0.58	1.72	2.88	4.32
	Minimum temperature	LB	-3.32	-1.07	0.02	1.32
Sea-level rise	Rainfall	UB	130.5	174.68	222.65	346.63
	Vapour pressure	LB	7.26	6.63	6.14	5.21
	Mean seal level pressure	LB	1009.21	1006.02	1003.08	997.9
	Mean wind speed	UB	12.2	14.36	16.44	21.04
Other	Cloud cover	UB	77.96	80.79	83.1	87.58
	Relative humidity	UB	86.38	87.91	89.07	91.1

Long term flood risk map is chosen for observing the probabilities of flooding events by rivers and sea. We will consider the whole ports including the outer connections on the webpage (https://flood-warning-information.service.gov.uk/long-term-flood-risk/map) and they come with four levels:

- High risk means that each year this area has a chance of flooding of greater than 3.3%. This takes into account the effect of any flood defenses in the area. These defenses reduce but do not completely stop the chance of flooding as they can be overtopped, or fail.

- Medium risk means that each year this area has a chance of flooding of between 1% and 3.3%. This takes into account the effect of any flood defenses in the area. These defenses reduce but do not completely stop the chance of flooding as they can be overtopped, or fail.
- Low risk means that each year this area has a chance of flooding of between 0.1% and 1%. This takes into account the effect of any flood defenses in the area. These defenses reduce but do not completely stop the chance of flooding as they can be overtopped, or fail.
- Very low risk means that each year this area has a chance of flooding of less than 0.1%. This takes into account the effect of any flood defenses in the area. These defenses reduce but do not completely stop the chance of flooding as they can be overtopped, or fail.

Finally, maximum sea level record and maximum skew surge record are collected from 45 UK ports from BODC. As it is extreme data already. We tried to separate them into five groups by 20^{th}, 40^{th}, 60^{th}, and 80^{th} percentiles, which are shown below. For forecasting, we used the UK climate projection values, long-term linear trend in skew surge (1951-2099) for return level of 10 years (mm/yr) and sea-level change, to foresee the sea-level and storm surge changes. Table 5 shows the

Table 5 Marginal values of climate variables from BODC for defining grades

Climate variables	Percentile 20^{th}	40^{th}	60^{th}	80^{th}
Maximum sea level record (m)	2.79	3.28	3.6	5.33
Maximum skew surge record (m)	0.75	0.87	1.04	1.22

By gathering data from different organizations, we can have a small summary for this framework for visualizing the full picture of it:

Table 6 Summary of CCRI climate variables

Types of disasters	EWEs	Climate variables	UB/ LB	Source	Monthly data	Forecast data
Warming trend/ Extreme temperature/ Drying Trend	Heatwave Drought Wildfires	Maximum temperature	UB	Met Office	Yes	Yes
		Mean temperature	UB	Met Office	Yes	Yes
		Minimum temperature	UB	Met Office	Yes	Yes
		Relative humidity	LB	Met Office	Yes	Yes
		Rainfall	LB	Met Office	Yes	Yes
		Cloud cover	LB	Met Office	Yes	Yes
Extreme precipitation	Flooding	Rainfall	UB	Met Office	Yes	Yes
		Days of rain >= 1.0 mm	UB	Met Office	Yes	No
		Days of rain >= 10.0 mm	UB	Met Office	Yes	No
		Long term flood risk map	N/A	Environment Agency	No	Yes
Snow cover	Coldwave/ Snow events	Days of air frost	UB	Met Office	Yes	No
		Days of ground frost	UB	Met Office	Yes	No
		Days of sleet and snow falling	UB	Met Office	Yes	No
		Days of snowlying	UB	Met Office	Yes	No
		Maximum temperature	LB	Met Office	Yes	Yes
		Mean temperature	LB	Met Office	Yes	Yes

		Minimum temperature	LB	Met Office	Yes	Yes
Damaging cyclone	Wind gust/ Storminess	Rainfall	UB	Met Office	Yes	Yes
		Vapour pressure	LB	Met Office	Yes	No
		Mean seal level pressure	LB	Met Office	Yes	Yes
		Mean wind speed	UB	Met Office	Yes	Yes
Sea-level rise	Flooding	Maximum sea level record	N/A	BODC	No	Yes
		Maximum skew surge record	N/A	BODC	No	Yes
		Long term flood risk map	N/A	Environment Agency	No	Yes
Other	Fog	Cloud cover	UB	Met Office	Yes	Yes
		Relative humidity	UB	Met Office	Yes	Yes

2. Setting the criterion grades

So, assessment grade has been set up by percentile. All the historical datasets are selected as the reference of assessment grading:

Table 7 Assessment grades of CCRI climate variables

Source	Assessment Grade				
Met Office	Low risk	Moderately low risk	Medium risk	Moderately high risk	High risk
UB Percentile	*<=80*	*80.1 - 90*	*90.1 - 95*	*95.1 - 99*	*99.1 - 100*
LB Percentile	*>=20*	*10 – 19.9*	*5 – 9.9*	*1 – 4.9*	*0 – 0.9*
Environment Agency	Very low risk	Low risk	Medium risk	High risk	
BODC	Low risk	Moderately low risk	Medium risk	Moderately high risk	High risk
Percentile	*<=20*	*20.1 - 40*	*40.1 - 60*	*60.1 - 80*	*80.1 - 100*
All disasters	Low risk	Moderately low risk	Medium risk	Moderately high risk	High risk

Except long-term flood risks from Environment Agency with four grades, they are all with five grades: “Low risk”, “Moderately low risk”, “Medium risk”, “Moderately high risk” and “High risk”. The specific rules for connecting to father grade, “Extreme precipitation” and “Sea-level rise”, are set as below:

- “Very low risk” to 1 of “Low risk” to father grade;
- “Low risk” to 0.666 of “Moderately low risk” and 0.333 of “Medium risk” to father grade;
- “Medium risk” to 0.333 of “Medium risk” and 0.666 of “Moderately high risk” to father grade; and
- “High risk” to 1 of “High risk” to father grade

All disasters and CCRI index are come with five grades: “Low risk”, “Moderately low risk”, “Medium risk”, “Moderately high risk” and “High risk”. So, there are no other special for other connections.

3. Evaluating six seaports using climate data from the lowest level to top level criteria

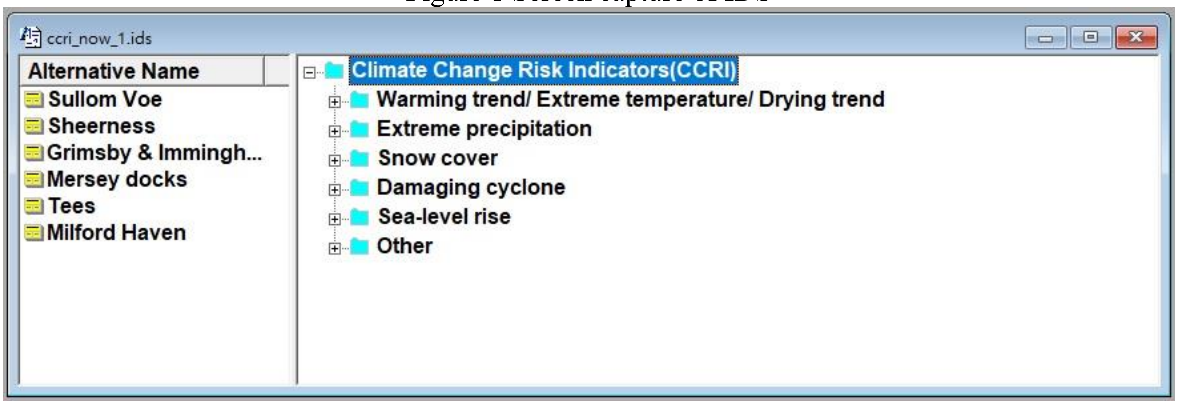
By assessing the dataset of the seaport, we can distinguish the grading of each criteria. Six seaports are chosen for evaluation: “Sullom Voe”, “Sheerness”, “Grimsby & Immingham”, “Mersey Docks”, “Tees”, and “Milford Haven”. They are from different parts of UK and they are all top ten busiest ports in UK.

The framework of CCRIs consists of three layers: “CCRI index”, “Types of disasters”, and “Climate parameters”. For “Climate parameters”, all attributes have equal weights. For “Types of disasters”, the weight assignment come from a sensitivity study for different critical infrastructures in Europe (Forzieri et al., 2018): “Warming trend/ Extreme temperature/ Drying Trend” as 29.93; “Extreme precipitation” as 30.17; “Snow cover” as 19.70; “Damaging cyclone” as 20.20; “Sea-level rise” as 30.17; and “Other” as 0. So, we can get a CCRI for each port at the highest level.

4. <u>Synthesizing all evaluations using the ER algorithm</u>

Calculation software IDS is used for assessing the result by implying the ER algorithm mentioned in Section 2.3. The assessment grades are given their corresponding values 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”]. The software IDS uses the concept of a utility interval to characterize the unassigned degree of belief (unknown percentage). The ER algorithm produces a utility interval which is enclosed by the two extreme cases where the unassigned belief moves either to “Slightly preferred with a minimum utility value” or to “Greatly preferred with a maximum utility value”.

Figure 1 Screen capture of IDS



4. Result

By assessing the six seaports for each month, we can observe some finding, further analysis in the result is taken place by comparing the results between ports and months. Also, now and future, as known as historical and forecasting, comparison is done.

4.1. Comparison between six seaports

Figure 2 CCRI index of the UK seaports in January

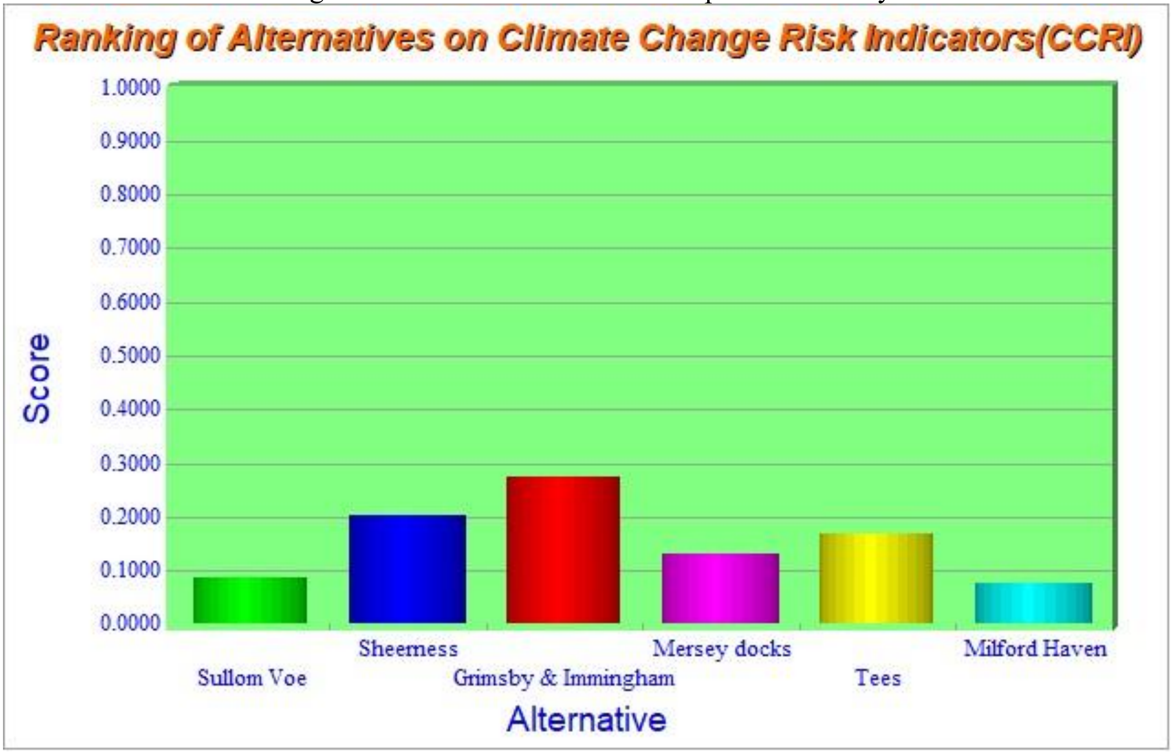
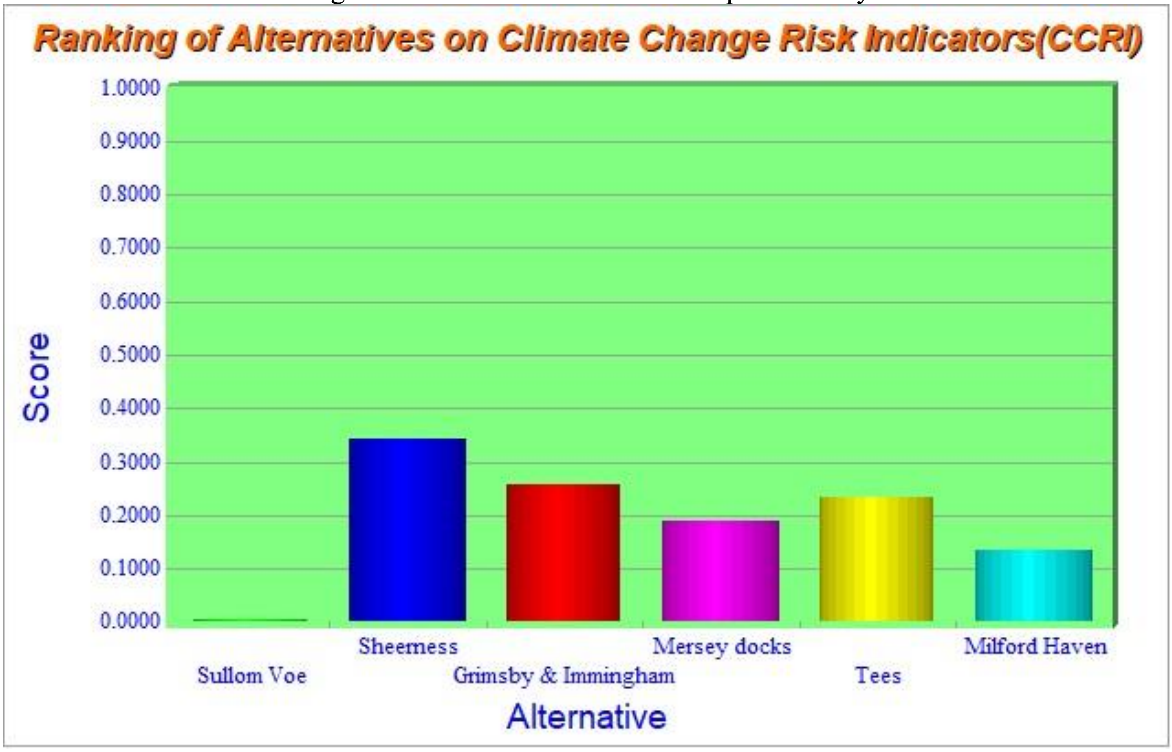


Figure 3 CCRI index of the UK seaports in July



By obtaining the CCRI index of six seaports of January (in Figure 2) and July (in Figuer3), we can observe the risk difference between seasons by showing a Table 8 below:

Table 8 CCRI Index of six seaports in the UK

Month/ Location	Sullom Voe	Sheerness	Grimsby & Immingham	Mersey docks	Tees	Milford Haven
January	0.0857	0.2044	0.2756	0.1309	0.1703	0.0768
Rank	5	2	1	4	3	6
July	0.004	0.3419	0.257	0.1886	0.2341	0.1339
Rank	6	1	2	4	3	5

In January, “Grimsby & Immingham” is with the highest risk and “Milford Haven” is with the lowest risk. In July, “Sheerness” scores the highest and and “Sullom Voe”. Also, “Sullom Voe” and “Grimsby & Immingham” are with higher indices in January and the remaining vice versa. So, we can generally notify the higher risks in January for Northern port, including “Sullom Voe” and “Grimsby & Immingham”. Moreover, we can observe the lower risks in “Sheerness” and “Milford Haven”, which are in the Southern England.

4.2. Comparison between months

Figure 4 CCRI index of Grimsby & Immingham

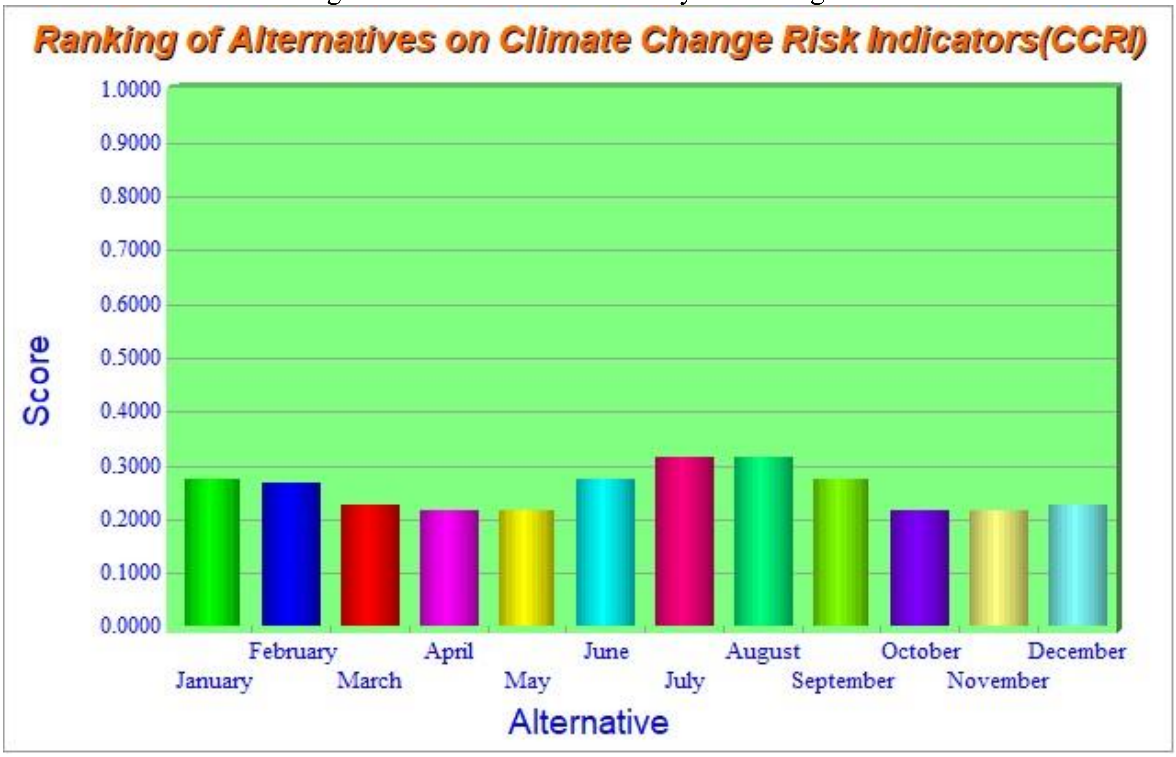
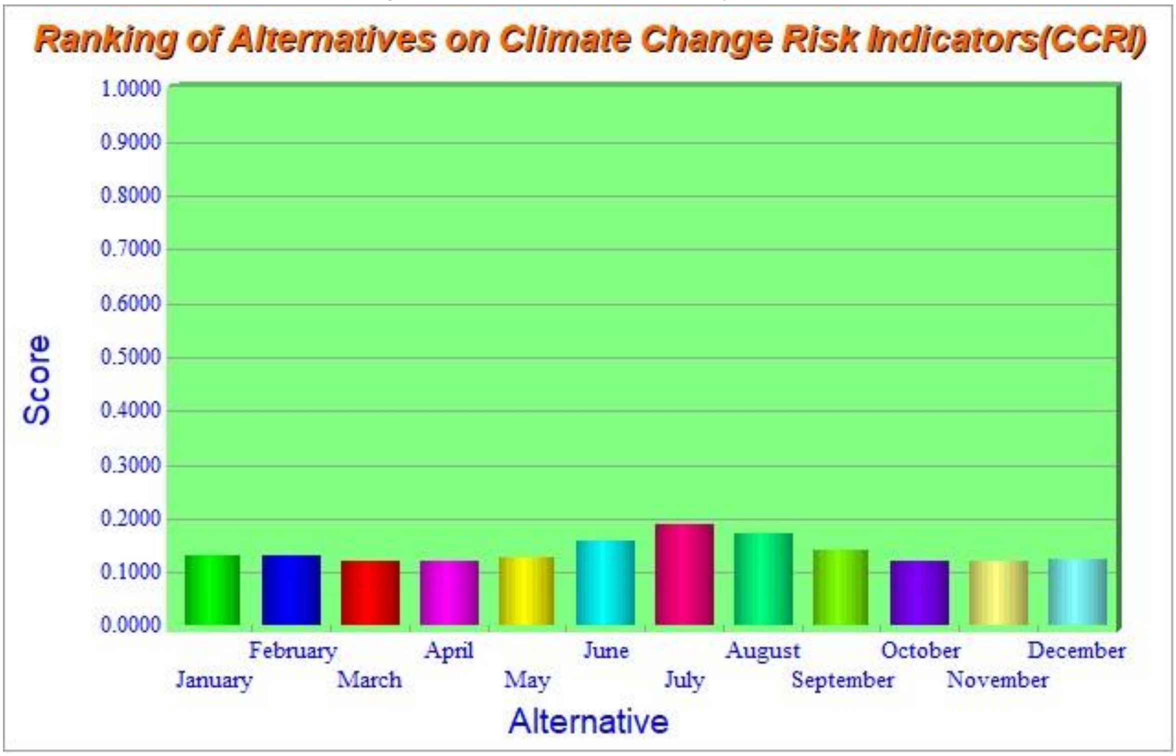


Figure 5 CCRI index of Mersey Docks



By the comparison between different months, we can spot out the dangerous seasons. “Grimsby & Immingham” and “Mersey Docks” are taken places for demonstration in Figure 4 and 5. We can see that there two crests, as known as summer and winter, in both figures. The highest index are both existing in July and “Grimsby & Immingham” sustain the highest value to August.

Table 9 CCRI Index of two the UK seaports in all months

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Grimsby & Immingham	0.276	0.268	0.226	0.217	0.217	0.276	0.316	0.316	0.276	0.217	0.217	0.229
Mersey Docks	0.131	0.131	0.121	0.121	0.129	0.159	0.189	0.172	0.140	0.121	0.121	0.125

4.3. Comparison between now and future

Figure 6 & 7 CCRI index of “Grimsby & Immingham” in January and July with forecasting

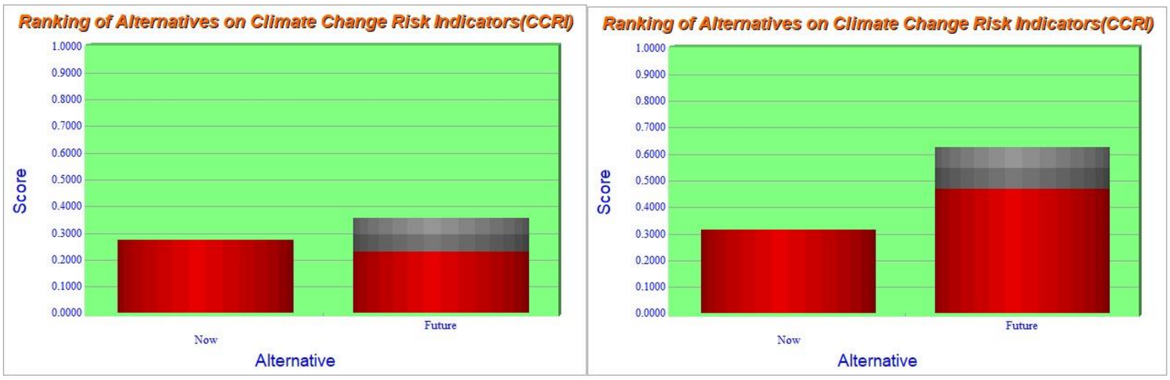
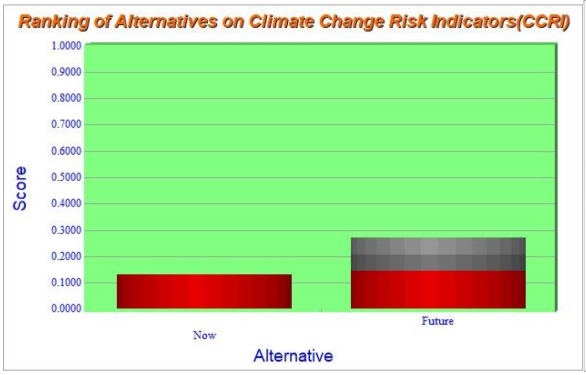
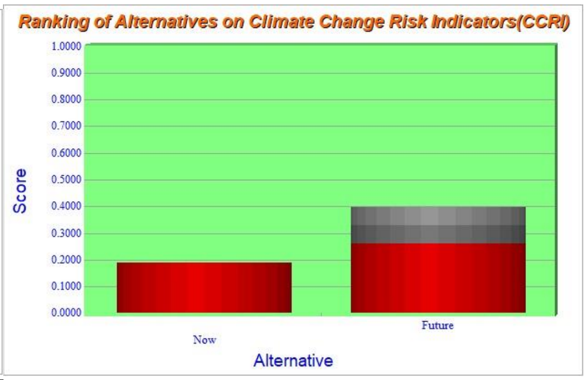


Figure 8 & 9 CCRI index of “Mersey Docks” in January and July with forecasting





The final analysis is to compare the now and future data. Figures 6 to 9 are used to observe the changes of CCRI indices of January and July in two different ports, “Grimsby & Immingham” and “Mersey Docks”. The comparison is shown in Table 10:

Table 10 CCRI Index of two the UK seaports in January and July with forecasting

Port	Grimsby & Immingham		Mersey Docks	
Month	January	July	January	July
Now	0.2756	0.3159	0.1309	0.1886
Best Possible Future	0.2299	0.4681	0.1451	0.2621
Average Future	0.2939	0.5477	0.2079	0.3298
Worst Possible Future	0.128	0.1592	0.1256	0.1354

Both locations do not have a great change in January but with a great boost in July. We can foresee the higher risks in July in the future.

5. Comparison of China and the UK in climate change impacts of seaports

After the demonstration of CCRI framework by the UK data input, comparing the UK with different countries is important to see the possibilities to implement the model to another systems. First, United Kingdom is approximately 243,610 sq. km, while China is approximately 9,596,960 sq. km which mean 34 times bigger. China's landscape is vaster and more diverse than United Kingdom. Taking Shanghai’s monthly maximum temperature as example, they have five months, from May to September, reached the highest grade if we implement the UK model to China.

Also, they do not have the same format of data. Several monthly climate variables existed in the CCRI framework cannot be found on National Meteorological Information Centre’s website (National Meteorological Information Center, 2017). They include “Days of rain >= 1.0 mm” and “Long term flood risk map” etc.

Besides, we have collected historical disaster data from an international disasters database (EM-DAT, 2018). The related disasters happened in the previous 50 years has been listed below:

Table 11 Climate disasters happened in China and UK in 1969 - 2018

Types of disasters	China	The UK
Flood	78 (36.97%)	25 (40.32%)
Storm	92 (43.60%)	29 (46.77%)

Drought	25(11.85%)	0 (0%)
Wildfire	6 (2.84%)	0 (0%)
Heatwave	6 (2.84%)	3 (4.84%)
Coldwave	4 (1.90%)	5 (8.06%)
Total	211	63

Flooding and storm occupied similar proportions in both countries. Drought and wildfire are not happened in UK but China. Heatwave is more common in China while coldwave is more common in UK in the extreme temperature categories.

6. Conclusion

A new case study is suggested to be done for fitting in the situation of China, or in particular region such Yangtze River Delta and Big Bay Delta. Further data is needed to be collected which required cooperation with the professions in China. Also, UK Climate Projection is implementing an update project (UKCP18) in November 2018. UKCP18 updated the probabilistic projections over land and provided a set of high-resolution spatially-coherent future climate projections for the globe at 60km scale and the UK at 12km scale. So, it may be possible to use as a reference for building a new CCRI framework outside UK. Also, a further qualitative survey from seaport stakeholders is required to be done to enhance the practicability of CCRI. Furthermore, CCRI framework can be applied to the other kind of transportation mode, such as airports and railways.

7. Reference

ASSOCIATED BRITISH PORTS 2011. Climate Change Adaptation Report. Associated British Ports (ABP).

BAKER, N. & GRANT, A. 2018. London Tube left so hot during 34C heatwave that it's above the legal limit for transporting CATTLE. *The Sun*.

BRITISH OCEANOGRAPHIC DATA CENTRE. 2018. *British Oceanographic Data Centre, a national facility for preserving and distributing marine data* [Online]. Natural Environment Research Council (NERC). Available: https://www.bodc.ac.uk/ [Accessed 28/11/2018 2018].

DEFRA 2011. Climate resilient infrastructure: preparing for a changing climate. Department for Environment, Food and Rural Affairs.

EM-DAT. 2018. *EM-DAT The international Disaster Database* [Online]. Centre for Research on the Epidemiology of Disasters - CRED. [Accessed 20/11/2018 2018].

ENVIRONMENT AGENCY. 2018. *Long term flood risk information* [Online]. Crown copyright. Available: https://flood-warning-information.service.gov.uk/long-term-flood-risk/map [Accessed 20/11/2018 2018].

FELIXSTOWE DOCK AND RAILWAY COMPANY 2011. Climate change adaptation report. Felizstowe dock and railway company.

FIELD, C. B., BARROS, V. & STOCKER, T. F. 2012. *Managing the risks of extreme events and disasters to advance climate change adaptation. Special report of the Intergovernmental Panel on Climate Change (IPCC)*, Cambridge University Press, New York, NY (United States).

FIELD, C. B., BARROS, V. R., DOKKEN, D. J., MACH, K. J. & MASTRANDREA, M. D. 2014.

Climate Change 2014 Impacts, Adaptation, and Vulnerability : Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge, Cambridge : Cambridge University Press.

FORZIERI, G., BIANCHI, A., SILVA, F. B. E., MARIN HERRERA, M. A., LEBLOIS, A., LAVALLE, C., AERTS, J. C. J. H. & FEYEN, L. 2018. Escalating impacts of climate extremes on critical infrastructures in Europe. *Global Environmental Change,* 48**,** 97-107.

HA, M.-H., YANG, Z., NOTTEBOOM, T., NG, A. K. Y. & HEO, M.-W. 2017. Revisiting port performance measurement: A hybrid multi-stakeholder framework for the modelling of port performance indicators. *Transportation Research Part E: Logistics and Transportation Review,* 103**,** 1-16.

HO, J. 2010. The implications of Arctic sea ice decline on shipping. *Marine Policy,* 34**,** 713-715.

HOSHINO, S., ESTEBAN, M., MIKAMI, T., TAKAGI, H. & SHIBAYAMA, T. 2016. Estimation of increase in storm surge damage due to climate change and sea level rise in the Greater Tokyo area.(Report). 80**,** 539.

JAN BROOKE ENVIRONMENTAL CONSULTANT LTD 2011. Adapting to Climate Change, Harwich Haven Authority Report to the Secretary of State. Harwich Haven Authority.

JIAN-BO, Y. & SINGH, M. G. 1994. An evidential reasoning approach for multiple-attribute decision making with uncertainty. *Systems, Man and Cybernetics, IEEE Transactions on,* 24**,** 1-18.

LAM, J. S. L., LIU, C. & GOU, X. 2017. Cyclone risk mapping for critical coastal infrastructure: Cases of East Asian seaports. *Ocean and Coastal Management,* 141**,** 43-54.

MERSEY DOCKS AND HARBOUR COMPANY LTD 2011. Climate Change Adaptation Report Report to Defra under the Adaptation Reporting Powers. Peel Ports Group.

MET OFFICE. 2018. *UK climate* [Online]. Available: https://www.metoffice.gov.uk/climate [Accessed 20/11/2018 2018].

MILFORD HAVEN PORT AUTHORITY 2011. Adapting to Climate Change, Milford Haven Port Authority Report to the Secretary of State.: Milford Haven Port Authority.

NATIONAL METEOROLOGICAL INFORMATION CENTER. 2017. *国家气象信息中心 National Meteorological Information Center* [Online]. China Meteorological Administration. Available: http://data.cma.cn/ [Accessed 20/11/2018 2018].

PD TEESPORT LTD 2011. PD Teesport (Ports of Teesport and Hartlepool) Climate Adaptation Assessment Report to Defra under the Adaptation Reporting Powers. PD Teesport Ltd.

PEEL PORTS GROUP 2011. Port of Sheerness Ltd Climate Adaptation Assessment, Report to Defra under the Adaptation Reporting Powers. Peel Ports Group.

POO, M. C.-P., YANG, Z., DIMITRIU, D. & QU, Z. 2018. Review on Seaport and Airport Adaptation to Climate Change: A Case on Sea Level Rise and Flooding. *Marine Technology Society Journal,* 52**,** 23-33.

PORT OF DOVER 2011. Climate change adaptation report. Dover: Port of Dover.

PORT OF LONDON AUTHORITY 2011. Adapting to Climate Change Port of Lodon Authority Report to the Secretary of State. Jan Brooke Environmental Consultant Ltd.

SCHUBERT, S. D., WANG, H., KOSTER, R. D. & SUAREZ, M. J. 2014. Northern Eurasian Heat Waves and Droughts. *Journal of Climate*.

STAMOS, I., MITSAKIS, E., SALANOVA, J. M. & AIFADOPOULOU, G. 2015. Impact assessment of extreme weather events on transport networks: A data-driven approach. *Transportation Research Part D,* 34**,** 168-178.

UK CLIMATE PROJECTION. 2018. *UK Climate Projection* [Online]. Crown Publisher. Available: http://ukclimateprojections-ukcp09.metoffice.gov.uk/ [Accessed 20/11/2018 2018].

WALLEMACQ, P., BELOW, R. & MCLEAN, D. 2018. 2018 world's strongest storm: Typhoon Mangkhut barrels through Philippines toward China. *abc NEWS*.

WANG, J. & YANG, J. B. 2001. A subjective safety and cost based decision model for assessing safety requirements specifications. *International Journal of Reliability, Quality and Safety Engineering,* 8**,** 35-57.

YANG, Z., MASTRALIS, L., BONSALL, S. & WANG, J. 2009. Incorporating uncertainty and multiple criteria in vessel selection. *Proc. Inst. Mech. Eng. Part M- J. Eng. Marit. Environ.,* 223**,** 177-188.

YANG, Z., NG, A. K. Y., LEE, P. T.-W., WANG, T., QU, Z., RODRIGUES, V. S., PETTIT, S., HARRIS, I., ZHANG, D. & LAU, Y.-Y. 2018. Risk and cost evaluation of port adaptation measures to climate change impacts. *Transportation Research Part D: Transport and Environment,* 61B**,** 444-458.