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Risk and cost evaluation of port adaptation measures to climate change impacts

Risk and Cost Evaluation of Port Adaptation Measures to Climate Change Impacts

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Abstract

The long term impact posed by climate change risk remains unclear and is subject to diverse interpretations from different maritime stakeholders. The inter-dynamics between climate change and ports can also significantly diversify in different geographical regions. Consequently, risk and cost data used to support climate adaptation is of high uncertainty and in many occasions, real data is often unavailable and incomplete. This paper presents a risk and cost evaluation methodology that can be applied to the analysis of port climate change adaptation measures in situations where data uncertainty is high. Risk and cost criteria are used in a decision-making model for the selection of climate adaptation measures. Information produced using a fuzzy-Bayesian risk analysis approach is utilized to evaluate risk reduction outcomes from the use of adaptation measures in ports. An evidential reasoning approach is then employed to synthesize the risk reduction data as inputs to the decision-making model. The results can assist policymakers in developing efficient adaptation measures that take into account the reduction in the likelihood of risks, their possible consequences, their timeframe, and costs incurred.

A case study across 14 major container ports in Greater China (Hong Kong, Taiwan and Mainland China) is presented to demonstrate the interaction between cost and risk analysis, and to highlight the applicability of the stated methodology in practice. The paper offers a useful analytical tool for assessing climate change risks to ports and selecting the most cost-effective adaptation measures in uncertain conditions. It can also be used to compare the practitioners' perceptions of climate risks across different geographical regions, and to evaluate improvements after implementation of the selected adaptation measures with potential budgetary constraints. The methodology, together with the illustrative cases, provides important insights on how to develop efficient climate change adaptation measures in a complex supply chain context to improve the sustainability of development and enhance adaptation measures for ports, port cities, intermodal transport, supply chains, and urban and regional planning in general.

Key words: Climate change, port, adaptation, maritime risk, risk-cost modelling, multiple criteria decision-making, Greater China

1. Introduction

Climate change is at the forefront of research across disciplines as it is argued that it is an irreversible process which could pose catastrophic risks to human welfare (Keohane and Victor, 2010). Hence, the study of climate change is gradually moving away from purely mitigation towards a strategy of addressing mitigation and adaptation simultaneously (Ng et al., 2016).

Ports are highly vulnerable to climate risks in terms of both their facilities and operations (Becker et al., 2012). Given the critical role that ports play in the global economy and supply chains (Ng and Liu, 2014), their inability to adapt to such risks poses a significant contemporary problem. Thus, it is important to find effective ways for ports to adapt to the climate change challenges. Further, policymakers and other port stakeholders must understand the potential risks to ports in order to develop appropriate adaptation planning and strategies. However, the impact of climate change on ports remains unclear, and there are diverse interpretations from different stakeholders, and across geographical regions. Although there is an urgent need for knowledge development and the optimising of solutions to assist ports in assessing the relationship between climate change risks and adaptation strategies, so far, little research has been undertaken, particularly from a methodological perspective.

The purpose of the paper is to better understand the risks posed by climate change on ports, and how to effectively adapt to and manage such risks. This study has two major objectives. First, it strives to understand how port stakeholders can use risk analysis to select rational adaptations to climate change. Second, it develops a risk and cost evaluation methodology to generate the best practices and guidelines for providing appropriate long-term resilience and adaptation to climate change risks. The applicability of the methodology will be illustrated through a technical case study across 14 major container ports in Greater China (Hong Kong, Taiwan and Mainland China). It is one of the first studies to examine the major risks posed to ports by climate change, and how adaptation measures can be developed taking into account cost factors. It offers vital information on how to enhance resilience, and will assist ports in improving their ability to tackle the uncertainties in responding to these risks. The outcomes of this study will be of value to port planners, policymakers and industrial practitioners, helping them to create and implement adaptation plans, strategies and practices.

The rest of the paper is structured as follows. The literature review can be found in section 2. The risk and cost evaluation methodology will be presented in section 3. In section 4, the data collected from the 14 ports across Greater China (Hong Kong, Taiwan, and Mainland China) will be described, followed by the methodology's calibration. The findings are presented in section 5 and the conclusion, including contribution and relevance for further research in section 6.

2. Literature review

There is an abundance of research investigating climate change risks, notably sea level rise (SLR) (e.g., Jevrejeva et al. 2012; Liu 1997; Schaeffer et al. 2012), vulnerability of coastal areas (e.g., McGinnis and McGinnis 2011; Awuor et al., 2008), impacts on transport systems (Koetse and Rietveld, 2009) and the use of marine eco-systems for coastal defence (Chemane et al. 1997). The risk source most relevant to port adaptation is flooding (e.g., Aerts, undated; Lehner et al., 2006; Dawson et al, 2009; Edjossan-Sossou et al, 2014; Hattermann et al., 2014; Koks et al., 2015), although studies on other areas also exist, for example landslide (e.g., Refice and Capolongo, 2002; Dai et al, 2002); groundwater pollution (e.g., Neshat et al., 2015) and drought (e.g., Wilhite et al., 2000). Many of these studies illustrate the urgent need for mitigation and adaptation plans. However, while recognizing adaptation as an integral component of risk reduction (Posas, 2011; Wheeler et al., 2009), they are dominated by mitigation approaches, usually quantitative measurement and control of GHG emissions (Peters, 2009; Scott et al. 2004; Yang et al, 2012; Rodrigues et al., 2015), with shipping and ports being no exception (Berechman and Tseng, 2012; Corbett, 2009; Eide et al. 2009; Eide, 2011; Geerlings and van Duin 2011; Psaraftis and Kontovas, 2010; Villalba and Gemechu, 2011). This is, perhaps, not surprising, given the much wider availability of international and bilateral protocols and regulations on mitigation (Keohane and Victor, 2010).

However, some studies on adaptation exist. For instance, Preston et al. (2011) evaluated 57 climate adaptation plans, while Osthorst and Manz (2012) investigated the changing relationship between stakeholders and their surrounding regions while developing climate adaptation strategies in Germany. Becker et al. (2013) reviewed the challenges for seaports in adapting to climate change while ICF International (2008) addressed planning for climate change impacts at US ports. Messner et al. (2013) analyzed climate change and sea level rise impacts on ports and proposed a methodology to evaluate both vulnerability and risk. Scott et al. (2013) provided climate change adaptation guidelines for ports to enhance the resilience of seaports to a changing climate. Stenek et al. (2011) launched an analysis of climate risks in the port sector as a part of a series of case studies that analyze climate risks to various sectors and offer practical approaches for the assessment of relevant impacts and adaptation options.

In recent years, there has been a growth in the level of discussion attributable to climate risk-based adaptation. For example, Wilby et al. (2009) emphasized the need for the integration of climate risk information in development planning across different sectors and countries. Füssel (2007) identified key themes in planning adaptation for climate change and emphasized that when a decision on adaptation is made in the context of long term policy making, climate risk is a key consideration. Schipper and Pelling (2006) discussed policy linkages for climate change responses, while Kelly and Adger (2000) addressed the relationship between vulnerability to climate change and the changes necessary for adaptation. However, many are desk studies based on information laid down in the adaptation plans and which lack a longitudinal investigation of the development process.

More recently, risk analysis for climate change adaptation has been developed, supported by a range of techniques and approaches. For instance, Hallegatt et al. (2011) propose a simplified catastrophe risk assessment entailing a statistical analysis of storm surge (SS) characteristics, geographical-information analysis of population and asset exposure, combined with aggregated vulnerability information. Wilby et al. (2009) reviewed different classifications and quantitative approaches to risk analysis in climate adaptation and classify them into three main approaches:

1) Methods requiring limited resources (e.g., sensitivity analysis, change factors, climate analogues and trend extrapolation);
2) Statistical methods (e.g., pattern-scaling, weather generation and empirical downscaling); and
3) Techniques requiring significant computing resources (e.g., dynamic downscaling and coupled climate models (ocean–atmosphere/global climate model).

Willows and Connell (2003) provided a detailed discussion on the statistical tools, techniques, and specialized software available for risk assessment and decision analysis related to climate change impacts and adaptation. However, such studies reveal that current risk analysis methods associated with climate change mainly investigate climate impacts, rarely on the likelihood of occurrence, with a focus on a specific type of climate risk source. Very few studies attempt to combine impacts and likelihood with uncertainty to evaluate and compare the risk levels of multiple climate threats. This is arguably due to the incompleteness and availability of the risk data. Issues related to sources of uncertainty, influencing factors, barriers to adaptation and enablers of adaptation require empirical studies and qualitative analysis while evaluation of climate risks is undertaken using a range of quantitative assessment approaches. Clearly, more research is urgently required to enrich the current literature.

3. Risk reduction and cost analysis of climate change adaptation measures

Selecting cost effective climate change adaptation measures requires the analysis of both risk reduction and the associated costs incurred after the implementation of such measures. This creates two major research challenges. One is often the unavailability or incompleteness of objective or secondary data to be able to precisely evaluate risk reduction and costs, while the other is that different units are used to express risks and costs. Thus, it is difficult to synthesize the evaluated risk and cost results. A pioneer study (see Yang et al., 2016) was conducted to address the first challenge by using fuzzy set approaches to model subjective input data (i.e., linguistic terms) of climate risk estimates based on stakeholders' perceptions formulated from their current best understanding of climate risks' frequencies, consequences and the timeframes in which they occur. Although attractive in prioritising risk perceptions of climate threats to ports, they have been criticized due to inherent drawbacks including loss of useful information in fuzzy operations, the ignorance of non-linear relationships among the defined risk parameters, a lack of ease in inferring risk, and difficulties in dealing with a large amount of risk input data. Further, there are a lack of solutions to the second challenge in the most recent literature. In this section, we therefore first propose a new fuzzy Bayesian approach for climate risk estimates (Section 3.1) and then apply the evidential reasoning (ER) approach to synthesize the risk reductions and the associated adaptation costs for the selection of the best adaptation measures (Section 3.2).

3.1 A fuzzy Bayesian approach for climate change risk analysis in ports

Many conventional risk assessment approaches (e.g., Quantitative Risk Assessment (QRA)) which have been widely used to carry out risk analysis across many sectors, are not well-suited to deal with climate change risks as high levels of uncertainty in the data exists due to the serious scarcity of historical/statistical data (UNCTAD, 2012). Fuzzy set theory is employed to model linguistic data collected based on subjective judgements (Wang et al., 1996). In this theory, linguistic variables, used to describe the stakeholders' perceptions to climate risks, can be characterized by their membership functions, of which they describe the degrees of the linguistic variables.

In this paper, three parameters closely related to climate change risk are identified based on the Failure Mode and Effect Analysis (FMEA) approach, (Yang et al., 2008; 2009), namely *timeframe (T)*, *likelihood (L)* and *severity of consequences (S)* (Ng et al., 2013;Yang et al., 2016). Typical linguistic variables and their membership functions for the three risk parameters may be defined with reference to the work by Yang et al. (2008).Triangular/trapezoidal fuzzy membership functions developed on a [0-1] utility domain have been widely used to define different risk grades/descriptors. The typical membership functions for five linguistic variables are defined and characterized based on a balanced linear distribution in Tables 1-3 (Wang, 1997; Yang et al., 2009). It is possible to have some flexibility in the definition of membership functions to suit different risk scenarios. However, it is noteworthy that the changes of the defined membership functions require a very careful justification from domain experts. New definitions of memberships need to be verified through empirical tests before being applied in practice. The linguistics terms are suggested by domain experts through the *Ad Hoc* Expert Meetings organized by the United Nations Conference on Trade and Development (UNCTAD) (UNCTAD, 2012). The design of the timeframe for this study (see Table 1) is based on the typical time periods of port planning.

Table 1. Timeframe

Grade	Linguistic terms	Description	Fuzzy memberships
1	Very Short (VS)	Less than 1 year	**(0, 0, 0.1, 0.3)**
2	Short (S)	Approximately 5 years	**(0.1, 0.3, 0.5)**
3	Medium (M)	Approximately 10 years	**(0.3, 0.5, 0.7)**
4	Long (L)	Approximately 15 years	**(0.5, 0.7, 0.9)**
5	Very Long (VL)	More than 20 years	**(0.7, 0.9, 1, 1)**

Table 2. Severity of Consequence

Grade	Linguistic terms	Description	Fuzzy memberships
1	Catastrophic (CA)	Very severe economic loss and/or disruption on the facilities/systems/services requiring a very long period and very high cost of recovery	**(0, 0, 0.1, 0.3)**
2	Critical (CR)	Severe economic loss and/or disruption on the facilities/systems/services requiring a long period and long cost of recovery	**(0.1, 0.3, 0.5)**
3	Major (MA)	Significant economic loss and/or disruption on the facilities/systems/services requiring certain length of time and cost of recovery	**(0.3, 0.5, 0.7)**
4	Minor (MI)	Some economic loss and/or disruption on the facilities/systems/services requiring some time and cost of recovery	**(0.5, 0.7, 0.9)**
5	Negligible (NE)	A bit of disruption on the facilities/systems/services, and possibly with some economic loss, but with no real impacts on the continuance of services, nor does it require significant time and cost of recovery	**(0.7, 0.9, 1, 1)**

Table 3. Likelihood

Grade	Linguistic terms	Description	Fuzzy memberships
1	Very High (VH)	It is very highly likely that the stated effect will occur, with a probability around 90% of at least 1 such incident within the indicated timeframe	**(0, 0, 0.1, 0.3)**
2	High (H)	It is highly likely that the stated effect will occur, with a probability around 70% of at least 1 such incident within the indicated timeframe	**(0.1, 0.3, 0.5)**
3	Average (A)	It is likely that the stated effect will occur, with a probability around 50% of at least 1 such incident within the indicated timeframe	**(0.3, 0.5, 0.7)**
4	Low (L)	It is unlikely that the stated effect will occur, with a probability around 30% of at least 1 such incident within the indicated timeframe	**(0.5, 0.7, 0.9)**
5	Very Low (VL)	It is very unlikely that the effects will occur, with a probability around 10% of at least 1 such incident within the indicated timeframe	**(0.7, 0.9, 1, 1)**

Fuzzy logic employing fuzzy *IF-THEN* rules, where the antecedent and conclusion parts contain linguistic variables, can model the qualitative aspects of human knowledge and reasoning process without employing precise quantitative analysis. To construct such systems in the context of climate risk analysis, the three risk parameters, *T*, *C* and *L* are considered as the antecedent attributes in *IF-THEN* rules. Risk level (*R*) is expressed as the conclusion attribute. A conventional *IF-THEN* rule in climate risk analysis can be expressed as follows.

$$Rule_k\text{: IF } t_k \text{ and } c_k \text{ and } l_k\text{, THEN } r_k \quad (1)$$

where t_k, c_k and l_k donate the linguistic variables of *T, C and L* used in the k_{th} rule, $Rule_k$, respectively; r_k describes the consequence in $Rule_k$ expressed by one single linguistic variable, describing *R* such as one of the set {Very High (r_1), High (r_2), Medium (r_3), Low (r_4), Very Low (r_5)}.

Subjective degrees of belief (DoBs), β_k^j (j = 1, 2, …, 5) are assigned to the linguistic variables used to express the conclusion attribute *R* for modelling the incompleteness of expert judgements.

$$Rule_k\text{: IF } t_k \text{ and } c_k \text{ and } l_k\text{, THEN } \{(\beta_k^1, r_1), \ldots, (\beta_k^5, r_5)\}\left(\sum_{j=1}^{5} \beta_k^j = 1\right) \quad (2)$$

A proportion method (Alyani et al., 2014) is used to rationalize the DoB distribution. Specifically, the DoB belonging to a particular grade in the *THEN* part is calculated by dividing the number of the risk parameters, which receive the same grade in the *IF* part in terms of fuzzy membership functions (e.g., VH and CA having the same fuzzy membership (0, 0, 0.1, 0.3)), by three. For instance, in a specific rule, the number of the risk parameters receiving the grade associated with a fuzzy membership (0, 0, 0.1, 0.3) in the IF part is two. The DoB belonging to the same grade (i.e., Very High) in the THEN part is therefore computed as 67% (2/3×100%). In a similar way, the FRB used in climate risk analysis containing 125 rules (5×5×5) with a rational DoB distribution is obtained and presented in Table 4.

Table 4. FRB with belief structures for climate risk analysis

Rules	**Antecedent attributes**			**Risk Level (*R*)**				
	Timeframe (*T*)	Severity of occurrence (*C*)	Likelihood (*L*)	Very High	High	Medium	Low	Very low
1	Very Short (VH)	Catastrophic (CA)	Very High (VH)	100%	0	0	0	0
2	VH	CA	High (H)	67%	33%	0	0	0
3	VH	CA	Average (A)	67%	0	33%	0	0
…	…	…	…	…	…		…	…
123	Very Long (VL)	Negligible (NE)	A	0	0	33%	0	67%
124	Very Long (VL)	Negligible (NE)	Low (L)	0	0	0	33%	67%
125	Very Long (VL)	Negligible (NE)	Very Low (VL)	0	0	0	0	100%

After the *FRB* for climate risk analysis is constructed, it can be used to conduct risk inference using a *BN* technique. The rule base with belief structures is firstly represented in the form of conditional probabilities and then further expressed in the form of conditional probability as follows.

Given*T1*, and *C1*, and *L3*, the probability of *Rh* (h = 1, …,5) is (1, 0, 0, 0,0) or

$p(Rh|T1, C1, L1) = (1, 0, 0, 0, 0)$ (3)

where "|" symbolizes conditional probability.

Using a *BN* technique, the *FRB* constructed in Table 4 can be modeled and converted into a four-node converging connection. It includes three parent nodes, N_T, N_C, and N_L (Nodes *T*, *C* and *L*); and one child node N_R (Node *R*). Having transferred the rule base into a *BN* framework, the rule-based risk inference for the failure criticality analysis will be simplified as the calculation of the marginal probability of the node N_R. To marginalize *R*, the required conditional probability table of N_R, $p(S|L, C, P)$, can be obtained using (5), and the *FRB* shown in Table 4. It denotes a 5×5×5×5 table containing values $p(Rh|Ti, Cj, Lk)$ ($h, i, j, or\ k$ = 1, …,5).

The prior probabilities of N_T, $p(Ti)$ can be obtained through a questionnaire survey in which the question such as "using the defined linguistic variables (i.e., VS, S, A, L and VL), how soon do you think a particular climate threat will have a negative impact on port?" will be developed to collect the domain experts' risk perceptions. The results from multiple experts across ports and regions will be classified based on investigated ports and regions, purified to avoid the input of obvious subjective bias and finally aggregated using an ER calculation[1]. In a similar way, the prior probabilities of N_C, and N_L can be computed as $p(Cj)$, and $p(Lk)$, respectively. Having analysed all the prior probabilities of the four nodes, the marginal probability of N_R can be calculated as (Jensen, 2001)

$$p(Rh) = \sum_{i=1}^{5}\sum_{j=1}^{5}\sum_{k=1}^{5} p(Rh \mid Ti, Cj, Lk)\, p(Ti)\, p(Cj)\, p(Lk)\ (h = 1, \ldots, 5) \quad (4)$$

To prioritize the climate risks, Rh (h = 1, …,5) requires the assignment of appropriate utility values U_{Rh}. The utility values can be defined on the basis of a linear distribution as Rh (h = 1, …, 5) = {0, 0.25, 0.5, 0.75, 1}.

Then a new risk priority/ranking index can be developed as

$$RI = \sum_{h=1}^{5} p(Rh) U_{Rh} \quad (5)$$

where the larger the value of RI is the lower the risk level of potential climate threats. Furthermore, the risk reduction (RR_i^j) of the i^{th} climate threat by the use of the j^{th} adaptation measure can be obtained as follows

$$RR_i^j = RI_i^j - RI_i = \sum_{h=1}^{5} p(Rh)' U_{Rh} - \sum_{h=1}^{5} p(Rh) U_{Rh} \quad (6)$$

RI_i^j and RI_i are the risk index values of the i^{th} climate risk with and without the use of the j^{th} adaptation measure. The calculation process of RI_i^j and RI_i can be simplified by using a *Hugin* software package (Andersen *et al.*, 1990).

3.2ER algorithm for the synthesize of climate risk estimates and adaptation costs

The selection of a cost effective adaptation measure requires the evaluation of both the risk reduction and the associated cost incurred. The adaptation costs significantly vary in different cases and often would not be known until the associated measures are fully implemented. A new decision model is therefore needed, being capable of prioritizing adaptation measures when cost data remains uncertain (e.g., at the design stage). The ER approach has been widely used in effectively synthesizing pieces of evaluation from various criteria in both quantitative and qualitative forms and/or evaluators in group multi-criteria decision-making (Yang and Xu, 2002).

Although attractive, the ER approach still has practical problems in this application. The evaluations against all criteria (i.e., risk reduction and cost) need to be expressed on the same utility universe in order to have the ER applied for the synthesis. In this study, five cost effectiveness expressions are defined in Table 5 (i.e., "*Very Effective*", "*Effective*", "*Average*", "*Slightly Effective*" and "*Ineffective*"). However, in the cost effectiveness evaluation of adaptation measures, risk reduction will be expressed by a crisp value through Eq. (6) (i.e., quantitative data), while the cost evaluations are largely conducted by domain experts using linguistic terms (i.e., qualitative data). To facilitate the synthesis, both quantitative and qualitative data are transformed into the same scale defined by the five cost effectiveness expressions in Table 5.

[1] The details of the ER calculation can be found in Section 3.2.

Table 5. Cost effectiveness of adaptation measures

Linguistic terms	Fuzzy numbers
Very effective (VE)	**(0, 0, 0.1, 0.3)**
Effective (E)	**(0.1, 0.3, 0.5)**
Average (A)	**(0.3, 0.5, 0.7)**
Slightly effective (SE)	**(0.5, 0.7, 0.9)**
Ineffective (I)	**(0.7, 0.9, 1, 1)**

3.2.1Risk reduction modelling - quantitative data transformation

In Section 3.1, the risk reduction of the i^{th} climate threat by the j^{th} adaptation measure is expressed by RR_i^j . To map the numerical RR_i^j onto the five defined cost effectiveness expressions, five risk reduction grades are first defined as $\{RG_1, RG_2, RG_3, RG_4, RG_5\}$ and calculated as follows, respectively.

$$
\begin{aligned}
RG_1 &= \max\{ RR_i^j \} \\
RG_2 &= \frac{RG^1 + RG^3}{2} = \frac{3\max\{RR_i^j\} + \min\{RR_i^j\}}{4} \\
RG_3 &= \frac{RG^1 + RG^5}{2} = \frac{\max\{RR_i^j\} + \min\{RR_i^j\}}{2} \\
RG_4 &= \frac{RG^3 + RG^5}{2} = \frac{\max\{RR_i^j\} + 3\min\{RR_i^j\}}{4} \\
RG_5 &= \min\{ RR_i^j \}
\end{aligned}
\tag{7}
$$

Consequently, RR_i^j can be expressed by RG_k($k=1, 2, \ldots, 5$) when $RR_i^j = RG_k$. When $RR_i^j \neq RG_k$, RR_i^j belongs to RG_k with a belief degree of $\frac{RG_{k+1} - RR_i^j}{RG_{k+1} - RG_k}$ and RR_i^j belongs to RG_{k+1} with a belief degree of $\frac{RR_i^j - RG_k}{RG_{k+1} - RG_k}$. (8)

When an adaptation measure contributes to the maximal risk reduction (i.e., RG_1), it is considered to be "Very effective" in the utility universe as far as risk factor is concerned. Similarly, when risk reduction is RG_2, RG_3, RG_4 or RG_5, the adaptation measure is "Effective", "Average", "Slightly effective" or "Ineffective", respectively.

3.2.2 Cost modelling - qualitative data transformation

Normally, risk reduction and cost are two conflicting objectives, with higher risk reduction leading to higher costs. If the risk reduction associated with an adaptation measure is improved, higher costs will usually be incurred. The cost incurred for the risk reduction associated with an adaptation measure is usually affected by many factors, including the investment of a new system and cost of labour incurred in redesign of the system, if necessary, to meet some unexpected needs at the initial stage, etc. Such factors are of high uncertainties, and largely subject to the implementation of new adaptation measures. In the early design stage, it can be very difficult to assess the factors in quantitative forms[2]. With the fuzzy approach in risk estimation, it is not surprising that safety analysts often prefer to estimate costs incurred in risk reduction using linguistics variables (Wang et al., 2006). The cost incurred for adaptation measures can be described using linguistic variables such as { *"Very*

[2] If the cost can be expressed by a quantitate form, through rare, a similar transform can be conducted using the approach described in Section 3.2.1.

high", *"High"*, *"Average"*, *"Low"*, *"Very low"*}. Such linguistic variables can also be described, as shown in Table 6, in terms of membership values.

Table 6. Fuzzy numbers of cost expressions

Grade	Linguistic terms	Description	Fuzzy numbers
1	Very low (VL)	A minimal financial cost so as to comprehensively address the stated potential effect	**(0, 0, 0.1, 0.3)**
2	Low (L)	A financial cost (though not that significant) so as to comprehensively address the stated potential effect	**(0.1, 0.3, 0.5)**
3	Average (A)	A significant financial cost so as to comprehensively address the stated potential effect	**(0.3, 0.5, 0.7)**
4	High (H)	A high financial cost so as to comprehensively address the stated potential effect	**(0.5, 0.7, 0.9)**
5	Very high (VH)	A very high financial cost so as to comprehensively address the stated potential effect	**(0.7, 0.9, 1, 1)**

In Tables 5 and 6, cost and the utility expressions are defined by the same membership functions. Cost descriptions can be directly mapped onto the cost effectiveness utility universe as follows. When the cost is "Very low", the adaptation measure is "Very efficient" as far as the cost factor is concerned. Similarly, when the cost is "Low", "Average", "High" or "Very high", the adaptation measure is *"Effective"*, *"Average"*, *"Slightly effective"* and *"Ineffective*", respectively.

Having mapped the risk and cost factors on the utility universe, the ER approach can be used to synthesize the risk reduction and cost evaluations of the j^{th} adaptation measure with respect to the i^{th} climate threat to obtain its cost effectiveness result as follows.

$CE_{i,j}$ = {($\beta^1_{i,j}$, "*Very effective*"), ($\beta^2_{i,j}$, "*Effective*"), ($\beta^3_{i,j}$, "*Average*"), ($\beta^4_{i,j}$, "*Slightly effective*"), ($\beta^5_{i,j}$, "*Ineffective*")}

To select the most cost effective adaptation measure, it is necessary to describe the five utility expressions using numerical values. Using a centroid defuzzification method (Mizumoto, 1995), the crisp values of the five utility expressions in Table 5 are obtained as (1.1, 3, 5, 7, 8.9).

Naturally, a numerical cost effectiveness index of an adaptation measure can be obtained by the following calculation:

$$I(CE_{i,j}) = \beta^1_{i,j} \times 0.11 + \beta^2_{i,j} \times 0.3 + \beta^3_{i,j} \times 0.5 + \beta^4_{i,j} \times 0.7 + \beta^5_{i,j} \times 0.89 \qquad (9)$$

Consequently, the lower $I(CE_{i,j})$ *is*, the better the adaptation measure.

4. Case study – Risk reduction and cost analysis of adaptation measures across major ports in Greater China

To demonstrate the feasibility of the developed methodology, a technical case study investigating 14 ports from Greater China (1, 5 and 6 ports from Hong Kong, Taiwan and Mainland China, respectively) was conducted. Data were collected through a questionnaire survey involving 24 experts between early and mid-2014. The participants, as the key decision makers, represented the major groups who were involved in climate adaptation planning in the investigated ports. The identification of relevant respondents followed a snowball sampling technique starting from the senior officials (operations and climatic planning) of ports. This ensured that only the most appropriate respondents were invited, and guaranteed that the collected data would be of the highest quality. Understanding the nature of adaptation planning that involved engineering, operational, financial, and environmental aspects, we mainly targeted senior personnel responsible for financial issues/budgeting, engineering, operational, land use, and environmental planning for respective ports. Illustrative examples included the vice-president and senior planners of port authorities, the operations directors and financial directors of private terminal operators, and senior consultants appointed to develop port adaptation plans. To further ensure the reliability of the data, only those who possessed more than three years of direct job experience in this area were invited to participate in the survey.

The data were categorized into three groups, risk evaluation without the implementation of adaptation measures, risk evaluation with the implementation of adaptation measures, and cost evaluation of the adaptation measures for the ports in Hong Kong, Taiwan, and Mainland China. Hence, it presents a questionnaire containing more than 100 questions of high correlation. An initial data screening was conducted to eliminate "noisy" data characterized by incomplete input information, unknown ports/regions, and contradictory inputs between two correlated questions. As a result, 8 out of the 24 responses became invalid after the screening process. The consistency of the remaining 16 sets of data will be addressed through the comparative climate risk analysis among the three regions. The profiles of the experts used to evaluate the investigated ports were provided in Table 7. For not releasing their identifications, the names of the ports, terminals and/or companies that they serve are hidden, while job title and the area/region that their ports are located are provided.

Table 7. Background information of the employed experts

Expert/Respondent ID	Job Title	Area
1	Engineer from Planning Department	Hong Kong
2	Director of Operational Department	Hong Kong
3	Port Planner	Hong Kong
4	Vice-Captain	Mainland
5	Engineer from Planning Department	Mainland
6	Director of Electrical Department	Mainland
7	Technician from Planning Department	Mainland
8	Assistant Manager of Inventory Department	Mainland
9	Technician from Planning Department	Mainland
10	Director of Maintenance Department	Mainland
11	Manager of Operational Department	Taiwan
12	Chief Engineer	Taiwan
13	Vessel Planner	Taiwan
14	Terminal Assistant Manager	Taiwan

15	Manager of Environmental Department	Taiwan
16	Manager of Harbour Bureau	Taiwan

Based on the fuzzy Bayesian approach (Section 3.1), the risk results of each potential threat (PT) of environmental driver (ED) on the ports in each studied region (i.e., Hong Kong, Taiwan, and Mainland China) with and without the adaptation measures are calculated and expressed in Table 8 (values expressed in bold, italic and underlined refer to Mainland China, Hong Kong and Taiwan, respectively). For instance, evaluation of the three risk parameters of the PT "High waves that can damage the port's facilities" due to the ED "Sea level rise" with and without the adaptation measure "Build new breakwaters or Increase breakwater dimensions" from the one expert evaluating Mainland China are changed from "Very short" for the timeframe (T), "Negligible" for the severity of consequence (S) and "Very low" for the likelihood (L) to "Very long" for T, "Minor" for S and "Very low" for L, respectively. With reference to Tables 1-3, the fuzzy memberships of the linguistic evaluations of the three parameters with the adaptation measure are (0, 0, 0.1, 0.3), (0.7, 0.9, 1, 1), and (0.7, 0.9, 1, 1), respectively. The ones without the measure are (0.7, 0.9, 1, 1), (0.5, 0.7, 0.9), and (0.7, 0.9, 1, 1), respectively. Consequently, using Eq. (4) and Hugin software, the risk results, with and without the adaptation measure, are calculated as {33%, *R1*,0% *R2*, 0% *R3*, 0% *R4*, 67% *R5*} and {0%, *R1*, 0% *R2*, 0% *R3*, 33% *R4*, 67% *R5*}, respectively. Their individual risk index values are calculated using Eq (7) as 0.67 and 0.92 respectively. Using Eq (8), the risk reduction can be obtained as 0.25 (0.25 = 0.92 - 0.67).

Using the ER approach and its associated IDS software, the above results (expressed by *Rh*) are then synthesized with the evaluated risk results from other experts who provided the climate risk input data for Mainland China to obtain the risk level of "High waves that can damage the port's facilities" due to "Sea level rise" in Mainland China as {29.18%, *R1*,2.28% *R2*, 2.3% *R3*, 9.52% *R4*, 56.72% *R5*} and {18%, *R1*, 2.18% *R2*, 4.79% *R3*, 31.33% *R4*, 43.7% *R5*}. Their risk index values are calculated using Eq. (7) as 0.6558 and 0.7014 respectively. The risk reduction generated by the adaptation measure "Build new breakwaters or Increase breakwater dimensions" is 0.0456, as indicated in the first row of Table 8.

Table 8. Questionnaire results with respect to risk and cost analysis[3]

Environmental driver (ED) due to climate change	Potential threat (PT) of ED on the Port	Adaptation measure to address the potential threat of ED on the Port	Risk result without adaptation measures	Risk result with adaptation measures	Risk reduction (RR_i^j)	Cost {VH, H, A, L, VL}
Sea level rise (SLR)	A) High waves that can damage the Port's facilities	a) Build new breakwaters or Increase breakwater dimensions	**0.6558**	**0.7014**	**0.0456**	**{0.1484, 0.0742, 0.2374, 0, 0.5401}**
			0.6652	*0.6596*	*0*	*{0.3333, 0, 0, 0.3333, 0.3333}*
			0.5064	0.5265	0.0201	{0.4091, 0.4091, 0.0909, 0, 0.0909}
	B) Transport infra- and superstructures in the Port get flooded	a) Raise port elevation	**0.6292**	**0.6550**	**0.0258**	**{0.1506, 0, 0.1506, 0.1506, 0.5482}**
			0.5911	*0.6765*	*0.0854*	*{0.3333, 0, 0, 0.3333, 0.3333}*
			0.4908	0.5604	0.0696	{0.6559, 0.1720, 0.086, 0, 0.086}

[3] The zero value in the risk reduction column indicates that the relevant risk index value with the adaptation measure is smaller than the one without its measure. It is caused by the inconsistent input data for the correlated questions. The second data screening was therefore conducted to eliminate the inputs causing significant gap between the two risk indexes. It means that the extent to which the risk index value with the adaption is smaller than the one without it is constricted to be less than 0.1(the threshold). More effort was attempted to further purify the data and improve their consistency. However, any smaller threshold than the value of 0.1 threshold will need scarify much more input data causing no information representing certain investigated ports.

		b) Improve transport infra- and superstructures resilience to flooding	**0.6292**	**0.5874**	**0**	**{0.1613, 0.1613, 0.1613, 0.1613, 0.3548}**
			0.5911	*0.6765*	*0.0854*	*{0.3333, 0, 0, 0.3333, 0.3333}*
			0.4908	0.5821	0.0913	{0.6559, 0.1720, 0.086, 0, 0.086}
	C) Coastal erosion at or adjacent to the Port	a) Protect coastline and increase and beach nourishment programs	**0.6421**	**0.6730**	**0.0309**	**{0.1563, 0, 0.3438, 0.3438, 0.1563}**
			0.5850	*0.6718*	*0.0868*	*{0, 0.2857, 0, 0.7143, 0}*
			0.5094	0.6211	0.1117	{0.4091, 0.4091, 0.0909, 0, 0.0909}
	D) Deposition and sedimentation along the Port's channels	a) Increase and/or expand dredging	**0.5322**	**0.5719**	**0.0397**	**{0.1563, 0.1563, 0.3438, 0.3438, 0}**
			0.6555	*0.5776*	*0*	*{0, 0, 0.3333, 0.3333, 0.3333}*
			0.5142	0.5164	0.0022	{0.2737, 0, 0.6421, 0, 0.0842}
	E) Overland access (road/railway) to port/terminal will be limited due to flooding	a) Improve quality of land connection to port/terminal	**0.6491**	**0.6543**	**0.0052**	**{0.1462, 0, 0.3216, 0, 0.5322}**
			0.6555	*0.7434*	*0.0879*	*{0, 0, 0.3333, 0.3333, 0.3333}*
			0.5607	0.5980	0.0373	(0, 0, 0.9332, 0, 0.0668)
		b) Diversity land connections to port/terminal	**0.6491**	**0.6607**	**0.0116**	**{0.1357, 0, 0, 0.1357, 0.7286}**
			0.6555	*0.7434*	*0.0879*	*{0, 0, 0.3333, 0.3333, 0.3333}*
			0.5607	0.5474	0	{0.4186, 0.1860, 0.3023, 0, 0.093}
	F) All the risks and impacts above	a) Move facilities away from existing locations which are vulnerable to climate change risks and impacts	**0.6394**	**0.6757**	**0.0363**	**{0.1613, 0.1613, 0.1613, 0.1613, 0.3548}**
			0.6403	*0.7434*	*0.1031*	*{0.3333, 0, 0, 0.3333, 0.3333}*
			0.5185	0.5494	0.0309	{0.4186, 0.1860, 0.3023, 0, 0.093}
Storm surge (SS) intensity and/or frequency	A) Downtime in the Port operation due to high winds	a) Improve management to prevent effects	**0.5557**	**0.5346**	**0**	**{0, 0, 0.1357, 0.7286, 0.1357}**
			0.6484	*0.5701*	*0*	*[0, 0, 0.3333, 0.3333, 0.3333]*
			0.5075	0.4273	0	{0.0739, 0.8522, 0, 0, 0.0739}
	B) High waves that will damage port/terminal's facilities, and ships berthed alongside	a) Build new breakwaters or Increase breakwater dimensions	**0.6256**	**0.5974**	**0**	**(0.1484, 0.0742, 0.2374, 0, 0.5401)**

In Table 8, it is seen that the max(RR_i^j) = 0.1507, while the min(RR_i^j) = 0. Given Eq. (8), RG^k($k=1, 2, \ldots, 5$) = (0.1507, 0.1130, 0.0754, 0.0377, 0).

As a result, all the obtained RR_i^j in Table 8 can be transformed and presented by the utility linguistics expressions defined in Table 5. For example, $RR^{a}_{SLR,A}$ = 0.0456, which is a value between RG^3 (=0.0754) and RG^4 (=0.0377). By using Eq. (7), it can be calculated and presented as 20.95% RG^3 (Average) and 79.05% RG^4 (Slightly effective). In a similar way, each RR_i^j can be transformed and expressed by RG^k. Consequently, both risk reduction and cost results can be transformed and described by DoBs associated with the five utility expressions in Table 5. Next, the ER approach and its associated computing software package IDS are used to synthesize the risk reduction and cost analysis input for conducting the risk reduction and cost analysis of each adaptation measure. Assuming that the importance of risk reduction and cost is the same the synthesized results for the measure "Build new breakwaters or Increase breakwater dimensions" addressing the PT "High waves that can damage the port's facilities" by the driver "Sea level rise" are calculated as follows for Mainland China, Hong Kong and Taiwan, respectively.

For Mainland China - $CE_{A,a}^{SLR}$ = {(7.24%, "*Very effective*"), (3.62%, "*Effective*"), (24.23%, "*Average*"), (38.57%, "*Slightly effective*"), 26.35%, "*Ineffective*")}
For Hong Kong - $CE_{A,a}^{SLR}$ = {(14.29%, "*Very effective*"), (0%, "*Effective*"), (0%, "*Average*"), (14.29%, "*Slightly effective*"), 71.43%, "*Ineffective*")}
For Taiwan - $CE_{A,a}^{SLR}$ = {(20.03%, "*Very effective*"), (20.03%, "*Effective*"), (4.45%, "*Average*"), (26.11%, "*Slightly effective*"), 29.38%, "*Ineffective*")}

Using Eq. (9), the cost effectiveness index of the adaptation measure for Mainland China is obtained as $I(CE_{A,a}^{SLR}) = 0.6444$.

The above calculation was computerized and the result is shown in Figure 1. The numerical cost effectiveness indexes for Hong Kong and Taiwan are 0.7514, and 0.5486, respectively. This means that the measure "Build new breakwaters or Increase breakwater dimensions" is ranked the best in Taiwan and worst in Hong Kong.

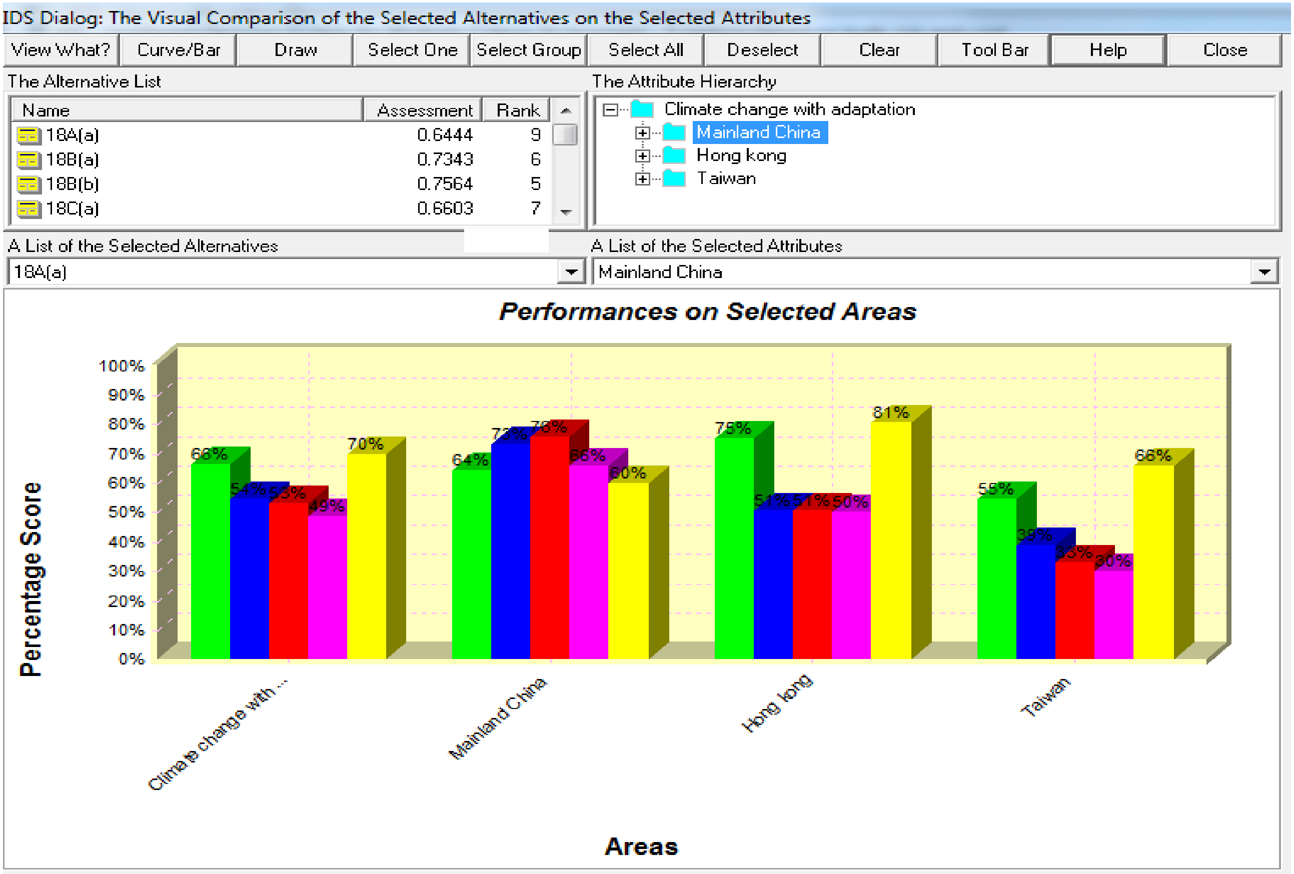

Figure 1. Comparison of the cost effectiveness result of adaptation measure "Build new breakwaters or Increase breakwater dimensions" among Mainland China, Hong Kong and Taiwan

Similarly, the cost effectiveness index of each adaptation measure with respect to different PTs is obtained and presented in Table 9.

Table 9. Cost effectiveness of adaptation measures

Environmental driver (ED) due to climate change	Potential threat (PT) of ED on the Port	Adaptation measure to address the potential threat of ED on the Port	Cost effectiveness index of adaptation measures for different regions	Cost effectiveness index of adaptation measures – overall
Sea level rise (SLR)	A) High waves that can damage the Port's facilities	a) Build new breakwaters or Increase breakwater dimensions	**0.6444** *0.7514* 0.5486	0.6627
	B) Transport infra- and super-structures in the Port get flooded	a) Raise port elevation	**0.7343** *0.5067* 0.3901	0.5444
		b) Improve transport infra- and superstructures resilience to flooding	**0.7564** *0.5067* 0.3324	0.5319
	C) Coastal erosion at or adjacent to the Port	a) Protect coastline and increase and beach nourishment programs	**0.6603** *0.5037* 0.3007	0.4881
	D) Deposition and sedimentation along the Port's channels	a) Increase and/or expand dredging	**0.5986** *0.8071* 0.6616	0.6964
	E) Overland access (road/railway) to port/terminal will be limited due to flooding	a) Improve quality of land connection to port/terminal	**0.7819** *0.5586* 0.6141	0.6485
		b) Diversity land connections to port/terminal	**0.8122** *0.5586* 0.6041	0.6754
	F) All the risks and impacts above	a) Move facilities away from existing locations which are vulnerable to climate change risks and impacts	**0.6470** *0.4597* 0.5380	0.5551
Storm surge (SS) intensity and/or frequency	A) Downtime in the Port operation due to high winds	a) Improve management to prevent effects	**0.8004** *0.8071* 0.6198	0.7674
	B) High waves that will damage port/terminal's facilities, and ships berthed alongside	a) Build new breakwaters or Increase breakwater dimensions	**0.7908** *0.7195* 0.3115	0.6247
	C) Transport infra- and super-structures and utilities in the port/terminal will get flooded or damaged in more intense or frequent storms	a) Improve transport infra- and superstructures resilience to flooding	**0.3775** *0.7494* 0.2375	0.4452
	D) Overland access (road, railway) to port/terminal will be limited due to more intense or frequent storms	a) Improve quality of land connections to port/terminal	**0.4533** *0.7225* 0.7139	0.6418
		b) Diversify land connections to port/terminal	**0.5840** *0.7225* 0.4905	0.6042
	E) All the risks and impacts above	a) Move facilities away from existing locations which are vulnerable to climate change risks and impacts	**0.4136** *0.5966* 0.4659	0.4934

From the analysis results in Table 9, when taking into account the climate risk perceptions from practitioners representing different regions, the most cost effective adaptation measure is "Improve transport infra- and superstructures resilience to flooding" to address the PT "Improve transport infra- and superstructures resilience to flooding" due to the driver "Storm Surge" for Taiwan (indicated by the index value of 0.2375), while the least cost effective is "Diversity land connections to port/terminal" to address the PT "Overland access (road/railway) to port/terminal will be limited due to flooding" due to the climate driver "Sea level rise" for Mainland China (as indicated by the index value of 0.8122).

When analysing the adaptation measures from an overall perspective, the best cost effective measure is "Improve transport infra- and superstructures resilience to flooding" to address the PT "Improve transport infra- and superstructures resilience to flooding" due to the driver "Storm Surge". It is followed by the measures "Move facilities away from existing locations which are vulnerable to climate change risks and impacts" to address the PT "all the risks and impacts above" due to "Storm Surge".

5. Discussion

This section is presented in two parts, containing the architecture development of the Bayesian ER model in the case analysis and the in-depth analysis of the adaptation ranking results in Section 4. The ER approach, together with its associated software IDS, is designed to tackle group multiple attribute decision-making problems. IDS is therefore designed to be able to accommodate multiple attributes in a multiple-level hierarchy. However, port adaptation analysis involves various attributes (i.e., drivers, PTs, adaptation measures, ports, regions, experts) at different dimensions.

An effective architectural design and development is crucial at the initial stage to enhance the capability of the model in data analysis and result presentation. Furthermore, uncertainty in data highlights the growing difficulty in the methodology's design. For instance, when conducting risk analysis without any adaptation measure, there was no initial risk input data on "All the risks and impacts above" due to "Sea level rise". It required us to synthesize all the risk inputs of all the other PTs due to "Sea level rise", which cause cross data presentation and make it impossible to present all the attributes in one ER hierarchy in IDS.

Meanwhile, both the Bayesian climate risk analysis model and the ER risk reduction and cost analysis model are capable of tackling uncertainty in the data. When screening the collected data, apart from the data inconsistency, another challenge, is the missing data due to the unknown answers given with respect to the risk parameters of a particular PT by the domain experts. Using even probability distributions enables the unknown information in the climate risk analysis to be effectively presented and accommodated. The ER model also presents its advanced capability in handling the missing data when it involves a larger range of parameters (than the one dealt with in the Bayesian model), evidenced by the generated supplementary data on the PT "All the risks and impacts above" due to the driver "Sea level rise". Despite the advances of the proposed methodology, considerable attention was given to data screening so as to minimize the negative impact of inconsistent and missing data to the accuracy of final findings, and hence address the concern that uncertainty in input data could jeopardize the accuracy of the analytical outcomes.

The findings from the technical case study are diverse. Appropriate classifications are developed to categorize them for comparative analysis of the three regions (Hong Kong, Taiwan, and Mainland China) performance in terms of climate adaptation individually and collectively, including the risk level rankings of PTs in each region (based on Table 8), and adaptation measure ranking in each region (based on Table 9).When no adaptation measures are used (Table 8), in Taiwan the highest risk PT is “Transport infra- and superstructures in the Port get flooded” due to “Sea Level Rise” (as indicated by 0.4908), followed by “Transport infra- and superstructures and utilities in the port/terminal will get flooded or damaged in more intense or frequent storms” due to “Storm Surge” in Taiwan (as indicated by 0.4916). For mainland China, the highest risk PT is “Transport infra- and superstructures and utilities in the port/terminal will get flooded or damaged in more intense or frequent storms” due to “Storm Surge” (as indicated by 0.5213), followed by “Deposition and sedimentation along the port’s channels” due to “Sea Level Rise” (as indicated by 0.5322). For Hong Kong, the highest risk PT is “High waves that will damage port/terminal’s facilities, and ships berthed alongside” due to “Storm Surge” (as indicated by 0.5502), followed by “Coastal erosion at or adjacent to the Port” due to “Sea Level Rise” (as indicated by 0.5850).

When the evaluations of the three regions are combined, the highest risk PT is “Transport infra- and superstructures and utilities in the port/terminal will get flooded or damaged in more intense or frequent storms” due to “Storm Surge” with a risk index value of 0.5463. When adaptation measures are implemented (Table 8), the most effective one (in terms of risk reduction) is “Improve transport infra- and superstructures resilience to flooding” to address “Transport infra- and superstructures and utilities in the port/terminal will get flooded or damaged in more intense or frequent storms” due to “Storm Surge” in Mainland China (as indicated by 0.1507), followed by the same measure in Taiwan (as indicated by 0.1235). In Hong Kong, the most effective measure is “Move facilities away from existing locations which are vulnerable to climate change risks and impacts” to address “All the risks and impacts above” due to “Sea Level Rise” (as indicated by 0.1031).

When adaptation measures are implemented (Table 9), the most ‘cost effective’ measure (subject to the equal importance between risk reduction and cost) is given at the end of Section 5. For each region, the best solution is “Improve quality of land connections to port/terminal” to address “Overland access (road, railway) to port/terminal will be limited due to more intense or frequent storms” due to “Storm Surge” in Mainland China (as indicated by 0.4533), “Move facilities away from existing locations which are vulnerable to climate change risks and impacts” to address “All the risks and impacts above” due to “Sea Level Rise” in Hong Kong (as indicated by 0.4579), and “Improve transport infra- and superstructures resilience to flooding” to address “Transport infra- and superstructures and utilities in the port/terminal will get flooded or damaged in more intense or frequent storms” due to “Storm Surge” in Taiwan (as indicated by 0.2375). When the evaluations of the three regions are combined, the most cost effective measure is “Improve transport infra- and superstructures resilience to flooding” to address “Transport infra- and superstructures and utilities in the port/terminal will get flooded or damaged in more intense or frequent storms” due to “Storm Surge” (as indicated by 0.4452).

However, the above cost effectiveness analysis is based on the assumption that cost and risk reduction are assigned the same weight/importance, and it is of interest, as well as practical importance, to investigate the impact of the importance change between cost and risk reduction on the adaptation ranking. As shown in Figure 2, when the importance of cost increases, the cost effective index values of two adaptation measures increase accordingly, namely “Improve transport infra- and super-structures resilience to flooding” to address “Transport infra- and super-structures and utilities in the port/terminal will get flooded or damaged in more intense or frequent storms” due to “Storm Surge” and “Diversify land connections to port/terminal” to address “Overland access (road, railway) to port/terminal will be limited due to more intense or frequent storms” due to “Storm Surge”. This suggests that the two stated measures are a high cost feature in nature. Also, it leads to the result that the most effective measure (when cost and risk reduction are equally important) does not remain as the best solution, and is replaced by “Improve transport infra- and superstructures resilience to flooding” and “Raise port elevation” to address “Transport infra- and superstructures in the Port get flooded” due to “Sea Level Rise” when the cost is three times more important than risk reduction. Indeed, its preferential ranking is even taken over by “Protect coastline and increase and beach nourishment programs” to address “Coastal erosion at or adjacent to the Port” due to “Sea Level Rise” when cost is four times more important than risk reduction. However, when risk reduction is of high priority (compared to cost), the most cost effective measure remains the same. To a large extent, the preferential ranking order of all the adaptation measures is consistent.

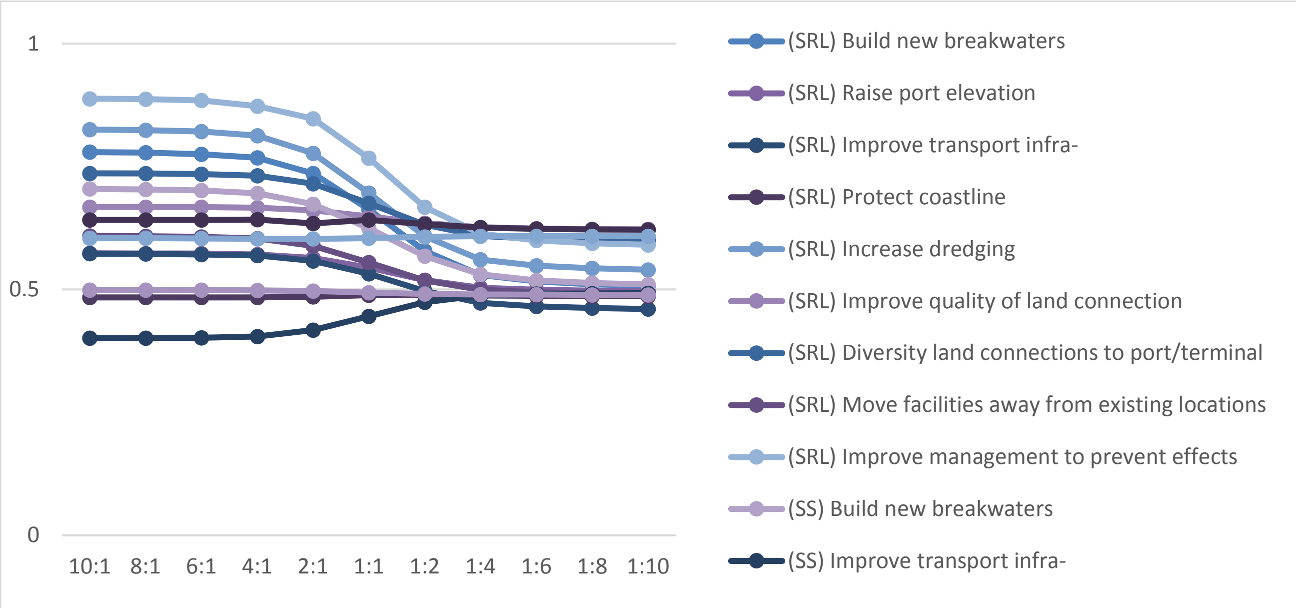

Figure 2. Adaptation measure ranking with different ratio between risk reduction and cost

The observed changes in the preferential ranking order of adaptation measures in relation to costs complements the works of Zhang and Ng (2016), who found that port stakeholders could be indifferent (even resistant) to adaptation measures due to cost commitments and the rather short port planning timeframe (compared to climate change impacts), even if they are well aware of the potential risks accompanied with climate change. The results also pose further questions on Xiao et al. (2015)'s queries on the appropriate roles of governments in developing and implementing adaptation measures to climate change risks.

7. Conclusion

Climate change adaptation is currently a key topic and a core element of sustainable management in any area of the economy. In ports, climate change is likely to impact on their operations, as well as on their strategic development and growth. However the evaluation of climate risks and the possible adaptation measures requires the uncertainty in data to be appropriately tackled. This paper proposed a hybrid fuzzy evidential reasoning approach to provide a possible solution to ranking climate adaptation measures in ports. The findings in this study indicate that the application of climate change adaptation measures recommended in the literature can bring a considerable reduction of the likely climate change risks affecting port operations. It was found that the main climate change threats to port operations are, flooding at a port due to both sea level rise and extreme storms, high waves damaging port facilities caused by high winds and coastal erosion. Although the effectiveness of the range of climate change adaptation port-related measures has been evaluated and the results of the modelling highlight that climate change adaptation can be a solution for achieving continuity of port operations under extreme weather conditions, there are a wide range of climate change adaptation measures which can be adopted by ports. Also, each port should prioritize, based on the likelihood and expected severity of climate change events and the funds available to them. Generally speaking, in Greater China (Hong Kong, Taiwan, and Mainland China), when climate risk reduction is of a high priority, it appears that the most cost effective measure is to improve transport infra- and superstructures resilience to flooding due to high winds. When the cost becomes more important in decision-making, the measure of improving transport infra- and superstructures resilience to flooding and raising port elevation against sea level rise are more preferable. Further research on other regions is necessary to further test the feasibility of the developed conceptual framework on analysis of the relationship between climate change risk reduction and the costs of adaptation measures. It is important to conduct more research on the correlations between risk reduction, cost, and timeframe. This is pivotal in enhancing the overall quality of adaptation for ports, port cities, intermodal transport, supply chains, and urban and regional planning in general.

Acknowledgements
This study was supported by an EU funded project ENRICH (612546) Marie Curie IRSES, 2013–2017, the University of Manitoba's Transport Institute (Canada), and VTC, Hong Kong. An earlier version was presented during the International Conference of Asian Logistics Round Table (ALRT) 2015 (Yang et al., 2015). The authors would also like to thank the three anonymous reviewers for their constructive suggestions. The usual disclaimers apply.

References

Andersen S.K., Olesen K.G., Jensen F.V., Jensen F. (1990). Hugin – a shell for building belief universes for expert systems. Reading in Uncertainty, Shaferd G. Pearl J. (eds.), Morgan Kaufmann, pp. 332-337.

Aerts J. (undated) Adaptation cost in the Netherlands: Climate change and flood risk management. Available at: <http://www.climatechangesspatialplanning.nl/media/default.aspx/emma/org/10354094/34-44+Adaptation+cost+in+the+Netherlands+-+Climate+Change+and+flood+risk+management.pdf> (Accessed on 15 October 2015).

Alyami H., LEE P.T.W., Yang Z.L., Ramin R., Bonsall S., Wang J. (2014). An advanced risk analysis approach for container port safety evaluation. Maritime Policy and Management. 41, 434-450.

Awuor C.B., Orindi V.A., Adwera A.O. (2008). Climate change and coastal cities: the case of Mombasa, Kenya. Environment and Urbanization, 20(1), 231-242.

Becker A. H., Acciaro M., Asariotis R., Cabrera E., Cretegny L., Crist P., Ng A.K.Y. (2013). A note on climate change adaptation for seaports: a challenge for global ports, a challenge for global society. Climatic Change, 120(4), 683-695.

Becker A, Inoue S, Fischer M, and Schwegler B (2012). Climate change impacts on international seaports: knowledge, perceptions, and planning efforts among port administrators. Climatic Change 110(1), 5-29.

Berechman J., Tseng P.H. (2012). Estimating the environmental costs of port related emissions: the case of Kaohsiung. Transportation Research D: Transport and the Environment 17, 35-38.

Chemane D., Motta H., Achimo M. (1997). Vulnerability of coastal resources to climate changes in Mozambique: a call for integrated coastal zone management. Ocean and Coastal Management 37(1), 63-83.

Corbett J.J., Wang H., Winebrake, J.J. (2009). The effectiveness and costs of speed reductions on emissions from international shipping. Transportation Research D: Transport and the Environment 14, 593-598.

Dai, F.C., Lee, C.F., Ngai, Y.Y., (2002). Landslide risk assessment and management: an over- view. Eng. Geol. 64 (1), 65–87.

Dawson, R.J., Dickson, M.E., Nicholls, R.J., Hall, J.W., Walkden, M.J.A., Stansby, P.K., Mokrech, M., Richards, J., Zhou, J., Milligan, J., Jordan, A., Pearson, S., Rees, J., Bates, P.D., Koukoulas, S., Watkinson, A.R. (2009). Integrated analysis of risks of coastal flooding and cliff erosion under scenarios of long term change. Climatic Change, 95 (1-2), 249-288.

Edjossan-Sossou, A.M., Deck, O., Al Heib, M., Verdel, T.A (2014). Decision-support methodology for assessing the sustainability of natural risk management strategies in urban areas. Natural Hazards and Earth System Sciences, 14 (12), 3207-3230.

Eide M.S., Endresen O., Skjong R., Longva T., Alvik S. (2009). Cost-effectiveness assessment of CO_2 reducing measures in shipping. Maritime Policy & Management36(4), 367-384.

Eide M.S., Longva T., Hoffman P., Endresen O., Dalsoren S.B. (2011). Future cost scenarios for reduction of ship CO_2 emissions. Maritime Policy & Management 38(1), 11-37.
Füssel, H.M. (2007). Adaptation planning for climate change: Concepts, assessment approaches, and key lessons. Sustainability Science, 2 (2), 265-275.
Geerlings H., van Duin R. (2011).A new method for assessing CO_2 emissions from container terminals: a promising approach applied in Rotterdam. Journal of Cleaner Production 19, 657-666.
Hallegatee E., Ranger N., Mestre O., Dumas P., Corfee-Morlot J. Herweijer C. Wood R.M. (2011). Assessing climate change impacts, sea level rise and storm surge risk in port cities: a case study on Copenhagen. Climate Change, 104(1), 113-137.
Hattermann, F.F., Huang, S., Burghoff, O., Willems, W., Österle, H., Büchner, M., Kundzewicz, Z. (2014). Modelling flood damages under climate change conditions-a case study for Germany. Natural Hazards and Earth System Sciences, 14(12), 3151-3169.
ICF International (2008) Planning for climate change impacts at US ports. US Environmental Protection Agency, California.
Jevrejeva S., Moore J.C., Grinsted A. (2012). Sea level projections to AD2500 with a new generation of climate change scenarios. Global and Planetary Change 81-81, 14-20.
Keohane R.O., Victor D.G. (2010). The regime complex for climate change. Discussion paper 2010-33, The Harvard Project on International Climate Agreements, Cambridge, MA, January 2010.
Kelly, P.M. and Adger, W.N., (2000). Theory and practice in assessing vulnerability to climate change and facilitating adaptation. Climatic Change, 47(4), 325-352.
Koetse M. J., Rietveld P. (2009). The impact of climate change and weather on transport: An overview of empirical findings. Transportation Research Part D: Transport and Environment, 14(3), 205-221.
Koks, E.E., Jongman, B., Husby, T.G., Botzen, W.J.W. (2015). Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. Environmental Science and Policy, 47, 42-52.
Lehner, B., Döll, P., Alcamo, J., Henrichs, T., Kaspar, F. (2006). Estimating the impact of global change on flood and drought risks in Europe: A continental, integrated analysis. Climatic Change, 75 (3), 273-299.
Liu S.K. (1997). Using coastal models to estimate effects of sea level rise. *Ocean and* Coastal Management 37(1), 85-94.
McGinnis, M.V. and McGinnis, C.E. (2011). Adapting to climate impacts in California: the importance of civic science in local coastal planning. Coastal Management 39, 225-241.
Messner S., Moran L., Reub G., Campbell J. (2013). Climate change and sea level rise impacts at ports and a consistent methodology to evaluate vulnerability and risk. WIT Transactions on Ecology and the Environment, 169, 13.
Mizumoto, M. (1995). Improvement of Fuzzy Control Methods. In: Li, H. and Gupta, M. (Eds.) Fuzzy Logic and Intelligent Systems. Kluwer Academic Publishers, 1-16.
Neshat, A., Pradhan, B. and Javadi, S., (2015). Risk assessment of groundwater pollution using Monte Carlo approach in an agricultural region: An example from Kerman Plain, Iran. Computers, Environment and Urban Systems, 50, 66-73.
Ng, A.K.Y., Becker, A., Cahoon, S., Chen, S.L., Earl, P. and Yang, Z. (Eds.) (2016). Climate Change and Adaptation Planning for Ports. Routledge, Abingdon.
Ng A.K.Y., Chen S.L., Cahoon S., Brooks B. and Yang, Z. (2013). Climate change and the adaptation strategies of ports: the Australian experiences. Research in Transportation Business and Management 8, 186-194.
Ng A.K.Y. and Liu J.J. (2014). Port-Focal Logistics and Global Supply Chains. Palgrave Macmillan, Basingstoke.
NRC (National Research Council of the National Academies – USA) (2010a). Adapting to the Impacts of Climate Change, National Academies Press, Washington DC.
O'Brien, G., O'Keefe, P., Rose, J., Wisner, B. (2006). Climate change and disaster management. Disasters, 30 (1), 64-80.
Osthorst W., Manz C. (2012). Types of cluster adaptation to climate change: lessons from the port and logistics sector of Northwest Germany. Maritime Policy & Management 39(2), 227-248.

Peters G.P., Marland G., Hertwich E.G., Saikku L., Rautiainen A., Kauppi P.E. (2009). Trade, transport and sinks extend the carbon dioxide responsibility of countries: an editorial essay. Climatic Change 97, 379-388.
Posas P.J. (2011). Exploring climate change criteria for strategic environmental assessments. Progress in Planning 75, 109-154.
Preston B.L., Westaway R.M., Yuen E.J. (2011).Climate adaptation planning in practice: an evaluation of adaptation plans from three developed nations. Mitigation and Adaptation Strategies for Global Change 4, 407-438.
Psaraftis H. Kontovas C.A. (2010). Balancing the economic and environmental performance of maritime transportation. Transportation Research Part D: Transport and the Environment 15, 458-462.
Refice, A., Capolongo, D. (2002). Probabilistic modeling of uncertainties in earthquake-induced landslide hazard assessment. Computers and Geosciences, 28 (6), pp. 735-749.
Rodrigues V., Harris I., Pettit S. Beresford A., Yang Z.L. Ng, A. (2015). UK supply chain carbon mitigation strategies using alternative ports and multimodal freight transport operations. Transportation Research Part E: Logistics and Transportation Review. 78, 40-56.
Schaeffer M., Hare W., Rahmstorf S., Vermeerm M. (2012). Long-term sea-level rise implied by 1.5 ^{o}C and 2 ^{o}C warming levels. Nature Climate Change 2, 867-870.
Schipper, L., Pelling, M. (2006). Disaster risk, climate change and international development: Scopes for, and challenges to integration. Disasters, 30 (1), 19-38.
Scott M.J., Edmonds J.A., Mahasenan N., Roop, J.M., Brunello A.L., Haites E.F. (2004). International emission trading and the cost of greenhouse gas emissions mitigation and sequestration. Climatic Change 64(3), 257-287.
Scott H., McEvoy D., Chhetri P., Basic F., Mullett J. (2013) Climate change adaptation guidelines for ports, Enhancing the resilience of seaports to a changing climate report series, National Climate Change Adaptation Research Facility, Gold Coast, pp. 26.
Stenek V. Amado J., Connell R., Palin O., Wright S., Pope B., Hunter J., McGregor J., Morgan W., Stanley B., Washington R., Liverman D., Sherwin H., Kapelus P., Andrade C. Pabón J.D. (2011). Climate risk and business: Ports, International Finance Corporation, World Bank.
UNCTAD (2012). Ad Hoc Expert Meeting on Climate Change Impacts and Adaptation: A Challenge for Global Ports: Geneva, Palais des Nations, 29-30 September 2011: Main Outcomes and Summary of Discussions. UNCTAD, Geneva, Switzerland.
Villalba G., Gemechu E.D. (2011).Estimating GHG emissions of marine ports - the case of Barcelona. Energy Policy39, 1363-1368.
Wang J. (1997). A subjective methodology for safety analysis of safety requirements specifications. IEEE Transactions on Fuzzy Systems 5(3), 418-430.
Wang, J., Yang J.B., Sen P., (1996). Multi-person and multi-attribute design evaluations using evidential reasoning based on subjective safety and cost analyses. Reliability Engineering & System Safety, 52, 113-128.
Wheeler S.M., Randolph J., London J.B. (2009).Planning and climate change: an emerging research agenda. Progress in Planning 72, 210-222.
Wilby, R.L., Troni, J., Biot, Y., Tedd, L., Hewitson, B.C., Smith, D.M., Sutton, R.T. (2009). A review of climate risk information for adaptation and development planning International Journal of Climatology, 29 (9), 1193-1215.
Wilhite D.A., Hayes M.J., Knutson C., Smith K.H. (2000). Planning for drought: moving from crisis to risk management. Journal of the American Water Resources Association 36(4), 697–710.
Willows R., and Connell, R., (2003). Climate adaptation: risk, uncertainty and decision making. UKCIP Technical Report. May 2003.
Xiao Y., Fu X., Ng A.K.Y., Zhang, A. (2015) Port investments on coastal and marine disasters prevention: economic modeling and implications. Transportation Research Part B: Methodological 78, 202-221.
Yang, J.B., Xu, D.L., (2002). On the Evidential Reasoning Algorithm for Multiple Attribute Decision Analysis under Uncertainty. IEEE Transactions on Systems, Man and Cybernetics – Part A: Systems and Humans, 32(3), 289-304.

Yang Z.L., Bonsall S., Wang J. (2008). Fuzzy rule-based Bayesian reasoning approach for prioritization of failures in FMEA. IEEE Transactions on Reliability 57: 517-528.
Yang, Z.L., Bonsall, S., Wang, J. (2009). Use of fuzzy evidential reasoning in maritime security assessment. Risk Analysis 29(1), 95-120.
Yang, Z., Ng, A.K.Y., Lee, P.T.W., Wang, T., Rodrigues, V.S., Pettit, S., Harris, I. (2015). Modelling risk based cost analysis of port adaptation measures to climate change. Proceedings of the International Conference of Asian Logistics Round Table (ALRT) 2015, Taipei, Taiwan, 31 August - 1 September.
Yang Z.L., Zhang D., Caglayan O., Jenkinson I.D., Bonsall S., Wang J., Huang M., Yan X.P. (2012). Selection of techniques for reducing shipping NOx and SOx emissions. Transportation Research D: Transport and the Environment17, 478-486.
Yang Z.L., Cahoon S., Chen S.L., Ng A.K.Y. Austin B., (2016). In: Ng, A.K.Y., Cahoon S., Chen S.L., Austin B. (Eds.) Analyzing Risks Posed by Climate Change on Ports: A Fuzzy Approach. Climate Chang and Adaptation Planning for Ports, Routledge Publishing, UK, 24-44.
Zhang D., Yan X.P., Yang Z.L., Wall A., Wang J. (2013). Incorporation of formal safety assessment and Bayesian Network in navigational risk estimation of Yangtze River. Reliability Engineering & System Safety 118, 93-105.
Zhang, H., Ng, A.K.Y. (2016). Climate Change and Adaptation Planning for Ports: A Global Study. Proceedings of the World Conference on Transport Research (WCTR) 2016, Shanghai, China, 10-15 July.