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Impact analysis of climate change on rail systems for adaptation planning: A UK case

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ABSTRACT

Climate change poses critical challenges for rail infrastructure and operations. However, the systematic analysis of climate risks and the associated costs of tackling them, particularly from a quantitative perspective, is still at an embryonic phase due to the kaleidoscopic nature of climate change impacts and lack of precise climatic data. To cope with such challenges, an advanced Fuzzy Bayesian Reasoning (FBR) model is applied in this paper to understand climate threats of the railway system. This model ranks climate risks under high uncertainty in data and comprehensively evaluates these risks by taking account of infrastructure resilience and specific aspects of severity of consequence. Through conducting a nationwide survey on the British railway system, it dissects the status quo of primary climate risks. The survey implies that the top potential climate threats are heavy precipitation and floods. The primary risks caused by the climate threats are bridges collapsing and bridge foundation damage due to flooding and landslips. The findings can aid transport planners to prioritise climate risks and develop rational adaptation measures and strategies.

1. Introduction

With the occurrence of more frequent and severe events related to climate change, adapting to the risks posed by climate change has been a pivotal research topic influencing transport policies in recent years (e.g. Beiler et al., 2016). Variability of the climate seriously endangers transport infrastructure and operations. The related activities within transport networks are sensitive to heterogeneous weather extremes. These impacts might attribute to the considerable changes in temperature, precipitation winds, thunderstorms, frost, thaw, fog and sea-level/other-water levels (e.g., Schweikert et al., 2014; Love et al., 2010).

A number of scholars proposed railway adaptation strategies to climate change and applied them to various case studies in different nations (e.g. Strauch et al., 2015; Dobney et al., 2009; 2010). In the UK, despite the fact that the Network Rail has published its first adaptation report in 2011 and prepared several resilience measures for its eight national routes in recent years (Network Rail, 2015), there is little evidence showing the comprehensive adaptation measures implemented across every aspect of its rail systems

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(Dora, 2012). As Arkell & Darch (2006) implied, it is vital to adapt to the potential climate impacts by conducting cost-benefit analysis, in which quantifying the risk levels of climate threats becomes an effective facilitating tool.

In the context of climate adaptation, risk analysis as a critical element has been analysed through a variety of approaches and techniques such as sensitivity analysis, empirical downscaling and dynamical downscaling (Wilby et al., 2009). However, their practicability and effectiveness are challenged in existing climate risk studies (Yang et al., 2015). One of the main challenges is that unavailable or incomplete objective data sometimes fail to generate meaningful assessment results regarding climate risk. Traditional probabilistic risk analysis approaches (e.g., Quantitative Risk Assessment (Urciuoli, 2011)) are often unable to tackle the unavailability or incompleteness in climate risk data (Yang et al., 2018a).

Hitherto, a group of researchers applied fuzzy set approaches to evaluate climate risks on ports and roads in pioneering climate risk works in different regions (e.g., Greater China and the UK), in which a 'fuzzy set manipulation' was used to accommodate subjective data (Yang et al., 2015, 2016; 2018a; Wang et al., 2018a; 2019). In these studies, linguistic terms were regarded as variable grades to evaluate the stakeholders' perceptions on climate impacts (e.g., Yang et al., 2018a; Wang et al., 2019). Climate risks were assessed by three critical parameters, namely, their timeframes and likelihood of risk occurrence as well as the severity of consequences, by which researchers modelled these subjective linguistic terms based upon the stakeholders' opinions on the identified climate threats. Furthermore, a preliminary study on climate risk evaluation in road systems by Wang et al. (2019) proposed a new Fuzzy Bayesian Reasoning (FBR) model by incorporating more risk variables such as *'economic loss', 'human injuries/deaths',* and *'environmental damage'* to represent climate risk consequence severity. It hence increased expert confidence in evaluating their perceptions on climate risks by decomposition risk variables to a micro level where the subjective data can be collected with higher credibility.

Despite showing some attractiveness, previous studies in the relevant literature yet reveal applicable concerns in practice. From the theoretical perspective, there is little evidence to address the effect of new parameters (i.e. 'climate resilience') on climate risk evaluation (e.g. Beheshtian et al., 2018) and on climate safety perception in a selected transport sector, despite its increasing importance in transport risk assessment in general (e.g. Wang et al., 2019; Alyami et al., 2019). Within the context of climate risk, transport resilience is defined as 'the capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event in a required period and cost of recovery' (IPCC, 2012). Some recent articles have taken transport resilience into climate-related risk evaluation, together with advanced quantitative modelling approaches to address uncertainties in resilience assessment (e.g., Wan et al., 2018). In practice, there is a strong need to generate more experimental evidence to demonstrate the feasibility and significance of advanced uncertainty models in climate risk evaluation for a resilience transportation system.

A significant challenge in climate risk analysis is that the uncertain nature of climate change makes it hard for researchers to project and select appropriate risk scenarios in the future (Wu et al., 2013), in particular when social, economic, and political dimensions are unpredictable (Jaroszweski et al., 2010). Also, traditional risk analysis usually pays little attention to a particular type of climate change event or transportation assets.

The two issues, as Wu et al. (2013) suggested, could be addressed through gathering real survey data from domain experts for calibrating and assigning the weights of the defined risk parameters, and tailoring the proposed model diverse situations, respectively. Meanwhile, this requires transport planners to consider different climate threats for comparative analysis to rationalise the adaptation resource allocation, and undertake a reliable risk assessment and longer-term transport planning in a particular region. Accordingly, it requires comprehensive data collection from multiple stakeholders and the design of advanced risk assessment models based on local conditions to strengthen the robustness of existing risk models (Walker et al., 2011).

Acknowledged the fact that there is insufficient literature investigating the long-term climate threats, in particular within the rail sector, it is highly necessary to develop a generic climate risk analysis framework and apply it to carry out a country-specific risk evaluation to enhance the resilience of rail systems for climate adaptation planning. To effectively tackle the risks of climate change on railways, this paper first proposed a new climate risk assessment methodology using uncertainty modelling techniques such as fuzzy and Bayesian networks and then conduct a systematic climate risk evaluation in the UK rail systems with first-hand climate data collected by a nationwide survey as a pioneering step of collecting empirical evidence to support the newly developed methodology.

With a comprehensive review of the climate risks in the British rail sector and the analytical results of the FBR model, this study reveals the primary climate threats from the perspectives of both industry and academia with region-specific customisation and ongoing trend observation. It calls for more attention to climate risks assessment and adaptation planning in the rail systems. Hence, the findings present an overview of the UK rail community and perceptions that stakeholders hold towards climate hazards, which contributes to fill knowledge gaps in climate risks assessment. Meanwhile, it will provide valuable contributions to rail planners, decision-makers and professionals in the industry by supporting them when designing long-term adaptation plans and implementing adaptation strategies in a rational way.

From a methodological perspective, this work has embedded a new feature to a well-established Fuzzy Bayesian Reasoning (FBR) model to tailor it for climate risk analysis. The classical two-tier BN has been extended to a three-layer structure in which more detailed risk consequence parameters can be accommodated to reflect the demand caused by the large diversity of climate risk consequences from human, economic and environmental viewpoints. It helps initiates the new thinking on the development of extended FBR for making it possible to use multiple source raw data to avoid risk information loss in the analysis process. Furthermore, this work has also pioneered the incorporation of the climate resilience concept into a risk model by introducing a new risk parameter "transport resilience" to describe the different reaction of transport systems to the same climate threat. In terms of applied researcher, in the work, a carefully thought climate risk and adaptation questionnaire was designed and used for a nationwide survey in the UK rail sector. The questionnaire and the method of collecting the risk data can be tailored and used for investigating climate risk of railways in other countries and regions, and to a wider range, even for other transport systems (e.g. road, seaports and airports).

The remainder of this study is organised as follows. The status quo of existing research on the British rail sector and climate risk assessment is firstly reviewed in Section 2. Section 3 conducts an investigation of the applications of fuzzy theory and BNs for risk analysis, followed by the formation of the FBR risk model[1] for climate risk analysis, including a step-by-step risk analysis and synthesis framework. This new model lays down a foundation for adaption to climate risks and tackles the uncertainties in risk analysis. Most importantly, on the basis of the proposed FBR model (Wang et al., 2019), this paper explains core concepts and major developments of fuzzy set and Bayesian Networks (BNs), and the procedure of model implementation in the context of rail transportation. In Section 4, the FBR model is further examined to discourse the primary climate risks and climate adaptation in the case study of UK rail systems. The exemplification of the FBR model in British railways systems are realised by conducting a large-scale questionnaire survey amongst 20 rail stakeholders[2]. The expert participants represent the major sectors involving climate adaptation in the UK rail systems, including government officers, rail system infrastructure providers and operators, academic professionals and non-profit organisations (NGOs). Finally, the discussion and conclusion on research implications and further research directions are presented in Sections 5 and 6, respectively.

2. Critical review of the risk posed by climate change in the UK railways

The number of articles concerning the impacts posed by climate change on transport infrastructure and operations has rapidly grown in different nations and regions in recent years. The research includes diverse evaluation and projection of climate change impacts. However, climate-related studies mainly focus on short-term climate threats (e.g. Koetse & Rietveld, 2009) and in transport sectors such as ports (e.g. Yang et al., 2018a; Ng et al., 2018; Wang et al., 2016) and road (e.g. Wang et al., 2019) but not yet in the rail sector. Therefore, the country-specific evaluations and quantification of impacts to enhance the resilience of rail systems for climate change is urgently needed.

Previous studies (e.g. Jenkins, 2009; Peterson et al., 2008, Jaroszweski et al., 2010; Hooper & Chapman, 2012) investigated the estimated tendency of climate change taking into account its impact on the UK rail sector. They include the effects of an increased number of hot days, a decreased number of cold days, increased heavy precipitation, drought, sea level change, seasonal change, extreme events and winds. The extreme events posed the most devastating impacts (e.g. heat waves and storms) on rail transport. Higher temperatures in summer may cause rail buckling as well as decreased thermal comfort, while heavier precipitation in winter could cause landslips, flooding and bridge scour. Dora (2012) discovered that changes in temperature and precipitation were the primary impacts to infrastructure and operations of UK rail transport systems. It stressed the effects, including the increase in track buckling, days of track maintenance and exposure of staff to heat stress and overhead power cables sagging in poor weather.

Flooding has significant impacts on rail networks (EPA, 2009). The damage caused by climate change on railway networks took into account approximately 29–71% of the total infrastructure value (Chatterton et al., 2007). The floods that hit Cumbria had severe impacts as recorded, affecting large areas and major river basins (PERC UK, 2015). During the most catastrophic floods that occurred in 2015 (Met Office, 2015), rail services suffered from delays or cancellations, including the West Coast Main Line in coastal locations (BBC News, 2015). On the Settle & Carlisle railway line, a severe landslip caused the route to be blocked for several months before reopening in March 2017. During the recent flooding events in October 2017, the floods between Carlisle and Maryport led to enormous disruption and blocked rail lines (BBC News, 2017). This storm was estimated to cause damages of £1 billion and claimed 18 lives (News & Star, 2017).

Storms are the main threats for Devon County. The cumulative result of the rapid succession of over 10 strong storms in the winter 2013–2014 in Devon was the worst since the 1950s (Devon Maritime Forum, 2014; Met Office, 2014). They mainly effected the South West main rail network with the sectional collapse of the sea wall at Dawlish on the South Devon coast. This had significant impacts on transport resilience and the local economy across the South West Peninsula (Devon County Council, 2014). In total, the storms had resulted in the two-month closure of the mainline and over 7000 service cancellations (Devon Maritime Forum, 2014). In a recent storm in early 2017, high waves in coastal areas crashed over flood barriers and flooded sections of railway lines. The boats, lighthouses and seafront rail track were impaired by surges and some trains between Newton Abbot and Exeter St Davids were temporarily cancelled (The Sun, 2017).

Overall, there have been widespread effects on the UK rail networks in different locations, however it is only very recently that companies/organisations responsible for operating British railways have started paying serious attention to the impacts of climate change (Hooper & Chapman, 2012). Network Rail's latest adaptation report (Network Rail, 2015) summarised its understanding of the existing and potential impacts posed by climate change on its rail performance and safety. A few significant climate hazards on rail infrastructure were recognised through an internal risk analysis supported by METEX and GIS tools. They mainly included the

[1] In Wang et al., 2019 work, the model was not fully explored and tested and even its theoretical development was not introduced in details as it should be because of the limited space allowed by the conference. From the modelling perspective, the preliminary work addressed a two-tier hierarchy of risk parameters and each tier involves three risk parameters. However it did not present the solution to the new development of a fuzzy rule base involving over three parameters at the same level.

[2] As demonstrated in previous studies (e.g. Yang et al., 2018), climate adaptation in the transport sector is emerging and many industrial organisations have yet developed relevant expertise. The 20 responses are from a national survey targeting all the major rail operators, infrastructure providers and all the regional councils in the UK.

changes in temperature precipitation change, leading to increased flooding, but also extreme events such as lightning, seasonal changes and sea level rises. For instance, cold weather such as snow and ice would threaten overhead lines; heat may increase the risk of rail bucking and derailment; heavy rainfall and flooding could cause scour of embankment material and damage of electricity equipment.[3] Nevertheless, owing to the kaleidoscopic nature of long-term climate change impacts and insufficiency of precise data on change rate and extreme events (Network Rail, 2015), the existing adaptation plan still focuses on identification of several climate thresholds and selection of the best risk scenario.

Some issues in the rail sector were also revealed in Dora's report (2012), which included poor air quality in urban areas and remarkable differences between the North and South of the UK due to the rising temperatures, the increased possibility of track inundation and of scouring that affects river bridges' stability and incidence of landslips posed by extreme precipitation. Due to the high uncertainty related to the climate change in the future, adaptation measures should be robust to retain the option value of the measure portfolios. Hence, through conducting a nationwide survey of UK rail systems, this paper examines the new climate risk perception analysis model, which enables an comparative analysis of different climate threats and overcomes the shortage of data and the uncertainty of climate risks to reveal the real situation of climate change in British railways.

To identify the vulnerabilities of transportation systems to the risks of climate change, a few approaches and practices have been developed in recent years. These studies not only covered the evaluation of environmental impacts to transportation and the entire supply chain (e.g., Walker et al., 2011; Wu et al., 2013; Wan et al., 2019), but also the quantification of economic consequences of the impacts based on the different scientific models and regional studies (e.g., Yevdokimov et al., 2015; Neumann et al., 2015).

Despite the previous studies on risk assessment for climate change, a few dilemmas remain in existing transportation research. Firstly, One of the research challenges is that the kaleidoscopic nature of climate change makes it hard to select and develop appropriate risk (e.g., low-risk, medium-risk or high-risk) scenarios (Jaroszweski et al., 2010). However, the analysis of different scenarios and improving system's resilience can make a difference in responding to unexpected changes (e.g., Mikovits et al., 2018). Secondly, because traditional risk analysis usually only refers to a particular type of climate change event or a transportation mode, future scenario development is expected to cover diverse climate-related events (Wu et al., 2013). A nationwide risk analysis for enhancing the resilience of the UK rail systems to climate change is therefore devised.

3. Methodology: New application of a fuzzy Bayesian reasoning (FBR) model for climate risk assessment involving transport resilience

This section illustrates a new risk analysis model and framework to bridge the existing gaps in climate risk analysis in UK rail systems. It starts with a critical review of the applications of fuzzy theory and BNs in risk analysis. Afterwards, we propose a step-by-step climate risk analysis framework involving a new risk parameter, transport resilience.

3.1. Fuzzy set and Bayesian networks

Fuzzy logic has been widely used in risk assessment, providing a theoretical framework to support expert decision making under uncertainty (Sii and Wang, 2002). When multiple sets of data (from different experts) are employed, it is challenging to utilise standard fuzzy rule inference mechanisms, because the involved calculations are usually not very accessible to mathematically unsophisticated users. BNs is an effective tool to tackle randomness and increase knowledge with new available evidence. This is achieved by combining probability distributions or functions of different parameters, and updating their probabilities when new data emerges (Wang, 2003).

Bayesian modelling is a proven interdisciplinary tool (Tebaldi et al., 2005). There are a variety of benefits when using BNs including integrating different types of data within a framework, and efficiently being updated when new information becomes available (Castelletti & Soncini-Sessa, 2007, Cinar & Kayakutlu, 2010). In particular, BNs are capable of compensating the absence of historical statistics and handling incomplete uncertainty by combining various pieces of information and making use of expert judgments (Tighe et al., 2007). BNs have achieved a wide range of applications in transportation safety assessment (e.g. Zhang et al., 2013; Bertone et al., 2015; Yang et al., 2018b).

A few research have identified some benefits from combining fuzzy logic and Bayesian reasoning, especially in the applications of Fuzzy-Bayesian approaches in safety and reliability research (Bott & Eisenhawer, 2002). Fuzzy Bayesian Networks has been proven to deal with randomness and fuzziness of uncertainty by linking fuzzy set theory to BNs (e.g., Yang, 2006). In a recent study, for instance, Wan et al (2019b) developed an advanced fuzzy Bayesian-based model to assess the risk factors of maritime supply chains to cope with the high uncertainty within risk data. Through combining fuzzy set theory and BNs, we propose a new application of the FBR approach to model subjective linguistic variables, cope with the discrete problem, and handle incomplete information and uncertainty.

Previous studies using FBR in climate risk analysis (Yang et al., 2018a) have exposed modelling weaknesses, including the definitions of risk variables not being specific enough for raw data collection from domain experts. The innovative theoretical contributions of this work lie in the addition of a new climate risk parameter 'transport resilience' in the climate risk model for the first time and decomposes the climate consequence severity parameter into three sub parameters. Such a change requires substantial changes in climate risk modelling. New features are presented in the ensuing section to tailor FBR in the context of climate risk to rail systems.

[3] An interview with a senior expert from Network Rail on April 6th 2018.

3.2. Application of FBR with new features for climate risk analysis in rail

This section describes how the FBR model is tailored to enable the climate risk assessment of the British rail sector. To avoid unnecessary repetitions regarding the original FBR modelling work (incl. equations and algorithm), which are explained in Yang et al. (2018a) and Wang et al. (2019), this paper stresses the key elements in the four-step modelling construction procedure with new features of two tier modelling (i.e. decomposition of climate consequence severity) and the newly added risk parameter 'transport resilience'. By doing this, we can emphasise how the original FBR can be tailored to incorporate the two new features for climate risk assessment of the UK rail systems.

3.2.1. Investigation of environmental drivers

Based on the literature review in relation to the impacts posed by climate change in the UK, four main environmental drivers affecting British railways have been identified (e.g., RSSB, 2016; Network Rail, 2015; Hooper & Chapman, 2012; Dora, 2012; Jaroszweski et al., 2010; Jenkins, 2009). They include higher temperature, heavier precipitation or floods, more frequent or intense storm and high wind, and sea level rise (SLR). The potential climate threats resulting from the four environmental drivers are identified and examined by interviewing eight representative stakeholders in the UK rail sector ranging from rail operation companies and associations, rail infrastructure providers, and consulting companies to local city councils.[4] The 11 pivotal threats are then identified and listed in the questionnaire survey (see Table 3). Thus, the specific goal of this study is to prioritise the climate risk levels of all listed threats associated with above environmental drivers.

3.2.2. Identification of fuzzy risk input and output variables

Referring to the previous climate risk parameters in (Yang et al., 2018a; Wang et al. 2019), this paper develops a new three-layer hierarchy to model new parameters for rail climate risk assessment. They include a single parameter on the top layer, namely "*Climate Risk Level (CRL)*" (e.g. Ng et al., 2013; Yang et al., 2015, 2016). On the second layer, there are four parameters including classical *"Timeframe (T)", "Likelihood (L)" "Severity of Consequences (C)"* used in previous climate risk analysis (e.g. Yang et al., 2008, 2009; Ng et al., 2013; Yang et al., 2016) and a new one "*Transport Resilience (S)*". On the third layer, the three sub-parameters including *"Damage to Infrastructure (INF)"*, *"Injuries and/or Loss of Lives (INJ)"*, and *"Damage to Environment (ENV)"* are considered as the three critical aspects of *"Severity of Consequences (C)"* (Wang et al., 2018a, 2018b, 2019). Our previous studies on climate risk analysis revealed the difficulty for domain experts to directly evaluate the severity of the consequence caused by climate threats, given they often cause different level damages in terms of INF, ENV and ING.

Accordingly, there are total eight input variables connecting to an output variable *"CRL",* in which the four variables *"T", "L" "C"* and *"S"* on the second level are used to directly evaluate the first level variable "CRL", while the three variables on the third level *"INF", "INJ"* and *"ENV"* are employed to assess the variable *"C"*.

Fig. 1 illustrates the three-layer structure with linguistic terms of the involved eight parameters in this climate risk evaluation. The linguistic terms used refer to the previous climate risk studies using FBR (e.g. Yang et al., 2018a; Wang et al., 2019). The linguistic terms used to describe 'Transport resilience' are derived from the Intergovernmental Panel on Climate Change (IPCC, 2012).

Domain experts can then use a value or degree associated with a linguistic term (e.g. 0.8 'Very high' likelihood) to describe their perception on an investigated climate threat. The risk result is presented in a form of belief degrees. To prioritise the climate risks, we assign a utility value to each of the five linguistic terms of CRL (fuzzy risk output variable) using a centroid defuzzification method (Yang et al., 2009). We determine the weight of each risk parameter equally, and meanwhile, the weight of each expert is considered equally when combining their judgement for risk prioritization.[5]

We choose trapezoidal and triangular membership functions (Dyck et al., 2014), considering their simplicity and accessibility to a wide audience as well as common utilisation in risk evaluation. A typical membership function for the risk parameters is defined and characterized in Table 1 as an illustrative example. Here, these functions are expressed by five sets of overlapping trapezoidal or triangular curves (e.g. Yang et al., 2018a; Wang et al., 2019).

3.2.3. Modelling of the relation among multi-layer variables through fuzzy rule bases

On the basis of fuzzy theory, this paper applies IF-THEN rules to gather experts' knowledge and integrate them into a single system so as to realise an effective transformation from knowledge bases to non-linear mappings (e.g. Yang, 2006).

By introducing the concept of degrees of belief (DoBs) to model incomplete data, the method utilises fuzzy linguistic variables to project the attribute values in decision making (Yang et al., 2009). Accordingly, to model the incomplete survey data from experts,

[4] An associate director of freight and a transport engineer from a leading UK consulting company, a CEO and performance programme manager from two UK rail operation associations, an environmental manager and a principal technologist of logistics from two UK rail operation companies, a climate change adaptation strategy manager from a UK infrastructure provider, and a policy maker from a British city council.

[5] The weights of the risk parameters can be allocated differently when strong evidence is shown to support it in other applications of the model. The different weights can be effectively incorporated into the model through adjusting the belief degrees in the THEN part of the fuzzy rule based using the weighted fuzzy rule base approach (Alyami et al., 2014). In terms of equal weight assigned to the experts, we use very critical selection and exclusion criteria to recruit the participants which allows us measure the important data sources directly and ignore unreliable or unrepresentative answers to avoid common bias. In return, the selected experts have rich experience working in climate risk and adaptation planning related areas. The value of their feedbacks is therefore equally presented in this work. If in other applications, the different weights to experts becomes necessary, then they can be combined with their judgements using a weighted sum approach.

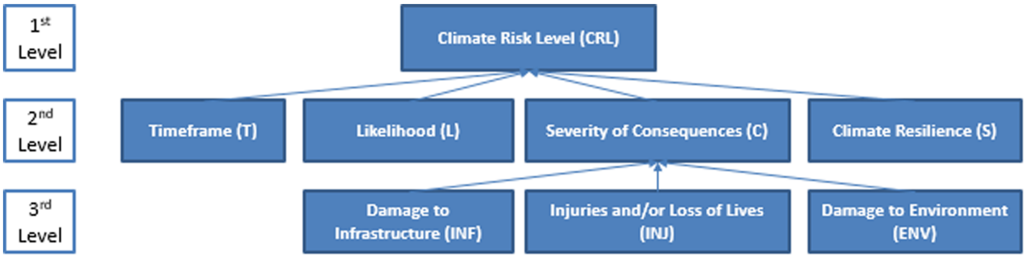

Fig. 1. Three-layer structure of the FBR model.

Table 1
Climate resilience.

Grade	Linguistic terms	Capacity of transportation system	Time of recovery	Cost of recovery	Fuzzy memberships
1	Very Weak (VW)	< 20%	A year	> £10million	(0, 0, 0.1, 0.3)
2	Weak (W)	20–39%	A month	£1million-£ 9.9million	(0.1, 0.3, 0.5)
3	Average (A)	40–59%	A week	£100, 000-£999,999	(0.3, 0.5, 0.7)
4	Strong (S)	60–80%	A day	£10,000-£99,999	(0.5, 0.7, 0.9)
5	Very Strong (VS)	> 80%	12 h	< £10,000	(0.7, 0.9, 1, 1)

Source: Derived from IPCC (2012).

subjective DoBs are assigned to the linguistic terms to generate the output data.[6] In this process, a proportion method (Alyami et al., 2014) is applied to rationalise DoB distribution in the THEN part of the rules. As a result, we assemble the four fuzzy input parameters on the second layer containing 20 (5 + 5 + 5 + 5) linguistic variables to produce 625 (5 × 5 × 5 × 5) antecedents. Meanwhile, the three parameters on the third layer and the second-layer parameter which include 15 (5 + 5 + 5) linguistic variables are assembled to generate 125 (5 × 5 × 5) antecedents.

3.2.4. Prioritisation of risk levels through a BN approach

In the last step, a BN method is used to synthesise the above fuzzy rules and to assess climate risks. For example, for the rule bases modelling the relationship between the risk parameters in the 2nd and 3rd layer, a four-node converging network is converted, containing one child node N_C (Node C) and three parent nodes, N_{INF}, N_{INJ} and N_{ENV} (Nodes *INF, INJ,* and *ENV*). The DoB in the THEN part of each involved fuzzy rule is converted and expressed by conditional probabilities (Yang et al., 2008).

In the national survey, participants are asked to evaluate the impact of each climate threat on the British rail networks regarding the eight risk parameters with reference to their individual linguistic terms. By doing so, we can gather the prior probability information of all nodes. To obtain the prior probabilities of N_S, $p(S)$, for instance, we ask the question, "how resilient is your rail network when facing an investigated climate threat?" All the data collected from the participants are averaged and used as the prior probabilities in the BN.

The given prior probabilities finally allow the calculation of the marginal probability of climate risk level N_{CRL}. The linguistic descriptions are given the utility values as {0.11, 0.3, 0.5, 0.7, 0.89} based on the centroid defuzzification approach (Yang et al., 2009). Then, the final climate risk ranking value can be calculated by multiplying the obtained marginal probabilities and the corresponding utility value of the five linguistic terms of CRL. As the utility values of the five linguistic terms (i.e., from "*Very High*" to "*Very Low*") are from low to high, the lower the climate risk ranking value is, the higher risk level.

4. Case study: A nationwide online survey on climate risk assessment for the UK rail systems

4.1. Sampling

A nationwide survey was undertaken by distributing questionnaires online to collect the primary information by assessing the perception of rail transport planners and stakeholders in terms of the threats posed by climate change within the rail systems. It illustrates the overview of climate threats in the UK rail systems, justifying the necessity and importance of embedding adaptation planning to rail organisations.

A pilot study was initiated between March and April 2017 via consulting with eight domain rail stakeholders[7] to guarantee the validity and shape of the design of a questionnaire. From May to December 2017, a nationwide online survey was completed by 20 rail stakeholders to evaluate their perception of climate change impacts, including general and specific impacts on their rail operations, performance as well as infrastructure resilience.

[6] An example of fuzzy rule with degrees of belief can be referred to the work by Wang et al. (2019).
[7] Same as the rail stakeholders we described in Section 3.2.1.

The survey was sent to all the rail stakeholder groups in the UK, rail companies and authorities, governmental departments, academics and NGOs. The databases of the national rail networks were used to select the transport entities (Network Rail, 2016). We applied a non-probability sampling approach, which integrates judgment sampling with snowballing, considering the unique and complex features of climate impacts on the transportation sector (e.g., Wang, 2015; Wang et al., 2019).

The participants in the railway survey were chosen from members of the Railway Industry Association (RIA) and the Rail Freight Group (RFG) representing major UK-based suppliers of the world's railways and the leading body for rail freight in the UK (RIA, n.d; RFG, n.d.). Over 200 member companies crossing the whole range of railway supply with diverse skills and resources are typical rail entities in the UK national railway. However, this survey excludes several small entities located in remote regions largely due to their limited readiness and maturity on knowledge of climate risks.

Next, we used a snowball sampling approach which is particularly useful for investigating the population hard to research (Lee, 1993). Ten participants who have a relevant background and are willing to engage in the survey (e.g., CEOs, senior managers and policy makers) were invited from the listed organisations to assist with the distribution of these online questionnaires. Afterwards, they were asked to provide contacts of other potential participants to enlarge feedbacks (Dabney & Berg, 1994). A sample of 30 administrators on behalf of the vital transport stakeholders covering diverse geographic locations of the UK (e.g., Network Rail, Leeds City Council, Arriva Rail North, etc.) was finally formed. The 30 questionnaires were then distributed online through Bristol Online Survey website (BOS, 2017) tool by sending emails and calling the targeted respondents. After intimal data screening by eliminating incomplete input information and incorrect responses, by December 2017, we received 20 out of 30 effective responses with a high response rate 66.7%.[8]

The selection and exclusion criteria of targeted participants allow us measure the important data sources directly and ignore unreliable or unrepresentative answers to avoid common bias (Spector & Brannick, 2009; Jakobsen & Jensen, 2015). However, it is the case that there are only a few cases, in which more than one responses are received from the same origination, probably because of the emerging feature of climate adaptation in the UK rail sector. We do not consider that it causes a method bias. Firstly, the pilot study as mentioned helps effectively guarantee the reasonable survey design prior to the distribution of the questionnaire, through deleting the ambiguous, complex or abstract context to minimise the bias. Secondly, the survey involves the common source as different employee at different level within a group have diverse perceptions for a climate risk event.

4.2. Geographic distribution, position of participants, primary climate risks and adaptation plans

To illustrate the overview of the primary impacts of climate change, this survey covers all of the UK regions, including Scotland, Wales, Northern Ireland and the regions of England. By asking 'Which region of the railway does your company/organisation operate in?' (Q3a), the geographic distribution number of the respondents' rail entity is analysed, and the results are shown in Fig. 2. It is noted that almost 80% of participants are from the railways in England, where the major rail networks are managed by National Railways. The responses from Wales, Scotland and Northern Ireland occupy around 8%, 9% and 4% of the total number respectively.

Meanwhile, the data regarding the current position of participants at their companies or organisation are collected (Q4). Fig. 3 illustrates that the participants are unequally distributed in diverse positions. However, besides the category of 'others', including transport and supply chain managers, associate directors, climate adaptation strategy managers, performance programme manager and principal freight and logistics technologists, CEOs/transport directors are the main participants, followed by transport engineers and scholars.

Before evaluating the specific threats of the four environmental drivers, respondents were asked to rank the different types of risk that they have witnessed or experienced posed by climate change on the railway their company/organisation are associated with (Q5). Fig. 4 illustrates the ranking values of the mean and standard deviation of each potential climate threat in the UK rail systems. Overall, flooding ($M = 4.29$), landslide ($M = 4.82$) and extreme weather ($M = 5.06$) are the most concerned impacts, followed by high winds ($M = 5.18$) and precipitation change ($M = 5.29$), while sea level rise ($M = 6.41$) is considered the lowest risk. In particular, high winds ($SD = 2.32$) and precipitation change ($SD = 2.31$) relatively invariably occur, whereas the top three risks might have varying influence in different regions. For instance, flooding has the highest SD (3.35). In Section 4.3, we further analyse the main climate threats to the railways in four regions in the UK.

By vertically comparing the results of the four regions in the UK (Table 2), it can be observed that flooding and landslide are the common climate threats for the all four regions, with particularly the highest ranking in England ($M = 2.98$ for flooding and $M = 3.10$ for landslide). Except from Wales, the SDs of landslide are small, which means a stable occurrence. Surprisingly, the SDs of flooding in the four regions are relatively large, which hints that flooding has variable impacts in different regions. For instance, floods ($M = 2.98$) in England are more severe than others. Besides, extreme weather commonly occurs in Northern Ireland and England. High winds are common impacts for Wales and Scotland, storm surges are a common one for Wales and England, together with relatively low SDs. As 79% of response comes from England, the main threats posed by climate change in the UK have affected by the regional opinions, and therefore, flooding, extreme weather and landslides are deemed as the top risks.

Furthermore, by inquiring participants the details about the impacts posed by climate change on the rail their company/organisation are associated with in the past ten years (Q6), the results show that some rail lines have been damaged due to severe flooding and landslide. There was a particular issue on the east coastline between Scotland and Newcastle, and also on the west coastline between Scotland and Carlisle. Extreme wet weather caused landslips and embankments to slip on to running lines. Some significant

[8] The questionnaire can be found in Appendix A.

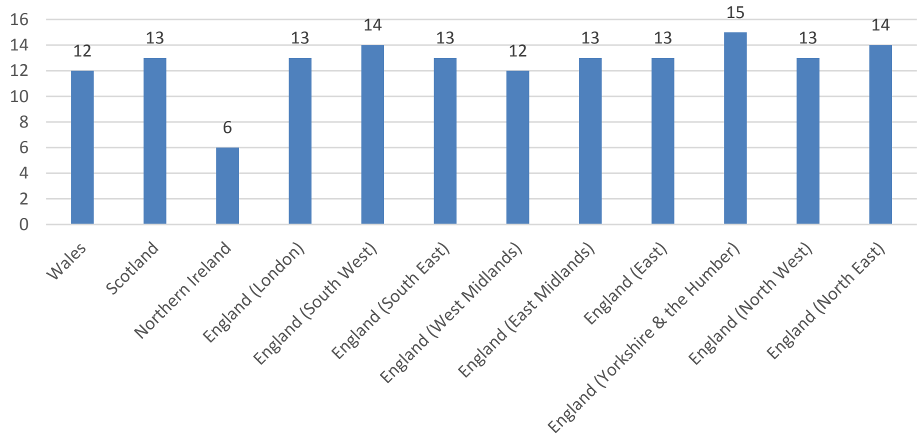

Fig. 2. Geographic distribution of responses.

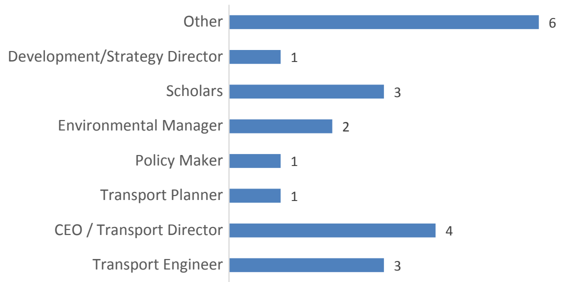

Fig. 3. Distribution of participant positions.

events can be witnessed from the flooding at Dawlish (Railway Line) in 2013/2014 and at Exeter (Railway Line) junction with Barnstaple line, as well as landslips on the Aberdeen-Inverness line in 2016 and flooding affecting various bridges on the Aberdeen-Dundee route.

In respect to the implementation of climate adaptation plans on railways (Q7), although most of the participants have acknowledged the significance of climate risks, when talking about climate adaptations, only 32% of them have undertaken an adaptation plan while 47% of the total will consider developing one in the future.

4.3. Risk prioritisation by the FBR model

Data screening was further conducted on the relevant eight questions (Q8 to Q15) before proceeding with the risk analysis using FBR. Accordingly, 3 out of 20 feedbacks became invalid after the screening process to avoid missing and ineffective data (e.g. adaptation measures leading to increased risk values). The consistency of the remaining 17 sets of data was addressed through the comparative climate risk analysis. Finally, associated data from the eight questions were put into the proposed FBR model to rank and analyse the top potential risks posed by climate change.

The climate risk result of each potential climate threat of the four environmental drivers related to UK rails was calculated with a detailed elaboration in Table 3. The impacts of temperature increase, for instance, were divided into two potential threats, namely, “A1. Track buckling causing derailment risks & reducing opportunities for track maintenance” and “A2. Unreliable signalling, power lineside systems, failure of temperature controls and overheating of electronic equipment”. Supported by Hugin software (Andersen et al., 1990; HUGIN v. 8.5, 2017), we calculate the risk results of “A1. Track buckling causing derailment risks & reducing opportunities for track maintenance” as {11.54% *Very High*, 18.08% *High*, 30.03% *Average*, 19.22% *Low*, 21.16% *Very Low*}. After the utility values being assigned to the five linguistic terms, we can obtain the risk index value of “A1” as 0.54. The results of climate risk analysis on “A1” by Hugin is shown in Fig. 5.

The overall risk ranking of all the threats in Table 3 indicates that the highest potential climate threats to the railways in Britain are, in sequence, “B1. Bridge foundations damaged leading to bridge collapse and derailment risk”, “B2. Landslips causing obstruction in increasing derailment risk” and “B4. Track drainage overloaded leading to flooding of the track” due to the heavier precipitation or floods, as well as “D1. Breach of seawall, flooding and derailment risk” due to SLR.

Interestingly, almost all the top potential climate threats are attributed to the intense rainfall/flooding. This finding is consistent with, and provides scientific experimental numerical evidence to support, the current priorities for tackling flooding issues in climate adaptation in the UK. The lowest threats are “B3. Heavy rain affecting visibility, and scheduled work may have to be rescheduled for

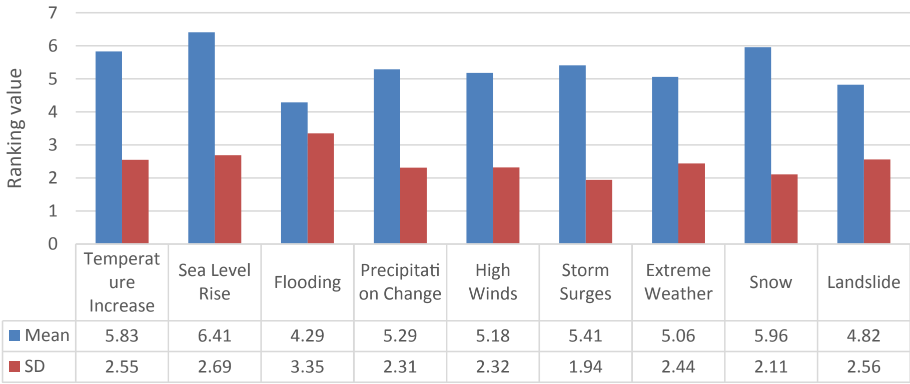

Fig. 4. Ranking of the primary climate threats to the UK railways.

Table 2
Questionnaire results of primary climate threats to the UK railways.

		Temperature Increase	SLR	Flooding	Precipitation Change	High Winds	Storm Surges	Extreme Weather	Snow	Landslide
Wales	Mean	6.67	6.00	4.56	6.22	5.44	5.44	5.56	5.56	5.22
	SD	2.74	2.74	3.61	2.17	2.51	2.13	2.13	2.24	2.73
Scotland	Mean	4.70	4.37	4.08	4.19	3.97	3.79	3.84	3.90	3.98
	SD	2.78	2.31	0.67	2.87	2.08	2.35	2.42	2.34	1.76
Northern Ireland	Mean	4.22	3.85	3.23	3.86	3.50	3.43	3.49	3.51	3.42
	SD	1.87	1.68	1.75	1.78	1.53	1.53	1.57	1.56	1.50
England	Mean	3.83	3.49	2.98	3.52	3.17	3.11	3.17	3.18	3.10
	SD	1.74	1.58	1.48	1.62	1.43	1.42	1.45	1.45	1.40
UK	Mean	5.88	6.41	4.29	5.29	5.18	5.41	5.06	5.94	4.82
	SD	2.55	2.69	3.35	2.31	2.32	1.94	2.44	2.11	2.56

safety and welfare reasons“ owing to the increase in intense rainfall/flooding. It reflects that in the UK rail climate adaptation planning, stakeholders worry more on the negative impact on infrastructure than operations, possibly due to the direct losses/ consequences from the two are not at the same scale.

4.4. Risk analysis of different stakeholder groups

To further investigate the opinions from different stakeholder groups regarding climate threats on railways, this survey questionnaire asked for the information of participants' positions and names of their organisations. We analysed this data by dividing it into three categories: (1) Engineer, CEO, manager or scholar by the respondent's position;[9] (2) consulting company, NGO, transport company or academia by the organisation's type; (3) small-size, middle-size or large-size entities by the organisation's scale.[10] Fig. 6 illustrates the percentage distribution of each group. Small companies/organisations and CEOs take account the most substantial portion (40%) of the total responses in terms of the scale of the entity and participants' position. Meanwhile, transport companies and consulting companies are the primary types of entities, occupying 30% of the total responses, respectively.

The modelling results of climate risk level, including the utility values and rankings of all potential climate threats owing to the four environmental drivers, are calculated in each category.[11]

With regard to the participants' positions, the two lowest utility values are attributed to engineers (0.36 and 0.38) regarding "B1" and "B2" risks caused by intensive rainfall/flooding, respectively. It indicates that they expect stronger, sooner, more likely and weaker resilient climate risks on their railways compared to CEOs and scholars. This is probably because engineers are the people who are involved in day-to-day rail operations and witness the direct damage to the rail infrastructure caused by climate change. However, for managers, CEOs and scholars their information about climate risks is gained from official documents and publications. In particular, scholars hold the lowest risk-level opinions for all the four environmental drivers ("A2", "B3", "C2", "C3" and "D2"). It shows the importance of experimental evidence from climate impact for climate adaptation in promoting the relevant education and training in future.

[9] The engineers include transport engineers, freight and logistics technologists; CEOs includes associate directors, transport directors, strategy and development director; managers include supply chain managers, transport managers, strategy managers, performance programme managers and environmental managers; scholars include rail research fellows and PhD candidates

[10] The large-size organisation means the one has over 10,000 employees, middle-size organisation means the one has 1,000–10,000 employees and small-size organisation means the one has less than 1,000 employees.

[11] The results of climate risk analysis for each category are shown in Appendix B.

Table 3
Survey results of climate risk assessment on British railways.

Environmental drivers	climate threats	CRLs	Utility values	Ranking
Higher temperature	A1.Track buckling causing derailment risks & reducing opportunities for track maintenance	{0.1154, 0.1808, 0.3003, 0.1922, 0.2116}	0.54	6
	A2.Unreliable signalling, power lineside systems, failure of temperature controls and overheating of electronic equipment	{0.0858, 0.2016, 0.3228, 0.2116, 0.1783}	0.54	6
Heavier precipitation or floods	B1.Bridge foundations damaged leading to bridge collapse and derailment risk	{0.1083, 0.3299, 0.2613, 0.2109, 0.0896}	0.47	1
	B2.Landslips causing obstruction in increasing derailment risk	{0.1590, 0.2313, 0.2406, 0.2700, 0.0991}	0.48	2
	B3. Heavy rain affect visibility, scheduled work may have to be rescheduled for safety and welfare reasons	{0.0621, 0.1617, 0.2115, 0.3192, 0.2455}	0.6	8
	B4.Track drainage overloaded leading to flooding of track	{0.0927, 0.2874, 0.2502, 0.2716, 0.0981}	0.5	3
More frequent or intense storm and high winds	C1.Trees falling onto the line	{0.1138, 0.2045, 0.2863, 0.2944, 0.1010}	0.51	4
	C2.High winds affect visibility, and scheduled work may have to be rescheduled for safety and welfare reasons	{0.0997, 0.2689, 0.2229, 0.1833, 0.2252}	0.53	5
	C3.Instability of structures	{0.0500, 0.1482, 0.4197, 0.1832, 0.1899}	0.56	7
SLR	D1.Breach of sea wall, flooding and derailment risk	{0.0830, 0.2974, 0.3390, 0.2142, 0.0663	0.48	2
	D2.Reduced maintenance opportunities, bridges/ sea walls may not be safely inspected	{0.0156, 0.2488, 0.3305, 0.2458, 0.1594}	0.56	7

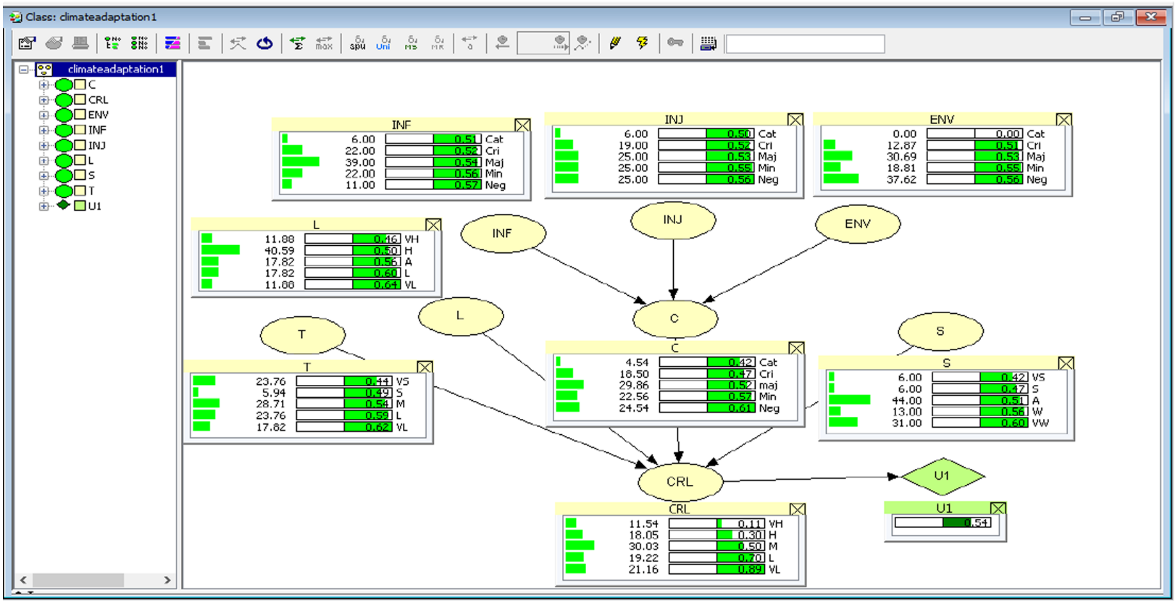

Fig. 5. Climate risk analysis of “A1. Track buckling causing derailment risks & reducing opportunities for track maintenance” using Hugin.

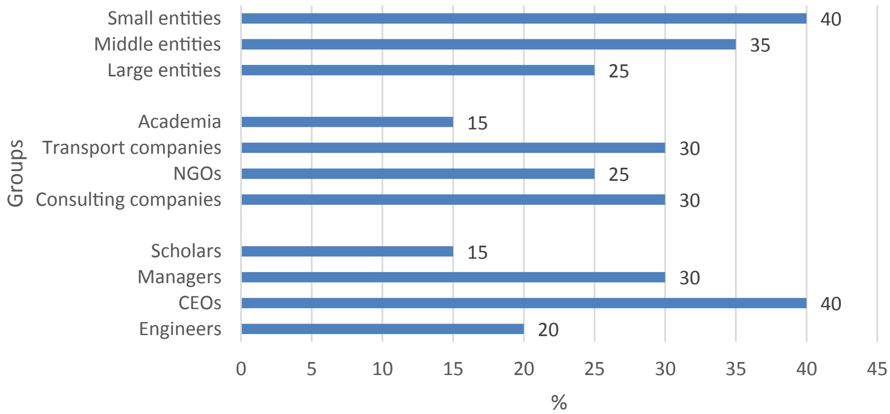

Fig. 6. The distribution of responses by participants’ position, type and scale of their entity.

Table 4
Survey results of climate risk evaluation by different groups.

Category		Average utility value	Overall ranking of risk level
Position	Engineer	0.49	1
	CEO	0.50	2
	Manager	0.53	3
	Scholar	0.63	4
Type	Consulting	0.45	1
	NGO	0.48	2
	Transport Company	0.58	3
	Academia	0.64	4
Scale	Large	0.47	1
	Middle	0.58	3
	Small	0.54	2

After all, from the research perspective, climate risk in rail systems has a backseat role, despite growing attraction of interest, compared to other rail research such as optimisation. Regarding the type of participants' entity, NGOs and consulting companies present the highest-level climate risks concerning "B2" (flooding) and "D1" (SLR). They have more chances to engage with different stakeholders and projects in the rail systems and are more likely to have comprehensive views in considering multiple perspectives of railways, including climate impacts. Similarly, the lowest risk-level is attributed to academia, in particular, for the impacts posed by intensive rainfall/flooding and increased intensity and/or frequency of high wind and/or storms ("B3", "C2" and "C3").

In terms of the organisation scale, large-size companies/organisations estimate a highest-level risk scenario due to intensive rainfall/flooding, including "B1" and "B2". On the contrary, small-size and middle-size organisations hold the lowest risk-level perspectives regarding more frequent and intense storms and high winds as well as SLR ("C2", "C3" and "D2"). This is probably because large organisations usually have more resources to look at climate risk issues from a strategic perspective and to collect diverse information about climate risks as well as devote resources in climate assessment and adaptation.

Finally, the overall group ranking of climate risk level can be obtained by averaging the utility values of each category of an individual group (Table 4). Engineers from large consulting companies have the highest risk-level opinions. Their top concerns, according to the above group analyses, are "B1" and "B2" caused by heavier precipitation or floods, which is consistent with the previous findings in Table 2. Besides the aforementioned threat posed by "B3" due to the intensive rainfall/flooding increases, "C2. High winds affect visibility, and scheduled work may have to be rescheduled for safety and welfare reasons" and "C3. Instability of structures" owing to more frequent or intense and storms and high winds received the least attention from academics and small companies/organisations. Interestingly, it is noticeable that the invisibility and rescheduling issues ("C2") triggered by high winds or storms are similar to the issues owing to heavy rain ("B3"), with the least likely to generate critical damages to infrastructure and operations in the short term.

5. Discussion

Although relevant stakeholders in the rail sector has started paying more attention to handle the climate threats (Hooper & Chapman, 2012), the quantification of climate risks and costs for rational adaptation is still at an embryonic phase (Network Rail, 2017). Compared to the previous academic literature, the major theoretical contribution of this work lie in the new development of an extended FBN risk model to enable the quantification of climate risk under uncertainty in data. The developed model is presented in a generic manner first and later applied within the context of the UK railways. It for the first time introduces a new risk assessment method to quantify climate risks based on stakeholders' perceptions, which can be adopted to deal with climate risks in different sectors and hence realise the risk informed climate adaptation planning. Meanwhile, to test the model and demonstrate its feasibility, we have also piloted a large-scale national survey on climate risks facing the UK railway systems. It reveals a real picture of diverse environmental drivers and climate threats on rail transportation in the UK and address the high demand on empirical evidence on climate risks in the current literature.

The investigation shows that flooding, landslide and extreme weather are the top three climate threats, whereas their impact to the rails might be varying in different areas. The other main threats (i.e. high winds and precipitation change) occur more invariably. SLR is regarded as the lowest risk overall. Moreover, through analysing and comparing the results of the four regions in the UK, we notice that flooding and landslides are the common primary climate threats. Similar to the overall ranking, flooding has variable impacts in each area, with the most serious influence in England. However, the landslide has a stable occurrence except for Wales. Additionally, extreme weather is a common threat for the rails in Northern Ireland and England, high winds are a common risk for Wales and Scotland, and storm surges are a common one for Wales and England. The above risk assessment presents an overall picture of how climate change possesses threats to the UK rail transport system.

Four primary environmental drivers due to climate change are identified through the literature review. The climate risk level for each potential climate threats is evaluated by a combined risk index from the four parameters of the timeframe and likelihood of risk occurrence, the severity of consequences, as well as transport resilience. The top climate threats are highly related to the heavier precipitation and floods ("B1", "B2" and "B4"), which coheres with the current priorities of flooding adaptation in the UK. The research findings reinforce the most significant climate threats in the rail sector by providing new empirical evidence. More importantly, it provides the risk estimates in a quantitative manner, an effective and essential instrument for rationalising climate adaptation planning. Flooding and landslide are deemed to be most critical threats as mentioned by respondents, which mainly affect the east coastline between Scotland and Newcastle and the west coastlines. For instance, the storm in Devon closed the line at Dawlish after the coastal railway fell into the sea. Increased temperature shows particular impacts on urban areas, such as London Underground. Ayrshire coastlines are electrified and are subject to tripping when sea surges lead to short-circuiting power lines.

Through dissecting the perception of different groups, engineers from large consulting companies hold the highest risk-level perception. Simultaneously, "B1. Bridge foundations damaged leading to bridge collapse and derailment risk" and "B2. Landslips obstructing increasing derailment risk" posed by intense rainfall/flooding are still the top issues from the perspective of engineers at large consulting companies. By contrast, the invisibility and rescheduling issues ("C2. High winds affect visibility, and scheduled work may have to be rescheduled for safety and welfare reasons" and "B3. Heavy rain affects visibility, and scheduled work may have to be rescheduled for safety and welfare reasons") posed by high winds or storms and heavy rain are considered to pose the lowest risk threats in overall, with a low possibility of leading to catastrophic damages to rail infrastructure and operations in the short term.

Although climate change risk and its impact on rail systems attract increasing attention in the UK (Hooper & Chapman, 2012), only one-third of our survey participants have implemented an adaptation plan. Nevertheless, nearly half the participants who have yet developed any adaptation plans acknowledge that they will consider developing adaptation plans in the future.

The recently published official UKCP18 (UK Climate Projections, 2018) by the UK government provides useful global information covering the full range of climate variables at a more detailed resolution . Supplementary with the results of this survey, the projection is also expected to offer scientific guidance for dealing with the challenges of estimation and selection of risk scenarios under diverse climate conditions. Thus, it will be great timing for regions, where there is a lack of detailed and dated climate information for risk assessment, to be able to produce a climate adaptation plan. The findings revealed from this work, together with the novel FBR modelling method, are expected to provide researchers and transport planners with reference to risk assessment and cost-benefit analysis for climate adaptation planning in the future.

6. Conclusion and implications

This paper uses an in-depth investigation of relevant literature, and an advanced mathematical model supported by a large-scale survey to systematically implement a climate risk analysis within the context of the UK rail systems. Overall, the analytical results and modelling innovation will significantly contribute to further studies in climate change, transport safety and planning, supply chain and logistics risk management and other interdisciplinary areas. Both theoretical and practical contributions have been discussed and summarised as follows.

We conducted a thorough literature review and a nation-wide questionnaire survey to reveal the major climate threats in the UK rail systems. The evidence of major rail accidents by climate threats emphasises the necessity of investigating climate change threats in railway systems. Meanwhile, it bridges the existing research gaps regarding the climate risk assessment in the UK rail sector. The major climate threats facing the UK railways include “*B1. Bridge foundations damaged leading to bridge collapse and derailment risk”, “B2. Landslips causing obstruction in increasing derailment risk” and “B4. Track drainage overloaded leading to flooding of the track” due to the heavier precipitation or floods, as well as “D1. Breach of seawall, flooding and derailment risk”, which are attributed to the intense rainfall/flooding and SLR. Flooding and landslide are regarded as the common climate threats for the all UK regions, with the highest ranking in England. Meanwhile, the highest risk-level perception was hold by engineers from large consulting companies.*

Methodologically, an advanced FBR approach is for the first time introduced to quantify the climate risks facing railway systems. It not only addresses the high uncertainty of the climate data, but also realises accurate risk assessments based on subjective perception with the addition of new features on the fuzzy rule base structure (moving from two-layer to three-layer) and incorporation of a new risk parameter ‘transport resilience’ in the climate risk analysis. Using a pioneering questionnaire survey on the UK rail systems, the modelling results offer experimental evidence to support major climate threats and adaptation issues documented in the existing literature (e.g., flooding, landslides and SLR). More importantly, the findings prioritise the risk levels of the major climate threats in a quantitative manner, which provides a solid foundation to rationalise adaptation planning studies in future.

In practice, it provides railway practitioners with a new methodology by integrating qualitative analysis with mathematical modelling. After the findings are shared with survey participants and wider audience through their networks, we receive the consistent feedback that the study offers a scientific interpretation of the risk perception of the climate threats in the UK railway systems.

This study makes a pioneering attempt in climate risk analysis. It can be used either as a standing-alone result to compare the risk levels of climate threats in the UK rail systems in a quantitative manner, or as a basic element to be incorporated into a broader comparative study of climate risks and adaptation affecting the rail systems at the next stage.

Further research may include a comprehensive analysis on adaptation planning in terms of identifying the feasibility, deficiency and resilience in organisations that have already considered and engaged with adaptations as well as motivation and challenges faced by non-engaged organisations. It is also noted that due to sampling limit, it is possibly under-reporting some threats (e.g. snow in Scotland) and opinions from other groups (e.g., large entities and scholars) leading to the requirements of further investigation involving a broader pool of stakeholders in under-reached regions. Moreover, future research might also consider testing the effect of having different weights of the risk parameters on the final result ranking under diverse risk scenarios.

CRediT authorship contribution statement

Tianni Wang: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Zhuohua Qu:** Conceptualization, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Zaili Yang:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Timothy Nichol:** Writing - review & editing, Supervision, Project administration, Funding acquisition. **Delia Dimitrio:** Writing - review & editing. **Geoff Clarke:** Validation, Writing - review & editing. **Daniel Bowden:** Validation, Writing - review & editing.

Acknowledgements

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Appendix A:. Questionnaire

INFORMATION CONSENT

You are cordially invited to participate on the captioned research study conducted by the principal investigator, Tianni Wang, who is a Ph.D. student of Liverpool Business School of Liverpool John Moores University (UK), under the supervision of Dr. Zhuohua Qu. This project will be a significant part of Tianni's thesis. Understanding your experiences and prestige in this area, you are invited to participate in a 20minute online survey.

Prior to your decision to participate, it is important that you understand why the research is being done and what it involves. Please take time to read the following information (the Participant Information Sheet and sign the Participant Consent Form). Please contact - if there is anything that is not clear or if you like some more information.

1. Participant's agreement

□ I understand the information regarding participation in the project and agree to participate in this survey.

2. Date

DD/MM/YYYY ______/____ /_______

BACKGROUD INFORMATION

3. What is the name of your company/organisation? Which geographic areas of the railway are your company/organisation responsible for/operate on?

____

____

4. What is your current position at your company/organisation? (Optional)

☐ CEO or Transport Director

☐ Planner

☐ Transport Engineer

☐ Transport Operator

☐ Environmental Manager

☐ Public Relations Director

☐ Development Director

☐ Safety or Security Director

☐ Environmental Academics

☐ Other (please specify) ________________________________

5. In your view, what types of risks are posed by climate change on the railway your organisation associated with? (Please rank the following items which impacted your company; if not at all, please specify)

( ) High Temperature
( ) Sea Level Rise
( ) Flooding
( ) Precipitation Change
( ) High Winds
( ) Storm Surges
( ) Extreme Weather
( ) Snow
( ) Landslide
( ) Other (please specify) _______________________________

6. If the rail your company/organisation are responsible for has been impacted by climate change in the past 10 years, please details including <u>line name(s)</u>(e.g., east coast main line), <u>happened year</u>(s), and <u>main damages</u>.

____

____

____

7. Has your company/organization made an adaptation plan for climate change?

□ Yes, we have implemented an adaptation plan

□ No, we have not implemented an action plan but will consider doing so in the future

□ No, we have not, nor do we have any plans to implement a climate adaptation plan in the future

ADAPTATION STRATEGIES IN THE FUTURE

- **What climate risks would you expect the railway to be exposed to in the FUTURE if your company/organisation does NOT undertake any ADAPTATION measures?**

Description of Variables

Timeframe *- when you expect to first see this impact:*

1. <u>Very Long (VL)</u>--More than 20 years

2. <u>Long (L)</u>--Approximately 15 years

3. <u>Medium (M)</u>--Approximately 10 years

4. <u>Short (S)</u>--Approximately 5 years

5. <u>Very short (VS)</u>--Less than 1 year

Severity of consequences *of this impact:*

Three subcategories are included— ***damage to property (PRO), damage to injures and loss of lives (INJ) and damage to the environment (ENV)***

The damage to properties (PRO):

1. <u>Catastrophic (Ca)</u> -- the damage committed to property is valued at more than £2 million

2. <u>Critical (Cr)</u> -- the damage committed to property is valued between £1million and £2 million

3. <u>Major (Maj)</u> -- the damage committed to property is valued between £500,000 and £1 million

4. <u>Minor (Min)</u> -- the damage committed to property is valued between £100,000 and £500,000

5. <u>Negligible (Neg)</u> -- the damage committed to property is valued at less than £500,000

The damage to injuries and loss of lives (INJ):

1. <u>Catastrophic (Ca)</u>-- major injures and loss of more than 10 lives

2. <u>Critical (Cr)</u> -- many major injuries or/and loss of 5 to 10 lives

3. <u>Major (Maj) --</u> major injures and loss of less than 5 lives

4. Minor (Min) -- minor injuries and no loss of life

5. Negligible (Neg)--no injuries and no loss of life

The damage to environment (ENV):

1. Catastrophic (Ca)—the event contributes to over 50% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations;

2. Critical (Cr)-- the event contributes to 30-50% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations

3. Major (Maj)-- the event contributes to 20-30% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations

4. Minor (Min)-- the event contributes to 10-20% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations

5. Negligible (Neg)-- the event contributes to less than 10% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations

***Likelihood** that the effect will occur:*

1. Very High (VH)--It is probable that the stated effect will occur, with a likelihood of around 90%

2. High (H)--It is highly likely that the stated effect will occur, with a probability of around 70%

3. Average (A)--It is likely that the stated effect will occur, with a probability of around 50%

4. Low (L)--It is unlikely that the stated effect will occur, with a probability of around 30%

5. Very low (VL)--It is very unlikely that the stated effect will occur, with a probability of around 10%

***Climate Resilience**: the capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event in a timely and efficient manner, including through ensuring the preservation, restoration, or improvement of its essential basic structures and functions (IPCC, 2012)*

1. Very Strong (VS)—Very strong (80% above) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event in a very *timely and efficient manner (12hrs) and requiring slight cost of recovery (0-£1,000)*

2. Strong (S)-- Strong (60-80%) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event in a relatively timely and efficient manner (a day) and requiring some cost of recovery (£10,000-£100,000)

3. Average (A)—Average (40-60%) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event and requiring certain length of time (a week) and cost of recovery (£100, 000-£1million)

4. Weak (W)—Weak (20%-60) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event and requiring a long period (a month) and high cost of recovery (£1million above)

5. Very Weak (VW)— Very weak (0-20%) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event and requiring a very long period (a year) and very high cost of recovery(£10millions above)

It can be descried by the following three parameters. The worse-case scenario is applied to assess the system's resilience. For instance, if the capacity of the transport system to recover is "Very Strong", the time of the recovery is "Strong" and the cost of recovery is "Weak", then the final assessment result should be "Weak".

Please describe each of the SIX items in the following question 8-11.

8. Temperature Increase

	Timeframe	Severity of Consequences			Likelihood	Climate Resilience
		PRO	INJ	ENV		
(a)Track buckling causing derailment risks & reducing opportunities for track maintenance	______	__	__	__	_____	______
(b) Unreliable signalling and power line side systems & failure of temperature controls and overheating of electronic equipment	______	__	__	__	______	______
(c) Sag of overhead line & risk of dewirement	______	__	__	__	______	______

9. Intense Rainfall /Flooding

	Timeframe	Severity of Consequences			Likelihood	Climate Resilience
		PRO	INJ	ENV		
(a) Bridge foundations become undermined leading						

to bridge collapse and derailment risk ______ __ __ __ ______ ______

(b) Landslips causing obstruction in cutting

derailment risk ______ __ __ __ ______ ______

10. More intense and/or frequent high wind and/or storms

	Timeframe	Severity of Consequences			Likelihood	Climate Resilience
		PRO	INJ	ENV		
(a) Trees being blown on to the line	______	__	__	__	______	______
(b) Dewirement of overhead traction power lines	______	__	__	__	______	______

11. Sea Level Rise

	Timeframe	Severity of Consequences			Likelihood	Climate Resilience
		PRO	INJ	ENV		
(a) Breach of sea wall, flooding and derailment risk	______	__	__	__	______	_____
(b) Overtopping waves damaging & affecting vehicles	______	__	__	__	______	______

- **If your company/organisation undertakes planned ADAPTATION measures, how do you anticipate the climate risks will change in the FUTURE? (If your company/organisation will not undertake any adaptation measures, please skip this part)**

Description of Variables

***Financial cost** of adaptation:*

1. Very High (VH)--involves a very high financial cost so as to comprehensively address the stated potential effect

2. High (H)--involves a high financial cost so as to comprehensively address the stated potential effect

3. Average (A)--involves a significant financial cost so as to comprehensively address the stated potential effect

4. Low (L)--involves a financial cost (though not that significant) so as to comprehensively address the stated potential effect

5. Very low (VL)--involves a minimal financial cost so as to comprehensively address the *stated potential effect*

***Timeframe** for when you expect to first see this impact:*

1. Very Long (VL)--More than 20 years

2. Long (L)--Approximately 15 years

3. Medium (M)--Approximately 10 years

4. Short (S)--Approximately 5 years

5. Very short (VS)--Less than 1 year

***Severity of consequences**:*

*Three subcategories are included— **damage to properties (PRO), injuries and loss of life (INJ) and damage to environment (ENV)***

The damage to properties (PRO):

1. Catastrophic (Ca) -- the damage committed to property is valued at more than £2 millions

2. Critical (Cr) -- the damage committed to property is valued at more than £1million and less than £2 millions

3. Major (Maj) -- the damage committed to property is valued at between £500,000 and £1 million

4. Minor (Min) -- the damage committed to property is valued at between £100,000 and £500,000

5. Negligible (Neg) -- the damage committed to property is valued at less than £500,000

The damage to injuries and loss of lives (INJ):

1. Catastrophic (Ca)-- major injures and loss of more than 10 lives

2. Critical (Cr) -- many major injuries or/and loss of 5 to 10 lives

3. Major (Maj) -- major injures and loss of less than 5 lives

4. Minor (Min) -- minor injuries and no loss of life

5. Negligible (Neg)--no injuries and no loss of life

The damage to environment (ENV):

1. Catastrophic (Ca)—the event contributes to over 50% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations;

2. Critical (Cr)-- the event contributes to 30-50% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations
3. Major (Maj)-- the event contributes to 20-30% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations
4. Minor (Min)-- the event contributes to 10-20% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations
5. Negligible (Neg)-- the event contributes to less than 10% of the total amount of potential damage to be caused to the surrounding environment for whole the period of industrial operations

Likelihood *that the effect will occur:*
1. Very High (VH)--It is very highly likely that the stated effect will occur, with a probability of around 90% of at least one such incident within the indicated timeframe
2. High (H)--It is highly likely that the stated effect will occur, with a probability of around 70% of at least one such incident within the indicated timeframe
3. Average (A)--It is likely that the stated effect will occur, with a probability of around 50% of at least one such incident within the indicated timeframe
4. Low (L)--It is unlikely that the stated effect will occur, with a probability of around 30% of at least one such incident within the indicated timeframe
5. Very low (VL)--It is very unlikely that the stated effect will occur, with a probability of around 10% of at least one such incident within the indicated timeframe

Climate Resilience*: the capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event in a timely and efficient manner, including through ensuring the preservation, restoration, or improvement of its essential basic structures and functions (IPCC, 2012).*

It can be descried by the following three parameters. The worse-case scenario is applied to assess the system's resilience. For instance, if the capacity of the transport system to recover is "Very Strong", the time of the recovery is "Strong" and the cost of recovery is "Weak", then the final assessment result should be "Weak".

1. Very Strong (VS)—Very strong (80% above) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event in a very *timely and efficient manner (12hrs) and requiring slight cost of recovery (0-£1,000)*

2. Strong (S)-- Strong (60-80%) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event in a relatively timely and efficient manner (a day) and requiring some cost of recovery (£10,000-£100,000)

3. Average (A)—Average (40-60%) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event and requiring certain length of time (a week) and cost of recovery (£100, 000-£1million)

4. Weak (W)—Weak (20%-60) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event and requiring a long period (a month) and high cost of recovery (£1million above)

5. Very Weak (VW)— Very weak (0-20%) capacity of the transportation system to anticipate, absorb, accommodate, or recover from the effects of a climate event and requiring a very long period (a year) and very high cost of recovery(£10millions above)

It can be descried by the following three parameters. The worse-case scenario is applied to assess the system's resilience. For instance, if the capacity of the transport system to recover is "Very Strong", the time of the recovery is "Strong" and the cost of recovery is "Weak", then the final assessment result should be "Weak".

Please describe each of the SEVEN items in the following question 12-15.

12. Temperature Increase

	Financial Cost Of Adaptation	Timeframe	Severity of Consequences			Likelihood	Climate Resilience
			PRO	INJ	ENV		
(a) Track buckling causing derailment risks & reducing opportunities for track maintenance (Adaptation Measure: Maintain tracks to narrower temperature tolerances, such as change to more resistant specifications)	______	______	__	__	__	______	______
(b) Track buckling increasing risk of derailment & reducing opportunities for track maintenance (Adaptation Measure: Impose speed restrictions at 'compromised' sites)	______	______	__	__	__	______	______

(c) Track buckling causing derailment risks
& reducing opportunities for track maintenance

(Adaptation Measure: Restrict ballast disturbance activity during hot weather) ______ ______ __ __ __ ______ ______

(d) Track buckling causing derailment risks & reducing opportunities for track maintenance (Adaptation Measure: Paint rails white at critical locations) ______ ______ __ __ __ ______ ______

(e) Unreliable signalling and power line side systems, failure of temperature controls and overheating of electronic equipment (Adaptation Measures: Use active or passive cooling of Equipment cabinets) ______ ______ __ __ __ ______ ______

(f) Unreliable signalling and power line side systems, failure of temperature controls and overheating of electronic equipment (Adaptation Measures: Make use of high thermal inertia design) ______ ______ ______ ______ ______

(g) Unreliable signalling and Power line side systems & failure of temperature controls and overheating of electronic equipment (Adaptation Measures: Position cabinets in shade) ______ ______ __ __ __ ______ ______

(h) Unreliable signalling and Power line side systems & failure of temperature controls and overheating of electronic equipment (Adaptation Measures: Re-specify and replace equipment)_____ ______ __ __ __ ______ ______

(i) Sag of overhead line & risk of dewirement (Adaptation Measures: Strengthen mast and wire system) ______ ______ __ __ __ ______ ______

13. Intense Rainfall /Flooding

	Financial Cost Of Adaptation	Timeframe	Severity of Consequences	Likelihood	Climate Resilience
(a) Bridge foundations become undermined leading to bridge collapse and derailment risk			PRO INJ ENV		

(Adaptation Measure: Improve scour resilience during routine renewal of scour protection systems) ______ ______ __ __ __ ______ ______

(b) Bridge foundations become undermined leading to bridge collapse and derailment risk (Adaptation Measure: Design future bridges to withstand climate change) ______ ______ __ __ __ ______ ______

(c) Bridge foundations become undermined leading to bridge collapse and derailment risk (Adaptation Measure: Introduce flood risk monitoring linked to flood agency forecasts and monitor river levels) ______ ______ __ __ __ ______ ______

(d) Landslips causing obstruction in cutting Derailment risk (Adaptation Measure: Map water concentration locations) ______ ______ __ __ __ ______ ______

(e) Landslips causing obstruction in reducing Derailment risk (Adaptation Measure: Identify and introduce resilience measures at vulnerable sites, such as shaping to reduce slope angles)______ ______ __ __ __ ______ ______

(f) Landslips causing obstruction in cutting Derailment risk (Adaptation Measure: Vegetation management) ______ ______ __ __ __ ______ ______

(g) Landslips causing obstruction in cutting Derailment risk (Adaptation Measure: Improve earthworks and drainage management)______ ______ __ __ __ ______ ______

14. More intense and/or frequent high wind and/or storms

	Financial Cost Of Adaptation	Timeframe	Severity of Consequences	Likelihood	Climate Resilience
			PRO INJ ENV		
(a) Trees being blown on to the line (Adaptation Measure: Identify at-risk locations)	______	______	__ __ __	_____	______
(b) Trees being blown on to the line					

(Adaptation Measure: Vegetation management) ______ ______ __ __ __ ______ ______

(c) Dewirement of overhead traction power lines (Adaptation Measure: Identify at-risk locations) ______ ______ __ __ __ ______ ______

(d) Dewirement of overhead traction power lines (Adaptation Measure: Strengthen existing equipment, at renewal stage if possible)______ ______ __ __ __ ______ ______

(e) Dewirement of overhead traction power lines (Adaptation Measure: Design new equipment with uncertainty in mind, making provision to retrofit or– if economically sound – build in resilience) ______ ______ __ __ __ ______ ______

15. Sea Level Rise

	Financial Cost Of Adaptation	Timeframe	Severity of Consequences (PRO INJ ENV)	Likelihood	Climate Resilience
(a) Breach of sea wall, flooding and derailment risk (Adaptation Measure: Rebuild wall to appropriate standards)	______	______	__ __ __	______	______
(b) Breach of sea wall, flooding and derailment risk (Adaptation Measure: Introduce a sea level rise forecasting system)	______	______	__ __ __	______	______
(c) Overtopping waves damaging & affecting vehicles (Adaptation Measure: Rebuild wall to appropriate standards)	______	______	__ __ __	______	______
(d) Overtopping waves damaging & affecting vehicles (Adaptation Measure: Introduce a sea level rise forecasting system)	______	______	__ __ __	______	______

OTHER COMMENTS

16. Additional Comments:

____

THIS IS THE END OF THE SURVEY. THANK YOU VERY MUCH FOR YOUR TIME AND CONTRIBUTIONS!!

Appendix B:. Survey results

Table A1–A3.

Table A1
Survey results of climate risk assessment on British railways by participants' position.

Environmental drivers	Potential climate risks on the railway	Positions	Utility values	Ranking of CRLs
Higher temperature	A1.Track buckling causing derailment risks & reducing opportunities for track maintenance	Engineer	0.55	14
		CEO	0.51	11
		Manager	0.47	5
		Academic	0.53	12
	A2.Unreliable signalling, power line side systems, failure of temperature controls and overheating of electronic equipment	Engineer	0.51	11
		CEO	0.49	7
		Manager	0.48	6
		Academic	0.68	21
Heavier precipitation or floods	B1. Bridge foundations damaged leading to bridge collapse and derailment risk	Engineer	0.38	2
		CEO	0.50	9
		Manager	0.54	13
		Academic	0.54	13
	B2.Landslips causing obstruction in increasing derailment risk	Engineer	0.36	1
		CEO	0.46	4
		Manager	0.43	3
		Academic	0.51	11
	B3.Heavy rain affect visibility, scheduled work may have to be rescheduled for safety and welfare reasons	Engineer	0.57	15
		CEO	0.55	14
		Manager	0.54	13
		Academic	0.70	22
	B4.Track drainage overloaded leading to flooding of tracks	Engineer	0.48	6
		CEO	0.58	16
		Manager	0.51	11
		Academic	0.53	12
More frequent or intense storm and high winds	C1.Trees falling onto the line	Engineer	0.51	11
		CEO	0.51	11
		Manager	0.47	5
		Academic	0.55	14
	C2.High winds affect visibility, scheduled work may have to be rescheduled for safety and welfare reasons	Engineer	0.53	12
		CEO	0.51	11
		Manager	0.63	18
		Academic	0.73	23
	C3.Instability of structures	Engineer	0.49	8
		CEO	0.48	6
		Manager	0.61	17
		Academic	0.77	23
SLR	D1.Breach of seawall, flooding and derailment risk	Engineer	0.50	10
		CEO	0.43	3
		Manager	0.49	8
		Academic	0.67	20
	D2.Reduced maintenance opportunities, bridges/ sea walls may not be safely inspected	Engineer	0.46	4
		CEO	0.49	8
		Manager	0.65	19
		Academic	0.73	23

Table A2
Survey results of climate risk assessment on British railways by type of organisations.

Environmental drivers	Potential climate risks on the railway	Types	Utility values	Ranking of CRLs
Higher temperature	A1.Track buckling causing derailment risks & reducing opportunities for track maintenance	Consulting	0.47	8
		NGO	0.49	9
		Rail operator	0.51	11
		Academia	0.53	13
	A2.Unreliable signalling, power line side systems, failure of temperature controls and overheating of electronic equipment	Consulting	0.54	14
		NGO	0.57	21
		Rail operator	0.64	24
		Academia	0.68	21
Heavier precipitation or floods	B1. Bridge foundations damaged leading to bridge collapse and derailment risk	Consulting	0.50	10
		NGO	0.43	5
		Rail operator	0.46	7
		Academia	0.56	16
	B2.Landslips causing obstruction in increasing derailment risk	Consulting	0.38	2
		NGO	0.36	1
		Rail operator	0.50	10
		Academia	0.51	11
	B3.Heavy rain affect visibility, scheduled work may have to be rescheduled for safety and welfare reasons	Consulting	0.51	11
		NGO	0.51	11
		Rail operator	0.68	24
		Academia	0.70	25
	B4.Track drainage overloaded leading to flooding of tracks	Consulting	0.47	8
		NGO	0.47	8
		Rail operator	0.61	19
		Academia	0.61	19
More frequent or intense storm and high winds	C1.Trees falling onto the line	Consulting	0.42	4
		NGO	0.52	12
		Rail operator	0.55	15
		Academia	0.65	22
	C2.High winds affect visibility, and scheduled work may have to be rescheduled for safety and welfare reasons	Consulting	0.43	5
		NGO	0.46	7
		Rail operator	0.66	23
		Academia	0.71	26
	C3.Instability of structures	Consulting	0.44	6
		NGO	0.51	11
		Rail operator	0.63	20
		Academia	0.77	27
SLR	D1.Breach of the sea wall, flooding and derailment risk	Consulting	0.40	3
		NGO	0.44	6
		Rail operator	0.55	15
		Academia	0.68	24
	D2.Reduced maintenance opportunities, bridges/ sea walls may not be safely inspected	Consulting	0.43	5
		NGO	0.56	16
		Rail operator	0.58	18
		Academia	0.68	24

Table A3
Survey results of climate risk assessment on British railways by scale of organisations.

Environmental drivers	Potential climate risks on the railway	Scale	Utility values	Ranking of CRLs
Higher temperature	A1.Track buckling causing derailment risks & reducing opportunities for track maintenance	Large	0.48	8
		Middle	0.57	14
		Small	0.52	12
	A2.Unreliable signalling, power line side systems, failure of temperature controls and overheating of electronic equipment	Large	0.45	4
		Middle	0.61	17
		Small	0.54	13
Heavier precipitation or floods	B1.Bridge foundations damaged leading to bridge collapse and derailment risk	Large	0.41	2
		Middle	0.50	10
		Small	0.45	5
	B2.Landslips causing obstruction in increasing derailment risk	Large	0.40	1
		Middle	0.51	11
		Small	0.42	3
	B3.Heavy rain affect visibility, scheduled work may have to be rescheduled for safety and welfare reasons	Large	0.50	10
		Middle	0.73	21
		Small	0.58	15
	B4. Track drainage overloaded leading to flooding of tracks	Large	0.48	8
		Middle	0.67	19
		Small	0.46	6
More frequent or intense storm and high winds	C1.Trees falling onto the line	Large	0.48	8
		Middle	0.51	11
		Small	0.60	16
	C2.High winds affect visibility, and scheduled work may have to be rescheduled for safety and welfare reasons	Large	0.47	7
		Middle	049	9
		Small	0.73	21
	C3.Instability of structures	Large	0.52	12
		Middle	0.48	8
		Small	0.73	21
SLR	D1.Breach of seawall, flooding and derailment risk	Large	0.48	8
		Middle	0.66	18
		Small	0.47	7
	D2.Reduced maintenance opportunities, bridges/ sea walls may not be safely inspected	Large	0.50	10
		Middle	0.68	20
		Small	0.48	8

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