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Poo, MC-P, Yang, Z, Dimitriu, D and Qu, Z

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An advanced climate resilience indicator framework for airports: A UK case study

Abstract

Due to increased extreme weather events, climate adaptation has become an essential issue to be addressed by all transport infrastructures, including airports. This paper aims to develop a Climate Resilience Indicator (CRI) framework for assessing airport climate resilience, which for the first time, considers: climate exposure, vulnerability and adaptive capacity simultaneously and advances the development of climate risk analysis of airports to a point where their adaptation and resilience can be quantified under uncertainty in data. Climate-related data was collected from multiple sources to evaluate an airport's performance against each indicator. An evidential reasoning (ER) approach is used to evaluate each airport by integrating all the indicators to derive its final CRI score. The findings provide valuable insights into how urgently an airport needs to deal with climate change and reveal information to help with resource allocation for different airports nationally through proactive adaptation planning.

Keywords: Climate change adaptation; Climate vulnerabilities assessment; Climate change risk indicators; Airport resilience; Climate resilience

1. Introduction

Climate change is the most significant environmental threat and affects humanity both severely and frequently (Wang and Ng, 2021). More extreme weather events are expected as the climate continues to change. The intensity, frequency, duration, extent and timing of events are increasing and may lead to the fundamental transformation of many established socio-economic systems. The world has

experienced more uncertainties as a result of climate change (IPCC, 2014). These uncertainties create risks, which result in catastrophic incidents. For instance, the 2017 Atlantic hurricane season caused over \$200 billion in damages from 17 storms (Drye, 2017). Such risks significantly impact global transport systems, among which airports are the most sensitive, hence stimulating research into climate risk and resilience. Various studies are working on climate change vulnerabilities and trends in climate change adaptation (Poo et al., 2018, Poo et al., 2019, Poo et al., 2021, Wang et al., 2019, Wang et al., 2020). There are also a growing number of climate risk studies on critical infrastructures due to cyclones (Lam et al., 2017, Hoshino et al., 2016) and heat waves (Schubert et al., 2014), including some data-driven studies for visualising climate resilience (Stamos et al., 2015) and the escalation of extreme climate impacts (Forzieri et al., 2018). Based on the established climate data models, Stamos et al. (2015) compared the climate impacts by the number of extreme weather events (EWE), wind gusts, snowfalls, blizzards, heavy rains, heat waves and cold spells. Forzieri et al. (2018) also revealed climate sensitivities by literature reviews, expert surveys, vulnerabilities for geographic information system data collection and hazard projections.

Although some studies prove the value of climate adaptation, these papers reveal some theoretical and practical problems in their applications. There is little research in the existing literature investigating a new generic methodology where: 1) all climate indicators influencing airport resilience are identified and effectively integrated, 2) the objective data (e.g. annual climate data) and subjective data for qualitative indicators are combined for a single assessment score to give a Climate Resilience Indicator (CRI) for airports, and 3) uncertainty in both objective and subjective data on climate indicators are well dealt with and are transformed from input to output to guide rational adaptation planning.

In order to narrow the research gap, this paper aims to develop a quantitative CRI framework for airports and uses cases within the United Kingdom (UK) to generate insights and guide adaptation planning for airport climate resilience. This paper is structured as follows: Section 2 presents a thorough review of the literature on airport climate adaptation and resilience, Section 3, the relevant airport climate resilience reports and data are analysed. In Section 4, the CRI assessment framework is developed using an ER approach and is explained step by step and in Section 5, 11 representative airports in the UK are assessed for their CRI scores to demonstrate the feasibility of the CRI framework. Finally, in Section 6, the main findings of this paper are summarised as a conclusion.

2. Airport climate adaptation and resilience

Compared to climate mitigation studies in transportation, there are few studies on climate adaptation, and those involving air transportation is even less. Within the context of airport climate adaptation, current studies are carried out from two perspectives: risk assessments and operational strategies. Keokhumcheng et al. (2012) undertook a flood risk assessment in Bangkok's Suvarnabhumi Airport region. Herath et al. (2015) utilised temporal downscaling and spatial approaches to develop relations between intensity, duration, and frequency. This study can be used for sub-daily rainfall extremes in the Perth airport area. Kuok et al. (2016) completed a similar assessment in Kuching city. Furthermore, Coffel et al. (2017) found that the significant temperature rise trend affected airport operations by lowering the aircraft take-off performance. These studies prove that climate risks threaten airport safety and operations. Dunn and Wilkinson (2016) stated that it is possible to build up an adaptive air traffic network to increase the resilience of airport operations. In 2016, EUROCONTROL, which works to achieve safer and smoother air traffic management across entire Europe, clarified the expected climate impacts for airports and provided further insights and directions for building aviation climate resilience (Burbidge, 2016). The critical review of the existing work in airport climate adaptation, and resilience reveals that there is no systematic methodology available to guide and evaluate airport climate resilience. Many available studies focus on one aspect of climate threats or risks for developing climate adaptation. There is no a single framework in which all the indicators influencing airport climate resilience are taken into account.

Along with the new feature of the first attempt on the development of the CRI framework for airports,

this paper will make other new contributions as follows:

- Most CRIs are evaluated by the support of big quantitative data. From a methodological perspective, the new feature of a CRI framework lies in the big data driven ER inference mechanism. In the existing ER applications in risk studies, many are based on subjective data through fuzzy logic (e.g. Yang et al., 2018).
- ii) Indicators classified in three different dimensions and weighted by AHP and synthesized by ER with a dynamic feature against which any irrelevant indicator(s) for a particular investigated airport can be assigned a zero weight to deactivate it in the analysis. In terms of the generalization of the proposed methodology, this new thought is important and significant for airport climate resilience analysis given the fact that different airports may suffer from various climate threats and adaptive capability. It is likely that some indicators in the proposed framework might not necessarily be engaged for all airports.
- iii) The proposed ER approach allows for the analysis and benchmark of airport resilience at the overall top level as well as against individual bottom level indicators so that the best practice (strengths) with regards to a particular indicator from a leader in the analysis can be adapted by the other airports to address their resilience weaknesses.

3. Climate resilience related data collection and analysis

In order to develop a new CRI framework, both the airport's climate resilience and adaptation papers and data have been reviewed and analysed. As a result, the current state of airport CRIs and the associated methodologies are analysed and presented. Climate adaptation reports from different UK airports have been studied to identify and classify all the climate risks they face. Next, public climate data for the UK has been collected from the MET office, which provides the UK national weather service.

3.1. Review and analysis of climate change adaptation reports

On 9th May 2011, the UK Government published a document stating the needs of climate change preparations for different infrastructures (DEFRA, 2011). It presented the government's views and plans for transportation infrastructures to adapt to climate change, as shown in Table 1.

Infrastructure	Key risks
Roads	Flooding from heavy precipitation and extreme storminess
	Bridge damaged by increased river flow
	• Roads damaged due to the weather variation between wetter winters and drier summers
Railways	Flooding from heavy precipitation and extreme storminess
	• Bridge damage due to increased river flow resulting from rainfall and storminess
	• Roads damaged due to the weather variation between wetter winters and drier summers
	• Overheating at the underground stations and in the trains by increased temperatures
Ports	• Increased sea level at ports due to high tides/storm surges
	Increased coastal storminess causing high winds
Airports	High winds by increased storminess

Table 1 Summary of climate risks to transport infrastructures (DEFRA, 2011)

Defra invited nine UK airport reporting bodies, which are listed in Table 2, to submit reports following the guidelines of the Climate Change Act 2008 (Pielke Jr, 2008).

Reporting bodies	Airports	References
Birmingham Airport	Birmingham Airport (BHX)	(Birmingham Airport Holdings
Holdings Ltd.		Ltd, 2011)
Abertis Infraestructuras,	Cardiff Airport (CWL)	(Abertis Infraestructuras S.A.,
S.A.		2011)
Edinburgh Airport Ltd.	Edinburgh Airport (EDI)	(Edinburgh Airport Ltd., 2011)
Gatwick Airport Ltd.	Gatwick Airport (LGW)	(Gatwick Airport Ltd., 2011)
Glasgow Airport Ltd.	Glasgow Airport (GLA)	(Maclachlan, 2011)
Heathrow Airport Ltd.	Heathrow Airport (LHR)	(Heathrow Airport Limited,
_		2011)
London Luton Airport Ltd.	London Luton Airport (LTN)	(London Luton Airport Ltd.,
-	- · ·	2011)

Table 2	Summary of	of climate	change ada	ptation re	ports by	UK airports

Manchester Airports Group plc. (MAG)	Manchester Airport (MAN) And East Midlands Airport (EMA)	(Manchester Airports Group plc, 2011)
BAA Airports Ltd.	London Stansted Airport (STN)	(Jefferson, 2011)

All the airports (except for Edinburgh Airport) have implemented risk assessments. 207 risk issues were found in the reports in total. Even though not all the issues can be compared directly, there are some insights from statistical analyses and visualisation of the climate risks in this century. In the meantime, although Aberdeen International Airport has not submitted its adaptation report, it is considered in this study because it is among the top ten busiest airports in the UK for both passengers and freight (CAA, 2020). Each risk has been put into one of three independent categories based on the statistical analysis. They are categorised by types of climate threats, seasons, and operational sectors, which allows for a clear understanding of climate risks within airport climate resilience.

Initially, different climate threat types are classified by referencing the IPCC working group II in the Fifth Assessment Report, which are "Extreme precipitation", "Heatwave/ High temperature", "Cold spell/ Increased snow events", "Sea-level rise (SLR)/ Storm surge", and "Storminess" (IPCC, 2014a). Climate threats are identified by the airports mentioned in Table 3, which are "Drought", "Seasonal changes of fog events", "Seasonal changes of lightning events", "Seasonal changes of weather patterns", and "Seasonal changes of wind speeds and directions". Each reported item can be associated with more than one threat. For example, STN has stated a threat, "Increased energy demand for cooling in the summer, and for heating during winter extremes increases energy spend and emissions. High temperatures reduce the performance of some planes". This threat counted for both "Heat wave/ High temperature" and "Cold spell/ Increase in winter precipitation".

For analysing the risk items, occupancy, the ratio of used space to the total amount of available space (Law, 1998), is used to measure the amounts of different categories against the total for the upcoming statistical analysis. Taking "Heat wave/ High temperature" as an example, 93 risk items have been put into this category, giving an occupancy rate of 44.93% (93/207). Table 3 shows the occupancy distribution of different climate threats. "Heat wave/ High temperature" plays the most critical role in

affecting airports' operation, and their occupancy rate is more than 44%. "Cold spell/ Increase in snow events" is the second most important at more than 22%. The remaining threats/concerns have their occupancies between 11% and 15%.

Table 3 Occupancy of different climate threats				
Climate threats	Occupancy			
Cold spell/ Increase in snow events	47/207 (22.71%)			
Drought	29/207 (14.01%)			
Extreme precipitation	28/207 (13.53%)			
Heat wave/ High temperature	93/207 (44.93%)			
Pollution	23/207 (11.11%)			
Sea-level rise (SLR)/ Storm surge	27/207 (13.04%)			
Seasonal changes of fog events	24/207 (11.59%)			
Seasonal changes of lightning events	36/207 (17.39%)			
Seasonal changes to weather pattern	27/207 (13.04%)			
Seasonal changes to wind speed and direction	28/207 (13.53%)			
Storminess	30/207 (14.49%)			

In Table 4, it can be observed that airports are exposed to more risks in summer than in winter. Furthermore, more than half of these climate threats are non-seasonal. On the other hand, it is needed to classify the airport's infrastructure and its operational activities into different risk categories based on the definition of Airport Council Internation (2018): "Airfield (including Runways, Taxiways and Aprons)", "Terminals and Landside Infrastructure", "Support Facilities, Navigational Aids, Fuel Storage, and Others", "Aircraft Operation", "Air/Ground Navigation Control", "Wildlife Hazard Management", "Other Operational Aspects", "Environment Management", and "Personnel and Passengers". After categorising risk items by different infrastructures and types, some risks cannot fit into any defined group, e.g. "difficulties in climate forecasting" or "increases in insurance costs". Therefore, "Technical standards and assurance" was taken from the Heathrow Airport climate adaptation report for analysis (Heathrow Airport Limited, 2011).

Table 4 Occupancy	v of climate	risks in	different seasons
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Season	Winter	Summer	Annual (Non-seasonal)
Occupancy	67/207 (32.37%)	34/207 (16.43%)	106/207 (51.21%)

When considering "Airfield (including Runways, Taxiways, and Aprons)", the risk is associated with the airfield's deterioration and contamination. Drainage and electrical systems at the airside infrastructures are also included in this category. "Terminals and Landside Infrastructure" considers the difficulties of surface access, damage to terminals and corresponding ground foundations. "Support Facilities, Navigational Aids, Fuel Storage, and Others" includes damage to facilities and the corresponding increase in maintenance. Electrical system failure and fire risk are more significant and hence require more safety consideration. "Aircraft Operation" deals with the decrease of lift and of the rate of climb of planes at higher temperatures. Also, there may be changes in wind direction. As aircraft can encounter more extreme weather, more maintenance, repair, and overhaul are required. Reduction in visibility affects air transport safety and the "Air/Ground Navigation Control" system is more likely to fail. "Wildlife Hazard Management" includes changes in ecosystems, distributions of wildlife, wildlife attractants and the corresponding increase of wildlife strikes. "Emergency Management" includes climate emergencies and airport use for different relief logistics and operations. "Other Operational Aspects" include water shortage, the increased energy demand of air conditioning, flight delay and flight cancellation. "Environment Management" consists of differences in noise emission patterns, increased complaints, changes in ecosystems and associated risks, and air quality reduction. "Personnel and Passengers" includes the risks of heat-related exhaustion of staff, variations in tourism patterns and communicable epidemical risks. "Technical standards and assurance" includes documentation and insurance issues.

Table 5 describes the risks distributed in different parts of airports, as classified by the Airport Council Internation (2018). From the infrastructure side, "Airfield (including Runways, Taxiways and Aprons)", "Terminals and Landside Infrastructure", and "Support Facilities, Navigational Aids, Fuel Storage, and Others" occupy 20.77%, 15.46%, and 15.94% of all risk items respectively. Risks are distributed in different areas of airports. From an operations perspective, "Aircraft Operation", "Other Operational Aspects", and "Personnel and Passengers" occupy 14.98%, 14.01%, and 12.56% of all risk items respectively. "Aircraft Operation" has a slightly higher occupancy because of the potential lower take-off performance. "Other Operational Aspects" have a significant percentage because every airport recognises flight interruption and increased energy demand. "Personnel and Passengers" have a higher occupancy rate 12.56% because more extreme weather affects passengers' travel patterns. "Environment

Management" is the fourth largest sector because there are increases in disease vectors and local air pollutants. "Air/Ground Navigation Control", "Wildlife Hazard Management", and "Technical standards and assurance" have lower occupancy rates. "Emergency Management" is the only category without any suitable risk items. This category is about the use of airports as emergency shelters or relief locations for climate-related disasters. Some risk items are categorised as both infrastructure risk and operational risk.

 Table 5 Occupancy of different infrastructure and operation suffering from climate risks

 Category
 Occupancy

	Occupancy
Infrastructure	
Airfield (including Runways, Taxiways and Aprons)	43/207 (20.77%)
Terminals and Landside Infrastructure	32/207 (15.46%)
Support Facilities, Navigational Aids, Fuel Storage, and Others	31/207 (15.94%)
Operation	
Aircraft Operation	31/207 (14.98%)
Air/Ground Navigation Control	8/207 (3.86%)
Wildlife Hazard Management	7/207 (3.38%)
Emergency Management	0/207 (0%)
Other Operational Aspects	29/207 (14.01%)
Environment Management	20/207 (9.66%)
Personnel and Passengers	26/207 (12.56%)
Technical standards and assurance	3/207 (1.45%)

By the statistical analysis, airport climate resilience is across various areas, and there are many climate threats. The findings provided the key messages that airports will be exposed to more climate risks in the future. It is essential to give details for further investigation in climate exposures, especially for adaptation resources allocation. In the meantime, the results also help realise that a comprehensive climate resilience assessment framework requires more criteria such as sensitivity and adaptive capacity. Therefore, the definitions of climate resilience and vulnerability are reviewed. Also, it is necessary to overview all related open data and possible methodologies for the full framework implementation.

3.2. Climate resilience and vulnerability definitions

In this study, the definition of vulnerability to extreme weather is reviewed with reference to IPCC documents. It is defined as "the degree to which a system is unable to deal with adverse effects of

climate change, such as climate variability and extremes" (IPCC, 2014b). The three key dimensions are defined as follows:

• Exposure: The presence of people, livelihoods, species, ecosystems, environmental functions, services, infrastructures, resources, or assets in places and settings that could be adversely affected (IPCC, 2014a);

• Sensitivity: The degree to which a system is affected, either beneficially or adversely, by weatherrelated stimuli (McCarthy et al., 2001);

• Adaptive Capacity: The ability or potential of a system to respond to climate fluctuations and changes successfully. This also includes adjustments in behaviour, resources and technologies (Parry et al., 2007).

For the coastal vulnerability indices (CVI) assessment for coastal regions, sensitivity and adaptive capacity need to be assessed separately from exposure (Alsahli and Alhasem, 2016). Vulnerability and resilience are two theoretical concepts, but sometimes they are defined similarly and regarded as opposites (Gallopín, 2006, Tyler and Moench, 2012). In this study, they are regarded as opposites. The higher the vulnerability is, the lower the resilience is and vice versa. The framework is named a CRI framework because the ultimate findings can be used to compare vulnerabilities of different airports and then utilised to optimise resource allocation and strategic grouping. Füssel (2010) suggested seven factors for structuring information that may assist in prioritising of international adaptation. These are:

- The magnitude of regional climate variation
- Biophysical sensitivity
- Socio-economic impact
- Lack of adaptive/coping capacity (non-governance)
- Lack of adaptive/coping capacity (governance)
- Environmental-economic adaptability

• Aid effectiveness (governance)

These seven factors provided a valuable reference for identifying CRIs in this paper.

3.3. Review and analysis of public data in the UK

A comprehensive CRI framework requires data on a large scale, including exposure, sensitivity, and adaptive capacity. The CRI hierarchy is developed by the combination of the established Climate Change Risk Indicator (CCRI) frameworks in the literature (Poo et al., 2018, Poo et al., 2019, Poo et al., 2021) and the CVI evaluation (McIntosh and Becker, 2019, McIntosh et al., 2018). Specifically, Poo et al. (2018a, 2019, 2021) provide a EWE based hierarchy on climate exposure, while McIntosh et al. (2018) reveal a hierarchy with three categories (as shown in Figure 1). For the first time, the combination of three dimensions with much more detailed indicators under each dimension has been used to generate a CRI for measuring the climate resilience of airports.

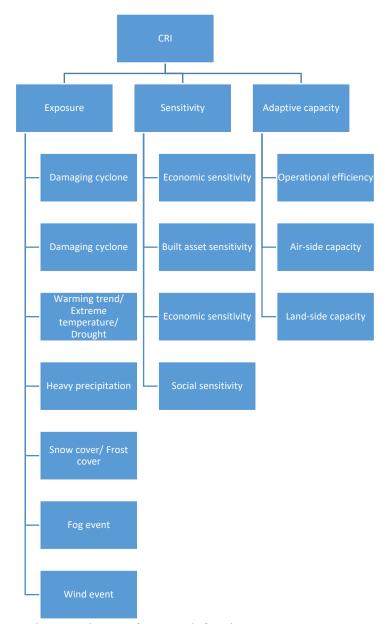


Figure 1 The CRI framework for airports

The CRI hierarchy is initially designed for analysis on climate change adaptation for airports on the same platform. In the process of its development, 40 indicators under the three dimensions have been identified by reviewing the references. To verify them, professionals were invited to justify and weigh the indicators.

4. Methodology: Advanced CRI framework for airports

Having collected the supporting data in Section 3, it is critical to employ an advanced reasoning

technique to cope with uncertainty (i.e. incompleteness) in climate data. All the CRIs need to be synthesised against the comprehensive CRI hierarchical structure to produce a final CRI index. Different CRIs are used to assess different climate threats independently. In the hierarchical framework, the risk indicators at a higher level refer to those at the lower levels. Therefore, it is essential to synthesise the airport resilience measurement from the lowest level indicators to the highest-level ones. In assessing the climate risks, the two significant uncertainties that decision-makers may encounter include multiple climate indices and incomplete data sets. Within the data utilised for this paper, there are fog event data, wind event data, and built asset sensitivity, which are incomplete. As well-established multi-attribute decision-making (MADM) approach, ER shows its capability to develop the CRI framework with the aforementioned uncertainties (Yang and Singh, 1994).

ER has been widely implemented for risk analysis relating to environmental issues in transport industries (Alyami et al., 2019, Poo et al., 2021, Wan et al., 2019, Yang et al., 2014, Yang et al., 2018, Yang and Wang, 2015, Zhang et al., 2016). Its main idea is to integrate the ER algorithm with the concept of the Dempster–Shafer (D–S) theory for modelling the hypothesis dataset. The D–S theory is a general mechanism of the Bayesian theory of subjective probability. Degrees of belief are for one question on the subjective probabilities for a related question. Thus, they represent epistemic plausibilities, but they also can accommodate findings that contradict those arrived at using probability theory (Dempster, 2008, Sentz and Ferson, 2002, Zadeh, 1986).

The detailed ER algorithms are documented in the literature, such as the studies on CCRI (Poo et al., 2021, Poo et al., 2019). The 5 steps for the implementation of the ER approach within the CRI context are listed below and detailed in Section 3:

- 1. Defining the indicator framework
- 2. Setting up the evaluation grades for each indicator
- 3. Evaluating the climate resilience of airports from the lowest level indicators

- 4. Assigning the weights to all indicators in the hierarchy
- 5. Synthesising the evaluation throughout the whole framework using the ER algorithm

The main added component in the methodology is the introduction of the Analytical hierarchy process (AHP) to weigh all components and layers by consulting a group of experts. Although AHP is commonly used with ER algorithms (Yang et al., 2020), the CRI framework is designed with four innovations. Firstly, it develops the new CRI hierarchy, including all the indicators essential to measure airports' climate resilience. Secondly, a national survey was conducted to evaluate the importance of the indicators. Initially, raw data is input to assess the importance of different factors on climate resilience. Thirdly, qualitative and quantitative climate data are integrated to obtain the CRI indexes for airports. Using big quantitative data where possible can ensure that the assessment is accurate and representative. Fourthly, airport climate resilience can be compared across different levels of indicators so that the best practice in the leading performer against a specific indicator can be effectively identified and learnt by the other airports.

4.1. Step 1: Defining the CRI hierarchy

As mentioned, the new CRI hierarchy refers to the previous climate change risk analysis frameworks (Poo et al., 2018, Poo et al., 2019) and the coastal vulnerability analysis approaches (McIntosh and Becker, 2019, McIntosh et al., 2018). To ensure the defined attributes can fit in the airport climate resilience context, they were reviewed and verified by related professionals. 11 domain experts were invited through professional consultations. Their profession includes academic, environmental scientist, airline, airport management, logistics agent, logistics management, and environmental engineering, but all highly relating to airport climate and/or environment areas. Therefore, the related consultations are shown in Table 6. The consultation results from 11 experts were very consistent. All 38 indicators were confirmed to be the most relevant without the requirement of any addition and removal.

ID	Profession	Years of experience
1	Academic	12
2	Academic	10
3	Environmental scientist	23
4	Academic	7
5	Airline	5
6	Airport management	14
7	Airport management	4
8	Logistic agent	5
9	Logistic agent	6
10	Logistic management	4
11	Environmental engineer	2

Table 6 Professional background of CRI hierarchy consultation

After the development of the CRI hierarchy, the CRI framework needs an ER approach (described in Section 2.4) to classify and analyse the climate data. The data was collected from a variety of sources, including the Met Office (Met Office, 2018), British Oceanographic Data Centre (BODC) (British Oceanographic Data Centre, 2018), Joint Nature Conservation Committee (JNCC) (JNCC, 2018), DEFRA (Vitolo et al., 2016), Climate Projection (UK Climate Projection, 2018), National Housing Federation (NHF) (National Housing Federation, 2019), Eurostat (Eurostat, 2019), Office for National Statistics (ONS) (Fenton, 2019), Department of Transport (DfT) (DfT, 2020), Climate Just (Lindley et al., 2011), Her Majesty's (HM) Land Registry (HM Land Registry, 2020), TomTom International (TomTom N.V., 2017), and UK Environment Agency (EA) (Environment Agency, 2020). Some data are found from the Civil Aviation Authority (CAA) (CAA, 2020), HM Government (HM Government, 2017) and Airport codes (Fubra Limited, 2020). They are all open data available from the associated websites. The comprehensive CRI framework for airports is shown in Annex 1.

For environmental sensitivity sector, there are three associations providing data. JNCC is the public organisation responsible for national and international nature conservation, which are suitable for providing data for the airport surrounding environment, such as the number of Special Areas of Conservation in the country where the investigated airport(s) is located. DEFRA provides UK Air Information Resources (UK AIR) on daily air pollution record count of days with Air Quality Daily index higher than moderate. National Housing Federation (NHF) is a trade association representing and grouping British housing providers, and it can provide a brownfield ratio for assessing the sensitivity

of hazardous materials (HAZMAT).

For economic sensitivity sector, regional and airport indicators are collected and the data are from Eurostat, ONS, Maritime UK, and the UK Department of Transport. Eurostat is a directorate-general department of the European Commission for providing statistics information for European cities and ONS is the UK Statistics Authority's executive office. Eurostat provides Gross domestic product (GDP), while ONS provides regional Gross Value Added (GVA). CAA provides the market share and HM office provides direct employment for airports. Climate Just and HM Land Registry are two organisations to provide an open dataset in terms of social sensitivity. Climate Just is an informative tool designed by the Environmental Agency to help deliver equitable responses to climate change at different local authorities, and it provides socio-spatial vulnerability indices for the surrounding population's sensitivity. HM Land Registry is a non-ministerial department, and provides the details of UK house prices.

As far as operational efficiency is concerned, TomTom International is a Dutch multi-national developing company of location technologies, such as congestion index, which can support the CRI framework. Further, Airport code provides the detail of direct rail connections. Regarding airside capacity, the data of airport size was collected from World Airport Codes, and the details of passengers and freights are collected from CAA. Concerning land-side capacity, EA is a non-departmental public body to provide airport planning availability, including master plans, adaptation plans and sustainability plans. Finally, the annual percentage change in throughput and market share are collected from CAA for assessing airport growth.

Further explanations of the data features are presented in Table 7, and the description, units, types, and sources of the indicators are detailed in Table 8. The full details of CRIs are shown in Annex 1. In Table 8, the quantitative indicators are evaluated using the raw data directly. The qualitative indicators are evaluated by pre-defined qualitative linguistics grades.

Top level	Category	Sub-category	Table 7 Climate resilie Sub-sub-category		Description		
			Precipitation	1	Monthly total precipitation amount (Upper bound)		
			recipitation		Day of more than 10mm precipitation in a month (Upper bound)		
		Damaging cyclone	Wind	3	Monthly mean wind speed 10 m above ground level (Upper bound)		
		ConI = 0.0150	Pressure	4	Monthly average of hourly mean sea-level pressure (Lower bound)		
		ConR = 0.0130	Flessure	5	Monthly average of hourly vapour pressure (Lower bound)		
			Storm Surge	6	Average of Top 10 skew surges records		
			Lightning	7	Days of thunder in a month		
		Sea-level rise	Sea level	8	Average of Top 10 sea-level records		
			Storm Surge	6	Average of Top 10 skew surges records		
	г	Warming trend/	Temperature	9	Monthly average of daily maximum air temperature (Upper bound)		
	Exposure	Extreme temperature/	Relative humidity	10	Monthly average of hourly relative humidity (Lower bound)		
CRI	ConI	Drought	Precipitation	11	Monthly total precipitation amount (Lower bound)		
index ConI	= 0.0301 ConR	ConI = 0.0465 ConR = 0.0517	Cloud cover	12	Monthly average of hourly total cloud cover (Lower bound)		
= 0.0530	= 0.0243		Precipitation	1	Monthly total precipitation amount (Upper bound)		
ConR				2	Day of more than 10mm precipitation in a month (Upper bound)		
= 0.0913			Temperature	13	Monthly average of daily minimum air temperature (Lower bound)		
		Snow cover/ Frost		14	Day of the minimum air temperature lower than 0 °C in a month (Upper bound)		
				cover ConI = 0.0001	Frost	15	Day of the minimum grass temperature lower than 0 $^{\circ}$ C in a month (Upper bound)
		ConR = 0.0002	Snow	16	Day of snow falling or sleet falling in a month (Upper bound)		
			Snow	17	Day of more than half of the ground covered by snow in a month (Upper bound)		
		Fog event	Seasonal changes of fog events		No indicator		
		Wind event	Seasonal changes to wind speed and direction		No indicator		
	Sensitivity	Environmental	Surrounding Environment	18	Number of Special Areas of Conservation in airport county		
	ConI	Sensitivity ConI = 0.0020	Air Quality	19	Day of Air Quality Daily index higher than 5 in a month		
	= 0.0367	ConR = 0.0020 ConR = 0.0035	Hazmat	20	Brownfield ratio higher than 0.5%		

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ConR		Land-Side Built Asset		
= 0.0407	Built Asset Sensitivity	Sensitivity		No indicator
		Air-Side Built Asset Sensitivity		No indicator
		Regional Economic Sensitivity –		Gross domestic product of a region
	Economic Sensitivity		22	Gross value added per head per month
	Leononne Sensitivity	Airport Economic Sensitivity	23	Airport market share in the UK
		Thiport Leonomie Sensitivity	24	Direct employment made by the airport
		Surrounding	25	Socio-spatial vulnerability index on flooding
	Social Sensitivity	PopulationSensitivity	26	Socio-spatial vulnerability index on heating
	boolar bonshi vity	Surrounding Structures / Asset	27	
		Sensitivity	27	UK House Price Index
		Airport Operational Efficiency	28	Average length of flight delays
	Operational Efficiency	The efficiency of Transport	29	TomTom Traffic Index
Adaptive		Connections	30	Presence of direct rail connections
Capacity	Airside Capacity	Aircraft	31	The longest runway length in the airport
capacity	ConI = 0.0032	Passenger	32	Total passenger traffic in a year
ConI	ConR = 0.0055	Cargo	33	Total freight traffic in a year
= 0.0001	Land-side Capacity	Flavikility	34	Number of runways
ConR = 0.0002		Flexibility	35	Number of terminals
- 0.0002	ConI = 0.0035	Port Planning	36	Availability of a sustainability plan
	ConR = 0.0060	Port Growth	37	Positive annual percentage change in passenger or freight
		FUILOIUWIII		Positive annual percentage change in market share

*ConI and ConR mean consistent index and consistent ratio, respectively.

	Ta	ble 8 Climate resilience in	dicator li	st			
						Contribution for	
No.	Description	Short name	Units	Types	Level	CRI index	Data Source
1	Monthly total precipitation amount (Upper bound)	Precipitation UB	mm	Qualitative	5	2.73910%	Met Office
2	Day of more than 10mm precipitation in a month (Upper bound)	Days of rain >= 10 mm UB	Days	Qualitative	5	2.73910%	Met Office
3	Monthly hourly mean wind speed 10 m above ground level (Upper bound)	Mean wind speed UB	knots	Qualitative	5	1.26103%	Met Office
4	Monthly average of hourly mean sea-level pressure (Lower bound)	Mean sea level pressure LB	kts	Qualitative	5	0.46068%	Met Office
5	Monthly average of hourly vapour pressure (Lower bound)	Mean vapour pressure LB	kts	Qualitative	5	0.46068%	Met Office
6	Average of Top 10 skew surges records	Skew surges records	m	Qualitative	5	3.71617%	BODC
7	Day of thunder in a month	Days of thunder	Days	Qualitative	7	0.80536%	Met Office
8	Average of Top 10 sea-level records	Sea-level records	m	Qualitative	5	2.53345%	BODC
9	Monthly average of daily maximum air temperature (Upper bound)	Maximum temperature UB	°C	Qualitative	5	1.54600%	Met Office
10	Monthly average of hourly relative humidity (Lower bound)	Relative humidity LB	%	Qualitative	5	0.62080%	Met Office
11	Monthly total precipitation amount (Lower bound)	Precipitation LB	mm	Qualitative	5	1.21115%	Met Office
12	Monthly average of hourly total cloud cover (Lower bound)	Cloud cover LB	%	Qualitative	5	0.52114%	Met Office
13	Monthly average of daily minimum air temperature (Lower bound)	Minimum temperature LB	°C	Qualitative	5	1.27345%	Met Office
14	Day of the minimum air temperature lower than 0 °C in a month (Upper bound)	Days of air frost UB	Days	Qualitative	5	0.34474%	Met Office
15	Day of the minimum grass temperature lower than 0 °C in a month (Upper bound)	Days of ground frost UB	Days	Qualitative	5	0.34474%	Met Office
16	Day of snow falling or sleet falling in a month (Upper bound)	Days of sleet or snow falling UB	Days	Qualitative	5	0.39949%	Met Office
17	Day of more than half of the ground covered by snow in a month (Upper bound)	Days of snow lying UB	Days	Qualitative	5	0.39949%	Met Office
18	Number of Special Areas of Conservation in airport county	Number SAC	N/A	Quantitative	N/A	5.23811%	JNCC
19	Day of Air Quality Daily index higher than 5 in a month	AQ Daily Index	Days	Quantitative	N/A	4.18742%	UK Air Information Resources

20	Brownfield ratio higher than 0.5%	Brownfield ratio	%	Qualitative	2	3.99425%	National housing federation
21	Gross domestic product of a region	GDP	£milli	Quantitative	N/A	0.92180%	Eurostat
			on				
22	Gross value added per head per month	GVA	£	Quantitative	N/A	0.92180%	ONS
23	Airport market share in the UK	Market share	%	Quantitative	N/A	1.98838%	Maritime UK
24	Direct employment by the airport	Direct employment	Numb	Quantitative	N/A	1.98838%	Maritime UK
			er of jobs				
25	Socio-spatial vulnerability index on flooding	SoVI flood	N/A	Qualitative	N/A	1.23088%	Climate Just
26	Socio-spatial vulnerability index on heating	SoVI heat	N/A	Qualitative	N/A	1.23088%	Climate Just
27	UK House Price Index	House price	£	Quantitative	N/A	3.92956%	HM Land Registry
28	Average length of flight delays	Punctuality statistics	min	Quantitative	N/A	12.55565%	CAA
29	TomTom Traffic Index	Congestion index	N/A	Qualitative	N/A	4.94580%	TomTom International
30	Presence of direct rail connections	Rail connection	N/A	Qualitative	4	4.94580%	World Airport Code
31	The longest runway length in the airport	Runway length	m	Quantitative	N/A	3.03993%	World Airport Code
32	Total passenger traffic in a year	Passenger traffic	Passen	Quantitative	N/A	4.39359%	CAA
			ger				
33	Total freight traffic in a year	Freight traffic	Tonna	Quantitative	N/A	2.78958%	CAA
			ge				
34	Number of runways	Runway number	N/A	Qualitative	2	1.51259%	World Airport Code
35	Number of terminals	Terminal number	N/A	Qualitative	2	1.51259%	World Airport Code
36	Availability of a sustainability plan	Sustainability plan	yes /	Qualitative	2	3.85829%	UK Environment
			no				Agency
37	Positive annual percentage change in passenger or freight	%change throughput	yes /	Qualitative	2	1.37484%	CAA
			no				
38	Positive annual percentage change in market share	%change market share	yes /	Qualitative	2	1.37484%	CAA
	and I D maan upper bound and lower bound respectively		no				

*UB and LB mean upper bound and lower bound respectively.

For exposure sector, there are seven sub-categories which are: damaging cyclone, snow cover/ frost cover, precipitation hazard, sea-level rise, warming trend/ extreme temperature/ drought, seasonal changes in fog events and seasonal changes in wind events. The data was collected from the Met Office, Climate Projection and BODC. The sub-sub-categories of exposure are the measurements of the EWEs, such as temperature and relative humidity. For sensitivity sector, there are four sub-sectors, environmental sensitivity, built asset sensitivity, economic sensitivity, and social sensitivity. Environmental sensitivity data is collected from JNCC, UK Air Information Resources, and the National Housing Federation. For economic sensitivity, regional data is from Eurostat and ONS. Airport data is from HM government and CAA. For economic sensitivity, surrounding population data is from Climate Just, and surrounding structures/ asset data is from HM Land Registry. As far as adaptive capacity is concerned, the congestion index is from TomTom International, and planning indicators are from the UK Environmental Agency. Punctuality statistics and other airport data are collected from the CAA.

The weights of all the CRIs are generated from a questionnaire using an AHP. The questionnaire was written on Jisc online platform and 11 domain experts (as shown in Table 6) were invited to participate via email. AHP presents the judgments (x_{ji}) made by decision-makers in the form of a reciprocal matrix, which is a number from 1 to 9. A reciprocal matrix of comparisons satisfies the property of $x_{ji} = 1/x_{ij}$ for all i, j = 1,2, ... 11. After data collection, the next step is to validate the weight assignment by Consistent index (ConI) and then Consistency Ratio (ConR) (Saaty, 1990). ConI represents the consistency of all judgments by considering the highest eigenvalue of a component (a row) of the matrix and the number of independent rows. Suppose the matrix is entirely consistent, CI = 0. ConRs of all indications in the CRI framework is calculated to validate the framework (as shown in Table 7). All ConRs are lower than 0.1, which demonstrates the weight assignment is acceptable. Then, ConR is used to deal with more significant number of pair-wise comparisons coming with a higher possibility of consistency error. It is calculated by ConR = ConI/RI, where Random index (RI) is defined in Table 9 (Saaty, 1990).

|--|

Number of factors	2	3	4	5	6	7	8	9	10
Random index	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.51

4.2. Step 2: Defining the assessment grades

For the exposure indicators, monthly observations were collected using a grid of 5 km squares covering the whole of the UK. Then, 95th, 80th, 80th, 70th, and 60th percentile values classify the upper bound (UB) assessment grades into five categories and 5th, 10th, 30th, 20th and 40th percentile values divide the lower bound (LB) assessment grades. All datasets can fit the five linguistic grades set by the utility mapping technique, commonly implemented with ER (Yang et al., 2009a). As extreme data present the maximum skew surge records and the maximum sea-level records from BODC, they are different from the standard climate data defined by UB and LB. The data was linearly separated into five groups by five values at 90th, 70th, 50th, 30th, and 10th percentiles (Poo et al., 2020).

To transform the percentile data into the actual values of each indicator, the maximum and minimum values of the indicators need to be identified. For the generality of the grade definitions, the relevant values of 23 strategic port regions in the UK (Poo et al., 2021) are obtained and analysed. The maximum and minimum values among twenty-three locations are designated as the best attribute value and the worst attribute value. For example, the maximum and minimum values of "Number of Special Areas of Conservation in the airport county" are 74 and 0. The top region is South East, and the bottom regions are Suffolk, Lothian, Birmingham City, and Glasgow. For all the qualitative indicators, gradings are set up with the reference from the corresponding organisations, including the World Port Index and Climate Just. For example, the five gradings for "Shelter Afforded" are defined by World Port Index, and they are "E – Excellent", "G – Good", "F – Fair", "P– Poor", and "N– None".

Manchester Airport is chosen as an illustrative example to provide the raw qualitative dataset in Table 10. Raw data for Manchester Airport is split into different sets of linguistic grades manually, and they

are progressed and placed into five linguistic grade sets {L1 "Very Low ", L2 "Low", L3 "Average ", L4 "High ", L5 " Very High" resilience} to calculate the final CRI indexes for different airports.

	Table 10 Qualitative climate res			,	
ID	Lowest level CRIs	Unit	Level	Value	Linguistic grades
1	Precipitation UB	mm	5	87.3066	1 (100%)
2	Days of rain $\geq 10 \text{ mm UB}$	Days	5	2.2918	1 (100%)
3	Mean wind speed UB	knots	5	10.6931	4 (100%)
4	Mean sea level pressure LB	kts	5	1012.0859	1 (60%), 2(40%)
5	Mean vapour pressure LB	kts	5	7.0611	3 (70%), 4 (30%)
6	Skew surges records	m	5	N/A	N/A
7	Days of thunder	N/A	7	4	4 (100%)
8	Sea-level records	m	5	N/A	N/A
9	Maximum temperature UB	°C	5	20.2894	4 (15%), 5 (85%)
10	Relative humidity LB	%	5	69.9394	5 (100%)
11	Precipitation LB	mm	5	52.5601	1 (100%)
12	Cloud cover LB	%	5	68.8741	1 (50%), 2 (50%)
13	Minimum temperature LB	°C	5	1.9610	2 (10%), 3 (90%)
14	Days of air frost UB	Days	5	8.4705	3 (100%)
15	Days of ground frost UB	Days	5	15.9095	2 (50%), 3 (50%)
16	Days of sleet or snow falling UB	Days	5	5.3634	3 (70%), 4 (30%)
17	Days of snow lying UB	Days	5	2.7739	3 (70%), 4 (30%)
20	Brownfield ratio	N/A	2	>=0.5%	2 (100%)
25	SoVI flood	N/A	7	7	7 (100%)
26	SoVI heat	N/A	7	7	7 (100%)
30	Rail connection	N/A	2	Yes	1 (100%)
34	Runway number	N/A	2	>=2	1 (100%)
35	Terminal number	N/A	2	>=2	1 (100%)
36	Sustainability plan	yes / no	2	Yes	1 (100%)
37	%change throughput	yes / no	2	Yes	2 (100%)
38	%change market share	yes / no	2	Yes	2 (100%)

Table 10 Oualitative climate resilience indicators of Manchester (MAN) airport

In Table 11, the quantitative data for Manchester Airport is listed. All airports' extreme values are used to define the lowest graded values and the highest graded values (respectively). Then, the data is converted to the same five linguistic assessment grades given to the qualitative data by a linear distribution (Yang et al., 2009b). Taking Gross value added per head per month (ID = 22) (i.e., the value added by production activity in an area to the resident population of that area) as an example, {16857, 23699.75, 30542.5, 37385.25, 44228 (£)} is used to scale the five linguistic grades, and the indicator value (i.e. 36136) in the Manchester Airport case is therefore represented as {0% L1, 0% L2, 18% L3, 82% L4, 0% L5}.

Table 11 Quantitative climate resilience indicators of Manchester Airport

			Lowest	Highest	
ID	Lowest level CRIs	Unit	graded value	graded value	Value
18	Number SAC	N/A	0	74	3
19	AQ Daily Index	Days	37	0	8
21	GDP	£million	24042	108023	87288
22	GVA	£	16857	44228	36136
23	Market share	%	0.5404	27.4086	7.0611
24	Direct employment	%	4	22	12
27	House price	£	120489	406255	184661
28	Punctuality statistics	min	0	23.4382	16.2657
29	Congestion index	%	19	40	32
31	Runway length	m	12799	6000	10000
32	Passenger traffic	Passenger	80100311	1057073	16766552
33	Freight traffic	Tonnage	1699663	1459	26193

4.3. Step 3: Evaluating airport resilience data

After setting the indicators grades, the raw input dataset is used to evaluate airports to model the lowest level indicators in the CRI framework. Ten airport reporting bodies (those mentioned in Table 2, which were invited to submit climate change adaptation reports about airport risks in line with the Climate Change Act 2008) were chosen to be evaluated for airport selection. Also, Aberdeen International Airport was selected as it serves an urban area in the North of the UK, and it is one of the top ten busiest airports in the UK for both passengers and freight.

4.4. Step 4: Evaluating airports by indicators from the lowest to the highest level

The weighting for compliance with climate resilience comes from the AHP survey results. Therefore, airports' final climate resilience indicators can be evaluated, which means the evaluation transforms from the lowest to the highest level. Taking GVA per head per month (ID = 22) as an example again represents 50% of economic sensitivity (as shown in Table 7). Economic sensitivity represents 18% of sensitivity, and sensitivity accounts for 31% of the CRI index, as shown in Figure 1 and Table 7. Therefore, the linguistic assessment grades of GVA, {0% L1, 0% L2, 18% L3, 82% L4, 0% L5}, contributes 2.79% of the final CRI index.

Each investigated airport's CRI was evaluated using the ER algorithm and its associated calculation software Intelligent Decision System (IDS) (Xu and Yang, 2003).

5. Case analysis and discussions of UK airports' climate resilience

5.1. Analysis of the CRI weights

The weighting of all indicators is based on the questionnaire responses from eleven domain experts. There are variations between different professions. To facilitate the analysis, the professions are divided into three categories: academic group (academic and environmental scientists), airport management group (airline and airport management), and others (logistics agent, logistics management, and environmental engineering). The geometric mean of three different categories and all experts are obtained and shown in Figure 2. It is noted that the academic group are mainly concerned with exposure and sensitivity, while the airport management group focus on sensitivity and adaptive capacity. For example, the academic group concerns exposure and sensitivity, while the airport management group focus for all the experts lie broadly between these two.

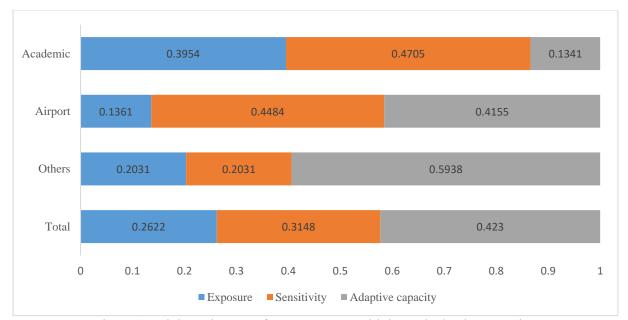


Figure 2 Weight assignment for exposure, sensitivity and adaptive capacity

5.2. Analysis of CRI indices

In this section, airports are evaluated from different perspectives, exposure, sensitivity and adaptative capacity using the five steps (which were outlined in Section 3), where the weights of the three perspectives are 0.2622, 0.3148 and 0.423 (as shown in Figure 2), respectively. This demonstrates that adaptive capacity contributes more to the final CRI index and exposure represents a smaller portion. The ranks are assigned to airports and they are arranged from high to low resilience. The results for all the investigated airports with respect to each of the three climate dimensions and the overall combined one are shown in Table 12.

When considering Table 12, Cardiff Airport is the most climate-exposed airport, while Aberdeen International Airport ranks the highest as it is the least climate-exposed airport. Cardiff is in South Wales, therefore, it is likely to experience more severe heatwaves and sea-level rise because of its location. Aberdeen International Airport has a minor threat due to heatwaves and sea-level rise as it is in North Scotland. This also reflects that the current climate change focuses more on the warming effect, evidenced by the indicator weighting results from the AHP. It could be suggested that the airports which are less exposed to high temperatures and heatwaves, recently tend to benefit more from climate

exposure.

London Stansted Airport is the least climate-sensitive airport, and Cardiff Airport is the most climatesensitive airport. The environmental sensitivity indicators are mainly used to decide their ranking. The corresponding authority of Cardiff has the greatest number of SACs ("Number SAC" ID = 18) compared to other regions. Also, the corresponding region of Cardiff has less than 0.5% of Brownfield ratio ("Brownfield ratio" ID = 20).

While London Luton Airport has the lowest adaptive capacity, Heathrow Airport has the highest adaptive capacity. The rank is based on such factors as operational efficiency and land-side capability, against which Heathrow obtains the highest position in the category. The best practice on climate adaptative capacity against various indicators will provide valuable insights to guide the other airport climate adaptation planning. Heathrow Airport ranks the overall highest, and London Luton Airport ranks the overall lowest. As adaptive capacity is the dominant component, Heathrow Airport has the highest values of both adaptive capacity and final CRI index, and London Luton Airport ranks the lowest of adaptative capacity and CRI index.

				Adaptive		CRI	
Exposure	Rank	Sensitivity	Rank	capacity	Rank	index	Rank
0.3689	1	0.4418	6	0.6365	6	0.5207	5
0.4371	4	0.3401	3	0.6834	9	0.5319	7
0.5912	11	0.5548	11	0.645	7	0.6129	10
0.4129	3	0.4642	8	0.6573	8	0.5494	8
0.4519	7	0.3362	2	0.6223	5	0.5016	3
0.5201	10	0.3814	5	0.535	2	0.4874	2
0.4605	8	0.3696	4	0.6024	4	0.5023	4
0.4424	5	0.5027	9	0.4022	1	0.432	1
0.4465	6	0.4602	7	0.7794	11	0.6206	11
0.403	2	0.5102	10	0.5857	3	0.5259	6
0.4693	9	0.3092	1	0.7589	10	0.5633	9
	0.3689 0.4371 0.5912 0.4129 0.4519 0.5201 0.4605 0.4424 0.4465 0.403	0.437140.5912110.412930.451970.5201100.460580.442450.446560.4032	0.368910.44180.437140.34010.5912110.55480.412930.46420.451970.33620.5201100.38140.460580.36960.442450.50270.446560.46020.40320.5102	0.3689 1 0.4418 6 0.4371 4 0.3401 3 0.5912 11 0.5548 11 0.4129 3 0.4642 8 0.4519 7 0.3362 2 0.5201 10 0.3814 5 0.4605 8 0.3696 4 0.4424 5 0.5027 9 0.4465 6 0.4602 7 0.403 2 0.5102 10	ExposureRankSensitivityRankcapacity0.368910.441860.63650.437140.340130.68340.5912110.5548110.6450.412930.464280.65730.451970.336220.62230.5201100.381450.5350.460580.369640.60240.442450.502790.40220.446560.460270.77940.40320.5102100.5857	ExposureRankSensitivityRankcapacityRank0.368910.441860.636560.437140.340130.683490.5912110.5548110.64570.412930.464280.657380.451970.336220.622350.5201100.381450.53520.460580.502790.402210.446560.460270.7794110.40320.5102100.58573	ExposureRankSensitivityRankcapacityRankindex0.368910.441860.636560.52070.437140.340130.683490.53190.5912110.5548110.64570.61290.412930.464280.657380.54940.451970.336220.622350.50160.5201100.381450.53520.48740.460580.369640.602440.50230.442450.502790.402210.4320.46320.5102100.585730.5259

Table 12 Climate regiliance indexes for all eleven simeent

By the ER algorithm, some airports with incomplete datasets can be analysed by the same framework.

Exposure and sensitivity are two components with missing indicators and possible variation. Indicators for sea-level rise, wind events, and asset sensitivity are missing for some airports, and therefore the components are represented by linguistic grade sets which are less than 100% in total. Taking Heathrow Airport as example, linguistic grade sets of exposure, sensitivity and CRI index are {27%, 1%, 18%, 10%, 11%} (67% in total), {24%, 15%, 13%, 5%, 30%} (87% in total), {29%, 9%, 26%, 12%, 14%} (90% in total). As adaptive capacity comes with a complete database, CRI index is more complete than exposure and sensitivity. The minimum, average, and maximum CRI index values are obtained by the ER approach are presented in Table 13.

	Tab	ole 13 Clir	nate resilien	ce indexes v	variations	of eleven air	ports		
		Exposure	e		Sensitivit	y		CRI inde	x
Airport	Minimum	Average	Maximum	Minimum	Average	Maximum	Minimum	Average	Maximum
Aberdeen									
International Airport	0.297	0.3689	0.4408	0.3428	0.4514	0.56	0.4673	0.5102	0.5531
Birmingham Airport	0.2685	0.4371	0.6057	0.296	0.3589	0.4218	0.471	0.5201	0.5692
Cardiff Airport	0.5203	0.5912	0.6621	0.4569	0.5684	0.6799	0.5576	0.6003	0.643
Edinburgh Airport	0.3408	0.4129	0.485	0.3606	0.4746	0.5886	0.5039	0.5478	0.5917
East Midlands									
Airport	0.2846	0.4519	0.6192	0.288	0.3504	0.4128	0.448	0.4965	0.545
Glasgow Airport	0.3542	0.5201	0.686	0.2939	0.4058	0.5177	0.4136	0.4747	0.5358
Gatwick Airport	0.2922	0.4605	0.6288	0.311	0.3752	0.4394	0.4451	0.4946	0.5441
Heathrow Airport	0.274	0.4424	0.6108	0.4349	0.4987	0.5625	0.4021	0.4513	0.5005
London Luton									
Airport	0.2781	0.4465	0.6149	0.4064	0.4692	0.532	0.5663	0.6148	0.6633
Manchester Airport	0.2342	0.403	0.5718	0.4496	0.5129	0.5762	0.464	0.5131	0.5622
London Stansted									
Airport	0.3014	0.4693	0.6372	0.2623	0.3252	0.3881	0.5099	0.5598	0.6097

Table 13 Climate resilience indexes variations of eleven airports

By the implications of the analysis, all airports can first be evaluated on the same platform for effective comparison and benchmarking for improvement. An airport with a low ranking against a particular indicator could learn best practices from the category leader. One significant contribution of the proposed CRI framework is to fill the gap in research to quantify climate resilience for transport infrastructures with incomplete datasets (McIntosh and Becker, 2019) and to meet the research challenge of adaptative capacity lacking quantitative indicators. Therefore, a national policymaker can use the data for adaptation planning and sustainability planning for airports. Airports and airlines can

use the CRI indexes and logistics companies can provide suitable remedial measures to enhance climate resilience. Also, it is noted that CRI weight assignments from the academic group are very different, which means the definition and understanding of climate resilience are still controversial. Much effort is required to conduct an extensive scale survey (both nationally and internationally) to uniformly define airport climate resilience and enable rational policymaking in the future. The methodology can adapt to other regional and international assessments by adding new indicators or removing the existing ones and revising the weighting by distributing more questionnaires. For example, airports in China may need to consider sandstorms as a climate threat, which is relatively rare in the UK. Therefore, it is necessary to distribute the questionnaires and implement the weight assignment corresponding to the new locations and regions.

Another important finding is that the CRI index rank is irrelevant to location, which is inconsistent with previous climate change risk studies (Poo et al., 2021). It scientifically proves and supports that climate risk exposure objectively exists and affects transport infrastructures, while the resilience of the transport infrastructures can be achieved by human-made effort by adjusting their sensitivity and adaptive capacity. Hence, this study shows how to rationally allocate adaptation planning resources to improve and reinforce airport resilience in the most cost-effective manner. One possible solution is that neighbouring airports can form strategic partnerships for emergency logistics within a specific region in a country. For example, airports near Manchester and Liverpool can further discuss an emergency adaptation plan to tackle each identified climate change risk item and improve the airports' resilience and adaptation from the current position where the emergency plans among the partner airports are developed in general and typically centrally controlled by national air transport authorities.

6. Conclusion

By implementing ER and AHP techniques, an advanced generic CRI framework has been developed and UK representative (leading) airports are evaluated and analysed. The framework considers the climate threats mentioned in airport climate adaptation reports. The CRI framework is a pioneer from any other existing climate risk analysis framework in the literature, known mainly as climate exposure oriented and full dataset required. As a result, the findings reveal that the resilience of an airport is not strongly related to its location and climate risk exposure is does not play a dominating role. Therefore, sensitivity and adaptive capacity also have essential roles for contributing to the final climate resilience performance, which can provide valuable insights to the national governing bodies for resources allocation on adaptation measures. Taking Heathrow airport as an example, it ranks as first because it has a higher capacity and number of terminals and runways. Furthermore, it numerically proves that a spared capacity offset the climate risk can higher the climate resilience. Also, the difficulties among different airports are visualised by considering the values of exposure, sensitivity, and adaptive capacity independently. Some further interesting numerical findings include:

1) Among the identified 207 risk items influencing UK airport climate resilience, 93 are linked to Heat waves/High temperature and 47 are associated with Cold wave/Increase in snow events

2) In terms of seasonal effect, UK airports are more sensitive to winter (involving 67 reported risk items) than summer (34 risk items)

3) The most influenced infrastructure and operation by climate change are Airfield (including Runways, Taxiways and Aprons) (43 reported risk items) and aircraft operation (31 risk items) respectively

4) The most important indicators in the dimensions of climate exposure, sensitivity and adaptive capability are "Skew surges records" (ID = 6) (3.71617%), "Number SAC" (ID = 18) (5.23811%) and "Punctuality statistics" (ID = 28) (12.55565%), respectively

5) The most resilient airports in terms of climate exposure, sensitivity, adaptive capability and their combination (the overall) are Aberdeen International Airport (with an index value of 0.3689), London Stansted Airport (0.3092), Heathrow Airport (0.432) and Heathrow Airport (overall), respectively

Airport stakeholders can use the indexes to prepare adaptation measures to enhance climate resilience.

Scholars and operators can investigate adaptation resource allocation and measure the selection for airports with CRI index as references for self-assessment during different time windows or benchmarks between different airports. Also, the framework has the flexibility to implement the global assessment for airports around the world due to its generic step development. For instance, the indicators can be used individually when a particularly concerned indicator is selected to support adaptation measure development. By using the proposed method, it is possible could find out which airports perform best and worst against the concerned indicator across all investigated airports. The results can then be used for a benchmark purpose to allow the worst performer to learn from the best in terms of the adaptation measures for the individual indicator. Collectively, the proposed methods allow for the syntheses of the performance of each investigated airport against all the indicators to provide an overall evaluation of its climate resilience. The collective analysis results can be used for airport climate resilience ranking for optimal adaptation resource allocation on one hand and for a single airport to conduct a longitude study to ensure its overall climate resilience improvement with time on the other hand. Therefore, the assessment can be expanded in different locations. In the future, it is beneficial to expand the study to larger geographical areas, such as the Atlantic Region and Southeast Asia, for the generality of the case findings. As more airports are analysed on the same platform, network analyses can be implemented to assess the climate risks of the network by optimisation models.

The CRI framework can be extended to investigate the other transport modes to implement comparative analysis to observe similarities and differences. It reflects the high possibilities for cooperation between different transport modes for enhancing the climate resilience of the whole urban transport system in a given country. Also, the results can be integrated with studies on adaptive measures for choosing suitable measures for dedicated airports. The CRI framework findings can be used to level up the climate exposure, sensitivity, and adaptive capacity. Therefore, suitable measures can be suggested based on the values of different categories.

7. References

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Index number	1	Unit	mm
Indicator	Precipitation UB	Reference	(Poo et al., 2021)
Description	Monthly total precipitation am	ount (Upper boun	nd)
Data source	UK's weather service. UK clim to summarise historical clima resolutions are in 5 km x 5 km percentile margins of upper bo	ate projections 20 te data and to es gird and 12 km x und are 60th, 70th	fice, which is responsible for the 09 (UKCP09) service is a project stimate future climate data. The 12 km grid resolutions. Criterior 8, 80th, 90th, and 95th. Moreover 40th, 30th, 20th, 10th, and fifth.
Example value	Glasgow airport in December:	147.72 mm	
Index number	2	Unit	N/A
Indicator	Days of rain >= 10 mm UB	Reference	(Poo et al., 2021)
Description	Day of more than 10mm precip	pitation in a mont	h (Upper bound)
Data source	Same as Index 1		
Example value	Glasgow airport in December:	3.99	
Index number	3	Unit	knots
Indicator	Mean wind speed UB	Reference	(Poo et al., 2021)
Description	Monthly mean wind speed 10	m above ground l	evel (Upper bound)
Description			
Data source	Same as Index 1		

Annex 1 List of climate resilience indicators for airports

Index number	4	Unit	hPa
Indicator	Mean sea level pressure LB	Reference	(Poo et al., 2021)
Description	Monthly average of hourly mea	n sea-level pressur	e (Lower bound)
Data source	Same as Index 1	•	
Example value	Glasgow airport in December:	010.25 hPa	
Index number	5	Unit	hPa
Indicator	Mean vapour pressure LB	Reference	(Poo et al., 2021)
Description	Monthly average of hourly vapo	our pressure (Lowe	r bound)
Data source	Same as Index 1	A	,
Example value	Glasgow airport in December: 7	7.35 hPa	
Index number	6	Unit	m
Indicator	Skew surges records	Reference	(Poo et al., 2021)
Description	Average of Top 10 skew surges	records	

skew surge records are listed.	•	•
Leith 0.82 m		
7	Unit	N/A
Days of thunder	Reference	(Poo et al., 2021)
Days of thunder in a month		. ,
Same as Index 1		
Glasgow airport in December: 4	to 6 days	
8	Unit	m
Sea-level records	Reference	(Poo et al., 2021)
Average of Top 10 sea-level rec	ords	
Same as Index 6		
Leith 3.51 m		
9	I Init	°C
-		(Poo et al., 2021)
*		
	(oppe	
	6.75 °C	
	national marine environment. T skew surge records are listed. analysis. Leith 0.82 m 7 Days of thunder Days of thunder Days of thunder in a month Same as Index 1 Glasgow airport in December: 4 8 Sea-level records Average of Top 10 sea-level rec Same as Index 6 Leith 3.51 m 9 Maximum temperature UB Average of daily maximum air to Same as Index 1	Leith 0.82 m7UnitDays of thunderReferenceDays of thunder in a monthSame as Index 1Glasgow airport in December: 4 to 6 days8UnitSea-level recordsReferenceAverage of Top 10 sea-level recordsSame as Index 6Leith 3.51 m9UnitMaximum temperature UBReferenceAverage of daily maximum air temperature (Upper

1.0		. <i></i>
10	Unit	%
Relative humidity LB	Reference	(Poo et al., 2021)
Monthly average of hourly re	elative humidity (Lov	wer bound)
Same as Index 1		
Glasgow airport in Decembe	er: 86.82 %	
11	Unit	%
Precipitation LB	Reference	(Poo et al., 2021)
Monthly total precipitation a	mount (Lower bound	l)
Same as Index 1		
Glasgow airport in Decembe	er: 147.72 mm	
12	Unit	%
Cloud cover LB	Reference	(Poo et al., 2021)
Monthly average of hourly to	otal cloud cover (Low	ver bound)
Same as Index 1		
	Monthly average of hourly re Same as Index 1 Glasgow airport in December 11 Precipitation LB Monthly total precipitation a Same as Index 1 Glasgow airport in December 12 Cloud cover LB Monthly average of hourly to	Relative humidity LBReferenceMonthly average of hourly relative humidity (LowSame as Index 1Glasgow airport in December: 86.82 %11UnitPrecipitation LBReferenceMonthly total precipitation amount (Lower boundSame as Index 1Glasgow airport in December: 147.72 mm12UnitCloud cover LBReferenceMonthly average of hourly total cloud cover (Low

Example value	Glasgow airport in December: 73.22%		
Index number	13	Unit	°C
Indicator	Minimum temperature LB	Reference	(Poo et al., 2021)
Description	Average of daily minimum air temperature (Lower bound)		
Data source	Same as Index 1		
Example value	Glasgow airport in December: 1.37 °C		
Index number	14	Unit	N/A
Indicator	Days of air frost UB	Reference	(Poo et al., 2021)
Description	Day count if the minimum air	temperature lower	r than 0 °C (Upper bound)
Data source	Same as Index 1		
Example value	Glasgow airport in December:	: 10.61	
Index number	15	Unit	N/A
Indicator	Days of ground frost UB	Reference	(Poo et al., 2021)
Description		nperature lower the	an 0 °C in a month (Upper bound)
Data source	Same as Index 1		
Example value	Glasgow airport in December:	: 17.53	
Index number	16	Unit	N/A
Indicator	Days of sleet or snow falling UBReference(Poo et al., 2021)		
Description	Day of snow falling or sleet falling in a month (Upper bound)		
Data source	Same as Index 1		
Example value	Glasgow airport in December:	: 3.59	
Index number	17	Unit	N/A
Indicator	Days of snow lying UB	Reference	(Poo et al., 2021)
Description	Day of more than half of the ground covered by snow in a month (Upper bound)		
Data source	Same as Index 1		
Example value	Glasgow airport in December:	2.25	
Index number	18	Unit	N/A
Indicator	Number SAC	Reference	(McIntosh and Becker, 2019)
Description	Number of Special Areas of Conservation in airport county		
Data source	Joint Nature Conservation Committee (JNCC) is a public organisation that focuses on advising the UK Government and involved administrations on nature conservation.		
Example value	West Wales and The Valleys:	/+	
Index number	19	Unit	N/A
Indicator	AQ Daily Index	Reference	(McIntosh and Becker, 2019)
Description	Day of Air Quality Daily inde	x higher than 5 in	a month

Data sourceDefra provides the Daily Air Quality Index (DAQI) about air pollution levels and
provides recommended actions and health advice. The index is from 1 (low) to 10
(very high), to compare levels of air pollution, like the pollen index or sun index.

Glasgow Urban Area: 2

Example value

Index number	20	Unit	N/A
Indicator	Brownfield ratio	Reference	(McIntosh and Becker, 2019)
Description	Brownfield ratio higher than 0.5%		
Data source	The National Housing Federation (NHF), a trade or industry body representing housing providers, much of it termed affordable housing in England. An interactive map is designed to make it easier to locate available brownfield sites in England for providing comprehensive information on all brownfield sites.		
Example value	Manchester: 1.3%		
Example value Index number	Manchester: 1.3%	Unit	€ million
•		Unit Reference	€ million (McIntosh and Becker, 2019)
Index number	21	Reference	
Index number Indicator	21 GDP Gross domestic product of a reg Eurostat is responsible for provi	Reference tion ding statistical in g statistical meth	

Index number	22	Unit	€ million
Indicator	GVA	Reference	(McIntosh and Becker, 2019)
Description	Gross value added per head per month		
Data source	The Office for National Statistics, the UK Statistics Authority's executive office and a non-ministerial department provides the data.		
Example value	Inverclyde, East Renfrewshire, and Renfrewshire: £19,082		
Index number	23	Unit	%
Indicator	Market share	Reference	(McIntosh and Becker, 2019)
Description	Airport market share in the UK		
Data source	The Civil Aviation Authority is the statutory corporation that oversees all civil aviation aspects in the United Kingdom.		
Example value	Manchester: 9.7%		
Index number	24	Unit	%
Indicator	Direct employment	Reference	(McIntosh and Becker, 2019)

Data source	HM government presents the regional breakdown of direct employment and employees' compensation directly supported by the aviation sector.		
Example value	Heathrow: 22%		
Index number	25	Unit	N/A
Indicator	SoVI flood	Reference	(McIntosh and Becker, 2019)
Description	Socio-spatial vulnerability index on flooding		
Example value	Climate Just is an information tool designed to help deliver adaptative responses to climate change in local communities. Its focus is to help develop socially just responses to extreme events and support more comprehensive adaptation plannings. It also includes issues related to poverty severity and carbon emissions. There are seven levels, from extremely high to slight. Manchester: 7		
Index number	26	Unit	N/A
Indicator	SoVI heat	Reference	(McIntosh and Becker, 2019)
Description	Socio-spatial vulnerability index on heating		
Data source	Same as Index 31		
Example value	Manchester: 7		

Index number	27	Unit	£
Indicator	House price	Reference	(McIntosh and Becker, 2019)
Description	UK House Price Index		
Data source	It uses house sales data from HM Land Registry, Registers of Scotland, Land and Property Services Northern Ireland, and is calculated by the Office for National Statistics.		
Example value	Manchester: £184661		
Index number	28	Unit	min
Indicator	Punctuality statistics	Reference	(McIntosh and Becker, 2019)
Description	Average delay of flights		
Data source	Same as Index 23		
Example value	Heathrow: 12.95 mins		
Index number	29	Unit	%
Indicator	Congestion index	Reference	(McIntosh and Becker, 2019)
Description	TomTom Traffic Index		

Data source	TomTom N.V. is a Dutch mult and consumer electronics to p		r & creator of location technology ad congestion levels in cities
Example value	London: 37%		
Index number	30	Unit	N/A
Indicator	Rail connection Presence of direct rail connect	Reference	(McIntosh and Becker, 2019)
Description			1
Data source	1 I		or almost every airport globally, ons, airport codes, and runway
Example value	Manchester: Yes		
Index number	31	Unit	N/A
Indicator	Runway length	Reference	(McIntosh and Becker, 2019)
Description	The longest runway length in the airport. Three types are defined, ">3048m", "2438 – 3048 m", and "< 2438 m".		
Data source	Same as Index 30		
Example value	Manchester: >3048m		
Index number	32	Unit	Passenger
Indicator	Passenger traffic	Reference	(McIntosh and Becker, 2019)
Description	Total passenger traffic in a year	ar	
Data source	The Civil Aviation Authority is the corporation that is responsible for the regulation of civil aviation aspects in the UK.		
Example value	Manchester: 28254970		
Index number	33	Unit	Passenger
Indicator	Freight traffic	Reference	(McIntosh and Becker, 2019)
Description	Total freight traffic in a year		
Data source	Same as index 32		
Example value			
Example value	Heathrow: 1699663.498		
Index number	Heathrow: 1699663.498	Unit	N/A
		Unit Reference	N/A (McIntosh and Becker, 2019)
Index number	34	Reference	(McIntosh and Becker, 2019)
Index number Indicator	34 Runway number	Reference	(McIntosh and Becker, 2019)
Index number Indicator Description	34 Runway number Number of runways. Two type	Reference	(McIntosh and Becker, 2019)
Index number Indicator Description Data source	34 Runway number Number of runways. Two type Same as Index 30	Reference	(McIntosh and Becker, 2019)
Index number Indicator Description Data source Example value	34 Runway number Number of runways. Two type Same as Index 30 Heathrow: >2	Reference es are defined, ">2	(McIntosh and Becker, 2019) 2" and "1". N/A
Index number Indicator Description Data source Example value Index number	34 Runway number Number of runways. Two type Same as Index 30 Heathrow: >2 35	Reference es are defined, ">2 Unit Reference	(McIntosh and Becker, 2019) 2" and "1". N/A (McIntosh and Becker, 2019)
Index number Indicator Description Data source Example value Index number Indicator	34 Runway number Number of runways. Two type Same as Index 30 Heathrow: >2 35 Terminal number	Reference es are defined, ">2 Unit Reference	(McIntosh and Becker, 2019) 2" and "1". N/A (McIntosh and Becker, 2019)

Index number	36	Unit	Binary
Indicator	Sustainability plan	Reference	(McIntosh and Becker, 2019)
Description	Availability of a sustainability plan		
Data source	Climate change adaptation reports under the Climate Change Act, reporting to Environment Agency.		
Example value	Manchester: Yes		
Index number	37	Unit	Binary
Indicator	%change throughput	Reference	(McIntosh and Becker, 2019)
Description	Positive annual percentage change in passenger or freight		
Data source	Same as Index 23		
Example value	Manchester: Yes		
Index number	38	Unit	Binary
Indicator	%change market share	Reference	(McIntosh and Becker, 2019)
Description	Positive annual percentage change in market share		
Data source	Same as Index 23		
Example value	Manchester: Yes		