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Climate Risk Analysis in Transport: Uncertainty Modelling

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Introduction

Climate change and its impact on transportation need to be addressed from both mitigation and adaptation perspectives. The development of rational adaptation measures in transport requires quantitative climate risk analysis to ensure that the benefits of the measures (i.e., climate risk reduction) can outweigh the associated cost of implementing them. However, quantification of risks often involves high uncertainty, particularly in the climate change context where historical risk data are not always available or accessible. To deal with the high uncertainty in climate risk data, a few advanced climate risk analysis methods are developed using different uncertainty theories, including fuzzy logic, Dempster-Shafer (D-S), and Bayesian probabilistic theories. They are applied in various transport modes including road, rail, ports, and airports. This article aims to critically analyse such methods and their applications to allow their advances to be disseminated in the wider transport community.

Climate risk concept and parameters

Risk is defined as the combination of the likelihood of a hazard/threat and the consequence that the hazard/threat causes when it occurs. Climate change results in high stake risks such as flooding, heatwaves, sea level rises, which have generated significant negative impact on transport operations, and infrastructure health. In the context of climate risk analysis, different parameters are developed to model the characteristics of the above-named risks. Timeframe, occurrence likelihood, and severity of consequence are among the most used parameters (Yang et al., 2018).

Here, timeframe refers to how soon a climate threat could occur, likelihood means how frequent a climate threat could occur, and severity of consequence describes how bad the negative impact is when a climate threat occurs. Obviously, it is sometimes difficult to use the current available knowledge in the domain to precisely estimate the three parameters of a climate threat. The climate risk is defined in Equation 1.

$$R = (C, L, T, SoE/BK) \qquad (1)$$

where C represents the consequences of a climate threat, L is a quantified measure of the likelihood associated with this consequence, T means the occurrence urgency of the threat and SoE a qualitative description of the strength of evidence for the quantified uncertainty measure. BK is the background knowledge, on which the risk description is conditional.

Climate risk analysis modelling and applications

To address the SoE and BK in Eq (1), fuzzy logic (i.e., fuzzy rule base) and evidential reasoning (ER) based on D-S theory and Bayesian networks (BNs) are used collectively to support the development of climate risk analysis modelling in transport. The advances of the modelling methods are analysed below with a particular focus on how they deliver insightful results to guide adaptation measures using uncertain climate data.

Fuzzy rule base

When objective data is not available to describe C, L and T, subjective judgements are often used to compensate data incompleteness and unavailability in risk analysis. In this process,

linguistics terms characterised by fuzzy numbers are used to facilitate the risk analysis under uncertainty. For instance, Table 1 lists the linguistics variables used to describe L. A fuzzy rule base involving multiple IF-THEN rules had been developed to model climate risks. The IF part of a rule includes the three risk parameters, while the THEN part consists of the risk levels by Degrees of Belief (DoB). An illustrative IF-THEN rule in climate risk analysis can be expressed as follows.

IF T is very short and C is catastrophic and L is very high, THEN R is very high with a DoB of 90% and high with a DoB of 10%

where R donates the climate risk level. If and when multiple rules are involved in a particular climate risk analysis, different fuzzification inference algorithms (e.g., Min-Max and ER) can be used to obtain a quantitative defuzzified result to express the climate risk level for ranking and prioritisation purposes. This fuzzy rule-based climate risk analysis has been applied to deal with port's climate risk analysis and the details are found from Yang et al. (2018)

Bayesian Network

The fuzzy rule-based method has the advantages of modeling incomplete and unavailable risk data and capturing the non-linear relationship between the three risk parameters and climate risk. However, the used fuzzy inference algorithms reveal some problems in their applications. For instance, the min-max method results in loss of useful information in the inference process, while ER is mathematically complicated. To address such problems, a BN inference model has been developed and applied in road (Wang et al., 2019) and rail (Wang et al., 2020) climate risk analysis. In the model, R is treated as the child of three parent nodes T, C and L. Its conditional probabilities are assigned based on the DoB in the above-mentioned IF-THEN rules.

Evidential Reasoning

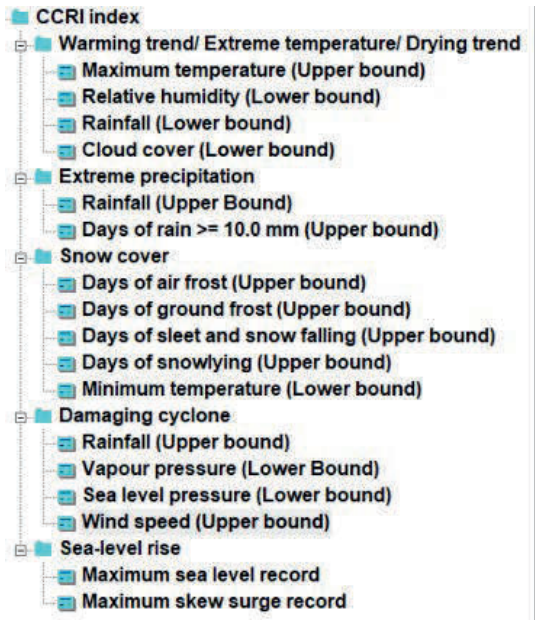
While the above BN model helps facilitate climate risk inference, it, relying on three pre-defined risk parameters (i.e., T, C, and L), is criticised in terms of the accuracy of subjective linguistics judgements. For instance, domain experts may have little knowledge on how frequent a climate threat could occur. With regards to Table 1, L could be between 'Very high'

Table 1. Likelihood (L) (Yang et al., 2018)

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

and 'High', but no certain estimates can be obtained. The fuzzy rule-based BN model is also lacking the ability in accommodating both objective and subjective data. A climate change risk index (CCRI) framework is developed and applied in the climate risk analysis of seaports (Poo et al., 2021). In the framework, detailed risk indicators are proposed in Figure 1 to quantify climate change risk. Such indicators can be described by both objective and subjective data. ER is used to synthesise them to obtain a quantitative CCRI value.

Figure 1. CCRI hierarchy (Poo et al., 2021)



Conclusion

This article reviews the quantitative development of climate risk analysis methods using three main uncertainty methods (i.e., fuzzy, ER, and BN). While their principles including advantages and disadvantages are presented here, more technical details and their applications and practical implications are given through a few featured publications listed in the references. The relevant work in future could be climate resilience analysis by adding more parameters, such as climate sensitivity and adaptive capability of transport operations and/or infrastructure beyond the risk focus (e.g., CCRI indicators in Figure 1). Climate risk research could be extended to the whole transport network level, in which transport vulnerability/ sensitivity to climate threats can be incorporated appropriately.

References

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