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Unlocking effective ice-jam risk management: Insights from agent-based modeling and comparative analysis of social theories in Fort McMurray, Canada

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ABSTRACT

Ice jams pose a major flood hazard in communities along northern rivers, resulting in high backwater levels and overbank flooding during ice-cover breakup. Mitigation measures, including large-scale projects by government agencies and individual actions by asset owners, can help reduce flood risk and protect human life and assets. This study examines ice-jam flood risk and explores the effectiveness of adaptive strategies in mitigating such risks in Fort McMurry, Canada. It evaluates the effectiveness of top-down (government-led artificial breakup) and bottom-up (resident-led flood-proofing) strategies, comparing the Rational Choice Theory (RCT) and the Protection Motivation Theory (PMT) models. The objective is to explore the potential enhancements to the ice-jam flood risk model through the integration of the PMT as a decision-making framework under uncertainty. This study seeks to assess whether and to what extent such integration can improve the modeling of ice-jam flood risk. The findings highlight the benefits of incorporating socio-economic factors in the PMT model. Economic factors, such as income tax and the cost of flood-proofing, shape overall flood risk, especially when artificial breakup measures are not implemented. The study emphasizes the importance of considering heterogeneity in decision-making processes and diverse characteristics of individuals when designing flood risk management strategies. Response efficacy and self-efficacy coefficients are significant factors influencing flood risk and the adoption of flood-proofing measures. Enhancing individuals' belief in their actions' effectiveness and their confidence in self-protection contributes to more effective flood risk management. These findings inform the development of more effective flood risk management strategies.

1. Introduction

Ice jams can be a major flood hazard in communities along many northern rivers. During ice-cover breakup, the damming effect of ice jams due to the accumulation of rubble ice along rivers can cause very high backwater levels and overbank flooding. Important characteristics of ice-jam flooding, in comparison to open-water floods, is the rapidity of the formation of ice jams and subsequent backwater staging making such events very difficult to forecast with very little response time to prepare and counter the impacts of such events. Also, small changes in the morphology of ice jams, in terms of the amount of rubble or slush ice that can accumulate in the jams and the location of the jam lodgements, can exacerbate the flooding situation. Oftentimes, flood water levels for certain exceedance probabilities can exceed those of open-water floods, making it crucial that such events are included in determining thresholds of flood levels used in the design and installation of infrastructure and construction developments. Measures to help mitigate ice-jam flooding can help reduce those threshold levels and reduce the risk to human assets and life that can ensue from such flooding. These measures can be in the form of large-scale, top-down projects implemented and operated by government agencies (e.g., the artificial breakup of the ice cover) or in individual, bottom-up measures that can be implemented by the owners of such assets (e.g., flood-proofing of buildings). Both top-down and bottom-up measures do involve decisions that have to be made on the degree of mitigation carried out related to social preferences and values but also within the constraints of financial budgets, policy regulations, and land availability. A modeling approach is required that not only views the physical and engineering aspects of the

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design and construction of mitigation measures but also considers the social and cultural milieu in which these measures are being placed.

Several studies have investigated the influence of dynamic adaptive behavior on estimating flood vulnerability and risk levels, incorporating different social theories such as the Rational Choice Theory (RCT) and Protection Motivation Theory (PMT) (Erdlenbruch and Bonté, 2018; Grothmann and Reusswig, 2006; Han et al., 2022; Richert et al., 2017). The RCT emphasizes that individuals make decisions based on a rational assessment of costs and benefits, aiming to maximize their self-interest (Jager et al., 2000). On the other hand, the PMT focuses on how individuals with bounded rationality perceive and respond to threats (Rogers, 1975). This theory suggests that individuals are motivated to protect themselves when they perceive a threat to their well-being. Motivation is influenced by two key factors: threat appraisal and coping appraisal. Threat appraisal involves evaluating the severity of the threat and the individual's vulnerability while coping appraisal entails assessing the effectiveness of protective measures and the individual's self-efficacy in implementing them. However, despite the growing body of literature on flood risk management, there remains a gap in understanding the importance of incorporating bounded rationality (e.g., PMT) into flood risk modeling, particularly in the context of ice-jam floods.

Agent-based modeling is a valuable bottom-up approach in modeling water-human systems, particularly in capturing individual decision-making, heterogeneity of human decision-making, and feedback mechanisms between individuals across various scales (Epstein, 1999; Ghoreishi et al., 2023; Ghoreishi, Razavi, et al., 2021; Wilensky and Rand, 2015). These models allow for the representation of individual-level behaviors, enabling a fine-grained analysis of the dynamics and interactions between different actors, and explore/explain the emergent phenomena at the system scale. With the individual-level representation, heterogeneity can be incorporated into agent-based models, allowing for the exploration of how diverse characteristics and preferences influence collective outcomes. Furthermore, agent-based models excel in capturing feedback loops between individuals and their environment across various scales (e.g., interactions between residents at a local scale and government at a large scale), enabling the study of how individual behaviors and interactions propagate and shape emergent phenomena.

The use of agent-based modeling in the context of flood risk has gained considerable attention in recent years. Several studies have employed agent-based models to investigate the dynamics and complexities of flood risk management, considering the interactions between individuals, their decision-making processes, and the physical environment (Anshuka et al., 2022; Haer et al., 2016, 2017). While past studies have contributed valuable insights to the broader understanding of flood risk, a critical research gap remains in the specific domain of ice-jam flood risk. In fact, there is a need for further research that integrates the PMT into agent-based models to explore the potential enhancements to the ice-jam flood risk model. The selection of PMT is grounded in its proven effectiveness in representing human decision-making responses to floods by the past studies (Bubeck et al., 2012; Grothmann and Reusswig, 2006; Koerth et al., 2013). In comparison to other bounded rational theories, such as the theory of planned behavior, these studies on flood risk consistently highlights PMT as a more fitting representation of human decision-making dynamics under conditions of uncertainty and limited information. Additionally, more studies are needed to investigate the interaction across scales in the context of flood risk, such as the interplay between local-scale residents' adaptation and basin-scale government adaptation. Bridging these gaps in the literature will provide a more comprehensive understanding of ice-jam flood risk and enhance the effectiveness of flood risk management strategies in these contexts.

This study builds upon the methodology developed by Ghoreishi and Lindenschmidt (2024), where they constructed an agent-based model to evaluate ice-jam flood risk incorporating top-down (i.e., artificial breakup by governments) and bottom-up (i.e., flood-proofing by residents) adaptive strategies. The decision-making processes of both residents and the government were guided by the RCT. Also, individual behaviors were influenced by the potential reduction in flood risk through the artificial breakup, while the government's actions were influenced by the potential risk reduction through flood-proofing at the system level.

The objective of this study is to explore the potential enhancements to the ice-jam flood risk model, previously developed model by Ghoreishi and Lindenschmidt (2024), through the integration of the PMT as a decision-making framework under uncertainty. This study seeks to assess whether and to what extent such integration can improve the modeling of ice-jam flood risk with the case study of the Athabasca River at Fort McMurray. By comparing the model outputs under both the RCT and PMT, this research seeks to assess the impact of different social theories on the model response and understand how they shape flood risk management outcomes. Furthermore, a sensitivity analysis is conducted to explore the significance of socio-economic factors in the model and evaluate their influence on the overall results. Ultimately, this study aims to provide insights into the implications of alternative social theories, such as the PMT, on the model output and its associated uncertainties, contributing to a more realistic understanding of ice-jam flood risk and informing more effective flood risk management strategies.

2. Methodology

2.1. Description of the agent-based model for ice-jam flooding in Fort McMurry

The study site is the Athabasca River at Fort McMurray. This part of the Athabasca River is quite conducive to ice jamming since there is a large change in the river's fluvial geomorphology along the stretch, where water flows from a relatively steep and narrow stretch upstream of the town's bridge (See Fig. 1) to a flatter, wider downstream stretch. The downstream stretch has many islands, sandbars, and channel constrictions (between islands and riverbanks) providing areas where the ice rubble running down the river can easily lodge and jam. Certain characteristics of the tributary, the Clearwater River, increase the severity of ice jamming and flooding in the Athabasca River. For one, the Clearwater River's slope is much flatter than that of the Athabasca River allowing backwater to flow from the Athabasca River into the tributary when an ice jam forms on the Athabasca River. The backwater flow also reduces flow velocities in the Athabasca River allowing accumulated ice to remain lodged in the ice jams longer during floods. For another, the

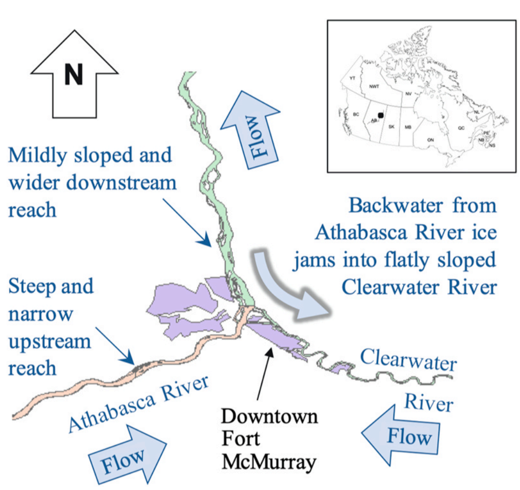

Fig. 1. Athabasca and Clearwater rivers at Fort McMurray and its ice-jam formation.

banks of the lower Clearwater River are relatively low allowing this backwater flow to overtop its banks and inundate the floodplain on which downtown Fort McMurray lies.

In the study by (Ghoreishi and Lindenschmidt, 2024), the researchers focused on ice-jam risk assessment in the Athabasca River region. To simulate ice-jam processes, they used RIVICE, which is a one-dimensional, hydrodynamic, and river-ice hydraulic model. It simulates variations in the longitudinal direction of a river while averaging variations in the lateral and depth directions. The model incorporates the dynamic wave of the St. Venant equations, allowing for the simulation of backwater flow. It includes processes related to river ice, such as the generation of border ice, frazil ice, and consolidated ice covers. RIVICE has been successfully used for various applications, including forecasting ice-jam flooding (Lindenschmidt et al., 2019), calculating ice-jam flood hazard (Lindenschmidt, 2023), and assessing the effectiveness of mitigation measures for ice-jam flood risk reduction (Lindenschmidt, 2024). The study also estimated ice-jam flood risk by assessing the potential economic damages caused by flood events. This involved estimating flood depths and extents using water level outputs and applying a depth-damage relationship to estimate damages to buildings.

To evaluate the dynamic ice-jam flood risk, an agent-based modeling approach was employed. The model incorporated human adaptation behaviors, including artificial breakup and flood-proofing. Two types of agents, residents and the government, were modeled based on rational decision-making. Residents considered the benefit-cost ratio to decide whether to implement flood-proofing measures, while the government used the same ratio to determine whether to carry out artificial breakage. The interactions between residents and the government influenced the overall flood risk.

2.2. Bounded rationality for ice-jam flooding in Fort McMurry

To explore the improvement of the ice-jam flood risk model developed by Ghoreishi and Lindenschmidt (2024), the residents' adaptation decision-making process in this study was modeled using the PMT, which captures bounded rationality (See Appendix for the full description of the model based on ODD + D protocol). According to the PMT, residents make decisions based on threat appraisal and coping appraisal. Threat appraisal involves evaluating the severity and probability of ice-jam flood events, represented by flood risk in this study. Coping appraisal includes perceived response efficacy, perceived self-efficacy, and the costs associated with adaptation measures.

This study incorporated two supplementary factors, namely social network and appraisal of past flood experience, recommended by previous studies (Erdlenbruch and Bonté, 2018; Haer et al., 2019). Social network represents the influence of other agents on an individual's decision-making regarding risk reduction measures. Past flood experience reflects how individuals learn from previous ice-jam floods and adjust their risk-reduction behaviors. To model the residents' decision-making process, a logit model was used. This model calculates the probability of one event out of two alternatives, assuming that the logarithm of the odds of the event occurring is a linear combination of independent factors (socio-economic factors in this study). The logit (logistic) model has been effectively used in various studies to model individuals' adaptation to flood and drought (Erdlenbruch and Bonté, 2018; Uddin et al., 2014). Eq. 1 represents the probability of residents adopting risk reduction measures for a specific agent at a given time. For each successive simulation time loop, a random number is generated for each agent, ranging from 0 to 1. If this number is lower than the calculated probability for residents adopting risk reduction measures (also ranging from 0 to 1), the agent decides to adopt flood-proofing. This stochastic approach allows for the incorporation of the complexity of human decision-making and factors not explicitly included in the model, such as beliefs, introducing uncertainty into the adaptive behavior of the residents.

$$P_{i,t} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot (FR_{i,t}) + \beta_2 \cdot (CP) + \beta_3 \cdot (RE_i) + \beta_4 \cdot (SE_i) + \beta_5 \cdot (FE_{i,t}) + \beta_6 \cdot (SN_{i,t}))}} \tag{1}$$

In this equation, $FR_{i,t}$($) represents the flood risk for agent i at time t, CP($) denotes the cost of flood-proofing for agents, and β_0 is a constant term. The coefficients β_1 to β_6 are the weights associated with the socio-economic variables, namely flood risk, cost of flood-proofing, response efficacy (RE_i), self-efficacy (SE_i), flood experience ($FE_{i,t}$), and social network ($SN_{i,t}$), respectively. RE and SE vary between 0 and 1. The socio-economic variables are considered as independent factors in the model, and the values of response efficacy, self-efficacy, and weights are sampled from a normal distribution for agents in the model setup, following previous studies (Bertella et al., 2014; Du et al., 2017; Marino et al., 2008). The flood experience variable is updated for each resident (i.e., agent i) by the difference between their observed level of water and the averaged historical water level data from 40 years ago (based on the model timespan developed by Ghoreishi and Lindenschmidt (2024)) due to ice-jam flooding events. This process allows for capturing the residents' past exposure to ice-jam flooding and facilitates modeling of their adaptation decisions based on their previous water level conditions.

The social network, as given by Eq. (2), is calculated as the ratio of the number of agents in the social network who have adopted risk-reduction measures ($A_{i,t}$) in the specified radius to the total number of agents in the same radius (N_i), following the study by Du et al. (2017). This social network implies that agents are influenced by their connected agents' decisions.

$$SN_{i,t} = \frac{A_{i,t}}{N_i} \tag{2}$$

3. Sensitivity analysis

To address the inherent stochasticity of the agent-based model and the challenges associated with a sensitivity analysis (see Ghoreishi, Sheikholeslami, et al., 2021), we performed comprehensive sensitivity analyses to ensure the robustness and reliability of our findings. We employed a multi-run approach, running the model multiple times with varying sets of socio-economic factors, ranging from 1 to 1000 repetitions. This rigorous approach allowed us to comprehensively assess the impact of stochasticity on the model outputs and obtain robust and reliable results. By capturing the variability inherent in the stochastic model, we aimed to provide a more comprehensive understanding of the system dynamics and enhance the validity of our analysis.

In addition to the multi-run analysis, we conducted a global sensitivity analysis to identify the most influential parameters within the agent-based model. With the potential ranges of the model parameters (as outlined in Table 1), we assessed the impact of model parameters on the model outputs. To achieve this, we utilized the Variogram Analysis of Response Surfaces (VARS) framework, which combines derivative-based and variance-based approaches commonly employed in the global sensitivity analysis (Razavi and Gupta, 2016). In our study, we focused on ice-jam flood risk and newly adapted residents (averaged over time) as the model responses. The VARS sampling strategy was implemented with a sampling setting of 50 stars and a sampling resolution of 0.1, resulting in a total of 5000 model runs (Razavi and Gupta, 2016 provides further details on the VARS sampling strategy). The parameter ranges were determined by localized information specific to our case study. (CBC, 2019; Fixr, 2022).

By conducting these sensitivity analyses, including the multi-run analysis and global sensitivity analysis using VARS, we obtained robust and comprehensive insights into the behavior of the agent-based model and the influence of various socio-economic factors and parameters. These analyses enhance the reliability and validity of our findings and contribute to a more rigorous understanding of the system dynamics under study.

Table 1
The ranges of model parameters for the global sensitivity analysis.

Model Parameters	Units	Lower Bound	Upper Bound
Income Tax	$	1500000	1800000
Cost of flood-proofing	$	200	2000
Mean of a normal distribution for individual risk coefficient	-	0	1
Mean of a normal distribution for cost of flood-proofing coefficient	-	0	1
Mean of a normal distribution for response efficacy coefficient	-	0	1
Mean of a normal distribution for self-efficacy coefficient	-	0	1
Mean of a normal distribution for flood experience coefficient	-	0	1
Mean of a normal distribution for social network coefficient	-	0	1
Mean of a normal distribution for self-efficacy	-	0	1
Mean of a normal distribution for response efficacy	-	0	1
Heterogeneity (standard deviations of normal distributions)	-	0	0.3

4. Scenario analysis

To gain a deeper understanding of the agent-based model under different theoretical frameworks, we conducted scenario analyses by defining distinct scenarios. Fig. 2 illustrates the socio-economic scenarios implemented in the agent-based model under the RCT and PMT. These scenarios were created based on two primary categories, characterized by varying levels of socio-economic factors. For each category, we assigned values to represent low and high levels of these factors, allowing us to explore their influence on the model outcomes. Specifically, we performed the scenario analysis on the agent-based model under the RCT using the following scenarios:

- Scenario A: This scenario represents a favorable economic situation with high-income tax and a low cost of flood-proofing for residents facilitated by government subsidies. In this scenario, we set the values of high-income tax and low cost of flood-proofing at $1700,000 and $200, respectively.
- Scenario B: This scenario reflects an unfavorable economic situation with low-income tax and a high cost of flood-proofing for residents despite government subsidies. Here, we defined the values of low-income tax and high cost of flood-proofing as $1600,000 and $1800, respectively.

To perform scenario analysis on the model under the PMT, we further subcategorized scenarios A and B. This was done by

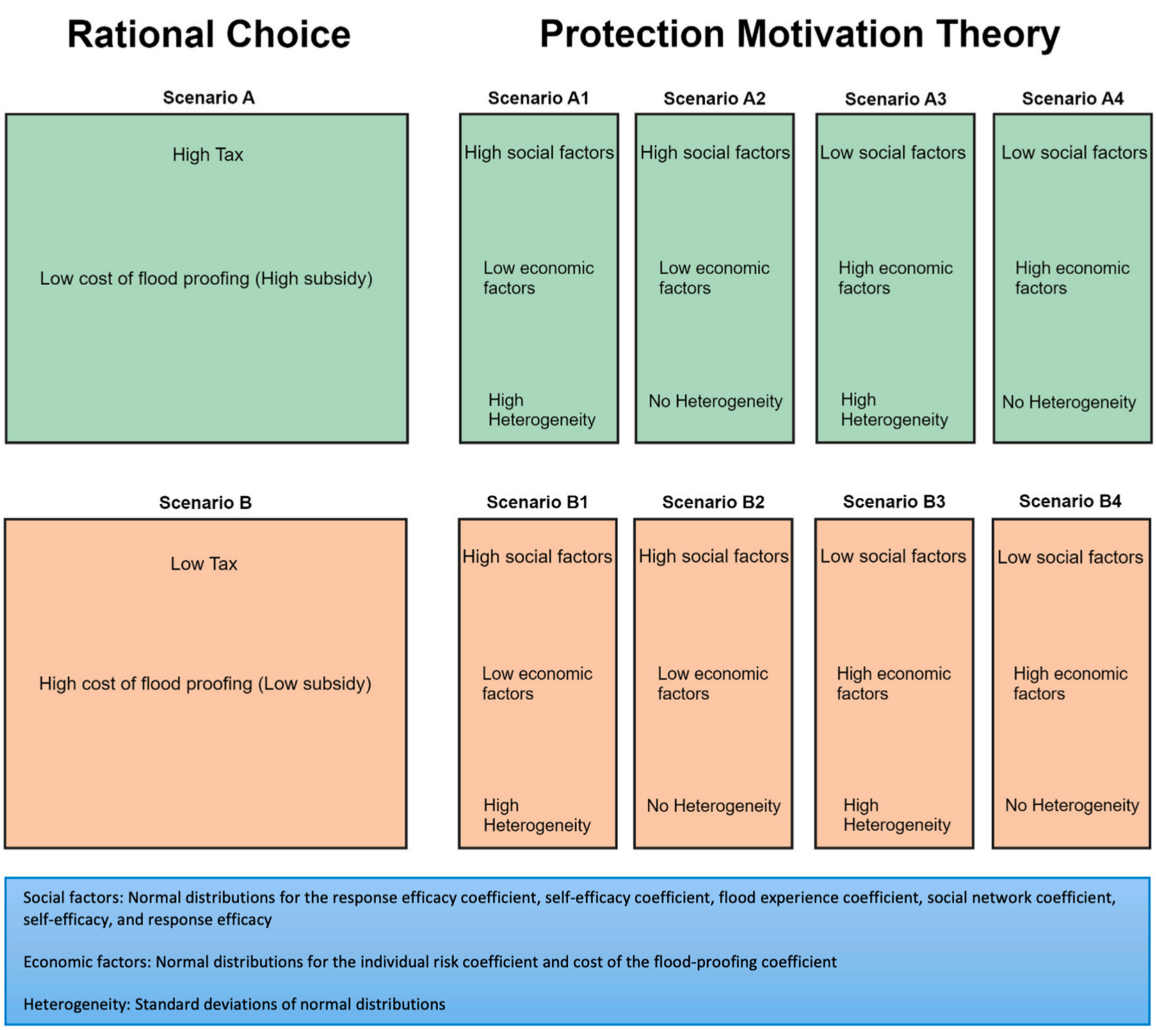

Fig. 2. Socio-economic scenarios on the agent-based model under rational choice theory and protection motivation theory.

introducing additional variability in the social factors through means of a normal distribution for the response efficacy coefficient, self-efficacy coefficient, flood experience coefficient, social network coefficient, self-efficacy, and response efficacy. The economic factors were defined as means of a normal distribution for the individual risk coefficient and cost of the flood-proofing coefficient. Thus, with the same values of other economic factors in each above scenario (A and B), we conducted another scenario analysis on the agent-based model under the PMT through the sub-categories of A and B:

- Scenarios A1/B1: This scenario represents a favorable/unfavorable economic situation of scenario A/B with high social factors, high heterogeneity, and low economic factors. In this scenario, we defined the values of high social factors, high heterogeneity, and low economic factors as 0.8, 0.3, and 0.2, respectively.
- Scenarios A2/B2: This scenario represents a favorable/unfavorable economic situation of scenario A/B with high social factors, no heterogeneity, and low economic factors. In this scenario, we defined the values of high social factors, high heterogeneity, and low economic factors as 0.8, 0, and 0.2, respectively.
- Scenarios A3/B3: This scenario represents a favorable/unfavorable economic situation of scenario A/B with low social factors, high heterogeneity, and high economic factors. In this scenario, we defined the values of high social factors, high heterogeneity, and low economic factors as 0.2, 0.3, and 0.8, respectively.
- Scenarios A4/B4: This scenario represents a favorable/unfavorable economic situation of scenario A/B with low social factors, no heterogeneity, and high economic factors. In this scenario, we defined the values of high social factors, high heterogeneity, and low economic factors as 0.2, 0, and 0.8, respectively.

By simulating the model under these defined scenarios, we aimed to examine how different socio-economic conditions, as represented by varying income tax and flood-proofing costs, influence the model outcomes. The scenario analysis provides valuable insights into the implications of economic factors on flood risk management and the behavior of residents within the modeled environment.

5. Result

The trajectories of ice-jam flood risk and the adaptation of residents are compared for the boundaries of model factors from 2001 to 2021 under the dynamic adaptation through the RCT and the PMT (Fig. 3). The simulation based on the PMT captures gradual changes between different model variables compared to the simulation based on the RCT, which covers the response surface in a more discrete way. According to Fig. 3a, the results of PMT and RCT follow a similar trend. Similar to the result of the study by Ghoreishi and Lindenschmidt (2024), PMT also shows a regime shift attributed to the significant role of dynamic adaptation by governments and residents. Similar to the result of the study by Ghoreishi and Lindenschmidt (2024), the model under PMT also reveals that the dynamic adaptation of governments and residents can significantly influence abrupt changes and sudden shifts between two distinct system states—a phenomenon known as regime shifts (Scheffer et al., 2001). In simpler terms, perturbations in the model factors have the potential to induce a shift within the system, resulting in two states characterized by different patterns and trends in the dynamics of ice-jam flood risk. In contrast to the RCT model, the results of the PMT model exhibit higher variability in ice-jam flood risk across the sampled factors. Although the PMT model introduces more uncertainty, the bounded rationality in this model reflects a behavioral model that aligns better with reality (Epstein, 1999; Simon, 1991). Furthermore, the lower bound of uncertainty in the PMT model highlights the potential for a greater reduction in ice-jam flood risk when compared to the RCT model. This disparity can be attributed to the significant influence of socio-economic factors on human decision-making processes.

According to Fig. 3b, the model simulations by the RCT and PMT also exhibit a similar trend from 2001 to 2021. As discussed by Ghoreishi and Lindenschmidt (2024), the high level of adaptation in 2001 can be justified by the elevated ice-jam flood risk and the occurrence of ice-jam floods in 1875, 1977, 1978, 1979, and 1997 (IBI and Golder, 2014), as well as the assumption in the model that no residents had undertaken flood-proofing before 2001. However, the model simulation by the PMT indicates a higher degree of uncertainty in capturing the socio-economic factors influencing human decision-making in 2001. After 2001, both the RCT and PMT simulations display similar variability. Although the total flood risk decreases in 2011, the PMT model shows an increase in newly adapted residents compared to the RCT model. This increase is attributed to the influence of social factors, which will be discussed further in the result of the scenario analysis.

The results obtained from running the model multiple times with varying sets of socio-economic factors revealed a low variability attributed to the stochastic features of the model. As an example, Fig. 4 shows the outcome of 1000 possible trajectories based on one specific set of socio-economic factors. This finding indicates that the impact of stochasticity on the model outputs is relatively minimal. Consequently, we can confidently perform GSA using a relatively low number of model repetitions. Thus, in this study, we chose 100 for model repetitions. By conducting the GSA with fewer repetitions, we can efficiently explore the sensitivity of the model to its parameters and identify the most influential factors driving the system dynamics. This approach saves computational resources and allows for a more efficient and streamlined analysis of the model's behavior.

Table 2 presents a comprehensive comparison of the parameter sensitivity analysis results for the agent-based model, considering two theoretical perspectives: RCT and PMT. The results indicate that economic factors exhibit the highest level of sensitivity in both models. Similar to the findings of the model under the RCT, the model under the PMT identifies income tax as the most critical parameter influencing

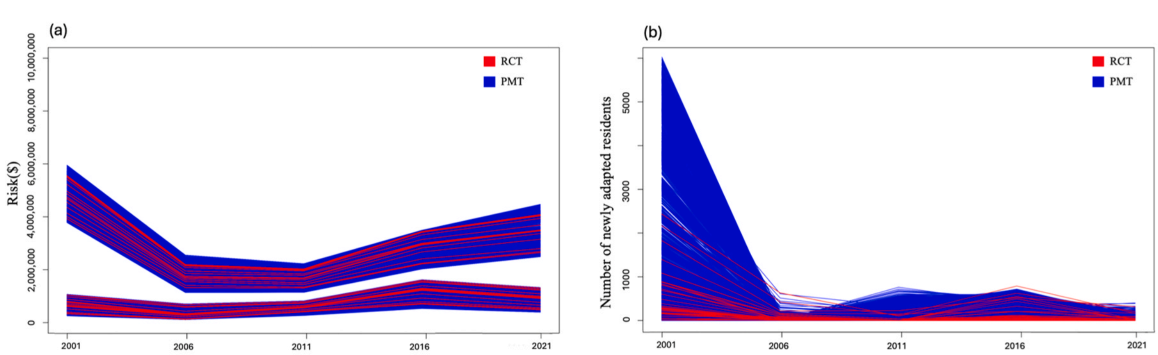

Fig. 3. The trajectories of (a) ice-jam flood risk and (b) the number of newly adapted residents in response to ice-jam flood risk by flood-proofing for the boundaries of model factors under the rational choice theory (RCT), and the protection motivation theory (PMT) from 2001 to 2021.

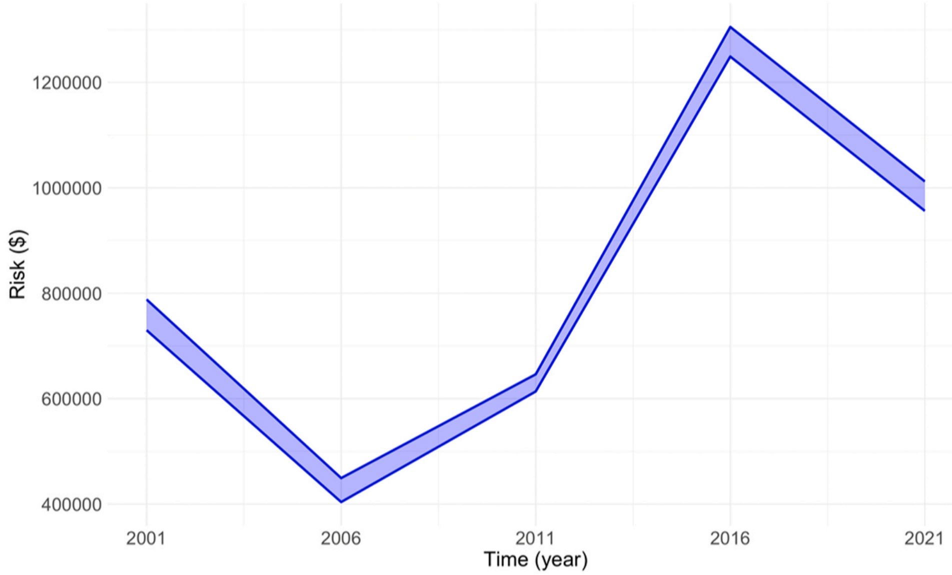

Fig. 4. The envelope of 1000 possible trajectories regarding the stochasticity in human decision-making based on one specific set of socio-economic factors.

Table 2
Rankings of the parameters using the sensitivity analysis. The most sensitive parameters for the model response show low values.

	Social Theories	Rational Choice Theory		Protection Motivation Theory	
	Model Response	Total flood risk	Adapted Residents	Total flood risk	Adapted Residents
Model Parameters	Income tax	1	1	1	2
	Cost of flood-proofing	2	2	4	4
	Mean of a normal distribution for individual risk coefficient	-	-	2	3
	Mean of a normal distribution for cost of flood-proofing coefficient	-	-	3	1
	Mean of a normal distribution for response efficacy coefficient	-	-	9	9
	Mean of a normal distribution for self-efficacy coefficient	-	-	8	8
	Mean of a normal distribution for flood experience coefficient	-	-	10	11
	Mean of a normal distribution for social network coefficient	-	-	11	10
	Mean of a normal distribution for response efficacy	-	-	6	6
	Mean of a normal distribution for self-efficacy	-	-	7	7
	Heterogeneity	-	-	5	5

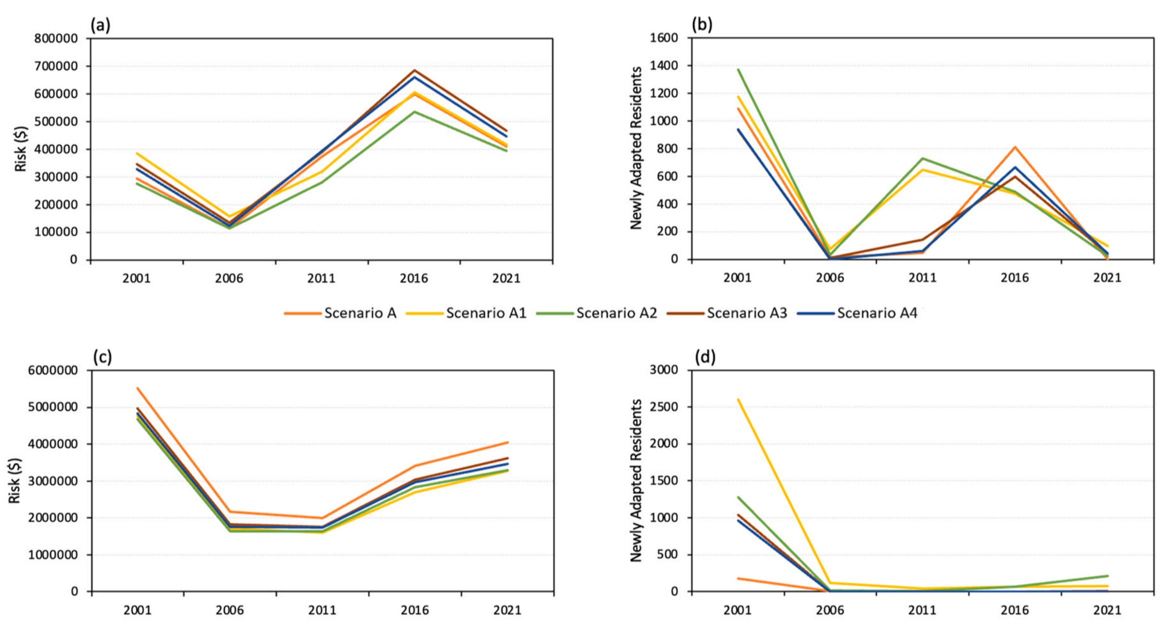

Fig. 5. The trajectories of ice-jam flood risk and the number of newly adapted residents for scenarios A-A4 (a and b) and B-B4 (c and d) under the protection motivation theory from 2001 to 2021.

total flood risk. However, the coefficient of cost of flood-proofing surpasses income tax in terms of importance when considering the number of newly adapted residents. This suggests that individuals' attention to the cost associated with flood-proofing plays a vital role in their adaptation decision, a notion supported by prior research in other regions (Botzen and Van Den Bergh, 2008; Kreibich et al., 2011).

Moreover, the sensitivity analysis highlights the significance of heterogeneity as one of the key socio-economic factors affecting both total flood risk and the adoption of flood-proofing measures by residents. This observation aligns with previous research conducted by Brown and Robinson (2006), emphasizing the influence of heterogeneity in decision-making processes. By employing an agent-based modeling approach, this study effectively incorporates the diverse characteristics and decision-making behaviors of individuals, providing a valuable advantage over traditional approaches.

Furthermore, the coefficients of response efficacy and self-efficacy emerge as important factors contributing to both total flood risk and the number of newly adapted residents. This finding is consistent with the studies conducted by Bubeck et al. (2012) and Grothmann and Patt (2005), which demonstrate the significance of response efficacy and self-efficacy in flood risk management strategies. It is noteworthy to highlight that we tracked the stability and convergence of the GSA results. The thorough analysis affirmed the reliability of the results obtained.

Fig. 5 presents the results of the scenario analysis conducted on the agent-based model. The scenarios, labeled A-A4 and B-B4, examine the impact of varying income tax, cost of flood-proofing values, and other socio-economics factors. In scenarios A-A4 (Figures a and b) where income tax is high and the cost of flood-proofing is low, the total flood risk is lower compared to the model under scenarios B-B4 (Figures c and d). Overall, within scenarios A-A4, the total flood risk exhibits a consistent trend across different scenarios, with similar values observed before 2011. The model under scenarios A-A4 (Figures a and b), which incorporate high social factors (scenarios A1 and A2), demonstrates a lower total flood risk compared to scenarios with low social factors (scenarios A3 and A4). This discrepancy is attributed to a higher number of newly adapted residents in 2011. The presence of a substantial population adapting to flood-proofing measures contributes to the reduction in total flood risk beyond 2011. This finding indicates that even with low total flood risk, attention to social factors can lead to an increase in the number of residents adopting adaptive measures. For the model under scenarios A1 and A2, the number of newly adapted residents decreases in 2016 due to a smaller population remaining unadapted to flood-proofing measures.

According to Figs. 5c and 5d, the model under scenarios B-B4 exhibits a consistent trend for both total flood risk and newly adapted residents. Notably, the model under scenarios with high social factors (scenarios B1 and B2) showcases lower total flood risk values and higher numbers of newly adapted residents compared to scenarios with low social factors (scenarios B3 and B4). The results of the scenario analysis highlight the role of social factors in influencing both the total flood risk and the adoption of flood-proofing measures. The findings support the notion that considering and addressing social dynamics can lead to more effective flood risk management strategies (Aerts et al., 2018; Grothmann and Reusswig, 2006).

6. Discussion

6.1. Complexity versus uncertainty

A crucial aspect in selecting or developing a water-human model is to determine the appropriate level of complexity that aligns with the objectives of evaluating management measures. The level of complexity directly impacts the model's ability to reduce uncertainty, which refers to the disparities between observed data and simulated results. A more complex model encompasses a broader range of processes, potentially leading to reduced model uncertainty. However, an increase in complexity also introduces a higher number of parameters and variables, which may result in increased model uncertainty. Model uncertainty quantifies the variation in output results resulting from changes in input data, such as parameter values and initial or boundary conditions. Also, a complex model can introduce the issue of over-parameterization that arises when the number of parameters and variables becomes excessive for the available data or the complexity of the system being modeled. Over-parameterization can complicate the calibration process, increase model uncertainty, and limit the model's predictive power. It is essential to find a equilibrium between the complexity of the model and the number of parameters. This balance is critical to prevent over-parameterization, ensuring that the model accurately captures system dynamics without introducing unnecessary complexity or uncertainty.

Snowling and Kramer (2001) proposed a hypothesis, addressing the relationship between model uncertainty, complexity, and sensitivity. According to their hypothesis, "model sensitivity increases with complexity due to the larger number of degrees of freedom and the interplay between parameters and state variables. Simultaneously, modeling uncertainty tends to decrease with increasing complexity, as more intricate models have the capacity to better simulate reality by incorporating more processes and minimizing simplifying assumptions" (Snowling and Kramer, 2001). This hypothesis can provide valuable insights into the trade-off between model complexity and uncertainty in water-human modeling.

In this study, we conducted a comparative analysis of two theoretical frameworks, namely the RCT and PMT, for assessing ice-jam flood risk. The PMT model, in contrast to the RCT model, incorporates a higher level of complexity by considering a greater number of socio-economic factors. This enhanced model captures a more comprehensive decision-making process and aligns more closely with real-world conditions. However, it should be noted that the increased complexity of the PMT model introduces additional uncertainty and the potential issue of over-parameterization. As discussed in the results section, both theoretical frameworks demonstrate similar trends over the study period, with a few exceptions observed in the patterns of adapted residents. Furthermore, our analysis reveals the presence of regime shifts in the model outputs under both theoretical frameworks.

Although this study confirms that increased model complexity can potentially elevate uncertainty, such a conclusion is not universally applicable. In fact, instances exist where heightened model complexity results in a reduction of uncertainty. A good example is found in a few agent-based models incorporating learning capabilities among agents (e.g., see Lin and Yang 2022). In these models, the evolving uncertainty, which may reduce over time, exhibits variability dependent on the specific structural attributes governing the learning capabilities of agents within the model (Karthe et al., 2021). Therefore, a comprehensive assessment of the relationship between model complexity and uncertainty necessitates a nuanced examination, taking into account domain-specific factors and structural intricacies inherent to the modeling framework under consideration.

6.2. Implications for ice-jam flood risk management

The understanding of model complexity, uncertainty, and the comparison of the different theoretical frameworks (RCT and PMT) can be valuable for informing flood risk management strategies. This knowledge can be applied in the following ways:

- The insights gained from assessing the trade-off between model complexity, and uncertainty can guide the selection of an appropriate modeling approach for flood risk management. Decision-makers can consider the level of complexity that aligns with their specific objectives and available data. They can also assess the trade-off between model performance and the interpretability and uncertainty associated with more complex models.

- The comparison of different theoretical frameworks can shed light on the effectiveness of various adaptation strategies in managing flood risk. By examining the behavior of adapted residents and the presence of regime shifts in model outputs, decision-makers can gain insights into the dynamics of community response and the resilience of different adaptation measures. This knowledge can inform the development of targeted and context-specific strategies that consider both physical and socio-economic dimensions of flood risk.
- The sensitivity analysis showed that economic factors, such as income tax and the cost of flood-proofing, have a significant influence on flood risk. Understanding the importance of these factors can help prioritize resource allocation and policy interventions. Moreover, the analysis highlighted the role of heterogeneity in decision-making processes, emphasizing the need to consider diverse characteristics and behaviors of individuals when designing flood risk management strategies. Also, the coefficients of response efficacy and self-efficacy were found to be important factors affecting both flood risk and the adoption of flood-proofing measures. This indicates that enhancing individuals' belief in the effectiveness of their actions and their confidence in their ability to protect themselves can contribute to more effective flood risk management.

7. Conclusion

Ice-jam floods pose a significant risk to communities along northern rivers, characterized by rapid formation and limited forecasting time. Mitigation measures are crucial to reduce the impact of such floods, which can be implemented through top-down government projects or bottom-up individual actions. Understanding the decision-making process and incorporating bounded rationality, such as the Protection Motivation Theory (PMT), is essential in ice-jam flood risk modeling.

To assess ice-jam flood risk, this study extends the previous study by Ghoreishi and Lindenschmidt (2024) by integrating the PMT into the developed agent-based model. Agent-based model is a valuable approach in modeling water-human systems as it captures individual decision-making, heterogeneity, and feedback mechanisms across scales. By comparing the model outputs under the Rational Choice Theory (RCT) and PMT, the effectiveness of top-down and bottom-up adaptive strategies in mitigating ice-jam flood risk is evaluated. The research also conducts a sensitivity analysis to assess the significance of socio-economic factors in the model under PMT and RCT. The findings of our study are as follows:

- By comparing two theoretical frameworks, the study acknowledges the potential benefits of a more complex model (PMT model) that incorporates comprehensive socio-economic factors and represents provides a more accurate and reliable representation of ice-jam flood risk dynamics compared to the RCT model. However, it also acknowledges the challenges that come with increased complexity, including higher uncertainty and the issue of over-parameterization. These insights contribute to a better understanding of the strengths and limitations of different modeling frameworks.
- Both the RCT and PMT models exhibit similar trends over the study period, with some exceptions in the behavior of adapted residents. The results show a regime shift in ice-jam flood risk due to significant dynamic adaptation by governments and residents. This suggests that both frameworks can provide valuable insights into ice-jam flood risk assessment.
- The sensitivity analysis underscores the significance of economic factors in shaping overall flood risk, particularly the income tax and the cost of flood-proofing, which emerge as crucial factors. Notably, the cost of flood-proofing exhibits greater influence when the government does not implement artificial breakup measures. Also, the result of the scenario analysis shows that despite a low overall flood risk, focusing on social factors can result in a higher rate of residents adopting adaptive measures.
- The PMT model demonstrates the important role of socio-economic factors in ice-jam flood risk management. The analysis underscored the importance of heterogeneity in decision-making processes, emphasizing the necessity of taking into account the diverse characteristics and behaviors of individuals when designing strategies for managing flood risk. The response efficacy and self-efficacy coefficients played a significant role in influencing flood risk and the adoption of flood-proofing measures. This suggests that improving individuals' perception of the effectiveness of their actions and their confidence in their ability to protect themselves can positively impact flood risk management outcomes.

The limitations of the study can be summarized as follows:

- While the study integrates the PMT as an acceptable and well-known social theory in the flood context, it is important to acknowledge that other theories may also influence decision-making processes. The study focuses on the PMT and RCT as the guiding social theories, potentially overlooking the impact of additional theories on flood risk management outcomes. Thus, the future studies need to explore the influence of other social theories such the theory of the planned behavior on the ice-jam flood risk.
- As with any modeling study, there are inherent uncertainties and assumptions associated with the agent-based model used in the analysis. The model's accuracy and reliability depend on the underlying assumptions and data availability. It is important to acknowledge these limitations and carefully interpret the model results.
- The study's findings and conclusions may be specific to the context and conditions considered in the analysis. The applicability and generalizability of the results to other regions or scenarios with different socio-economic factors and flood risk characteristics may be limited. Future research endeavors should systematically broaden their scope by focus on diverse case studies with distinct conditions. This methodological expansion is important to foster a more robust foundation for generalizing results. The incorporation of a wider range of cases will enhance the study's capacity to explain overarching patterns and trends, thereby contributing to a more comprehensive and nuanced understanding of the phenomena under investigation.
- Human decision-making processes are inherently complex and influenced by numerous factors, including cognitive biases, social norms, and external influences. While the study incorporates social theories to capture decision-making processes, it is challenging to fully represent the complexity and variability of human decision-making in a model. To address this challenge, future research should focus on accumulating a more extensive dataset through systematic observation. This enriched dataset will serve as a valuable resource for refining and enhancing the development of the model.

CRediT authorship contribution statement

Mohammad Ghoreishi: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Karl-Erich Lindenschmidt:** Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work MG used ChatGPT in order to improve the writing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envsci.2024.103731.

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