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# A stratified decision-making model for long-term planning: Application in flood risk management in Scotland ☆

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ABSTRACT

In a standard decision-making model for a game of chance, the best strategy is chosen based on the current state of the system under various conditions. There is however a shortcoming of this standard model, in that it can be applicable only for short-term decision-making periods. This is primarily due to not evaluating the dynamic characteristics and changes in status of the system and the outcomes of nature towards an a priori target or ideal state, which can occur in longer periods. Thus, in this study, a decision-making model based on the concept of stratification (CST), game theory and shared socio-economic pathway (SSP) is developed and its applicability to disaster management is shown. The game of chance and CST have been integrated to incorporate the dynamic nature of the decision environment for long-term disaster risk planning, while accounting for various states of the system and an ideal state. Furthermore, an interactive web application with dynamic user interface is built based on the proposed model to enable decision makers to identify the best choices in their model by a predictive approach. The Monte Carlo simulation is applied to experimentally validate the proposed model. Then, it is demonstrated how this methodology can suitably be applied to obtain ad hoc models, solutions, and analysis in the strategic decision-making process of flooding risk strategy evaluation. The model's applicability is shown in an uncertain real-world decision-making context, considering dynamic nature of socio-economic situations and flooding hazards in the *Highland and Argyll* Local Plan District in Scotland. The empirical results show that *flood forecasting* and *awareness raising* are the two most beneficial mitigation strategies in the region followed by *emergency plans/response, planning policies, maintenance*, and *self help*.



## 1. Introduction

Since the publication of the book *The Theory of Games and Economic Behavior* by Von Neumann and Morgenstern in 1944 [114], game theory has been extensively utilized as a logical approach in various research realms, such as economics and management [24,37,49,77]. The obtained solutions in game theory are generally acquired by considering the interactions among the involved players. This process can be recognized in the form of "interactive decision theory" [125]. In decision making, not only is a strategy outcome seldom fully predictable, but the strategy-performance relationships would also need to adapt. This circumstance indicates the importance of adaptive decision making depending on the observed performances of previous choices, which can be more crucial when other decision factors also change [55,66]. Game theory is the science of strategic decision making [57]. In some games, such as games of chance or statistical games (i.e., one-player game against nature) [70], the dynamic changes in various states of the system over a long-term decision-making time frame should also be considered knowing that there is a defined a priori target or ideal state. Game theory represents an abstract model of decision making, not the social reality of decision-making itself. Thus, while game theory ensures that a result follows a model logically, it cannot ensure that the result itself represents reality unless the model is accurate [57]. In games of chance, the current system's state has been unchanged during the decision-making timescale. This fixed state of the game makes the obtained decision useful in a longer time frame only if the current state at the time of arriving at a decision persists, which rarely occurs. The reason for this might

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be due to lack of a suitable theory to formulate dynamic changes in states throughout a longer decision-making period accounting for a priori target state. In this study, the concept of stratification (CST) and game of chance involving risk are integrated, to construct an effective model for long-term decision-making planning. The proposed model introduces a generic stratified decision-making framework for this purpose. The comparative analysis to other similar methods such as Markov chains and methods based on Bayes principle are also discussed.

The CST is a computational system in which the objects of the computation are strata of data. The CST has the potential for significant applications in planning, robotics, optimal control, multi-objective optimization, exploration, search, and other fields. An example of a system with a stratified structure can be a multilayer perception. Other simple examples of stratifications are dictionaries, directories, and catalogues. In neuroscience, it has also been discussed that the human brain employs stratification to store information. For example, it would be natural to represent a concept such as a chair as a collection of strata with one or more strata representing a type of chair [123]. On the other hand, Colman [26] explained that games of chance are individual decision making under conditions of risk or uncertainty. In this study, the proposed model is in fact a *stratified group decision-making model under risk,* which, is called here *a stratified decision-making model*. The stratified model is surmised to be a suitable tool for interpreting the interplay between socio-economic situations and natural disasters in this study, to make an optimum decision on a long timescale accounting for a priori target state. The outcomes of a game of chance depend partly on the player's choices and partly on nature, who is a second player. Although the player does not know with certainty what moves will be made by nature, the player knows the approximate meaningful probability of each of nature's responses and therefore knows the probability of success for each of their strategies or actions. The multi-dimensionality feature in the proposed model (a two-dimensional model is introduced in this paper) helps model and calculate the occurrence probability of each state in a more practical sense with more information.

The aim of the study is to introduce and verify the applicability of a novel stratified decision-making model. The model is validated by both a set of numerical experiments via Monte Carlo simulation as well as a practical case study. Moreover, an interactive web application with dynamic user interface is provided which is available open access in order for decision makers to implement the proposed stratified decision-making model in real-world cases. In the current real-world case study, the proposed model is applied to the most significant natural disaster risk in the UK (i.e., flooding) for long-term planning (5+ years) in reference to socio-economic status [59,111]. The applicability of the proposed decision model for evaluating flooding risk mitigation strategies in the *Highland and Argyll* Local Plan District in Scotland is illustrated. This problem is significant in this region, in 2015, 4,600 residential and 2,700 non-residential properties were at risk of flooding, with estimated annual damage accrued to £26.5m [98]. In a recent estimation, there are 15,000 homes and businesses at risk of flooding, and this is projected to grow by around 23,000 by the 2080s [100]. The application uses primary data obtained from experts, who were asked to prioritize flooding risk mitigation strategies recommended by the Scottish Environment Protection Agency (SEPA). The SEPA is Scotland's strategic flood risk management authority and has provided strategies for 14 Local Plan Districts in Scotland.

The two dimensions of the model are (I) shared socio-economic pathway (SSP) and (II) flooding risk impacts for long-term decision making (5+ years) [117]. The contributions of this study are categorized and articulated with reference to Nicholson et al. [80] as follows:

(I) *A revelatory contribution*: Nicholson et al. [80] discussed the meta-category of revelatory contributions and proposed two sub-category of *using multiple lenses* and *assumption challenging* or *problematization*. In this study, a novel stratified decision-making model is introduced on the basis of the CST, game theory, and SSP. This is a revelatory contribution [80] that tries to challenge an underlying assumption where the current system's state in games of chance stays unchanged during the decision-making timescale without accounting for any a priori target state. It contributes to the decision-making body of knowledge by adopting a prospector approach and the strategy of transferring theories across domains [17] such as CST, game theory, and SSP. In this contribution, the predilection to combine CST and game theory in order to include a priori target state in the proposed model is also in line with the multimethodology approach in management science discussed by Mingers and Brocklesby [74].

(II) *An incremental contribution*: Nicholson et al. [80] discussed the meta-category of incremental contributions and proposed three sub-categories of *neglect, confusion*, and *new context*. In this study, the contribution is managing the impacts of flooding risk in the *Highland and Argyll* Local Plan District in Scotland by identifying the most suitable strategies and proposing priorities for action based on the stratified decision-making model. This is an incremental contribution that aims at extending the application of the proposed model to a new context to show its validity, originality, interestingness and value. The merits of the application of the proposed model in flood risk management are discussed in the section research gaps and highlights (Section 2.4).

(III) *A replicatory contribution:* Nicholson et al. [80] discussed the meta-category of replicatory contributions and proposed three sub-categories of *exact, close* and *differentiated replication* strategies. Differentiated or quasi-replication is a deliberate design to establish the generalization of a previous study [80]. In this study, the contribution is about providing an interactive web application with dynamic user interface and making it available open access. This tool can be then used by practitioners, analysts, and researchers to implement the model in their cases regardless of the scale and size of the decision-making problem. This is a replicatory contribution because of the provided tool for differentiated replication [80]. This contribution helps establish the generalization of the study concerning conceptual aspect of the research design through implementation of the model in another industry, culture or country [46].

The rest of this paper is organized as follows. Section 2 presents a literature review of climate change and flood risk in the UK, EU, and the CST. Section 3 develops the methodology used (i.e., stratified decision-making model). Section 4 describes the interactive web application with dynamic user interface and simulation experiments. Section 5 presents an illustrative real-world model and application in flooding risk management including data collection, scenario settings, parameter settings, results, sensitivity analysis, and discussion. Ultimately, conclusions are presented in Section 6.

## 2. Literature review

### 2.1. Climate change and flood risk in the UK and EU

The UK has been a pioneer in developing a national evaluation of climate change risks [115] and has been ranked in the 11th best placed for its combination of vulnerability and preparedness against risks such as climate change. This ranking is based on the Notre Dame Global Adaptation Initiative (ND-GAIN) [78]. Following the 2008 Climate Change Act, the UK Government was obliged

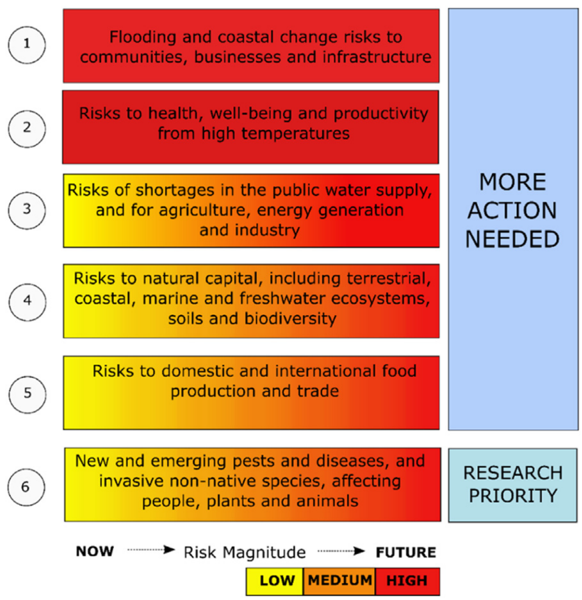


**Fig. 1.** The top six UK climate change risks [27].

to evaluate the risks of current and estimated impacts of climate change through Climate Change Risk Assessment (CCRA) reports (R. F. [115]). The aim is to inform priorities for the UK Government's National Adaptation Program (NAP). Two rounds of CCRA have been performed thus far, implementing different methodologies: CCRA1 in 2012, CCRA2 in 2017 and CCRA3 is due in 2022. The CCRA2 was conducted in partnership with the Adaptation Sub-Committee (ASC) (R. [116]). Warren et al. [116] explained that in CCRA2, the goal was to determine where immediate actions are required over the five-year period of NAP (2018-2022) by recognizing adaptation choices. The CCRA2 recognized flooding and coastal change as one of the six risks with high priority in need of urgent action in the UK [28,96]. Flooding impacts can be identified at multiple levels and their assessment is important in understanding both mitigation and recovery [73]. Currently, flood damage costs the UK approximately £2 billion yearly [95], and these expenses are expected to increase. In Fig. 1, with reference to CCRA2, the top six areas of interconnected climate change risks for the UK are provided. The CCRA2 estimates that in the future, if no mitigation strategy is put in place, there will be a significant increase in both the number of people at risk from flooding and its related costs [28].

In the EU, floods are also major threats to lives and local communities with approximately 1000 fatalities occurring. This within the period of 2002 to 2013 due to flooding in Europe resulting in over 1.7m people evacuating their homes and incurring a total damage cost of €150b [2]. Similar to the UK, the risk of floods is critical in the EU, particularly in long-term planning as the risk is predicted to grow approximately six-fold by 2050 due mainly to projected socio-economic change and the likely impacts of climate change [2,53]. In the EU, there are both regulation and directives in place regarding climate action and flood management. The Regulation (EU) 2021/1119 establishes the framework for achieving climate neutrality [113]; this is a long-term objective of the Energy Union project in line with the 2015 Paris Agreement on climate change [16,64]. Furthermore, the EU Floods Directive (2007/60/EC) was first introduced in 2007 with the aim of reducing the negative consequences of floods for the environment, human health, economic activity, cultural heritage and infrastructure [91]. The Floods Directive (FD) introduced a three-stage process for flood risk management on all the EU territory which include (I) identifying risks (preliminary flood risk assessments or PFRAs), (II) evaluating risks (flood hazard and risk maps or FHRMs), and (III) reacting to risks (flood risk management plans or FRMPs) [2]. The results of the current study can contribute to the third stage in the FD, in terms of a useful model to deal with mitigating flood risks by proposing efficient strategies, taking into account longer time frames.

### 2.2. Concept of stratification

The CST, as an innovative version of stratification, was introduced by Zadeh [123]. In CST, a number of states should be traversed by a system to reach the target set (i.e., a desired state). Inputs and outputs of any state are incrementally stratified on the basis of their distance from the target set [5,90]. The CST is a very similar concept to dynamic programming (DP), but is more straightforward to comprehend and then apply. The following concepts are defined in the CST [90]:

- *System:* The system is defined as a set of objects that traverses states towards a state in the target set.
- *State:* $SE_t$ signifies the $t^{th}$ state and is characterized by the values of its related variables, which are determined by experts. The system would transition from one state to the other by changing the values of the variables.
- *State-transition function:* This function moves the system from the $\mathrm{i}^{\mathrm{th}}$ state to the $(\mathrm{i}+1)^{\mathrm{th}}$ state and $\mathrm{SE}_{(\mathrm{t}+1)} = \mathrm{f}(\mathrm{SE}_\mathrm{t}, \mathrm{u}_\mathrm{t})$. If the system is situated at state $t(SE_t)$, by receiving an input $u_t$, it transitions from $SE_t$ to $SE_{t+1}$
- *Inputs and outputs:* Many inputs ($u_t$) might exist for $SE_t$. $v_t = g(SE_t, u_t)$ shows the relation between each input and an output ($v_t$).
- *Target state:* The goal of the system is to reach the target set.
- *Target set:* This set is defined when there are multiple target states.
- *Stratum:* Stratum $N$ is defined as a set of states from which a system can obtain the target state in $N$ or less than $N$ steps.
- *Reachability:* It exists when there would be a path between two states.

An incremental enlargement process would equip CST with high dynamicity. The primary goal of enlargement is identifying possible paths towards the target where reaching the target is costly, consumes excessive resources or is presently vague, but becoming gradually clearer [9]. The foundation of the CST is a model named the finite-state machine (FSM), which is a discrete-time, discrete-state dynamical system. The importance of FSM lies in the fact that by using granulation and/or quantization, nearly any type of system can be approximated by a finite state system. Target set reachability plays a central role in FSM. Reachability includes moving or transitioning from a state $SE_t$ to a state in the target set $T_0$ within the minimum number of steps [123]. The stratified approach has gained attention in the academic literature. However, there are only a handful of studies that explore the capability of CST to date. For instance, Selvaraj and JeongHwan [97] proposed a decision making technique to achieve stratified target performance (DEMTASTAP) and applied it in innovation policy investment in South Korea. Ecer and Torkayesh [35] proposed a stratified fuzzy decision-making approach to address sustainable circular supplier selection problem in the textile industry. Torkayesh and Simic [106] extended the S-BWM and introduced the hierarchical stratified best-worst method (H-SBWM) to address the recycling location selection problem in Turkey. Asadabadi et al. [7] proposed a framework to incorporate innovation for environmental sustainability in supplier selection by integrating the stratified best-worst method (SBWM) and the technique for order of preference by similarity to ideal solution (TOPSIS). Asadabadi and Zwikael [6] proposed an extended version of stratified MCDM to address an important challenge in time and cost estimations in project management. Torkayesh et al. [107] developed and applied the SBWM to solve sustainable waste disposal technology selection problem. Asadabadi et al. [8] showed the practicality of the CST in the field of logistic informatics modeling and revealed how the user would benefit from hybrid utilization of a fuzzy inference system (FIS) and CST. Asadabadi [5] developed a stratified multiple criteria decision-making (S-MCDM) method. Asadabadi et al. [9] discussed and proposed bi-objective CST (BO-CST) and fuzzy bi-objective CST (FBO-CST) models for unequal importance objective weights in the original CST.

### 2.3. Decision-making models and methods for flood risk management

Flood risk management involves complex decision-making where various dimensions must be taken into consideration by including many specialists' and stakeholders' viewpoints [29]. The current trends in the risk management literature demonstrate that employing multidimensional risk management approach has become largely common in dealing with risks, and this has made a direct impact to policy making by proposing efficient measures to counteract risks [31]. There is a plethora of models and methods in the flood risk management literature. However, these models are different depending on what factors, variables and dimensions are considered in the model, the timeframe of decision-making, the availability and types of data, the congruence levels between involved dimensions, the implications of the outputs in terms of societal, economic, and environmental impacts etc. In this section, the parallels are drawn and summarized by a particular focus on types of recent methodological decision-making approaches in dealing with flood risk management.

#### 2.3.1. Mathematical optimization

Postek et al. [87] studied two challenges of identifying the optimum flood protection strategy in a long-term timescale are studied. Authors addressed the challenges of (1) uncertainty regarding future sea level rise and (2) adjustability regarding adaptability of decisions to the realized uncertainties from earlier periods by implementing a robust optimization model in the Netherlands. Woodward et al. [120] employed a multi-objective genetic algorithm in combination with Real Options technique [119] to identify the optimal flood risk adaptive strategies in the case of Thames Estuary in London.

#### 2.3.2. Simulation

Zhuo and Han [126] reviewed the literature of agent-based modeling (ABM) and flood research. They indicated that there is a growing interest in the use of ABM to handle challenges of flood risk. They identified three topics to tackle research challenges in the area: long-term flood adaptation planning, flood hydrological modeling, and real-time flood emergency management. Limitations of ABM models are also discussed. Abebe et al. [1] utilized ABM and flood models to study the impact of flood risk policies by modeling actors' behavior associated with urban development and policies in the Caribbean island of Sint Maarten. Jiang et al. [48] utilized system dynamics modeling via scenario-based simulations to study the impact of the Three Gorges Dam in China on flood management.

#### 2.3.3. Participatory modeling

Maskrey et al. [71] studied the role of participatory modeling through facilitating engagement and co-generation of knowledge via flood risk management modelers, stakeholders and practitioners. Three popular participatory methods are: system dynamics, Bayesian networks and fuzzy cognitive mapping. The limitations of each participatory method are discussed in Maskrey et al. [71]. Ceccato et al. [21] explored the effectiveness of participatory interactions between researchers and local actors for decision-making in flood risk management in two case studies in Asia and Europe. The importance and necessity of a more nuanced understanding between flood risk management authorities and communities are discussed in Mehring et al. [72]

#### 2.3.4. Artificial intelligence

Chen et al. [23] employed six machine learning models for flood risk management in the Pearl River Delta in China. Rifat and Liu [94] applied artificial neural networks (ANN) and Markov chain model to assess flood risks impact on various urban growth scenarios in Miami, USA. Pham et al. [86] used artificial intelligence (AI) models to create a flood susceptibility map in Vietnam. Sermet and Demir [101] introduced an AI-based system (i.e., Flood AI) for improving community preparedness against flooding using natural language processing (NLP) and voice recognition.

#### 2.3.5. Data mining and statistics

Barker and Macleod [13] utilized data mining on the Twitter platform to improve stakeholder awareness of floods in Great Britain. Ali et al. [4] employed bivariate statistics including frequency ratio (FR) and statistical index (SI) in their study to manage flood risks in Slovakia. Kotzee and Reyers [62] applied principal component analysis (PCA) to assess flood resilience taking into account 24 indicators associated with ecological, social, economic, and infrastructural dimensions in South Africa.

#### 2.3.6. Multi-dimensional frameworks

Koop et al. [61] proposed a governance capacity framework which focuses on five governance challenges one of which is flood risk. Nine governance conditions were identified and empirically tested in the Netherlands. Their findings contribute to the understanding of the critical conditions and illustrating the governance capacity to reveal solutions for urban challenges related to climate change, waste and water. Brockhoff et al. [18] utilized the governance capacity framework to understand governance capacity for pluvial flood risk via citizen engagement in Utrecht, the Netherlands.

#### 2.3.7. Multi-attribute decision making (MADM)

da Silva et al. [29] in a literature review indicated that use of MADM comprise about 70% of the approaches implemented by researchers in flood risk management. Perosa et al. [85] reviewed the literature of multi-criteria analysis and decision support systems in Germany. Ha-Mim et al. [44] utilized the analytic hierarchy process (AHP) to compute weights of flood exposure in Bangladesh. Pathan et al. [84] used the technique for order preference by similarity to ideal solution (TOPSIS) in combination with AHP to produce flood risk maps in Gujarat, India. Ali et al. [4] as part of their applied model utilized decision-making trial and evaluation laboratory (DEMATEL) and analytic network process (ANP) to derive the criteria weights and then compute the flood susceptibility index in the Topla river basin, Slovakia. Soldati et al. [104] employed the preference ranking organization method for enrichment evaluation (PROMETHEE) to study flood risk at the regional level in Ferrara province, Italy.

### 2.4. Research gaps and highlights

The decision-making around modern flood risk management needs to consider a portfolio of structural and non-structural measures [43,50]. Additionally, handling flooding risk by taking into account socio-economic factors and environmental process through a sustainable policy and planning framework is important [22]. It is indicated in the literature that accounting for uncertainty is critical for properly incorporating resilience into climate change and flood risk management models [12,75,92,118]. The reason is that uncertainty in the long-term horizon has gained a prominent role within the flood risk management area particularly due to climate change impact [91,111]. Additionally, a flood management program should be assessed against a more comprehensive set of criteria, such as those related to climate change adaptation [10]. Zhuo and Han [126] in their review identified long-term flood adaptation planning among the three important topics in the flood risk management. Moreover, Xu and Li [121] in their review study, identified that flood related applications encompassed the majority of the case studies with around 46% of all cases. They argued that ecological engineering should be the main focus of engineering management application to improve the quality of human life. As reviewed in the literature and emphasized in da Silva et al. [29], there is a need to work more on formal procedures for climate modeling in multi-dimensional frameworks. Furthermore, there is a gap in the methodological approaches in the literature as no utility-based methods such as multi-attribute utility theory (MAUT), prospect theory, or rank-dependent utility are utilized [29]. Research gaps and highlights are summarized as follows:

- *Dynamic current system's state in games of chance:* The proposed model challenges an underlying assumption where the current system's state in games of chance stays unchanged during the decision-making timescale without accounting for any a priori target state. Filling this gap, will provide an efficient model for long-term decision-making planning. A discussion and comparison with similar models such as Markov chains and Bayesian networks are provided in the discussion section.
- *Multi-dimensional and long-term decision-making capability*: As the verification of adaptation measures often takes a long time and requires a huge investment [69], there has been a need for a modeling framework that evaluate the suitability of different solutions for enhanced long-term decision making [126]. Thus, in the current study, an approach based on two dimensions of socio-economic and environment is taken, by introducing a decision-making model that can capture the interactions of dimensions to enhance long-term decision making in flood risk mitigation strategy selection. The proposed model, unlike similar techniques such as system dynamics, is not overly focused on long-term trends, but also considers socio-economic decisions which are often impacted by short-term pressures such as government policy, funding etc.
- *Theoretical support*: The proposed stratified decision-making model covers lack of theoretical support in prior models such as ABM for flood risk management by providing a theoretical underpinning (i.e., CST, SSP and game theory) and help stakeholders to identify most efficient mitigation measures or strategies in the long-run planning taking into account socio-economic and flood hazard levels. Moreover, utility theory is also utilized in the evaluation of risk mitigation strategies in the proposed model. Merits of decision-making models such as the proposed model in the current study which is based on theory compared to ad-hoc implementations in the flood risk management literature are fostering interdisciplinary communications, easier improvements, ability to test alternative theories even when sparse data is available, and faster and robust scientific advancement [14,41,60,89,126].
- *Real-world applicability of the model*: The model's practicality is shown through several numerical experiments as well as a real-world case study in the UK. The application of the proposed model is illustrated in managing the impacts of flooding risk in the *Highland and Argyll* Local Plan District in Scotland by identifying the most suitable strategies and proposing priorities for action (see Section 5).
- *Flexibility and versatility of the model*: The proposed stratified decision-making model is flexible, versatile and capable of application in other similar decision-making situations in disaster management. Such as in a widespread disease outbreak for mitigation strategy selection in the long-term by considering several scenarios. The provided interactive web application with dynamic user interface can be useful for implementation of the model in such future case studies.

## 3. A stratified decision-making model

The proposed stratified decision-making model is an integration of CST and games of chance that involve risk. Generally, there are three types of games: *games of skill, games of chance*, and *games of strategy*. Apart from games of skill, which are one-player games, the other two groups of games involve at least two players. Games of strategy involve two or more players, not including nature, each of whom has partial control over the outcomes [57]. Games of chance or statistical games [70] are grouped as either involving risk or involving uncertainty and are one-player games against nature. The nature does not act against or in favor of the other player (i.e., decision maker) and the player does not exert any influence on the state of nature [108]. Games of chance have also been called individual decision making under risk or uncertainty. In the game of chance involving risk, although the player does not know with certainty what moves will be made by nature, the player is aware of the meaningful probability of responses of nature and thus realizes the success probability of each of their strategies or actions. The expected monetary/utility value (EMV) can be utilized to reach a decision in this type of game [26]. In games of chance under uncertainty or ignorance, the a priori probabilities of the states of nature are unknown. Many principles or criteria have been suggested in the literature for deciding in such circumstances [108]:

- *The Bayes criterion*: It is used under the condition of risk when the a priori probabilities of the states of nature are known.
- *The optimistic approach (i.e., maximax criterion)*: It recommends that the player chooses the strategy that contains the greatest payoff.
- *The pessimistic risk-averse strategy approach (i.e., maximin principle or Wald criterion)*: It recommends that a player should avoid the worst possible payoff. In other words, the player should choose the strategy that offers the best worst-case scenario.
- *The criterion of realism (i.e., Hurwicz criterion)*: It recommends a compromise between the optimistic and pessimistic approach. A coefficient of realism ($\alpha$) is defined between 0 and 1.
- *The equally likely approach (i.e., Laplace criterion)*: It recommends that no state of nature is more likely than the other.
- *The greatest regret avoidance (i.e., minimax principle or Savage criterion):* It is a good balance between the super-optimistic and the super-pessimistic and recommends that a player should avoid the strategy of greatest regret. Utilizing this approach, the payoff matrix must first be transformed into a regret matrix [57].

In this study's real-world case study, the proposed model considers both the socio-economic status of the UK influencing the adaptation options, utilizing the concept of SSP (i.e., *low* challenges to mitigation and adaptation, *moderate* challenges to mitigation and adaptation, *high* challenges to mitigation and adaptation) [63] and the impact level of the flooding risk (i.e., mild, moderate and severe). The model also considers the transitions between various possible states in a longer timeframe (5+ years) [117] by accounting for the transition probabilities between the socio-economic status and the flooding risks. This approach helps provide a model that can be more reliable in identifying the most effective strategies for long-term planning. The benefits obtained

**Table 1**
The payoff values in the stratified game table.

| PLAYER 1 | | PLAYER 2 (NATURE) | | | |
|---|---|---|---|---|---|
| | | OUTCOME 1 | OUTCOME 2 | … | OUTCOME M |
| STATUS 1 | Strategy 1 | $pf_{111}$ | $pf_{112}$ | … | $pf_{11M}$ |
| | Strategy 2 | $pf_{121}$ | $pf_{122}$ | … | $pf_{12M}$ |
| | … | … | … | … | … |
| | Strategy $n_1$ | $pf_{1n_11}$ | $pf_{1n_12}$ | … | $pf_{1n_1M}$ |
| STATUS 2 | Strategy 1 | $pf_{211}$ | $pf_{212}$ | … | $pf_{21M}$ |
| | Strategy 2 | $pf_{221}$ | $pf_{222}$ | … | $pf_{22M}$ |
| | … | … | … | … | … |
| | Strategy $n_2$ | $pf_{2n_21}$ | $pf_{2n_22}$ | … | $pf_{2n_2M}$ |
| … | … | … | … | … | … |
| STATUS N | Strategy 1 | $pf_{N11}$ | $pf_{N12}$ | … | $pf_{N1M}$ |
| | Strategy 2 | $pf_{N21}$ | $pf_{N22}$ | … | $pf_{N2M}$ |
| | … | … | … | … | … |
| | Strategy $n_N$ | $pf_{Nn_N1}$ | $pf_{Nn_N2}$ | … | $pf_{Nn_NM}$ |

from strategies in each state (payoff or utility values) would not always be easy to assess precisely in quantitative values, especially when the strategies include policy, regulatory, and community responses in addition to engineering responses. Much of the evidence of adaptation activity for the UK infrastructures concentrates on engineering responses rather than policy, regulatory or community responses, and the reason is that for engineering responses, quantitatively assessing the benefits is typically easier [30].

### 3.1. Notations

The proposed two-dimensional stratified decision-making model comprises $N$ status ($SS$) and $M$ outcomes ($OC$), while under each $SS_i$, there are $n_i$ strategies that result in various payoff ($pf$) values under different nature's outcomes. Because the proposed model is a game of chance that involves risk, there would be a meaningful probability about each of nature's moves or the outcomes. Table 1 shows the payoff matrix of the proposed model.

$P$: status transition probability matrix
$Q$: outcome transition probability matrix
$S$: state transition probability matrix
$p_{ij}$: the probability of transition from status $i$ ($SS_i$) to status $j$ ($SS_j$)
$q_{ij}$: the probability of transition from outcome $i$ ($OC_i$) to outcome $j$ ($OC_j$)
$s_{ij}$: the probability of transition from state $i$ ($SE_i$) to state $j$ ($SE_j$)
$pf_{ijk}$: the payoff value under $SS_i$, strategy $j$ and $OC_k$
$op_k$: the occurrence probability of $OC_k$ ($k = 1, \ldots, M$)

### 3.2. Status transition probability matrix

There are $N$ status in the model, and given that the probability of a transition between $SS_i$ and $SS_j$ is $p_{ij}$, the status transition probability matrix $P$ can be shown as in Eq. (1). For instance, $p_{11}$ is the probability of persistence at the current $SS_1$.

$$P = \left[p_{ij}\right]_{N\times N} \tag{1}$$

### 3.3. Outcome transition probability matrix

There are $M$ outcomes, and given that the probability of transition from $OC_i$ to $OC_j$ is $q_{ij}$, the outcome transition probability matrix $Q$ can be shown as in Eq. (2).

$$Q = \left[q_{ij}\right]_{M\times M} \tag{2}$$

For instance, $q_{11}$ is the probability of persistence at the current $OC_1$. In Fig. 2, the status and outcome transitions are depicted.

### 3.4. State transition probability matrix

There are $N \times M$ states, as represented in Fig. 3. Given $s_{ij}$, the probability of transition from state $i$ ($SE_i$) to state $j$ ($SE_j$), then the state transition probability matrix $S$ can be represented as in Eq. (3).

$$S = \left[s_{ij}\right]_{N\times M} \tag{3}$$

For instance, $s_{11}$ is the probability that $SE_1$ persists, which means that $SS_1$ and $OC_1$ persist and can be calculated as $s_{11} = p_{11} \times q_{11}$. As an illustrative example, the $S$ matrix is represented for $N = 3$ and $M = 4$ in Appendix A-Table A.1 (Supplementary Materials). It is clear that as the dimensions of the matrix ($N$ and $M$) increase, the computational time will rise dramatically. The Algorithm 1 for calculating the matrix $S$ is represented below, and the state transitions and respective probabilities are shown graphically in Fig. 3. The proposed algorithm can be helpful for calculating large matrices where coding in programming languages is essential. ***Algorithm 1.*** *Calculation of the state transition probability matrix*

Input:
***N***: number of status
***M***: number of outcomes
$P = [p_{ij}]_{N\times N}$:
$Q = [q_{ij}]_{M\times M}$:
Output:
$s_{ij}$: the probability of transition from state $i$ to state $j$
**for** $l = 1$ to $N$
**for** $k = 1$ to $N$
**for** $i = kM - M + 1$ to $kM$
**for** $j = lM - M + 1$ to $lM$
$s_{ij} = p_{kl} \times q_{(i-kM+M)(j-lM+M)}$
**End**
**End**
**End**
**End**

### 3.5. Model assumptions

In the proposed model, it is assumed that the following assumptions are in place:

1) The same strategies exist under various status of the model, which means that $n_1 = n_2 = \ldots = n_N = B$
2) The payoff values all acquire the benefit nature, which means that their maximization is the aim ($Z = Max pf_{ijk}$). Payoff values can also be represented as utility values in situations where obtaining monetary values is difficult or they are more based on decision-makers' perceptions and evaluations rather than tangible monetary values ($Z = Max u_{ijk}$). The utility value is a dimensionless number between 0 and 1. As per the maximization assumption, the higher the utility value (i.e., closer to 1), the better the utility.
3) It is presumed that the payoff/utility values stay constant throughout the state change.
4) The summation of all status transition probabilities is 1, and the same is correct for the outcomes' transition probabilities, as shown in Eqs. (4) and (5).

$$\sum_{j=1}^{N} p_{ij} = 1 \ \forall i = 1, \ldots, N \tag{4}$$

$$\sum_{j=1}^{M} q_{ij} = 1 \ \forall i = 1, \ldots, M \tag{5}$$

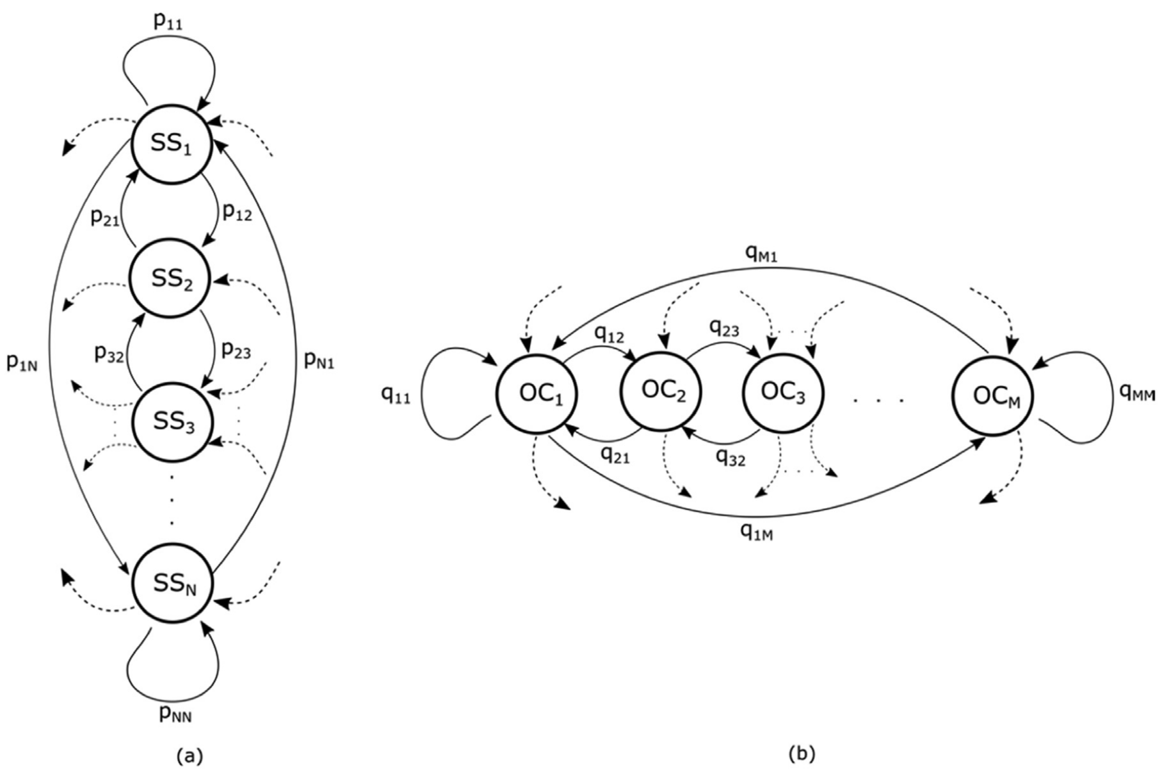


**Fig. 2.** Graphical representation of (a): status transitions, (b): outcome transitions, and respective probabilities.

**Table 2**
The after-transition payoff/utility decision matrix.

| STRATEGY | STATE | | | |
|---|---|---|---|---|
| | **STATE 1** | **STATE 2** | **...** | **STATE N*M*** |
| **STRATEGY 1** | $v_1^1$ | $v_1^2$ | ... | $v_1^{NM}$ |
| **STRATEGY 2** | $v_2^1$ | $v_2^2$ | ... | $v_2^{NM}$ |
| | ... | ... | ... | ... |
| STRATEGY B | $v_B^1$ | $v_B^2$ | ... | $v_B^{NM}$ |

5) In order for the proposed model to be applicable and practical, it is presumed that the number of status, outcomes and strategies should be at least two (i.e., $\geq 2$, $M \geq 2$, $B \geq 2$).

### 3.6. Solution approach

Given the assumptions, considering that the current state of the system is $x$, by using Eq. (6), the value of strategy $b$ ($v_b^x$) given $b = 1, \ldots, B$ can be obtained ($NM = N \times M$). Knowing that $k = 1$ if $j = \{1,\ M+1,\ 2M+1, \ldots, NM-M+1\}$, $k = 2$ if $j = \{2,\ M+2,\ 2M+2, \ldots, NM-M+2\}$,..., and $k = M$ if $j = \{M,\ 2M,\ 3M, \ldots, NM\}$. If utility values are used, then Eq. (7) is utilized.

$$v_b^x = \sum_{i=1}^{N} \sum_{j=iM-M+1}^{iM} S_{xj}\, pf_{ibk} \qquad (6)$$
$$\forall b = 1, \ldots, B, \forall x = 1, \ldots, NM, k = \{1, 2, \ldots, M\}$$

$$v_b^x = \sum_{i=1}^{N} \sum_{j=iM-M+1}^{iM} s_{xj} u_{ibk} \qquad (7)$$
$$\forall b = 1, \ldots, B, \forall x = 1, \ldots, NM,\ 0 \leq u_{ibk} \leq 1,\ k = \{1, 2, \ldots, M\}$$

Then, the after-transition payoff/utility decision matrix is obtained, as shown in Table 2. If the current state (before-transition state) of the system is known, then only the corresponding column of that state in Table 2 is considered; otherwise, it is necessary to give a probability to those states for which there is uncertainty. Then, by calculating the EMV of each strategy, the final strategy can be obtained[1]. In Fig. 4, the implementation steps and process for the proposed stratified decision-making model is illustrated.

For example, the EMV for each strategy $b$ ($EMV^b$) considering equal probabilities can be calculated as Eq. (8).

$$EMV^b = \frac{\sum_{i=1}^{NM} v_b^i}{NM} \ \forall b = 1, \ldots, B \qquad (8)$$

## 4. An interactive web application and simulation experiments

An interactive web application with dynamic user interface[2] (see Appendix B for a detailed user guidance) based on R code[3] is developed. This web application tool assists decision makers to implement the proposed stratified decision-making model in any problem setting regardless of the size of their model and solve it. In other words, the tool can be applicable under any number of status ($N$), any number of outcomes ($M$), and any number of strategies ($B$) as long as the input data is provided. The input data can either come from the decision maker or from the option of randomly generating values embedded in the code based on model's circumstances. This tool is constructed based on the state transition model where the state 1 is the target state. The tabular CST for state transitions is presented in Table 3. In Fig. 5 the transitions starting at state 9 for $N = 3$ status and $M = 3$ outcomes are illustrated. The input data and outputs of the interactive web application are explained in the following sections.

[1] The term EMV is used for both the expected monetary value and the expected utility value.

[2] The web app is accessible at this link: https://amvaf.shinyapps.io/SDMM/

[3] The R Shiny code and function for the app are available open access at this link: https://github.com/AminVafadar/RShiny_SDMM.git

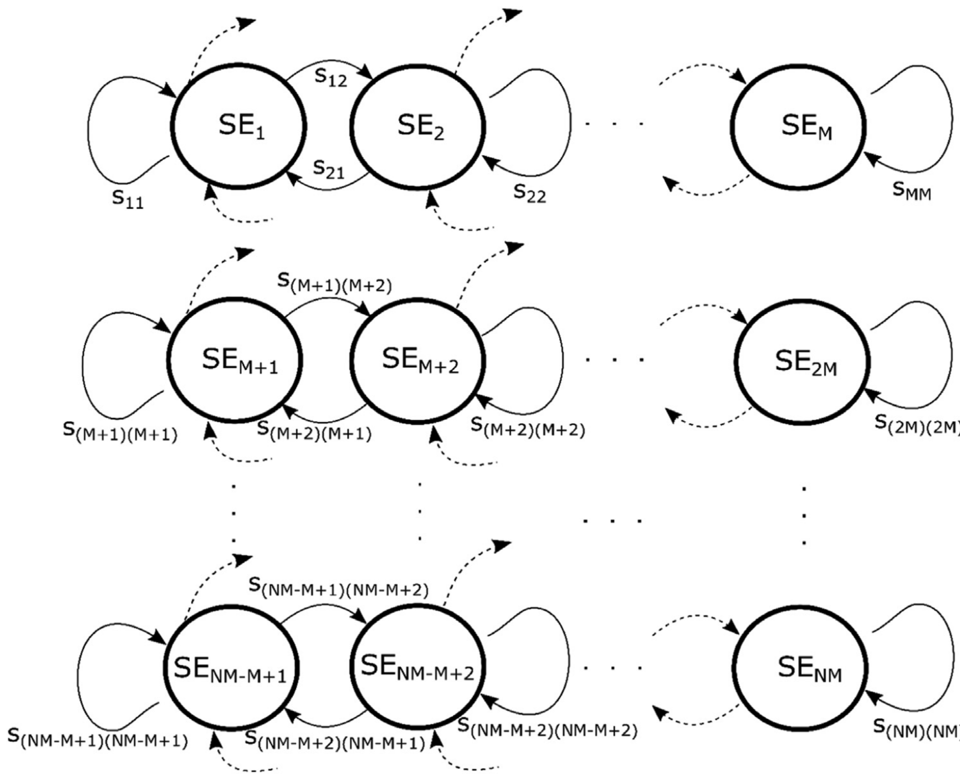


**Fig. 3.** Graphical representation of state transitions and their respective probabilities.

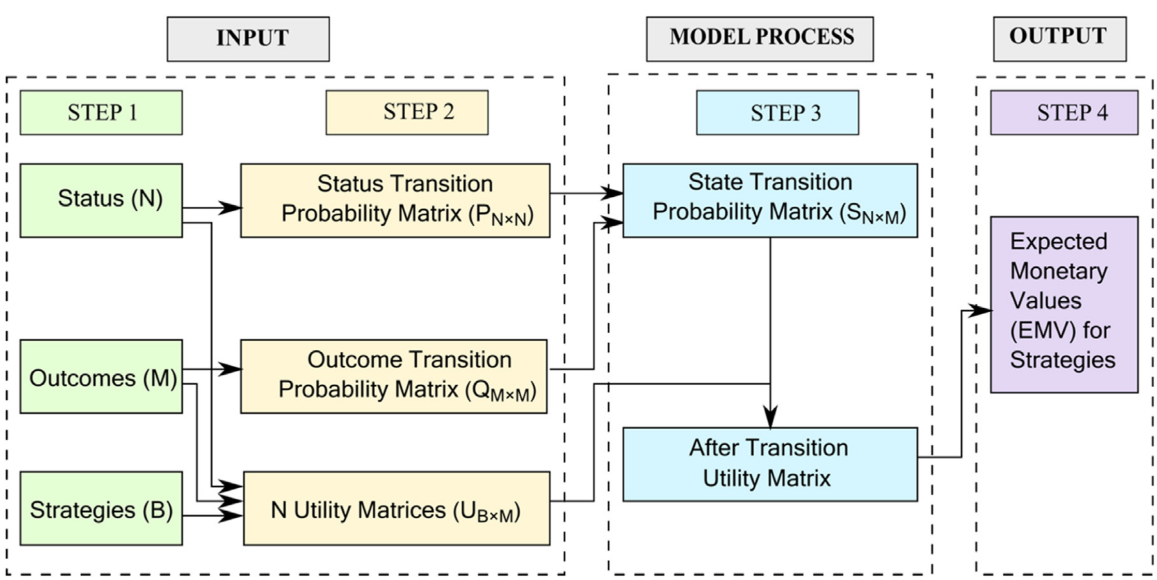


**Fig. 4.** A framework for implementation steps and process of the model.

## 4.1. Input

*4.1.1. Status, outcome, strategies*

All status and number of status ($N$), all outcomes and number of outcomes ($M$), and strategies and number of strategies ($B$) should be defined in the model. In the web application (Fig. 6), users can input the required parameters $N$, $M$, and $B$.

*4.1.2. Probability of the current state*

$W$ is the vector of probability of the current state. We assume the probabilities in $W$ are equally distributed in the provided web application and are equal to $\frac{1}{N\times M}$. However, these probabilities-if known from the decision makers' experience or knowledge- can be set based on the circumstances of the real-world model. This will be discussed and analyzed in the case study in Section 5.

*4.1.3. Status transition probability matrix*

One status transition probability matrix ($P_{N\times N}$) is required. This matrix is a lower triangular matrix in which the data elements below the main diagonal and on the main diagonal (except $p_{11} = 1$) are given by the decision maker as input data. The sum of each row must be equal to 1. An example of a $P_{3\times 3}$ status transition

**Table 3**
Tabular CST for state transitions for $N = 3$ status and $M = 3$ outcomes.

| | Status | Outcome | $SE_{t+1}$ |
|---|---|---|---|
| 1 | 1 | 1 | 1 |
| 2 | 1 | 2 | 1,2 |
| 3 | 1 | 3 | 1,2,3 |
| 4 | 2 | 1 | 1,4 |
| 5 | 2 | 2 | 1,2,4,5 |
| 6 | 2 | 3 | 1,2,3,4,5,6 |
| 7 | 3 | 1 | 1,4,7 |
| 8 | 3 | 2 | 1,2,4,5,7,8 |
| 9 | 3 | 3 | 1,2,3,4,5,6,7,8,9 |

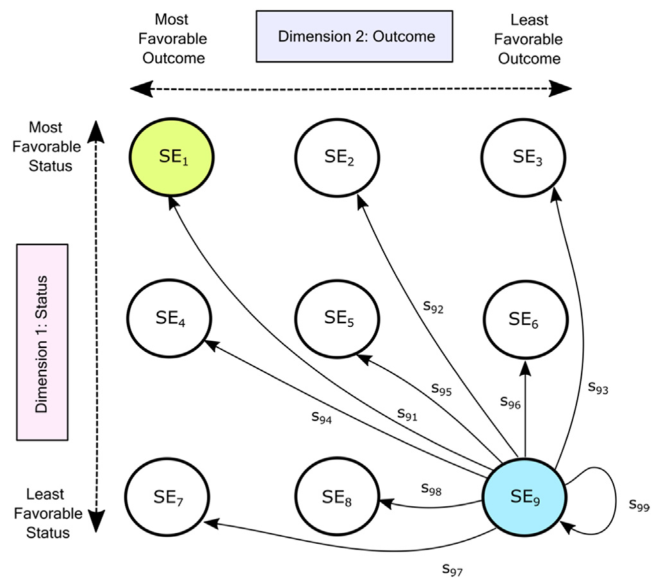


**Fig. 5.** State transitions starting at state 9 for $N = 3$ status and $M = 3$ outcomes.

probability matrix based on the assumed CST is shown in Eq. (9).

$$P_{3\,\times\,3} = \begin{bmatrix} 1 & 0 & 0 \\ p_{21} & p_{22} & 0 \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \tag{9}$$

*4.1.4. Outcome transition probability matrix*

One outcome transition probability matrix ($Q_{M\times M}$) is required. This matrix is also a lower triangular matrix in which the data elements below the main diagonal and on the main diagonal (except $q_{11} = 1$) are given by the decision maker as input data. The sum of each row must be equal to 1. An example of a $Q_{3\,\times\,3}$ outcome transition probability matrix based on the assumed CST is shown in Eq. (10). In the web application, as shown in Fig. 7, users can input both matrix $P$ and $Q$.

$$Q_{3\,\times\,3} = \begin{bmatrix} 1 & 0 & 0 \\ q_{21} & q_{22} & 0 \\ q_{31} & q_{32} & q_{33} \end{bmatrix} \tag{10}$$

*4.1.5. Utility matrices*

$N$ utility matrices ($U_{B\times M} = [u_{ibk}]$) are required. Utility values are elements of the utility matrices and range within $[0, 1]$ as shown in Eq. (11) where $N$ is the number of status or number of utility matrices, $M$ is the number of outcomes, and $B$ is the number of strategies.

$$U_i = [u_{ibk}]_{B\times M}\ \forall i = 1, \ldots, N \forall b = 1, \ldots, B\ \forall k = 1, \ldots, M \tag{11}$$

An example of $U_{4\,\times\,3}$ utility matrices for $N = 3$ (number of status or number of utility matrices), $M = 3$ (number of outcomes), $B = 4$ (number of strategies) is shown in Eq. (12). In the provided web application (Fig. 8), users can input all utilities in one setting. See the guidance in Appendix B for instruction on how to insert utility values in the app.

$$U_i = \begin{bmatrix} u_{i11} & u_{i12} & u_{i13} \\ u_{i21} & u_{i22} & u_{i23} \\ u_{i31} & u_{i32} & u_{i33} \\ u_{i41} & u_{i42} & u_{i43} \end{bmatrix} \forall i = 1, 2, 3 \tag{12}$$

## 4.2. Output

*4.2.1. State transition probability matrix*

The matrix state transition probability matrix ($S_{N\times M}$) will be generated as explained in Section 3.4.

*4.2.2. After transition utility matrix*

The after-transition utility decision matrix is obtained. This matrix can be recalled by running the ATPFM command in the provided R code. More details on after-transition utility decision matrix are provided in Table 2 in Section 3.6.

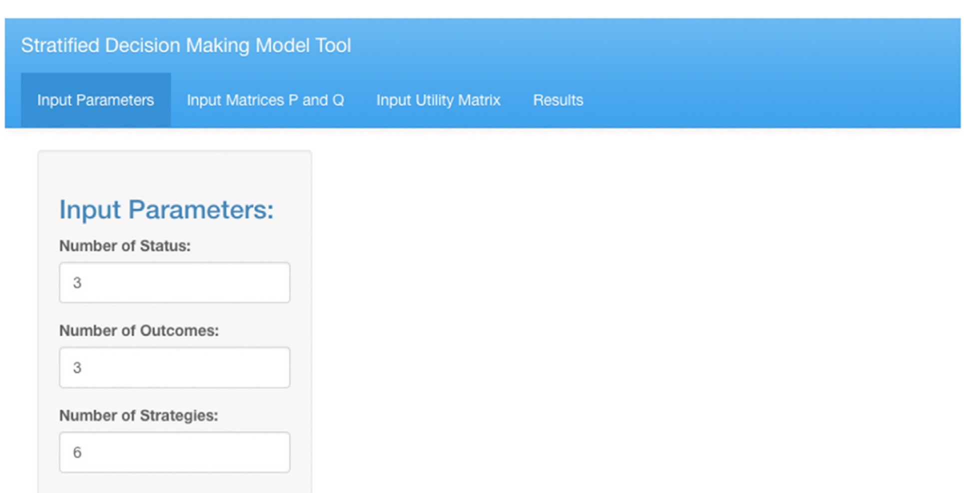


**Fig. 6.** Input parameters tab in the web application tool.

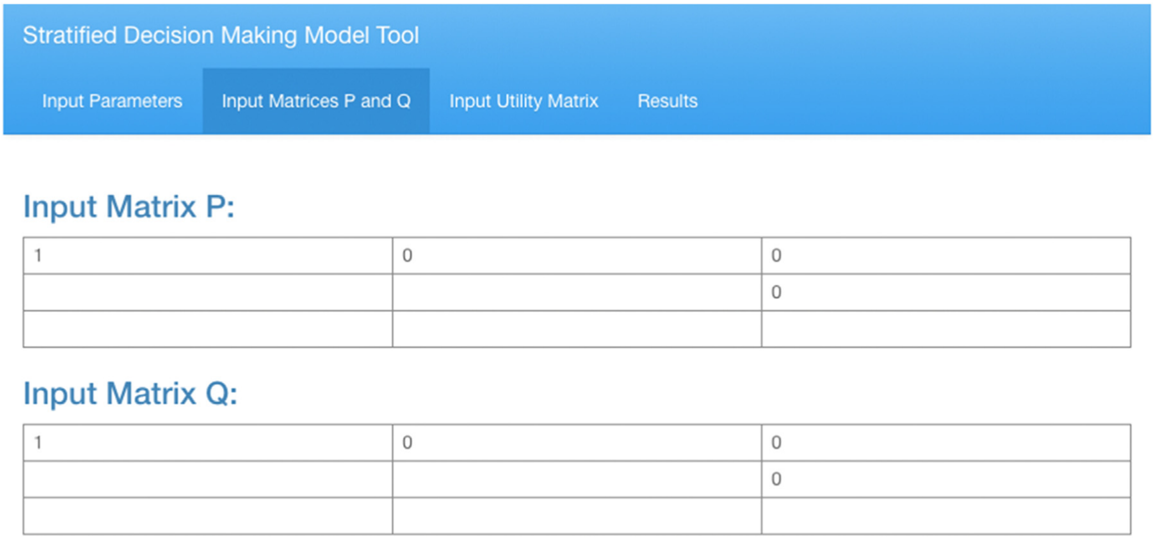


**Fig. 7.** Input matrices P and Q tab in the web application tool

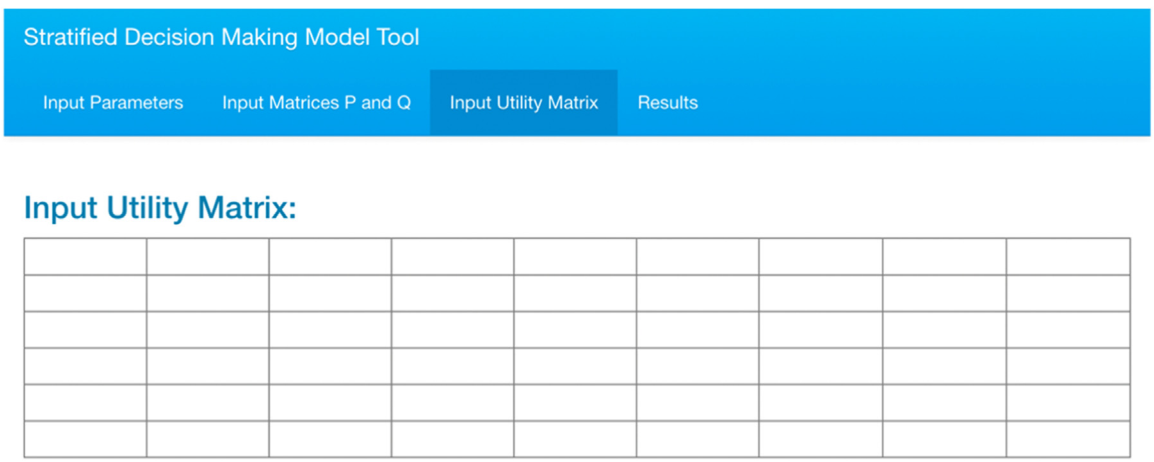


**Fig. 8.** Input utility matrix tab in the web application tool.

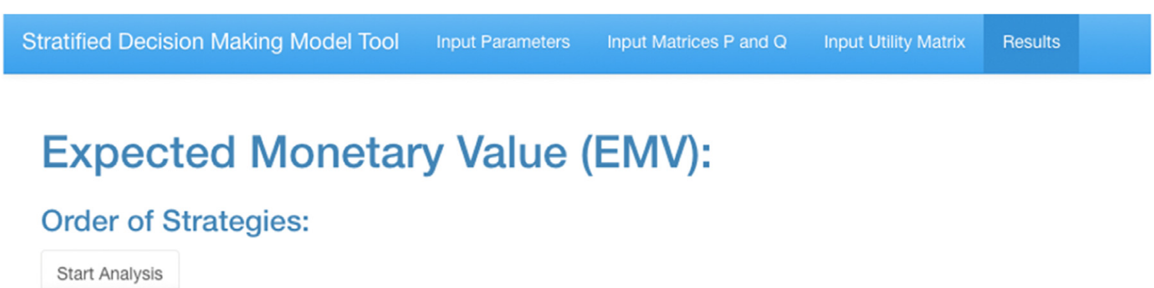


**Fig. 9.** Results tab in the web application tool.

#### 4.2.3. *Expected monetary values*

The expected monetary value for each strategy $b$ ($EMV^b$) is calculated and represented in decreasing order based on the Eq. (8).

In the provided web application (Fig. 9), users can click on start analysis button and see the final order of strategies as well as expected monetary values for all strategies.

### 4.3. *Monte Carlo simulation*

To validate the proposed stratified decision-making model described above, a series of Monte Carlo computer simulations are conducted. All simulations were run using the R Studio using the provided simulation code[4] explained in Sections 4.1. and 4.2. A series of experiments were designed while controlling for utility values as presented in Table 4 to check the performance of the proposed model and to verify its accuracy.

Under any defined number of strategies (i.e., $B = 2,\ 5,\ 10$), four graphs each representing the trend of mean EMV in three simu-

[4] The simulation code available open access here: https://github.com/AminVafadar/Simulation_SDMM.git

**Table 4**
Mean EMVs of strategies in numerical experiments controlling for utility values.

| Iteration | 30 | 150 | 750 | 30 | 150 | 750 |
|---|---|---|---|---|---|---|
| $B=2$ | $M=2$ | $M=2$ | $M=2$ | $M=10$ | $M=10$ | $M=10$ |
| $N=10$ | $\begin{bmatrix}0.53\\0.30\end{bmatrix}$ | $\begin{bmatrix}0.54\\0.31\end{bmatrix}$ | $\begin{bmatrix}0.53\\0.31\end{bmatrix}$ | $\begin{bmatrix}0.60\\0.52\end{bmatrix}$ | $\begin{bmatrix}0.59\\0.52\end{bmatrix}$ | $\begin{bmatrix}0.59\\0.52\end{bmatrix}$ |
| $N=10$ | $\begin{bmatrix}0.37\\0.52\end{bmatrix}$ | $\begin{bmatrix}0.37\\0.52\end{bmatrix}$ | $\begin{bmatrix}0.37\\0.52\end{bmatrix}$ | $\begin{bmatrix}0.56\\0.58\end{bmatrix}$ | $\begin{bmatrix}0.56\\0.58\end{bmatrix}$ | $\begin{bmatrix}0.56\\0.58\end{bmatrix}$ |
| Iteration | 30 | 150 | 750 | 30 | 150 | 750 |
| $B=5$ | $M=2$ | $M=2$ | $M=2$ | $M=10$ | $M=10$ | $M=10$ |
| $N=2$ | $\begin{bmatrix}0.50\\0.67\\0.43\\0.43\\0.91\end{bmatrix}$ | $\begin{bmatrix}0.50\\0.68\\0.44\\0.42\\0.91\end{bmatrix}$ | $\begin{bmatrix}0.51\\0.66\\0.43\\0.42\\0.91\end{bmatrix}$ | $\begin{bmatrix}0.52\\0.36\\0.50\\0.53\\0.47\end{bmatrix}$ | $\begin{bmatrix}0.53\\0.37\\0.49\\0.53\\0.46\end{bmatrix}$ | $\begin{bmatrix}0.53\\0.37\\0.49\\0.53\\0.47\end{bmatrix}$ |
| $N=10$ | $\begin{bmatrix}0.58\\0.42\\0.51\\0.52\\0.48\end{bmatrix}$ | $\begin{bmatrix}0.58\\0.42\\0.51\\0.51\\0.49\end{bmatrix}$ | $\begin{bmatrix}0.58\\0.42\\0.51\\0.51\\0.48\end{bmatrix}$ | $\begin{bmatrix}0.50\\0.50\\0.43\\0.46\\0.46\end{bmatrix}$ | $\begin{bmatrix}0.50\\0.50\\0.43\\0.46\\0.47\end{bmatrix}$ | $\begin{bmatrix}0.50\\0.50\\0.43\\0.46\\0.47\end{bmatrix}$ |
| Iteration | 30 | 150 | 750 | 30 | 150 | 750 |
| $B=10$ | $M=2$ | $M=2$ | $M=2$ | $M=10$ | $M=10$ | $M=10$ |
| $N=2$ | $\begin{bmatrix}0.56\\0.59\\0.46\\0.39\\0.35\\0.37\\0.61\\0.36\\0.38\\0.82\end{bmatrix}$ | $\begin{bmatrix}0.56\\0.60\\0.46\\0.40\\0.32\\0.39\\0.58\\0.36\\0.38\\0.82\end{bmatrix}$ | $\begin{bmatrix}0.56\\0.60\\0.46\\0.40\\0.32\\0.39\\0.58\\0.36\\0.38\\0.83\end{bmatrix}$ | $\begin{bmatrix}0.41\\0.39\\0.42\\0.30\\0.43\\0.59\\0.50\\0.48\\0.51\\0.60\end{bmatrix}$ | $\begin{bmatrix}0.41\\0.39\\0.42\\0.30\\0.43\\0.60\\0.50\\0.48\\0.52\\0.60\end{bmatrix}$ | $\begin{bmatrix}0.41\\0.38\\0.42\\0.30\\0.43\\0.60\\0.50\\0.48\\0.51\\0.60\end{bmatrix}$ |
| $N=10$ | $\begin{bmatrix}0.47\\0.58\\0.55\\0.63\\0.75\\0.64\\0.35\\0.53\\0.56\\0.39\end{bmatrix}$ | $\begin{bmatrix}0.48\\0.58\\0.54\\0.63\\0.74\\0.64\\0.36\\0.53\\0.56\\0.39\end{bmatrix}$ | $\begin{bmatrix}0.48\\0.57\\0.55\\0.63\\0.74\\0.64\\0.36\\0.52\\0.56\\0.39\end{bmatrix}$ | $\begin{bmatrix}0.50\\0.54\\0.54\\0.39\\0.45\\0.53\\0.45\\0.51\\0.51\\0.43\end{bmatrix}$ | $\begin{bmatrix}0.49\\0.54\\0.54\\0.40\\0.46\\0.53\\0.45\\0.50\\0.51\\0.44\end{bmatrix}$ | $\begin{bmatrix}0.49\\0.54\\0.54\\0.40\\0.46\\0.53\\0.45\\0.50\\0.51\\0.44\end{bmatrix}$ |

lation runs (i.e., 30, 150, 750[6]) are depicted in Figs. 10, 11 and 12. Utility values in each of the four graphs in Figs. 10, 11, and 12 is different from the other one as the number of status ($N$) and number of outcomes ($M$) has altered. However, in each of the four settings the utility values are controlled for over three simulation runs (i.e., 30, 150, 750). Note that the outcome transition probability matrix ($Q_{M\times M}$) and status transition probability matrix ($P_{N\times N}$) are randomly generated as explained in previous section and are changing over three simulation runs (i.e., 30, 150, 750). This can reveal the negligible extent that changes in values of $Q_{M\times M}$ and $P_{N\times N}$ can change the order of strategies while utility values remained unchanged over three simulation runs (i.e., 30, 150, 750).

The simulation results for $B=2$ under four settings, as shown in Fig. 10, indicate that the order of strategies is not sensitive to the changes in values of $Q_{M\times M}$ and $P_{N\times N}$ while controlling for utility values when the number of strategies is low.

As shown in Fig. 11, the simulation results for $B=5$ under four different parameter settings indicate that as the number of strategies grows from $B=2$ to $B=5$ a slight change in order of strategies appears after the increase in simulation runs from 30 to 150 in three graphs. However, no change in order of strategies was observed after the increase in simulation runs from 150 to 750. This result shows that the order of strategies in large simulation runs (i.e., 750) while controlling for utility values, is not sensitive to changes in values of $Q_{M\times M}$ and $P_{N\times N}$ when the number of strategies grows from $B=2$ to $B=5$.

As depicted in Fig. 12, when the number of strategies grows from $B=5$ to $B=10$ a slight change in order of strategies appears in all four graphs after the increase in simulation iterations from 30 to 150. Like the cases of $B=5$ and $B=2$ the change occurs from 30 to 150. This evidence recommends that there is slightly higher chance of results sensitivity in terms of order of strategies by altering values of $Q_{M\times M}$ and $P_{N\times N}$ and controlling for utility values when the size and scale of the problem is larger. In the next section, the application of the proposed model in a real-world case is shown.

## 5. Illustrative real-world model of flooding risk mitigation problem

The selected case study is the *Highland and Argyll* Local Plan District in Scotland. This district is one of the 14 Local Plan Districts for flood risk management purposes in Scotland. It is in the north and northwest of the mainland Scotland including most of the islands off the west coast. It covers an area of nearly 29,000 km$^2$ and a coastline with a length of around 4,190 km. There exist 40 potentially vulnerable areas in the *Highland and Argyll* Local Plan District. Around 7% of properties at risk of flooding nationally are in this district and the annual average damages from flooding are nearly £26.5m (45% river flooding, 44% coastal flooding, and 11% surface water flooding) [98]. There are 15,000 homes and businesses at risk of flooding, and this is projected to grow by around 23,000 by the 2080s [100]. The annual flood damage in Scotland is approximately £252m (56% river flooding, 23% surface water flooding, and 21% coastal flooding) within 2016-2021. This amount can be increased considering the climate change effects as well as challenges to mitigation and adaptation that the country might face in its long-term planning [58,99]. This considerable cost of flooding has sparked interest in flood risk assessment by policy makers, necessitating sophisticated techniques to address long-term strategy selection via informed decisions. The most suitable flooding risk mitigation strategies are selected by accounting for the dynamics of the UK challenges to adaptation and mitigation based on SSP and flooding risk impacts. The strategies are defined and proposed by SEPA [98]. The definitions provided for each strategy are based on SEPA [98] and shown in Table 5.

### 5.1. Shared socio-economic pathway (SSP)

In order for the proposed model to provide a basis for making projections about long-term socio-economic scenarios, it is necessary to adopt a framework with clear storylines to enable the model to establish a range of status or trajectories. For this reason, the literature on scenario development frameworks, particularly in climate change research, is reviewed. There are two frameworks that have been used to produce integrated scenarios encompassing climate model projections, socio-economic conditions, and climate policy assumptions. They provide the potential for straightforward comparisons between studies and then communicating model results. One is representative concentration pathways (RCPs), and the other is shared socio-economic pathways (SSPs). The RCPs reflect on projections about greenhouse gas emissions and the resulting atmospheric concentrations separated in standardized scenarios used widely in the IPCC literature (where they are referred to as the 2.6, 4.5, 6.0 and 8.5 W/m$^2$ pathways). The RCPs, however, do not provide socio-economic narratives which is the gap that SSPs have come to cover. The SSPs define various combinations of socio-economic changes regarding how the world might evolve on issues relevant to climate change [34]. The SSPs describe

[6] The difference between values for more than 750 iterations was tested and realized as negligible.

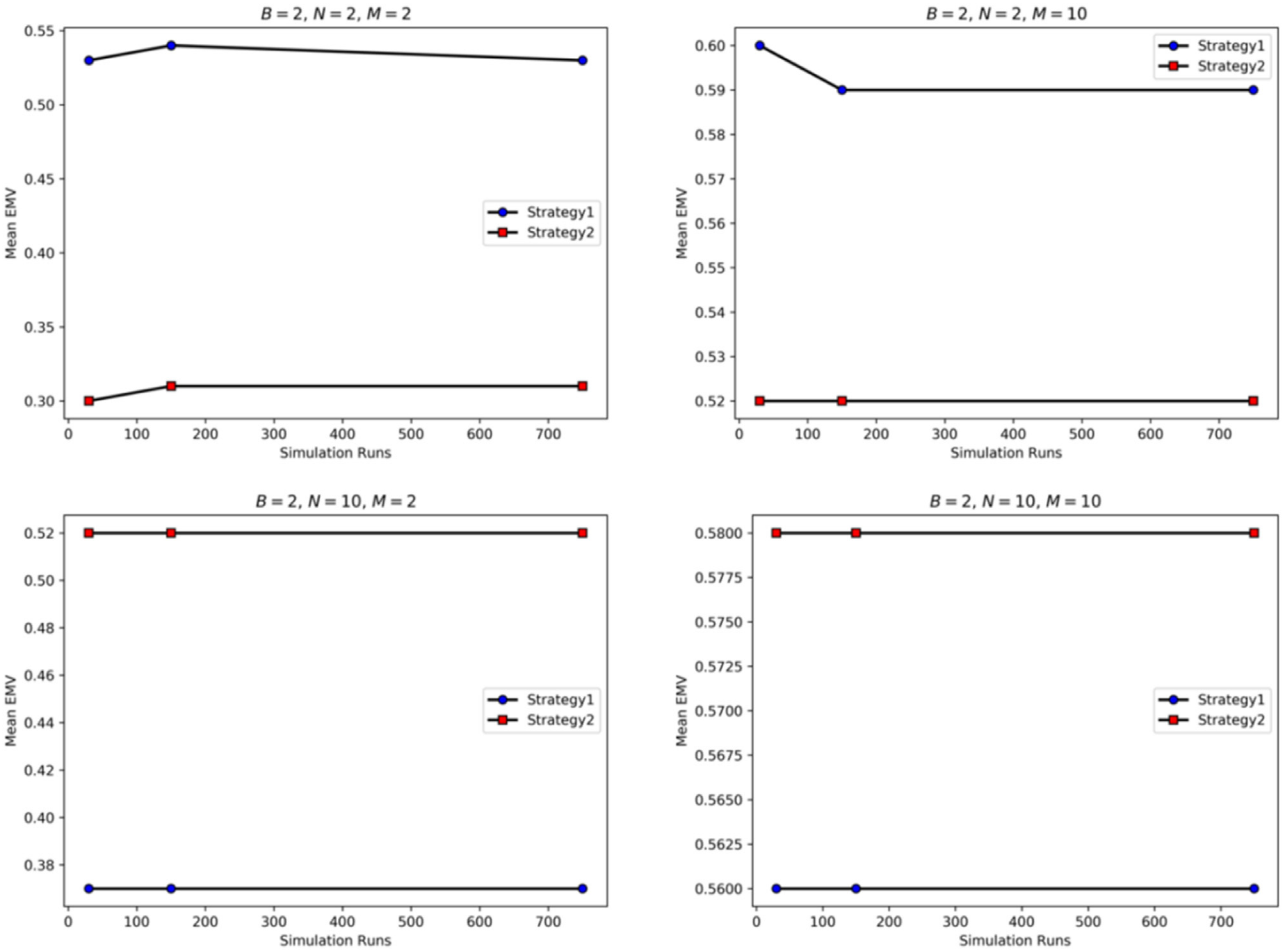


**Fig. 10.** Simulation results for $B = 2$.

**Table 5**
Flooding risk mitigation strategies.

| No. | Strategy | Characteristics |
|---|---|---|
| **1** | Awareness raising | Raising public awareness of flood risk is the duty of responsible authorities. Enhanced awareness of individuals, homes, and businesses regarding flood risk and related measures can lessen the total impact. |
| **2** | Emergency plans/response | Many organizations have the responsibility to provide an emergency response to flooding, including local authorities and emergency services. This response can be supported by voluntary organizations. |
| **3** | Flood forecasting | Issuing flood warnings by the Scottish Flood Forecasting Service (SFFS) via guidance statements can provide the public with information to lower flooding impacts. |
| **4** | Self help | Property and business owners can ensure that they are protected against flood damage by taking simple, yet effective steps such as arranging a flood plan or property level protection by registering at Floodline and the Resilient Communities Initiative. |
| **5** | Maintenance | It is local authorities' duty to evaluate watercourses and do clearance and repair works where such actions would significantly mitigate the flood risk. |
| **6** | Planning policies | The Scottish Planning Policy supports a catchment scale approach for sustainable flood risk management. It suggests that new development in areas with medium to high likelihood of flooding should be avoided. |

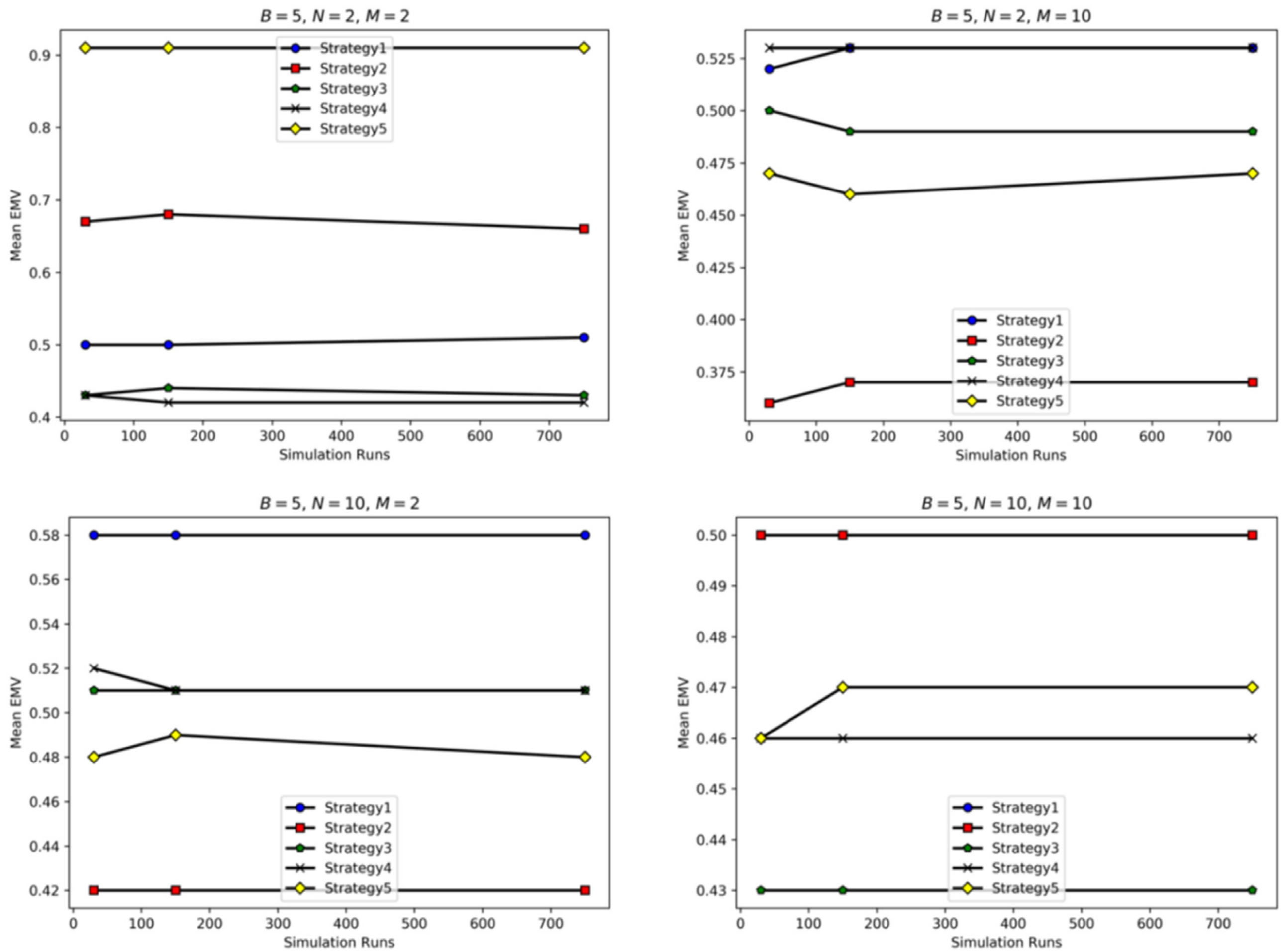


**Fig. 11.** Simulation results for $B = 5$.

plausible alternative trends in the evolutionary progress of societies and eco-systems until 2100 [52,83]. Birkmann et al. [15] emphasized the importance of socio-economic scenario development in terms of vulnerability and adaptive capacity. When compared to other frameworks such as RCPs [112], the SSPs are capable of including the socio-economic narratives leading to a more comprehensive approach. Thus, RCPs do not include any socio-economic narratives to be considered. As a result, SSP is chosen in this study as the most comprehensive and suitable for the stratified decision-making model.

The SSPs, as discussed in Kriegler et al., [63], are defined by two dimensions:

1- *Challenges to Adaptation:* Socio-economic conditions that, in the absence of climate-related policies, would result in higher vulnerability and lower adaptation capacity for a given level of climate change.
2- *Challenges to Mitigation:* Socio-economic conditions that, in the absence of climate-related policies, would result in higher emissions and poorly suited technological or institutional conditions to reduce emissions.

The possible SSPs based on the three-point scale on each dimension are presented in Fig. 13. In this study, the three SSPs (i.e., SSP1, SSP5, and SSP9[7]) are considered for simplicity. These SSPs correspond to low challenges to adaptation and mitigation (sustainability-taking the green road), moderate challenges to adaptation and mitigation (middle of the road), and high challenges to adaptation and mitigation (regional rivalry-a rocky road) in Riahi et al. [93], respectively.

### 5.2. Flooding risk impacts

Climate hazards were categorized based on the impact severity into three levels, mild (MI), moderate (MO), and severe (SV), in line with the categorization of the flood risk matrix of Scottish Flood Forecasting Service (SFFS) (Fig. 14). As shown in Fig. 14, the potential impacts of flooding (river, tidal/coastal, and surface water) can be categorized into four levels, minimal, minor, significant, and severe, based on the SFFS [102]. However, for the sake of simplicity in later computational steps and considering other international definitions, such as those of the Malaysian National Security Council [88], only mild (MI) level has been defined along with moderate (MO) and severe (SV). The three levels of MI, MO, and SV can be representative of the severity impact of floods. Risk assessment can be conducted on the basis of impact and likelihood of flooding to give a combined risk, as shown in Fig. 14. In this study, only the potential impact of flooding is considered at the three levels of MI, MO, and SV in the introduced model, and the likelihood of flooding risk is not considered, because this consideration would have to be based on climate modeling, which is not the focus of this paper.

The three levels *I*, *II* and *III* or MI, MO, and SV have been defined as follows [88]:

[7] Note that the chosen SSPs are equal to SSP1, SSP2 and SSP3 in Riahi et al. [93].

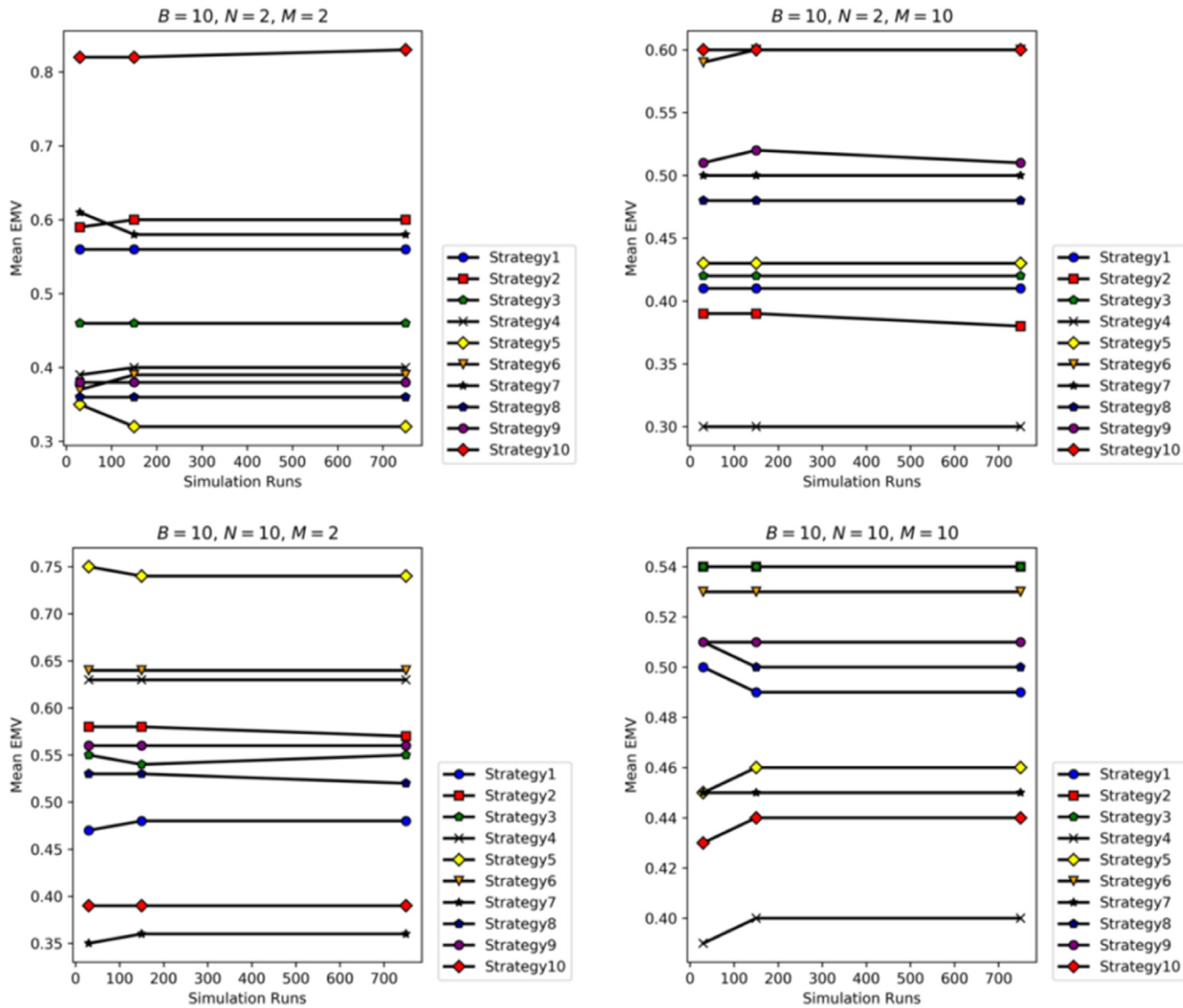


**Fig. 12.** Simulation results for $B = 10$.

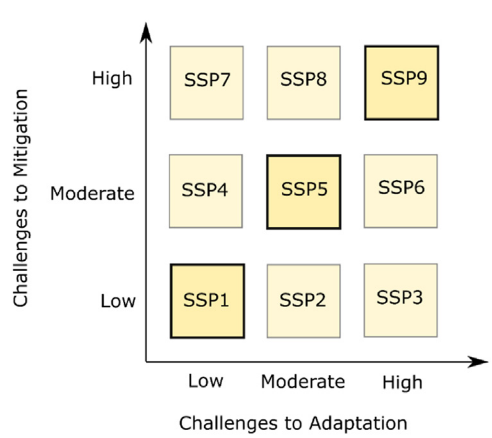


**Fig. 13.** SSPs on two dimensions of challenges to mitigation and adaptation.

*Level I, or MI:* Climate hazards are controllable and have no possibility of spreading out. They are not complicated and could cause minimal damage to life and property.

*Level II, or MO:* Climate hazards cover a wide range area and have the potential to spread out while affecting public daily activities. They could possibly cause damage to a large number of properties and could cause loss of life.

*Level III, or SV:* Any disaster caused at this level is more complex in nature compared to other levels and affects a wide area (more than two provinces) while causing the highest damage possible to life and property.

It is assumed that the socio-economic situation can cause low (L), moderate (M), or high (H) challenges to mitigation and adaptation based on the SSP (Fig. 13). Furthermore, the impact of flooding can be mild (MI), moderate (MO), or severe (SV). Thus, a stratified game table with three status ($N = 3$) and three outcomes ($M = 3$) can be constructed, as shown in Table 6.

### 5.3. Data collection

The data collection was conducted in two phases: (1) screening and (2) actual data collection.

*1) Screening:* In the screening phase, 57 potential experts with sufficient knowledge and expertise in flood management were chosen[8]. They were sent a short online survey to self-evaluate their

[8] The initial 57 experts were chosen out of 464 potential contacts with management experience in Scotland and available on Prolific database.

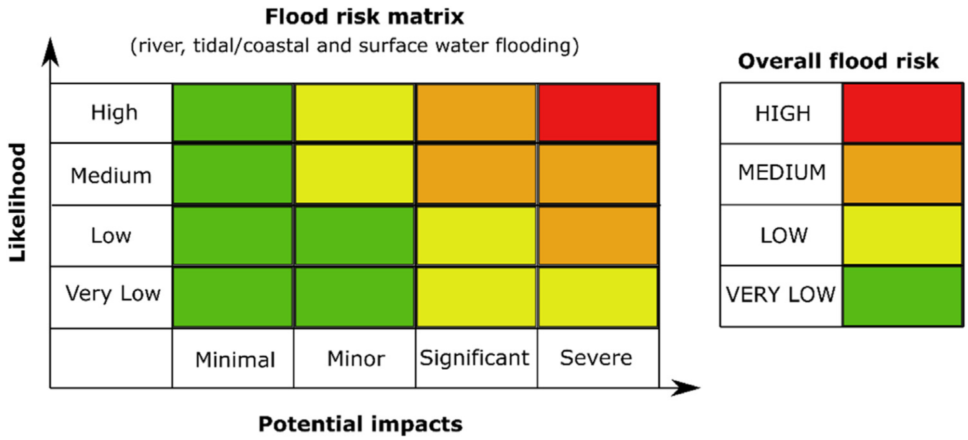


**Fig. 14.** Flood risk matrix and overall flood risk [102].

**Table 6**
Stratified game table of flood risk management for $N = 3$ and $M = 3$.

| Socio-economic situation | Strategies | Climate hazards (flooding) | | |
|---|---|---|---|---|
| | | Mild (MI) | Moderate (MO) | Severe (SV) |
| **Low challenges to mitigation and adaptation (L)** | 1. Awareness raising<br>2. Emergency plans/response<br>3. Flood forecasting<br>4. Self help<br>5. Maintenance<br>6. Planning policies | $SE_1$ | $SE_2$ | $SE_3$ |
| **Moderate challenges to mitigation and adaptation (M)** | 1. Awareness raising<br>2. Emergency plans/response<br>3. Flood forecasting<br>4. Self help<br>5. Maintenance<br>6. Planning policies | $SE_4$ | $SE_5$ | $SE_6$ |
| **High challenges to mitigation and adaptation (H)** | 1. Awareness raising<br>2. Emergency plans/response<br>3. Flood forecasting<br>4. Self help<br>5. Maintenance<br>6. Planning policies | $SE_7$ | $SE_8$ | $SE_9$ |

**Table 7**
The verbal scale for obtaining utility values.

| Linguistic Phrase | Score | SVTNN | Expected Utility |
|---|---|---|---|
| **No Effectiveness (NE)** | 0 | $<(0.0,0.0,0.0,0.0);0.0,0.0,0.0>$ | 0.00 |
| **Low Effectiveness (LE)** | 1 | $<(0.2,0.3,0.4,0.5);0.6,0.2,0.2>$ | 0.26 |
| **Fairly Low Effectiveness (FLE)** | 2 | $<(0.3,0.4,0.5,0.6);0.7,0.1,0.1>$ | 0.38 |
| **Medium Effectiveness (ME)** | 3 | $<(0.4,0.5,0.6,0.7);0.8,0.0,0.1>$ | 0.50 |
| **Fairly High Effectiveness (FHE)** | 4 | $<(0.7,0.8,0.9,1.0);0.8,0.2,0.2>$ | 0.68 |
| **High Effectiveness (HE)** | 5 | $<(1.0,1.0,1.0,1.0);0.9,0.1,0.1>$ | 0.90 |
| **Absolutely High Effectiveness (AHE)** | 6 | $<(1.0,1.0,1.0,1.0);1.0,0.0,0.0>$ | 1.00 |

level of knowledge and expertise in flood risk management in Scotland using a scale of 1 to 100. Out of those who evaluated themselves having a grade value greater than 70, 13 experts in total, were chosen for the data collection stage.

*2) Actual:* In actual data collection, 13 surveys were sent to experts, and 10 responses were received, which were considered for analysis. In Appendix C (Supplementary Materials), the questions used in the survey are explained in detail. The survey questions are constructed based on the rating scales provided in Tables 7 and 8. In Table 7, the linguistic scale utilized by experts for estimating the utility values of each flooding risk mitigation strategy is provided by using a single-valued trapezoidal neutrosophic number (SVTNN) to effectively address uncertainty within subjective judgments [109,110]. The SVTNNs are beneficial and capable of addressing the complex problems in relation to indeterminacy, falsity and truth and they can retain as much information as possible [38,105].

Table 8 is introduced based on Haase et al. [42] and Govindan et al. [40] to obtain the estimated status transition and outcome transition probabilities. The trapezoidal intuitionistic fuzzy number (TrIFN) is applied to capture the subjective uncertainty of experts in probability estimations by Govindan et al. [40].

### *5.4. Scenario settings for inputs in CST*

The performance of the considered strategies is evaluated in 5+ years [117] planning horizon via the proposed model. The influence of inputs on the state change should be evaluated considering that state 1 is the target state and cannot be further improved. Incremental enlargement in CST as a tool to identify possible paths to-

**Table 8**
The rating scale used for acquiring probability estimations.

| Linguistic Phrase | Score | TrIFNs | Expected Probability |
|---|---|---|---|
| Almost Zero (AZ) | 0 | <(0.0,0.0,0.0,0.0), (0.0,0.0,0.0,0.0)> | 0.00 |
| Very Small (VS) | 1 | <(0.0,0.1,0.2,0.3), (0.0,0.1,0.2,0.3)> | 0.15 |
| Small (S) | 2 | <(0.1,0.2,0.3,0.4), (0.0,0.2,0.3,0.5)> | 0.25 |
| Moderate (M) | 3 | <(0.3,0.4,0.5,0.6), (0.2,0.4,0.5,0.7)> | 0.45 |
| Large (L) | 4 | <(0.5,0.6,0.7,0.8), (0.4,0.6,0.7,0.9)> | 0.65 |
| Very Large (VL) | 5 | <(0.7,0.8,0.9,1.0), (0.7,0.8,0.9,1.0)> | 0.85 |
| Almost Certain (AC) | 6 | <(1.0,1.0,1.0,1.0), (1.0,1.0,1.0,1.0)> | 1.00 |

**Table 9**
Tabular CST for the flood risk management example.

| | Socio-economic situation | Flooding hazard | $SE_{t+1}$ | |
|---|---|---|---|---|
| | | | Scenario 1 | Scenario 2 |
| 1 | L | MI | 1 | 1 |
| 2 | L | MO | 1,2 | 1,2 |
| 3 | L | SV | 1,2,3 | 2,3 |
| 4 | M | MI | 1,4 | 1,4 |
| 5 | M | MO | 1,2,4,5 | 1,2,4,5 |
| 6 | M | SV | 1,2,3,4,5,6 | 2,3,5,6 |
| 7 | H | MI | 1,4,7 | 4,7 |
| 8 | H | MO | 1,2,4,5,7,8 | 4,5,7,8 |
| 9 | H | SV | 1,2,3,4,5,6,7,8,9 | 5,6,8,9 |

wards the target state is considered in various ways in each scenario (Table 9).

*Scenario 1: optimistic improvement:* In this scenario, all possible improvements are considered, even those that can make an enormous difference. In other words, transition by incremental enlargement from the worst state to the best state is possible.

*Scenario 2: cautious improvement:* In this scenario, the state transitions are occurring towards the improvement of the system or not becoming worse. The incremental enlargement takes place at one step towards the target state, which means that inputs of the system cannot make the transition possible from a very poor situation to the very best situation in one move, which indicates cautious or more realistic improvement.

State 1 is the target state. With regard to control by the system analysts and associated authorities, inputs can be categorized into variables that are *partly in control* or *out of control*, such as climate change and natural disasters, or *in control*, such as economic policies.

### 5.5. Parameter settings

In this section, parameter settings for the status and outcome transition probabilities and utility function values are explained.

#### 5.5.1. Status and outcome transition probability values

In scenario 1, the values of $p_{11} = 1$ and $p_{12} = p_{13} = p_{23} = 0$ and $q_{11} = 1$ and $q_{12} = q_{13} = q_{23} = 0$ are fixed. In scenario 2, the values of $p_{11} = 1$ and $p_{12} = p_{13} = p_{23} = p_{31} = 0$, and $q_{11} = 1$ and $q_{12} = q_{13} = q_{23} = q_{31} = 0$ are fixed, as shown in Table 10 and Appendix C (Supplementary Materials). The status and outcome transitions are explained in Sections 3.2 and 3.3. Other probabilities can change based on the experts' opinions and collected data (Table 10). The average values obtained by experts are taken into consideration, and all experts' opinions are treated with the same level of importance. Details about the utilized surveys and how probability values are acquired are presented in Appendix C (Supplementary Materials).

The values for the two scenarios are calculated based on the provided probabilities in Table 10 and Eq. (3). The graphical CST with transition probabilities based on the optimistic (1) and cautious (2) scenarios are shown in Fig. 15.

#### 5.5.2. Equilibrium distribution

The proposed model is analyzed to see whether it will converge to the target state (i.e., state 1) in the long-term behavior (just scenario 1 has been considered here). As there is a finite state space with more than two communicating classes, but only one closed communicating class (i.e., state 1), we can conclude that the equilibrium (stationary) distribution exists [67]. This aim is achieved by calculating the equilibrium distributions based on Markov chains [67]. As can be seen in Fig. 15(a), the distributions are aperiodic and reducible, therefore it may or may not converge in the long-term behavior. The analysis has been carried out and as illustrated in Fig. 16, the eight graphs present the probability of reaching to state $k$ ($\forall k = 1, \ldots, 9$) from state $x$ ($\forall x = 2, \ldots, 9$) in $t$ steps, as $t$ changes: $(P^t)_{x,k}$. The start state $X_0$ can be any state ($\forall x = 2, \ldots, 9$). The result of the analysis shows that the long-term behavior of the proposed model based on the calculated equilibrium distribution in the Markov chains tend to converge to the target state (i.e., state 1). In Fig. 16, it is clear that the probability of target state (i.e., state 1) is converging to 1 while other states' probabilities are converging to 0 over time. This behavior does not always occur in classical Markov chains because there is no de-

**Table 10**
Status and outcome transition probabilities for different scenarios based on average experts' opinions.

| Scenario 1: optimistic | | | | | | | |
|---|---|---|---|---|---|---|---|
| Status transition probability matrix | | | | Outcome transition probability matrix | | | |
| $\boldsymbol{P}$ | $\boldsymbol{p}_{11} = 1$ | $\boldsymbol{p}_{12} = 0$ | $\boldsymbol{p}_{13} = 0$ | Q | $\boldsymbol{q}_{11} = 1$ | $\boldsymbol{q}_{12} = 0$ | $\boldsymbol{q}_{13} = 0$ |
| | $p_{21} = 0.37$ | $p_{22} = 0.63$ | $\boldsymbol{p}_{23} = 0$ | | $q_{21} = 0.43$ | $q_{22} = 0.57$ | $\boldsymbol{q}_{23} = 0$ |
| | $p_{31} = 0.35$ | $p_{32} = 0.40$ | $p_{33} = 0.25$ | | $q_{31} = 0.32$ | $q_{32} = 0.34$ | $q_{33} = 0.34$ |
| **Scenario 2: cautious** | | | | | | | |
| Status transition probability matrix | | | | Outcome transition probability matrix | | | |
| $\boldsymbol{P}$ | $\boldsymbol{p}_{11} = 1$ | $\boldsymbol{p}_{12} = 0$ | $\boldsymbol{p}_{13} = 0$ | Q | $\boldsymbol{q}_{11} = 1$ | $\boldsymbol{q}_{12} = 0$ | $\boldsymbol{q}_{13} = 0$ |
| | $p_{21} = 0.46$ | $p_{22} = 0.54$ | $\boldsymbol{p}_{23} = 0$ | | $q_{21} = 0.44$ | $q_{22} = 0.56$ | $\boldsymbol{q}_{23} = 0$ |
| | $\boldsymbol{p}_{31} = 0$ | $p_{32} = 0.39$ | $p_{33} = 0.61$ | | $\boldsymbol{q}_{31} = 0$ | $q_{32} = 0.44$ | $q_{33} = 0.56$ |

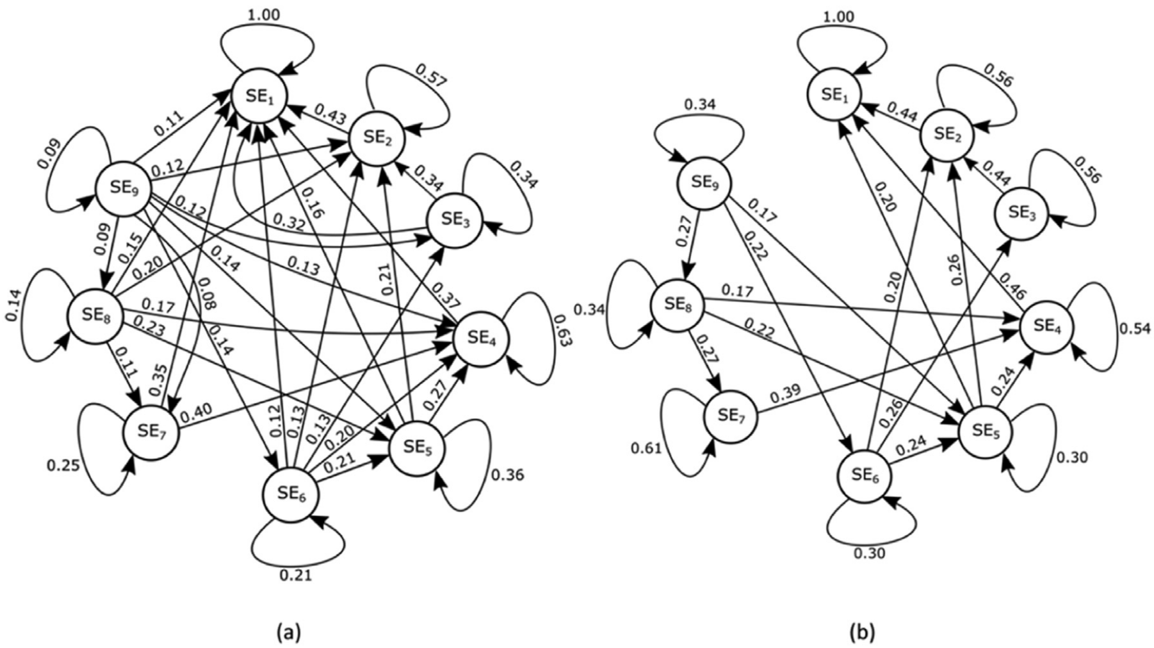


**Fig. 15.** Graphical CST with transition probabilities for flood risk planning (a): scenario 1 (b): scenario 2.

fined a priori target state in classical Markov chains. This feature differentiates the proposed model from classical Markov chains by having the merit of *target state* through applying the stratified decision-making model in a game setting. Furthermore, the multi-dimensionality feature in the proposed stratified decision-making model (i.e., two dimensions of status and outcome in the model) helps model and calculate the occurrence probability of each state in a more practical sense with more information. In Section 5.7, the sensitivity analysis on the probability of the current state is shown when there is an assumption of no consensus on current state as is in the current case study. Ultimately, unlike classical Markov chains, there are utility values integrated within the proposed stratified decision-making model which are discussed in the next Section.

*5.5.3. Utility values*

Based on the rating scale provided in Table 7 and the survey explained in Appendix C (Supplementary Materials), the strategies' utility values are obtained on the basis of the average values offered by all experts (Table 11).

In Fig. 17, the trends in the utility values for each strategy under various flooding risk impact levels and the socio-economic status are illustrated.

**Table 11**
Utility values.

| | | | Outcome | | |
|---|---|---|---|---|---|
| status | strategy | | MI | MO | SV |
| **L** | 1 | Awareness raising | 0.5960 | 0.5140 | 0.5400 |
| | 2 | Emergency plans/response | 0.5450 | 0.5110 | 0.5050 |
| | 3 | Flood forecasting | 0.5110 | 0.5100 | 0.5320 |
| | 4 | Self help | 0.4620 | 0.4720 | 0.4460 |
| | 5 | Maintenance | 0.4820 | 0.4880 | 0.4800 |
| | 6 | Planning policies | 0.4670 | 0.4770 | 0.4650 |
| **M** | 1 | Awareness raising | 0.4720 | 0.5250 | 0.5480 |
| | 2 | Emergency plans/response | 0.5520 | 0.5120 | 0.5143 |
| | 3 | Flood forecasting | 0.5730 | 0.5860 | 0.6080 |
| | 4 | Self help | 0.4940 | 0.5160 | 0.5180 |
| | 5 | Maintenance | 0.4960 | 0.4850 | 0.5700 |
| | 6 | Planning policies | 0.5350 | 0.5680 | 0.5970 |
| **H** | 1 | Awareness raising | 0.5613 | 0.6220 | 0.5310 |
| | 2 | Emergency plans/response | 0.5220 | 0.5680 | 0.5460 |
| | 3 | Flood forecasting | 0.6547 | 0.6310 | 0.6450 |
| | 4 | Self help | 0.5140 | 0.5620 | 0.5600 |
| | 5 | Maintenance | 0.6430 | 0.6200 | 0.6830 |
| | 6 | Planning policies | 0.6180 | 0.6240 | 0.6000 |

*5.6. Results*

The after-transition utility decision matrices for scenario 1 and 2 (Table 12) are calculated based on Eq. (7) and Table 2. The EMVs are also calculated based on Eq. (8) and are illustrated in Fig. 18. The calculations are conducted under the assumption of equal current state probabilities (i.e., 0.11). The current state is the state at the present time of planning with the current or very near future in which the socio-economic status and flooding risk impact can be framed. If there is full certainty about the current state, then it will be assigned the probability 1 and the other states will be assigned the probabilities of 0 and will automatically be removed from the EMV calculation. In Section 5.7., a sensitivity analysis of the current state probabilities under various schemes is provided. The analysis findings suggest that in the *Highland and Argyll* Local Plan District in Scotland, the best long-term flood mitigating strategy is flood forecasting (i.e., strategy 3), followed by awareness raising (i.e., strategy 1), emergency plans/response (i.e., strategy 2), planning policies (i.e., strategy 6), maintenance (i.e., strategy 5), and self help (i.e., strategy 4).

*5.7. Sensitivity analysis*

To test the robustness of the results, the sensitivity of the rankings based on the probability of the current state is analyzed for scenarios 1 and 2, verifying how sensitive the final ranking is to changes in the current state's probability. As can be seen in Table 13, five schemes of various probabilities are suggested, while in all of them, the sum of the probabilities is equal to 1. In the default scheme, equal probabilities for all states are considered, which was also used as the main analysis in the previous section. Scheme 1 emphasizes the occurrence of high socio-economic situations (i.e., high challenges to mitigation and adaptation-SSP9 in Fig. 13) by assigning the highest probability to

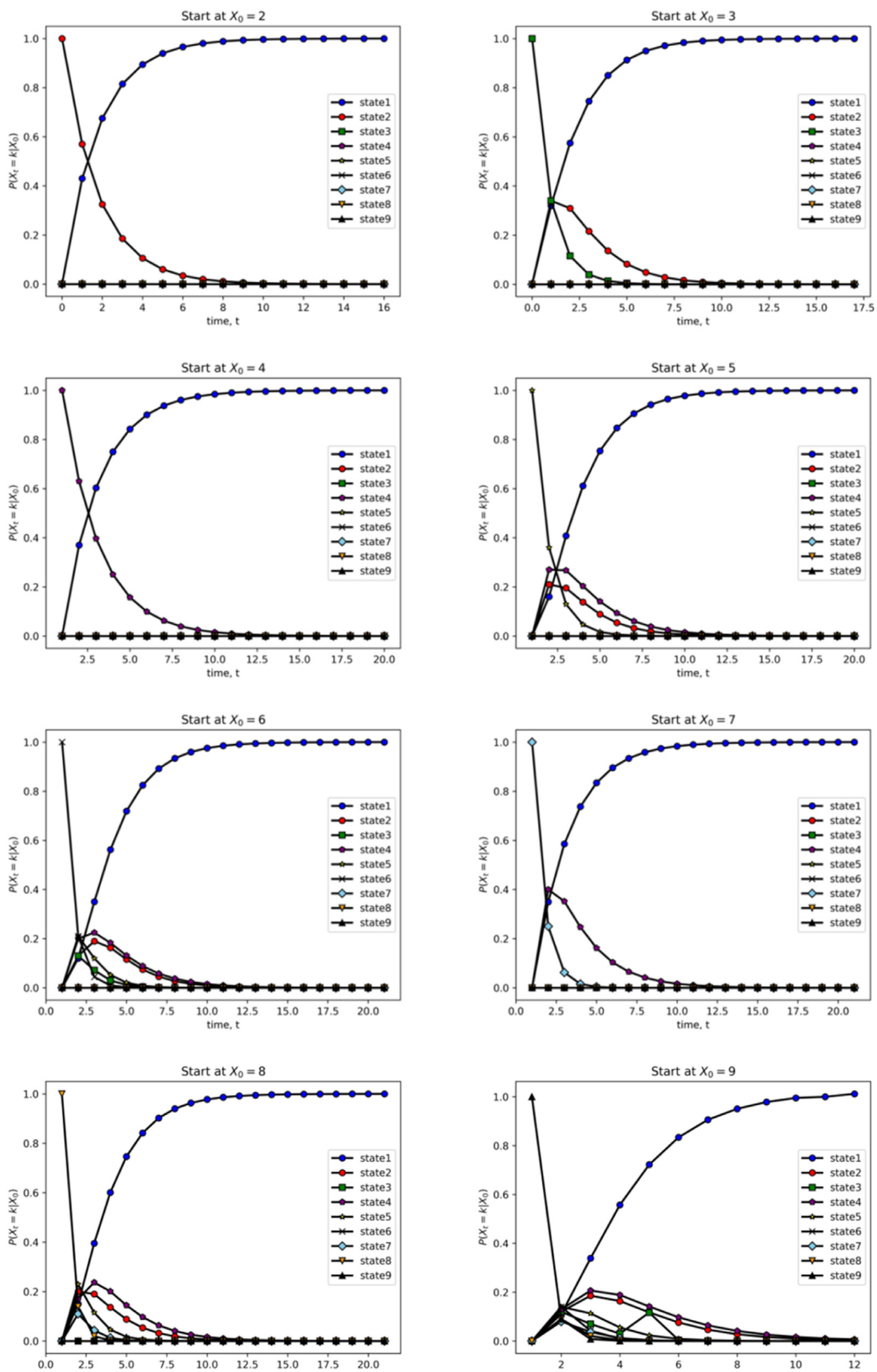


**Fig. 16.** Equilibrium distribution starting at different states for scenario 1.

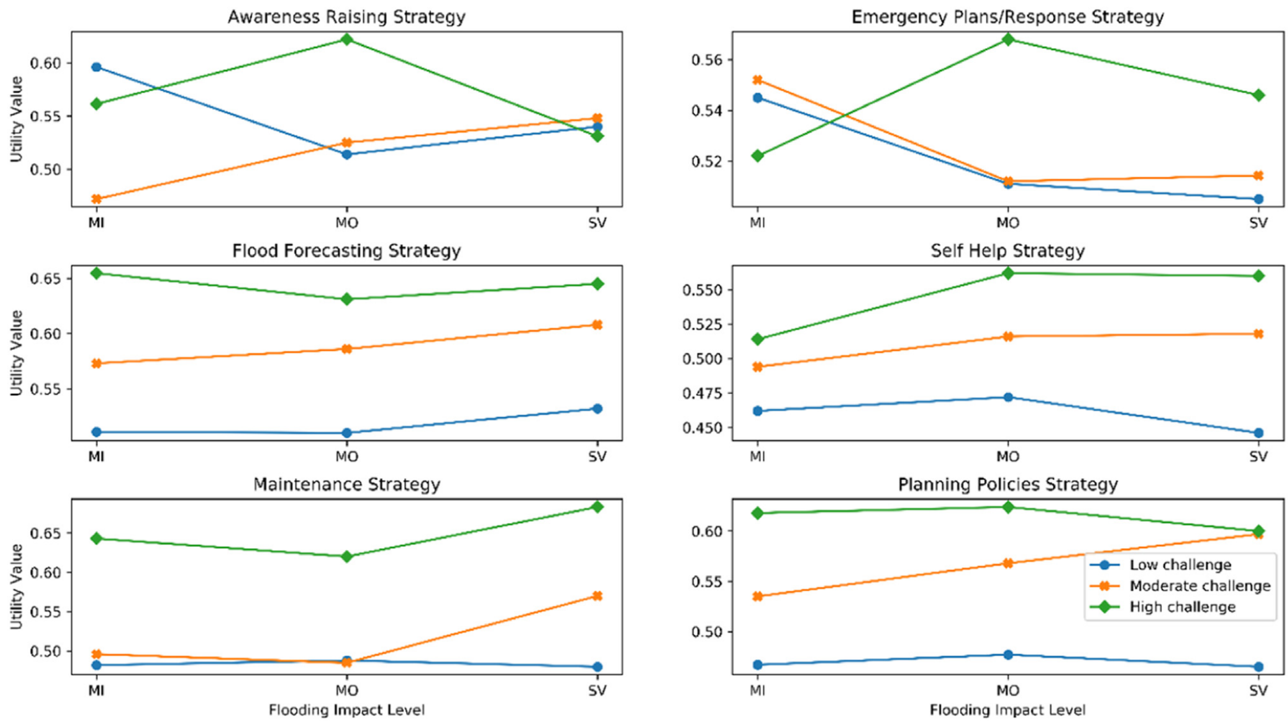


**Fig. 17.** Utility values for each strategy under various flooding risk impact levels and socio-economic status as determined by experts.

**Table 12**
The after-transition utility decision matrix (scenarios 1 and 2).

| Current state probability | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Scenario 1 | | | | | | | | | | |
| Strategies | $SE_1$ | $SE_2$ | $SE_3$ | $SE_4$ | $SE_5$ | $SE_6$ | $SE_7$ | $SE_8$ | $SE_9$ | EMV |
| Strategy 1 | 0.5960 | 0.5493 | 0.5491 | 0.5179 | 0.5196 | 0.5282 | 0.5377 | 0.5421 | 0.5414 | ~0.54(2) |
| Strategy 2 | 0.5450 | 0.5256 | 0.5198 | 0.5494 | 0.5279 | 0.5235 | 0.5421 | 0.5327 | 0.5286 | ~0.53(3) |
| Strategy3 | 0.5110 | 0.5104 | 0.5178 | 0.5501 | 0.5545 | 0.5629 | 0.5717 | 0.5711 | 0.5778 | ~0.55(1) |
| Strategy 4 | 0.4620 | 0.4677 | 0.4600 | 0.4822 | 0.4922 | 0.4913 | 0.4878 | 0.5017 | 0.5013 | ~0.48(6) |
| Strategy 5 | 0.4820 | 0.4854 | 0.4834 | 0.4908 | 0.4881 | 0.5048 | 0.5279 | 0.5233 | 0.5383 | ~0.50(5) |
| Strategy 6 | 0.4670 | 0.4727 | 0.4697 | 0.5098 | 0.5238 | 0.5312 | 0.5320 | 0.5423 | 0.5448 | ~0.51(4) |
| Scenario 2 | | | | | | | | | | |
| Strategies | $SE_1$ | $SE_2$ | $SE_3$ | $SE_4$ | $SE_5$ | $SE_6$ | $SE_7$ | $SE_8$ | $SE_9$ | EMV |
| Strategy 1 | 0.5960 | 0.5501 | 0.5286 | 0.5290 | 0.5239 | 0.5336 | 0.5265 | 0.5588 | 0.5581 | ~0.54(2) |
| Strategy 2 | 0.5450 | 0.5260 | 0.5076 | 0.5488 | 0.5279 | 0.5107 | 0.5337 | 0.5407 | 0.5391 | ~0.53(3) |
| Strategy 3 | 0.5110 | 0.5104 | 0.5223 | 0.5445 | 0.5482 | 0.5634 | 0.6228 | 0.6176 | 0.6230 | ~0.56(1) |
| Strategy 4 | 0.4620 | 0.4676 | 0.4574 | 0.4793 | 0.4885 | 0.4897 | 0.5062 | 0.5274 | 0.5438 | ~0.49(6) |
| Strategy 5 | 0.4820 | 0.4854 | 0.4835 | 0.4896 | 0.4878 | 0.5100 | 0.5857 | 0.5754 | 0.6074 | ~0.52(5) |
| Strategy 6 | 0.4670 | 0.4726 | 0.4703 | 0.5037 | 0.5163 | 0.5318 | 0.5856 | 0.5949 | 0.6003 | ~0.53(4) |

**Table 13**
Test schemes for sensitivity analysis of current state probability.

| $SE_t$ | Socio-economic situation | Flooding risk | Default scheme | Scheme 1 | Scheme 2 | Scheme 3 | Scheme 4 |
|---|---|---|---|---|---|---|---|
| 1 | L | MI | 0.11 | 0.03 | 0.20 | 0.03 | 0.20 |
| 2 | L | MO | 0.11 | 0.03 | 0.20 | 0.10 | 0.10 |
| 3 | L | SV | 0.11 | 0.03 | 0.20 | 0.20 | 0.03 |
| 4 | M | MI | 0.11 | 0.10 | 0.10 | 0.03 | 0.20 |
| 5 | M | MO | 0.11 | 0.10 | 0.10 | 0.10 | 0.10 |
| 6 | M | SV | 0.11 | 0.10 | 0.10 | 0.20 | 0.03 |
| 7 | H | MI | 0.11 | 0.20 | 0.03 | 0.03 | 0.20 |
| 8 | H | MO | 0.11 | 0.20 | 0.03 | 0.10 | 0.10 |
| 9 | H | SV | 0.11 | 0.20 | 0.03 | 0.20 | 0.03 |

them. Scheme 2, in contrast to scheme 1, considers the probability of low socio-economic situations (i.e., low challenges to mitigation and adaptation- SSP1 in Fig. 13) to be higher than others. In scheme 3, the SV flood risk has the highest probability, and finally, in scheme 4, the MI flooding risk has the highest probability.

The obtained EMVs from the sensitivity analysis under scenario 1 are shown in Table 14. The trends and rankings of EMVs for strategies under various schemes in scenario 1 are depicted in Fig. 19. The three lowest ranking strategies (strategies 4 to 6) in the default scheme are not sensitive to changes in the current state

**Table 14**
EMVs and rankings of strategies under various schemes (scenarios 1 and 2).

| | Default Scheme | Scheme 1 | Scheme 2 | Scheme 3 | Scheme 4 |
|---|---|---|---|---|---|
| **Scenario 1** | | | | | |
| Strategy 1 | 0.5369 (2) | 0.5316 (2) | 0.5441 (1) | 0.5344 (2) | 0.5400 (1) |
| Strategy 2 | 0.5274 (3) | 0.5285 (3) | 0.5263 (2) | 0.5221 (3) | 0.5331 (3) |
| Strategy 3 | 0.5420 (1) | 0.5570 (1) | 0.5262 (3) | 0.5443 (1) | 0.5399 (2) |
| Strategy 4 | 0.4781 (6) | 0.4864 (6) | 0.4692 (6) | 0.4796 (6) | 0.4761 (6) |
| Strategy 5 | 0.4976 (5) | 0.5098 (5) | 0.4862 (5) | 0.5000 (5) | 0.4956 (5) |
| Strategy 6 | 0.5053 (4) | 0.5226 (4) | 0.4869 (4) | 0.5083 (4) | 0.5020 (4) |
| **Scenario 2** | | | | | |
| | Default Scheme | Scheme 1 | Scheme 2 | Scheme 3 | Scheme 4 |
| Strategy 1 | 0.5395 (2) | 0.5376 (4) | 0.5429 (1) | 0.5369 (2) | 0.5422 (2) |
| Strategy 2 | 0.5257 (3) | 0.5288 (5) | 0.5229 (3) | 0.5198 (5) | 0.5317 (3) |
| Strategy 3 | 0.5570 (1) | 0.5846 (1) | 0.5303 (2) | 0.5597 (1) | 0.5545 (1) |
| Strategy 4 | 0.4864 (6) | 0.5028 (6) | 0.4705 (6) | 0.4900 (6) | 0.4826 (6) |
| Strategy 5 | 0.5177 (5) | 0.5460 (3) | 0.4920 (4) | 0.5218 (4) | 0.5143 (5) |
| Strategy 6 | 0.5217 (4) | 0.5536 (2) | 0.4906 (5) | 0.5255 (3) | 0.5177 (4) |

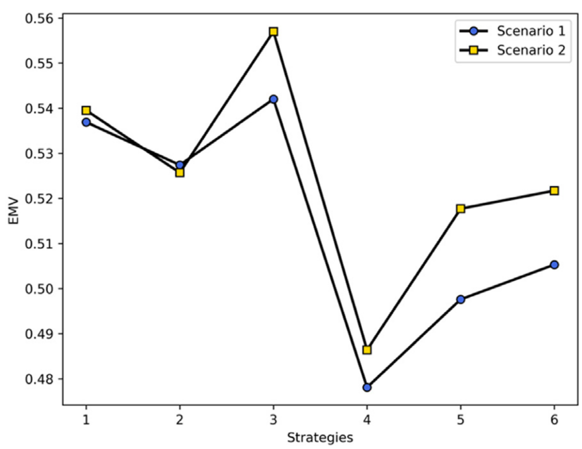


**Fig. 18.** The EMVs for strategies in scenarios 1 and 2.

probability, while the first three strategies (strategies 1 to 3) are more sensitive in schemes 2 and 4. This finding shows that when the current socio-economic situation is facing low challenges to adaptation and mitigation (scheme 2), the most prioritized strategy would be awareness raising (strategy 1), followed by emergency plans/response (strategy 2) and flood forecasting (strategy 3). In scheme 4 (under mild flood risk), raising awareness (strategy 1) is the most useful strategy, followed by flood forecasting (strategy 3) and emergency plans/response (strategy 2). The sensitivity analysis findings in scenario 2 (Table 14) indicate that the last prioritized strategy, which is self-help (strategy 4), is not sensitive to changes in the current state probability. Furthermore, the most significant strategy in scenario 2 (flood forecasing), which is ranked first in almost all schemes, (except for scheme 2), is not sensitive to the changes. In Fig. 19, the trends and rankings of EMVs for strategies under various schemes (scenario 2) are shown.

### *5.8. Discussion*

Flooding is a major threat to life, infrastructure, and business in the UK. Its impact is not diminishing and is predicted to grow in the future due to climate change and severe weather conditions [39,81]. Flood damage costs the UK approximately £2 billion yearly [95], and these expenses are expected to increase. In this study, uncertainty and climate change adaptation criteria were used together with flood risk impacts in a decision-making model. The main contribution of this study was proposing a stratified decision-making model for long-term decision making. This approach considered the system's dynamism on the basis of the CST, game theory and SSP.

As a comparison to other similar methods, Bayes principle has been used in games of chance under risk (i.e., a priori probabilities are known) which has not been the case in the current study. In addition, Bayesian belief networks (BBN) [33,54,65] or Bayesian games [124] such as Bayesian Nash equilibrium (BNE) [45,47] are also different from the proposed model in the current study. First, BNE are games of strategy (i.e., two-player games) and not games of chance (i.e., one player against nature). Second, although BBN can be modeled as a game of chance, but it is based on the conditional probabilities and the player's action is dependent on the nature's action which will change payoff values depending on the nature's state. On the contrary, in the proposed model, they are independent from each other, and payoff values stay constant throughout the state changes. Finally, there is no ideal state in the BBN or BNE and no dynamism is considered in them to allow the system to traverse to achieve the ideal state. As explained before, the proposed model has similar features to classical Markov chains, however there is no defined a priori target state in classical Markov chains which differentiates the proposed model from classical Markov chains by having the merit of *target state* through applying the stratified decision-making model in a game setting. Furthermore, the multi-dimensionality feature in the proposed model helps model and calculate the occurrence probability of each state in a more practical sense with more information. Ultimately, unlike classical Markov chains, utility values are integrated within our model.

In the literature, various decision analysis methods, such as MCDM [32], have been used for flood risk management; however, it is believed that the proposed stratified decision-making model is unique and innovative, because it can offer predictive insights by incorporating the advantages of CST, game theory, and SSP into one model for long-term planning. The integration of CST and game theory provides a stratified model while accounting for a priori target state enabling a more dynamic model to overcome the staticity issue. This model was then implemented through utilizing an interactive web application with dynamic user interface which has been made available open access and verified through a set of numerical experiments by conducting Monte Carlo simulation. This tool can be used by practitioners, analysts, and researchers for their cases regardless of scale and size of the decision-making problem. Finally, to apply the proposed model in the context of disaster management (i.e., flooding), the SSP framework was included to understand UK socio-economic conditions at three levels

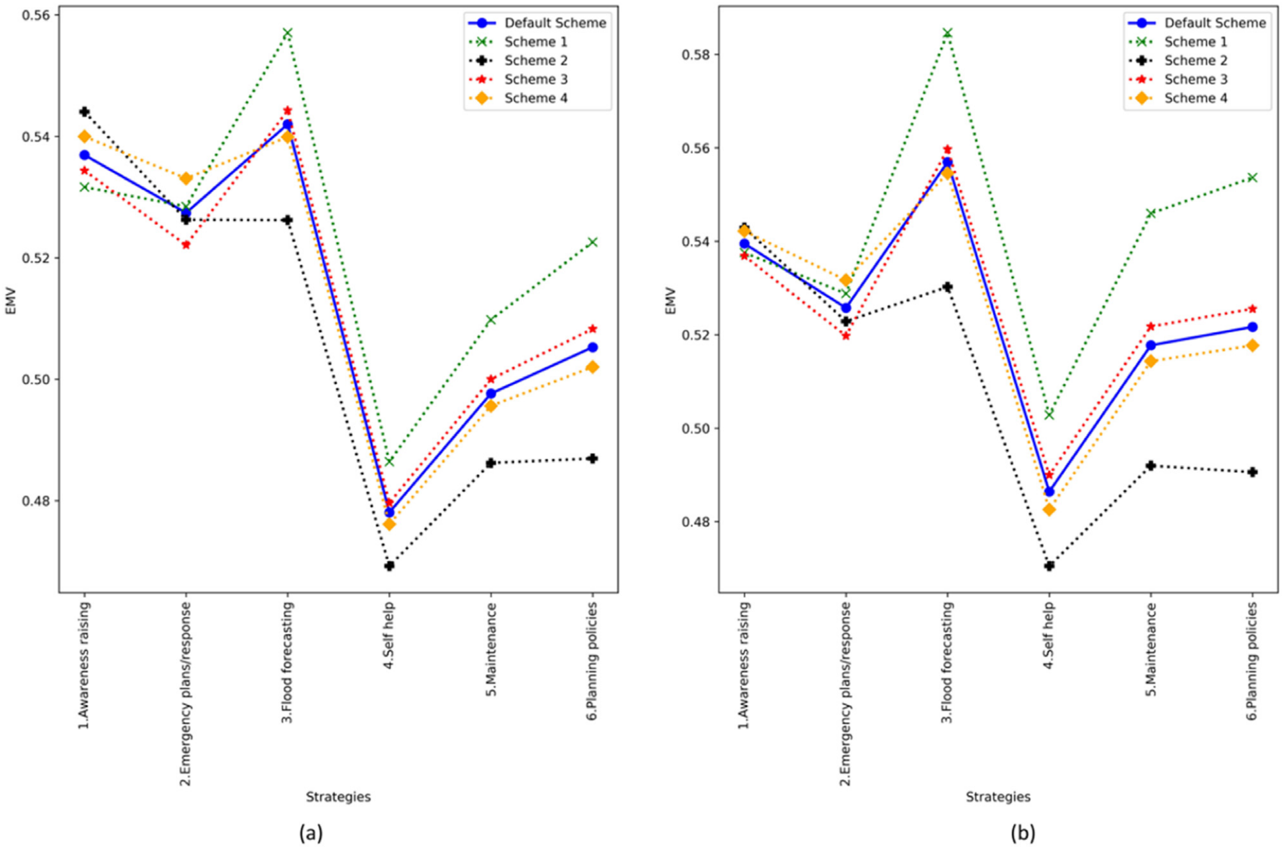


**Fig. 19.** Trends and rankings of EMVs for strategies under various schemes (a): scenario 1, and (b): scenario 2.

(i.e., L, M, and H). Because the proposed model has two dimensions, the impact of flooding was considered, based on SFFS [102], by providing three impact levels (i.e., MI, MO and SV).

The model's applicability was verified in the case of flooding risk mitigation strategy in the *Highland and Argyll* Local Plan District in Scotland. The most suitable flood risk mitigation strategies were selected by accounting for the dynamism of the UK challenges to adaptation and mitigation based on SSP and flooding risk impacts considering MI, MO, and SV levels. After primary data were collected from the involved experts in the region of Scotland, the proposed model was applied and analyzed. A sensitivity analysis of the probabilities of the current state was provided to verify the obtained results. The final order of strategies is flood forecasting (i.e., strategy 3), awareness raising (i.e., strategy 1), emergency plans/response (i.e., strategy 2), planning policies (i.e., strategy 6), maintenance (i.e., strategy 5) and self-help (i.e., strategy 4). The literature in the flood disaster management supports the importance of *flood forecasting*, as many studies have explored this by developing various techniques, such as neural network models [19], artificial intelligence [3] and MCDM [68]. Neal et al. [79] supported the finding in this study that *flood forecasting* should be prioritized to effectively address flood impacts proactively. Elluru et al. [36] also emphasized on the proactive approach for resilience analysis in supply chains disaster management. They indicated that a medium- to long-term forecast of coastal flooding can be useful for the UK government and response agencies. Nye et al. [82] emphasized on the criticality of the *awareness raising* strategy in the literature, which confirms the identification of this strategy as the second most suitable flooding risk mitigation strategy in this study. They indicated that social aspects of flooding, especially flood warning and awareness raising, can lead to a more balanced socio-technical risk management portfolio [51]. Carter et al. [20] also emphasized raising awareness of the flood risk threat among stakeholders and indicated that it can be enhanced by sustainability appraisals. Coles et al. [25] highlighted the significance of the third important strategy in this study, which is *emergency plans/response*. They proposed an integrated model of numerical modeling and geographical analysis of service areas for ambulance, fire and rescue services by demonstrating two floods in York, UK, to assess the vulnerability of sheltered and care homes. Finally, one approach to handling the impacts of flooding that the UK policy guidelines suggest is the community resilience concept by designing interventions that is close to the concept of a *self-help* strategy in the obtained result, which ranks sixth [81].

## 6. Conclusions

A hybrid risk mitigation model based on CST, game theory and SSP was proposed to obtain a reliable and applicable model for flooding risk mitigation strategy selection in the long term (5+ years) [117]. The Monte Carlo simulation results revealed that when the number of strategies is relatively low, the order of strategies was not sensitive to the changes in values of the outcome transition probability and status transition probability matrices while controlling for utility values. However, when the size and scale of the problem is larger, there is a slightly higher chance of results sensitivity in terms of order of strategies by altering values of outcome transition probability and status transition probability matrices while controlling for utility values. The model was also applied in the *Highland and Argyll* Local Plan District in Scotland based on primary data obtained from experts to prioritize flooding risk mitigation strategies that were recommended by SEPA. The model accounts for both UK socio-economic situations and flooding risk impacts. The application aim was to address the most significant climate change risk to the UK infrastructure (i.e., flooding) for long-term policy making (5+ years) [117] with reference to the

UK socio-economic status. In this study, the game of chance involving risk and CST were integrated to incorporate the dynamic nature of the decision environment for long-term disaster risk planning, while accounting for various states of the system with an a priori target or ideal state. The findings indicated that the most important strategies that can provide long-term benefit in mitigating flooding risk impact in the *Highland and Argyll* Local Plan District in Scotland are flood forecasting (i.e., strategy 3), awareness raising (i.e., strategy 1), emergency plans/response (i.e., strategy 2), planning policies (i.e., strategy 6), maintenance (i.e., strategy 5) and self-help (i.e., strategy 4).

Despite the merits of the proposed model, it does have a few limitations. First, for the sake of simplicity, the two dimensions of challenges to adaptation and mitigation based on SSP were used to conceptualize the socio-economic conditions at only three levels (low, moderate, and high). However, in future studies, to account for the full picture, researchers can apply a model with all possible levels. This approach could pose another obstacle, that of acquiring data, which would make it extremely difficult for decision makers to offer their assessments due to the high number of evaluations required. For future research, scholars can take advantage of mixed primary and secondary data and decrease the dependence of the results on subjective judgments in real-world cases. Moreover, adding a third dimension of sustainable development goals to the model could be an interesting future research topic. It is important to understand the potential synergic or dysergic behavior of strategies apart from the adaptation and mitigation challenges and impact level dimensions, especially over a longer time frame. However, this step might add an extra level of complexity to the model, which requires researchers to add more innovative features into the proposed stratified model. In other words, it would be beneficial to realize whether strategies can potentially offer more helpful merits in terms of social justice or community well-being at the time that a flood has recently occurred. Secondly, the proposed model can be utilized in similar strategic decision-making settings, such as natural disasters or energy systems in other countries or regions. In this way, the applicability and versatility of the model can be confirmed. The proposed model can address types of problems that are comprised of two dimensions, such as socio-economic situations and climate hazards (as in the current study), for strategic, long-term, or even medium-term decision making. One application can be the evaluation of strategies for addressing the impact of pandemics such as COVID-19 under various levels of readiness of governments or local authorities for choosing the best strategies to respond in medium-term decision-making timeframes. Finally, it is also interesting to conduct comparative analysis and apply other ambiguity attitudes such as neo-additive decision weighting [11] instead of expected utility values and transition probabilities as in the current stratified model. In addition, there are other extensions of neutrosophic set (NS) such as interval valued NS [76], type-2 NS [103], linguistic single-valued neutrosophic soft sets [56], as well as other uncertainty theories such as Pythagorean fuzzy set [122] that can also be useful in capturing experts' uncertainty in dealing with subjective judgments in utility values.

## Declaration of Competing Interests

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.

## CRediT authorship contribution statement

**Amin Vafadarnikjoo:** Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization. **Konstantinos Chalvatzis:** Methodology, Writing – original draft, Writing – review & editing, Project administration, Supervision, Validation. **Tiago Botelho:** Methodology, Writing – original draft, Writing – review & editing, Supervision, Validation. **David Bamford:** Writing – original draft, Writing – review & editing, Resources, Validation.

## Data Availability

Data will be made available on request.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.omega.2022.102803.

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