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Spatial modelling of natural disaster risk reduction policies with Markov decision processes

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A B S T R A C T

The 2010/2011 floods in Queensland, Australia inflicted significant damages to government's critical infrastructures, private properties and businesses reaching an estimated amount of AU$16 billion. Mitigating the devastating effects of floods to the community and critical infrastructures entails competing financial requirements at the different levels of government. Hence, the main objective of this study was to examine the financial optimality of disaster risk reduction measures by integrating Markov decision processes (MDP for short) with geographic information system (GIS). Conducted in the core suburbs of Brisbane City, we organised the MDP variables using the following: 1) flood risk levels as the states of the urban system; 2) Queensland's disaster risk reduction measures as the action variables; 3) percentage of government expenditures by disaster risk reduction category as the state transition probabilities; 4) total lost earnings to businesses affected by the flood events as the reward variables; and 5) the weighted average riskless rate of return, the weighted average rate of return, and rate of return for a riskier asset as discounting factors. We analysed 36 MDP scenarios at four-level iteration and then calculated the expectimax values to find the optimal policy. The results from the analyses revealed that the Commonwealth government optimised the use of its natural disaster risk reduction expenditures to recovery while the State government focused on mitigation. When both government expenditures combined, the mitigation measure was identified as the optimum natural disaster risk reduction policy. The methodology presented in this study allowed a spatial representation and computationally feasible integration of complex flood disaster risk model with government expenditures and business earnings. The insights from this integrated approach emphasise the viability of finding optimum expenditures, and re-examine if necessary, in implementing natural disaster risk reduction policies and climate adaptation strategies.

Introduction

A variety of studies have been conducted to discuss significant issues on flood disaster risk reduction measures and specific climate adaptation strategies for the urban community in general and critical infrastructures in particular. The pre-disaster planning for effective post-disaster response and recovery (Grzeda, Mazzuchi, & Sarkani, 2014; NRC, 2007) needs critical consideration to anticipate potential impacts while preventing additional harm (Solis, Hightower, Sussex, & Kawaguchi, 1995). However, mitigating the devastating effects of floods to the community and critical infrastructures entails competing financial requirements either from the federal, state or local government. Hence, the main objective of this study was to examine the financial optimality of disaster risk reduction measures or climate adaptation strategies by integrating the tool called Markov Decision Process(es) (MDP for short) with geographic information system (GIS). To the best of authors' knowledge, this approach has never been used in flood mitigation decision making.

The 2010/2011 floods in Queensland, Australia inflicted significant damages to government's critical infrastructures, private properties and businesses. In a joint report prepared by The World Bank and Queensland Reconstruction Authority (2011) in relation to the aforesaid flood events, they observed that: 1) the adverse impacts of flooding to the State reached at least AU$15.7 billion; 2) the amounts indicated by the Commonwealth and State governments for rebuilding the flood-affected areas were AU$5.6 billion

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and AU$2.1 billion, respectively; and 3) the State government's share was AU$3.9 billion taken from the Natural Disaster Relief and Recovery Arrangements (NDRRA).

The Disaster Management Act 2003 provides the legal basis for the Queensland's disaster management arrangements which had been established in three levels of hierarchy: the State Disaster Management Group, district disaster management groups, and local disaster management groups (Queensland Government, 2011). The Queensland Reconstruction Authority (QRA) (2011) identified four disaster risk reduction measures that are being implemented in the State: mitigation, preparedness, response and recovery. Each of these measures has corresponding natural disaster related expenditures from the Commonwealth and State Governments which were then used in the Markov Decision Process (MDP) analysis.

Markov Decision Process (MDP) relies on theory to model feasible action with associated transition matrix containing the probabilities that performing the action in state s will move the system to state s' (Schapaugh & Tyre, 2013). As a stochastic process, MDP is a decision-making model for finding optimum policy under certainty (Dufour & Prieto-Rumeau, 2014; Eun-Kim, 1994; White & White, 1989). For examples, Krougly, Creed, and Stanford (2009) presented a stochastic model simulating fire behaviour in a forested landscape and illustrated the total disturbance impact under different initial conditions and scenarios. In Tianjin coastal area, China, Ma, Zhang, Zhang, Zhao, and Li (2012) used Markov chain as a stochastic model in assessing wetland change dynamics and demonstrated three main conclusions: 1) a continuing 'exchange' of wetland area occurs between artificial wetlands and natural wetlands categories; 2) pollution and construction were the predominant causes for wetland changes; and 3) the natural wetlands will be in great decline in 2020 and 2050.

There were also numbers of studies conducted for modelling decision-making problems in different areas, such as finding optimum hydro-power production (Lamond & Boukhtouta, 1996), maintenance policy of repairable power equipment (Tomasevicz & Asgarpoor (2009), inventory control problem for optimal ordering decisions (Ahiska, Appaji, King, & Warsing, 2013), and natural resources conservation and management (Williams, 2009).In rangeland management, for example, Freier, Schneider, and Finckh (2011) investigated a dynamic land use decision model using Markov chain meta-model and revealed two significant results: 1) the drought simulations show a decrease in profits from pastoralism by up to 75%; and 2) pastoral land use of the rangeland increases surface runoff by 20%, doubles infiltration, and thus influences irrigation agriculture.

Moreover, urban growth modelling with Multi-Criteria Evaluation framed in Markov Cellular Automata model (Vaz, Nijkamp, Painho, & Caetano, 2012) and simulation through Markov analysis on the land use, and effects of urban, agricultural, forest and wetland dynamics (Vaz, Walczynska, & Nijkamp, 2013) are some analytical tools used in assessing the consequences of regional environmental changes. Integrated with GIS, those studies revealed a set of promising tools for the strategic development of rural and/or urban areas in response to environmental challenges arising from exploitation of land-use resources, economic prosperity, increasing population, growth of infrastructures (Vaz et al., 2012), and natural disasters.

In a study conducted by Arsanjani, Helbich, Kainz, and Boloorani (2013), they analysed the suburban in the metropolitan area of Tehran, Iran by using the hybrid model consisting of logistic regression model, Markov chain, and cellular automata. They found a satisfactory performance to predict land use maps for 2016 and 2026 illustrating a new wave of suburban development for the next decades. In Mumbai, India, Moghadam and Helbich (2013) implemented an urban growth model by integrating Markov Chains–Cellular Automata (MC–CA) that characterised the open land and croplands having mostly affected by degradation. Further, their forecast revealed that built-up areas will increase by 26% in 2020 and 12% in 2030 and mostly pronounced towards the north along the main traffic infrastructure and eastern areas. Similar trend was observed in a study conducted by Guan et al. (2011) that built-up areas in Saga, Japan will undergo an upward trend affecting agricultural land and forestland areas. This was further supported in the study conducted by Haibo, Longjiang, Hengliang, and Jie (2011) in Tai'an City, China wherein the Markov model revealed that farmland was mainly changed to lawn or residential land. Agricultural expansion is the main driving force for loss of forest, wetland and marshy land and has the potential to continue in the future (Behera et al., 2012).

Xin, Xin-Qi, and Li-Na (2012) compared the performance of MC–CA model with Ant Colony Optimisation–Markov Chain–Cellular Automata (ACO–MC–CA) model in the spatiotemporal assessment of land use change in Beijing, China. The latter revealed a promising result being more appropriate to use in predicting the quantity and spatial distribution of land use change in the study area (Xin et al., 2012). Within the same city, Wang, Zheng, and Zang (2012) explored the accuracy of MC–CA simulation through the calculation of Kappa index for location and quantity. Their analysis revealed that simulation accuracy of small cell size is better than big cell size which gives a better understanding on how to select best spatial resolution for simulation. In order to grip land use changes better, Sang et al. (2011) proposed that simulation can be divided into two parts: one is the quantitative forecast by using the Markov model, and the other is the simulating the spatial pattern changes by using the CA model. Validating the performance of CA–Markov model, statistics revealed that accuracy is slightly higher when this model is combined with multi-objective land allocation (MOLA) procedure in the land use and land cover (LULC) change analysis (Surabuddin, Sharma, Kappas, & Garg, 2013). In 2009, the Markov–CA–MOLA procedure was used in simulating future land use/cover changes (up to 2030) and predicted a continuing downward trend in woodland areas and an upward trend in bare land areas (Kamusoko, Aniya, Adi, & Manjoro, 2009). To reduce bias in the non-spatial error term of those models, Finley, Sang, Banerjee, and Gelfand (2009) offered a knot-based predictive process approach set in the Markov chain Monte Carlo models.

We further examined the application of Markov models in natural disaster risk reduction. The binomial cluster analysis and MDP were used in optimal-decision making such as the identification and selection of disaster debris management sites (Grzeda et al., 2014) and optimum utilisation of open space for emergency response (Li, Lee, & Liu, 2013), respectively. The Markov–CA–MOLA procedure was used in Nigeria to predict the areas where desert conditions are likely to spread to by the year 2030. Musa, Gajere, and Akinyede (2012) emphasised that the valleys of the Rivers Kamandagu Gana and Kamandugu Yobe are among the most vulnerable areas from desertification. Applied in the vegetation restoration assessment at landslide areas caused by catastrophic earthquake in Central Taiwan, the Markov-chain model showed that vegetation restoration at the Chiufenershan and Ninety-nine peaks landslide areas is ongoing, but has been disturbed by natural disasters (Chuang, Lin, Chien, & Chou, 2011). In modelling emergency evacuation for major hazard industrial sites, Georgiadou, Papazoglou, Kiranoudis, and Markatos (2007) used the Markov–Monte Carlo model to support decisions for emergency response concerning for example areas that must be evacuated or not in certain circumstances and for land use planning issues such as providing information about the need to increase transportation network capacity and safe shelters.