A spatial framework for regional-scale flooding risk assessment

Yun Chen
CSIRO Land and Water, CSIRO Water for a Healthy Country National Research Flagship, yun.chen@csiro.au

Damian Barrett
CSIRO Land and Water, CSIRO Water for a Healthy Country National Research Flagship

Rui Liu
CSIRO Land and Water, CSIRO Water for a Healthy Country National Research Flagship, East China Normal University

Lei Gao
CSIRO Land and Water, CSIRO Water for a Healthy Country National Research Flagship

Mingwei Zhou
CSIRO Ecosystem Sciences

See next page for additional authors

Follow this and additional works at: https://scholarsarchive.byu.edu/iemssconference

Part of the Civil Engineering Commons, Data Storage Systems Commons, Environmental Engineering Commons, and the Other Civil and Environmental Engineering Commons

Chen, Yun; Barrett, Damian; Liu, Rui; Gao, Lei; Zhou, Mingwei; Renzullo, Luigi; Cuddy, Susan; and Emelyanova, Irina, "A spatial framework for regional-scale flooding risk assessment" (2014). International Congress on Environmental Modelling and Software. 18. https://scholarsarchive.byu.edu/iemssconference/2014/Stream-H/18

This Event is brought to you for free and open access by the Civil and Environmental Engineering at BYU ScholarsArchive. It has been accepted for inclusion in International Congress on Environmental Modelling and Software by an authorized administrator of BYU ScholarsArchive. For more information, please contact scholarsarchive@byu.edu, ellen_amatangelo@byu.edu.
A spatial framework for regional-scale flooding risk assessment

Yun Chen*, Damian Barrett*, Rui Liu*, Lei Gao*, Mingwei Zhou*, Luigi Renzullo*, Susan Cuddy*, Irina Emelyanova*

*CSIRO Land and Water, CSIRO Water for a Healthy Country National Research Flagship, Canberra, Australia, Yun.Chen@csiro.au

Key Laboratory of Geographic Information Science (Ministry of Education), East China Normal University, China

CSIRO Land and Water, CSIRO Water for a Healthy Country National Research Flagship, Glen Osmond, South Australia

CSIRO Ecosystem Sciences, Highett, Victoria, Australia

CSIRO Land and Water, CSIRO Water for a Healthy Country National Research Flagship, Floreat, Western Australia

Abstract: The mining sector in Australia and globally has always been vulnerable to extreme weather with excess water due to flooding and deficient water through drought. Estimating flood inundation risk at a regional scale is essential for understanding sustainable mine water management, such as the Bowen Basin in Queensland, Australia. In this region, many coal mines have been facing a major challenge of increasing risk of flooding caused by intensive rainfall events. This research develops a spatial multi-criteria decision making (SMCDM) framework to assess flooding risk at regional scale using part of the Bowen Basin as a case study. Spatial data, including climate, hydrology, topography, vegetation and soils, were collected and processed in ArcGIS. Several indices were generated based on long-term observations and modeling analysis taking account of average recurrence interval (ARI) of rainfall and stream flow, potential soil water retention, elevation and slope extracted from DEM, drainage density and proximity derived from river network. These spatial indices were weighted using the analytical hierarchy process (AHP) method. The weighted criteria were integrated in the risk evaluation model. A regional flooding risk map was delineated and verified using the inundation extent corresponding to the maximum ARI detectable by MODIS imagery in the region. The result provides baseline information to help Bowen Basin coal mines identify and assess flooding risk when making adaptation strategies and implementing mitigation measures in the future. The framework and methodology applied in this study is expected to offer an effective approach in managing flooding risk and uncertainty in water availability under climate change for the Australian mining industry.

Keywords: Multi-criteria decision making; AHP; GIS; MODIS; inundation

1 INTRODUCTION

The mining sector in Australia and around world is facing increasing challenges in water-resource management under extreme climates. Flooding of mining pits (underground or open cut), which can be caused by flash flooding from short-periods of intensive rainfall and inundation from surrounding water courses due to prolonged extensive rainfall, has the potential to be the largest and most critical impact on a mine. 2011’s cyclone Yasi and the ensuing flood shut down 85% of all coal mines in Queensland, costing $2.5 billion (Smith, 2013). As climate change is forecast to increase the exposure of the mining sector to flooding risk, identifying and understanding the potential risks of flooding is critical to inform strategies and actions for financially vulnerable mining industry to avoid or manage dangerous levels of changes and to minimise possible damages.
Flood risk is the probability of flood occurrence and its potential consequences. Risk is thus a function of the hazard (i.e., frequency of the flood) and the vulnerability (susceptibility) of the receptor exposed to the hazard. Mapping has become the keystone for flood risk management and communication in representing the spatial relationship between hazard and vulnerability and resulting risk.

In general, the approaches to assess flood risk fall into two categories: qualitative and quantitative. Qualitative methods depend on expert opinions. Quantitative methods are based on numerical modelling, such as hydraulic, hydrological and hydro-dynamic models. The most commonly used analytical hierarchy process (AHP; Saaty, 1980) in multi-criteria decision making (MCDM) is a semi-quantitative method which has a partly subjective nature. It integrates the idea of ranking and weighting with the knowledge of experts. The AHP-based MCDM have been widely used because of their simplicity in implementation and interpretation, the capability in handling scarcity of quality data, and the efficiency in regional studies (Dewan et al., 2007; Chen et al., 2010; Wang et al., 2011; Chen et al., 2013b). GIS is an appropriate tool for processing spatial data on flood risk. Processing of spatial data along with attributes is an important step in effective estimation of flood risk. GIS-based spatial MCDM (SMCDM) is a suitable method to incorporate all relevant types of consequences without measuring them on just one monetary scale (Chen et al., 2009; Chen and Paydar, 2012).

In light of growing climate change concerns and the predicted escalation of flooding, this research seeks to develop a GIS-based framework for regional-scale flood risk assessment using SMCDM. There is an abundance of literature about SMCDM (For a complete review on SMCDM, see Malczewski, 2004; Chen et al., 2010). However, the application of SMCDM in flood risk analysis and management is relatively rare (Tkach and Simonovic, 1997; Simonovic and Nirupama, 2005; Thinh and Vogel, 2006; Wang et al., 2011).

This paper presents some primary results to demonstrate the approaches adopted in the research using a case study in a sub-catchment in the Bowen Basin. The basin contains the largest coal reserves in Australia. There are plans to significantly increase production through current mine expansions and by developing new mines (Zhang et al., 2014). Hence, it is very important to evaluate flood risk and to develop risk maps for future water resources management in the region.

2 CONCEPTUAL FRAMEWORK

After a review of similar research in literature, a SMCDM framework for risk assessment is conceptualised and outlined in Figure 1. It starts with data acquisition, followed by criteria selection, data processing and derivation of criterion indices. The choice of criteria depends on data availability and the consideration of control and impact factors. Various indices form comprehensive indicators of flood risk. The AHP was employed to weight each criterion. The weighted criteria were then classified into different risk levels and aggregated to produce a final risk map.

![Figure 1. Conceptual framework.](image-url)
3 METHODOLOGY

3.1 Study Area

The study area is situated at the Fitzroy catchment in Queensland. It covers an area of 8,520 km$^2$. The average annual precipitation is approximately 820 mm. The mean annual discharge from the gauge station at the catchment outlet is 2,224 GL (gigalitre). The study area includes three mines. The mining area is on the terrain of fluvial plain in the northwest region.

3.2 Data Source and Data Processing

Major data sources can be classified into three categories: (1) time series observations, including daily precipitation (1889-2013) and stream flow (1966-2013); (2) rasters, including DEM (25m resolution), daily rainfall (2000-2013, 5km resolution), MODIS imagery (2001-2013, 500m resolution), land cover (50m resolution) and soils (1km resolution); (3) vectors, including the catchment boundary and the river network. Data processing was performed in ArcGIS version 10.1. The vector datasets were rasterised. All datasets were then projected, resampled to 25m, clipped to catchment boundary and registered, so all input layers have the same projection, cell size and extent.

3.3 Select Criteria /Risk Factors

Flood risk arises from the combination of hazards and vulnerabilities at a particular location. Flood risk assessment requires systematic collection and analysis of data, and should consider the dynamic nature of hazards and vulnerabilities which results from processes, such as environmental degradation and climate change. The focus of this study is precipitation and landscape.

Precipitation is the driven factor for flood risk disaster. Landscape factor refers mainly to the factors of underlying surfaces, including topography, water system, vegetation, soils. They are formative factors playing a vital role in the re-distribution of flood. Particularly, topography and rivers have the most significant influence on floods.

Based on data availability, several factors were identified to be considered when deriving risk assessment criteria. These are climate (rainfall), hydrology (river network), topography (elevation and slope), soils and land cover (retention). These factors interactly influence and control the dynamic processes of flood. Six indices were defined from these factors, which were used as risk assessment criteria. The average recurrence interval (ARI) of rainfall was derived as an hazard, other measures such as elevation, slope, drainage density, distance to nearest creeks/rivers, and potential soil water retention were estimated to represent the vulnerabilities.

3.4 Criteria/Indices Derivation

(1) Rainfall ARI derivation

The ARIs can provide insight to flood inundation risk. Base on the analysis of daily rainfall surfaces (at 5km resolution) available between 2000 and 2013, 14 years annual highest peak discharge were extracted. They were then ranked by the order of magnitude. The annual exceedance probabilities (AEPs) were predicted (Huang, et al., 2014) by adopting the most commonly used Gringorten’s model (Gringorten, 1963):

$$AEP = (r - 0.44)/(N + 0.12)$$

where $r$ is the rank of the annual flow peaks from highest to lowest, $1 \leq r \leq 14$ in this study; $N$ is the number of years for the record length, $N=14$ in this study.
Typical ARIs, i.e. 1-in 2 year, 1-in-5 year, 1-in 10 year and 1-in-100 year, can be converted from AEP. The relationship between AEP and ARI is defined by the formula below (Laurenson, 1987):

$$AEP = 1 - e^{(-1/ARI)}$$

The computed ARIs were used to represent flood probability at different key levels of rainfall from minor up to the probable maximum in this study.

(2) Soil Water Retention (SWR) modelling
Floods are influenced by how much water is stored in the soil from previous flooding and local rainfall, described as 'antecedent conditions'. Prolonged, severe drought depletes stores of water in soil, which means that larger flows are then required for inundation to occur. The potential maximum soil water retention was calculated cell by cell using a spatial hydrological modelling approach, which is driven by the Soil Conservation Service Curve Number (SCS CN) method (McCuen. 1982). Soil and land cover data were intersected to determine spatial distribution of CN using ArcGIS (Chen, et al., 2014).

On the basis of the CN method, the potential maximum SWR at cell $$i$$ ($$SWR_i$$) is parameterised as a function of a CN ($$CN_i$$) value for the cell. This is given by

$$SWR_i = SWR_0 \times (100/CN_i - 1)$$

where $$CN_i$$ is an integer, $$0 < CN_i < 100$$; $$SWR_0$$ is a scale factor depending upon the unit used, e.g. $$SWR_0 = 10$$ for units of inches, and $$SWR_0 = 254$$ for units of millimetres.

(3) Topographic characteristics extraction
Topography has important influence on flood formation and re-distribution. Surface with a lower elevation has a higher risk because it is easier to be inundated by flood. Elevation can be obtained directly from DEM. Slope also has a great impact on flood. Surface with a steeper slope has lower possibility of being inundated because the flood can be easily drained towards down-slope. Both elevation and slope were generated from the DEM using the 3D Analyst Tools in ArcGIS.

(4) Drainage feature delineation
The occurrence of flood disaster is related to the distribution of drainage system. Drainage indices were designed to account for inundation from individual creek and multiple creeks, respectively. These are drainage proximity and drainage density, the former indicates the distance to the closest river and the latter refers to the length of rivers per unit area. They were derived from river network in ArcGIS. The proximity was generated using the Multiple Buffer operator, and the density was from calculated from the Line Density function using a 2km radius.

(5) Inundation extent mapping
Long-term daily stream flow (megalitre/day) from the downstream gauge was examined to derive ARIs from return period analysis. The flow-derived ARIs were then linked to rainfall-derived ARIs. Available MODIS images corresponding to the date of the largest flood event (equivalent to 1-in-5 ARI) observed in the area (2001-2013) were acquired. The inundation extent was detected from these images using the OWL (Open Water Likelihood) algorithm/index (Chen et al., 2013; Huang et al., 2014), and then aggregated to probable maximum flood inundation extent map in the area. The resultant inundation extent map is a surrogate for ground truthing, which is used for the verification of the final flood risk map.

3.5 Criteria Weighting and Standardisation

The weight of each criterion causing floods is achieved with the AHP method (Saaty, 1980). AHP is a commonly used and widely accepted decision making tool. It is uniquely equipped to compare quantitative and qualitative criteria in a common framework. Pair-wise comparison is the basic
measurement mode of the AHP procedure which provides a mathematically robust way to derive criteria weights. One of the emphases of applying AHP is to avoid the ad hoc nature of even weighting. The approach requires experts' best judgment to the relative intensity of importance of one assessment index against another in a comparison matrix. Experts' advice and decision-makers' involvement were seriously obtained during the course of selection and weighting of criteria.

The risk assessment also considered likely impacts of criterion indices at different levels, i.e. high risk, medium risk, low risk and no-risk. The weights for each index and the threshold values for risk levels classified under each index were assigned based on previous experience, comprehensive literature review and professional expertise.

3.6 Risk Assessment Model

In this study, flood risk in this study is defined as a weighted sum, which is a compensatory aggregation function. Based on the criterion indices, the flood risk assessment model was established as follows:

\[
Risk_i = \sum_{l=1}^{n} w_l I_l(x, y) = w_1 I_1(x, y) + w_2 I_2(x, y) + w_3 I_3(x, y) + w_4 I_4(x, y) + w_5 I_5(x, y) + w_6 I_6(x, y) = 0.3082 I_1(x, y) + 0.0637 I_2(x, y) + 0.1443 I_3(x, y) + 0.1742 I_4(x, y) + 0.1256 I_5(x, y) + 0.1840 I_6(x, y)
\]

where \( w_l \) is the weight of the \( l \)-th criterion index; \( I_l(x, y) \) is the contribution function of that normalized criterion index; the \( I_l(x, y) \) follows the order of (1) ARI derived from daily rainfall surfaces, (2) potential maximum soil water retention derived from soil and land cover, (3) elevation derived from DEM, (4) slope derived from DEM, (5) drainage proximity derived from river network, and (6) drainage density derived from river network; \( x, y \) are the geographical coordinates of the cell/pixel, and \( n \) is the number of indices used, \( n=6 \) in this study.

4 RESULT AND DISCUSSIONS

A flood risk map was obtained through the above risk assessment model in the developed framework. According to the risk assessment indices input into the model (Figure 2a-f), the level of risks are divided to four levels: high, medium, low and no-risk by dividing points of 2.5, 3.0, and 3.5. The results were verified at the probable maximum flood inundation extent map (Figure 2g). The assessment results conform basically and reasonably to the actual disaster data (Figure 2h). The actual inundation overlays almost entirely with the areas of high and medium risk areas. Such a satisfactory match shows that the proposed linear model describes the complicated nonlinear processes well, and the evaluation result is meaningful.

The resultant risk map shows the extent and distribution of the flood risk classes. The highest risk locations are in red, and the safe lands are in green. It can be clearly seen that the red areas coincide well with the areas where ARI is greater than 1-in-20 year since this criterion index received the highest weight among the others. Therefore, we expect a high influence of ARIs in the resultant map. The density proximity and soil water retention have been assigned the smallest weight partly due to their almost uniform values across the region. As a result, both have no significant impact on the evaluation result. The effect of drainage density is critical to overbank inundation. Slope and elevation are not only essential factors, but also reliable criteria derived from the high resolution DEM. They can generate fine discrimination of land units to delineate areas of different risk levels for a detailed assessment. These two indices accordingly received higher weights. They produced relatively significant impacts on the resultant map.

For each risk class, the percentage of area in the catchment was calculated from Figure 2h. About 40%of the total study area is classified as high risk, no-risk land covers about 11%, and medium and low risk classes represent 26 and 23% of the land area, respectively. Area with flooding risk is found mainly in on the floodplain in the east of the catchment where the land is dominated by flood frequency or return period greater than 20 years, and alluvial fans and flats of smaller streams where
Figure 2. Criteria indices (a: ARI derived from daily rainfall surfaces; b: Potential maximum soil water retention derived from soil and land cover; c: Elevation derived from DEM; d: Slope derived from DEM; e: Drainage proximity derived from river network; and f: Drainage density derived from river network); g: MODIS detected inundation extent; and h: resultant risk map).

varying areas of land with better drained soils are vulnerable to flooding. Generally, most of the relatively safe areas are located in the west to northwest of the catchment where the surface is undulating with a high altitude. The three mine in the study area (Figure 2g) lie in the risk zone. Therefore, the resultant risk assessments map is helpful in prioritising flood warning system needs and guiding preparations for disaster prevention and responses.

5 CONCLUDING REMARKS

A spatial framework for the assessment of regional flood risk for the mining area was developed. The SMCDM approach presented in this study couples AHP-based MCDM techniques with GIS. Incorporating GIS enhances the visualisation capability and increases the assessment efficiency.

The following points can also be drawn from this study:

1. Selection of criteria is crucial to flood risk assessment. Criteria considered in such an analysis are also diverse and complex. The GIS approach integrates spatial variability of climate, hydrology, terrain, vegetation, soil and other relevant parameters. This allows delineation of areas of various risk ratings for a detailed assessment;

2. The determination of the weights for each criterion or index is vital because they would directly affect the evaluation result. AHP can be one of the fit-for-purpose options. One of the benefits of AHP is the use of a standardized process by which to compare criteria presented with both quantitative and qualitative data, although some suggest that the scale used for comparisons should be non-linear; and

3. The integration of spatial data and application of the SMCDM procedures can provide a comprehensive database and a guide map for decision makers in order to achieve sustainable water resource management in mining.

Finally, the authors restricted their analysis to the environmental vulnerability. The selection of criteria was largely limited due to data availability. Several issues need to be further investigated to ensure an adequate and detailed flood risk assessment. These include the use of coarse resolution precipitation data which has directly influenced the assessment results, and the model validation which was limited
by using 1-in-5 ARI inundation extent, instead of the possible maximum extent, due to image availability. Therefore, the study only gives preliminary results. A more comprehensive data collection and an improved assessment are recommended to extend this approach to the whole Bowen basin. It is expected that the framework will provide an important technical basis for determining measures to prevent flood disaster and enhance the safety of coal mines.

ACKNOWLEDGMENTS

This research is funded by the Australian Coal Association Research Program (ACARP) as “project C21037”, and CSIRO Water for a Healthy Country National Research Flagship as appropriation research project “Strategic Water Management in Mining”.

REFERENCES

Smith, M.H., 2013. Assessing climate change risks and opportunities for investors – Mining and minerals processing sector. IGCC (Investor Group on Climate Change) reports, Australian National University.