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Towards an Integrated Approach to Natural Hazards Risk Assessment Using GIS: With Reference to Bushfires

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ABSTRACT / This paper develops a GIS-based integrated approach to risk assessment in natural hazards, with reference to bushfires. The challenges for undertaking this approach have three components: data integration, risk assessment tasks, and risk decision-making. First, data integration in GIS is a fundamental step for subsequent risk assessment tasks and risk decision-making. A series of spatial data integration issues within GIS such as geographical scales and data models are addressed. Particularly, the integration of both physical environmental data and socioeconomic data is examined with an example linking remotely sensed data and areal census data in GIS. Second, specific risk assessment tasks, such as hazard behavior simulation and vulnerability assessment, should be undertaken in order to understand complex hazard risks and provide support for risk decision-making. For risk assessment tasks involving heterogeneous data sources, the selection of spatial analysis units is important. Third, risk decision-making concerns spatial preferences and/or patterns, and a multicriteria evaluation (MCE)-GIS typology for risk decision-making is presented that incorporates three perspectives: spatial data types, data models, and methods development. Both conventional MCE methods and artificial intelligence-based methods with GIS are identified to facilitate spatial risk decision-making in a rational and interpretable way. Finally, the paper concludes that the integrated approach can be used to assist risk management of natural hazards, in theory and in practice.

Natural hazards include geological and meteorological events such as earthquakes, floods, cyclones, droughts, tornadoes, hailstorms, landslides, bushfires, and tsunamis. As complex spatial phenomena, they vary greatly in magnitude and frequency, and result in death or injury for human beings, damage to the built environment and socioeconomic activities, and broadly speaking, even ecosystems. In recognition of the catastrophic losses worldwide, the 1990s was proclaimed by the United Nations as the International Decade for Natural Disaster Reduction (IDNDR). To mitigate the devastating consequences, the IDNDR Scientific and Technical Committee has called for better application of current information technologies such as geographical information systems (GIS) and remote sensing in natural hazards reduction (Bruce 1994). Using GIS for understanding the complex natural hazards in spatial and temporal contexts is considered vital (e.g., Coppock 1995, Granger 1998, Schneider 1999). Alexander (1997) and Blong (1997) reviewed several natural hazards studies in the past and have suggested that information technologies such as GIS can play an important and integral role in lessening the adverse impacts of natural hazards on society.

KEY WORDS: Natural hazards; Risk assessment; Geographical information systems; Integrated approach; Bushfires

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Natural hazard risk results from the interaction between a hazard agent and a vulnerable community (Burton and others 1978, Blaikie and others 1994, Cannon 1994, Cutter and others 2000). The equation risk = hazard × vulnerability can be used to elaborate the relationship between these three concepts. This understanding embraces a fundamentally important relationship between the natural environment and humans and offers a holistic perspective on natural hazards risk assessment. Risk assessment can be defined differently in various contexts. However, it primarily concerns the degree to which population, built environment, and socioeconomic activities are susceptible to damage from a hazard event with physical aspects (e.g., location, magnitude, frequency, duration, process). As hazards and vulnerability are spatially distributed, risk is inherently a spatial phenomenon, and risk assessment should address both the degree of risk and its spatial variations (Emmi and Horton 1995). Risk assessment requires a wide range of physical and socioeconomic knowledge and expertise, and therefore it is multidisciplinary in nature.

GIS can be used for database establishment, analytical modeling, and decision support in a decision-making process. A large number of GIS applications for natural hazards and emergency management have been developed, particularly during the past decade (e.g., Carrara and Guzzetti 1995, Cova 1999). For example, in landslide risk assessment, Chung and others (1995) proposed GIS-based multivariate regression methods for mapping landslide hazard areas, based on the statistical relationships between historical landslides and relevant spatial data layers (e.g., land use, geology). Risk assessment also uses a combination of GIS and knowledge-based expert systems, which provide a basis for converting data into information and then into practical knowledge. Wadge and others (1993) demonstrated a case study using the Arc/Info GIS and the Nexpert Object expert system for landslides in Cyprus. From a user perspective, GIS and relevant spatial technologies have been increasingly applied in government and corporate agencies at local, regional, and national levels during the past two decades. For example, in the insurance industry GIS have been used in underwriting systems and to assess damage to property for a number of natural hazards (e.g., the Loma Prieta earthquake of October 1989 in California, USA; Hurricane Andrew of 1992 in Florida, USA; and Newcastle earthquake of 1989 in New South Wales, Australia) (Francica 1993, Blong 1997).

With the increasing popularity of GIS in natural hazards risk assessment, there is a need to systematically examine many issues. GIS-based risk assessments previously reported are more concerned with spatial analytical modeling than data integration and risk decision-making issues, and more concerned with physical hazard modeling than vulnerability assessment. Issues such as the characteristics of spatial data and deficiencies of decision support tools should also be addressed. Therefore, this paper examines some key components of an integrated approach to natural hazards risk assessment using GIS, with reference to bushfire risk assessment. The next section introduces a GIS-based integrated approach to risk assessment in natural hazards, followed by explanations and examples of its respective components.

An Integrated Approach

An integrated approach to natural hazards risk assessment includes three components supported by GIS: data integration, risk assessment tasks, and risk decision-making (Figure 1). The conceptual framework represents a holistic and multidisciplinary approach to natural hazards risk assessment, and the three components comprise a work flow for a risk assessment process. The flow from data to modeling is a typical research methodology for many environmental subjects and is embedded in this conceptual framework. Here modelling includes the development of spatial analytical models for evaluating different risk assessment tasks and the development of decision support tools for risk decision-making, based on a collection of data sets. There are three essential components:

- In data integration, large amounts of data and information regarding hazard and risk factors are collected and combined. This stage lays a foundation for subsequent risk assessment tasks and risk decision-making.
- Risk assessment tasks examine individual aspects of hazard and vulnerability. For example, the movement of a bushfire can be understood through the study of its behavior; the population and resources that need to be evacuated as a bushfire approaches can be identified in vulnerability analysis. The knowledge obtained at this stage contributes directly to risk decision-making.
- Risk decision-making concludes a risk assessment process and produces useful decisions to assist risk management in practice. Informed risk decision-making (e.g., conflict resolution between different stakeholders for a bushfire prescribed burning) can be realized from the understanding of the many aspects of risk assessment tasks.

Natural hazards risk assessment benefits greatly from GIS because spatial methodologies can be fully explored in the whole risk assessment process, from data integration to risk assessment tasks and then to risk decision-making. First, reliable and up-to-date spatially referenced data are important in natural hazards risk assessment: risk assessment tasks and ultimately decision-making are constrained by the availability and quality of data inputs. Second, GIS spatial analysis with various methods and techniques has the ability to employ physical environmental and socioeconomic data for hazard and vulnerability analysis. Finally, the aim of the risk assessment process is to support rational decision-making, and to take relevant practical measures in risk management. The decision-making process should be capable of providing systematic and defined procedures for measuring the acceptability of risks. One of the key advantages of using GIS-based decision support tools in a decision-making process is the efficient use of

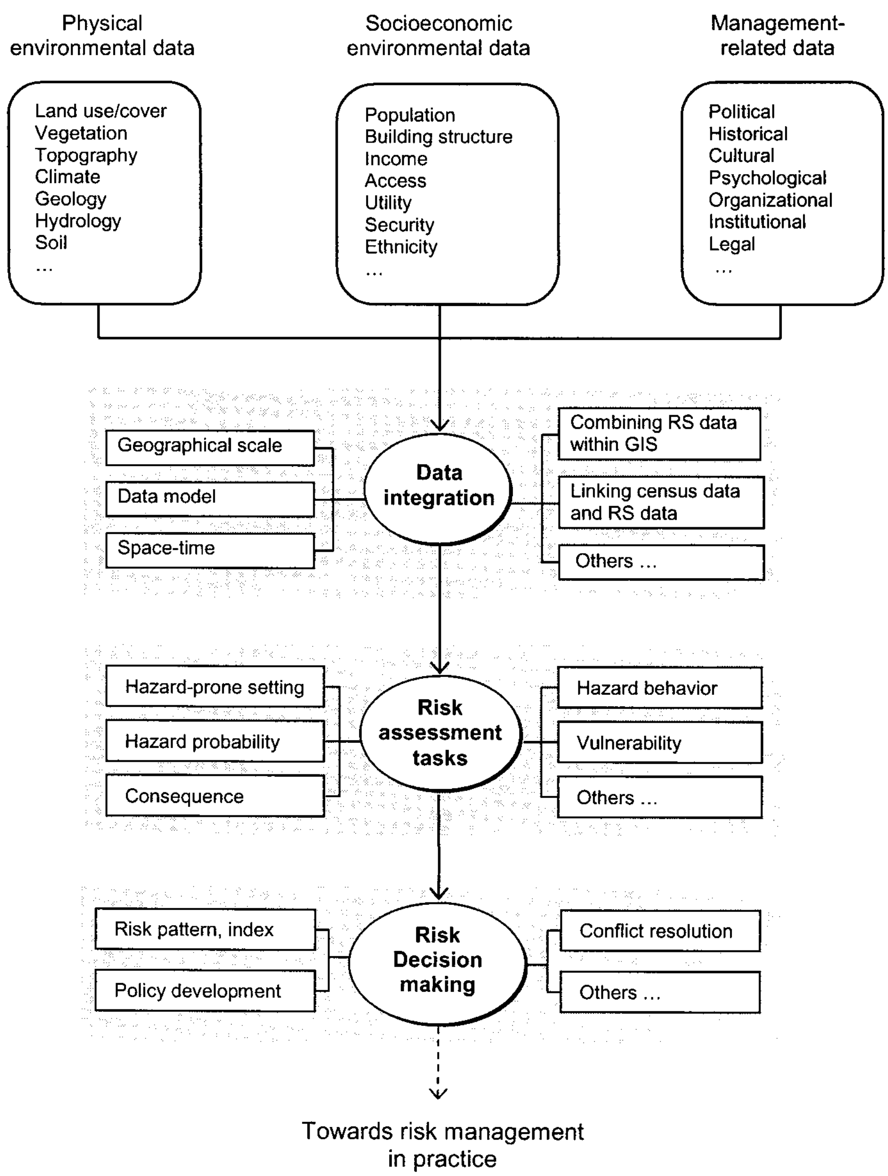


Figure 1. An integrated approach to natural hazards risk assessment using GIS.

"what if" analyses by varying parameters and generating alternative scenarios in a spatial context. The generation and consideration of alternative solutions enables the investigation of possible trade-offs between multivariate and/or conflicting factors, and the identification of potentially undesirable characteristics of decision solutions.

Data Integration

Data integration includes combining data received from different sources, linking data of different types (e.g., spatial, attribute), and building GIS databases. In the natural hazards context, the required data can be divided into three categories—physical environmental data, socioeconomic environmental data, and management-related data (Figure 1). They form three parallel groups, but management-related data are often qualitative in nature and least easily quantified or mapped.

Data Sources

A hazard is usually described by physical environmental data. Typical data layers, including land use, land cover, vegetation, topography, meteorology, and geology, are acquired or derived from in situ observations and remotely sensed imagery. Many GIS-based hazards applications manipulate these data layers.

Socioeconomic environmental data are used to assess community vulnerability and include population and housing census data and data on utilities and access. With the increasing emphasis on community vulnerability assessment, collecting socioeconomic data is essential. Granger (1998) proposed that detailed information on setting, shelter, sustenance, security, and society is required. For example, data on shelter include construction materials of the walls, roofs, and floors, and the ages of buildings. Data on utilities (e.g., water, electricity, telecommunication, gas, waste disposal pipes), data on security facilities (e.g., hospitals, police stations, emergency operations centres), and data on access (e.g., roads, bridges, tunnels, railways) are also required, wherever possible. Cannon (1994) discussed the inclusion of some socioeconomic factors in risk assessment, including income distribution, household security and insurance, nutrition, and health.

Management-related data influence the whole process of risk assessment and in particular decision-making. It is difficult to define them. Davidson (1997) discussed several legal, political, and cultural variables in the context of earthquake risk assessment. Risk assessment studies are similar to sustainable development applications in the sense that the latter also require a multidisciplinary approach and use information from physical, socioeconomic, and other fields. Many indicators for risk assessment are compatible with indicators for sustainable development. Moldan and others (1997) provided a rich set of such indicators (e.g., psychological indicators, organizational indicators, welfare indicators, dependence indicators), which have potential to be used in risk assessment.

The data listed in Figure 1 are by no means exhaustive. Many of them are strongly spatial and temporal. It may be impractical to include all types of data in a risk assessment, and specific, definable, and meaningful data for the objective of the project are important. Some criteria that can guide the data selection process include data availability and quality, spatial suitability, clarity, applicability, and decision utility. Selection of useful data is not a pure science and is often finalized after compromises.

Data Integration with GIS

Issues in data integration with GIS are concerned not only at the stage of building the spatial database, but also have far reaching implications on subsequent spatial analysis and modeling for risk assessment tasks and risk decision-making. Five issues are examined here from an application perspective.

Geographical scale. Most data are collected at particular geographical scales; for natural hazards this may be global, continental, national, regional, local, or even site-specific scales. Risk assessment can be examined across different scales, from a top-down (from global to local) perspective, from a bottom-up (from local to global) perspective, or in a parallel way.

Scale is related to spatial resolution and aggregation. For community-based risk assessment at scales such as 1:25,000 and 1:10,000, spatial resolutions of 30 m, 5 m, and even 1 m are often used with raster-based data sets. With aggregated areal data, it is important to recognize the effects of different geographical scales and areal aggregations. For example, for bushfire risk assessment at a local scale, three levels can be explored depending upon data availability (Figure 2):

- Census collection units: Census data are collected using hierarchical units. In Australia, the smallest areal units for census collection are census collection districts (CCD). Each CCD contains, on average, 250 dwellings in an urban area (Australian Bureau of Statistics 1993).
- Street blocks: Streets are physical boundaries in the built environment and contain social implications for hazards prevention, emergency access, and evacuation. A census collection unit is generally formed from underlying street blocks.
- Site-specific individual dwellings: Dwellings are the basic units in the built environment and the most impacted by hazards. Current data sources and modeling practices pose a major challenge to the implementation of detailed and pragmatic risk assessments at this level.

Data models. Two major data models for representing spatial phenomena and objects are raster and vector. The selection of an appropriate data model is application specific. In the raster data model, continuous geographical space is tesselated into cells. Each cell has one associated attribute value. An inherent assumption is that the attribute value is uniform over the whole spatial unit it represents. In reality, this is hardly ever the case as many attribute values (e.g., terrain) vary continually. Many factors such as temperature and wind in natural hazards use the raster model. In the vector data model geographical objects are represented as points, lines, and areas. Examples of such spatial objects include dwellings and utilities required in vulnerability analysis. In risk assessment, hazards-related data often use the raster data models while vulnerability-related data rely on the vector data models.

Spatial and temporal dimensions. The spatial data for risk assessment often require the addition of time as a fourth dimension for further analysis. For example, in

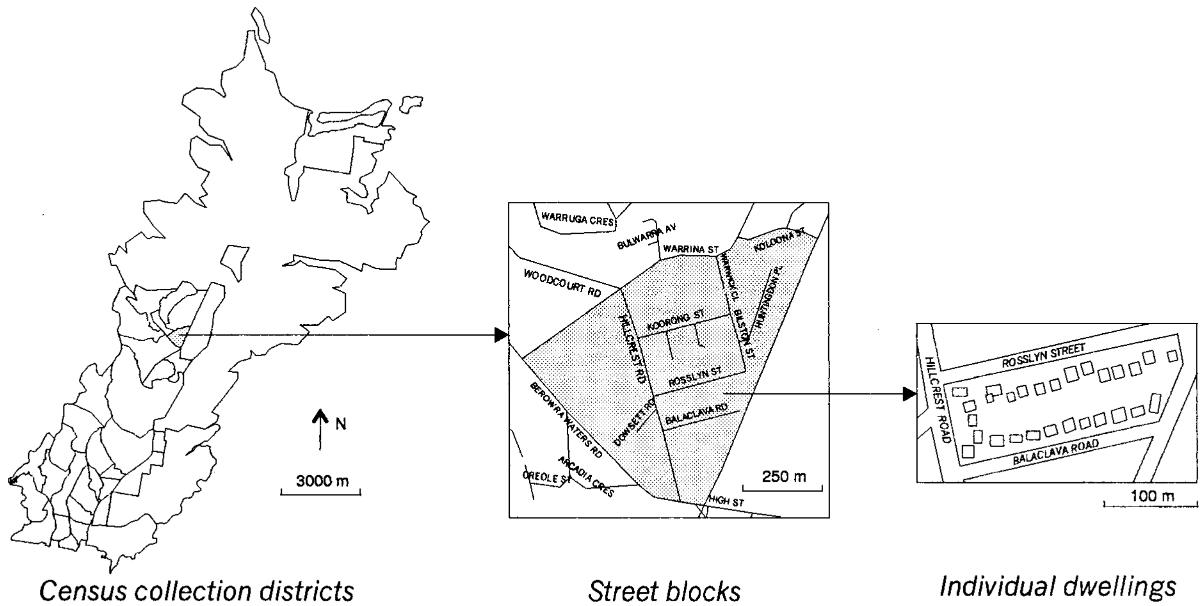
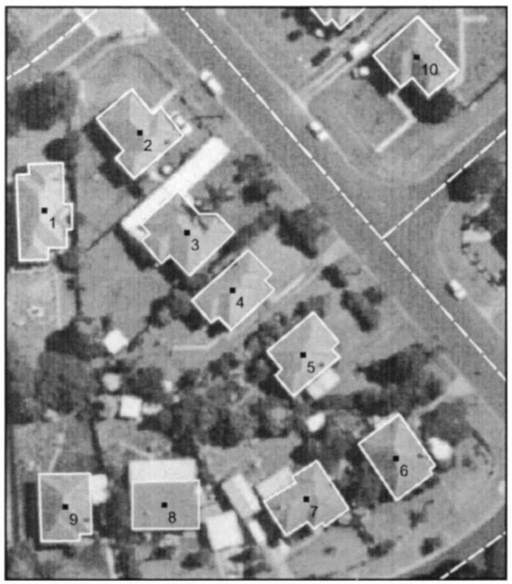


Figure 2. Three local levels for GIS-based risk assessment.

bushfire risk assessment input data (e.g., fire movement, changing meteorological conditions) can be different from regional to local scales in a spatial perspective and from daily to hourly times in a temporal perspective. Selecting the appropriate spatiotemporal dimensions for the data and subsequent risk modeling is important. Possible relationships between spatial and temporal dimensions can be identified from a review of published materials, although it is sometimes difficult to justify the legitimacy of them. For example, fire behavior modeling may use data with spatial resolutions ranging from 1 cm to 100 m and with temporal resolutions ranging from seconds to hours (e.g., Yuan 1997). For bushfires at the urban fringe, predictive fire spread models need data at a spatial resolution of meters and a temporal resolution of minutes to ensure the predicted result is as accurate as possible for damage prevention. On the other hand, for a bushfire in remote areas, a fire behavior model based on data at a 100-m spatial resolution and 1-hour temporal resolution will probably be sufficient and cost-effective.

Combining remotely sensed data within GIS. Remote sensing and GIS are inherently linked technologies, and the combination of them provides many advantages (Star and others 1997). Users need spatially referenced and frequently updated remotely sensed images and GIS can provide a suite of tools for efficient storage, manipulation, and visualization of them. Environmental data on hazards and their consequences (e.g., burning fronts of bushfires, burn scars, destroyed properties, flooded areas, volcanic lava movement) across different geographical scales can be obtained with optical and radar images. In recent years, the Committee on Earth Observation Satellites (CEOS) Disaster Management Support Group (DMSG) (http://disaster.ceos.org) has advocated improved utilization of existing and planned Earth Observation Satellite data for disaster management through recommendations and case studies. The new high spatial resolution images (e.g., IKONOS-2 1-m panchromatic and 4-m multispectral images; QuickBird 0.7-m panchromatic and 2.8-m multispectral images) appear to hold promise for innovative applications. High temporal resolution imagery also would enable accurate monitoring during events and quick damage assessment after events.

The spatial and temporal requirements of remotely sensed images for risk assessment at a local scale are demanding. As suggested by Jensen and Cowen (1999), typical predisaster planning requires images with 1- to 5-m spatial resolution and 1- to 5-year temporal resolution. The acquisition of detailed damaged-related data on communities (e.g., buildings, infrastructures, lifelines) in risk assessment may require images with even higher resolutions. The practical way to derive such information relies more on the use of aerial photography with submeter resolutions. Figure 3 shows an example of the extraction of building features (e.g., roof plan areas) from an Ausimage image, which is a color, fully orthocorrected digital aerial photograph with a spatial resolution of 0.2 m. After manual digitizing



Data extracted from images						Applications		
House_ID	Centroid_X (m)	Centroid_Y (m)	Area (m^2)	Perimeter (m)	...	Areal difference (%)	Replacement cost ($) ($1000/m^2)	...
1	882.53	1420.96	142.72	54.50		+21.25	142720	
2	899.83	1435.06	126.73	49.22		+7.66	126730	
3	908.50	1416.92	140.00	51.13		+18.93	140000	
4	916.83	1406.43	112.13	45.07		-4.74	112130	
5	929.73	1394.59	106.88	43.67		-9.20	106880	
6	946.64	1375.72	112.13	42.92		-4.74	112130	
7	930.33	1368.30	109.35	45.74		-7.10	109350	
8	904.38	1367.24	104.42	41.43		-11.29	104420	
9	886.44	1366.91	108.59	42.64		-7.75	108590	
10	950.32	1448.79	113.75	45.94		-3.36	113750	
11	932.86	1462.10	118.10	49.00		+0.33	118100	
...								
Average	-	-	117.71	46.48		-	117710	

Figure 3. Extraction of building features with a high resolution aerial photograph.

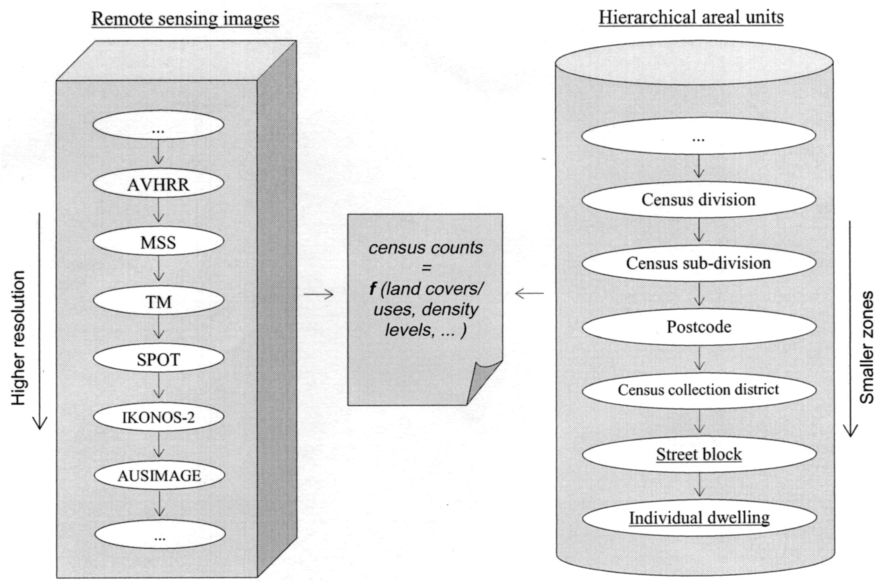


Figure 4. An example of linking remotely sensed images with census data on hierarchical areal units.

and/or semiautomated image classification, extracted parameters include locations, areas, and perimeters of separate houses. Using the parameter of area, applications such as the estimation of replacement cost if a house is totally destroyed can be performed (Figure 3).

Linking remotely sensed data and areal census data. Remotely sensed data in a raster format are often used for hazard analysis while census data on hierarchical areal boundaries are used for vulnerability analysis. For risk assessment that addresses the interaction between a hazard and a vulnerable community, it is important to develop linkages between remotely sensed data and areal census data for data integration within a GIS environment. The key is to disaggregate areal census data at an appropriate spatial resolution level compatible with raster-based data sets, using an image classification approach. It is possible to establish statistical and cartographical correlations between detailed land classifications (e.g., land covers, densities) and areal census data at different hierarchical boundary levels (Chen 2002).

An example is shown in Figure 4: the left side indicates different types of remotely sensed images with increasing resolutions from the top to bottom, and the right side represents socioeconomic data with a series of hierarchical areal units, which could vary greatly among countries. Census data on the first four areal levels (i.e., census division, census subdivision, postcode, and census collection district) are available in Australia (Australian Bureau of Statistics 1993). The middle box indicates that there exists a "many-to-many" set of relationships between remotely sensed data with different resolutions and areal census data on hierarchical areal units. More very high spatial resolution images are becoming available, enabling detailed socioeconomic and urban infrastructure data (e.g., building areas, materials, utilities) for community vulnerability assessment to be extracted, and thus the relationship between functional census data and high resolution images can be pursued.

A successful integration of the above two data sources in a spatially valid way is necessary for modeling risk and decision-making. Socioeconomic data in the form of an areal aggregation do not explicitly indicate spatial distributions within an area. This can be seen in Figure 5A, where only the dwelling count of each census collection district is shown. Information on whether the dwelling distribution is evenly scattered or concentrated in a part of the zone is not known. If these spatially lumped data are used in damage and loss estimations along with spatially explicit hazard distributions, the result tends to be approximate and coarse. However, using remote sensing classification approaches we can emphasize spatial differences and heterogeneity within the areal units. Figure 5B and C show the division of residential and nonresidential areas, and three residential density levels, respectively. As a result, areal socioeconomic data are remodeled to spatially valid representations that are compatible with remotely sensed data.

Besides the statistical relationships and cartographic representations between remotely sensed data and areal census data, selecting suitable analysis units in relation to effective spatial representation of areal cen-

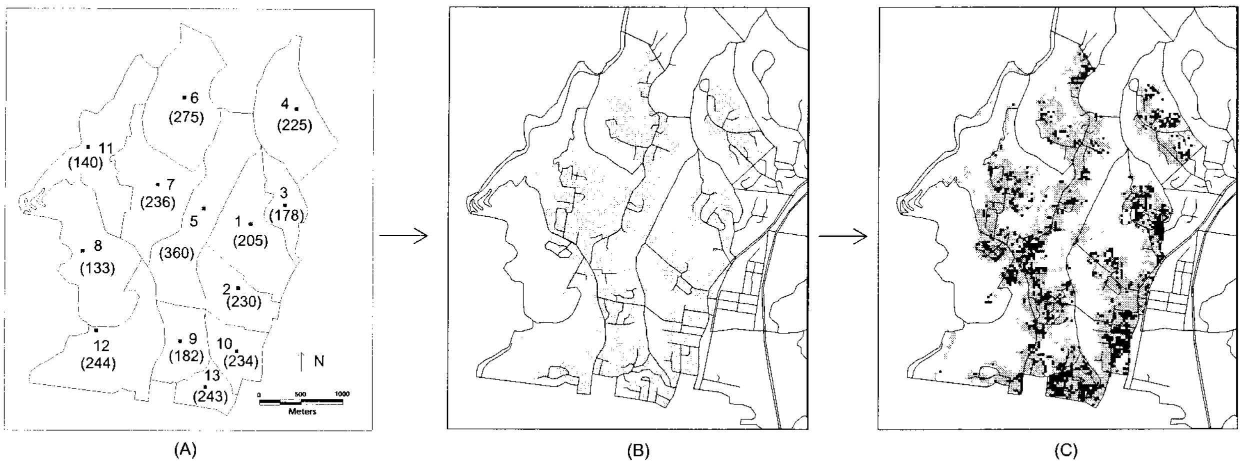


Figure 5. Three methods for representing dwelling distributions. (**A**) Dwelling counts of 13 census collection districts (CCD) are in parentheses. (**B**) Classified residential and non-residential areas. (**C**) Three classified residential density levels.

sus data, when combining heterogeneous data sources for modeling risk assessment tasks, is important and illustrated in the next section.

Risk Assessment Tasks

The integration between environmental modeling and GIS has been increasingly emphasized during the past decade (Goodchild and others 1993), and the use of GIS results in the development of spatially distributed models replacing simple spatially aggregated or lumped parameter models (e.g., McArthur forest fire danger meter). GIS-based bushfire behavior simulation models (e.g., Ball and Guertin 1992) are quintessential examples of the spatially distributed models. GIS with a range of spatial analysis techniques and tools are helpful for identifying, measuring, diagnosing, and assessing many aspects of natural hazards and their consequences.

Risk assessment tasks are used to examine individual aspects of a hazard and vulnerability and their interactions in a whole risk assessment context, including the identification of the hazard-prone environment, hazard occurrence and/or recurrence probability, hazard behavior, and vulnerability assessment (Figure 1). Models for individual risk assessment tasks can be either inductive or deductive. Inductive models are used to estimate the probabilities of bushfire occurrence, through examining statistical correlations among environmental and socioeconomic variables with GIS overlays or other methods (e.g., linear regression, and logistic regression) (e.g., Chou 1992). Deductive models are often used to simulate hazard behavior and dynamics, for example, bushfire behavior models (Cheney and Sullivan 1997). The implementation of either model can be within GIS or with standalone programs importing GIS data.

Typical Risk Assessment Tasks

The complex physical and socioeconomic factors of the hazard-prone environment can be assessed qualitatively and quantitatively. In this stage, physical and socioeconomic conditions of a study area and recipients of a potential hazard (e.g., humans, properties, protected species) can be provided. For example, the environment of a bushfire-prone area at the urban fringe can be evaluated with factors such as terrain and dwelling and vegetation distributions. The identification of the hazard-prone environment is particularly useful in prehazards planning.

The probability of a hazard recurrence can be calculated using records of past hazard events, although to obtain reliable and sufficient historical records is not easy. For hazard recurrences, there is a frequency–magnitude relationship: rare events with large magnitude, or frequent events with small magnitude. From the locations obtained from historical records, an approximate areal extent for hazard recurrence can be determined.

Modeling the hazard behavior involves devising an appropriate mathematical representation of the hazard phenomena and then using this to simulate the hazard over an area of interest. Sufficient knowledge of the physical process of a hazard is assumed. However, some caveats should be noted when modeling hazard behavior. First, some variables for the hazard behavior could be poorly understood and difficult to model. Sensitivity analysis should be conducted as part of the modeling process. Second, a mathematical model is an abstract model, involving some degree of simplification. Third, models derived from a relatively small area may not be applicable to another area or to a large region with more diverse conditions, and vice versa. Fourth, the determination of discrete time intervals is important when modeling the variability of hazard dynamics.

Vulnerability assessment is one of the least investigated tasks, due partly to the lack of relevant detailed socioeconomic data and the difficulty of their effective spatial representation for integration with physical environmental data on hazards. Vulnerability assessment is an important task in risk assessment and has social significance for a hazard-prone vulnerable community. Granger (1998) and his colleagues developed a systematic approach to describing the elements at risk in the urban community and their vulnerability to hazards impact in their "Risk-GIS" framework for multihazards risk assessment in Australia. According to Schneider (1999), the HAZUS team in the United States has developed methods and tools for comprehensively estimating potential damage to buildings and lifelines, and direct and indirect socioeconomic loss from earthquakes.

Selecting a Valid Spatial Analysis Unit

When modeling risk assessment tasks, such as the identification of a hazard-prone environment and hazard consequences, it is common to integrate both pixel-based physical environmental data and area-based socioeconomic data. However, combining these heterogeneous data is difficult due to their incompatible data models. Moreover, the use of area-based socioeconomic data in spatial analysis is associated with the modifiable areal unit problem (MAUP) (Openshaw 1984), which arises due to the scale effect and the zoning effect when areal units are aggregated to form units of different spatial arrangements. Fotheringham and Wong (1991) provided strong empirical evidence on the unreliability of multivariate analysis undertaken with areal socioeconomic data at different zone levels. Therefore, in order to integrate socioeconomic data with physical environmental data for effective risk assessment, the selection of spatial analysis units that are compatible with these two data sources is important. The following example illustrates this issue with an example of quantitatively assessing the hazard environment for a bushfire-prone area at a local scale.

Berowra is a part of the urban fringe of Sydney, surrounded by extensive bushlands and exposed to a significant bushfire risk (Figure 6A, B). In this area, the generally flat surfaces between the steep valleys have been used for housing development, and the dry schlerophyll bushland, typical of the Sydney region, extends right to the edge of the developed areas. As the urban and bushland interface is subject to extensive interactions with physical, ecological, and human processes, it is necessary for a hazard-prone environment assessment to include physical environmental data and socioeconomic data. A socioeconomic factor (i.e., dwelling counts extracted from census collection districts, CCD) and three physical environmental factors (i.e., slope, aspect, and normalized difference vegetation index, NDVI, all with a 30-m spatial resolution) were included. For integrating these heterogeneous data, two choices with regard to the use of spatial analysis unit are obvious: either use the census collection districts based on socioeconomic data or use cells based on physical environmental data as spatial analysis units.

If the first choice is applied and physical environmental data are aggregated into the census collection districts level, then for the area no obvious and correct correlations between related data sets such as aspect and slope, or slope and dwelling count, can be identified (Table 1). On the other hand, CCD-based census dwelling counts may be disaggregated using cells with a high spatial resolution as the spatial analysis unit. In this example, the size of 30 m is too small since it may not cover even one property. Detailed dwelling counts were manually estimated for 90×90-m cells using local orthophoto maps (scale 1:4000), cadastral maps (scale 1:8000), and colored aerial photos (scale 1:25,000). For the dashed rectangle area in Figure 6B, there exist a total of 12 dwelling count levels (Figure 6C). Figure 6D shows a topographic representation of the dashed rectangle area. Then, three physical environmental factors were normalized and aggregated at 12 dwelling count levels with a 90-m resolution. Finally, a 4×12 matrix was formed to implement correlation analysis. Table 2 shows the correlations of four factors at 12 dwelling count levels. The positive correlation between aspect and dwelling count ($r = 0.841$ at 0.0006 level of confidence) and the negative correlations between slope and dwelling count ($r = -0.761$ at 0.004 level of confidence) and slope and aspect ($r = -0.735$ at 0.006 level of confidence) all suggest that more dwellings have been built on the ridges with flat and very gentle slopes.

This example shows that disaggregation is important for deriving a detailed and valid spatial representation of area-based socioeconomic data; correlations among dwelling distributions and physical environmental characteristics are revealed since the analysis is conducted using the valid analysis unit. When combining hetero-

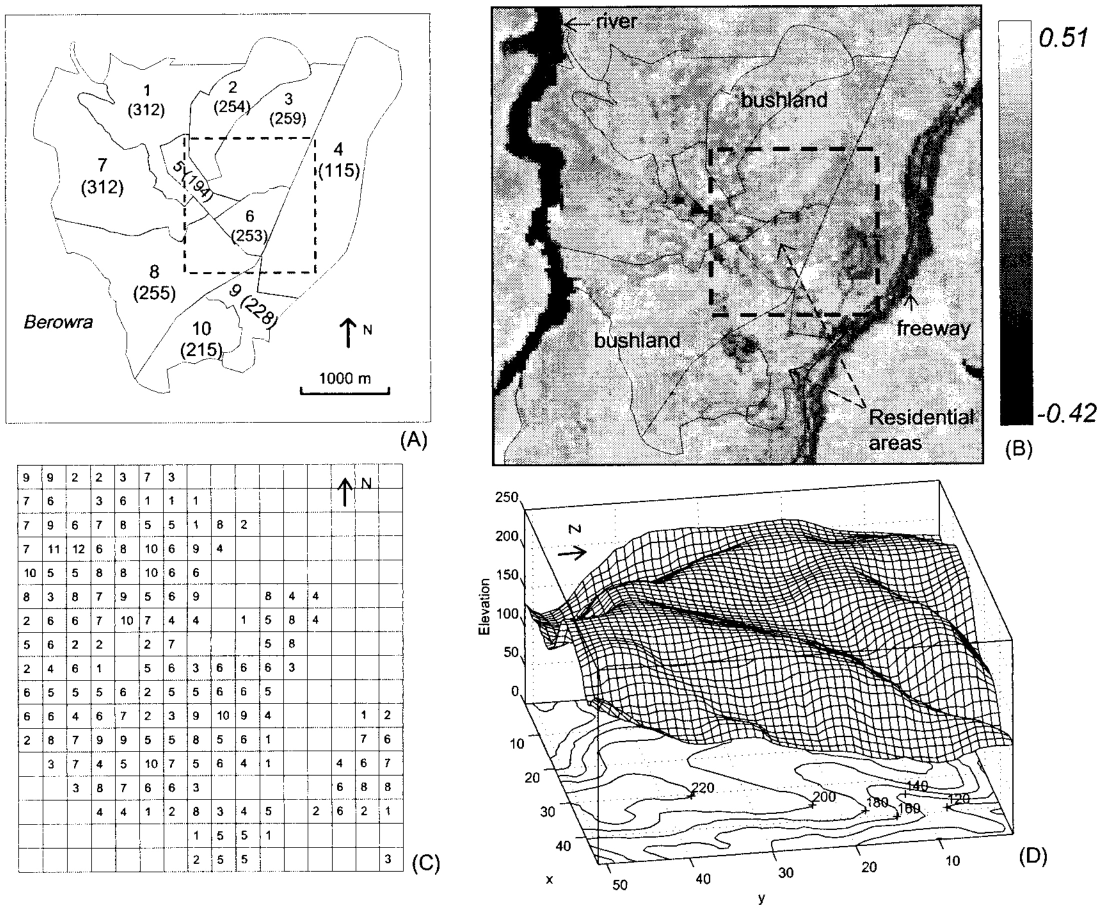


Figure 6. (A)The Berowra area covers ten census collection districts (CCD), and their census dwelling counts in parentheses obtained from the Australian census survey in 1991. (**B**) An NDVI image in 1991 superimposed with CCD boundaries. Major features including bushland, residential areas, river, and freeway are shown. The dashed rectangle area is the same as the one in (A). (**C**) Distribution of dwelling counts for the dashed rectangle area (size 17 × 16 with a resolution of 90 m). (**D**) A topographic representation for the rectangle area (size 51 × 48 with a resolution of 30 m).

Table 1. Correlations of four factors at ten census collection districts (CCD) level

	Aspect	NDVI	Slope	Dwelling count
Aspect	1.000			
NDVI	−0.275	1.000		
Slope	0.156	0.270	1.000	
Dwelling count	0.166	0.095	0.364	1.000

Table 2. Correlations of four factors at 12 dwelling count levels

	Aspect	NDVI	Slope	Dwelling count
Aspect	1.000			
NDVI	0.070	1.000		
Slope	−0.735	0.162	1.000	
Dwelling count	0.841	−0.299	−0.761	1.000

geneous socioeconomic and physical environmental data that have strong spatial dependency but incompatible data models, the selection of a meaningful and effective spatial analysis unit (as opposed to the arbitrary areal census zones) is vital. This finding is fundamental and potentially applicable to the spatial analysis of other integrative risk assessment tasks.

Risk Decision-Making

The risk assessment tasks discussed in the previous section increase understanding of the different aspects of natural hazards and their consequences and thus support the risk decision-making process. Risk decision-making is a multidimensional and multidisciplinary activity embracing physical, socioeconomic, and management-related factors. Some common risk decision-making tasks for natural hazards are assessing risk patterns and calculating risk indices, conflict resolution, and making rational policy.

Risk decision-making should attempt to understand semi- or ill-structured decision-making tasks by streamlining thinking and devising rational procedures, rather than prescribing a definitive solution to a problem in the complex real world. Formulating a risk decision-making process is not simple. First, risk decision-making is integrated in nature, incorporating multiple factors. A decision-making process should reflect the competing interests and values of different stakeholders, therefore it is important to devise specific mechanisms of consensus building. Risk decision-making is likely to be complicated by political issues. Second, procedures to carry out decision-making should be rational, open, and interpretable, otherwise, decision-making processes may be conceived as guesswork. Often, a "one-answer" scenario is not enough, and a conclusion based on "many answers" derived from a series of decision support models is more enlightening. Third, it is desirable that decisions be spatially oriented, allowing risk to be evaluated at appropriate spatial scales. Fourth, in addition to decision theories and methods, the development of operational decision support tools to produce solutions effectively and efficiently is essential. Such tools can readily support and evaluate "what-if" scenarios by altering parameters used in different decision support methods.

An MCE-GIS Typology

Investigations have indicated that spatial multicriteria decision-making methods tackle multiple factors simultaneously, provide insights into various value judgements, and help decision-makers and experts penetrate complex and implicit decision-making tasks (e.g., Thill 1999). Multicriteria evaluation (MCE) with GIS is often used to support decision procedures (e.g., evaluation, prioritization, selection) during a risk decision-making process. To understand the nature of risk decision-making for natural hazards, this paper proposes an MCE-GIS typology from the following three perspectives: data types, data models, and methods development (Figure 7).

The first dimension concerns the type of data employed. Presently, most GIS applications deal with hard data. However, many risk criteria and risk ratings cannot be defined precisely. The difficulties come from the often unquantifiable and incomplete information available to the risk decision-making process. Fuzzy set theory, first introduced by Zadeh (1965), can be used to model imprecise, vague, and uncertain concepts or

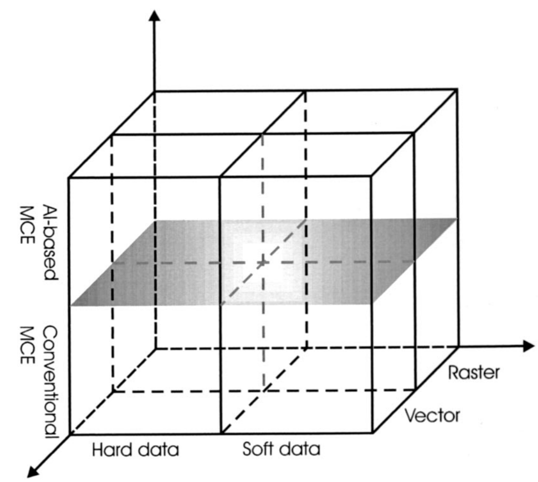


Figure 7. A multicriteria evaluation (MCE)–GIS typology for spatial risk decision-making.

objects in risk decision-making, and produce soft data expressed by fuzzy membership functions. A fuzzy set is a class of objects with a continuum of membership grades or values in the range [0, 1]. If the grade of membership for an object in a set is 1, the object is absolutely in that set; if the grade of membership is 0, the object is absolutely not in that set. Depending on the proposition of a risk decision-making task, any criterion subject to the proposition can be assigned by fuzzy membership functions. When selecting specific membership functions, the relative importance between various states of a single criterion should be taken into account.

For linguistic terms-based data (e.g., high, medium, low) to be quantitatively assessed along with other variables having well-defined boundaries in an integrated risk decision-making process, a practical approach is to use a numerical approximation system that systematically converts linguistic terms to corresponding fuzzy sets and then to crisp scores (e.g., Chen and Hwang 1992). For example, linguistic terms of different risk levels, from low risk to high risk, can be converted to fuzzy sets and normalized by values between [0, 1]. Using the latest information processing theories and paradigms about linguistic terms, such as computing with words (Wang 2001), for quantitative risk assessment is worthwhile.

The second dimension concerns the data models on which spatial data and MCE methods rely—raster and vector. Because of the integrated nature of risk decision-making and the fact that many risk factors need to be included, it is often necessary to combine both hazard-related and vulnerability-related data that have incompatible data models. The issue of how to combine data with raster and vector data models and the selection of valid areal units for effective spatial analysis was discussed in a previous section.

For each data model there is also an issue of spatial applicability. When a decision-making task can be examined at different spatial resolutions of raster data or at different areal units of census data, the resolutions or areal units affect decision outcomes. For example, if a decision-making task of assessing risks of property damage from bushfire is made at a census collection district level, its result cannot be directly applied for every street block and individual dwelling. If a census collection district has a very high risk, in fact, only those buildings at the interface between bushlands and urban lands are genuinely susceptible to potential fires. This demonstrates that the modifiable areal unit problem should not be ignored in spatial analysis and decision-making when data from different spatial resolutions or areal units are used.

The third dimension concerns the development of the MCE-GIS methods that are applicable to the above two dimensions. Two types of the MCE-GIS methods are possible: conventional MCE-GIS methods and artificial intelligence-based methods. Many conventional MCE-GIS methods (e.g., weighted linear combination) are capable of integrating criteria using GIS overlay operations. During the past decade conventional MCE methods have been applied spatially to facilitate environmental decision-making issues using various GIS software (e.g., Carver 1991, Eastman 1997, Malczewski 1999). They provide a mechanism to assemble, weight, synthesize, and analyze a wide range of spatial data layers and are particularly suitable for risk decision-making tasks for which simple rules can be formulated among factors.

However, conventional multicriteria methods are often confronted with difficulties (e.g., Hwang and Yoon 1981, Wang 1994), including (1) determining relative weights between criteria is a subjective process; and (2) simple aggregation methods may be not sufficient in handling criteria that are essentially nonlinear. A modeling technique that is capable of effectively integrating various data layers, evaluating complex rules, and learning nonlinear relationships across a variety of spatial criteria is needed. Recent developments in spatial decision-making show that artificial intelligence (AI), including artificial neural networks (ANN), fuzzy logic, approximate reasoning, optimization methods such as genetic algorithms and simulated annealing, along with intelligence information systems, offers new methods to combine criteria and to explore patterns among them. For example, ANN are most likely to be superior to other statistical methods when (1) data exhibit significant unpredictable nonlinearity; (2) patterns important to the required decision are subtle or deeply hidden; and (3) data are fuzzy oriented involving human opinions, ill-defined categories, or subject to possible error and uncertainty (e.g., Hagan and others 1996, Ripley 1996). The basic procedure when using ANN for risk decision-making analysis is to establish a mapping function from the input space representing the measurements of various influencing risk factors to an output space representing a set of risk patterns. Because AI-based analysis also deals with multivariate criteria, it may be seen as an extension of the conventional multicriteria evaluation methods.

AI-based methods play an important role in developing complex decision-making systems for geographical and environmental applications (e.g., Hewitson and Crane 1994, Openshaw and Openshaw 1997). During the past decade, many advanced paradigms integrating individual components of artificial intelligence have emerged, such as soft computing (Jang and others 1997). A notable research area is in developing hybrid systems that can integrate neural networks, fuzzy sets theory, and genetic algorithms for examining complex spatial risk decision-making tasks, which would be impossible to address when exploiting individual methodologies.

Risk Decision Support Tools and Applications

To complement and operationalize the above typology in support of risk decision-making, an MCE-RISK tool kit has been developed (Chen and others 2001). The program spans the gap between external MCE modeling and current GIS programs. The main analytical modules include (1) general data processing methods (e.g., data normalization, weightings, sensitivity analysis); (2) conventional MCE-GIS methods (e.g., weighted linear combination, compromise programming, the technique for order preference by similarity to ideal solution-TOPSIS); and (3) fuzzy membership functions and operators (e.g., triangular, trapezoidal, Gaussian functions). MCE-RISK was developed using a loose coupling approach between conventional MCE modules and GIS, with two-way communication using data files. GIS serve as a front end for preparing and manipulating data before multicriteria evaluation. The MCE component then performs specific functions of evaluation and produces outputs that are passed back to GIS for further spatial analysis and visualization.

An MCE-GIS approach for risk decision-making should include the following steps: (1) identify the risk decision; (2) identify the criteria that are relevant to the decision; (3) assign values to the criteria and conduct

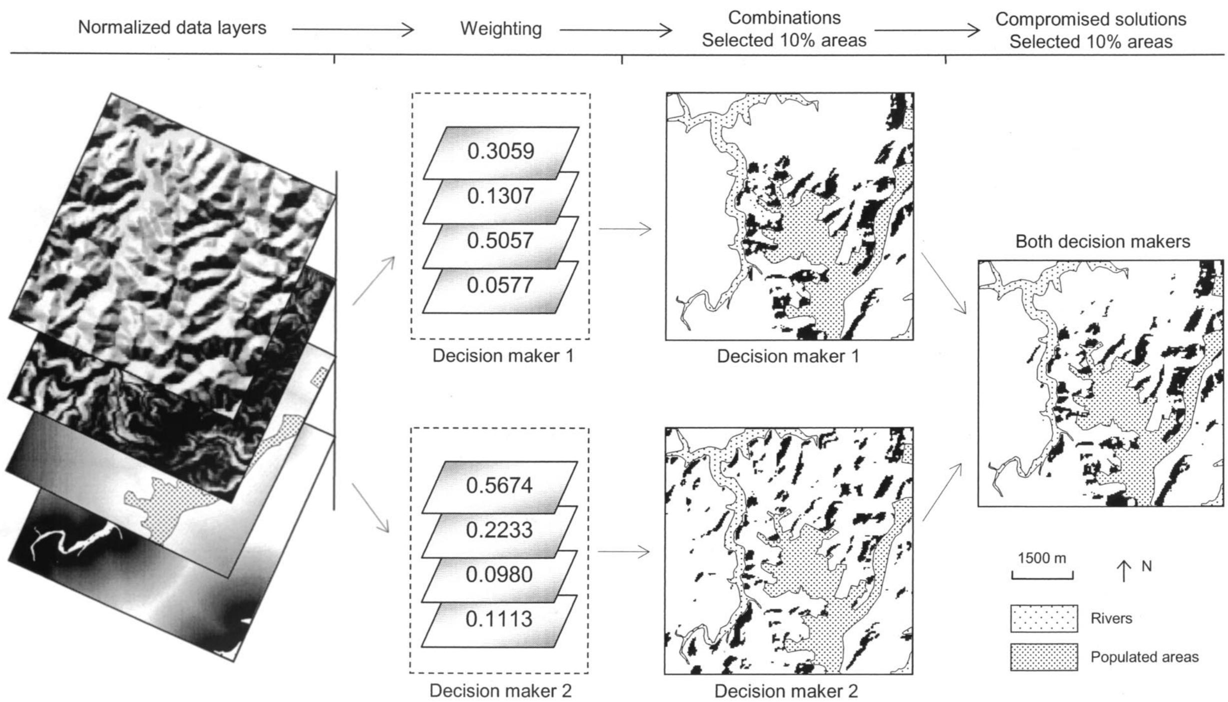


Figure 8. An example of selecting 10% of a study area for bushfire prescribed burning planning with an MCE-GIS approach. Four data layers, namely aspect, slope, proximity to populated areas, and proximity to rivers, are included and normalized (left, from the top to bottom). Each has the size of 6 × 6 km (or 200 × 200 pixels). Two decision-makers are involved, through individual weighting and multicriteria combination, the finally compromised solutions of selecting 10% of the study areas best suited for prescribed burning are produced (right).

normalization; (4) determine relative weights between criteria; (5) link criteria and weights with MCE-GIS methods; (6) make a provisional decision; (7) perform sensitivity analysis; and (8) interpret.

The MCE-RISK program provides a set of tools to support the quantitative steps (3, 4, 5, and 7). Using the program, Chen and others (2001) reported an example of bushfire prescribed burning planning for a local bushfire-prone area at the urban fringe (Figure 8). The object was to select 10% of the study area best suited for prescribed burning, with two decision-makers involved. Decision-maker 1 represented the local bushfire service group, aiming to burn appropriate bushland close to residential areas and to protect buildings from potential fires; decision-maker 2 represented a group of local residents and conservationists, wishing to preserve the bushland near the populated areas and rivers. First, four data layers (i.e., aspect, slope, proximity to populated areas, and proximity to rivers) were considered and normalized (left, Figure 8). For each decision-maker a weighting process was employed to evaluate the relative importance of individual factors. In this process, the different and conflicting interests of each decision-maker were reflected for the task investigated. For example, decision-maker 1 put a high weight (0.5057) on the factor of proximity to populated areas, while decision-maker 2 put a very low weight (0.0980) on this factor (Figure 8). Then, using an MCE method called TOPSIS a decision output was produced for each decision-maker. It is evident that the decision outputs of two decision-makers are very dissimilar for the study area. However, as this is a group decision-making process, the decision-makers need to compromise on their interests and preferences to generate a final solution (right, Figure 8).

Besides the conventional multicriteria evaluation methods, artificial intelligence-based approaches can be applied to many risk decision-making applications. For example, a preliminary study using artificial neural networks for assessing the risk patterns of house survival during bushfires on a property-by-property level indicates that the ANN approach has capabilities and flexibility for risk pattern classification, discovering the hidden relationships between complex input and output factors under different configurations (Chen 2000). As the ANN approach can model virtually any linear or nonlinear function, it can be used to supplement and even replace traditional statistical approaches, which are based on the assumption of a linear additive nature of hazard and vulnerability factors. The potential applications of artificial intelligence-based methods for risk decision-making tasks concerned with spatial preferences and/or patterns are immense, and innovative and wider applications of such methodologies should be encouraged and pursued in the near future.

Concluding Remarks

An integrated approach to natural hazards risk assessment is enhanced when examined in a GIS environment. The challenges in data integration, risk assessment tasks, and risk decision-making include creatively dealing with spatial data-related issues (e.g., geographical scales, integration with physical environmental and socioeconomic data); exploring spatial analysis methods for effectively modelling hazards, vulnerability, and risk assessment tasks; and developing methodologies and tools for supporting rational risk decision-making applications. High-quality GIS databases support subsequent risk assessment and rational decision-making in a spatial and temporal context, which can help hazard risk managers and the public understand how complex hazards and their consequences will affect vulnerable communities.

This paper has promoted a structured and integrated approach to natural hazards risk assessment primarily from a quantitative perspective. The approach can have further positive implications. First, the integration of environmental and socioeconomic data and subsequent spatial analyses in a GIS environment will provide insights into the interactions between physical hazards and community vulnerabilities. Second, the integrated approach is conducive to a multiple natural hazards risk assessment and multiple hazards mapping. Third, as the integrated approach to risk assessment is compatible with other types of GIS applications, risk assessment can be systematically conducted along with, or embedded within, regional development planning of different economic sectors (e.g., building, energy, tourism, transportation).

The issues examined in this paper are by no means exhaustive. Some concerns, such as errors and uncertainties associated with data and modeling, are generic to GIS applications and should be always considered for any reliable natural hazards risk assessment. As computing and other technologies evolve, there will be an increasing demand for innovative theories and practical applications of risk assessment in natural hazards. The recent development of the Internet and advanced visualization techniques also will provide a chance to effectively convey the risk to the public.

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