SELECTING 3D URBAN VISUALISATION MODELS FOR DISASTER MANAGEMENT: A RULE-BASED APPROACH

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Keywords

3D Urban Modelling, Visualisation, CityGML, Disaster Management

Abstract

Urban 3D visualisation rarely considers integrated data visualisation in disaster management. In general, such methods should incorporate interoperable approaches and data to avoid duplicating efforts and to reduce costs. To achieve such interoperability, it is important to investigate the link between the types of potential hazards and the needs of the appropriate 3D model. Since a given hazard may affect particular urban features, the link between the hazard type and the relevant urban features can be described by a set of criteria that depend on the type of disaster and characteristics of the urban area. This paper presents a rule-based approach to derive the relation between the disaster/hazard type and the level of detail needed in the selected 3D model. The 3D urban model features (and the spatial resolution) considered in our approach are compliant with the level of detail (LoD) definitions specified in CityGML.

1. Introduction

The perceptions of decision makers tasked with dealing with a particular natural hazard are highly influenced by the manner in which the hazard is visualised. Disaster managers often use digital maps; using 3D graphical representations significantly reduces the cognition effort needed to interpret the situation and improves the efficiency of the decision-making process. When used appropriately, 3D visualisation can assist with the entire disaster management process. In general, 3D models of cities (constructed from heterogeneous data) remain quite

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expensive to construct (in terms of effort and time); therefore, completed models should be utilized for any natural disaster visualisation application for a given urban area. Various criteria influence the appropriateness of a given 3D urban model for a specific natural disaster or group of disasters. In this article, the definition of an appropriate urban model is handled as a decision-making problem by applying a decision rule approach that enables the ranking of alternatives.

In principle, the characteristics of urban models are associated with the disaster impact area and the features of the urban areas exposed to disaster. Therefore, a relationship should be established between the urban model and the hazardous event. The urban model may comprise several resolutions (levels of detail). In this paper, we use the levels of detail (LoD) defined by CityGML (Kolbe et al. 2005). CityGML is an OGC standard that allows semantic and geometric information to be integrated into a single one model. Semantic, geometric and topological aspects of 3D city models are covered using the CityGML class definitions.

This paper is organised into five sections. The next section provides the needed background information. Section 3 introduces the rule-based approach for selecting an appropriate LoD for a specific disaster/risk visualisation. Section 4 demonstrates how the decision rule must be applied. The paper concludes with a discussion of the advantages and disadvantages of the rule-based approach used and outline possible topics for future research.

2. Background

In order to establish a link between a natural hazard type and a particular 3D model, two groups of criteria must be considered, namely *urban* and *hazard*. While urban criteria take into account the characteristics of a specific urban area, the hazard criteria attempt to classify the hazard.

Urban systems are complex, comprising physical and socio-economic sub-systems. Moreover, an urban texture on a small area with a high population density makes these complex structures difficult to understand, hence the need for a more detailed approach. Urban areas can be characterised by two sub-criteria (Sudhira et al. 2004):

- The *Urban Area Extent* is related to the size of the urban area. An area with a population above 5000 and without an adjacent settlement within a 3-km buffer is assumed to be an urban area (Balk and Yetman 2004).
- The *Population Density*, in this paper, is defined as the number of people residing within in one hectare.

In the literature, hazards are classified according to their cause, i.e., natural or man-made/technological (Mitroff 1988, Haddow and Bullock 2003, Shaluf 2007), and their environment, i.e., atmosphere-, hydrology-, lithosphere- and biosphere-related (Kaplan 1996, Richardson 1994). In general, there is no adequate scale to compare the magnitudes of different types of natural hazards. Magnitude comparison could be accomplished using scales that have been constructed to take into account the effect of the natural disaster on the socio-economic and physical environment; these scales are specially-devised for certain hazard types, and were developed to enable the comparison of different disaster incidents. Examples of such scales include the Modified Mercalli earthquake intensity scale (Wood and Neumann 1931), the tsunami intensity scale (Soloviev 1978), the volcanic eruption scale (Tsuya 1955, Newhall & Self 1982, Fedetov 1985) and the landslide damage intensity scale (Alexander 1986b). The intensity of the hazard and the extent of its spatial effect on affected areas form the basis of urban modelling studies. In the literature, no mature classification method exists to compare the spatial effects of different types of disasters. Kemec et al. (2009) introduced a

spatial hazard approach to compare hazardous event characteristics. According to this approach, six sub-criteria reflecting the prevalence of the disaster are defined as follows:

- The *Frequency* reflects the time interval in which a natural disaster occurs. For example, earthquakes may occur with a log-normal frequency, while landslides may occur seasonally.
- The *Duration* is the period of time over which the disaster continues. Hence, it can vary from seconds to years. For example, earthquakes are very short, while some types of landslides (e.g., creeping slopes) are long-term processes.
- The *Spatial Dispersion* refers to the distribution pattern of a hazard over the geographic area in which the hazard can occur. This parameter can range from small to large.
- The *Speed of Onset* is an important variable since it defines the warning time. Extreme events such as earthquakes, mud flows and flash floods can occur with virtually no warning. Other disasters, such as creeping slopes, drought and desertification, act slowly over a period of days, months or years.
- The *Areal Extent* is the spatial density of the disaster over the whole earth, e.g., earthquake zones are limited, as they are governed by tectonic plates.
- The extent of *Indoor Penetration* refers to the degree to which LoD extending to the interior of buildings is needed to adequately visualize the disaster effects. Some natural hazards commit their fatal effects on the built environment by intruding hazard material (e.g., soil, mud or rock in the case of landslides, or water in cases of floods and tsunamis) into built structures. In addition to addressing the question of whether and to what extent indoor LoD are needed in the visualisation (note that the amount of detail needed may differ from case to case), this parameter captures other criteria that are urban- and disaster-oriented, as appropriate. For instance, a floor-level indoor representation would be beneficial in cases of tsunamis and floods, which are pervasive hazards, to help identify the potentially affected parts of the building objects.

In order to establish a link between these two classification systems (hazard and urban), a rule-based approach is used. This study concentrates on the multi-attribute decision rule described by (Malczewski 1999). The aim of Multi-Attribute Decision Analysis (MADA) is to choose the best or most preferred alternative using decision criteria and attributes. The decision is made by applying four main MADA attribute combination rules (Malczewski 2006): weighted summation, ideal/reference/point, outranking methods and analytic hierarchy process (AHP).

The first rule assumes that all attributes have a linear relation with the decision. This linear relation implies that the decision can be made by summing the standardized values of the attributes. The weights are often obtained simply by asking the decision-maker to assign numerical values directly to each criterion or sub-criterion according to a pre-defined maximum and minimum quantisation scale (i.e., 0-1 or 0-100). In the second rule, there is an assumed ideal solution (in theory), and the set of possible alternatives is ordered according to their closeness to this hypothetical ideal solution. The closest alternative to this point is chosen as the best alternative (Malczewski 1999). The outranking method deals with situations in which some attributes have incomplete values. This method provides only an indication for the ranking of alternatives (Malczewski 2006). The AHP methods are the only ones that order the criteria, the sub-criteria and their attributes in a tree. These methods work based on three principles: decomposition, comparative judgment and synthesis of priorities.

Decomposition requires that the criteria must be grouped accordingly, while comparative judgment requires careful consideration of the place in the tree, and the synthesis of priorities refers to the consideration of the branches in the tree. These principles are applied to construct the hierarchy (Malczewski 1999). The AHP method is found to be most appropriate for our study since the weights of the attributes for the situations we consider cannot be considered equal.

3. Decision Rule

We apply the AHP approach to build relations between the different criteria, sub-criteria and their attributes in our rule-based tree. The criteria examined in this study are the valuation principles that are applied in the decision-making process. Some criteria may also have sub-criteria. All of the criteria (sub-criteria) have attributes with measurable items, which take on well-defined values. The values are used ultimately to compare different alternatives.

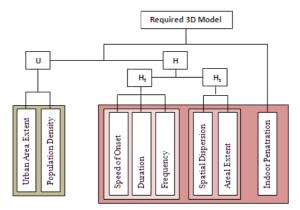


Figure 1. Rule-based decision tree

According to the decomposition principle, the relation of the criteria to the decision are organised in a decision tree. The decision tree consist of thee levels, in which the criteria, subcriteria and attributes are placed. The weights of the attributes are derived from the location of the attribute in the tree. Branches at the same level have the same weight. For example, the urban criteria U and hazard criteria H both have weights of 50% (Figure 1).

Our decision tree should assist with making a decision to find the required 3D model. As mentioned earlier, there are two main categories of criteria that influence this decision: urban and hazard. These are, therefore, found at the first level below the root of the tree. In the second level of the decision tree, the two sub-criteria of the hazard are placed: one sub-criterion relates to the spatial characteristics H_s and the other relates to the temporal characteristics of the hazard H_t . The third level contains the attributes of the sub-criteria. While the hazard's spatial characteristics, H_s are represented by spatial dispersion and areal extent attributes, the hazard's temporal characteristics, H_t are given by the speed of onset, duration and frequency attributes. The urban area extent and population density are the attributes of the urban-related criterion u. The urban urban

Following the AHP approach, we can derive the weights of the attributes, as follows. Urbanand hazard-related criteria have the same effect on our decision, so they have equal weights. Similarly, each temporal and spatial hazard sub-criterion has a 50% weight. The attributes of each of the sub-criteria also have equal weights. As the urban criterion does not have subcriteria, its attributes are given higher weights compared to the attributes of the hazard criteria. Thus, the two urban-related attributes have weights of 25%, while the temporal and spatial hazard attributes have weights of 8.3% and 12.5%, respectively. The synthesis of all of these weights constitutes the decision priorities.

The decision tree is further used to derive a mathematical expression to compute the output of the 3D model and, more specifically, the LoD. We define a function *intensity value*, I_{ν} , which, together with the *indoor penetration i*, defines the LoD of the 3D model. We note that the parameter i does not follow the AHP approach. It is added to the result obtained for the intensity value (equation 9).

The intensity value function I_{ν} is defined as the product of the hazard and urban criteria. The intensity function represents the risk of hazard. In general, the risk in a given area is defined in the literature as the product of the potential for hazard and its consequences (Duzgun and Lacasse 2005, Basta et al. 2007) or the product of hazard, elements at risk and vulnerability (ISDR glossary). The elements at risk in our case are given by the urban criteria. Therefore:

$$I_{v} = (H \times U), \tag{1}$$

where I_v is the *intensity value*, H is the value associated with the *hazard-related criteria* and U is the value associated with the *urban-related criteria*. H can be subdivided into contributions from *temporal* and *spatial* sub-criteria:

$$H = H_t + H_s \tag{2}$$

where, H_t is the value associated with hazard *temporal sub-criterion* and H_s the value associated with hazard *spatial sub-criterion*. The temporal sub-criterion has three attributes: *speed of onset, duration* and *frequency*:

$$H_t = ((s_0 + d + f) / 3)$$
(3)

where s_o is the *speed of onset*, d, the duration and f, the frequency. The spatial sub-criterion has two attributes: *spatial dispersion* and *areal extent*:

$$H_s = ((s_d + a_e) / 2)$$
 (4)

where s_d is the *spatial dispersion* and a_e , the *areal extent*. The urban criterion does not contain sub-criteria, but has two attributes, as specified earlier: urban areal extent and population density; it can therefore be represented as:

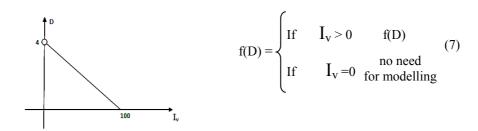
$$U = (a_{ue} + p) / 2)$$
 (5)

where, a_{ue} is the *urban area extent*, and p, the *population density*. Substituting (2), (3), (4) and (5) into (1) results in the extended representation of I_v with all of the attributes:

$$I_{v} = [(((s_{o} + d + f) / 3) + (((s_{d} + a_{e}) / 2)) / 2) \times ((a_{ue} + p) / 2)]$$
(6)

In the decision rule, I_{ν} can vary between 0 and 100. Figure 2 represents the relation between I_{ν} and D. Attribute values are rated in the prevalence direction, which means that a high I_{ν} indicates a pervasive situation that requires low spatial detail, and a low I_{ν} indicates an intensive situation requiring high spatial detail.

Figure 2. I_v value and level of detail relation



For $I_v = 0$, the function f(D) gives the most detailed result. However, this case should be interpreted as one in which modelling is not required; hence the partial function of (7) eliminates this case. We define the *normalised intensity value* I_{vnorm} as:

$$I_{vnorm} = ((I_v - I_{vmax}) / (I_{vmin} - I_{vmax})) \times 4)_{round}$$
(8)

where I_{vmax} is the maximum intensity value and I_{vmin} is the minimum intensity value. We apply a linear transformation with four levels of quantisation, because we have five different alternatives with respect to LoD0 to LoD4. The obtained result is rounded because the LoD must be an integer (0 to 4). Finally, we can compute the required LoD, denoted with D, of the 3D model as follows:

$$D = I_{\text{vnorm}} + i/2 \tag{9}$$

The indoor penetration attribute i is a Boolean value that indicates whether there is (1) or is not (0) indoor penetration. Thus, an integer value of D implies that there is no need for indoor modelling, while the opposite is true otherwise. For example, in the case that D=2.5, the required 3D model will have outdoor LoD of 2 (as defined in CityGML) and an indoor LoD that is compatible with the outdoor LoD. For a building, this means only floor compartments are needed.

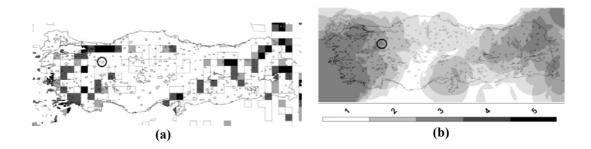
4. Application

To test the proposed rule-based approach, we use the earthquake history of Eskisehir, Turkey as a test case. Eskisehir, located in central Turkey with a population of about 500.000, is an important centre of industry in Turkey; a number of dams and two universities are located within and near the city. Due to its rapid development, Eskisehir has become a popular location for new investment. Most of the city is situated on alluvium. The largest recorded earthquake (Ms: 6.4) affecting this area occurred in 1956. A 3D urban model environment is used to visualise the previously calculated social, physical and accessibility vulnerability indices of each building object (Kemec and Duzgun 2006). The 3D urban modelling pilot area used in this study covers part of the city centre and shows kinds of city development textures, like low rise, historical buildings and high-rise apartments, and contains nearly four hundred buildings in the study area.

To determine the frequency of earthquakes in Eskisehir and compare this to the computed value of f, we use the Columbia University CHRR 2005, Global Earthquake Hazard Frequency and Distribution data. The earthquake database used (Global Seismic Hazard Program) covers earthquakes with magnitudes >4.5 on the Richter scale occurring between 1976 and 2002. The grid data used show the global frequency distribution of earthquakes. Grid values were categorised (1-10), as shown in Figure 3a. The density function of ESRI ArcGIS software, with a frequency weight, was applied to the grid data to disperse the frequency information across the whole country, in order to compare information about the frequency of earthquakes in Eskisehir with that of other settlements in Turkey. (The density function used a conic kernel with a smoothly curved surface; the centre of the kernel takes higher value than the edges and this kernel is passed over each point of the study area.) The

generated raster density data were then categorised into groups numbered 1-5 (Figure 3b), with 5 indicating the areas of Turkey with the most frequently occurring earthquakes. According to the results, Eskisehir's f value is 5.

Figure 3. (a) Columbia University Global Earthquake Hazard Frequency and Distribution output; dark grids indicate geographic areas with higher frequencies of earthquakes. (b)Frequency distribution of earthquakes across Turkey.

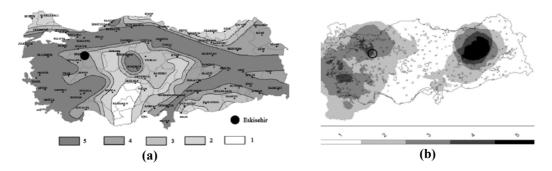


The temporal hazard attributes d and s_o were derived from empirical comparisons. Compared to other natural hazards, earthquakes can be classified as hazards of short duration and fast speed of onset (Burton et al. 1993). Therefore, the d and s_o attributes are both given values of 1 on the scale of 1-5.

The spatial hazard extent attribute a_e is related to the spatial density of the hazard. The earthquake database of the General Directorate of Disaster Affairs Earthquake Research Department (DAD 2009) was used to identify earthquakes that occurred between 1991 to 2009 and had magnitudes greater than 4 on the Richter scale. An earthquake spatial density map (Figure 4b) was generated using this dataset. The same Kernel density function (obtained using ESRI ArcGIS software, as in the f calculation) that was applied to calculate f was used again, with the magnitudes of the earthquakes constituting the weights. Eskisehir is in the second-highest earthquake occurrence zone, so the attribute value of a_e is 4.

The attribute s_d refers to the spatial distribution pattern of a hazard over the geographic area in which the hazard can occur. A probabilistic approach was applied by Özmen et al. (1997) to find the earthquake hazard zones for a 50-year period with a confidence level 90% (Figure 4a). According to this study, Eskisehir is in the fourth most severe hazard zone on the scale of 1-5, where five indicates areas of most danger; hence, s_d was assigned a value of 4. The indoor penetration parameter i was assigned a value of 0, since there are no leaks of hazardous material into the built environment during earthquakes.

Figure 4. (a) Turkey earthquake hazard zones (Özmen et al. 1997), (b) Earthquake spatial density classification



Evaluation of the attributes p and a_{ue} was conducted for 339 settlements in Turkey. The definition of urban in the database used, which includes the SEDAC gridded population of the world and the global rural – urban mapping project, is a place with a population above 5.000 for which there are no adjacent settlement points within a 3-km buffer of the urban area (Balk and Yetman 2004). Data processing steps to compute area sizes and population densities include a map projection conversion of a global spherical system (WGS84) to a local Cartesian system (UTM) and a spatial join operation between urban extent polygon objects and urban point objects using settlement population information. Calculation of the area and population density a_{ue} and p, respectively, constitutes the last step in process of defining the complete model attributes for the Eskisehir test case. To define p and a_{ue} , a geometric interval classification was applied to convert measurements to the reclassified attribute values. The relation between areal extent and the needs of the model detail is not linear; therefore, the areal extent adds complexity to the urban system, necessitating a more detailed modelling approach. The same degree of added complexity is true for the population density parameter. It was determined that a geometric value/utility function better suits both of these attributes than a linear one; the geometric interval classification calculates intervals by subtracting the minimum from the maximum intensity value (Joseph 2007). The conversion coefficient for the dataset is calculated by dividing the result for the previous interval by that of the current interval.

Statistics related to the population density attribute: The minimum population density value is 0.65 per/ha and the maximum is 108.05 per/ha, with a mean of 6.88 and a standard deviation of 6.84. Eskisehir, with a population density of 14.11 per/he, is classified as p = 2 (Table 1). In this attribute approach, high population density values map to low p attribute values, indicating that they require intensive modelling approaches.

Table 1. Distribution of population density values

Classification	# of settlements	%	p
$0.65 < pop_dens \le 4.47$	108	0.31	5
$4.47 < pop_dens \le 5.30$	46	0.14	4
$5.30 < pop_dens \le 9.12$	119	0.35	3
$9.12 < pop_dens \le 26.74$	64	0.19	2
26.74 < pop_dens ≤108.05	2	0.01	1

Statistics related to the area extent attribute: The minimum urban areal extent is 726 ha and the maximum is 199632 ha, with a mean of 12736 and standard deviation of 21944. For Eskisehir, the value of a_{ue} 5, given its areal extent of 34208 hectares (Table 5).

Table 2. Distribution of areal extents

Classification	# of settlements	%	a _{ue}
726 < area size ≤ 4516	90	0.27	1
$4516 < area size \le 5089$	22	0.06	2
5089 < area size ≤ 8880	108	0.32	3
$8880 < area \ size \le 33940$	98	0.29	4
$33940 < \text{area size} \le 199632$	21	0.06	5

Figure 5. (a) Values of the (a) p and (b) a_{ue} attributes for Eskisehir and nearby areas

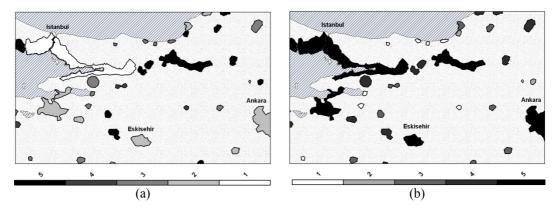


Table 3 represents the attribute values for the case study. A decision rule was applied using these values to determine the level of detail needed for the urban model.

Table 3. Eskisehir earthquake attributes

Criteria	Н					U		
Sub-criteria	H_t			H _s				
Attribute	f	d	So	a _e	S _d	i	P	a _{ue}
Value	5	1	1	4	4	0	2	5

$$I_{v} = \left[\left(\left(\left(1 + 1 + 5 \right) / 3 \right) + \left(\left(\left(4 + 4 \right) / 2 \right) \right) / 2 \right) \times \left(\left(5 + 2 \right) / 2 \right) \right] = 11.08 \tag{10}$$

Entering these attribute values into equation (6):

$$I_{vnorm} = ((11.08 - 25) / (0 - 25)) \times 4)_{round} = (2.23)_{round} = 2$$
 (11)

and normalizing the calculated value of I_{ν} using equation (8) yields:

$$D = 2 + (0/2) = 2 \tag{12}$$

The result of the decision rule is that the detail level (D) of the urban model (D) required for this specific type of disaster and this particular city must be 2. According to the LoD2 definition of the CityGML, this requires that building objects show differentiated roof structures and textures, and vegetation objects may also be represented.

We note that *i* take a value of zero here, because there is no indoor penetration for the disaster. This attribute is closely related to the indoor LoD. In some cases, coarse indoor detail may be more appropriate than a finely detailed LoD, as given by LOD4 of CityGML. Moreover, combinations of indoor/outdoor CityGML LODs may be more appropriate. For example, a low outdoor (LOD1) resolution with a low indoor resolution (floor level) can be used for a hazard application that is pervasive and has indoor penetration (e.g., tsunami).

5. Conclusions

Eight attributes are incorporated into the proposed decision rule to establish a link between the hazard type and the level of spatial detail needed in a 3D urban model for visualising vulnerabilities in disaster management. The attributes are divided into two main groups: hazard-related attributes, including f (frequency), d (duration), s_d (spatial dispersion), s_o (speed of onset), a_e (areal extent) and i (indoor penetration); and urban-related attributes, including a_{ue} (urban area extent) and p (population density). The variable D (level of indoor/outdoor detail) directly provides the needed LoD of the 3D model. The presented rule-based approach can be used by the technical disaster decision-maker group as a tool to decide

on the needed levels of details in the 3D model representations of indoor and outdoor features for a particular disaster simulation and/or visualisation application.

Although the first application of this approach is very promising, further tests with different cities, countries and disasters are needed. Three of the attributes (s_o, d, i) are related to the empirical characteristics of the considered hazard (an earthquake in this case). Five $(f, s_d, a_e, a_{ue}, \text{ and } p)$ are related to the local specification of the hazard and the settlement considered for the 3D urban modelling application. Attributes with local specifications are case-dependent. For example, the same hazard case may need a different model detail level in a different settlement. The reverse is also true. The same settlement may require different 3D models if different types of hazards are considered. Future research will investigate these possibilities in detail.

Another important observation from this first test case is that LODs, as currently defined by CityGML, may not be sufficient for all types of disasters. The hierarchical approach applied for the outdoor LoD could be beneficial for the indoor LoD. Further investigations may also be needed to optimize the process for multi-hazard applications. Future work will explore these possibilities in detail.

References

Alexander, D.E., (1986), Landslide Damage to Buildings, Environmental Geology and Water Science 8, 147-51

Basta, C., J.M.M. Neuvel, S. Zlatanova and B. Ale (2007) Risk-maps informing land-use planning processes: A survey on the Netherlands and the United Kingdom recent developments, Journal of Hazardous Materials, Vol. 145, pp. 241-249

Balk, D., G. Yetman, (2004), The Global Distribution of Population: Evaluating the gains in resolution refinement, Center for International Earth Science Information Network (CIESIN), Columbia University

Burton, I., Robert, W.K. and Gilbert, F.W., 1993, the Environment as Hazard, Guilford Press, New York

DAD, (2009), General Directorate of Disaster Affairs Earthquake Research Department (DAD) earthquake database, DAD Earthquake catalogue data http://sismo.deprem.gov.tr/, last access (2009)

Duzgun, H.S.B., S. Lacasse, (2005), Vulnerability and Acceptable Risk in Integrated Risk Assessment Framework, Landslide risk management: proceedings of the International Conference on Landslide Risk Management, Vancouver, Canada, 31 May-3 June 2005

Fedetov, S.A., (1985), Estimates of Heat and Pyroclas Discharge by Volcanic Eruptions Based upon the Eruption Cloud and Steady Plume Observations, Journal of Geodynamics 3, 275-302

Haddow, G.D. and J.A. Bullock, (2003), Introduction to Emergency Management, Butterworth-Heinemann, Stoneham, MA

Joseph, M., (2007), A Gis-Based Modeling Of Environmental Health Risks In Populated Areas Of Port-Au-Prince, Haiti, Master Thesis, The University Of Arizona, http://www.memoireonline.us/01/09/1868/A-GIS-based-modeling-of-environmental-health-risks-populated-areas.html

Kaplan, L.G. (1996), Emergency and Disaster Planning Manual, McGraw-Hill, New York, NY

Kemec, S. and Duzgun, S., (2006), 3D Visualization for Urban Earthquake Risk in Geohazards, Farrokh Nadim, Rudolf Pöttler, Herbert Einstein, Herbert Klapperich, and Steven Kramer Eds, ECI Symposium Series, Volume P7 2006

Kemec, S., H.S. Duzgun, and S. Zlatanova, (2009), A Conceptual Framework for 3D Visualization to Support Urban Disaster Management, Joint Symposium of ICA Working Group on CEWaCM and JBGIS Gi4DM, Cartography and Geoinformatics for Early Warning and Emergency Management, Prague

Kolbe, T.H., Gröger G., Plümer L., (2005), CityGML-Interoperable Access to 3D City Models, Oosterom, Zlatanova, Fendel (Eds.): Proceedings of the Int. Symposium on Geoinformation for Disaster Management on 21-23 March 2005 in Delft, Springer Verlag

Malczewski, J., (1999), GIS and Multicriteria Decision Analysis, New York: Wiley

Malczewski, J., (2006), GIS-Based Multicriteria Decision Analysis: A Survey of the Literature, International Journal of Geographical Information Science, 20:7,703 — 726

Mitroff, I.I., (1988), Crisis Management: Cutting Through the Confusion, Sloan Management Review, Vol. 29 No. 2, pp. 15-20.

Newhall, C.G., and S. Self, (1982), the Volcanic Explosivity Index (VEI): An Estimate of Explosive Magnitude for Historical Volcanism, Journal of Geophysical Research 87, 1231-8

Özmen, B., M. Nurlu, H. Güler, (1997), Coğrafi Bilgi Sistemi ile Deprem Bölgelerinin İncelenmesi, Bayındırlık ve İskan Bakanlığı, Afet İşleri Genel Müdürlüğü, Ankara

Richardson, B. (1994), Socio-Technical Disaster: Profile and Prevalence, Disaster Prevention and Management, Vol. 3 No. 4, pp. 41-69

Shaluf, I.M., (2007), Disaster Types, Disaster Prevention and Management, Vol. 16 No. 5, 2007, pp. 704-717

Tsuya, H., (1955), Geological and Petrological Studies of Volcano Fuji, Tokyo Daigaka Jishin Kenkyusho Iho 33, 341-2

Wood, H.O., and F. Neumann, (1931), Modified Mercalli Intensity Scale of 1931, Seismological Society of America, Bulletin 21, 277-83

Soloviev, V., (1978), Tsunamis, In the Assessment and Mitigation of Earthquake Risk, Paris: UNESCO Press

Sudhira, H.S., T.V. Ramachandra, K.S. Jagadish, (2004), Urban sprawl: metrics, dynamics and modelling using GIS, International Journal of Applied Earth Observation and Geoinformation 5 (2004) 29–39

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