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Paper Abstract

Paper title: **Dynamic travel demand for emergency evacuation: the case of bushfires**

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Abstract (200 words): There are two types of emergencies; those which can be anticipated and those that cannot. Among those that can be anticipated are such events as cyclones, floods, bushfires, and tsunamis. When such events are anticipated, one course of action that may be taken is the evacuation of residents from a threatened area. When evacuation takes place, there often remains a need to provide access for emergency vehicles and personnel to the threatened area creating a conflict between the needs to maximise capacity for evacuation, while continuing to provide access to the threatened area. Relatively little is known about when residents will decide to evacuate. A model of evacuation behaviour is needed that would predict the proportions of the population that would leave within certain time periods, thus leading to the development of an evacuation travel demand model. Under a contract from Emergency Management Australia, the authors developed a method to predict evacuation decisions by residents from bush fires. This paper describes the methods used to determine when a household would evacuate, and describes the resulting model that predicts how many partial and full household evacuations will take place by time period from when the emergency is first perceived.

Introduction

The occurrence of natural disasters is increasing and these natural disasters, to a degree, are evolving (Hooke, 2000; Newkirk, 2001). Despite improvements in technology to be able to predict better the onset of bizarre weather conditions (leading to drought and bushfires, cyclones and floods), these tools may still not be accurate enough. However, even if they are accurate, the hazard may arise so quickly that sufficient warning, regarding the intensity or ferocity of the hazard, may not eventuate in time (Hook, 2000). The threat is compounded by the concentration of populations into "megacities", placing more people at risk; hence, more people will require evacuation if a natural disaster is predicted to strike the area in question (Hook, 2000).

Evacuation is defined generally, as the collective movement of people, and evacuations are commonly referred to as "round" trip events (Sorensen *et al*., 1987; Church and Cova, 2000). There are three types of evacuations defined by the type of evacuation order: mandatory, recommended, and voluntary (Rasid *et al*., 2000). In terms of a bushfire emergency, it has been found that people do not like a mandatory evacuation because it prevents them from taking part in any activity associated with property protection (Rasid *et al*., 2000). They appreciate being given the warning; however, they prefer making the decision to evacuate themselves. In addition, the types of evacuation order will directly impact when and how many households decide to evacuate. This in turn will effect how emergency vehicles and equipment will enter the affected area given the level of traffic flowing out of the affected area. The ability to satisfy evacuation demand depends on the rate that demand can be exerted and the capacity of the network (Church and Cova, 2000).

A major problem identified with large scale emergency evacuations is that population growth has outstripped the improvements to infrastructure (road capacity); hence, mass evacuations will be more difficult and time consuming (Barrett *et al*., 2000). On a small scale, there are increasing instances of suburbs being built in former bush land, often with only a single access road to the development. Streets within such suburbs are often planned to be circuitous to control traffic movements under normal conditions. Evacuations of such suburbs is also of increasing concern.

Travel needs in emergency situations differ from everyday travel needs and have been identified as the following:

1. Increased route capacity,
2. Limited travel demand resulting from evacuation,
3. Good information systems to allow for the accurate delivery of traffic flow and traveller information, and
4. Better coordination between regional and interstate agencies in relation to large scale (interstate) evacuations (Urbina and Wolshon, 2002).

Underpinning these needs is evacuation behaviour.

Evacuation Behaviour and Analysis

Understanding evacuee behaviour is essential if an evacuation plan is to be successful (De Silva, 2001). What needs to be understood is how people perceive an evacuation, in terms of threat and risk, and how this perception influences the decision to evacuate or not (Sorensen *et al*., 1987).

Individual behaviour can result in evacuation shadow (people voluntary evacuate when it is unnecessary to do so; this is most commonly seen in chemical reactor emergencies whereby residents within a 25 kilometre radius of the reactor evacuate, despite having been told not to do so, resulting in excessive evacuation, Reisman, 2001), panic, convergence (people head towards the area that should be evacuated placing more people at risk), failure to use allocated transport routes, evacuation stress, and failure to respond to an evacuation warning (Sorensen *et al*., 1987). The decision of people to evacuate is influenced by their belief in the evacuation warning, (warnings issued by emergency personnel are effective in getting people to evacuate), the level of the perceived risk, a plan to evacuate (the success of this plan relates to evacuation experience), and the family context in which the warning was received (Sorensen *et al*., 1987; Rasid *et al*., 2000; Dow and Cutter, 2000). For example, after a cyclone warning was issued for parts of Tropical Queensland, Australia, people prepared their homes inadequately because of a lack of experience, lack of good information about what should be removed, and a general feeling of complacency (Raggatt *et al*., 1993). People with less warning time were more likely to be in denial and did not take the warning seriously (Raggatt *et al*., 1993). However, people are likely to respond to an evacuation order if it is addressed to them, and the mode of message delivery is personal (Baker, 1991).

Participation in evacuation procedures depends on the confidence of the public in the authorised evacuation process. Residents require more information on evacuation routes, track of the storm or natural hazard, and maps graphically depicting this information. Transport related information was considered extremely important to individuals and they wanted to receive this information, thus highlighting the importance of transport in an evacuation (Dow and Cutter, 2000). Independent decision making requires information to enable individual risk assessment. Public perception of risk is different to expert perception and this must be acknowledged (Dow and Cutter, 2001). It has been identified that three social-network variables affect warning response. These are: community involvement, age, and family interactions (extended family links are important in explaining evacuation response regardless of age; warning messages from family and friends are more effective than media sources in stimulating adaptive behaviour) (Sorensen *et al*., 1987; Baker, 1991; Dow and Cutter, 2000). Members of the same household exhibit the same evacuation behaviour thus demonstrating the effects of family interactions on evacuation behaviour (Heath *et al*., 2001).

It was also found that households with children are more likely to evacuate and long term residents were not likely to evacuate (Dow and Cutter, 2000). Access to homes after an evacuation, protection of property, job obligations, and the well being of pets can often outweigh advice on safety and hence prevent households from evacuating (Dow and Cutter, 2000; Heath *et al*., 2001). Evacuation delay was observed for older households and households with pets due to inappropriate transport: owning pets was the most significant reason why childless households did not participate in the evacuation procedure (Heath *et al*., 2001). The reasons for households not evacuating can be summarised by the following:

1. Wanted to stay to protect property,
2. Did not see neighbours evacuate, and
3. The inconvenience associated with evacuating (Baker, 1991).

Evacuation rates are much higher for floods and chemical spills than for cyclones possibly due to the level of uncertainty of landfall; therefore, people do not decide to evacuate until they become more certain that they are located in the direct path of the cyclone (Southworth, 1991). This is also the case in bushfire situations given that residents may actively participate in fire fighting to protect their property. A summary of the influential factors towards evacuation behaviour are displayed in Figure 1.

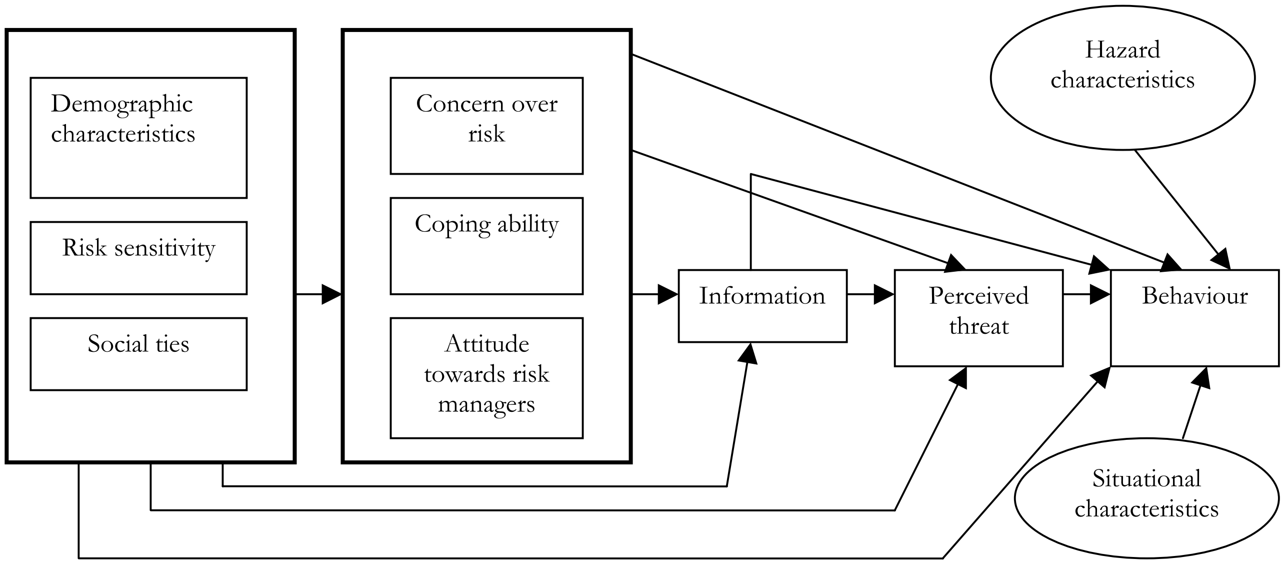

Figure 1: A general model of evacuation behaviour
Source: Sorensen *et al*., 1987.

As is shown in Figure 1, evacuation behaviour is complex and difficult to quantify. However, estimates need to be made for modelling purposes. Evacuation behaviour is quantified through the estimation of evacuation time. Evacuation time consists of response time (the time required for respondents to physically travel to safety, also known as clearance time), decision time (time between incident detection and an official decision to order an evacuation), notification time (evacuation warning), and preparation time (Southworth, 1991; Urbina and Wolshon, 2002; Barret *et al*., 2000). An understanding of the components of evacuation time is extremely important when conducting evacuation behavioural analysis.

Response times may be depicted graphically in response curves (Figure 2). In any evacuation plan, evacuation times must be determined, or approximated, to allow planners to develop strategies that enable the safe evacuation of residents of threatened areas (Hobeika *et al*., 1985). This information will be used in modelling techniques: knowledge of evacuation behaviour enables the estimation of evacuation travel demand and this is a vital input of evacuation models. However, a problem with the definition of evacuation time is that it only considers evacuation based on a mandatory evacuation order. Recommended and voluntary evacuations are not considered. Thus, evacuation models to date only incorporate evacuation behaviour based on mandatory evacuations. The most recent bushfire experience in Sydney involved recommended and voluntary evacuations. The exclusion of evacuations resulting from voluntary and recommended evacuation orders leads to an underestimation of evacuation travel demand: a vital input of evacuation models.

Given the complexities associated with understanding evacuee behaviour in an emergency situation, such as bushfires, it was realised that focus groups of affected residents would need to be conducted to help in the development of the survey instrument, and in particular the stated choice component.

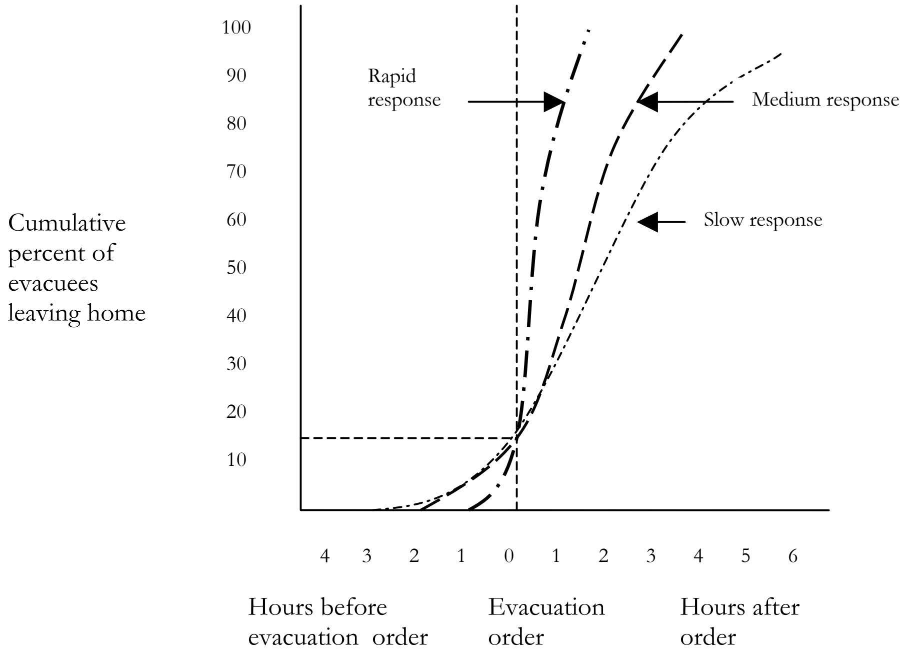

Figure 2: Behavioural response curves
Source: Lewis, 1985.

Survey Implementation and Sample

Two focus group discussions were conducted with members from fire affected communities from the Hornsby and Hawkesbury regions of Sydney. The primary objective was to explore residents' perceptions of bushfire threat, including the attributes of a bushfire that make the fire threatening to residents as well as the language used by residents to describe the levels of threat within each of these attributes. The intention was to use this insight to aid in the development of a Stated Choice experiment that was subsequently conducted on a sample of residents from areas that were threatened by bushfires in the past one to two years, in order to determine likely evacuation behaviour under various scenarios. This research also provided an opportunity to identify factors considered by residents in their decision to evacuate some or all members of their household in response to a bushfire threat and to obtain feedback on the proposed stated-choice survey instrument.

After the qualitative data were analysed, the design of the survey instrument commenced. It was decided that households that have had bushfire experience, either imminent or potential, would be recruited to take part in the survey. The study area was metropolitan Sydney. Therefore, it was also initially decided that a face to face survey mode was not an option because of the distances interviewers would have to cover to obtain responses. Computer Aided Telephone Interviewing (CATI) was also not considered an option because of the high costs involved, even though this cost is not as high as the cost for personal interviews.

With this in mind, and the fact that almost sixty percent of households in Australia have access to the internet, the internet was chosen as the survey mode for data retrieval.

Employing the internet allowed for automation of the data entry process, which frees up valuable resources and saves time. The telephone was to be used in the recruitment process.

Careful consideration went into the design of the survey instrument. The survey is implicitly divided into two sections. The first asks demographic, residential location, and bush fire experience questions, whilst the second section shows the respondent numerous bush fire scenarios and asks the respondent about total and partial household evacuations. The household decision maker was targeted to answer the survey, because the scenario questions were directed towards this individual. Attributes and attribute levels specified in the scenarios were obtained from the qualitative data analysis.

Sampling Strategy

Before deciding on the sampling strategy to be adopted, numerous print media articles that specifically dealt with the bushfire crisis faced in Sydney in late 2002 and early 2003, were collected. From these articles, a list of 43 suburbs was created and, using TRANSCAD®, a transport based Geographic Information System that incorporates all of metropolitan Sydney and surrounds in terms of street networks and bush and parkland, a list of street names for all streets within a specified distance of bush was created for each of the 43 suburbs. This list was used to assist in the *stratified random sampling* selection procedure. Before conducting the pilot survey, the main sample was drawn and the pilot sample was drawn from the remaining addresses, so as not to create sample bias in the main sample.

Pilot Survey. A recruitment script and a list of identification numbers were devised for the recruitment of thirty households from bushfire affected areas in outer metropolitan Sydney, for the pilot test. During the recruitment process, e-mail addresses for successfully recruited respondents were obtained to allow the Web address of the survey to be provided to respondents, and to allocate identifications numbers to respondents. A reminder e-mail was sent five days after the original message was e-mailed to prospective respondents. The pilot test of the internet survey was conducted in June, 2003, and ran for almost three weeks. From the telephone numbers attempted, 13.8 percent of households were recruited, of which 50 percent successfully completed the internet survey. This gave an overall response rate of 6.9 percent.

Some difficulties arose in the recruitment for the pilot survey. This is partly the result of certain selection criteria that had to be met for a household to be eligible to take part in the study: the household must have encountered a bushfire threat, either imminent or potential, in the past two years, as well as have access to the internet. Also, the recruitment response rate incorporates all telephone numbers dialled during this stage of the survey; a total of 209 numbers were dialled of which 46 percent could not be contacted in five calls, and 29 percent of households contacted refused to participate. During the data retrieval stage, however, the response rate increased to 50 percent. This was expected given the feedback from respondents who had successfully completed the internet survey: the general consensus was that respondents enjoyed completing the survey over the internet and did not find any of the questions difficult to answer. However, the survey instrument was further refined: a few more scenarios and bushfire related questions were added to the final instrument.

The recruitment response rate meant that for the main survey, in order to achieve 450 complete surveys, at least 900 households would have to be recruited. This meant that almost

11,000 phone calls would have to be made. This was clearly beyond budget limitations and the number had to be revised downwards to 450 *recruited* households.

Main Survey. The same recruitment process was employed for the main survey as for the pilot survey except that an extra e-mail reminder was sent to boost the number of responses to the main survey. The recruitment rate for the main survey was 12.5 percent, of which 54 percent completed the internet survey, giving an overall response rate of 6.8 percent.

Response rates, for the main and pilot surveys, are almost identical. During the recruitment phase of both the main and pilot surveys, the refusal rate was almost identical, 28 percent and 29 percent respectively. This relatively high rate of refusal was a surprise given the level of media and public interest in the survey topic. However, no incentive was provided to take part in the study and the time of contact could have adversely affected the participation rate. The final sample size, therefore, (completed internet surveys) was 257; 243 from the main survey and 14 from the pilot survey.

To conclude, some unavoidable problems were encountered during the retrieval stage:

- Households had incompatible internet browsers therefore could not access the survey, and
- The server encountered numerous interruptions due to a global virus problem. This ultimately affected respondents' ability to access the survey.

The next section describes the experiment and the models used to analyse the data.

Model Development: The Mixed Logit Model[1]

The utility-theoretic approach to modeling discrete choice was developed by McFadden (1974). Consider a situation in which a sample of individuals is evaluating a finite number of alternatives. Let subscripts *i*, *j*, and *k* refer to individual *i*, alternative *j*, and attribute *k*. The utility for any given alternative in choice situation *s* may be written as

$$U_{ijs} = \beta_{ijk}' x_{ijks} + \varepsilon_{ijs}. \qquad (1)$$

where μ_{ijs} is the utility for individual *i* for alternative *j* in choice situation *s*, x_{ijks} is a vector of explanatory variables that are observed by the analyst which may include the attributes of the alternatives as determined by the SP experimental design, the socio-economic characteristics of the respondents undertaking the choice task, the descriptors of the decision context in which the choice task is being undertaken as well as the choice task itself. β_{ijk}' is a vector of weights (or parameters) corresponding to each x_{ijks}. ε_{ijs} represents the unobserved influences for respondent *i* for alternative *j*. At no stage are β_{ijk}' or ε_{ijs} observed by the analyst and are therefore treated as stochastic influences within the modelling process.

For estimation purposes, it is common to assume that ε_{ijs} is independently and identically distributed (IID) extreme value type 1. This assumption results in the well-known multinomial logit (MNL) model, shown as equation (2).

[1] For a more thorough review of the ML model, see Hensher and Greene (2003).

$$P_{ijs} = \frac{e^{\beta_{ijk}'x_{ijks}}}{\sum_j e^{\beta_{ij}k'x_{ijks}}} \tag{2}$$

Whilst the IID assumption and the behaviourally comparable assumption of Independence of Irrelevant Alternatives (IIA) allow for ease of computation (as well as providing a closed form solution), as with any assumption, violations both can and do occur. When violations do occur, the cross-substitution effects observed between pairs of alternatives are no longer equal given the presence or absence of other alternatives within complete list of available alternatives within the model (Louviere et al., 2000). The Mixed logit (ML) model relaxes the IID assumption through partitioning the stochastic component additively into two parts. The first component is allowed to be correlated over alternatives and heteroskedastic whilst the second component maintains the IID over alternatives and individuals as shown in equation (3).

$$U_{ijs} = \square_{ijk}'x_{ijks} + [\square_{ijs} + \square_{ijs}] \tag{3}$$

Where $\square_{ijs}$ is a random representation with a mean and distribution over individuals and alternatives dependent on underlying parameters and observed sample data relating to alternative *j* and individual *i.* The ML model assumes a general distribution for $\square_{ijs}$ such that $\square_{ijs}$can take on any number of distributional forms such as normal, lognormal, uniform or triangular. Within the ML framework, $\square_{ijs}$ is treated as a random term with zero mean that is IID over alternatives and which is independent of the underlying parameters or sample data.

We denote the joint density of $[\square_{1is}, \square_{2is}, .., \square_{Jis}]$ as $f(\square_{is}|\square)$ where the elements of $\square$ are the parameters of the distribution (i.e., mean and standard deviation) and η_{is} denotes the vector of *J* random components across the universal set of utility functions in choice situation *s*. Given $\square_{ijs}$ is distributed IID extreme value type 1, we may state that for any value of $\square_{ijs}$, the *conditional* probability for choice *j* is logit in choice situation *s*. Hence:

$$P_{ijs}(\beta_{ijk} \mid \eta_{ijs}) = \frac{e^{(\beta_{ijk}' + \eta_{ijs})}}{\sum_j e^{(\beta_{ijk}' + \eta_{ijs})}} \tag{4}$$

Equation (4) is equivalent to equation (2) with the addition that for each sampled individual we now have additional information with regard to the unobserved sources of influence as defined through $\square_{ijs.}$ The unconditional choice probability is calculated as this logit probability integrated over all values of $\square_{ijs}$ and weighted by the density of $\square_{ijs}$ is as shown in equation (5) (Hensher and Greene, 2003):

$$P_{ijs}(\beta_{ijk}| \Omega) = \square_{\eta_{1is}} \square_{\tilde{\eta}_{2is}} \square_{\eta_{Jis}} L_{ijs}(\square_{ijk} \square \square_{ijs}) f(\square_{ijs}|\square) d\tilde{\square}_{Jis}\, d\square_{2is} d\square_{1is} \tag{5}$$

An important output of the ML model which is not incorporated within the simple multinomial model is the standard deviation parameter of the model. The standard deviation of an element of the β_{ijk} (random) parameter vector, denoted σ_{ijk}, accommodates the presence of preference heterogeneity in the sampled population around the mean of the random parameter.

The Experiment

A stated choice experiment was conducted, as part of a broader research effort examining potential impacts upon evacuation choice under threat of a bushfire, on suburbs surrounding metropolitan Sydney. The universal choice set comprised evacuating the entire household, evacuating part of the household, or not evacuating at all. Respondents evaluated scenarios describing various weather conditions as well as fire descriptors developed from pre-study focus groups. The purpose of the exercise was to observe and model their observed strategies in each scenario.

Three alternatives appeared in each choice scenario: a) total household evacuation; b) partial household evacuation; and, c) no evacuation. Six four-level attributes and three two-level attributes were used to describe the weather and provide a description of the fire. These are shown in Table 1.

A dynamic SP experimental design was employed based on the distance shown from the household to the fire. Three sets of distances were used; one set representing thousands of metres, one hundreds of metres and one tens of metres (see Table 2). Respondents were first shown a choice scenario with attribute level distances in the thousands. If the decision maker elected to evacuate the entire household, the next choice scenario was presented (at a distance in the thousands of metres). If the decision maker elected, given the attribute level descriptors, not to evacuate at all, the same choice scenario was shown. However, the distance to the fire was now drawn from the set of levels representing hundreds of metres (i.e., all attribute levels were fixed except for the distance attribute which was moved from thousands of metres to hundreds of metres). For those not evacuating, this represented an advance of the fire front toward the household after some unspecified period of time. Given this advance, the respondent was then asked once more if they would evacuate fully, evacuate partially, or stay. If in the initial choice scenario (i.e., when the fire was thousands of metres away), the respondent elected to partially evacuate the household, then the same system of representing an advance of a fire front was used. However, the alternatives made available to the respondent were limited to evacuating themselves or staying. In this case, it was assumed that the partial evacuation had already occurred. If under either circumstance, some or all of the household remained, the fire was advanced to the tens of metres distance from the household and the procedure repeated.

Table 1: Attribute levels of SP experiment

Weather characteristics	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Humidity	10%	30%	50%	70%
Temperature	20 degrees	25 degrees	30 degrees	35 degrees
Wind speed	10 k/hr	30 k/hr	50 k/hr	70 k/hr
Current wind direction	Favourable	Unfavourable		
Fuel load	Last fire backburn six months ago	Last fire backburn 12 months ago	Last fire backburn 18 months ago	Last fire backburn more than two years ago
Description of fire	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Fire type	Cold (ground)	Hot (tree-top)		
Fire distance	See below	See below	See below	See below
Access1	1 road in/out	2 road in/out	3 road in/out	4 road in/out
Access2	Road currently not threatened	Road currently threatened		

Table 2: Distance of Fire from household attribute level descriptors

Level	Distance 1	Distance 2	Distance 3
1	4 km	900m	100m
2	3 km	650m	75m
3	2 km	400m	50m
4	1 km	150m	25m

Two access route attribute levels were also created to avoid confusion, given that some localities naturally have limited points of access and egress. Prior to the SP experiment, respondents were asked how many access/egress routes could be used to evacuate from their property. If it was one or two, then the experimental design used the second access route attribute. If it was more than two, the first access attribute was used in the experimental design. An example choice set is shown in Figure 3.

The master design for the travel choice task was an $8 \times 4^6 \times 2^3$ orthogonal fractional factorial, which produced 60 scenarios or choice sets. The eight-level factor was used to block the design into eight versions consisting of either seven or eight choice sets. Whilst it is preferable that all respondents view the same number of choice sets, for reasons discussed below, this was not possible. The $4^6 \times 2^3$ portion of the master design is an orthogonal main effects design, which permits independent estimation of all effects of interest.

The final experimental design was complex. This is because, from the preliminary focus groups conducted, it was determined that certain combinations of attribute levels made little or no sense (e.g., high levels of humidity with a fire described as a "cold fire"). For practical purposes, it was also felt that high wind speeds should only be shown in concert with unfavourable wind directions because if the wind speed was high but blowing the fire in the opposite direction, then evacuation, both partial or full, was highly improbable. The linking of the presence or absence of attribute levels from two or more attributes requires that those attributes be 'nested' in the design. The nesting of attributes ensures that cognitively sensible scenarios are generated, albeit at considerable complexity to the design itself. In this instance, this meant that uneven numbers of choice sets where shown across design blocks and that the versions were unbalanced (meaning that each respondent did not see every level of each attribute exactly once). Neither of these properties is desirable, resulting in a loss of statistical efficiency; however it was felt that any loss of statistical efficiency was justified in order to create cognitively sensible choice scenarios.

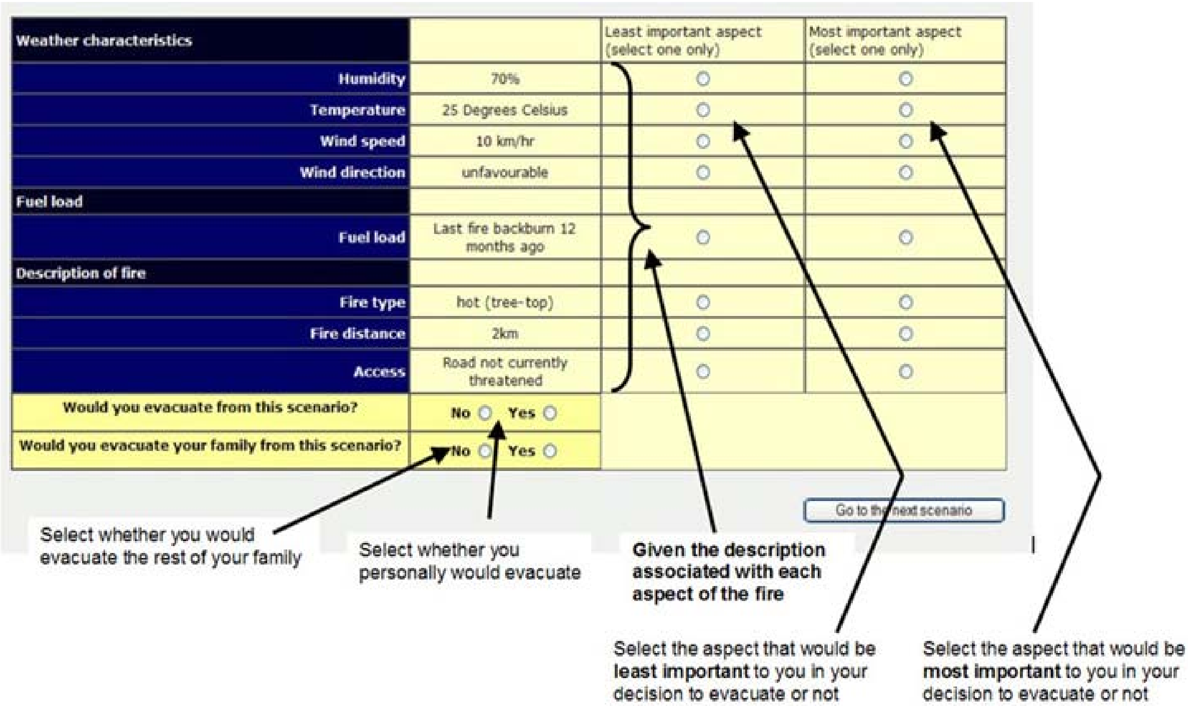

Figure 3: Example Choice Scenario

Two choice responses were collected as part of each choice set. The first involved whether the respondent would evacuate themselves given the scenario description. Instructions prior to each scenario informed the respondents that self evacuation would also involve the evacuation of the entire household. The second involved the choice of evacuating family members but not themselves. This choice therefore represented the partial evacuation of the household.

Results

Table 3 shows the final multinomial (MNL) and mixed logit (ML) models for the household decision maker evacuation stated choice experiment. The overall goodness of fit for both models is similar (pseudo R^2s are both 0.359). The log-likelihood functions are similarly alike. Unfortunately, there exists no test as to whether the simpler MNL model is preferred to the ML model.[2] Four parameters in the ML model have been specified using a constrained triangular distribution to ensure that the random parameter estimates are restricted to one side of zero (see Hensher and Greene, 2003). Despite the lack of a formal test of comparison between the MNL and ML models, the statistical significance of the standard deviation parameters (using constrained triangular distributions) imply a structural advantage in selecting the mixed logit specification over the MNL form.

[2] In the ML model specified here, we have used a constrained triangular distribution. Under such a specification, the ML model does not add any new parameters, only new sources of variation in the model, in the form of heterogeneity. This means that the log-likelihood test normally used will have zero degrees of freedom (see Greene *et al*., 2005).

Table 3: Decision maker self evacuation models

Attribute	**Alternative**	**Multinomial Logit**		**Mixed Logit**	
Constant	Stay	1.664	(5.36)	1.655	(5.29)
Humidity	Evacuate	0.162	(0.82)	0.162	(0.81)
Fuel load	Evacuate	0.005	(0.86)	0.005	(0.86)
Household Number of vehicles	Evacuate	-0.255	(-4.23)	-0.257	(-4.25)
Decision maker's age	Stay	0.132	(1.77)	0.134	(1.78)
Decision maker's gender (1 = female)	Stay	-0.802	(-8.53)	-0.808	(-8.54)
No. of 0-17 year olds in household	Stay	0.130	(3.07)	0.131	(3.07)
No. of 18-65 year olds in household	Stay	-0.198	(-3.23)	-0.200	(-3.24)
No. of 66-74 year olds in household	Stay	-0.342	(-3.86)	-0.345	(-3.87)
No. of 75 + year olds in household	Stay	-0.736	(-4.12)	-0.739	(-4.11)
Years of residency in area	Stay	0.021	(3.71)	0.021	(3.70)
Random Parameters in Mixed Logit (Std Dev = mean for constrained triangular distribution)					
Fire distance	Evacuate	-0.220	(-6.60)	-0.235	(-6.21)
Wind Speed	Evacuate	0.009	(3.58)	0.009	(3.66)
Wind Direction (1 = Unfavourable)	Evacuate	0.221	(1.97)	0.220	(1.99)
Fire type (1 = Hot fire)	Evacuate	0.175	(1.96)	0.174	(1.97)
Model Fits					
Log-likelihood at zero		-3420.68		-3420.68	
Log-likelihood at convergence		-2186.94		-2186.74	
Pseudo-R^2		0.359		0.359	
No. of choice observations		4935		4935	

In neither model are the humidity and fire load parameters significant. The access attribute was also found to be insignificant and its inclusion resulted in a significant worsening of the model fits, so it was removed from the final model specification. We hypothesise that this is because the access attribute held little or no relevance to the sampled population. The attributes used in the experiment were determined from existing evacuation literature and from focus groups. The focus group participants were mainly drawn from areas where access to and from households could easily be threatened by bushfires approaching from multiple directions; whereas the sampled population for the main study was drawn from areas on the fringe of suburbia, meaning that bushfires are more likely to approach from a direction opposite to the access routes of the suburb, thereby reducing the perceived level of threat.

The remaining design attributes were specified as random parameter estimates in the ML model drawn using 500 Halton draws from constrained triangular distributions (see Hensher *et al.*, 2005). All random parameter estimates were significant suggesting the presence of heterogeneity in the marginal utilities for these attributes. By constraining the mean to equal the spread parameter in the triangular distribution, the marginal utility density begins at zero, rises linearly to the mean before declining to zero again at twice the mean (see Hensher and Greene, 2003; Greene *et al.*, 2005). The negative random parameter for the distance to fire indicates that the greater the distance from the household to the fire, the less likely the decision maker is to evacuate. The positive wind speed parameter indicates that higher wind speeds are more likely to result in the decision maker evacuating. Similarly, an unfavourable wind direction and a 'hot' fire are more likely to result in the decision maker evacuating themselves and remaining household members. All of these are intuitively appropriate.

Several non-design variables were entered into the utility specifications of the models. The number of vehicles owned by a household was found to be a significant determinant of whether to evacuate or not. The more vehicles owned by a household, the less likely the decision maker will evacuate the entire household. *Ceteris paribus*, older decision makers are more likely not to evacuate, whilst female household decision makers are more likely to evacuate than male household decision makers, holding everything else constant. Interestingly, those with younger children present in the household are more likely not to evacuate themselves than those with no children. Households with older household members are more likely to evacuate themselves. This confirms what was stated in the literature (Dow and Cutter, 2000). Those who have lived in the area for longer are less likely to evacuate themselves than those with a shorter period of local residency, *ceteris paribus*. This is because such residents are more likely to have experienced bushfires than those new to the bushfire prone areas, from which the sampled population was drawn. The level of experience in evacuation affects the rate of participation in evacuation and this also confirms what was stated in the literature (Sorensen *et al.,* 1987; Rasid *et al*., 2000; Dow and Cutter, 2000).

Table 4 shows the model results for the household evacuation stated choice experiment. As with the decision maker results, the results shown are for a MNL and ML model. Once more, the two models show similar model fits. However, the two models are not comparable because they are not nested models. The two models shown have the same utility specification as the models shown in Table 3.

As with the decision maker evacuation models, the four random parameter estimates of the household ML evacuation model are statistically significant and are all of the expected sign. Holding all else constant, the further the fire is from the household, the less likely the decision maker will decide to evacuate household members from the threat. Higher wind speeds, an unfavourable wind direction and the approach of a 'hot' as opposed to 'cold' fire, all result in higher probabilities of evacuation. The significant spread parameters for these attributes suggest, however, that heterogeneity exists as to the influence each has on the probability of evacuation over the sampled population.

Table 4: Household evacuation models

Attribute	Alternative	Multinomial Logit		Mixed Logit	
Constant	Stay	0.071	(0.26)	0.055	(0.20)
Humidity	Evacuate	0.063	(0.36)	0.062	(0.34)
Fuel load	Evacuate	0.012	(2.34)	0.012	(2.34)
Household Number of vehicles	Evacuate	-0.130	(-2.46)	-0.134	(-2.49)
Decision maker's age	Stay	0.427	(6.19)	0.434	(6.17)
Decision maker's gender (1 = female)	Stay	-0.332	(-4.06)	-0.338	(-4.06)
No. of 0-17 year olds in household	Stay	-0.044	(-1.16)	-0.045	(-1.16)
No. of 18-65 year olds in household	Stay	-0.073	(-1.37)	-0.075	(-1.40)
No. of 66-74 year olds in household	Stay	-0.448	(-5.61)	-0.456	(-5.61)
No. of 75 + year olds in household	Stay	-0.308	(-1.98)	-0.309	(-1.96)
Years of residency in area	Stay	0.024	(4.72)	0.024	(4.70)
Random Parameters in Mixed Logit (Std Dev = mean for constrained triangular distribution)					
Fire distance	Evacuate	-0.215	(-7.86)	-0.224	(-7.49)
Wind Speed	Evacuate	0.013	(5.78)	0.013	(5.82)
Wind Direction (1 = Unfavourable)	Evacuate	0.244	(2.44)	0.239	(2.40)
Fire type (1 = Hot fire)	Evacuate	0.310	(3.78)	0.310	(3.77)
Model Fits					
Log-likelihood at zero		-2825.961		-2825.961	
Log-likelihood at convergence		-2491.748		-2491.824	
Pseudo-R^2		0.115		0.115	
No. of choice observations		4077		4077	

As with the decision maker evacuation model, humidity is not a significant contributor to household evacuation choice; however, the fuel load attribute is. The more months since the fuel load was reduced, the more likely the decision maker will evacuate other household members from potential danger. As with the previous two models, the more household vehicles owned, the less likely the household will be evacuated. Also, older decision makers are less likely to evacuate other household members than younger ones, and females are more likely to order a household evacuation than males. The number of children and adults under the age of 65 are not significant determinants of choice of whether to evacuate or not. However, decision makers with persons aged over 65 years of age are more likely to evacuate the household than those with no persons over the age of 65. This is also a finding stated in the literature (Dow and Cutter, 2000). As with the self evacuation models, those who have lived in the area longer are less likely to evacuate than those who are newer to the area.

Discussion

The experimental design approach used here and the models estimated allow for a dynamic travel demand forecast of emergency evacuation given bushfire threats to the fringes of suburban Sydney. The experiment included information on the fire distance, wind speed, and direction. Combined, these attributes allow for an estimation of the time before any fire front is likely to make contact with threatened households from a given distance. By substituting attribute levels for these and other attributes and variables in the utility functions of the models specified, evacuation probabilities can be obtained for individual households under varying conditions. Whilst the conditions are likely to be static for all households, substitution of household specific socio-demographic and decision maker specific socio-demographic characteristics allow for estimation of household specific evacuation probabilities, which may be summed to form suburb specific evacuation probabilities.

By substituting into the models attribute levels that describe a potential bushfire threat and the socio-demographic characteristics of households in the likely affected area, the two models are able to predict the likelihood that a household will either evacuate entirely or partially. To demonstrate, consider a bushfire threat as described by attribute levels shown in Table 5. The household socio-demographic characteristics and decision maker characteristics that are significant in the model are also represented in Table 5. Through simulation, the probability of a partial evacuation is 0.4499 whilst the probability of a full evacuation is 0.3558. Assuming 10 such households fit the profile shown in Table 5, we would predict three to four households would evacuate fully and four to five households would evacuate partially. Evacuation probabilities for other household profiles can similarly be calculated. Given that the distance to the fire front is also incorporated into the model and given assumptions as to the rate of advance of the fire, these choice probabilities may be calculated for different fire distances (and hence times), thus providing a dynamic element to the demand forecast application.

Table 5: Example context, household and decision maker characteristics

Context	Level	Characteristic	Level
Fire distance	150m	Household Number of vehicles	2
Wind Speed	30 km/hr	Decision maker's age	25-44
Wind Direction (1 = Unfavourable)	1	Decision maker's gender (1 = female)	1
Fire type (1 = Hot fire)	1	No. of 0-17 year olds in household	1
Humidity	50%	No. of 18-65 year olds in household	3
Fuel load	18 months	No. of 66-74 year olds in household	0
		No. of 75 + year olds in household	0
		Years of residency in area	10

Future Developments

This research has shown the potential of assessing evacuation behaviour through Stated Choice Experiments, and of developing models of evacuation behaviour that can show the time at which households will choose to evacuate, whether evacuating in their entirety or only evacuating some members of the household. However, despite the usefulness of the rather simplistic Excel® based DSS developed in this research (the models themselves however, were estimated using NLOGIT 3.0), a much more sophisticated DSS could be developed on a GIS base. In this case, there is potential to include actual data on the distribution of structures on the ground, the topography, the vegetation, and the specific length and direction of movement of the fire front. At present, we have ignored the length of the fire front, and have assumed that it is at least as wide as the suburb specified at the outset of the DSS. We have also assumed that the fire front is parallel to the boundary of this suburb with the bush, and have further assumed uniform density of residential development in the suburb. All of these assumptions could be removed, by developing a sophisticated GIS base on which to perform the modelling. In this case, the actual orientation of the fire front would be provided to the GISDSS, together with its current speed of movement. The model would then estimate, using a fire movement model, where the path of the fire would take it, and what properties would actually be threatened. The evacuation behaviour model would then be applied to the number of residential properties estimated to be in the path of the fire, within various time periods from the present. This would provide a much more sophisticated and accurate estimation of evacuation behaviour, and could allow dynamic changes in weather conditions to be input to determine likely changes in the evacuation behaviour as the fire front's movement changes in response to weather and other changes.

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