

Traffic modeling for wildland-urban interface fire evacuation

Intini, Paolo; Ronchi, Enrico; Gwynne, Steven; Pel, Adam

DOI

[10.1061/JTEPBS.0000221](https://doi.org/10.1061/JTEPBS.0000221)

Publication date

2019

Document Version

Accepted author manuscript

Published in

Journal of Transportation Engineering Part A: Systems

Citation (APA)

Intini, P., Ronchi, E., Gwynne, S., & Pel, A. (2019). Traffic modeling for wildland-urban interface fire evacuation. *Journal of Transportation Engineering Part A: Systems*, 145(3), 1-15. Article 04019002. <https://doi.org/10.1061/JTEPBS.0000221>

Important note

To cite this publication, please use the final published version (if applicable). Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.

TRAFFIC MODELLING FOR WILDLAND-URBAN INTERFACE FIRE EVACUATION

Paolo Intini*, Ph.D.

Post-doctoral Research Fellow

Technical University of Bari/Lund University

4 via Orabona, Bari, 70100 (Italy)/Box 118, 221 00 Lund (Sweden)

Tel: +390805963389; Email: paolo.intini@poliba.it; ORCID: 0000-0003-1696-8131.

Enrico Ronchi, Ph.D.

Senior Lecturer

Lund University

Box 118, 221 00 Lund (Sweden)

Tel: +462227200; Email: enrico.ronchi@brand.lth.se

Steven Gwynne, Ph.D.

Senior Research Officer

National Research Council Canada

Montreal Road Building M-59, Room 225, Ottawa, Ontario K1A 0R6 (Canada)

Email: steven.gwynne@nrc-cnrc.gc.ca

Adam Pel, Ph.D.

Associate Professor

Delft University of Technology

P.O. Box 5048, 2600 GA Delft (Netherlands)

Email: a.j.pel@tudelft.nl

*Corresponding author

ABSTRACT

Several traffic modelling tools are currently available for evacuation planning and real-time decision support during emergencies. In this article, we review potential traffic modelling approaches in the context of Wildland-Urban-Interface (WUI) fire evacuation applications. An overview of existing modelling approaches and features are evaluated pertaining to: fire-related, spatial and demographic factors, intended application (planning or decision support), and temporal issues. This systematic review shows the importance of the following modelling approaches: dynamic modelling structures, considering behavioural variability and en-route choice; activity-based models for short-notice evacuation planning; macroscopic traffic simulation for real-time evacuation management. Subsequently, the modelling features of twenty-three traffic models and applications currently available in practice and the literature are reviewed and matched with the benchmark features identified for WUI fire applications. Based on this review analysis, recommendations are made for developing traffic models specifically applicable to WUI fire evacuation, including possible integrations with wildfire and pedestrian models.

INTRODUCTION

1 Fires propagating near urban areas may often result in vehicle evacuations (Westhaver, 2017). Traffic modelling
2 may be important for both evacuation planning and real-time emergency management (Chiu et al., 2007; Wolshon
3 and Marchive, 2007). The present work focuses on traffic evacuation modelling in case of fires in
4 Wildland-Urban-Interfaces (WUI).

5 A wildfire is '*an unplanned and uncontrolled fire spreading through vegetative fuels, including any structures or*
6 *other improvements thereon*' (NFPA, 2013). If it develops where structures and vegetation merge in a wildfire-prone
7 environment, this is generally called WUI fire (Mell et al., 2010). WUI fires may result in severe consequences for
8 the population (Mell et al., 2010; Caton et al., 2016), at a worldwide level (Manzello et al., 2017). Climate changes
9 (Jolly et al., 2015) and population growth near/in WUI areas may increase the WUI fires frequency and severity
10 (Paveglio et al., 2015).

11 However, only a limited number of traffic evacuation modelling studies addresses WUI fires, compared to other
12 hazards (Kolen and Helsloot, 2012; Lindell and Prater, 2007; Wilmot and Mei, 2004; Wolshon, 2001). These studies
13 mainly adopt trigger modelling (Cova, 2005; Li et al., 2015): wildfire spread models are used to define the timing of
14 the evacuation order rather than its consequences. Trigger models can be dynamically integrated with evacuation
15 traffic simulation, such as agent-based simulation (Beloglazov et al., 2016; Scerri et al., 2010) for wildfires or WUI
16 fires (Dennison et al., 2007). These models could be helpful for evacuation planning (Wolshon and Marchive, 2007)
17 and/or real-time decision support, in particular for fire-prone communities with several households and few
18 evacuation routes (Cova et al., 2013).

19 Given gaps in existing understanding, a multi-disciplinary research project has been initiated to specify a simulation
20 system aimed at quantifying the WUI fire evacuation performances, considering pedestrian, fire and traffic
21 components (Ronchi et al., 2017). This study presents the traffic component, starting from the review of existing
22 WUI fire evacuation traffic modelling approaches. Factors potentially influencing the WUI fire evacuation process
23 (Stewart et al., 2017) are then considered. For instance, communities including WUIs can be very different in terms
24 of dimensions and population density (Wolshon and Marchive, 2007): the larger the affected area, the likely greater
25 are evacuating traffic volumes (Southworth, 1991). Moreover, the area actually affected by the fire over time and the

26 traffic evacuation process itself depend on many factors such as fire type, vegetation, topography, environment (fuel
27 load, wind, temperature, etc.) (Wolshon and Marchive, 2007).

28 As a result of the review conducted, the suitability of different modelling approaches is proposed for different WUI
29 fire evacuation scenarios and applications. Conclusions concerning WUI fire traffic evacuation modelling needs are
30 then drawn, also highlighting current research gaps.

31 **REVIEW STUDY: METHODS AND GOALS**

32 In this section, the methods used for the review conducted and the goals of the review study are presented, starting
33 from the reasons behind the conception of this article, and its contribution to the state of the art.

34

35 **Contribution to the state of the art**

36 Several review articles on evacuation modelling are available, which adopt various perspectives and/or with specific
37 focus on different types of incidents. Several general review articles outlined methodologies and frameworks which
38 can be used in different scenarios (e.g. Gwynne et al., 1999; Alsnih and Stopher, 2004,a; Pel et al. 2012). Several
39 review articles regarding hurricane evacuation studies exist typically addressing traffic evacuation (Wilmot and Mei,
40 2004; Wolshon et al., 2005,a,b; Huang et al., 2016). There were previously no systematic reviews of traffic
41 evacuation modelling concepts, strategies and methodologies in case of wildfires/WUI fires to the knowledge of the
42 authors (Ronchi et al., 2017). This is in contrast with other areas of fire evacuation modelling, such as in
43 underground infrastructures (Fridolf et al., 2013); buildings (Kuligowski et al., 2005; Kobes et al., 2010), and
44 high-rise buildings (Ronchi and Nilsson, 2013), where several reviews exist.

45 The contribution of this article is not just to produce a systematic review of previous research in the field of traffic
46 evacuation modelling in case of wildfires/WUI fires, but may also help practitioners and developers of WUI-specific
47 traffic evacuation models/applications, who may directly consider the discussion concerning the most suitable
48 approach to be used for each modelling step. For this aim, a consistent review methodology was used, explained as
49 follows.

50

51 **General review methodology**

52 The framework used for the review is a four-steps modelling approach, generally applied to transport modelling
53 (Cascetta, 2009; Ortuzar and Willumsen, 2011) but also to evacuation (Murray-Tuite and Wolshon, 2013; Pel et al.,
54 2012) and specifically wildfires (de Araujo et al., 2011).

55 The review of existing traffic modelling approaches conducted here was then split into the two main stages
56 composing the four-steps approach: travel demand modelling and traffic assignment. These two stages are then
57 further divided into several steps. The modelling approaches adopted for each step can be different or integrated
58 within a single stage (e.g. the traffic assignment may depend on the travel demand stage, Cascetta, 2009). However,
59 in case of WUI fire evacuation, they could be considered independent (especially the Generation step), since the
60 evacuation decision is generally not significantly affected by roads blocked by fire propagation (Alsnih et al.,
61 2004,b). Moreover, although several transport modes may be used, the main focus of the review is on road traffic
62 evacuation.

63 For each modelling stage/step, the most appropriate approaches to be used for a WUI fire traffic evacuation model
64 have been identified. The identification of the most suitable approaches is based on existing literature concerning
65 wildfire-related traffic evacuation and on a review of large-scale WUI fires (Ronchi et al., 2017). The recommended
66 modelling features are then compared against existing traffic models.

67

68 **Transferability of results from other hazards and time scales to the WUI fire evacuation case**

69 The review conducted covered areas where WUI fire evacuation-specific literature was scarce or even unavailable.
70 In this case, studies for other comparable hazards were considered, where the findings may still be relevant for WUI
71 fires. For example, there are several studies in the field of hurricane evacuation modelling, which may be relevant,
72 since hurricanes may be similar to wildfires in terms of both time and spatial scales compared to other types of
73 disasters (see Wang et al., 2016). Therefore, hurricane evacuation studies may act as sources, due to the large
74 quantity of real physical and behavioural data collected (see e.g. the early study by Baker, 1979, 1991; or Hasan et
75 al., 2010). Some of these results may be relevant for WUI fire evacuations too, while others may highlight the

76 uniqueness of the considered hazard and the difficult transferability of modelling approaches between different
77 hazards (Baker, 1991).

78 The transferability of evacuation modeling research outputs from the case of short-notice crisis due to generic
79 hazards to the case of long-notice disasters was also considered, if relevant. In fact, research studies in short-notice
80 crises (e.g. fire evacuation in buildings, see Kobes et al., 2010; and transportation systems, see Fridolf et al., 2013,
81 such as metros and tunnels) provides a series of theories that can be useful to explain behaviours in disasters with
82 more notice such as WUI fires. These studies were discussed in the appropriate sections, according to the specific
83 simulation step of evacuees' behaviour to which they are referred.

84

85 **Aims of the review study**

86 The systematic review of previous research is structured according to the four-steps of the traffic modelling
87 procedure, with the aim of presenting the most suitable approaches and features for WUI fire evacuation for each
88 modelling step. Secondly, the identified benchmark modelling approaches and features were examined in some of
89 the most widespread traffic modelling applications, to test their potential applicability for a WUI fire evacuation
90 scenario.

91 The strategy used for this review study has different goals, and is as follows:

- 92 • Define the state-of-the art of the research in the field of traffic modelling evacuation in case of WUI fires;
- 93 • Suggest possible practical modelling solutions (i.e. approach to be used for a specific modelling problem
94 and/or factors to be considered) for traffic modelers who should simulate WUI fire evacuation scenarios;
- 95 • Provide a possible benchmark structure for the development of a future integrated traffic modelling
96 framework specifically dedicated to WUI fires, based on the most suitable approaches and features
97 highlighted for each modelling step;
- 98 • Provide an overview of some existing software applications/modelling structures, in respect to their
99 applicability to WUI fire evacuation scenarios, useful for addressing both researchers and practitioners to
100 future studies/applications including simulations in this field.

101 Hence, this study may be beneficial to researchers and practitioners in: 1) the short-term dissemination of

102 information and practical solutions for different modelling stages and scenarios; 2) the long-term period and the
103 further development of modelling tools and simulation studies specifically dedicated to the considered hazard.

104

105 **TRAFFIC MODELLING APPROACHES FOR WUI FIRE EVACUATION**

106 Existing traffic modelling approaches for WUI fire evacuation scenarios are presented in Figure 1. Each approach
107 adopted for each stage/step is discussed as follows.

108

109 **Travel demand modelling for WUI fire evacuation**

110 An initial travel demand modelling choice is between trip modelling approaches (Pel, 2017): trip-based or
111 activity-based. In the trip-based approach (Cascetta, 2009; Ortuzar and Willumsen, 2011), the reference unit is the
112 *trip*: Origin *O* - Destination *D*. The total demand of evacuation (one-way) trips is estimated at the aggregated level.
113 It can be differentiated according to: population characteristics (e.g., considering vehicle availability, experience
114 with fires), purpose (e.g., reaching shelters, departing, firefighting, rescuing), time period (based on the evacuation
115 response over time and the hazard propagation), and available transport modes. The activity-based approach
116 (Cascetta, 2009; Bowman and Ben-Akiva, 2001) consists of estimating the travel demand (number of trips) by
117 modelling individual users' activities. The Origin-(final) Destination trip evolves into a tour: a chain of trips
118 including more Origins and Destinations.

119 Typical trip chains for WUI fire evacuations are presented in Figure 2. Through this approach, the possibility of
120 having joined trips with the same transport mode by individuals of the same household, is explicitly modelled.
121 Firefighting/rescuing trips can also be explicitly considered. Depending on the desired level of analysis and
122 modelling, the estimated tours may either be kept as such or can be converted into multiple trips (and conventional
123 OD matrices).

124 The two approaches mainly differ in modelling intermediate trips (Murray-Tuite and Wolshon, 2013). Since
125 households are likely to evacuate as a unit (e.g. parents collect children before evacuating, (Stern, 1989)), then
126 modelling intermediate trips may be crucial in no-notice evacuations (Murray-Tuite and Mahmassani, 2004; Van der

127 Gun et al., 2016). If they are ignored, the total trips could be underestimated and time estimates can become
128 unreliable (Murray-Tuite and Mahmassani, 2004; Pel et al., 2010,b; Van der Gun et al., 2016; Liu et al., 2011). In
129 contrast, in case of long evacuation processes, the impact of intermediate trips may be negligible and a trip-based
130 approach may still be suitable due to the complexity of activity models (Murray-Tuite and Wolshon, 2013; Pel et al.,
131 2012).

132 Hence, all scenarios including factors fostering an immediate evacuation process could make an activity-based
133 approach preferable. Among fire-related factors, fast fire spread rates may drastically reduce the available time,
134 leading to quicker evacuation. The WUI area among the interested area (and its topography) may affect the fire
135 propagation. Moreover, in sparsely populated areas, the evacuation can be slower (Murray-Tuite and Wolshon,
136 2013). The more appropriate approach will result from the assessment of possible trade-offs between computational
137 issues and needed accuracy for a given area.

138

139 *Modelling trip generation in WUI fire evacuation*

140 Trip generation concerns the decision: stay/evacuate (Murray-Tuite and Wolshon, 2013), related to the evacuation
141 demand estimation (towards safe places inside/outside the area (Cova et al., 2011)). The binary choice evacuate/stay
142 can be modelled through random utility models or descriptive methods (Barcelò, 2010). However, the *stay* decision
143 may involve some trips anyway (e.g. collecting family members, re-entry), potentially estimated by activity models.

144 Random utility models can simulate the departure decision, mainly adopting logit structures. They estimate the
145 probability to evacuate among n alternative options. The utility of the evacuation option depends on several factors
146 such as experience with evacuation, fear of looting (Murray-Tuite and Wolshon, 2013), type of evacuation
147 instructions (voluntary/mandatory) (Mozumder et al., 2008). Moreover, social networks may condition relationships
148 between evacuees and then their behaviour (Sadri et al., 2017,a). Hence, the influence of social networks may be
149 considered as another factor in the evacuation decision-making process. This influence was noted in the case of
150 hurricane evacuations and may also be applicable in WUI fire evacuations. Besides of simple logit models, other
151 research approaches may be used. For example, a latent class logit model may be employed, consisting of an ordered
152 logit approach with demand and event inputs (latent class) to predict risk perception, and supply inputs to predict

153 evacuation choices (Urata and Pel, 2017), being inspired by empirical and socio-psychological evacuation studies.
154 Mixed logit structures may also be used, that address different levels of characteristics of individuals, households,
155 and social networks (Sadri et al., 2017,b). Descriptive methods, such as cross-classification, can also be employed to
156 estimate evacuation participation rates (Murray-Tuite and Wolshon, 2013). Cross-classification methods consist of
157 different steps: 1) stratifying the population into layers based on different variables, 2) assigning the number of trips
158 to each combination of layers based on estimates (e.g. surveys) (Post, 2000). More elaborate descriptive approaches
159 involve regression analyses (Ortuzar and Willumsen, 2011), conducted on variables similar to those suggested for
160 logit models, used for estimating the total number of trips from each origin (transportation zone), for different
161 purposes and time periods.

162 Departure times can be estimated through empirical or activity models, in relation to the general structure of the
163 travel demand: trip or activity-based. Empirical formulations (i.e. sigmoid or S-curve) can be used for representing
164 the evolution of the percentage of evacuees from a given origin over time (Pel et al., 2012). Its application to WUI
165 fires depends on factors such as % of WUI area, population, density, size of affected area, fire propagation speed.
166 Moreover, a population sub-set may spontaneously leave before warnings (Murray-Tuite and Wolshon, 2013).
167 Depending on the intensity and propagation speed of the WUI fire, evacuations may progress in a comparable
168 manner to other hazards. For example, in hurricane evacuations, household location, type of destinations,
169 socio-economic variables, notice of evacuation and decision-making characteristics of households were found to be
170 related to the time at which people commenced evacuation (Hasan et al., 2013). Even if these factors are also
171 equivalently influential in WUI fire evacuations, the associated times are likely to be different. In fact, hurricane
172 evacuations may last for days (four days in the case study presented by Hasan et al., 2013), and a significant
173 percentage of evacuees may still decide to evacuate very close in time to the hurricane landfall, or wait even more
174 than 24 hours from the evacuation decision to the actual evacuation, according to different variables (Sadri et al.,
175 2013,b). These conditions may be different from typical WUI fire incidents.

176 There are a number of existing theories and models of evacuee behavior that might also be instructive of WUI
177 evacuation, mainly describing human behaviour in fires (see e.g. Wood, 1972; Bickman et al., 1977; Bryan and
178 Bryan, 1977; Green, 1980; Sime, 1983; Proulx, 1993; Brennan, 1995; Brennan, 1996; Brennan, 1999; Groner, 1996;
179 Yoshimura, 2000; Bruck, 2001; Santos and Aguirre, 2005). For instance, Canter's model (Canter et al., 1980) could

180 be applied to the WUI fires as well. This model describes a behavioural sequence of actions, namely 1)
181 interpretation, 2) preparation and 3) action. The potential actions which may take place increase in variety as the
182 behavioural sequences unfold. Such a framework might be applicable to WUI fires as it relates to the decisions that
183 person makes from the early stage of a fire and the uncertainties associated with them, whilst needing to place this
184 decision in context.

185 The number of trips for each time interval is estimated by multiplying the population, the participation percentage
186 obtained from the binary logit (stay/evacuate), and the specific time-interval departure percentage from the S-curve.
187 Another solution could be an integrated approach, with a binary logit sequentially repeated over time, considering
188 the evolution of the response and the utility of evacuating (Pel et al., 2012). This could allow to dynamically
189 consider the fire propagation and its effect on users' choices (not relying on S-curves).

190 A crucial factor in determining the number and the nature of trips in a given time period (before the actual
191 evacuation trip towards the safe place) can be the location of people at the warning dissemination, or hazard
192 perception (Van der Gun et al., 2016). This information may be achieved through activity-based population models,
193 providing daily schedule patterns of households (Van der Gun et al., 2016; Castiglione et al., 2015). Specific activity
194 patterns and trip chains for evacuation can be generated using logit models or computational models such as
195 decision trees (Murray-Tuite and Mahmassani, 2004; Arentze and Timmermans, 2000; Timmermans et al., 2002).
196 For example, comprehensive agent-based models covering aspects of travel demand (from trip generation to modal
197 split) have been developed for hurricane evacuations (Yin et al., 2014; Ukkusuri et al., 2016). They may generate
198 household activity-based travel patterns, by considering hurricane-related factors. Moreover, a traffic simulation
199 module based on the same strategy is integrated in the model proposed by Ukkusuri et al. (2016 as well).

200 In respect to the evacuation demand modelling, logit models may be preferable given their ability to capture the
201 variables affecting the departure choice (Pel et al., 2012; Fu and Wilmot, 2007). Several studies (Murray-Tuite and
202 Wolshon, 2013; Alsnih et al., 2004,b; Mozumder et al., 2008; Fischer et al., 1995) investigated the factors suitable
203 for modelling the wildfire evacuation decision. In particular, the calibration of descriptive methods may require
204 large data samples, especially if several layers are considered (Ortuzar and Willumsen, 2011). Hence, logit models
205 could be preferable for largely populated and large-sized areas affected by the fire (especially for high WUI
206 percentages, with more potentially endangered people). In this case, population density and fire propagation speed

207 may not affect the model choice. However, the fire propagation may influence the risk perceived by residents
208 (Mozumder et al., 2008). Since descriptive methods are easier to implement, they could be preferred for real-time
209 applications, for very dense and largely populated areas, high WUI percentages and adverse fire factors.

210

211 *Modelling trip distribution in WUI fire evacuation*

212 The final destinations of evacuation trips are safe places: households (if starting the trip from somewhere else),
213 houses of relatives/friends, hotels/motels, official shelters/refuges, etc. (Cuellar et al., 2009). However, depending on
214 evacuation, hazard types, fire propagation (environmental and fire factors); the target of evacuation modelling may
215 be immediately reach the first possible safe place, rather than desired final destinations (Lindell and Prater, 2007).
216 Two different modelling strategies can be used for the distribution step, namely descriptive and random utility
217 methods.

218 Among the descriptive methods, gravity models are mostly used for evacuation (Pel et al., 2012; Murray-Tuite and
219 Mahmassani, 2004), and specifically wildfires (de Araujo et al., 2011). These models consider the estimated trips
220 produced from a given origin, and the trips attracted by a given destination. They also include a constant (Cascetta,
221 2009) and a disutility function associated with O-D travel costs. The attraction can be estimated considering several
222 variables (e.g. population, number of hotels) (Cheng, 2007). The variables used for estimating the travel disutility
223 generally include travel time, distance, and safety or congestion-related variables. Travel distance was successfully
224 used in previous evacuation studies to calibrate gravity models (Cheng, 2007; Cheng et al., 2008). Additional
225 variables such as predicted threat, network conditions and accommodation availability can be also used (de Araujo et
226 al., 2011).

227 Random utility models, such as multinomial logit models, are usually employed at the distribution stage to simulate
228 the choice of destinations (shelters, safe places), according to their associated utility (Cascetta, 2009). Utilities can
229 be estimated based on travel-related variables, similarly to descriptive methods.

230 Nested logit models can be used to simulate hierarchical choices. The model firstly simulates the evacuees' selection
231 between different types of destinations, and hereafter, for each destination type (lower level nest, Figure 3), further
232 choices between transportation zones (or households/structures). This strategy was used by Mesa-Arango et al.

233 (2012) to model destination choices in case of hurricane evacuations. They explicitly considered individual
234 destinations such as public shelters, workplaces, churches and other shelters different than friends/relatives' houses
235 or hotels (as they accounted for 15 % of total destinations). This may be applicable as well for WUI fire scenarios if
236 the shelter-in-place decision is an option considered for the evacuation process.

237 The utilities related to the highest choice level (between different groups of safe places) can be modelled as a
238 function of hazard, severity, income, evacuation size and types, age, ethnicity, education, income, pet ownership
239 (Murray-Tuite and Wolshon, 2013; Whitehead et al., 2000). The utilities related to the lower level choices (between
240 alternative zones/units for the same group of safe places) can be modelled as a function of variables such as travel
241 distance, number of hotels, proximity to freeway (Cheng et al., 2008). However, since there could be several
242 alternatives, multinomial logit models require a simplification in the alternatives.

243 Similar nested structures can also be used to model evacuation trip chains in the activity-based approach. The first
244 choice is between stay or evacuate and the conditional choices represent further travels to intermediate and final
245 destinations (e.g. for collecting people, re-entry, relocating to another shelter). Nested structures can also be used to
246 simulate a higher departure time choice and a lower destination choice (Cheng et al., 2009).

247 In a no-notice (or very short-notice) evacuation, in which activity models may be particularly suitable (Murray-Tuite
248 and Mahmassani, 2004), information about final destinations may be unimportant or irrelevant, given the immediate
249 priority to leave the area (Lindell and Prater, 2007). In fact, people may only have the urgency of escaping from the
250 danger. In an average working day, the behavior may be governed by familiar choices (Colonna et al., 2016; Intini et
251 al., 2018) and descriptive/utility models may be applicable. A mixed logit model was used by Sadri et al. (2013)a,
252 for describing routing choices in hurricane evacuations including household and evacuation-related variables. In
253 no-notice evacuations instead, evacuees may likely be unfamiliar with the emergency conditions, having the driving
254 parameters, such as speed or response time, affected (Colonna et al., 2016; Yanko and Spalek, 2014). Descriptive or
255 random utility methods may be suitable for real-time decision support (especially descriptive methods,
256 computationally less demanding).

257

258 *Modelling modal split in WUI fire evacuation*

259 The main transport modes in WUI fire evacuations are vehicles on roads. In special circumstances, evacuation has
260 also been conducted via sea and air (Ronchi et al., 2017). Public transport may be the only option for specific groups
261 such as people in hospitals or jails.

262 The main approaches suitable for WUI fire evacuation modelling are descriptive, random utility and activity models.
263 Descriptive models estimate the probability of choosing a mode in a given time period, given its generalized cost.
264 Random utility models estimate the probability to use a given mode in different manners, e.g., through
265 multinomial/nested logit models (see Figure 3) if the elementary transport modes are previously grouped into higher
266 level categories (walk, private, public transport). The mode-associated utilities can depend on the same factors for
267 all transportation modes (travel times) or specific to a given mode, such as vehicles per adult per family (for cars,
268 motorcycles, bicycles); transfers (buses); age (e.g., cars, motorcycles). A nested structure was used by Sadri et al.
269 (2014) to model mode choices in the case of a hypothetical major hurricane evacuation. They found that special
270 evacuation buses may be a consistent choice among evacuees - a finding which may be useful should it be
271 transferrable to WUI fire evacuations.

272 Random utility models simulating the mode choice can also be nested with other travel demand steps (e.g.
273 destination/modes). Nested structures of random utility models could be used as well for the activity-based
274 approach. In this case, trip modal split is conditional to the mode chosen for the tour. However, other intermediate
275 choices should be modelled, concerning departure times, intermediate destinations and time windows of single trips,
276 which may complicate this approach. Moreover, the mode may not be the last choice in the sequence (Castiglione et
277 al., 2015). In fact, evacuees may not have private vehicles, yielding the destination conditional to the mode choice
278 (e.g. bus).

279 Activity models mainly use microsimulation for individual mode choices, and probabilistic approaches, e.g., Monte
280 Carlo methods (Castiglione et al., 2015). Choices are predicted considering explanatory variables for individuals
281 (and not for a population, as usual), but several simulation repetitions are needed to achieve convergence. The
282 information needed for developing activity models could be obtained through post-WUI fire evacuation surveys.

283 The choice of the most appropriate model is influenced by the need for considering multi-modality (Van der Gun et
284 al., 2016). In fact, both private and public modes of transport might be used and the fire (and its evolution over time)

285 may dynamically influence the number/type of routes available. However, the modal split under emergency
286 evacuation has not been investigated in depth in previous studies, focused on private transport (Murray-Tuite and
287 Wolshon, 2013; Pel et al., 2012; Wu et al., 2012).

288 In sum, activity models may be applied only given the availability of sufficient data. Descriptive and random utility
289 methods could be used for both evacuation planning and real-time management, mainly due to their lower
290 computational needs. An activity-based approach can still be pursued, by adapting random utility models through
291 nested structures. The modal split sub-models of the descriptive and random utility approaches should be possibly
292 coupled with wildfire models (similarly to trip distribution), taking into account the progressive modal elimination
293 due to the fire spread.

294

295 **Traffic assignment for WUI fire evacuation**

296 Different levels of refinement and strategies can be used for traffic assignment in WUI fire evacuation scenarios.
297 These include a strategy for modelling the chosen routes, tools for simulating the network flows, and interactions
298 between evacuees.

299 The possibility of considering traffic variations over time (static or dynamic approach) is another important
300 modelling question. A static assignment will generally rely on loading a typical peak-hour OD matrix into the
301 network. In a dynamic approach, the traffic loading and users' route choices are variable over time instead.

302 Previous studies argued that the static approach is inappropriate for modelling traffic evacuations (Pel et al., 2012;
303 Van der Gun et al., 2016). In fact, the conditions could be different during an emergency than a typical working day:
304 evacuees may be disoriented, unfamiliar and have incomplete information (Pel et al., 2012).

305 Moreover, the possible dynamic WUI fire evolution and its subsequent impact on the network (e.g. inaccessible link
306 or with reduced capacity due to the smoke/fire), on traffic assignment and departure time distribution should be
307 necessarily considered. In case of WUI fire evacuations, the variability of the traffic assignment characteristics
308 among each base time unit of the simulation should be taken into account. The route chosen by drivers may be
309 influenced by the evolution of the traffic flow over time indeed. The dynamic assignment considering the variability

310 of the traffic parameters in the simulation time unit is henceforth referred to as ‘Dynamic Traffic Assignment’
311 (DTA). A static approach may still be applicable for some objectives, such as obtaining a rough estimate of the total
312 network clearance, by loading the whole estimated evacuation trips on the network.

313

314 *Modelling route choice*

315 In route choice-related evacuation research, people are deemed to take different decisions in similar conditions:
316 concept of behavioural uncertainty (Ronchi et al., 2014). This is reflected in the use of deterministic or stochastic
317 approaches for pre-trip decisions in a user equilibrium approach. As the algorithms relevant for WUI fires are
318 mostly dynamic (i.e., Dynamic Traffic Assignment, DTA), deemed as appropriate for general evacuation modelling
319 (Pel et al., 2012), the corresponding alternative route choice dynamic modelling approaches are summarized in
320 Table 1.

321 Uncongested assignment algorithms are sub-cases of the congested case, excluding the iterative update of flows and
322 costs. Hence, only the assignment for congested networks is taken into account here. Dynamic deterministic and
323 stochastic approaches are then reviewed. The deterministic approach allows the consequences of a specific set of
324 behaviours to be established for ensuring a specific response; while stochastic approaches establish both the likely
325 response and their consequences with less control over specific responses enacted.

326 **Deterministic approach: DUE versus DSO.** The techniques for solving the DTA problem through a deterministic
327 approach reach the equilibrium through iterations. Two equilibrium conditions are usually considered (Wardrop,
328 1952; Ortuzar and Willumsen, 2011):

- 329 • Dynamic User Equilibrium (DUE). For evacuation this entails that *in networks in which congestion varies*
330 *over time, at the equilibrium condition, at each instant, the generalised costs on all routes used by the*
331 *evacuees are equal and less than those of any unused alternative route.* This may be generalized for
332 considering different departure times (Ortuzar and Willumsen, 2011).
- 333 • Dynamic System Optimum (DSO): For evacuation this entails that at the equilibrium condition, evacuees
334 follow routes such that the total sum of generalised costs as experienced by all evacuees is minimal.

335 **Stochastic approach: Dynamic SUE.** Stochastic route choice is only based on the UE approach. Route choice is
336 modelled through random utility models (Ben-Akiva and Lehman, 1985), accounting for behavioural variability,
337 such as multinomial/nested mixed logit (Ortuzar and Willumsen, 2011), probit models (Cascetta, 2009). Logit
338 functions can be adapted for considering the overlapping of alternative routes (Ben-Akiva and Bierlaire, 1999).
339 Typically, the utility of routes depends on their cost, mostly based on travel time, even if tolls could mostly be
340 disregarded during evacuations. Stochastic algorithms for performing the network loading under the UE condition
341 are generally adapted from the deterministic case, achieving convergence as well (Sheffi, 1985).

342 Additional to these DTA variants, the dynamic recourse assignment can take into account when travellers instead
343 rely on actions en-route in response to unfolding traffic conditions (Peeta and Hsu, 2009; Pel et al., 2009). Route
344 choice could then be rooted in pre-trip decisions, but the ultimate route decisions are simulated en-route. En-route
345 decisions should take into account the behavioural variability in adjusting the initial choices, by reacting in real-time
346 to unexpected situations (threat evolution). Hence, for en-route decisions (and the hybrid route choice), stochastic
347 route choice modelling is preferred (Pel et al., 2010,a).

348 From a modelling perspective, an optimal destination can be set individually or globally before the trip starts
349 (pre-trip choice): designated shelters, house of friends/relatives, hotel/motel. Evacuees will tend to reach them
350 through familiar routes, potentially preferring motorways (Chiu and Mirchandani, 2008). Familiar routes were also
351 preferred to routes recommended by the officials in hurricane evacuations (Sadri et al., 2013,a). However, those
352 routes may be affected by the threat (e.g. smoke or broken links). En-route decisions can lead to switching routes
353 through reactive behaviour. Hence, a hybrid (both pre- and en-route) choice process is generally recommended for
354 WUI fire evacuations, similarly to what is recommended for other scenarios (Pel et al., 2012). A stochastic route
355 selection model and the related assignment algorithm (Dynamic System Recourse Assignment, possibly rooted in
356 pre-trip (UE) route decisions) should be preferred, since it includes behavioural variability of en-route choices.

357 Some theoretical basis for modeling complex route choice processes can be found in the literature, by also
358 transferring research from other hazards or generic time scales. The theory of affiliation (Sime, 1984) can be used to
359 discuss the misconception that people should assume the use of the shortest route when representing emergency
360 evacuations. This theory suggests that people are more likely instead to move towards the familiar, i.e. people or
361 places that they know. A person's role can also be significant (as discussed by the role-rule model, see Sime, 1985),

362 as people who are familiar with a certain evacuation route may serve as leaders for others. This is linked to the
363 process of taking decisions in groups during WUI fire evacuation. These decisions can be explained with social
364 influence studies performed for short-term crises (e.g. building fires) (Deutsch and Gerard, 1955; Lovreglio et al.,
365 2015). Social influence can be divided into normative social influence (the influence to match the expectations of
366 others, which in this case may be the decision to leave the property made by a neighbor or the routes chosen by other
367 decision makers) and informational social influence (the influence to accept information obtained from others about
368 the current situation).

369 On the other hand, the need for a deterministic approach may arise while using system optimization (SO)
370 techniques, aiming at achieving the minimum cost for road users. In a planning stage, a SO approach will suggest to
371 authorities the optimal routes to be prescribed (e.g. through intelligent transport systems) in order to minimize total
372 travel times, and then the network clearance time (Sbayti and Mahmassani, 2006). Population and density may play
373 a prominent role in selecting a SO approach for WUI fire evacuations. In fact, the simulation of evacuation
374 management through real-time instructions can be obtained with a SO approach, to study reduced congestion during
375 evacuation in large and densely populated cities. However, in the simulation of mandatory evacuation orders through
376 the SO approach, with routes 'prescribed' by the authorities based on the evacuation planning analysis, two matters
377 should be highlighted:

- 378 1) Evacuees may not follow the instructions (non-compliance);
- 379 2) The true evolution of WUI fires can be faster or different compared to the simulated scenario.

380 Hence, for real-time evacuation management, even if the SO approach was used in a planning stage, real-time
381 en-route decisions should be considered. They may be based on the actual network conditions related to fire
382 propagation and size of the affected area. However, the compliance rate of evacuees could be simulated in advance
383 while designing evacuation plans (Pel et al., 2010,a), by optimizing evacuation plans accordingly (Pel et al., 2010,c;
384 Fu et al., 2015). Adaptive real-time frameworks for evacuation management can be used as well (Liu et al., 2011).

385

386 *The impact of background traffic*

387 Background traffic (including normal activities, shadow evacuation (Murray-Tuite and Wolshon, 2013) and
388 rescue/emergency services) (Van der Gun et al., 2016) should be considered in traffic evacuation modelling.
389 Otherwise, congestion may be underestimated and network capacity overestimated, as background traffic can
390 amount to a substantial part of the overall traffic and cause crossing flow conflicts (i.e. orthogonal and counter
391 flows).

392 Background traffic can be considered in two ways: by loading an additional OD matrix on the network, or using an
393 activity-based approach. The first approach relies on OD matrices disaggregated into time intervals, iteratively
394 assigned to the network (Wu et al., 1998). The main evacuation OD matrix represents the traffic evacuating from the
395 threatened area in a given period. However, another matrix may be used accounting for the background traffic, such
396 as an average or peak-hour OD matrix (worst possible case, see (de Araujo et al., 2011) for wildfire evacuation). In
397 the latter case, this share could be predominant among the components of the background traffic, and then include
398 the others. More sophisticated results can be obtained through activity models, used to identify the household travel
399 patterns in a normal working day (Van der Gun et al., 2016).

400 Some of the factors considered for WUI fire evacuations may lead to relax or strengthen the need for representing
401 background traffic. Quicker evacuations would be associated with a higher importance of the background traffic. In
402 fact, in longer evacuations (e.g. lasting > 1 day), the effect of background traffic may be diluted over time, thus
403 being important only at the beginning. However, this may be not applicable if evacuations are completed within one
404 day or faster (Hardy and Wunderlich, 2009).

405 Population may be influential since a highly populated zone will more likely be associated with a higher share of
406 daily travellers composing the background traffic. The size of the area affected can be important for determining the
407 evacuation speed. Moreover, the larger is the area affected by the fire, the larger could likely be the shadow
408 evacuation traffic coming from other zones endangered and crossing the area under study (see Dow and Cutter,
409 1998, for hurricanes; and Lamb et al., 2011, for floods). This also depends on the network configuration and the
410 position of the area in the region.

411 The modelling approach for representing background traffic largely depends on the travel demand approach chosen.
412 If an activity-based approach was selected, then it can be used for assessing the background traffic, thus likely being
413 more accurate. Otherwise, the estimate may be based on a worst-case scenario through peak OD matrices.

414

415 *Traffic simulation modelling*

416 Different simulation techniques can be used for network loading, all potentially suitable for WUI fire evacuations.
417 They can be divided into different categories according to: a) the scale of flow representation (not necessarily
418 restricted by the scale at which the travel demand was computed (Van der Gun et al., 2016b)), b) the functions
419 relating traffic flows to travel times (and costs). The three existing methods are macroscopic, microscopic and
420 mesoscopic simulation.

421 **Macroscopic simulation.** In the macroscopic simulation, link flows, speed, density, travel times and capacity are
422 explicitly determined at an aggregated level; while individual route choices are not modelled (Burghout, 2005). For
423 dynamic applications (DTA), inputs are continuously updated, and performance measures recalculated. The WUI
424 fire propagation may cause a broken link, inaccessible by vehicles. The fire-fronts may arise at great distances from
425 each other (i.e. kilometres, because of spot fires due to embers). The fire propagation will also produce smoke,
426 potentially spreading from the fire front at varying distances, and affecting traffic evacuation behaviour. In fact, a
427 link could be either broken or with reduced capacity. Such effects should be considered by updating over time the
428 speed-density relationship for those links.

429 In this regard, a comparison with fog, and adverse weather in general, could be useful. Adverse weather conditions
430 were found to greatly affect the capacity, the speed at capacity and the free flow speed (Rakha et al., 2007).
431 However, the same evidence found for rain was not found for fog, which may have the closest resemblance to
432 smoke regarding visibility. Limited and contradictory research findings have been retrieved in this area, showing
433 speeds and capacity decreasing in foggy conditions (e.g. Hoogendorn et al., 2010) or speeds even increasing (e.g.
434 Snowden et al., 1998).

435 Moreover, drops in capacity may generally be found during emergency evacuations (Sullivan et al., 2010). Most
436 evacuees are unfamiliar with the evacuation driving condition, and this may also lead to speed reductions with

437 respect to the familiar condition (Chiu and Mirchandani, 2008; Charlton and Starkey, 2013). Hence, given the
438 unclear influence of fog on traffic parameters, a reduction in capacity and speeds may be prudentially assumed.

439 **Microscopic simulation.** For the application to WUI fire evacuations, different variables should be modified in the
440 sub-models embedded in microscopic models (car-following, lane changing and gap acceptance models). These may
441 include target speeds, desired spacing, reaction times, aggressiveness; which determine speed differences,
442 accelerations/decelerations, headways, etc. Consistent quantitative estimations of those parameters in emergency
443 conditions are lacking (Tu et al., 2010), even if microscopic simulations are used for evacuation studies (Pel et al.,
444 2012; Cova and Johnson, 2003). The individual microscopic parameters can largely vary during evacuation (Tu et
445 al., 2010; Fries et al., 2016; Hamdar, 2004; Hamdar and Mahmassani, 2008): speeds and speed variance,
446 acceleration/deceleration rates, headways can decrease (to compel others to give way/accelerate); reactions and
447 aggressiveness can increase, lane-changing behaviour could be different, road and traffic signs may be ignored.

448 In case of WUI fires, network links can be divided into broken links, available links, and links partially
449 threat-affected. In dynamic frameworks (such as DTA), coupled with fire spread models (Dennison et al., 2007), the
450 information about links available should be constantly updated. For available links, the individual microscopic
451 parameters should be adapted considering their possible changes under emergency conditions. Considering the
452 comparison between smoke and fog made for the macroscopic simulation, speeds and acceleration rates were found
453 to significantly change in foggy conditions with headways increasing (Hoogendorn et al., 2010).

454 **Mesoscopic simulation.** Since the mesoscopic approach includes both macroscopic (capacity, speed-density
455 relationships) and microscopic features (car-following, interactions); then it includes also both the advantages and
456 disadvantages of the two approaches for WUI fire evacuation modelling. In fact, by explicitly considering capacity
457 and macroscopic traffic flow relationships, it can model the capacity drop in case of smoke for links partially
458 affected by fire; while by considering simplified behavioural models, it could limit the errors made in estimating the
459 microscopic parameters. However, given these advantages, the final result could be affected also by the uncertainties
460 of both approaches in determining the relevant factors for WUI fire evacuation.

461 The recommended level of granularity depends on the spatial and temporal scales considered in WUI fires (see
462 Figure 4). Macroscopic models are by definition not able to represent refined scales, given their level of resolution.

463 For instance, a macroscopic traffic model represents aggregated traffic flows, not describing movements or
464 decision-making of individual evacuees and the subsequent vehicle performances.

465 Temporal and spatial scales can largely affect the simulation approach choice. Macroscopic simulation tools may be
466 preferable for large spatial scales, if a lower level of detail may simplify the computation (e.g. very dense, largely
467 populated area), and for real-time applications. Microscopic tools may be preferable for small spatial scales, if more
468 details are required (e.g. corridor study), mostly for planning, or for not immediate evacuation management.
469 Mesoscopic tools are intermediate between the above two simulation tools. They could be a valid option if a
470 microscopic level of detail is needed, but the study area is large and/or a massive effort to represent its network is
471 required.

472

473 **BENCHMARK MODEL FEATURES AND COMPARISON WITH EXISTING MODELS**

474 Based on the previous discussion on modelling approaches and features, Figure 5 presents a summary of the
475 recommended model features for traffic modelling in case of WUI fire evacuation scenarios, and relates these to a
476 detailed review of existing potential modelling approaches. These recommended model features can be used as a
477 starting point for selecting and evaluating existing modelling tools to be used for the application of WUI fire
478 evacuations as well as future development of dedicated traffic models these applications.

479 For this review analysis, an overview is constructed of twenty-two existing traffic models available in practice and
480 the literature. The aim of this overview is to compare the benchmark characteristics of a WUI fire evacuation model
481 with the tools currently available (Table 2). To this end, a review template was developed in order to systematically
482 assess existing models, their key variables and sub-models, in light of the benchmark characteristics. Models are
483 classified according to their availability (open-source, commercial, academical, governmental); traffic simulation
484 type (macroscopic, microscopic, mesoscopic), possibility to simulate dynamic processes (static or dynamic
485 approach), and a list of variables identified based on the previous review:

- 486 • Demand-side variables (demographic data ‘*DD*’, background traffic ‘*BT*’, travel demand patterns ‘*TDP*’);
- 487 • Supply-side variables (capacity ‘*C*’, speed ‘*S*’, flow direction ‘*FD*’);

- 488 • User-side variables (driving behaviour ‘*DB*’, headway ‘*H*’, acceleration ‘*A*’, reaction time ‘*RT*’, route
489 choice ‘*RC*’);
- 490 • Dynamic variables (traffic management ‘*TM*’, dynamic road infrastructure ‘*DRF*’, adaptive choice
491 behaviour ‘*ACB*’, people compliance ‘*PC*’, real-time instructions ‘*RTI*’).

492 Although many models do not explicitly represent all variables under consideration, a number of them look
493 potentially suitable for WUI fire evacuation. However, no reviewed model was developed specifically for the WUI
494 fire case, considering a direct coupling with other modelling tools (e.g. wildfire models). Two additional models are
495 available on the market which attempt the coupling between wildfire and traffic models: the WUIVAC model
496 (Dennison et al., 2007), in which a simplified traffic modelling approach is coupled with a wildfire model; and the
497 framework by Beloglazov et al. (2016), who implemented the open-source traffic model SUMO, coupled with a fire
498 spread model. Nevertheless, also in these cases, some of the variables affecting evacuation can be implemented
499 mostly implicitly (e.g. no direct impact of smoke on traffic parameters is implemented), thus confirming the lack of
500 a comprehensive modelling tool for WUI fire evacuation.

501

502 **CONCLUSIONS**

503 The existing literature lacks of a dedicated framework for WUI fire traffic evacuation modelling. Based on an
504 extensive review of the existing modelling approaches, an attempt to define the benchmark features of WUI fire
505 traffic evacuation models has been made. Several aspects were addressed, considering a four-steps transport
506 modelling framework and its two main stages: travel demand and traffic assignment. The impact of specific WUI
507 fire-related factors (hazard propagation, size of the area affected), and non-fire-related factors (population,
508 density, % of WUI area) on the choice of appropriate modelling approaches were considered.

509 As a result of the review, a set of suggestions have been provided on suitable modelling approaches to be used for
510 WUI fire evacuation scenarios. These are judgement calls which rely on the type of scenario under consideration and
511 the model applications. Dynamic modelling approaches are preferable since they can take into account behavioural
512 variability and the impact of changes in route availability. Activity-based models should be preferred in case of
513 no-notice or short-notice evacuations at the planning stage. While microscopic traffic simulation tools may give the

514 most detailed results, macroscopic and mesoscopic traffic simulation tools could also be suitable for real-time
515 evacuation management. The need for coupling traffic models with fire spread models in a dynamic framework is
516 evident.

517 Based on the review of existing traffic models conducted, many of them seem able to (at least implicitly) represent
518 many of the variables affecting WUI fire evacuation. Nevertheless, the need for a dedicated dynamic modelling
519 framework able to directly integrate results from other models (e.g. fire/pedestrian models) appears evident for WUI
520 fire evacuations.

521

522 **ACKNOWLEDGEMENTS**

523 This work is funded by the National Institute of Standards and Technology (NIST) (grant: 60NANB16D282) and is
524 part of the project “Modelling requirements for an open-access Multiphysics approach to planning of urban
525 evacuations caused by wildfire disasters”. The authors wish to acknowledge the Fire Protection Research
526 Foundation (FPRF) at the National Fire Protection Association (NFPA) as administrator of the NIST grant. The
527 authors wish to thank Guillermo Rein and Rahul Wadhvani for their contribution on the fire modelling aspects of
528 the project. The authors also wish to acknowledge Amanda Kimball and Daniel Gorham at the FPRF as well as the
529 Technical Panel for their continuous support during the project. Paolo Intini wishes to acknowledge the Lericci
530 Foundation for providing financial support for his research at Lund University. All figures in the paper are provided
531 under Creative Commons license CC BY 4.0. On behalf of all authors, the corresponding author states that there is
532 no conflict of interest.

533 **REFERENCES**

534 Alsnihi, R., & Stopher, P. (2004)a. Review of procedures associated with devising emergency evacuation
535 plans. *Transportation Research Record: Journal of the Transportation Research Board*, (1865), 89-97.

536 Alsnihi, R., Rose, J., & Stopher, P. (2004)b. Dynamic travel demand for emergency evacuation: the case of
537 bushfires. *Institute of Transport Studies Working Paper* (ITS-WP-04-16).

538 Andrews, S. P. (2009). Computer-assisted emergency evacuation planning using TransCAD: Case studies in
539 Western Massachusetts.

540 Arentze, T., & Timmermans, H. (2000). *Albatross: a learning based transportation oriented simulation*
541 *system*. Eirass Eindhoven.

542 Baker, E. J. (1979). Predicting response to hurricane warnings: A reanalysis of data from four studies. *Mass*
543 *emergencies*, 4(1), 9-24.

544 Baker, E. J. (1991). Hurricane evacuation behavior. *International journal of mass emergencies and disasters*,
545 9(2), 287-310.

546 Balakrishna, R., Morgan, D., Yang, Q., & Slavin, H. (2012). Comparison of simulation-based dynamic
547 traffic assignment approaches for planning and operations management. In *Vortrag: 91st Annual Meeting of the*
548 *Transportation Research Board, Washington, DC*.

549 Barceló, J. (2010). *Fundamentals of traffic simulation* (Vol. 145). Springer.

550 Beloglazov, A., Almashor, M., Abebe, E., Richter, J., & Steer, K. C. B. (2016). Simulation of wildfire
551 evacuation with dynamic factors and model composition. *Simulation Modelling Practice and Theory*, 60, 144–159.
552 <https://doi.org/10.1016/j.simpat.2015.10.002>

553 Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel*
554 *demand* (Vol. 9). MIT press.

555 Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel
556 decisions. *Handbook of Transportation Science*, 23, 5–33.

557 Ben-Akiva, M., Koutsopoulos, H. N., Antoniou, C., & Balakrishna, R. (2010). Traffic simulation with
558 dynamit. In *Fundamentals of traffic simulation* (pp. 363–398). Springer.

559 Ben-Akiva, M., Koutsopoulos, H. N., Toledo, T., Yang, Q., Choudhury, C. F., Antoniou, C., & Balakrishna,
560 R. (2010). Traffic simulation with MITSIMLab. In *Fundamentals of Traffic Simulation* (pp. 233–268). Springer.

561 Bhaduri, B., Liu, C., & Franzese, O. (2006). Oak Ridge evacuation modeling system (OREMS): A PC-based
562 computer tool for emergency evacuation planning. In *Symposium on GIS for Transportation*.

563 Bickman, L., Edelman, P., & McDaniel, M. (1977). *A model of human behavior in a fire emergency*. Fire and
564 Human Behavior Research Center, Loyala University of Chicago.

565 Bliemer, M., Versteegt, H., & Castenmiller, R. (2004). INDY: a new analytical multiclass dynamic traffic
566 assignment model. In *Proceedings of the TRISTAN V conference, Guadeloupe*.

567 Borchardt, D. W., & Puckett, D. D. (2008). *Real-Time Data for Hurricane Evacuation in Texas*. Southwest
568 Region University Transportation Center, Texas Transportation Institute, Texas A & M University System.

569 Bowman, J., & Ben-Akiva, M. . (2001). Activity-based disaggregate travel demand model system with
570 activity schedules. *Transportation Research Part A: Policy and Practice*, 35(1), 1–28.
571 [https://doi.org/10.1016/S0965-8564\(99\)00043-9](https://doi.org/10.1016/S0965-8564(99)00043-9)

572 Brennan, P. (1995). Smoke Gets in Your Eyes: The effect of cue perception on behaviour in smoke. In
573 *ASIAFLAM'95. International Conference on Fire Science and Engineering 1st Proceedings* (pp. 187-197).

574 Brennan, P. (1996). Impact of social interaction on time to begin evacuation in office building fires:
575 implications for modelling behaviour. In *Interflam'96. International Interflam Conference, 7th Proceedings* (pp.
576 701-710).

577 Brennan, P. (1999) Modelling cue recognition and pre-evacuation response. In: *6th International*
578 *Symposium, International Association for Fire Safety Science* (pp. 1029–1040). Boston, MA.

579 Bryan, J. L., & Bryan, J. L. (1977). *Smoke as a determinant of human behavior in fire situations (Project*
580 *People)*. US Department of Commerce, National Institute of Standards and Technology.

581 Bruck, D. (2001). The who, what, where and why of waking to fire alarms: a review. *Fire safety journal*,
582 36(7), 623-639.

583 Burghout, W. (2005). Mesoscopic simulation models for short-term prediction. *PREDIKT Project Report*.

584 Canter, D., Breaux, J., Sime, J. (1980) Domestic, multiple occupancy, and hospital fires. In: Canter D. (ed)
585 Fires and human behaviour Wiley, Chichester, pp 117–136

586 Casas, J., Ferrer, J. L., Garcia, D., Perarnau, J., & Torday, A. (2010). Traffic simulation with Aimsun. In
587 *Fundamentals of traffic simulation* (pp. 173–232). Springer.

588 Cascetta, E. (2009). *Transportation systems analysis: models and applications* (Vol. 29). Springer Science &
589 Business Media.

590 Castiglione, J., Bradley, M., & Gliebe, J. (2015). *Activity-based travel demand models: A primer*. SHRP 2.
591 Strategic Highway Research Program. S2-C46-RR-1. Transportation Research Board.

592 Caton, S. E., Hakes, R. S. P., Gorham, D. J., Zhou, A., & Gollner, M. J. (2016). Review of Pathways for
593 Building Fire Spread in the Wildland Urban Interface Part I: Exposure Conditions. *Fire Technology*.
594 <https://doi.org/10.1007/s10694-016-0589-z>

595 Chang Chiu, Y., & Nava, E. (2011). *A Computationally Efficient and Temporally Scalable Dynamic Traffic*
596 *Simulation and Assignment System*. USA: University of Arizona.

597 Charlton, S. G., & Starkey, N. J. (2013). Driving on familiar roads: Automaticity and inattention blindness.
598 *Transportation Research Part F: Traffic Psychology and Behaviour*, 19, 121–133.

599 Cheng, G. (2007). *Friction Factor Function Calibration for Hurricane Evacuation Trip Distribution*.

600 Cheng, G., & Wilmot, C. G. (2009). *Time-Dependent Travel Cost Impact on Hurricane Evacuation*
601 *Destination Choice Models*.

602 Cheng, G., Wilmot, C. G., & Baker, E. J. (2008). A destination choice model for hurricane evacuation. In
603 *Proceedings of the 87th Annual Meeting Transportation Research Board, Washington, DC, USA* (pp. 13–17).

604 Chiu, Y.-C., & Mirchandani, P. B. (2008). Online behavior-robust feedback information routing strategy for

605 mass evacuation. *IEEE Transactions on Intelligent Transportation Systems*, 9(2), 264–274.

606 Chiu, Y.-C., Zheng, H., Villalobos, J., & Gautam, B. (2007). Modeling no-notice mass evacuation using a
607 dynamic traffic flow optimization model. *IIE Transactions*, 39(1), 83–94.
608 <https://doi.org/10.1080/07408170600946473>

609 Colonna, P., Intini, P., Berloco, N., & Ranieri, V. (2016). The influence of memory on driving behavior: How
610 route familiarity is related to speed choice. An on-road study. *Safety Science*, 82, 456–468.

611 Cova, T. J. (2005). Public safety in the urban–wildland interface: should fire-prone communities have a
612 maximum occupancy? *Natural Hazards Review*, 6(3), 99–108.

613 Cova, T. J., & Johnson, J. P. (2003). A network flow model for lane-based evacuation routing.
614 *Transportation Research Part A: Policy and Practice*, 37(7), 579–604.

615 Cova, T. J., Dennison, P. E., & Drews, F. A. (2011). Modeling evacuate versus shelter-in-place decisions in
616 wildfires. *Sustainability*, 3(10), 1662–1687.

617 Cova, T. J., Theobald, D. M., Norman, J. B., & Siebeneck, L. K. (2013). Mapping wildfire evacuation
618 vulnerability in the western US: the limits of infrastructure. *GeoJournal*, 78(2), 273–285.

619 Cuéllar, L., Kubicek, D., Hengartner, N., & Hansson, A. (2009). Emergency relocation: population response
620 model to disasters. In *Technologies for Homeland Security, 2009. HST'09. IEEE Conference on* (pp. 628–635).
621 IEEE.

622 de Araujo, M. P., Casper, C., Lupa, M. R., Brinckerhoff, P., Waters, B., & Hershkowitz, P. (2011). Adapting a
623 four-step MPO travel model for wildfire evacuation planning: A practical application from colorado springs.

624 Dennison, P. E., Cova, T. J., & Mortiz, M. A. (2007). WUIVAC: a wildland-urban interface evacuation
625 trigger model applied in strategic wildfire scenarios. *Natural Hazards*, 41(1), 181–199.

626 Deutsch, M., Gerard, H. B. (1955) A study of normative and informational social influences upon individual
627 judgment. *J Abnorm Soc Psychol* 51(3):629–636.

628 Dow, K., & Cutter, S. L. (1998). Crying wolf: Repeat responses to hurricane evacuation orders. *Coastal*

629 *Management*, 26(4), 237–252. <https://doi.org/10.1080/08920759809362356>

630 Fellendorf, M., & Vortisch, P. (2010). Microscopic traffic flow simulator VISSIM. In *Fundamentals of traffic*
631 *simulation* (pp. 63–93). Springer.

632 Fischer, H. W., Stine, G. F., Stoker, B. L., Trowbridge, M. L., & Drain, E. M. (1995). Evacuation behaviour:
633 why do some evacuate, while others do not? A case study of the Ephrata, Pennsylvania (USA) evacuation. *Disaster*
634 *Prevention and Management: An International Journal*, 4(4), 30–36.

635 Fridolf, K., Nilsson, D., & Frantzich, H. (2013). Fire evacuation in underground transportation systems: a
636 review of accidents and empirical research. *Fire technology*, 49(2), 451-475.

637 Fries, R. N., Ghale, K., Williamson, M. R., Bahaaldin, K., & Chen, X. (2016). Modeling the Impacts of
638 Driver Aggression during a Metropolitan Evacuation. In *International Conference on Transportation and*
639 *Development 2016* (pp. 1026–1038).

640 Fu, H., & Wilmot, C. G. (2007). Static versus dynamic and aggregate versus disaggregate: a comparison
641 between practice and research in hurricane evacuation travel demand modeling. In *Transportation Research Board*
642 *86th Annual Meeting*.

643 Fu, H., Pel, A. J., & Hoogendoorn, S. P. (2015). Optimization of evacuation traffic management with
644 intersection control constraints. *IEEE Transactions on Intelligent Transportation Systems*, 16(1), 376–386.

645 Green, C. H. (1980) Risk: Beliefs and Attitudes. In: Canter, D. (ed) *Fires and Human Behaviour*. John Wiley
646 & Sons, New York, pp 277–291.

647 Groner, N. E. (1996) Important “people” problems in hazard analyses can be modeled by using a cognitive
648 systems approach. In: *Proceedings of the Fire Risk and Hazard Assessment Symposium. Research and Practice:*
649 *Bridging the Gap* (pp. 422–429). California University, Berkeley.

650 Gwynne, S., Galea, E. R., Owen, M., Lawrence, P. J., & Filippidis, L. (1999). A review of the methodologies
651 used in the computer simulation of evacuation from the built environment. *Building and environment*, 34(6),
652 741-749.

653 Hamdar, S. H. (2004). *Towards modeling driver behavior under extreme conditions*.

654 Hamdar, S., & Mahmassani, H. (2008). From existing accident-free car-following models to colliding
655 vehicles: exploration and assessment. *Transportation Research Record: Journal of the Transportation Research*
656 *Board*, (2088), 45–56.

657 Hardy, M., & Wunderlich, K. (2009). Evacuation Management Operations (EMO) modeling assessment:
658 transportation modeling inventory, 2007. *Source: Http://Www. Its. Dot. Gov/Its_publicsafety/Emo/Index. Htm (Last*
659 *Access: 12/01/12)*.

660 Hasan, S., Ukkusuri, S., Gladwin, H., & Murray-Tuite, P. (2010). Behavioral model to understand
661 household-level hurricane evacuation decision making. *Journal of Transportation Engineering*, 137(5), 341-348.

662 Hasan, S., Mesa-Arango, R., & Ukkusuri, S. (2013). A random-parameter hazard-based model to understand
663 household evacuation timing behavior. *Transportation research part C: emerging technologies*, 27, 108-116.

664 Hoogendoorn, R., Tamminga, G., Hoogendoorn, S., & Daamen, W. (2010). Longitudinal driving behavior
665 under adverse weather conditions: Adaptation effects, model performance and freeway capacity in case of fog. In
666 *Intelligent transportation systems (itsc), 2010 13th international ieee conference on* (pp. 450–455). IEEE.

667 Huang, S. K., Lindell, M. K., & Prater, C. S. (2016). Who leaves and who stays? A review and statistical
668 meta-analysis of hurricane evacuation studies. *Environment and Behavior*, 48(8), 991-1029.

669 Intini, P., Berloco, N., Colonna, P., Ranieri, V., Ryeng, E. (2018). Exploring the relationships between
670 drivers' familiarity and two-lane rural road accidents. A multi-level study. *Accident Analysis and Prevention, in*
671 *press*.

672 Jolly, W. M., Cochrane, M. A., Freeborn, P. H., Holden, Z. A., Brown, T. J., Williamson, G. J., & Bowman,
673 D. M. (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications*, 6.

674 Jones, S. L., Sullivan, A. J., Cheekoti, N., Anderson, M. D., & Malave, D. (2004). Traffic simulation
675 software comparison study. *UTCA Report*, 2217.

676 Kobes, M., Helsloot, I., De Vries, B., & Post, J. G. (2010). Building safety and human behaviour in fire: A

677 literature review. *Fire Safety Journal*, 45(1), 1-11.

678 Kolen, B., & Helsloot, I. (2012). Time needed to evacuate the Netherlands in the event of large-scale
679 flooding: strategies and consequences. *Disasters*, 36(4), 700–722.

680 Krajzewicz, D. (2010). Traffic simulation with SUMO—simulation of urban mobility. In *Fundamentals of*
681 *traffic simulation* (pp. 269–293). Springer.

682 Kuligowski, E. D., Peacock, R. D., & Hoskins, B. L. (2005). *A review of building evacuation models*.
683 Gaithersburg, MD: US Department of Commerce, National Institute of Standards and Technology.

684 Lamb, S., Walton, D., Mora, K., & Thomas, J. (2011). Effect of authoritative information and message
685 characteristics on evacuation and shadow evacuation in a simulated flood event. *Natural Hazards Review*, 13(4),
686 272–282.

687 Li, D., Cova, T. J., & Dennison, P. E. (2015). A household-level approach to staging wildfire evacuation
688 warnings using trigger modeling. *Computers, Environment and Urban Systems*, 54, 56–67.
689 <https://doi.org/10.1016/j.compenvurbsys.2015.05.008>

690 Lindell, M. K. (2008). EMBLEM2: An empirically based large scale evacuation time estimate model.
691 *Transportation Research Part A: Policy and Practice*, 42(1), 140–154.

692 Lindell, M. K., & Prater, C. S. (2007). Critical behavioral assumptions in evacuation time estimate analysis
693 for private vehicles: Examples from hurricane research and planning. *Journal of Urban Planning and Development*,
694 133(1), 18–29.

695 Liu, S., Murray-Tuite, P., & Schweitzer, L. (2011). Relocating Children in Daytime No-Notice Evacuations:
696 Methodology and Applications for Transport Systems of Personal Vehicles and Buses. *Transportation Research*
697 *Record: Journal of the Transportation Research Board*, 2234, 79–88. <https://doi.org/10.3141/2234-09>

698 Lovreglio, R., Ronchi, E., and Nilsson, D. (2015) A model of the decision-making process during
699 pre-evacuation. *Fire Safety Journal* 78, 168-179.

700 Mahmassani, H. S., Fei, X., Eisenman, S., Zhou, X., & Qin, X. (2005). DYNASMART-X evaluation for

701 real-time TMC application: CHART test bed. *Maryland Transportation Initiative, University of Maryland, College*
702 *Park, Maryland*, 1–144.

703 Mahut, M., & Florian, M. (2010). Traffic simulation with dynameq. In *Fundamentals of Traffic Simulation*
704 (pp. 323–361). Springer.

705 Manzello, S. L., Bianchi, R., Gollner, M., McAllister, S., Planas, E., Rein, G., ... Suzuki, S. (2017).
706 Summary of Workshop Large Outdoor Fires and the Built Environment. *Special Publication (NIST SP)-1213*.

707 Mell, W. E., Manzello, S. L., Maranghides, A., Butry, D., & Rehm, R. G. (2010). The wildland–urban
708 interface fire problem – current approaches and research needs. *International Journal of Wildland Fire*, 19(2), 238.
709 <https://doi.org/10.1071/WF07131>

710 Mesa-Arango, R., Hasan, S., Ukkusuri, S. V., & Murray-Tuite, P. (2012). Household-level model for
711 hurricane evacuation destination type choice using hurricane Ivan data. *Natural hazards review*, 14(1), 11-20.

712 Moriarty, K. D., Ni, D., & Collura, J. (2007). Modeling traffic flow under emergency evacuation situations:
713 Current practice and future directions. In *86th Transportation Research Board Annual Meeting*.

714 Mozumder, P., Raheem, N., Talberth, J., & Berrens, R. P. (2008). Investigating intended evacuation from
715 wildfires in the wildland–urban interface: application of a bivariate probit model. *Forest Policy and Economics*,
716 10(6), 415–423.

717 Murray-Tuite, P., & Mahmassani, H. (2004). Transportation Network Evacuation Planning with Household
718 Activity Interactions. *Transportation Research Record: Journal of the Transportation Research Board*, 1894, 150–
719 159. <https://doi.org/10.3141/1894-16>

720 Murray-Tuite, P., & Wolshon, B. (2013). Evacuation transportation modeling: An overview of research,
721 development, and practice. *Transportation Research Part C: Emerging Technologies*, 27, 25–45.
722 <https://doi.org/10.1016/j.trc.2012.11.005>

723 Nagel, K., Stretz, P., Pieck, M., Donnelly, R., & Barrett, C. L. (1997). TRANSIMS traffic flow
724 characteristics. *ArXiv Preprint Adap-Org/9710003*.

725 National Fire Protection Association. (2013). NFPA 1144: Standard for Reducing Structure Ignition Hazards
726 from Wildland Fire.

727 Ortuzar, J. de D., & Willumsen, L. G. (2011). *Modelling transport*. 4th Edition. John Wiley & Sons.

728 Paveglio, T. B., Moseley, C., Carroll, M. S., Williams, D. R., Davis, E. J., & Fischer, A. P. (2015).
729 Categorizing the social context of the wildland urban interface: Adaptive capacity for wildfire and community
730 “archetypes”. *Forest Science*, 61(2), 298–310.

731 Peeta, S., & Hsu, Y.-T. (2009). Behavior modeling for dynamic routing under no-notice mass evacuation. In
732 *Proceedings of the 12th International Conference on Travel Behaviour Research, Jaipur, India*.

733 Pel, A. J. (2017). Evacuation Modelling in the field of Transport. In *Workshop New Approaches to*
734 *Evacuation Modelling* (pp. 52–63). Lund, Sweden: Department of Fire Safety Engineering, Lund University.

735 Pel, A. J., Bliemer, M. C. J., & Hoogendoorn, S. P. (2008). EVAQ: A New Analytical Model for Voluntary
736 and Mandatory Evacuation Strategies on Time-varying Networks (pp. 528–533). IEEE.
737 <https://doi.org/10.1109/ITSC.2008.4732655>

738 Pel, A. J., Bliemer, M. C. J., & Hoogendoorn, S. P. (2012). A review on travel behaviour modelling in
739 dynamic traffic simulation models for evacuations. *Transportation*, 39(1), 97–123.
740 <https://doi.org/10.1007/s11116-011-9320-6>

741 Pel, A. J., Hoogendoorn, S. P., & Bliemer, M. C. J. (2010)a. Evacuation modeling including traveler
742 information and compliance behavior. *Procedia Engineering*, 3, 101–111.
743 <https://doi.org/10.1016/j.proeng.2010.07.011>

744 Pel, A. J., Bliemer, M., & Hoogendoorn, S. (2009). Hybrid route choice modeling in dynamic traffic
745 assignment. *Transportation Research Record: Journal of the Transportation Research Board*, (2091), 100–107.

746 Pel, A. J., Hoogendoorn, S. P., & Bliemer, M. C. J. (2010)b. Impact of variations in travel demand and
747 network supply factors for evacuation studies. *Transportation Research Record: Journal of the Transportation*
748 *Research Board*, (2196), 45-55.

749 Pel, A. J., Huibregtse, O. L., Hoogendoorn, S. P., & Bliemer, M. C. J. (2010)c. Optimizing evacuation
750 instructions while anticipating traveler compliance behavior. *Proceedings IEEE Intelligent Transportation Systems*
751 *Conference*, 462-467.

752 Post, B. (2000). *Schuh & Jernigan, Inc.(PBS&J). Southeast United States Hurricane Evacuation Traffic*
753 *Study: Evacuation Travel Demand Forecasting System*. Technical Memorandum.

754 Proulx, G. (1993). A stress model for people facing a fire. *Journal of Environmental Psychology*, 13(2),
755 137-147.

756 Radwan, E., Mollaghasemi, M., Mitchell, S., & Yildirim, G. (2005). Framework for modeling emergency
757 evacuation.

758 Rakha, H., Farzaneh, M., Arafeh, M., Hranac, R., Sterzin, E., & Krechmer, D. (2007). Empirical studies on
759 traffic flow in inclement weather. *Virginia Tech Transportation Institute*.

760 Ronchi, E., Rein, G., Gwynne, S. M. V., Wadhvani, R., Intini, P., & Bergstedt, A. (2017). *e-Sanctuary: Open*
761 *Multi-Physics Framework for Modelling Wildfire Urban Evacuation*. Quincy, MA (USA): Fire Protection Research
762 Foundation.

763 Ronchi, E., & Nilsson, D. (2013). Fire evacuation in high-rise buildings: a review of human behaviour and
764 modelling research. *Fire science reviews*, 2(1), 7.

765 Ronchi, E., Reneke, P. A., & Peacock, R. D. (2014). A Method for the Analysis of Behavioural Uncertainty
766 in Evacuation Modelling. *Fire Technology*, 50(6), 1545–1571. <https://doi.org/10.1007/s10694-013-0352-7>

767 Sacks, J., Roupail, N. M., Park, B., & Thakuriah, P. (2002). Statistically-based validation of computer
768 simulation models in traffic operations and management. *Journal of Transportation and Statistics*, 5(1), 1–24.

769 Sadri, A. M., Ukkusuri, S. V., Murray-Tuite, P., & Gladwin, H. (2013)a. How to evacuate: model for
770 understanding the routing strategies during hurricane evacuation. *Journal of transportation engineering*, 140(1),
771 61-69.

772 Sadri, A. M., Ukkusuri, S. V., & Murray-Tuite, P. (2013)b. A random parameter ordered probit model to

773 understand the mobilization time during hurricane evacuation. *Transportation Research Part C: Emerging*
774 *Technologies*, 32, 21-30.

775 Sadri, A. M., Ukkusuri, S. V., Murray-Tuite, P., & Gladwin, H. (2014). Analysis of hurricane evacuee mode
776 choice behavior. *Transportation research part C: emerging technologies*, 48, 37-46.

777 Sadri, A. M., Ukkusuri, S. V., & Gladwin, H. (2017)a. Modeling joint evacuation decisions in social
778 networks: The case of Hurricane Sandy. *Journal of choice modelling*, 25, 50-60.

779 Sadri, A. M., Ukkusuri, S. V., & Gladwin, H. (2017)b. The role of social networks and information sources
780 on hurricane evacuation decision making. *Natural Hazards Review*, 18(3), 04017005.

781 Santos, G., & Aguirre, B. E. (2005) Critical review of emergency evacuation simulation models. In: R. D.
782 Peacock, E. D. Kuligowski (eds) *Workshop on building occupant movement during fire emergencies*. National
783 Institute of Standards and Technology, Gaithersburg, pp 27–52.

784 Sbayti, H., & Mahmassani, H. (2006). Optimal scheduling of evacuation operations. *Transportation*
785 *Research Record: Journal of the Transportation Research Board*, (1964), 238–246.

786 Scerri, D., Gouw, F., Hickmott, S., Yehuda, I., Zambetta, F., & Padgham, L. (2010). Bushfire BLOCKS: a
787 modular agent-based simulation. In *Proceedings of the 9th International Conference on Autonomous Agents and*
788 *Multiagent Systems: volume 1-Volume 1* (pp. 1643–1644). International Foundation for Autonomous Agents and
789 Multiagent Systems.

790 Sheffi, Y. (1985). Urban transportation network. *Pretince Hall*, 4.

791 Sime, J. D. (1983) Affiliative Behaviour During Escape to Building Exits. *Journal of Environmental*
792 *Psychology* 3:21–41

793 Sime, J. D. (1984). Escape behaviour in fires: ‘Panic’ or affiliation? PhD thesis, University of Surrey,
794 Guilford.

795 Sime, J. D. (1985) Movement toward the familiar—person and place affiliation in a fire entrapment setting.
796 *Environ Behav* 17(6):697–724

797 Snowden, R. J., Stimpson, N., & Ruddle, R. A. (1998). Speed perception fogs up as visibility drops. *Nature*,
798 392(6675), 450.

799 Southworth, F. (1991). *Regional Evacuation Modeling: A State of the Art Reviewing*. ORNL Oak Ridge
800 National Laboratory (US).

801 Stern, E. (1989). Evacuation intentions of parents in an urban radiological emergency. *Urban Studies*, 26(2),
802 191–198.

803 Stewart, S. I., Radeloff, V. C., Hammer, R. B., & Hawbaker, T. J. (2007). Defining the wildland–urban
804 interface. *Journal of Forestry*, 105(4), 201–207.

805 Sullivan, J., Novak, D., Aultman-Hall, L., & Scott, D. M. (2010). Identifying critical road segments and
806 measuring system-wide robustness in transportation networks with isolating links: A link-based capacity-reduction
807 approach. *Transportation Research Part A: Policy and Practice*, 44(5), 323–336.

808 Sykes, P. (2010). Traffic simulation with Paramics. In *Fundamentals of traffic simulation*. Springer.

809 Timmermans, H., Arentze, T., & Joh, C.-H. (2002). Analysing space-time behaviour: new approaches to old
810 problems. *Progress in Human Geography*, 26(2), 175–190.

811 Tong, D., & Canter, D. (1985). The decision to evacuate: a study of the motivations which contribute to
812 evacuation in the event of fire. *Fire Safety Journal*, 9(3), 257-265.

813 Tu, H., Tamminga, G., Drolenga, H., de Wit, J., & van der Berg, W. (2010). Evacuation plan of the city of
814 almere: simulating the impact of driving behavior on evacuation clearance time. *Procedia Engineering*, 3, 67–75.

815 Ukkusuri, S. V., Hasan, S., Luong, B., Doan, K., Zhan, X., Murray-Tuite, P., & Yin, W. (2017). A-RESCUE:
816 An Agent based regional evacuation simulator coupled with user enriched behavior. *Networks and Spatial
817 Economics*, 17(1), 197-223.

818 Urata, J., & Pel, A. (2017). People’s risk recognition preceding evacuation and its role in demand modelling
819 and planning. *Risk Analysis*, 38(5), 889-905.

820 Van der Gun, J. P., Pel, A. J., & Van Arem, B. (2016). A general activity-based methodology for simulating

821 multimodal transportation networks during emergencies. *European Journal of Transport and Infrastructure*
822 *Research*, 16(3), 190–511.

823 Van der Gun, J. P., Pel, A. J., & van Arem, B. (2016). Propagating agents with macroscopic dynamic
824 network loading: challenges and possible solutions. *Procedia Computer Science*, 83, 914–920.

825 Vorraa, T., & Brignone, A. (2008). Modelling traffic in detail with mesoscopic models: opening powerful
826 new possibilities for traffic analyses. *WIT Transactions on The Built Environment*, 101, 659–666.

827 Wang, H., Mostafizi, A., Cramer, L. A., Cox, D., & Park, H. (2016). An agent-based model of a multimodal
828 near-field tsunami evacuation: decision-making and life safety. *Transportation Research Part C: Emerging*
829 *Technologies*, 64, 86-100.

830 Wardrop, J. G. (1952). Some theoretical aspects of road traffic research. In *Inst Civil Engineers Proc.*

831 Westhaver, A. (2017). Why some homes survived: Learning from the Fort McMurray wildland/urban
832 interface fire disaster.

833 Whitehead, J. C., Edwards, B., Van Willigen, M., Maiolo, J. R., Wilson, K., & Smith, K. T. (2000). Heading
834 for higher ground: factors affecting real and hypothetical hurricane evacuation behavior. *Global Environmental*
835 *Change Part B: Environmental Hazards*, 2(4), 133–142.

836 Wilmot, C. G., & Mei, B. (2004). Comparison of alternative trip generation models for hurricane evacuation.
837 *Natural Hazards Review*, 5(4), 170–178.

838 Wood, P. G. (1972). *The Behaviour of People in Fires* (Rep. No. Fire Research Note No. 953). England:
839 Loughborough University of Technology.

840 Wolshon, B. (2001). “one-way-out”: contraflow freeway operation for hurricane evacuation. *Natural*
841 *Hazards Review*, 2(3), 105–112.

842 Wolshon, B., Urbina, E., Wilmot, C., & Levitan, M. (2005)a. Review of policies and practices for hurricane
843 evacuation. I: Transportation planning, preparedness, and response. *Natural hazards review*, 6(3), 129-142.

844 Wolshon, B., Urbina Hamilton, E., Levitan, M., & Wilmot, C. (2005)b. Review of policies and practices for

845 hurricane evacuation. II: Traffic operations, management, and control. *Natural Hazards Review*, 6(3), 143-161.

846 Wolshon, B., & Marchive, E. (2007). Emergency Planning in the Urban-Wildland Interface:
847 Subdivision-Level Analysis of Wildfire Evacuations. *Journal of Urban Planning and Development*, 133(1), 73–81.
848 [https://doi.org/10.1061/\(ASCE\)0733-9488\(2007\)133:1\(73\)](https://doi.org/10.1061/(ASCE)0733-9488(2007)133:1(73))

849 Wu, H.-C., Lindell, M. K., & Prater, C. S. (2012). Logistics of hurricane evacuation in Hurricanes Katrina
850 and Rita. *Transportation Research Part F: Traffic Psychology and Behaviour*, 15(4), 445–461.

851 Wu, J. H., Chen, Y., & Florian, M. (1998). The continuous dynamic network loading problem: a
852 mathematical formulation and solution method. *Transportation Research Part B: Methodological*, 32(3), 173–187.

853 Yanko, M. R., & Spalek, T. M. (2014). Driving with the wandering mind: the effect that mind-wandering has
854 on driving performance. *Human Factors*, 56(2), 260–269.

855 Yin, W., Murray-Tuite, P., Ukkusuri, S. V., & Gladwin, H. (2014). An agent-based modeling system for
856 travel demand simulation for hurricane evacuation. *Transportation research part C: emerging technologies*, 42,
857 44-59.

858 Yoshimura, H. (2000) Human behavior. In: *4th Proceedings of the Asia-Oceania Symposium on Fire Science*
859 *and Technology* (pp. 137–141). Osaka University, Tokyo.