An agent-based model for flood risk warning.

Thomas O'Shea[1], Paul Bates[1] and Jeffrey Neal[1]

[1] School of Geographical Sciences, University of Bristol, UK.

Correspondence: Thomas O'Shea (t.oshea@bristol.ac.uk)

Abstract

This paper presents a new flood risk behaviour model developed using a coupled Hydrodynamic Agent-Based Model (HABM). This model uses the LISFLOOD-FP Hydrodynamic Model and the NetLogo (NL) agent-based framework and is applied to the 2005 flood event in Carlisle, UK. The hydrodynamic model provides a realistic simulation of detailed flood dynamics through the event whilst the agent-based model component enables simulation and analysis of the complex, in-event social response. NetLogo enables alternative probabilistic daily routine and agent choice scenarios for the individuals of Carlisle to be simulated in a coupled fashion with the flood inundation. Experiments are also constructed using a novel, 'enhanced social modelling component', comprising the Bass Diffusion Model, to investigate the effect of direct or indirect warnings in flood incident response.

From the analysis of these coupled simulations, management stress points, predictable or otherwise, can be presented to those responsible for hazard management and post-event recovery. The results within this paper suggest that these stress points can be present, or amplified, by a lack of preparedness or a lack of phased evacuation measures. Furthermore, the methods here outlined have the potential for application elsewhere to reduce the complexity and improve the effectiveness of flood incident management. The paper demonstrates the influence that emergent properties have on systematic vulnerability and risk from natural hazards in coupled socio-environmental systems.

1. **Introduction**

Flood hazard, or flood incident, management is a challenge that incorporates aspects of the natural sciences (hydrology, ecology, etc.), the social sciences (economics, politics, psychology, culture, etc.) and engineering. It is important for the efficiency and efficacy of decision-making processes to recognise that decision-making during floods involves what has been termed "technical complexity" (Nunes Correia, Fordham, Da Graca Raravia & Bernardo 1998). Specifically, this is the social response to the hazard, and encompasses interactions between individuals, the diffusion of decision-making and collective, during-event, behaviours (Larsen, 2005). This complexity cannot, either theoretically or physically, be eliminated when planning for flooding incidents (Assaf & Hartford, 2002; Bennet & Tang, 2017; Correia, Rego, Saravia & Ramos, 1998 and Dawson, Peppe & Wang, 2011) and can be a threat to effective planning processes (Axelrod, 1970; Nunes Correia et al., 1998). In a broader sense, this complexity is a measure of the scale of the interactions within the affected area, encompassing dynamic multi-scale interactions and adaptions between individuals, groups, infrastructures, government and the economy, all contributing to the social, political and physical aspects of flood hazard management (Dugdale, Saoud, Pavard, & Pallamin, 2009; Fordham, 1992; IPCC, 2014; Kossiakoff & Sweet, 2002; Werrity, Houston, Ball, Tavendale & Black 2007 and Wisner, Blaikie, Cannon & Davies, 1994).

Recent decades have seen strong emphasis being placed on multi-scale, *participatory* methods for dealing with floods resulting in a paradigm shift from *flood defence* to *flood risk management* (Assaf & Hartford, 2002, Dawson et al., 2011, DEFRA, 2007; IPCC, 2014 and Wisner et al., 1994). Such participation means the inclusive involvement of individuals and multiple agencies in the processes of hazard management, policy implementation and post-event recovery. This emphasis is logical in that it aims to incorporate, as far as possible, the requirements of all those involved in the hazard planning process across a scale hierarchy that passes from government bodies to emergency services, and on to the affected individuals themselves. The complexity of such an ideal becomes apparent given that the intricate natures of human environments and environmental dynamics are, to a large degree, perceived as independent, and that when the two come into contact, complexity becomes amplified within a coupled socio-environmental system. For example, between 2010 and 2015, UK Government policy for flooding underwent a transformation that sought to address some of the known complexities of flood incident management (DEFRA, 2007; Eberlen, Scholz & Gagliolo 2017; The Environment Agency, 2012 & 2016). The UK Government's Department for Environment, Food & Rural Affairs (DEFRA) national framework for flood management emphasises the importance of localised decisions about flood risk and makes suggestions for developing community-based solutions to manage flood risk on a finer spatial scale. This transformation emphasised the need for innovative new approaches to managing the localised risk of flooding. This was expected to provide the foundation for better management at the larger scale as 'good practice' innovations spread across more communities. Thus, UK flood policy can be defined as moving from a top-down to bottom-up approach, often referred to as '*alternative action'* (DEFRA, 2007; Kossiakoff & Sweet, 2002).

89   Whilst both top-down and 'alternative action' bottom-up approaches will be likely to have
90   divergent outcomes owing to the different emphasis each places on variables within their
91   respective approaches, the shift towards a bottom-up strategy indicates an
92   acknowledgement of the need for greater local participation in decision making; something
93   which is difficult to achieve with the 'black-box' forms of assistance seen in most top-down
94   approaches (Sabatier, 1986). Conversely, to formulate an effective bottom-up approach, the
95   dynamics of the individual base elements, which in this model are individual people and are
96   termed 'agents', must be specified to a relatively intricate degree of detail. This is because
97   theory suggests individual and grouped responses will have a significant influence on the
98   dynamics which emerge at higher systematic levels and so accounting for as much detail as
99   possible at the individual level will have a bearing on the detail that can be developed within
100 the descriptions of the whole system (Bresser-Pereira, Maravall & Przeworski, 1993 & Müller
101 et al., 2013). Here, it is believed that Individual and grouped responses are defined by
102 environmental, inter-personal interaction and interpretation (Alexander, 1980; Assaf &
103 Hartford, 2002 and Axelrod, 1970) and that these are characteristic behaviours of sub-
104 systematic processes which are either not present or not considered in, coarser, top-down
105 models of physical process; despite potentially having a significant influence on the outcome
106 of an event in which they are involved (Nunes Correia et al., 1998).

107

108 Agent Based Models (ABMs), defined as "a computational method for simulating the actions
109 and interactions of autonomous decision-making entities in a network or system, with the
110 aim of assessing their effects on the whole system" (Dawson et al., 2011), provide a potential
111 means to characterise these interactions. Essentially, this is a form of computerised model
112 capable of simulating the emergent behaviour of complex systems. In such models,
113 individuals and organisations are represented as 'agents' within a simulated environment
114 (Railsback & Grimm, 2012). In recent years there has been a proliferation of ABM applications
115 within the research community and examples of these applications relevant to flooding
116 encompass: (i) the role of social media in flood evacuation processes (Du, Cai & Sun 2017); (ii)
117 human perception, understanding and anticipation of flash floods (Morss, Mulder, Lazo &
118 Demuth, 2016; Narsizi, Mysore, & Mishra, 2006); and (iii) the effectiveness of simultaneous
119 and staged flood evacuation strategies (Chu, 2015; Dawson et al., 2011; Zarboutis &
120 Marmaras, 2005). A key issue for such applications is the development of realistic flooding
121 scenarios to drive the behaviour of the modelled agents.

122

123 Hydrodynamic models can produce this information so long as they are developed with high
124 quality terrain and boundary condition information (see for example (Neal, Schumann &
125 Bates, 2012), but to date ABM applications have not taken full advantage of the latest
126 developments in flood inundation modelling. To date, the most comparable models to the
127 HABM that have driven an ABM with a hydrodynamic model are those of Dawson's (Dawson
128 et al., 2011), Lumbroso's (Lumbroso et al., 2011) and Medina's (Medina, Sanchez & Vojinovic,
129 2016), with Abebe's coupled flood agent-institution modelling framework (Abebe at al.,
130 2019) providing mentionable overlap also . In the example of Dawson's model, a simple
131 diffusive wave model which solves Manning's equation over a raster grid of cells was
132 implemented within an ABM to simulate a coastal flood and showed considerable potential.

However, this study initially coded the hydrodynamic model directly within the ABM meaning advantage could not be taken of recent developments in efficient numerical methods for solving the shallow water equations (Bates, Horrit & Fewtrell, 2010) and high-performance computing (*e.g.* Neal, Fewtrell, Bates & Wright 2010) architectures. As a result, computational costs were high, and this limited the domain size and resolution of the modelling that could be undertaken. Instead of directly embedding the hydrodynamic model within the ABM, a more pragmatic solution is to indirectly couple a separate, and highly optimized, hydrodynamic model with an existing ABM framework. This would allow each code to be properly optimized for the task it performs and enable each to be more easily updated as new methods become available. This is the objective of this paper, where we develop such a coupled hydrodynamic model/Agent-Based model framework (hereafter termed a Hydrodynamic Agent-Based Model, or HABM) and use this to address two currently unresolved questions relating to flood evacuation warnings. These two specific questions are:

1. During a flood, does the site-specific urban topography and morphology change the optimum evacuation warning strategy?

2. Do people (agents) respond better to direct or indirect (word of mouth) evacuation warnings for a flood event?

To date research on flood warnings and evacuation has examined the challenges and changes in thinking required to tackle the paradox of flood 'control' (Wisner et al., ch 6, 2015), the dynamic approaches required to address different forms of flood event (Berendracht, Viglione & Blöschl, 2017; Dawson et al., 2011; Gilligan, Brady, Camp, Nay & Sengupta, 2015; Smith & Tobin, 1979) and the roles of individuals and groups in flood warning and evacuative scenarios (Haer, Botzen & Aerts, 2016; Haer, Botzen & de Moel, 2016; Nunes Correia et al., 1998). However, so far, little work has been conducted on whether evacuation strategies need to be tailored to the specific geographical setting or explored whether different modes of communication (direct or indirect) affect the evacuee's response. Answering these questions is important if effective warning strategies for specific places are to be developed.

More broadly, answering these two questions encompasses the process of implementing alternative actions; these rely on positive social participation, diffusion of ideas and their implementation, and they require broader acknowledgement of, and a specific approach to addressing, the associated socio-environmental complexity (Wisner et al., 1994; Wong & Luo 2005; Zarboutis & Marmaras, 2005). The HABM framework enables us to properly explore the systematic, cross-scale sensitivity of social complexity to the physical flood phenomena and shows where the loci of *vulnerability* are within an affected system. Therefore, the goal of HABM use for this study is not to eliminate complexity from consideration, but rather to harness it as a compliment to more specific physical considerations within comprehensive hazard management strategies. This is tested by applying it to a test case in Carlisle, UK. The overall aim is to offer an assessment of the value of alternative actions within flood hazard management as a whole (Dawson et al., 2011; Müller, Bohn, Dreßler & Groeneveld, 2013).

176

2. Methods

2.1 Study Area

Figure 1: The area simulated in the HABM, highlighted in red with river locations indicated for the river(s) Caldew, Petteril and Eden. (Contains OS data © Crown copyright and database right (2019))

Carlisle, Cumbria UK, and specifically the 10.3 km2 study area of the city illustrated in figure 1, is a flood prone city with a history of contemporary study (Correia et al., 1998; DEFRA 2007; The Environment Agency: 2006; 2012; 2016; Horrit, Bates, Fewtrell, Mason & Wilson, 2010; Neal et al., 2009; Neal, Keef, Bates, Bevan & Leedal, 2013). Notable flood events have affected the city since 1700, with the recent 2015 flood event having been referred to as 'unprecedented' in scale due to the river Eden's flood level rising 0.6 metres above the previous record flood level of 2005. The location of the city at the confluence of the rivers Eden, Caldew and Petteril means it is a useful source of data for hydrological research. As the county town of Cumbria, with a total population of 108,000, it is a location of significant social scale whilst also offering a case study which is suitably complex to develop new insights through modelling and simulation.

The 2005 event affected approximately 1865 properties and led to the loss of 3 lives. The event had an estimated Annual Exceedance Probability (AEP) of 0.59% (1 in 170-year return period) and was a seminal event in that it prompted significant investment in the city's flood defences. The 2005 LISFLOOD-FP data set (Horrit et al., 2010) provides a robust and reliable foundation on which to build the agent-based component of the coupled model. This data set used for the model simulation consists of a series of input files including raster grids of floodplain friction coefficients and elevation heights in 2D, ARC-ascii format, boundary identification, time-varying boundary conditions and hydrodynamics. Since 2005, Carlisle has

204   been subjected to further large flood events in 2009 and 2012 with the mitigative measures
205   deployed post-2005 successfully curtailing the impact of these. Furthermore, the 2015 event,
206   overtopped the new defences and has led the Environment Agency to produce the Cumbria
207   Flood Plan. A novel feature of this is that it introduces and promotes community-based flood
208   resilience measures on a large scale for the UK. It is the essence of these measures that
209   prompted the development of the coupled model with a view to better understanding the
210   dynamics on which these measures were based (DEFRA, 2007; Dugdale et al., 2009; The
211   Environment Agency: 2006; 2012; 2016).

213   2.2**. The flood modelling component: LISFLOOD-FP**

215   For a viable exploration of different individual responses to flooding, detailed, accurate and
216   dynamic simulations of the flood at Carlisle were required. LISFLOOD-FP (Bates & De Roo,
217   2000; Bates et al., 2010; Neal et al., 2009; 2012), is a 2D hydrodynamic model specifically
218   designed to simulate floodplain inundation in an efficient manner over complex topography,
219   as is the case in urban areas. LISFLOOD-FP is capable of simulating grids of up to 10^7 cells for
220   dynamic flood events with airborne laser altimetry defining the DEM of the affected area.
221   From this, the LISFLOOD-FP model can accurately simulate the dynamic propagation of flood
222   waves by predicting water depths in each grid cell through a series of time steps, and over
223   the complex topographic forms within floodplains. The ABM element of the coupled model
224   can then operate from this reliable foundation, enabling exploration of different hypotheses
225   for social reactions and responses to the detailed, accurate and dynamic physical outputs
226   generated by LISFLOOD-FP; by adding the related elements of policy and systematic change
227   (Wheater, 2006; Wilson & Atkinson, 2005). Whilst LISFLOOD-FP was the chosen hydraulic
228   model for the HABM, similar 2D-hydraulic models could resolve flow problems to similar
229   degrees of accuracy and this would mean that these alternative models could be utilised in
230   place of the LISFLOOD-FP with the HABM modelling framework (Hunter et al., 2008;
231   Landstrom, Whatmore & Lane, 2011; Neal et al., 2012).

233   2.3. **The social modelling components: HABM & NetLogo**

235   With LISFLOOD-FP producing an accurate representation of the flood at Carlisle, the related
236   elements of flood incident policy options and agent behaviour were implemented through
237   the separate ABM program of NetLogo (Railsback & Grimm, 2012; Wilensky & Rand, 2015).
238   The HABM (figures 3 to 7), uses water depth output files from the LISFLOOD-FP at each model
239   time-step within a simulated version of the affected area (figures 5 - 7). For the simulation of
240   the Carlisle study area, a Digital Elevation Model (DEM), identical to that used by LISFLOOD-
241   FP as an input data set was used to provide a realistic topography for the flood-impacted area
242   in NetLogo (NetLogo, 1999; Wilensky & Rand, 2015). In addition to the simulation of the flood
243   event and physical landscape, NetLogo was used to generate a virtual population of *agents*
244   to occupy the virtual version of Carlisle. Using a pseudo-random, number of generator and
245   deterministic agent scheduling algorithms directed through probabilistic routines (Nunes
246   Correia et al., 1998; Wilensky & Rand, 2015; Wong & Luo, 2005) this then simulated the
247   population's interaction with the environment and response to the flood event. This

248 simulated interaction allows the possibility of identifying *emergent properties* likely to arise
249 at the complex interface between the social and environmental systems. These emergent
250 properties have a significant impact on objective 1, in that they occur subtly and at locations
251 that significantly influence human responses within the coupled physical and social systems.
252 This significance is found in the HABM's capacity to reveal systematic emergent phenomena
253 through the simulated co-evolution of a socio-environmental system, operating here through
254 a flood event that has impact upon the basic daily routine (figure 2) and the complex co-
255 existent entities *i.e.* the more complex, responsive *configuration* of evacuating groups
256 (figures 3 & 4). This then has a further impact on hypotheses regarding *risk*, *vulnerability* and
257 *resilience*, with the HABM providing an opportunity to analyse and evaluate these terms, from
258 a sub-systematic perspective. Here, *sub-systematic* is a term used to describe the
259 development of individual (micro) to community (meso) level characteristics in response to
260 the flood onset, with greater scope than has previously been possible with traditional
261 approaches to flood incident management (Borschev & Filippov, 2004; Chen & Zhan, 2008;
262 Gilbert & Troitzsch, 2005; Guo, Ren & Wang, 2008; Guyot & Holiden, 2006; Landstrom et al.,
263 2011; Namatame & Chen, 2016, Sanders & Sanders, 2004; Srbljinović & Škunca, 2003; Wei,
264 Zhang & Fan, 2003)).
265
266
267 2.4. **The enhanced social modelling component: Bass Model**
268
269 For objective 2 of this paper, and in planning for effective flood impact management on a
270 broader scale, we must incorporate elements from a whole range of *activities* (Axelrod, 1970;
271 Berendracht et al., 2017). These include the spatial and temporal variations in phenomena
272 (flooding in this instance), the non-linear relationship between small perturbations at a sub-
273 systematic level and large knock-on effects at a system-wide scale (the macro-level), the
274 understanding that these effects can extend beyond the physical impacts of the phenomena
275 and change social behaviours and routines within an affected area, thus changing the
276 characteristic function of the system as a whole. This suggests that objectives 1 and 2 are
277 intimately connected and so there is a need to consider the social dynamics and reflexive
278 nature of the human system in response to the flood event within the framework of the
279 hazard system to determine the sensitivity of the incident management response (Davies,
280 1979). To better understand this relationship between human system and environmental
281 phenomena (figure 2), the ABM was used to provide choices to the simulated agent
282 population of Carlisle as part of a synthetic daily routine (figures 3 & 4), further details of
283 which are to be found in section 3 of this paper. These agent choices and the routine were
284 combined to synthesise the dynamics of the socio-environmental interface and from this,
285 estimates were made for the influence that agent choices have on the characteristics of the
286 system being simulated. In the Carlisle HABM, the agents were given the choice of carrying
287 out their normal, linear, routine during the flood scenario, of becoming warned and taking
288 immediate action to evacuate, or of assessing this warning based on social interaction with
289 other agents in the immediate vicinity, and then acting post-interaction(figure 4). The
290 scenario of becoming warned and *evacuating immediately* is used in the HABM to reflect the
291 government policy instruction of 'what to do in a flood scenario' in the most direct form.

292 Within the model (DEFRA, 2007), this instruction is programmed as '*pre-preparedness'* and it
293 describes an adoption and undertaking of actions beyond the 'normal' daily routine, both
294 modelled and real (Chen & Zhan, 2008; Chu, 2015).

296 The Bass Diffusion Model provides a tool for interpreting the impact of these choices and
297 actions, by representing agents who adopt certain actions at a given time. The model,
298 originally conceived for marketing economics, is used to inform understanding of the diffusion
299 of frequently purchased or *adopted* products, and is based on a principle derived from the
300 following relationship (Bass, 1969):

$$\frac{f(t)}{1 - F(t)} = p + \frac{q}{M}\left[A(t)\right]$$

304 This states that "The portion of the potential market that adopts at time *t*, given that they
305 have not yet adopted, is equal to a linear function of previous adopters" (Bass, 1969; Davies,
306 1979). The basic premise of the model provides insight into interaction between adopters of
307 the *product* within a population; it then classifies these adopters as '*innovators*' or '*imitators'*.
308 In the HABM, the 'material product' concept of the Bass Model is replaced with the a priori
309 product of 'knowledge' regarding an imminent flood event, this is to say that agents within
310 the model can simply be set to act out evacuative measures immediately at the start of the
311 simulation and in all of the timesteps leading up to the flood inundation, if they choose to
312 stay. These 'innovative' agents are also freely able to communicate these measures to
313 proximal neighbouring agents who can then choose to imitate these informed agents; or carry
314 on with what they are doing. it should be stated that the sociological dynamic of *innovation*
315 and *imitation* is proliferated within the model by communication between agents who are
316 proximal and so this simple binary distinction could be regarded as a potentially useful one
317 for representing the apparently complex communication dynamics of a social system in a
318 relatively simple manner.

320 In the specific instance of the HABM, the *innovators* are set as *pre-prepared* prior to the flood
321 simulation onset and the *imitators* are those who would not be prepared, but who are given
322 the choice to adapt their routine at each timestep, based upon contact with the innovators.
323 This situation, describing people who are in possession of knowledge regarding the flood
324 event and then communicating it to those who are not, could have an impact on all aspects
325 of response and evacuation, as it is a crucial component of the boundary between the
326 processes of *warning* and *response* (Axelrod, 1970; Chen & Zhan, 2008; Chu, 2015). With
327 specific reference to the Bass Model terminology, there are three parameters (or
328 representative coefficients), that define the compatibility with the HABM, these are:

330 • (*M*) - The potential *market*, these are the ultimate number of potential adopters, i.e. the
331   population. This constitutes the number of members of the social system in which word-
332   of-mouth communication from past adopters is the driver of new adoptions. The Bass
333   Model assumes that *M* is constant, though in practice and over longer periods, M is often
334   slowly changing according to population change and product memory.

- **(*p*)** – The coefficient of innovation, so-called because its contribution to new adoptions does not depend on the number of prior adoptions. Since these adoptions are due to some influence outside the social system, the parameter is also called the 'parameter of external influence.'
- **(*q*)** – The coefficient of imitation has an effect that is proportional to cumulative adoptions A(t), implying that the number of adoptions at time t is proportional to the number of prior adopters. In other words, the more that people talk about a product, the more other people in the social system will adopt it. This parameter is also referred to as the 'parameter of internal influence'.

The other variables in the Bass Model relationship and calculated from *M*, *p*, *q* and *t*, are:
- *f(t)* - The portion of M that adopts at time t,
- *F(t)* - The portion of M that have adopted by time t,
- *a(t)* - The adopters (or adoptions) at t,
- *A(t)* - The cumulative adopters (or adoptions) at t.

The outcomes of the coupled application of these three components (sections 2.1, 2.2 & 2.3) towards the two objectives are further illustrated in section **4** and are discussed further in section **5**.

Of further interest here is how to qualify the communication taking place within the HABM. In sociological terms, the imitative process involved is broadly one of inter-agent communication and collective response. According to the sociologist Gabriel Tarde and his Laws of Imitation (Tarde, 1903), as applied to 'groups of people', innovations must undergo a process of diffusion over time to gain a foothold and become a component in the decision-making process linked to the innovation, be this *adoption* or *rejection*. Tarde's process involved in the diffusion of innovation has undergone some revisions in the decades since being first proposed and can now be defined through the following five steps:

- First Knowledge,
- Attitude formation,
- Adoption or rejection,
- Implementation,
- Confirmation of the decision.

Via the Bass Model, the HABM for Carlisle allows a simulated engagement with the first four steps of Tarde's process, the fifth being confirmed in the representation of the first four activities as the simulation advances over time. This interpretation of social imitation and adoption was used as a basis for investigating the influence of these processes in an event where time is relatively constrained and the stakes of action are high, such as during a flood onset. The values for this process of adoption were taken from the change in overall un-prepared population in Carlisle transitioning to a 'prepared state' based upon contact with a

'pre-prepared', or innovative, agent. This transition was represented by the percentage of the population in possession of the appropriate knowledge for effective flood evacuation who then reported this change back as an agent-orientated change of state throughout the simulation of the flood. This rate of change of state is then fed into the Bass Model functions to produce diffusion curves like those seen in figures 8a & b and discussed in further detail in sections 4 and 5.

3. **Core model construction and system dynamics**

Given the complexity caused by the incorporation of these diverse elements within considerations of a flood hazard system, the benefits of a standardised flood incident management strategy based on an understanding of these dynamics might not be immediately apparent. Further management of complexity might necessarily arise through the required interactions between the individuals and organisations who might very well have conflicting interests linked to contrasting elements in their expertise or experience (Hart, Nilsson & Raphael, 1968; Hornor, 1998). Furthermore, the feedbacks within a flood hazard system, particularly an urban one, can lead to a spectrum of dampening and amplification of behaviours within the system, the dynamics of which could be influential on outcome, yet difficult to account for in a standardised flood incident management strategy (Assaf & Hartford, 2002; Dawson et al., 2011; Rasmussen, Pejtersen and Goodstein, 1994.) It is here where the HABM concept reaches out to the concepts of phenomenology, poststructuralism, structuration theory, structural functionalism and symbolic interactionism to inform the conception of a modelling framework that incorporates the important social notions of these disciplines and thus anchors the modelling element of the HABM to the cardinal philosophical and sociological concepts underlying it and the outputs produced. The appeal of this approach lies primarily in the novelty of the undertaking in addition to the application of concepts from disciplines such as sociology, philosophy and psychology, which complement the model by offering access to new terminology and theoretical bases for better representing social systems, focussed on *relatedness* rather than *boundedness* between the dimensions and the whole (Alexander, 1980) ; within a coupled modelling framework. Here, the benefit of a more holistic representation can lead to the development of a more effective and holistic understanding of how to manage social dynamics, responses and functions within physical models where they can have further impact on effective planning for and outcomes from the whole system and the components comprising that system (Smith & Tobin, 1979; Zarboutis & Marmaras, 2005).

With these details in mind, and urban systems being the primary interest in this paper (figure 2), the first step beyond bringing together the initial HABM components was to devise a conceptual format that describes the key dimensions of the urban system within a parameterised and reproducible framework. In this paper they will be primarily referred to as *dimensions*, alternatively they can be called '*sets*' (or *centres* (Alexander, 1980), and can be broadly subdivided into three separate systems, that of the *Environment*, *Community* and *Built Infrastructure* (UNISDR, 2015; Wisner et al., 1994). Networks existing between these

dimensions, resulting from the co-evolution of the dimensions, are characterised by the immediate practical and physical influence that each has on the behaviour of the other to create an operational whole. Conceptually, this is analogous to the notion of the *Brunnian Link* in mathematics and the poststructural, psychoanalytical concept for *experience* or *jouissance*, proposed by Jacques Lacan's *Borromean Rings* construct in the 1970's (Zupančič, 2000). An urban system, concomitant with our physical perception and experience of it, can occur at the nexus of the topological sets illustrated in figure 2. Whilst these constituent dimensions could be deliberated in terms of scale, dynamic or boundary and seemingly experienced separately from one another by individuals or groups, it is important to understand that for the present analysis, the function of the urban system within the HABM framework arises in the form of the aforementioned Brunnian link. This is as an "extended and unbroken continuum of connections wherein the whole is necessarily unbroken and undivided" so that life may be supported, experienced and proliferated therein (Alexander, 1980).

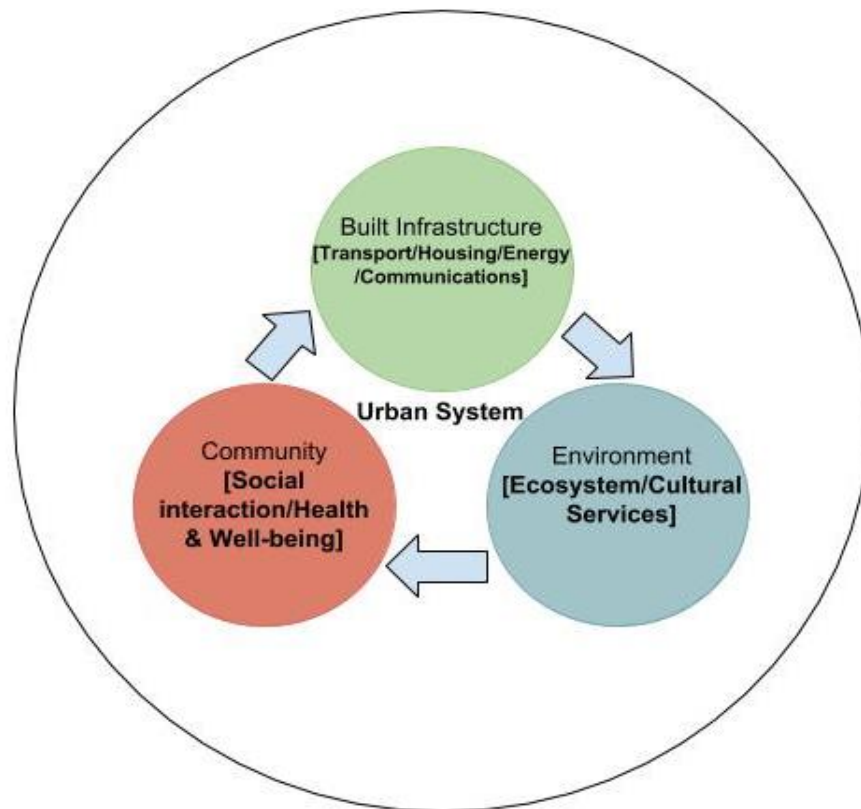



Figure 2: A simplified schematic illustrating the key centres of an urban system. Conceptualised from [Axelrod, 1970, Wisner et al., 1994] and the terminology given within the Sendai framework 2015-2030 [UNISDR, 2015].

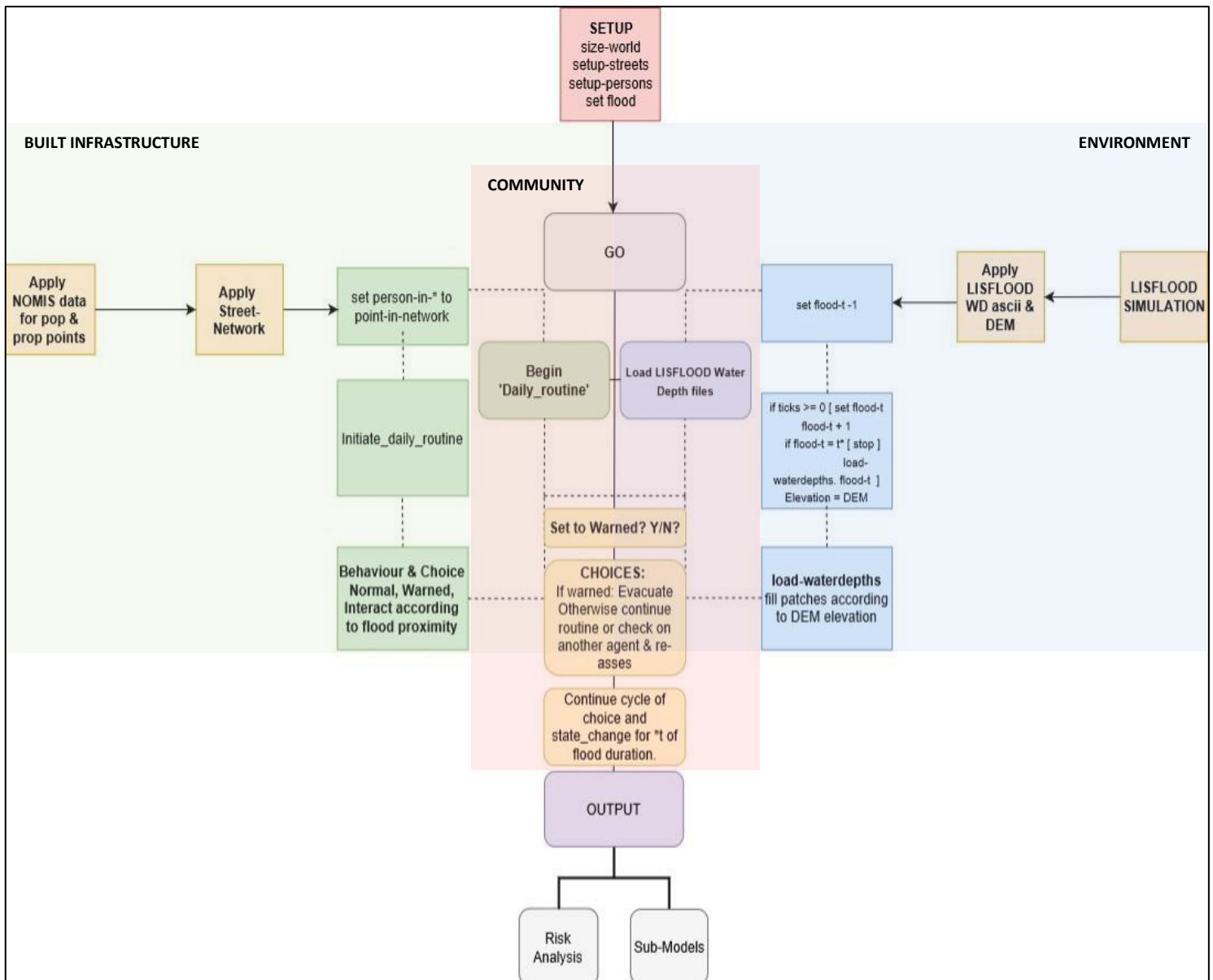
Specifically, this link is a mathematical and topological term used to describe the triviality and non-triviality of connection between the sets. As applied to the HABM system concept, when disconnected from the complete, interconnected, system set, the system no longer exists and cannot be experienced by people within it. Utilising the terminology applied within mathematical topology, the individual systems become '*trivial*' when disconnected from one another and '*non-trivial*' when all are in contact within the dimensions of the systematic whole. Thus, the individual systems are experienced in combination with one another, where

the boundaries, existing between these systems, would not be as discrete as those shown in figure 2. This would suggest an overlap in the systems whereby experience and interactions between these systems and people, *life*, occurs at the nexus of the three. A simplified scenario to support this understanding for Carlisle would be one where a *community* requirement for an advance in *built infrastructure* as a response to perceived, or experienced, *environmental* risk from flooding; something which could be considered an *emergent* characteristic from the onset of the flood hazard system. Consequently, were the topologies of each of the three dimensions existent separately, and not connected in a manner as suggested in figure 2, interactions between the elements of the three system sets, including the manifestation of physically *hazardous* phenomena, would not be possible (Alexander, 1980; Axelrod, 1970; Berendracht et al., 2017; Du et al., 2017; Dugdale at al., 2009; Eberlen et al., 2017; Fordham, 1992; Guyot & Honiden, 2006; Holland, 2014; Liu et al., 2015; UNISDR, 2015).

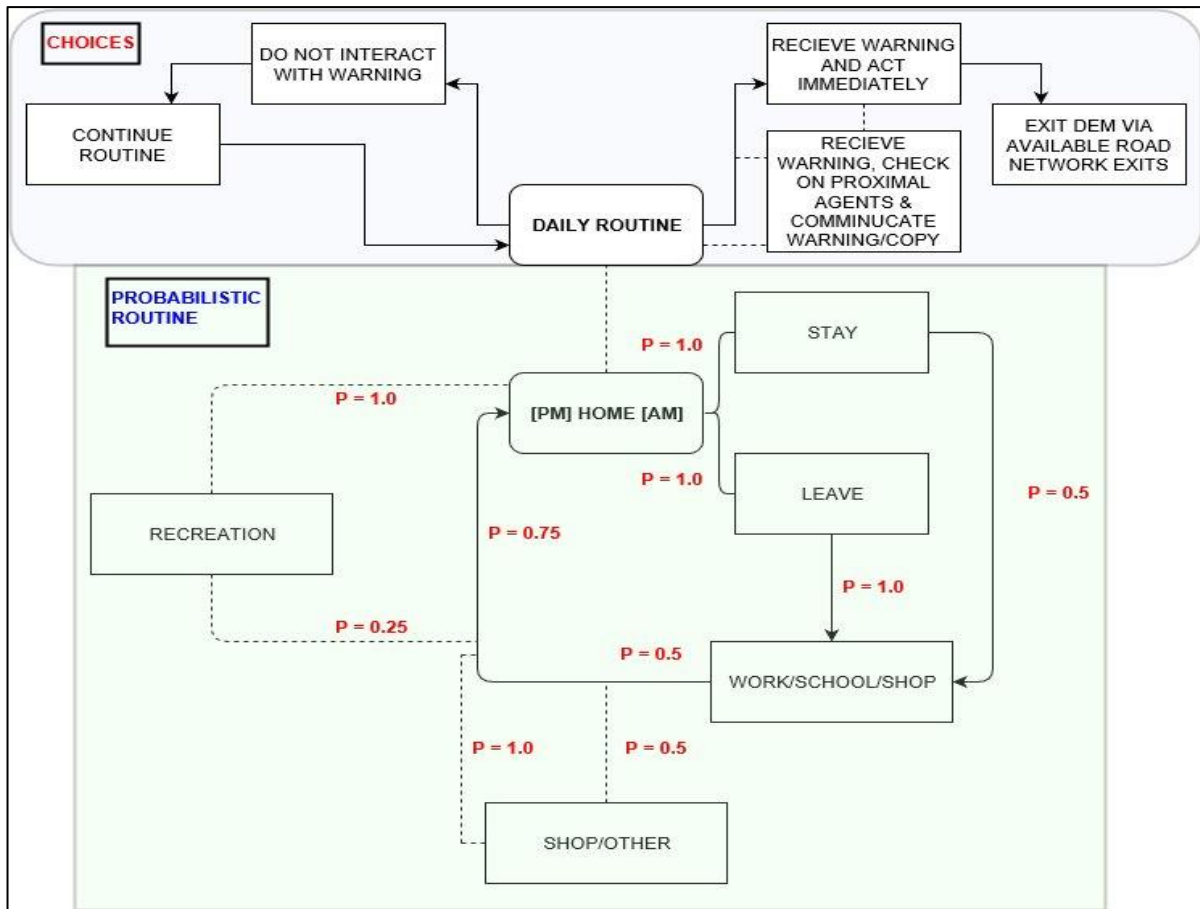
Thus, the simulations of the dynamics of Carlisle's urban system for the HABM focused on establishing the linked characteristics between the three dimensions to model a non-trivial system. The use of an ABM enables this through a focus on the community dimension, through simulation of activities and interactions which may then be used as metrics for change according to a specific environmental event, in this instance the 2005 flooding of the Rivers Eden, Petteril and Caldew. To perform these simulations, a correspondence between the conceptualised urban system, representing the three inter-linked elements of figure 2 and the modelling framework illustrated in figure 3, was developed. Figure 3 is a schematic of this correspondence and represents the overlying workflow of the HABM for simulations of the 2005 Carlisle flood. The layout for this figure was used to support workflow and model structure in relation to effective representation of the urban system shown in figure 2, within the ABM platform. The Layout of figure 3 is such that the structure of each set from figure 2 corresponds with the processes taking place in NetLogo to represent that set. In sum:

- The environmental set is simulated using the LISFLOOD-FP outputs and the site DEM,
- The Built infrastructure is emulated using census data sets and street network information,
- The community or social set overlaps both the built and environmental systems and is driven by the agent-orientated, probabilistic choice and interaction flowchart illustrated in figure 4.

The details of the diagram in figure 3 are the cardinal NetLogo commands that overlap between the system sets and so enable the simulation of the three dimensions within the HABM. This establishes a tangible link between the conceptual complexity of the urban system experienced by people with that experienced by agents, who represent people, within the simulated version of the urban system. This transferral from a conceptual topological figure to a logical modelling schematic was an important step which was taken to link the modelling system to the physical system being modelled. Whilst the format presented in figure 3 is not particularly novel in the sense of workflow or process for an ABM, it is relatively novel in the sense of how it illustrates this link between a conceptual construct of a system, figure 2, and the workflow steps required in simulating this system and representing dynamics

510 that can provide an analogue for events that occurred during an historical physical event, such
511 as that in Carlisle during 2005.
512

513 **Figure 3:** The core components of the HABM, an indication of the model cycle for these components, and the
514 elements of the urban system (**figures 1 and 2**) that they demonstrate. The schematic follows a similar format
515 to that of a Euler diagram [Whitehead & Russell, 1913], whereby the three centres of the urban system are
516 shown to contain the respective components of the model representing their function within the HABM. These
517 are (from right to left): Built Infrastructure, Community, Environment.
518
519 Figure 4 further extends this conceptual approach through to the community element of the
520 modelled system in offering simulated agents the choice to engage with a basic, probabilistic,
521 daily routine within the simulated system as well as engage in emergency response actions
522 following flood onset. This further enhances the realism of the simulated population of
523 Carlisle and provides an analogue for how variations in the physical interaction with a flood
524 might affect the evacuation response (Morss et al., 2016; Müller et al., 2013). The routine and
525 decision tree format, formulated through the ODD (Overview Design concepts & Details)

526 protocol (Wilensky & Rand, 2015), with a view to potentially producing '*emergent*' behaviour
527 for the modelled system, was initially referenced from the synthetic daily routine and
528 transport model used for simulating storm-surge evacuation by Dawson (et al., 2011). The
529 adopted elements of this routine were the basic formatting seen in figure 4, whereby
530 probabilities were assigned to activities for the agents in the model. Of note here is that a
531 discrete transport model was not included in this model for these initial findings as it was felt
532 that there has already been recent and significant advances in this area of interest (for
533 example: Coates et al., 2014; Pyatkova et al., 2019; Mostafizi, Wang & Dong, 2019). The
534 activities of interest were engaged with on a point-to-point basis as the agents navigated
535 through the simulated system of Carlisle until flood onset. With onset, the agents within the
536 simulated system can then choose to engage with the emergency routine or continue with
537 the elements of a daily routine until the next timestep. As there is already a wealth of
538 evidence available (see for example: Assaf & Hartford, 2002; Berendracht et al., 2017; Chu,
539 2015; Du et al., 2017; Dugdale et al., 2009; Eberlen et al., 2017) to suggest that the time of
540 event onset is influential in event outcome, this time-dependency was not implemented
541 within the simulations for Carlisle. This choice was made in favour of developing streamlined
542 simulations that emphasised agent-agent interactions between event onset and end.
543 However, time-dependency is something which is easily implemented within NetLogo if
544 desired and indeed was implemented in later iterations of the HABM for different
545 applications. In addition to this agent-agent focus, non 'pre-prepared' agents may also engage
546 with 'pre-prepared' agents in the model and initiate emergency action based upon their
547 interaction, demonstrating a synthesised form of communication and response. The
548 development of this step in the modelling procedure was crucial to allow interpretation of
549 the influence of an adopted policy directive on inter-agent interaction and choices made
550 during the onset of the flood event which may ultimately notbe time-dependent in nature

551 (DEFRA, 2007;Landstrom et al., 2011; Liu et al., 2015; Morss et al., 2016; UNISDR, 2015;
552 Waldorp, 1993).

553 **Figure 4:** An overview of the agent choice & probabilistic routine tree used to guide agent processes through
554 the simulated environment of Carlisle. Informed by reference to (Bennet & Tang, 2017) & (Dawson et al., 2011).
555
556 The format of figure 4 was beneficial in this instance as it offers a basic format for agents
557 operating within the model of Carlisle, a format by which they can navigate along the street
558 network in a manner reflective of what might be expected during an average day in Carlisle.
559 The probabilistic format of the routine ensures that upon each timestep agents will be at
560 specific points within the network. Whilst this attenuates the representative complexity of
561 the model, it is believed that it offers enough complexity of choice and action to reflect the
562 potential reality of a complex social and flood onset situation within Carlisle. The probabilities
563 shown in figure 4 were adapted slightly from the original synthetic routine proposed by
564 Dawson et al. to be more generalised and, for computational efficiency within NetLogo, were
565 implemented to be acted out on each time step, rather than continuously over flood onset.
566
567 In section 4, figures 5 to 7, the product of the co-action between the components of figures
568 2, 3 & 4 can be seen. These figures illustrate the model in a preliminary state of simulation
569 and so the full agent population is not in action. Whilst the largely autonomous processes of
570 NetLogo, outlined in section 2, influenced the extent to which the simulated agents engaged
571 with the routine and the choices provided, the implementation of a routine acted to
572 attenuate not only the representative complexity of the situation, but the outright

stochasticity of the NetLogo agents also. This means that whilst the agents would be interacting with 'commands' *e.g.* 'leave home point' or 'stay at home point for t(n)', these commands are not too far removed from a realistic analogue of basic choices a human might make on a given day (Bernardini, Camilli, Quagliarini & D'Orazio, 2017; Chu, 2015; Dawson et al., 2011) with the possible actions of the daily and emergency routines being more reflective of general and reactive behaviours expected during a flood onset (Du at al., 2017; Dugdale et al., 2009). The spatial distribution of the agent population within the HABM was informed with national UK Census statistics for Carlisle. However, as census data does not identify individuals against specific addresses, the distribution of agents within the simulated HABM environment was implemented in a slightly more utilitarian manner than the demographic-based distribution seen in Dawson (Dawson et al., 2011), by using a linear function of the population of Carlisle with agents being allocated to home points within the model according to building footprint (Bennet & Tang, 2017; Borschev & Filippov, 2004; Dechter & Pearl, 1986).

In terms of the Bass Model variables discussed earlier, (**M**) is represented by 108,000 agents (in the final simulations), the total population of Carlisle (The Environment Agency, 2016); (**p**), here, represents the 50% estimate by the EA for the population of Carlisle currently deemed as 'signed up to flood warnings' or *pre-prepared* and in possession of the, defined within the HABM as *innovative*, knowledge to respond to the flood upon onset (The Environment Agency, 2012). The coefficient (**q**) roughly equates to 30% which represents the one-third likelihood of those who encounter the innovators (**p**) adopting the innovation as defined by the Bass Model in a scenario where the rate of adoption between innovation and adaptation is linear or *seamless* (Bass, 1969). Despite this somewhat ideological perception of human communication (Jakkola, 1996), this rate of conversion was kept consistent in the instance of the Carlisle simulations as no evidence was found to suggest that social factors were present within Carlisle that would adversely affect it (widespread prejudice, social unrest, a despotic government etc.). In total 200,000 simulations were performed using this methodology within the NetLogo BehaviourSpace tool. These differed through scaling of 'pre-preparedness' between 0 and 100% and the outputs of interest from these simulations were the rate of change from '*un-prepared*' to an '*evacuative*' state, based upon agent contact and the number of potential casualties linked to the change of preparedness (%). Finally, regarding the status of 'potential casualties' within the HABM, this is a term and metric of the HABM used to describe agents physically impacted by the flood. This term does not account explicitly for 'death', rather it is a measure of those agents who may become cut-off from a clear escape route or inundated during evacuative procedure and actual agent fatality was extremely rare during the simulations. The simulation of fatality was defined differently to physical fatality in that it was only presented when an agent's grid cell became inundated, to a third of an agent's height, for one time-step, having had all escape routes cut off (Assaf & Hartford, 2002; Landstrom et al., 2011; Roland & Moriarty, 1990).

4. **Results**

Figures 5 to 7 are examples of these simulated flood sequences for the 2005 Carlisle flood by the HABM, showing inundation areas and agent locations, both prior to the flood (figure 5) and at later stages (figures 6 and 7) after flood onset and agents have been variously alerted. The time taken to model this process in NetLogo, over one complete event simulation, ranged from 45 seconds (2019) to 3 minutes 30 seconds (2017). The side panels on the left-hand side of the figures outline the basic controls for the model, whilst the charts on the right show model predictions for *potential casualties* in relation to populations and *pre-preparedness*, which is an apriori knowledge of the flood, as previously stated. These figures are representations of the modelled culmination of the concepts discussed in sections 1, 2 and 3 and illustrated in figures 2 to 4 within the NetLogo interface.

Figure 5: An overview of the preliminary HABM. Shown here as an example are agents engaging in the daily routine (green) prior to the initiation of the LISFLOOD-FP flood inundation. These figures represent only a small proportion (<1000 agents) of the full agent populations (~ 108,000 agents) simulated for the final results of the simulations

636

637 **Figure 6:** Agents marked in red are those whom have become aware of the incoming flood and are taking
638 evacuative action. Changes in agent colour on the GUI (Graphic User Interface) indicate that members of the
639 sample population are transitioning to a 'potential casualty' as the flood encroaches their vicinity but also that
640 the likelihood of casualty occurring will diminish over time as the message of 'preparedness' diffuses through
641 the population.

642 **Figure 7:** Further to preparedness and potential casualty, an indication of areas in which people are likely to
643 stay, areas from which people are most likely to move as well as the areas through which people are most likely
644 to pass may be observed within the HABM GUI and are indicated further in **figure 10**.

645 In applying the Bass model to the Carlisle HABM, two diffusion curves were produced (figures
646 8 a & b). These represent inter-agent communication regarding the adoption of policy
647 instructions to either evacuate the area immediately, i.e. to adopt an innovative instruction,
648 or to follow an imitative one after checking with nearby agents and only then deciding how
649 to respond. The coefficient (**q**) is typically represented by a much smaller value than 30% in
650 traditional applications of the model (Mahajan, Muller & Bass, 1990). However, owing to the
651 elevated risk involved in adopting, or not adopting, the product of evacuative knowledge
652 during a hazard scenario, the traditionally small value of (**q**) has been scaled up significantly.

653 This is to represent a one-third likelihood (~30%) of those who encounter the innovator (**p**)
654 agents, receiving the flood warning by communication and adopting directly from them.
655 Whilst this is a manipulation of the Bass Model function, it remains consistent with the Bass
656 Model theory, stipulating that human adoption of a process or product is more likely to
657 happen based upon internal systematic influence, or *imitation*, rather than through external
658 influence on the social system, or by *innovation.* Wherein the available choices may be
659 reduced to 'yes', 'no' and 'maybe', probabilistically represented as roughly one-third each for
660 a given scenario (Dechter & Pearl, 1986; Hart et al., 1968; Hornor, 1998; Mahajan et al., 1990;
661 Massiani & Gohs, 2015; Sultan, Farley & Lehmann, 1996).

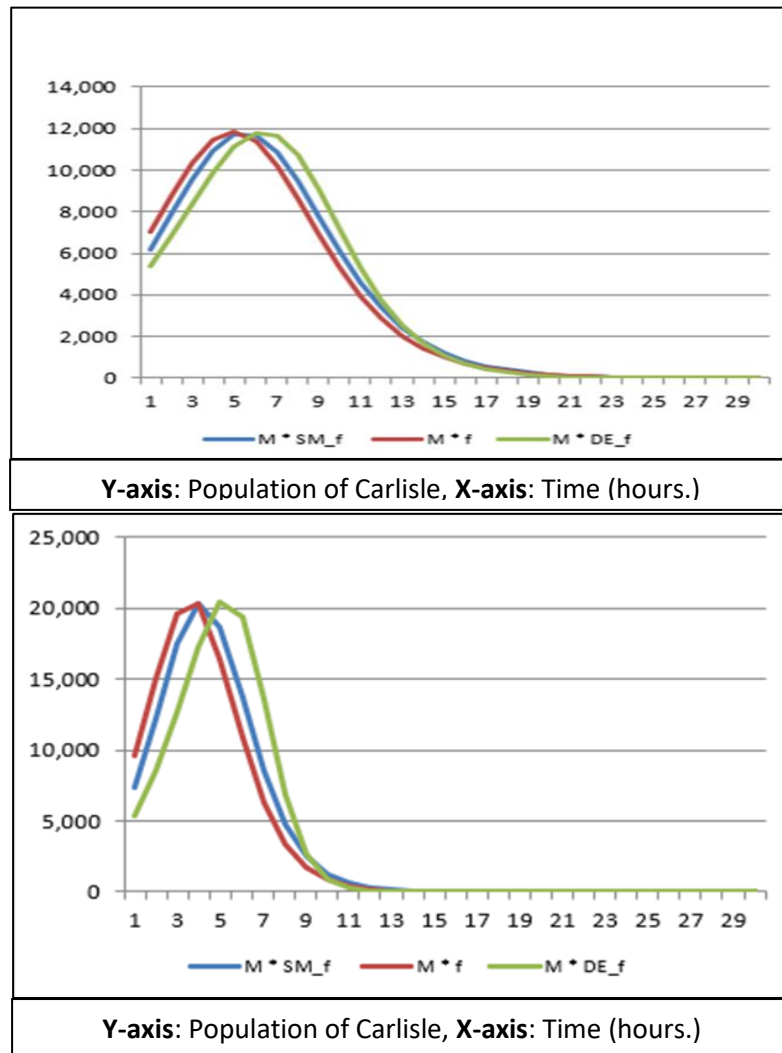
663 The fundamental difference between (**p**) and (**q**) is generated from this external-internal
664 distinction. Aligning this further with the sociological notions of Tarde, (**p**) is a representation
665 of an external factor that requires a change in operation of the internal system dynamics (**q**)
666 over time, thought of as an attunement, harmonisation or, in more traditional terms that may
667 be thought of as an *acceptance* (Tarde, 1903). This means that for an innovative process (**p**)
668 to become a naturalised component of the internal system dynamics (**q**), a significant amount
669 of time may be required for innovation to lead to imitation when there is a *risk* involved (
670 **Wheater, 2006**). In this application, the Bass model gives an indication of this duration based
671 on the relative probabilistic magnitudes of (**p**) and (**q**) for a population of 108,000 agents. The
672 overall significance of this application is that it allows conclusions to be made as to how
673 influential external policy protocols are for the population in relation to their internal 'sense'
674 during flood event response (Massiani & Gohs, 2015; Sultan et al., 2003).

676 The curves illustrated in figures 8a and b are the separate curves for the process of adoption
677 based upon the optimised Bass Model values for the coefficient of innovation (**p**) at 50% and
678 coefficient of imitation (**q**) at approximately 30% over 200,000 simulations for the Carlisle
679 model. The three separate lines are illustrations of the three different iterations of the
680 model's standard differential equation as functions of continuous and discrete time (**Bass,**
681 **1969**). Correspondence between the curves represents an agreement between the model's
682 functions and the data being plotted. Broadly, the curves show that the innovation of external
683 directive, seen in figure 8a (**p**), is more effective at promoting an immediate evacuation as a
684 lower number of the simulated population changing state over time would suggest that a
685 large proportion of the original innovators choose to act in the early onset of the flood and
686 evacuate the area without hesitation. The negative aspect of this function is that there will be
687 less agents available to communicate the innovative process and influence the less prepared
688 agents and so this process of innovation will take longer to diffuse throughout the agent
689 population leading to less agents taking appropriate action and exposing themselves to
690 potential danger.

692 The curve for figure 8b, (**q**), is the internal function for evacuative measures, which is reliant
693 on agent-agent interaction and suggests that the internal dynamics for the adoption of
694 evacuative measures, that is to say the adoption of the same actions as the agency directive
695 but not directly from the external directive (e-mail, text alerts etc.), according to
696 communication between agents, within the total flood affected population of Carlisle, is more

influential over a shorter duration than the operation of (**p**). The variance between the three lines would suggest that there is some disagreement between the baseline functions of the Bass Model differential equation and those for discrete and continuous time for (**q**) and it is believed that this is likely related to the unusually high value attributed to the 30% likelihood of agents *agreeing* to imitate the innovative agents and become imitators, as well as the general stochasticity related to the reliance on 'proximal contact' for communication between agents, which is likely but not guaranteed in any situation; particularly in one as frenetic as that involving a flood.

Y-axis: Population of Carlisle, **X-axis**: Time (hours.)

Y-axis: Population of Carlisle, **X-axis**: Time (hours.)

Figures 8 a & b: Example Bass diffusion curves for p or innovation (top), and q, or imitation (bottom), at Carlisle. Illustrated are the curves for the continuous time Bass Model functions (blue/ M*SM_f & red/ M*f) for discrete and incremental time-steps and the Bass Model differential equation (green/ M*DE-f). The Y-axis for both curves represents the maximum number of individual agents with potential to respond in accordance with the type of warning given and action taken,

This bridge between sociological and theoretical concepts of process diffusion, or between internal and external components, provides insight into the relationship existent between policy and responsive behaviour. Furthermore, the Bass Model's use in the analysis of flood response dynamics is a broadly useful one, providing quantitative evidence of behaviour, in

the form of diffusion curves (figures 8a & b) and, for the dynamics of during-event agent communication, thus implementing Tarde's sociological laws into the modelling process. In addition, it represents both the 'innovative' *i.e.* individual response to policy direction, and the 'imitative' processes related to this direction, which certainly have influence on the micro, and potentially macro, scale human responses to flood events (Bernardini, 2017, Guyot & Honiden, 2006).

As the flood depths in the Carlisle dataset were relatively shallow beyond the river channel during the early time-steps, very few agents were presented with a potentially fatal scenario that they could not escape from, registering them as a '*potential casualty*' instead of a fatality. Broadly, a *fatal* scenario in this instance was determined by total cell inundation surrounding an agent and preventing them from leaving. Whilst there are examples of models utilising depth and velocity as determinants for a fatal scenario (Chen & Zhan, 2008; Chu, 2015; Dawson et al., 2011) these were not functions implemented in this preliminary model but were implemented in the later iterations of the HABM. Whilst the HABM should not be regarded as a full predictive tool, it does enable the visualisation of individual and group interactions, which might lead to potential casualty over repeated simulations. This is a valuable insight given that it is often difficult to identify comparable levels of detail from historical examples and their related data for micro-scale factors that are influential in event outcome.

According to figure 9, once overall 'preparedness' of the agent population of Carlisle exceeds 30%, either through increased social interaction or directly from policy instruction, the likelihood of 'casualty' resulting from the flood scenario actually increases. This was an unexpected outcome and might, at first, seem counter-intuitive but is thought to be attributable to Carlisle's urban '*fabric*' (topography and morphology). When agents select to respond to the flood collectively and all at the same time, congestion of exit routes leads to an overall reduction in of movement away from flood inundated areas, so increasing agent exposure to the hazard (Wei et al., 2003; Werrity et al., 2007). This possibility is a valuable new insight produced by the HABM. Figure 9 illustrates the range of results from the 200,000 simulations of the 2005 Carlisle flood. Across these simulations, the percentage of the population pre-warned of the flood event was varied between 10 and 100 %. The current DEFRA estimation for Carlisle is that 50% of the population (~ 54,000 people) are classed as 'prepared' for a flood (termed 'population warned' or 'pre-prepared' in the HABM simulations). The population warned within the HABM will initiate evacuative behaviours, according to policy instruction, within the first hours (~ 1-3 timesteps) of the flood inundation taking place and are able to communicate this action to surrounding agents from the outset of the simulation, largely by-passing the time required for the autonomous decision-making process during the event and engaging directly with the apparent agent preference for imitative behaviour.

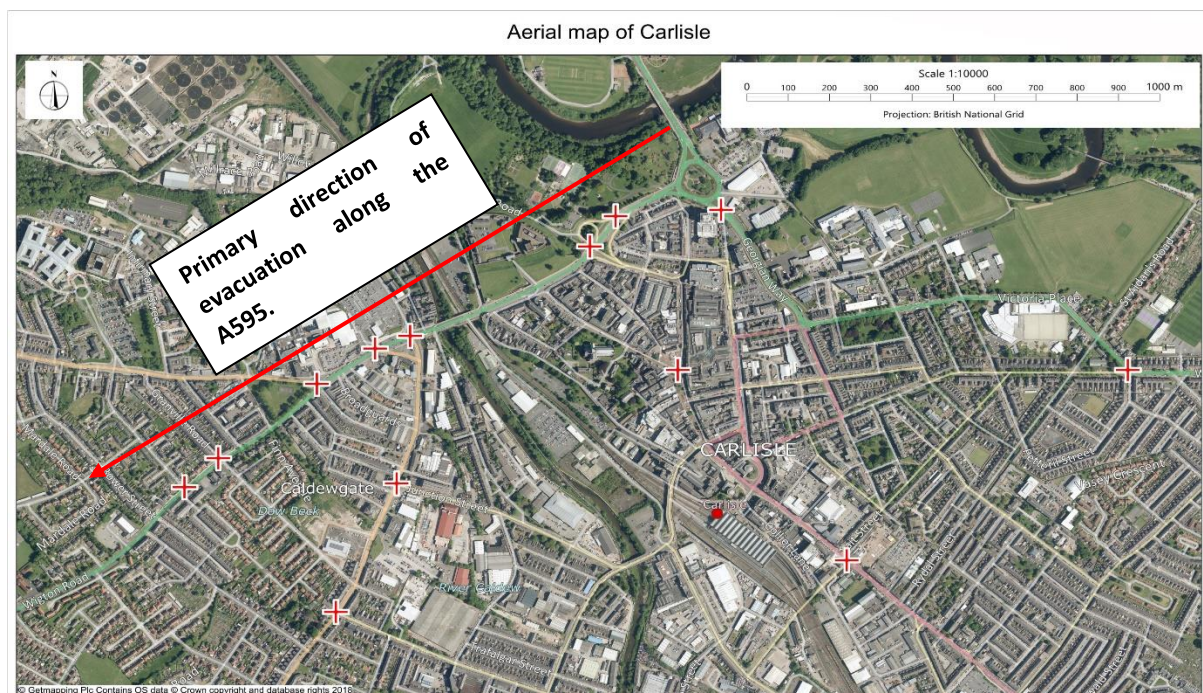
Figure 9: A box chart illustrating the range of values, sampled from 1000 agents (the most computationally stable sample size for batch runs on the available architecture) within the full agent population (108, 000), for the total number of potential casualties vs. % of population pre-warned for Carlisle from 200,000 simulations.

To assume that a higher percentage of pre-prepared agents would lead to an overall reduction in potential casualties would be a logical assumption to make (Axelrod, 1970; Chen & Zhan, 2008; Dawson et al., 2011; The Environment Agency, 2016). As highlighted by figures 9 and 11, overall potential casualties for the simulated population of Carlisle shows an *increasing* trend for higher percentages of pre-warned agents, particularly above 80% preparedness. As already mentioned, this reflects the way in which Carlisle has been constructed around the confluence of the river(s) Eden, Petterill and Caldew. It highlights the deficiencies of this urban structure when a large inundation event forces significant numbers of agents to evacuate

796 through a limited number of escape routes (figure 10), (Gilligan et al., 2015; Sanders &
797 Sanders, 2004).

798

799 According to the HABM results, Carlisle's agent population has a distinct 'preference' for
800 evacuation to the south-west of the city, along the arterial A595. This preference was
801 established through visual assessment of the simulations and was likely determined by the
802 number of sub-routes that had access to the A595 and that were not cut-off by flood waters.
803 Indeed, the most densely populated areas of Carlisle are divided into four distinct areas by
804 the three rivers shown in figure 1 and so this preferred escape route is only immediately
805 available to those who are either pre-prepared, reside within the immediate vicinity of the
806 A595, or who live or work to the west of the Eden and Caldew. As the flood progresses beyond
807 the first 5-6 hours of propagation, the number of escape routes diminishes yet the number of
808 agents prepared to evacuate has increased significantly. This creates a backlog in the system
809 whereby more agents choose to stay in their immediate vicinity or to evacuate at the same
810 time as everyone else, exacerbating the system congestion and increasing agent exposure to
811 the flood inundation. Whilst agent choices do vary from simulation to simulation according
812 the choices of their routine and the type of agents they make contact with, this pattern of
813 evacuation occurs across the whole set of simulations, and so could be taken as an indicator
814 of likely choices made by the population of Carlisle if a flood happened today.

815

816
817 **Figure 10:** An aerial image of Carlisle illustrating the preferential direction for escape to the south west along
818 the A595. Further illustrated are the most prominent chokepoints (**red crosses**) for reduced evacuative flow of
819 people between 80 and 100% preparedness. These points were identified from the HABM as the nodes in the
820 street network overlay which have the most consistently high densities of agents throughout the range of
821 simulations. (Contains OS data © Crown copyright and database right (2019))

822

823 As is illustrated in figure 11, with less than 30% preparedness, agents within the HABM show
824 a preference for evacuation away from Carlisle during the earlier stages of the flood onset

825 and so the social response to the flood is slow when there are fewer people in Carlisle to
826 disseminate the message of evacuation. This finding further reinforces the results presented
827 in the diffusion model (figures 8 a & b). Without a threshold number of the population being
828 aware of the impending flood there is less likelihood of contact with unaware agents. This
829 means that the response dynamics are more reliant on the innovative procedures of policy
830 uptake and arbitrary choice, both of which are shown to be less likely to produce a *successful*
831 evacuation outcome. The transition from micro to macro level response, from individual
832 agent interaction up to a large group response to changes in the environment, is realistically
833 a much more complex process than that illustrated in the HABM model. Thus, as a starting
834 point for testing hypotheses related to transitory-scale flood hazard response, it is a useful
835 tool for exploring the related and inherent complexity of the socio-environmental interface
836 present during a flood event (Wilensky & Rand, 2015; Wisner et al., 1994; Wong & Luo, 2005).

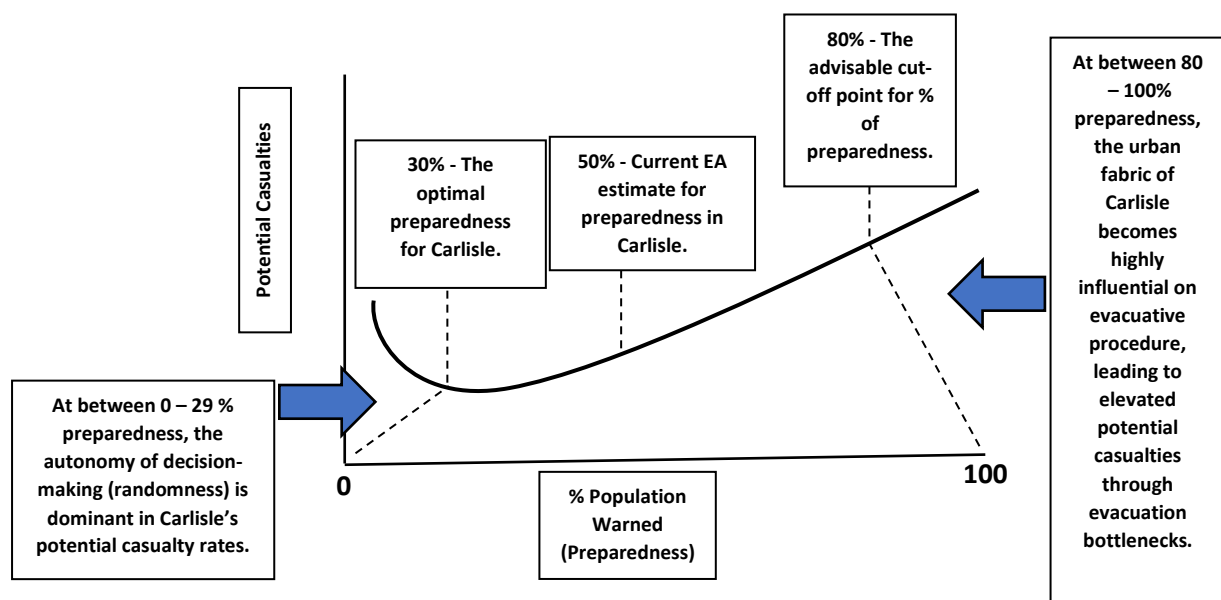



Figure 11: A representation of the key results shown in Figure 9 together with concepts that can be associated with them. It is expected that these percentages will vary with model parameterisation and changes in the area modelled.

5. **Discussion**

860 From further interpretation of figures 8 a & b, 9, 10 and 11 it is reasonable to infer that the
861 agents within the HABM, representing the local population of Carlisle, demonstrate a further
862 *preference* for basing their response to a flood event on interaction with their surrounding
863 neighbours, a social response, rather than acting directly from policy instruction. The 2005
864 event in Carlisle significantly overtopped existing defences, meaning that local and possibly
865 larger scale *management* actions would have been of little consequence to the event
866 dynamics and so it is here where the social response becomes influential in the risk and
867 resilience dynamics of the event (De Groot and Schuitema, 2012; Kinzig et al., 2013). With
868 respect to these dynamics of response, the rate of innovation (Figure 8a) impacts less of the

869   Carlisle population over a greater duration compared the rate of imitation (Figure 8b). It is
870   believed that this could be because there is a higher number of the influential, *aware* or *pre-*
871   *prepared*, agents leaving the vicinity of the flood prior to, or in the early timesteps of, flood
872   onset and so the message of adoption from these agents becomes less likely to diffuse
873   through the rest of the population (seen in figures 5 to 7). Conversely, when the remaining
874   proportion of the population begin to experience the effects of the flood and a greater
875   number of this population's daily routine becomes disrupted, a greater number of this
876   population will transition to the choice scenario (figure 4) and begin *checking* with those
877   agents around them about what an appropriate response will be. This proliferates the
878   imitative process of evacuation and so would explain why the rate of imitation is more
879   influential over a shorter period, particularly when the compact social network of Carlisle,
880   facilitated by a relatively constrained urban topology and morphology; is considered.

882   A likely explanation of the slightly better correspondence between the curves of Fig. 8a
883   compared to Fig. 8b is that they represent a direct instruction at the outset of the simulation
884   and so there is less time for choice to be considered, with agents taking direct action as soon
885   as possible. The issue with this is that the agents carrying the innovative knowledge will
886   encounter less agents as the event unfolds over time, having taken evacuative action from
887   the outset and left the area where the rest of the agents may not have encountered the flood
888   inundation yet and are therefore continuing with their daily routine. Consequently, when the
889   function of **(q)** is considered, a more effective and efficient process for diffusing the
890   evacuative information amongst the modelled population of agents is seen. To understand
891   why this is the case one must consider the dynamics at play in a broad sense, **(q)** is a descriptor
892   for internal influence and, within the HABM, is reliant on agent-agent interaction whilst **(p)** is
893   the innovative directive from a distal governmental agency which is reliant on engagement
894   from the population and so to simplify this process as much as possible for these simulations,
895   this directive was designated as an instruction to 'take evacuative measures immediately'.
896   Worthy of note here is that, for the applied parameters, the Bass Model is considered a
897   pessimistic forecasting tool with more optimistic alternatives, which have potential for
898   application in similar scenarios, being based on the shifted Gompertz and Weibull
899   distributions, both of which have superior forecasting and theory testing capabilities but do
900   not offer such a balance between normative and non-normative interpretation, necessary for
901   this format of analyses, as is the case with the use of the Bass Model (Jakkola, 1996).

903   Within the HABM specifically, the format for agent distribution and seeding is more
904   generalised, and the framework of the daily routine is more direct, than in comparable
905   models. This is, in some ways, a concession in relative precision, justified by the sustainable
906   operation of the model within the NetLogo format (Rasmussen et al., 1994; Wilensky & Rand,
907   2015; Wong & Luo, 2005). Furthermore, with the primary application of this model being
908   concentrated on the development of understanding regarding the complex nature of human
909   interaction with the urban and natural environments, under extraordinary or unusual
910   circumstance, the production of interpretable metrics using a new, interdisciplinary tool is
911   considered to be a significant first step in enhancing understanding in this area. The general
912   form of complexity explored in this paper has certainly been subject to greater scholarly

interest in recent times and this has been evident through the proliferation of publications on the subject and related phenomena, particularly through the last decade (Liu et al., 2015). As a result of this, complexity science has increasingly undergone a process of extension into quite different scientific fields (Alexander, 1980; Axelrod, 1970; Wilesnky & Rand, 2015)**.** This process, whilst a necessary element of scientific progress, has in some way acted to separate theory from application and has led to a diminished emphasis on cross-disciplinary applicability, leaving potentially useful scientific tools isolated or limited by the technological capability of the time. This has furthered the highly fragmented development of agent-based models and modelling frameworks (Axelrod, 1970; Müller et al., 2013; Namatame, 2016). These largely fall into one of two polar groups: those which over-emphasise a very specific use through a reductive process of refinement to meet validative expectations, or those which place themselves at the extremity of validation because of the physically unimaginable complexity that is being modelled (Ormerod & Rosewell, 2009). It is here, despite any shotcomings, where the value of the HABM is found; at the point of bifurcation between these groups (Assaf & Hartford, 2002; Eberlen & Scholz,2017; Guo et al., 2008; Liu et al., 2015; Morss et al., 2016; Nunes Correia et al., 1998; Waldorp et al., 1993; Wei et al., 2003; Werrity et al., 2007).

The provision of a probabilistic framework (Figure 4) for the 'pseudo-random', this being a term which describes the large array of numbers underlying the agent's movements (i.e. leave, stay, etc.), within the model environment (which are effectively limitless but are also bounded by the fractal (self-replicating) 'stochasticity' of the model layer implemented within NetLogo), has great importance for the general and trans-disciplinary application of the methods in this paper. This is particularly the case in the absence of empirical certanty for how the real population of Carlisle might individually act on the day. But the framework provides some necessary, general, parameters for human response in the event of a flood and so greatly reduces the possibility of an entirely chaotic modelling scenario, whilst also maintaining a realistic representation of choices that represent systematic functions of the community, infrastructure, and environmental dimensions within the urban and flood hazard system. Finally, it allows reproducibility for the HABM where components of future hydro-sociological models could simply be substituted for those of the HABM (Landstrom et al., 2011, Sabatier, 1986; Wong et al., 2005).

In reality, the social elements of the complexity explored here are as unpredictable as they are dynamic: this challenges forecasting behaviours in addition to their understanding. As evidenced in this paper, the social elements are represented by many different participants who adapt and influence one another, interacting in intricate ways that continually reshape their individual and collective responses. When performed collectively, these interactions form systems which are characterised by multi-scale interactions between the micro (individual) to the macro (demographic, economic and governmental). The collective coalescence of multi-scale interactions have been termed 'Complex Adaptive Systems' and they have a significant underpinning from research focused on their inter-disciplinary and methodological design so as to better understand the significant challenges presented by

their complexity (Dugdale et al., 2009; Gilligan et al., 2015; Holland, 2014; Liu at al., 2015; Morss et al., 2016.)

Ultimately, the design of, "holistic risk management strategies requires an accurate understanding of the level of risk across the various layers of society. One important remaining limitation in our understanding of flood risk is the way individuals perceive and respond to risk. Even if we manage to model population density and flood inundation with increasing accuracy, assumptions about peoples' risk reducing behavior, willingness to relocate, and access to information play a key role in the actual level of risk" (Jongman, 2018, pg. 2). Individual perception is an extremely complex phenomena and representing this from event and systematic complexity is paramount for developing further understanding of the nature of the physical-social interactions discussed here, so that evacuations may be better organised and the greatest number of lives may be saved in the event of a complex event, like a flood (Berendracht et al., 2017). Consequently, the non-linear characteristics associated with complex adaptive systems, including influential systematic processes such as heterogeneity, phase transition and emergence, require that our methods, such as those illustrated in the HABM, also attempt to represent the general complexity of adaptive systems. Given that such systems exist as macro networks of partially connected micro structures (fundamentally via individuals interacting in different groups which adapt to changes in the surrounding environment), the methods must then also include microscale models which are able to simultaneously simulate cross-scale operations, interactions and responses amongst multiple participants (Assaf & Hartford, 2002; Dawson et al., 2011), to provide interested parties with access to more representative insights of what is and could be unfolding in reality.

Finally, during the 2005 flood, as modelled by the HABM for this paper, three deaths occurred. During the 2015 flood event in Carlisle, the River Eden exceeded the 2005 flood level by 600mm, yielding only one fatality but with a much greater economic impact (The Environment Agency, 2016). Even with the generalised 'potential fatality' metric implemented into the HABM, set as such due the low number of actual fatalities which occurred during the 2005 event, if the results of the model's simulations are to be believed; then there is a much greater potential for a fatal impact within the flood inundation area than that which presented itself during the actual events of Carlisle in 2005 and 2015. Here, the true importance of the HABM and Bass Model results is that they offer a counter-intuitive scenario to be further deliberated, one which could prove significant for flood hazard management in Carlisle and risk management overall.

6. **Conclusion and future development**

This   paper   began   by   proposing   two   specific   questions:

1. During a flood, does site-specific urban topography and morphology, change the optimum evacuation warning strategy?

999

2. Do people (agents) respond better to direct or indirect (word of mouth) evacuation warnings during a flood event?

These questions were formulated to explore the UK governmental shift towards alternative, bottom-up, action for addressing flood vulnerability and risk, as especially affected by agent response and urban morphology. These objectives simplify what is a very complex scenario and so with respect to this complexity, a methodological framework for addressing these two objectives was formulated and demonstrated, producing results via a coupled hydrodynamic and agent-based model: the HABM. This model was used to explore the complexity of human responses and behaviours during a flood event with a view to better specifying the two basic elements of the flood hazard system, a physical flood interacting with a human urban system. From this investigation, a range of implications were uncovered by the model simulations of response and behaviour. Based upon observation of these implications, some practical recommendations can be made for flood warning delivery and strategy as follows:

- Agents operating within a system of change show a preference for action via a socially *imitative* process as opposed to one which operates from *innovation*. This would suggest that bottom-up approaches towards warning and evacuation would benefit from incorporating measures that harness this understanding of group processes.
- Owing to the influence of site topography on the outcomes of social response, and the creation of potential congestion points within affected sites, a phased response to flood events should be an actionable option within flood warning strategy and delivery.
- During the process of issuing a flood event warning, the geography (topography and morphology) of the affected site can significantly influence the success or failure of the evacuative process and so due attention to this influence should be given during planning. This reaction phase involving the response and movement of people does not normally receive much attention and likely should.
- Whilst it might be a desirable goal to achieve a 100% preparedness within a flood-prone area, the results from the HABM simulations suggest that this may not be necessary, or even desirable. Simulations support the idea that the 50% estimate of the EA for Carlisle is the best value for efficient evacuation, owing to the social dynamics and the topography of the site. The design of 'optimal' impacts for a ranging of percentages of prepared people, and for sites with differing layout and population dynamics, needs to be critically considered in future flood response strategies.

There are significant questions that arise from these recommendations which require further analysis. Enhanced development of the HABM and the related themes will look to provide this further analysis in the form of the following:

- The nature of the agent decision-making process in locations where interaction is concentrated, e.g. is social response hastened where there is a higher population density?

- The nature of agent response with respect to the physical attributes of the flood event, e.g. attenuation of the flood hydrograph & variations in flood volume influencing the process of evacuation.
- Different urban morphologies: will these give dramatically different results to those produced for Carlisle?

Whilst not a predictive tool, the implications of the results herein outlined, coupled with such future developments of the HABM, are useful in providing greater scope for including and quantifying relevant operative factors that are involved in flood vulnerability, risk and resilience as related to urban systems. The HABM offers a dynamic method for simulating important actions linked to these, with the potential to enhance quantitative analyses in support of the decision-making process for flood hazard management. This paper demonstrates that such quantification can involve not only flooding itself, but also potential human responses. These may exacerbate the risk if they are not accounted for during planning, or they may be diminished through improved response planning. Other hazard environments may similarly be analysed using the approach here outlined, providing many points of further discussion and consideration for stakeholders involved with risk assessment. The HABM can be a welcome and useful analytical tool for supporting and expanding on these points whilst moving forward.

Data availability: The population data was accrued and modified from the 2011 aggregate NOMIS (ONS) database found at: https://www.nomisweb.co.uk/census/2011
This was cross-referenced with the supporting flow data found at:
https://wicid.ukdataservice.ac.uk/
Building footprint data was taken from OSM, copyrighted to OpenStreetMap contributors and available from: https://www.openstreetmap.org/
The LISFLOOD dataset for Carlisle can be requested directly from Dr. Jeffrey Neal with further details on the LISFLOOD-FP available at:
http://www.bristol.ac.uk/geography/research/hydrology/models/lisflood/
Bass Model curves were informed by information found on The Bass's Basement Research Institute webpage, © 2008, 2009, 2010 Bass's Basement Research Institute, at:
http://www.bassbasement.org/BassModel/Default.aspx
The prototype Netlogo code for this model is currently still being used and modified as an active component of Thomas O'Shea's PhD thesis but it will be made available via open-source repository on the NetLogo Modelling Commons page at:
http://modelingcommons.org/account/login under the title of this paper.

Author contributions: Thomas O'Shea wrote this paper with assistance and input from Paul Bates and Jeffrey Neal.

Competing interests: The authors declare that they have no conflict of interest.

1086   **Acknowledgements:** The authors are indebted to Professor John Lewin, Toon Haer and his
1087   colleagues at the IVM, VU Amsterdam, Professor Nobuhito Mori and his colleagues at the
1088   Research Division of Atmospheric and Hydrospheric disasters, DPRI, Kyoto and our Bristol
1089   colleagues, Laurence Hawker and Jeison Sosa Moreno for their helpful thoughts on the pre-
1090   developmental stages of the HABM network.
1091
1092   **Financial Support:** Thomas O'Shea is supported by the EWS Educational Trust Exceptional
1093   Contribution Award. Paul Bates is supported by a Royal Society Wolfson Research Merit
1094   Award and Jeffrey Neal is supported by a NERC fellowship for interdisciplinary research on
1095   flooding in Vietnam.

References

1. Abebe, Y.A., Ghorbani, A., Nikoolic, I., Vojinovic, Z. and Sanchez, A. A coupled flood-agent-institution modelling (CLAIM) framework for urban flood risk management. Environmental Modelling and Software, 111, 483-492. 2019.

2. Alexander, C., The Nature of Order: An Essay on the Art of Building and The Nature of the Universe, Book 1: The phenomenon of life. The CES, Berkeley, CA. 1980.

3. Assaf, H. & Hartford, D.N.D., A virtual reality approach to public protection and emergency preparedness planning in dam safety analysis. In: Proceedings of the Canadian dam association conference, Victoria. 2002.

4. Axelrod, R., The Complexity of Cooperation: Agent-based models of competition and collaberation. Princeton, NJ: Princeton University Press. 1970.

5. Barendrecht, M., Viglione, A. & Blöschl, G., A dynamic framework for flood risk. Water Security, 1, 3-11, https://doi.org/10.1016/j.wasec.2017.02.001, 2017.

6. Bass, F.M., A new product growth for model consumer durables. Management Science, 215-227, https://doi.org/10.1287/mnsc.15.5.215, 1969.

7. Bates, P. D. & De Roo, A. P. J., A simple raster-based model for flood inundation simulation. Journal of Hydrology, 54-77, https://doi.org/10.1016/S0022-1694(00)00278-X, 2000.

8. Bates, P. D., Horrit, M.S. & Fewtrell, T.J., A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. Journal of Hydrology, 33-45, https://doi.org/10.1016/j.jhydrol.2010.03.027, 2010.

9. Bennet, D. & Tang, W., Representing Complex Adaptive Spatial Systems. Iowa City: University of Iowa. 2017.

10. Bernardini, G., Camilli, S., Quagliarini, E. & D'Orazio, M., Flooding risk in existing urban environment: from human behavioural patterns to a microscopic simulation model. Proceedings from the 9th International Conference on Sustainability in Energy and Buildings, SEB-17, Chania, Crete, Greece, 5-7 July 2017, Energy Procedia, 134, 131-140, 2017.

11. Borshchev, A. & Filippov, A., From System Dynamics and Discrete Event to Practical Agent Based Modelling: Reasons, Techniques, Tools. Proceedings from the 22nd Int. Conference of the System Dynamics Society, Jul 25 – 29, Oxford, England. 2004.

12. Bresser-Pereira, L.C., Maravall, J.M. & Przeworski, A., Economic Reforms in New Democracies: A Social-Democratic Approach. Cambridge University Press, UK. 1993.

13. Chen, X. & Zhan, F.B., Agent-based modelling and simulation of urban evacuation: relative effectiveness of simulations and staged evacuation strategies. Journal of the ORS. 59, 1, 25-33, https://doi.org/10.1057/palgrave.jors.2602321, 2008.

14. Chu, T.-Q., Agent-based models and machine learning in decison support systems. Paris: Lap Lambert Academic Publishing. 2015.

15. Coates, G., Hawe, G. I., Wright, N. G. & Ahilan, S. Agent-based modelling and inundation prediction to enable the identification of businesses affected by flooding. WIT Transactions on Ecology and the Environment. 184, 13-22, 2014.

16. Correia, F. N., Rego, F., Saraiva, M. G. & Ramos, I., Coupling GIS with Hydrologic and Hydraulic Flood Modelling. Water Resource Managment. 12, 3, 229-249, https://doi.org/10.1023/A:1008068426567 , 1998.

17. Davies, S., The Diffusion of Process Innovations. Cambridge: Cambridge University Press. 1979.

18. Dawson, R., Peppe, R. & Wang, M., An agent based model for risk-based incident management of Natural Hazards. Nat. Haz., 59, 1, 167-189, 2011.

19. Dechter, R. & Pearl, J., Generalised best-first search strategies and the optimality of A*. Journal of the ACM. 32, 3, 505-536, 1986.

20. DEFRA, EA & Coastal Erosion Risk Management R & D Programme. Risk assessment for flood incident management: framework & tools. Bristol: Environment Agency. 2007.

21. De Groot, J.I.M. & Schuitema, G., How to make the unpopular popular? Policy characteristics, social norms and the acceptability of environmental policies. Environmental Science & Policy, 19-20, 100-107, DOI: https://doi.org/10.1016/j.envsci.2012.03.004, 2012.

22. Du, E., Cai, X., Sun, Z. & Minsker, B., Exploring the Role of Social Media and Individual Behaviours in Flood Evacuation Processes: An Agent-Based Modeling Approach. Water Resources Research, 53, 11, 9164-9180, https://doi.org/10.1002/2017WR021192, 2017.

23. Dugdale, J., Saoud, N. B-B, Pavard, B. & Pallamin, N., Simulation and Emergency Management. In B. T. Van de Walle, Information Systems for Emergency Management, London: Sharp, pp. 229-253, 2009.

24. Eberlen, J., Scholz, G., & Gagliolo, M., Simulate this! An Introduction to Agent-Based Models and their Power to Improve your Research Practice. *International Review of Social Psychology*, *30*, 1, 149–160, http://doi.org/10.5334/irsp.115, 2017.

25. The Environment Agency, Creating a better place; Carlisle: Flood Investigation Report. Bristol: The environment Agency. 2016.

26. The Environment Agency, Flooding - Minimising the risk. Bristol: Environment Agency. 2012.

27. The Environment Agency. Risk assessment for flood incident management: Annex 4 Understanding and application of complex system risk assessment models. Bristol: Environment Agency. 2006.

28. Fordham, M. H., Ph.D. Thesis: Choice and Constraint in Flood Hazard Mitigation: The Environmental Attitudes of Floodplain residents and Engineers. London. 1992.

29. Gilbert, N. & Troitzsch, K., Simulation for the social scientist (2nd ed.). Milton Keynes: Open University. 2005.

30. Gilligan, J. M., Brady, C., Camp, J. V., Nay, J. J. & Sengupta, P., Participatory Simulations of Urban Flooding for Learning and Decision Support. Proceedings of the 2015 Winter Simulation Conference, pg. 2, Nashville, TN.: Vanderbilt University Press. 2015.

31. Guo, D., Ren, D. & Wang, C., Integrated Agent Based Modeling with GIS for Large Scale Emergency Simulation. In: Kang L., Cai Z., Yan X., Liu Y. (eds) Advances in Computation and Intelligence. ISICA 2008. Lecture Notes in Computer Science, vol 5370. Springer, Berlin, Heidelberg, https://doi.org/10.1007/978-3-540-92137-0_68, 2008.

32. Guyot, P. & Honiden, S., Agent-based participatory simulations: Merging multi-agent systems and role-playing games. Artificial Societies and Social Simulation, 9, 4, 35-39, http://jasss.soc.surrey.ac.uk/9/4/8.html, 2006.

33. Haer, T., Wouter Botzen, W.J. & Jeroen Aerts, C.J.H., The effectiveness of flood risk communication strategies and the influence of social networks – Insights from an agent-based model. Environmental Science & Policy, 60, 44-52, http://doi.org/10.1016/j.envsci.2016.03.006, 2016.

34. Haer, T., Wouter Botzen, W.J., de Moel, H. & Jeroen Aerts, C.J.H., Integrating Household Risk Mitigation Behaviour in Flood Risk Analysis: An Agent-Based Model Approach. Risk Analysis: An International Journal, 37, 10, 1977-1992, https://doi.org/10.1111/risa.12740, 2016.

35. Hart P. E., Nilsson, N. J. & Raphael, B. A., A formal basis for the heuristic determination of minimum cost paths. IEEE Trans System Science, 4, 2, 100-107, http://dx.doi.org/10.1109/TSSC.1968.300136, 1968.

36. Holland, J., Complexity. Oxford: Oxford University Press. 2014.

37. Hornor, M.S., Diffusion of Innovation Theory. Austin, Texas, US. Press. 1998.

38. Hunter, N.M., Bates, P.D., Neelz, S. et al., Benchmarking 2D hydraulic models for urban flood simulations. Water Management, 161, 1, 13-30, https://doi.org/10.1680/wama.2008.161.1.13, 2008.

39. Horritt, M.S., Bates, P.D., Fewtrell, T.J., Mason, D.C. & Wilson, M.D., Modelling the hydraulics of the Carlisle 2005 flood event. *Proceedings of the ICE - Water Management*, 163, 273 – 281, https://doi.org/10.1680/wama.2010.163.6.273, 2010.

40. IPCC. Climate Change 2014: Synthesis Report. Contribution of Working Groups I,II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva: IPCC. 2014.

41. Jakkola, H., Comparison and Analysis of Diffusion Models' in Kurtz, K. et al., Diffusion and Adoption of Information Technology. Springer Science & Business Media, Dordrecht, pp 60-70, 1996.

42. Jongman, B., Effective adaptation to rising flood risk. Nature Communications, 9, 1, 1-3, DOI: 10.1038/s41467-018-04396-1, 2018.

43. Kinzig, A.P., Ehrlich, P.R., Alston, L.J., Arrow, K., Barrett, S., Buchman, T.G., Daily, G.C., Levin, S., Oppenheimer, M., Ostrom, E. & Saari, D., Social Norms and Global Environmental Challenges: The

Complex Interaction of Behaviours, Values, and Policy. BioSciences, 63-3, 164-175, DOI: https://doi.org/10.1525/bio.2013.63.3.5, 2013.

44. Kossiakoff, A. & Sweet, W. N., System Engineering Principles and Practice. Washington: Wiley. 2002.

45. Landstrom, C., Whatmore, S. J. & Lane, S. N., Computer Simulation Modelling for Flood Risk Management in England. Science Studies, 3-22. 2011.

46. Larsen, G.D., Horses for courses: relating innovation diffusion concepts to the stages of diffusion process. Journal of Construction Management and Economics, 23, 8, 787-792, 2005.

47. Liu, J., Mooney, H., Hull, V., Davis, S. J., Gaskell, J., Hertel, T., Lubchenco, J., Seto, K.C., Gleick, P., Kremen, C. Shuxin, L. Systems integration for global sustainability. SCIENCE, 347(6225), DOI: 10.1126/science.1258832. 2015.

48. Lumbroso, D.M., Sakamotoo, D., Johnsone, W.M., Tagg, A.F. and Lence, B.J. The development of a Life Safety Model to settimate the risk posed to people by dam failures and floods. Dams and Reservoirs, 21, 1, 31-43, DOI: https://doi.org/10.1680/dare.2011.21.1.31 . 2011.

49. Mahajan, V., Muller E. & Bass, F.M., New Product Diffusion Models in Marketing: A Review and Directions for Research. Journal of Marketing, 54,1, 1-26, DOI: 10.2307/1252170 , 1990.

50. Massiani, J. & Gohs, A., The Choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. Research in Transportation Economies, 50, 17-28, DOI: 10.1016/j.retrec.2015.06.003, 2015.

51. Morss, R.E., Mulder, K.J., Lazo, J.K., & Demuth, J.L., How do People perceive, understand, and anticipate responding to flash flood risk warnings? Results from a public survey in Boulder, Colorado, USA. Journal of Hydrology, 541, 649-664, DOI:10.1016/j.jhydrol.2015.11.047, 2016

52. Mostafizi, A., Wang, H. & Dong, S., Understanding the Multimodal Evacuation Behaviour for a Near-Field Tsunami. Transportation Research Record: Journal of the Transportation Research Board. 2673, 11, 480-492, https://doi.org/10.1177%2F0361198119837511, 2019.

53. Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schwarz, N., Describing human decisions in agent-based models - ODD+D, an extension of the ODD protocol. Environmental Modelling and Software, *48*, 37–48, https://doi.org/10.1016/j.envsoft.2013.06.003, 2013.

54. Namatame, A. & Chen, S-H., Agent-based modeling and network dynamics. Oxford: Oxford University Press. 2016.

55. Narzisi, G., Mysore, V. & Mishra B., Multi-Objective Evolutionary Optimisation of Agent-Based Models: An Application to Emergency Response planning. Proceedings from the second IASTED International Conference on Computational Intelligence, pp. 228-232, San Francisco: IASTED. 2006

56. Neal, J. C., Bates, P. D., Fewtrell, T. J., Hunter, N. M., Wilson, M. D. & Horrit, M.S., Distrubuted whole city water level measurements from the Carlisle 2005 urban flood event and comparison with hydraulic model simulations. Journal of Hydrology, 42-55, 2009.

57. Neal, J., Fewtrell, T., Bates, P. and Wright, N., A comparison of three parallelisation methods for 2D flood inundation models. Environmental Modelling and Software, 25, 4, 398-411. DOI: 10.1016/j.envsoft.2009.11.007, 2010.

58. Neal, J. C., Keef, C., Bates, P. D., Beven, K. & Leedal, D., Probabilistic flood risk mapping including spatial dependence. Hydrological Processes, 1349-1363, DOI: 10.1002/hyp.9572, 2013.

59. Neal, J.C., Schumann, G. & Bates P.D., A sub-grid channel model for simulating river hydraulics and floodplain inundation over large and data sparse areas. Water Resources Research, 48, 11, 1-16, https://doi.org/10.1029/2012WR012514, 2012.

60. NetLogo. (E. Center for connected learning and computer-based modeling. Northwestern University, Producer) Retrieved from NetLogo: http://ccl.northwestern.edu/netlogo/, 2017, February 3rd, 1999.

61. Nunes Correia, F., Fordham, M., Da Graca Raravia, M. & Bernado, F., Flood Hazard Assessment and Management: Interface with the Public. Water Resources Management, 12, 3, 209-227, 1998.

62. Medina, N., Sanches, A. and Vojinovic, Z. The potential of Agent Based Models for Testing City Evacuation Strategies Under a Flood Event. Procedia Engineering, 154, 765-772, https://doi.org/10.1016/j.proeng.2016.07.581. 2016.

63. Ormerod, P. & Rosewell, B., Validation and Verification of Agent-Based Models in the Social Sciences. In: Squazzoni, F., Epistemological Aspects of Computer Simulation in the Social Sciences. EPOS 2006. Lecture Notes in Computer Science, Springer Berlin, 5466, 130-140, 2009.

64.

65. Pyatkova, K., Chen, S.A., Butler, D., Vojinovic, Z. & Djordevic, S., Assessing the knock-on effects of flooding on road transportation. Journal of Environmental Management, 244, 48-60, 2019.

66. Railsback, S. & Grimm, V., Agent-Based and Individual-Based Modeling: A Practical Introduction. Princeton, NJ: Princeton University Press. 2012.

67. Rasmussen, J., Pejtersen, A. M. & Goodstein, L. P., Cognitive systems Engineering. London: Wiley. 1994.

68. Roland, H. E. & Moriarty, B., System Safety Engineering and Management. Toronto: Wiley. 1990.

69. Sabatier, P.A., Top-down and bottom-up approaches to implementation research: a critical analysis and suggested synthesis. Journal of public policy, 6, 1, 21-48, https://doi.org/10.1017/S0143814X00003846, 1986.

70. Sanders, P. & Sanders F., Spatial urban dynamics: A vision on the future of urban dynamics: Forrester revisited. System Dynamics Review, 1-32, 2004.

71. Smith, K. & Tobin, G. A., Human Adjustment to the Flood Hazard. London: Longman. 1979.

72. Srbljinović, A., & Škunca, O., An Introduction to Agent Based Modelling and Simulation of Social Processes. Interdisciplinary Description of Complex Systems, 1, 1-2, 1–8, http://indecs.eu/2003/indecs2003-ppl-8.pdf , 2003.

73. Sultan, F., Farley, J.U. & Lehmann, D.R., Reflections on "A Meta-Analysis of Applications of Diffusion Models.". Journal of Marketing Research, 33, 247-249, 1996

74. Tarde, G. The laws of Imitation. New York: H. Holt & Co. 1903.

75. UNISDR, Sendai Framework for Disaster Risk Reduction: 2015-2030. 2015.

76. Waldrop, W. W., Complexity: The Emerging Science at the Edge of Order and Chaos. New York: Simon & Schuster. 1993.

77. Wei, Y., Zhang, L. & Fan, Y., SWARM based study on spatial-temporal emergence in flood. Keybernetes, 32, 5/6, 870-880, https://doi.org/10.1108/03684920210443941, 2003.

78. Werrity, A., Houston, D., Ball, T., Tavendale, A. & Black, A., Exploring the Social Impacts of Flood Risk and Flooding in Scotland. University of Dundee, School of Social Sciences - Geography. Dundee: University Press. 2007.

79. Wheater, H. S., Flood hazard and management a UK perspective. Philosophical Transactions of The Royal Society, DOI: 10.1098/rsta.2006.1817, 2135-2145, 2006.

80. Whitehead, A.N. & Russell, B., Principia Mathematica, part 1: Mathematical Logic 2009 ed., p. 56, Merchant Books. 1913.

81. Wilensky, U. & Rand, W., An Introduction to Agent-Based Modeling. Cambridge, MA: MIT University Press. 2015.

82. Wilson, M.D. & Atkinson, P. M., The use of elevation data in flood inundation modelling: A comparison of ERS interferometric SAR and combined contour and differential GPS data. International Journal of River Basin Management, 3, 1, 3-20, https://doi.org/10.1080/15715124.2005.9635241, 2005.

83. Wisner, B., Blaikie, P., Cannon, T. & Davis, I., At Risk: Natural Hazards, People's Vulnerability and Disasters. London: Routledge. 1994.

84. Wong, K. H. L. & Luo, M., Computational tool in infrastrature emergency total evacuation analysis. In Kantour, P.E., Intelligence and security informatics, Springer: Berlin, pp. 27-34, 2005..

85. Zarboutis, N. & Marmaras, N., Investigating crowd behaviour during emergency evacuations using agent-based modelling. Proceedings of EAM, pp. 17-19, Athens: EAM. 2005.

86. Zupančič, A., Ethics of the Real: Kant, Lacan. London: Verso. 2000.