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Agent-based modelling and flood risk management: a compendious literature review

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Abstract

The use of agent-based modelling (ABM) to tackle flood-related risk challenges is becoming increasingly popular in recent years. This paper reviews the literature at the interface of ABM and flood-related studies in view of understanding the technique's advantages and limitations to flood risk management, based on a set of 61 representative articles. In particular, to understand how this process-based technique can help to link human (also institutional) decisions and behaviour with flood risks through the whole human-flood systems. Overall, the temporal and spatial distributions demonstrate a growing interest in this research area around the world, especially since 2017. Three topic areas are identified, addressing different research challenges in the field: real-time flood emergency management, long-term flood adaptation planning, and flood hydrological modelling. The review has shown that the potential contribution of ABM to future flood risk management lays in its practical application to decision-making in adaptation policy and strategy planning. The review also critically reveals the limitation of ad hoc implementations of decision-making and behaviour in the ABM models that could make the application less realistic in the field. It is recommended that the future development should be guided/influenced by the continuing development and refinement of ABM modelling framework and theoretical foundations, and enhancement of model testing and documenting capabilities. More importantly, active collaborations between disciplines and sectors such as to involve more social and psychological sciences in ABM decision-making

28 modelling should be encouraged; and knowledge sharing will encourage more effective uses
29 of ABM by wider audiences.

30 **Keywords:** Agent-based modelling (ABM); flood risk management; review; coupled human
31 and natural systems (CHANS); adaptation planning; emergency management

32 **1. Introduction**

33 Among all weather-related natural hazards in the past two decades, floods are by far the most
34 common (47%) that have affected 2.3 billion people around the world (CRED-UNISDR, 2015).
35 Due to climate change and urban development, it is estimated the global cost from flood
36 disaster will rise from about 46 trillion USD to 158 trillion in 2050 (Jongman et al.,
37 2012;Poelmans et al., 2010). The damages caused by the recent catastrophic flood disaster in
38 Southern China (Everington, 2020), and the projections of even more extreme events around
39 the world, again demonstrate the urgent need for resilient flood disaster risk reduction strategies
40 globally (e.g., to provide effective flood risk assessment and management with resilient and
41 sustainable adaptation and mitigation policies), as also emphasized by the international
42 agreement on losses and damages (UNFCCC, 2013) and the Sendai Framework for disaster-
43 risk-reduction (UNDRR, 2015).

44 The formation of flood disasters is driven by multiple factors, for example, urbanization can
45 significantly increase flood damages due to population growth and assets exposures (e.g.,
46 infrastructures and buildings) within flood-prone zones (Jongman et al., 2012; Aerts et al., 2014;
47 Hallegatte et al., 2013); the land use change of natural surfaces into artificial impermeable
48 surfaces can result in an increase of flooding frequency due to poor infiltration (Huong and
49 Pathirana, 2013); and inadequate planning, risk dissemination and policies can lead to an
50 elevated number of exposures and vulnerabilities (Jha et al., 2012). Therefore, only focusing
51 on understanding the extent and magnitude of the hazard itself is clearly not sufficient for flood

52 risk management, while other interconnected elements such as urbanisation, socio-economy,
53 culture, community, institution and governance should also be taken into consideration (IPCC,
54 2014, 2012;O'Connell and O'Donnell, 2013). Since flood disaster is becoming more people-
55 centred (e.g., adaptation, mitigation, and rescue planning can all have impacts to the
56 consequence of a flood event) (O'Connell and O'Donnell, 2013), and due to the interactions
57 between hazard and people that span across multiple spatial, temporal and organisational scales,
58 as well as the influence of imperfect information, bounded rationality and continual adapting
59 feature on human decision-making, flood disaster should be seen as a Complex Human And
60 Natural System (CHANS) (Liu et al., 2007;Pahl-Wostl, 2015;Mitchell, 2009). In particular, in
61 order to understand from multiple dimensions or scales of how human decision-making and
62 behaviour lead to certain consequences of flood events, there is a clear need of a more process-
63 based approach to enable in-depth coupling of the two sub-systems (i.e., human and flood) (An,
64 2012).

65 Agent-based modelling (ABM) has become a major bottom-up tool to simulate CHANS, which
66 is process-based and capable of mimicking the real-world systems as open-ended dynamic
67 systems of interacting 'agents' (Tsfatsion, 2017; Tsfatsion et al., 2017). In particular, it is
68 very useful in simulating situations where individual behaviour can lead to collective outcomes
69 in ways that cannot be dealt with by aggregate models (Tonn and Guikema, 2018). With the
70 substantial development from computer science and social science, ABM has the advantage in
71 simulating the human decision-making process and behaviour and integrating these with the
72 contextual socio-environmental conditions (Bousquet and Le Page, 2004). Therefore, it can be
73 an efficient tool for understanding the human-flood systems, hence, useful for flood risk
74 management related studies.

75 The concept of ABM was first proposed in the late 1940s (e.g., (Von Neumann, 1951)). It is a
76 computational modelling method which can simulate the actions and interactions of individual,

77 heterogeneous, autonomous agents, or decision-making entities in a network or system
78 (Bonabeau, 2002). ABMs offer “a way to model social systems that are composed of agents
79 who interact with and influence each other, learn from their experiences, and adapt their
80 behaviours so they are better suited to their environment” (Macal and North, 2010). A typical
81 ABM is comprised with three components: a set of agents (as representations of the real-world
82 decision-makers); a set of agent relationships and methods of interactions (how and with whom
83 agents interact), and agents' environment (interactions with the environment) (Macal and North,
84 2010). Each agent (e.g., individuals, organisations) is encoded with behaviour rules to assess
85 its situation and make decisions. Even a simple ABM can generate complex behaviour patterns
86 due to a series of simple interactions between agents, and lead to rather complex system-scale
87 outcomes that cannot be predicted by simply aggregating the behaviours of individual agents
88 (e.g., due to interactions, feedback loops, nonlinearity and thresholds, heterogeneity) (Dawson
89 et al., 2011). Since ABM is able to analyse the effects of interactions on the system as a whole,
90 it has been widely used to provide decision-making guidance through many ‘what if ...’
91 scenario simulations (Banks, 2002; Dawson et al., 2011; Wilensky and Rand, 2015). With the
92 emergence of high-performance computing, and the off-the-shelf modelling programs such as
93 NetLogo (Tisue and Wilensky, 2004) and Multi-Agent Simulation of Neighborhoods
94 (MASON) (Luke et al., 2003), ABM has been increasingly recognised and applied in a number
95 of fields to tackle complex system problems, from civil violence (Epstein, 2002), land-use
96 change modelling (Evans and Kelley, 2004; Magliocca et al., 2011), shared autonomous
97 vehicle (SAV) operations (Fagnant and Kockelman, 2014), marketing and organisational
98 behaviour (Gómez-Cruz et al., 2017), to evacuation routes plan to fire and terrorist events, and
99 warning effectiveness test (Still, 1993; Owen et al., 1996; Wong and Luo, 2005), and business
100 resilience assessment (Sausser et al., 2018), and the trend is still rising. Among these fields,
101 research on artificial intelligence is noteworthy, for instance, in which multiple heterogeneous

102 agents are coordinated to solve planning problems (Bousquet and Le Page, 2004), also largely
103 contributing to ABM development is electrical electronic engineering, for instance modelling
104 the multi-carrier energy systems to understanding the interactions of production, delivery and
105 consumption (Krause et al., 2010). With the increasing focus on the human part of the human-
106 flood systems, it seems ABM has also started to attract more interests for flood risk
107 management studies (O'Connell and O'Donnell, 2013; O'Shea et al., 2020), albeit it is still
108 considered to be in its infancy. Therefore, there is an important need to explore this field to
109 encourage its research and application in flood-related studies. This paper aims to review the
110 literature at the interface of ABM and flood-related studies in view of understanding the
111 technique's advantages and limitations to flood risk management for both long-term planning
112 and real-time management applications. Although both research disciplines have gained
113 traction over many years, a current literature review at the interface is absent from the
114 publications. It is hoped that this review will benefit the flood research community by shedding
115 light upon the following points:

- 116 1) How has ABM made contributions to flood risk management development?
- 117 2) What are the strengths and weaknesses of the methodology based on past contributions?
- 118 3) What are the possible improvements that can be made for its future contributions in the
119 field?

120 The focus of this review paper is from that of flood risk management perspective and how the
121 ABM approach helps link human (also institutional) decisions and behaviour to flood risks
122 based on the whole human-flood systems. Section 2 presents the method to identify and analyse
123 literature at the interface of flood risk management and ABM. Section 3 describes how ABM
124 has contributed to flood risk management studies, from real-time flood emergency
125 management to long-term flood adaptation planning and flood hydrological modelling. This is

126 not intended to be comprehensive in the detailed individual methods for the selected studies,
127 but to touch on a variety of ways that ABM has been applied in the field. Section 4 discusses
128 ABM's benefits, limitations and potential areas for improvements in the field. Section 5
129 provides the conclusion of this study.

130 **2. Methods**

131 To achieve the paper's aim and objectives, the Web of Science was mainly used for the
132 literature selection. The first step was to construct a Boolean expression (search string) by
133 searching the Web of Science using the following combination of keywords: Topic = "agent-
134 based model" or "agent-based simulation" AND Topic = "flood". The first topic defined the
135 methodology of interest, while the second topic restrained further to only show papers within
136 the area of flood research. The second step was complementary to the first, which added journal
137 articles via author's personal archive (i.e., on ABM flood-related research) that has been
138 established since 2017. The third step was to search in Google Scholar (with the searching
139 keywords of 'agent-based' and 'flood', up to 2019 and articles only available online from 2020
140 were not included in this study due to incompleteness) to pick up any important publications
141 (research areas that were not covered by the papers selected from the first two steps) that were
142 missed from the first two steps. As the quality of the selected literature was important to draw
143 the conclusions of this review paper, any result that was not a journal article (e.g., conference
144 proceeding, book chapter, lecture notes) was not selected.

145 The main information extracted for each search included the title, author, institution, date of
146 publication, abstract, keywords and URL. In the above online search, 301 pieces of published
147 literature were found (up to 2019) from the first step. Out of these 301 papers, 200 were journal
148 articles. After checking each article manually, 145 were further excluded (i.e., off-topic,
149 unavailable to download due to paywall or similar, not written in English). The second step

150 resulted in another 23 articles, four of which were selected for the review after eliminating
151 those that were found to be duplicated (already chosen in the first step). From the third step, a
152 further two articles were added to the list. As a result, there was a total of 61 publications
153 included in this review, which makes up an important and representative part of the reference
154 list. The selected papers are listed in a table in the attached supplementary document. To the
155 best of the authors' knowledge, no particular ABM flood applications were categorically
156 excluded by the searching.

157 **3. Results**

158 **3.1 Temporal distribution of studies**

159 Figure 1 presents the temporal distribution of the selected 61 papers. The graph shows a clear
160 upward trend over the past 15 years (2005-2019). Only around two papers containing the
161 keywords agent-based model or simulation and flood in the topic were published each year
162 before 2014. The number of publications grew significantly to 14 in 2017 which was a 180%
163 increment from 2016 (5). This demonstrates a growing interest in applying ABM in the field
164 of flood risk management. The number then remain relatively stable between 2017 and 2019
165 (i.e., 14, 16, and 16 papers for 2017, 2018, and 2019, respectively). A similar trend pattern has
166 been observed in other research fields (for example, ABM in ecology (An, 2012)). An
167 exploration of the possible drivers of the sudden growth in 2017 and then stabilisation should
168 be further investigated, but is beyond the scope of this review.

169 **3.2 Spatial distribution of studies**

170 The global distribution of the 61 papers has been plotted in Figure 2. It is based on the case
171 study areas presented in the papers. It can be seen studies are distributed over all continents,
172 with the highest number from Europe (26 papers), Asia (16 papers) and North America (9
173 papers), covering both highly developed and developing countries. In Europe, the majority of

174 the studies were implemented by the UK (9 papers) and the Netherlands (8 papers). In Asia,
175 most researches were carried out by China and Australia (9 papers). Four papers used synthetic
176 cases and one paper was based on exploring the ABM application to the whole European Union.

177 **3.3 Using ABM to understand human-flood systems and increase flood resilience**

178 The techniques applied to modelling the coupled human-flood systems are mainly divided into
179 two types, that is the ABM which is the main focus of this review paper, as well as the system
180 dynamic models which are predominant in the flood risk domain (Barendrecht et al., 2017; Di
181 Baldassarre et al., 2013; Viglione et al., 2014). System dynamic models are based on systems
182 of a few coupled ordinary differential equations (Di Baldassarre et al., 2013; Viglione et al.,
183 2014), in a way that the change of one variable with time would depend on other variables.
184 Most differential equations are conceptual representations of the lumped system behaviour,
185 e.g., through aggregation or using a representative value for the whole domain. In contrast,
186 ABM is built based on the behaviour of individuals and the interactions are described using
187 decision rules. These interactions alter the agents' state (Blair and Buytaert, 2016). However,
188 for ABM, the outputs of the interacted behaviours are sometimes difficult to understand
189 because the connection between the variables is less clear at the macro-scale than the ones for
190 the system dynamic models (Barendrecht et al., 2017). In order to understand how ABM has
191 been applied in flood risk management, the 61 identified publications have been categorised
192 into three main areas: real-time flood emergency management, long-term flood adaptation
193 planning, and flood hydrological modelling. This section briefly describes the existing
194 contribution of ABM in the field.

195 **3.3.1 Real-time flood emergency management**

196 ABMs have been applied to model the movement of people, largely because of their flexibility
197 in incorporating the various components that influence an individual's movement through

198 space. By simulating an individual's dynamic environment and internal state (e.g., behaviours,
199 risk perception), ABMs are capable of simulating the two vital decisions that an individual
200 must continually make: when to move, and where to move (An, 2012). The individual's
201 response (state) to potential flood events can be influenced by multiple factors such as
202 individual's previous experience of flood incidents, warnings (e.g., 'false alarms'),
203 government's dissemination (e.g., flood warning, providing information on flood risk and
204 escaping plans to increase the awareness of flood risks), as well as the adaptation processes
205 (Parker et al., 2007); and accordingly, ABM can simulate these multi-interactional factors.
206 Specifically, individual's decision-making processes to flood response are often represented
207 by a spectrum of predefined simple to complex behaviour rules within the models, which are
208 mainly based on a combination of probabilistic and logical rules to take into considering the
209 uncertainties of the environment and perception capabilities (An, 2012). Through reviewing
210 the selected papers, a number of studies have been identified in the flood emergency
211 management area that mainly focused on modelling the movements of people under flood
212 threats. For example, Dawson et al. (2011) presented a quantified modelling approach to
213 estimate the likely exposures of people to flooding under different storm surge conditions. A
214 wide consideration of defence breach scenarios, flood warning times and evacuation strategies
215 were also tested. For the proposed ABM framework, the interactions and feedbacks between
216 floods and human responses were enabled through the simulation as the event evolved. In
217 particular, a probabilistic finite state machine was used to identify agents' behaviours,
218 including their possible states, the actions they could take and the transitions between states. A
219 similar concept was also adopted in Zhu et al. (2019) and Dai et al. (2020) for dynamic flood
220 exposures and vulnerabilities assessments. In the proposed HazardCM (hazard-human coupled
221 model) model, the probability of death or serious injury as a result of exposure to floods were
222 mainly controlled by the defined water depth and velocity thresholds, as well as individual's

223 characteristics including age, gender, employment status, education level, fitness level and
224 travel model. As discussed in Dawson et al. (2011), although the uncertainties surrounding
225 flood exposures might be large, by simulating a wide spectrum of events and parameterisations,
226 more robust options connected with the uncertainties would be identified. Similar to the above
227 studies but with a focus more on examining the effectiveness of emergency management
228 measures is the Lumbroso and Davison (2018) paper. The study proposed an ABM model
229 called Life Safety Model to particularly test a flood buddy system to potentially reduce loss of
230 life during low-probability flood events. It described detailed human evacuation behaviours
231 that were likely to occur within buildings (e.g., considering different floors, different building
232 types etc.), which provided more detailed building-scale simulations than the studies described
233 above. Moreover, a generic water depth versus velocity curve was adopted to assess the status
234 of agents at each time step. To reduce the associated uncertainties of the model, Monte Carlo
235 analysis was applied to run the model many times. Another interesting study was conducted by
236 Li et al. (2019), which combined a cellular automata model and a ABM system to simulate
237 crowd evacuations in flood disasters, and the model was evaluated by real-participant
238 experiments based on virtual reality (VR) environments. Similar studies on ABM applications
239 in flood evacuation are also found in Higo et al. (2017); Liu and Lim (2016, 2018); Yamamoto
240 and Takizawa (2019); Nakanishi et al. (2019); and Eivazy and Malek (2019).

241 Another challenging issue in flood risk management is the effectiveness of flood warning
242 systems. Although flood warning systems have been recognised as efficient tools for damage
243 mitigation and crisis management (Parker et al., 2007; Parker, 2017; Cloke and Pappenberger,
244 2009; Pappenberger et al., 2015), their effectiveness can be influenced by various
245 socioeconomic factors. ABMs have been used to explore this particular area. For example, Du
246 et al. (2017b) adopted an ABM modelling framework to investigate how individuals'
247 evacuation behaviours could be affected by their behavioural heterogeneity to flood warning,

248 warning accuracy and lead time. In this study, the agents' representations were simplified with
249 three types of physical attributes (agent's geographical location, maximum evacuation speed
250 and evacuation status) that were relevant to the evacuation process, and a psychological
251 attribute (a risk tolerance threshold based on agents' behavioural parameters) that was related
252 to the flood warning response. Being Carried out by the same lead author (Du et al., 2017a),
253 the framework was further developed by including opinion dynamics through ABM to explore
254 social media's influences on individuals' flood risk awareness, and the consequent
255 effectiveness of a flood warning system. However, it was noted both studies were implemented
256 based on a hypothetical residential area due to the lack of empirical data.

257 Another application of ABM has been found in the exploration of transportation-flood systems.
258 A common approach adopted in this area is by utilising existing ABM based traffic models and
259 applying different behaviour rules to better understand the interactions between the two
260 systems. For example, Suh et al. (2019) used the MATSim (Multi-Agent Transport Simulation)
261 software (Waraich et al., 2015) to assess the benefit of 'transportation infrastructure protection
262 plans' against sea level rise. Specifically, for each sea level rise and protection (levee) scenario,
263 the corresponding inundated links from the original traffic network were removed and the
264 resultant vehicle travel hour was then calculated. Similarly, Pyatkova et al. (2019) examined
265 how flood events could affect road transportation by integrating flood (InfoWorks; (Innovyze,
266 2020)) and traffic models (a microscopic ABM traffic model called SUMO (Simulation of
267 Urban MObility), (Krajzewicz et al., 2012)). And the interactions were based on described
268 behaviour rules (i.e., rerouting, reduced speed) and predefined threshold from water depth
269 information. A further two studies by Zhu et al. (2018) and Saadi et al. (2018) were found in
270 this research area, which adopted the similar research concept as described above (i.e., couple
271 flood hazard map/model with existing ABM based traffic models).

272 **3.3.2 Long-term flood adaptation planning**

273 Flood resilience in practice relies on an understanding of socioeconomic and environmental
274 systems and importantly their interactions (Chandra-Putra and Andrews, 2020), and is
275 maintained/improved by applying sustainable adaptation plans against flood risks. However,
276 because the adaptation measures often take a very long time (e.g., 30 years and more) to verify
277 and involve large investments (Löwe et al., 2017), there is a desire of a modelling framework
278 that could assess the effectiveness of different measures in advance for improved decision-
279 making. The assessment would focus on understanding how adaptation measures reduce risk
280 and how much risk remains after adaptation. In particular, there is a need to test the
281 effectiveness of rules, regulations, policies and implementations that aim to reduce flood risks,
282 as well as considering individuals react towards these aspects and adaptations (Tonn and
283 Guikema, 2018). ABM has the capabilities to realise these testing requirements, and assess the
284 robustness of a wide range of potential future developments/policies/strategies. Studies by
285 Dawson et al. (2011); Zhu et al. (2019); Du et al. (2017b); Lumbroso and Davison (2018) and
286 similar have conceptualized both human and flood subsystems within ABM frameworks and
287 considered the heterogeneous features within the decision making processes. But when it
288 comes to long-term flood adaptation planning, the main issue of these studies is that they do
289 not methodically consider the influence of socioeconomic factors (e.g., institutions, risk
290 perceptions, development plans, policies, societal preferences) to understand the drivers of
291 flood risks (Abebe et al., 2019b).

292 A number of ABM papers have been published specifically focusing on the socioeconomic
293 interactions for long-term flood adaptation and planning studies. For example, Jenkins et al.
294 (2017); Crick et al. (2018); and Dubbelboer et al. (2017) presented an ABM framework to
295 assess how Sustainable Drainage Systems, property level protection measures and flood
296 insurance scheme could affect local surface water flood risk in the context of various climate
297 change projections. With a similar research direction, a ABM approach has also been applied

298 to explore individual's adaptive decision making behaviours against coastal flood risks and
299 considered households' risk perception, insurance policies, and local flood mitigation measures
300 (Han and Peng, 2019).

301 To support the identification of adaptation measures that were economically efficient and
302 robust to changes of climate and urban layout, Löwe et al. (2017) proposed a framework based
303 on the 1D-2D MIKE FLOOD hydrodynamic simulation and the DAnCE4Water agent-based
304 urban development model to systematically understand the effectiveness of adaptations based
305 on the changes of water drainage system and urban planning policies. The DAnCE4Water
306 model simulated the urban evolution from a parcel level detail and directly provided
307 information on the shape and location of urban features such as buildings and streets, and
308 allowed the dynamic interactions among hazard, exposure and vulnerabilities. In a similar
309 research area, Becu et al. (2017) integrated a coastal flooding model with a spatially explicit
310 agent-based land planning model (LittoSIM) to simulate a coastal development area and its
311 management of flood prevention measures. Similarly, studies by Haer et al. (2019) presented
312 a multi-disciplinary approach integrating different types of adaptive behaviours of
313 governments (proactive and reactive) and households (rational and boundedly rational) in a
314 continental-scale risk-assessment framework for river flooding in the European Union. In
315 particular, the adaptive behaviour of households was built based on an economic decision-
316 making model called discounted expected utility, and at each time step these agents decided to
317 either flood-proof existing buildings or to elevate newly developed buildings. Similar micro-
318 (household) and macro (government) integrated ABM approaches have also been observed in
319 a number of papers that were reviewed, e.g., Abebe et al. (2019b); Mustafa et al. (2018); and
320 Abebe et al. (2019a).

321 For community flood risks, individual agents can mitigate risks by household mitigation or by
322 moving based on risk and coping perceptions and are influenced by other agents' mitigation

323 behaviours, whilst the community can mitigate or disseminate information to reduce risks. Both
324 can have a significant influence on each other, therefore, community flood risks are the
325 outcomes of an evolving process. To capture information on how community policies and
326 individual decisions can affect on the evolution of flood risks under different future climate
327 scenarios, Tonn and Guikema (2018) and Tonn et al. (2020) developed an ABM based
328 approach to understand the temporal aspects of flood risk by integrating behaviour, policy,
329 flood hazards and engineering interventions within a whole dynamic system. The ABM model
330 focused on simulating a number of adaptation and mitigation methods from the dissemination
331 of flood management information, installation of community flood protection, elevation of
332 household mechanical equipment, to elevation of homes.

333 To reduce the adverse impacts from flood events, risk communications play a vital role in the
334 aspect of increasing people's flood risk awareness. Risk communication is commonly done
335 through a top-down manner from the governments and organisations (e.g., brochures, media
336 campaigns, and internet websites). However, such an approach has been found less efficient,
337 because of the lack of considering of cultural differences and local circumstances (INTERREG,
338 2013; Burningham et al., 2008; Martens et al., 2009). ABM has been applied to assess the
339 effectiveness of flood communication strategies and influences of social networks in the
340 Netherlands (Haer et al., 2016). Its highlight was that the social-psychological simulation of
341 individual's flood-risk preparedness decision was firmly based on the Protection Motivation
342 Theory (Rogers, 1983). By the same first author (Haer et al., 2017), three economic decision
343 models were employed for simulating human behaviours (i.e., household investments in flood
344 loss-reducing measures) in flood risk analysis, based on an Expected Utility Theory which is a
345 traditional economic model of rational agents (Von Neumann and Morgenstern, 2007), a
346 Prospect Theory which takes account of bounded rationality (Wakker, 2010) and a Prospect

347 Theory model that accounts for changing risk perceptions and social interactions through a
348 process of Bayesian updating (Viscusi, 1989).

349 Hazard migration could also be modelled by ABM, which might be triggered by environmental
350 threats like flood events as well as temporal changes in resource availabilities (e.g., population
351 growth, employability, house price) along with a number of other factors. Hassani-Mahmoei
352 and Parris (2012) reported the development of an ABM tool on investigating the migration
353 dynamics that might arise in Bangladesh as a result of extreme hazards (include flood) that
354 were likely to occur due to climate change. This study was based on district-level, with each
355 district represented in the model by one main agent only who managed the interactions within
356 the district and made decisions on movement depending on the results of three factors (the push
357 factors that are associated with climate change scenarios and socio-economic conditions such
358 as poverty level and unemployment rate; the pull factors which are the socio-economic
359 conditions in the potential destinations; and intervening factors such as house ownership and
360 employment conditions). The districts were connected as a network with nodes representing
361 the centroids of the districts and links representing possible migration paths between districts.
362 Past stay/migration decision outcomes were used as inputs through feedback loops for their
363 future decisions. Similarly, Husby and Koks (2017) applied the ABM approach for post-hazard
364 household migration and coupled that with input-output and computable general equilibrium
365 models to estimate economy-wide flood disaster losses.

366 In addition to the aforementioned studies, ABM model has also been used in a wider range of
367 flood adaptation and planning cases, for example, assessed the effectiveness of a range of
368 physical/structural and social preparedness adaptation measures for manufacturing small and
369 medium-sized enterprises to reduce the impacts of and expedite recovery from major flood
370 events (Coates et al., 2019); determined when and where in a region flood investments should
371 take place through coupling with a regional annual maximum floods model and cost–benefit

372 analysis (O'Connell and O'Donnell, 2013); coupled with a property value estimation model to
373 simulate coastal real estate market performance after different storm-event scenarios (Chandra-
374 Putra and Andrews, 2020); used as a flood risk management teaching tool to allow participants
375 to play the role of decision makers in a developed ABM based gaming platform and found an
376 appropriate balance between flood associated socioeconomic and environmental challenges
377 (Taillandier and Adam, 2018; Shelton et al., 2018; Daré et al., 2018); as well as assessed various
378 management and adaptation plans on flood risks in a general way (Valkering et al.,
379 2005; Erdlenbruch and Bonté, 2018; Dressler et al., 2016; Baeza et al., 2019).

380 **3.3.3 Hydrological modelling**

381 Another area that ABM has been lightly explored in the field is on hydrological modelling
382 which is related to flood risk management. One specific application was on mapping the
383 connectivity of potential runoff source areas and flow paths to reduce flood risks, in particular,
384 to improve our understanding of the hydrological dynamics of low-frequency, high-intensity
385 rainfall events in semi-arid catchments (Reaney, 2008). The challenges of modelling such
386 events are due to the infrequent nature of the storms, as well as the complex interactions among
387 runoff generation, transmission and re-infiltration over short temporal scales (Cerdeña,
388 1995; Reaney et al., 2007). Most of the distributed hydrological models do not provide
389 sufficiently accurate information on the origin of runoff within a catchment. To tackle this
390 challenge, an ABM approach was applied in Reaney (2008) to trace the path taken by water
391 through a semi-arid catchment. Specifically, autonomous software agents were given
392 information on their local environment generated by the hydrological model and decided on
393 their next spatial locations based on probability theory (i.e., stay in the current cell, infiltrate
394 into the soil, or flow into a neighbouring cell). Another interesting area was explored by
395 Sanchez et al. (2014) on adopting ABM for evaluating flow path in urban drainage networks,
396 specifically to simulate raindrops movements over topography under the gravity rule. Each

397 agent has an elevation as a property and several agents can be stacked together until they reach
398 a positive gradient from the location to the nearest minimum neighbouring cell, hence
399 indicating the direction of flow in the pipes. Unlike most of the reviewed studies described in
400 this paper, the agents in this study were manually generated by clicking the computer's mouse
401 at particular points of interest,

402

403 **4. Discussions**

404 **4.1 ABM platforms/tools**

405

406 The availability of the off-the-shelf software has made the ABM developing procedures much
407 easier for flood risk management applications. A variety of studies have been carried on
408 evaluating different ABM tools in a general way (Abar et al., 2017;Allan, 2010;Arunachalam
409 et al., 2008;Kravari and Bassiliades, 2015;Nikolai and Madey, 2009;Railsback et al., 2006). In
410 particular, Abar et al. (2017) has compared over 80 ABM tools in the aspects of their technical
411 features and specifications including model development effort and modelling strength; and
412 Kravari and Bassiliades (2015) evaluated 24 ABMs platforms based on their operating ability
413 and pragmatics. Although a number of ABM tools/platforms are available as either open-
414 sourced or close-sourced, based on the reviewed papers, the most commonly used are found to
415 be Netlogo, Repast (Recursive Porous Agent Simulation Toolkit) (Collier, 2003), and MASON.
416 The comparison of the three tools is summarised in Table 1. They all have limitations and
417 benefits in relation to specific requirements, evaluation criteria and individual's programming
418 preference. Overall, Netlogo is the quickest to learn and the easiest to use which is particularly
419 suitable for beginners, but might not be the best option for building large and complex models.
420 Although Repast is slower than MASON, it has a significantly larger user base, meaning
421 getting support and advice from the community is easier. A comprehensive comparison of the

422 three tools is out of the scope of this study and interested readers are referred to Railsback et
423 al. (2006) and the above review papers for more details.

424 **4.2 Advantages**

426 ABM is an ideal tool for dynamically modelling the heterogeneity of individuals for flood-
427 related studies (Dawson et al., 2011), and in principle, agents can be simulated to almost any
428 level of details. Each agent can have state variables to represent their behaviour rules, as well
429 as interactional history with its surrounding environments and other agents (DeAngelis and
430 Grimm, 2014). Integrating each agent's decision makings will result in an overall consequence
431 of the whole community/population (Vincenot, 2018). Even the simplest decision-making rule
432 based on logical "if-then" structure can result in rather complex interactions. Not to mention
433 that the decision-making rules can become a lot more complicated such as probabilistic where
434 an array of possible actions response to some stimulus is defined for each agent and also adopt
435 complex theoretical models from economical, psychological and sociological fields as rule
436 representations (Haer et al., 2017). ABM allows a model to be designed in a way that is more
437 representative to the real-world systems rather than forcing the researchers to simplify system
438 representations purely for analytical tractability (Tsfatsion et al., 2017). In particular, the key
439 elements (e.g., physical, biological, institutional, individual, and communal) of the flood
440 system can be simulated interactively under one modelling framework, and accordingly,
441 important questions could be answered: under certain environmental conditions, what would
442 the agents do? What could they do? And what should they do? (Tsfatsion et al., 2017)

444 Although ABM models are only an approximation of the full complexity of the real-world
445 entity' behaviour, it is very effective for disentangling specific behavioural processes (Haer et
446 al., 2016). Moreover, by adjusting certain ABM parameters, it can be very useful in
447 investigating the key drivers, scope, and limitations for future flood adaptation and mitigation

448 plans, as well as visualize different planning scenarios for improved understanding among
449 relevant stakeholders. As such ABM has the advantage as being a bottom-up supporting tool
450 for flood-related policy-making (Van Dam et al., 2012). Besides, it can simulate real-time agent
451 behaviours when facing flood threats (Yang et al., 2018), making the model suitable for
452 delivering insights into emergent features such as evacuation, traffic plan, and exposure
453 assessment which are difficult to be extracted from other approaches (e.g., Event and Fault
454 trees, Bayesian Networks, Microsimulation, Cellular Automata, System dynamics as described
455 in Gilbert and Troitzsch (2005)) (Dawson et al., 2011). Another benefit of the ABM framework
456 is that it has the flexibility of quick revision and add/change modules (Crick et al., 2018). For
457 example, when new policy or literature on improved decision-making methods become
458 available, prompt updates could be made to the framework.

459 **4.3 Limitations and potential ways for improvements**

460 Despite a growing interest in ABMs across various research fields, there is still limited
461 application of this technique for flood-related studies. The main challenges of the ABM
462 modelling have been categorised into three areas: 1) model development, 2) model assessment
463 and testing, and 3) model documentation.

464 **Model development**

465 First, the ABM models applied in the field lack a clear conceptual framework and theoretical
466 support. As pointed out by Robinson and Rai (2015), the effectiveness of an ABM over other
467 methodologies, relies on a rigorous combination of theoretical and empirical foundations.
468 Therefore, when implementing ABM models to simulate studies that have an overall high
469 degree of sophistication, the model rigour should also meet the same standard. However, most
470 of the reviewed papers lack a sound theoretical underpinning (Kellens et al., 2013), and often
471 with a plethora of independent ad hoc assumptions of the decision-making process without

472 being grounded on the established behavioural theories. Although there is a few studies focused
473 on the testing of theories (Haer et al., 2016;Haer et al., 2017;Haer et al., 2019), they are based
474 on economic theories only, and ignoring other relevant disciplines, such as psychological (e.g.,
475 the theory of planned behaviour) field (Groeneveld et al., 2017). Using decision-making
476 models based on theory has several advantages over ad hoc implementations (Rai and Henry,
477 2016). For examples, it fosters interdisciplinary communications, makes improvement of
478 models easier, allows to test alternative theories even when data is sparsely available, and leads
479 to more robust and faster scientific progress (Groeneveld et al., 2017;Bell et al., 2015;Klabunde
480 and Willekens, 2016).

481 Instead of relying on fixed theoretical rules to control the way agents make decisions, we can
482 borrow concepts from other fields such as computing science and ecology to setup decision-
483 making processes and human behaviour based on technologies such as machine learning and
484 artificial life studies (e.g., artificial neural network (ANN), genetic algorithm (GA)) (Hamblin,
485 2013;Huse et al., 1999;DeAngelis and Diaz, 2019). For example, ANN can train the weights
486 of different inputs by continuously modifying these weights until the resulting decisions and
487 agent behaviours achieve required accuracy. It captures the decision-making processes by
488 learning from how individual's brain functions and once the model is trained, with any new
489 inputs it can determine the decisions that meet the required degree of accuracy and evolve
490 (Huse et al., 1999;Lek and Guégan, 1999). In ecology, when utilising ANN in ABMs, a
491 common way of training is by using the GA, which was also adopted in one of the reviewed
492 papers (Mustafa et al., 2018) for calibrating the ABM-based land-use change model. GA is an
493 optimisation tool that is based on the principles of crossing over and mutation to essentially
494 evolve the decision-making processes of individuals, without the need for probabilistic or
495 logistical rules (DeAngelis and Diaz, 2019).

496 Alternative approaches to inform model structure can also be learnt from other more
497 established fields such as ecology and land-use change. For instance, a strategy called Pattern
498 Oriented Modelling (POM) could provide a unifying framework for decoding the internal
499 organisation of the complex agent-based systems and might provide insight towards unifying
500 algorithm theories for building up the relationship between adaptive behaviour and system
501 complexity (Grimm et al., 2005), and reduce model uncertainty (Magliocca and Ellis, 2013).
502 Patterns are the defining characteristics of a system, hence important indicators for underlying
503 processes and structures. When modelling agent decisions with the POM, adopting “strong
504 inference” (Platt, 1964) by contrasting alternative decision models or “theories” (Auyang,
505 1998;Grimm and Railsback, 2005) is recommended as a useful strategy (Grimm et al.,
506 2005;Magliocca and Ellis, 2013).

507 For the simulation of human behaviours, in the majority of ABM applications, a rational actor
508 model is normally used, which is clearly insufficient to describe the complexity of the human
509 system. Furthermore, various decision-making processes might be applied to different agents,
510 and even by the same agent under various situations because humans are not constrained by
511 one identity or act following the predefined rules (Haer et al., 2017; Kurtz and Snowden, 2003).
512 Although there exist many theories scattered across different fields (Groeneveld et al., 2017)
513 for simulating human behaviours, most of them cover only a certain aspect of decision-making
514 and vary in their degree of formulation. A framework for behavioural theory comparisons and
515 alternative theory communications such as the one proposed by Schlüter et al. (2017) could be
516 useful in tackling those challenges.

517 Furthermore, different approaches could be adopted to empirically inform ABM development,
518 such as through sample surveys, participant observation, field and laboratory experiments,
519 companion modelling, and GIS and remotely sensed data as reviewed by Robinson et al. (2007).
520 In flood risk domain, for examples, survey data such as those about flood risk perception and

521 behaviour could be collected for model refinement through purposely designed questionnaires
522 (Haer et al., 2019; Dawson et al., 2011; Wang et al., 2018), experiments (e.g., VR experiment
523 used in (Li et al., 2019)) and role-playing games (e.g., Taillandier and Adam, 2018; Shelton et
524 al., 2018; Daré et al., 2018)). Since data collection capabilities are enhanced rapidly by
525 technologies, and global remote sensing data are becoming more available, it is expected the
526 ABM approach would become more popular in the field. Nevertheless, more coordinated
527 efforts are required for data sharing within the whole modelling community.

528 Given the flexibility of representation by the ABM, and the increment of data availabilities,
529 there is a need to identify the appropriate level of complexity in the models. If a model is too
530 simple, it neglects essential mechanisms of the real system; however, if a model is too complex,
531 it can become cumbersome and get bogged down in unnecessary details (Grimm et al., 2005).
532 In practice, ‘a simple model that can be well communicated and explained is more useful than
533 a complex model that has narrow applicability, high costs of data, and more uncertainty’
534 (Voinov and Bousquet, 2010). In order to find an optimal zone of model complexity, systemic
535 methods such as the POM, stepwise approaches (e.g., either building up components starting
536 with simple prototypes/models, or removing components progressively from complicated
537 models), and modular design (e.g., extensive planning phase, the use of unified model language
538 diagrams) can be used to guide modellers in reaching an appropriate level of model
539 complexities (Sun et al., 2016).

540 **Model assessment and testing**

541 ABM assessment and testing is the key to understand if development is appropriate to address
542 the question or problem at hand. While it is the advantage of an ABM that a wide range of
543 flood adaptation plans and risk management strategies could be compared, the method is still
544 limited by the lack of empirical data support for model testing. For instance, it is challenging

545 to firmly identify adaptive behaviours in a specific study area and obtaining these kinds of
546 datasets for model testing is normally challenging. In order to make the model robust,
547 uncertainty analysis to test a large range of parameter settings could be essential (Lumbroso
548 and Davison, 2018; Dawson et al., 2011; Jenkins et al., 2017; Du et al., 2017a). Moreover, there
549 is a continuing need for sensitivity analysis, especially in the forms tailored specifically for
550 ABM (e.g., global sensitivity analysis (Magliocca et al., 2018)), not just standard measures
551 such as Kappa that is more suitable for linear models (O’Sullivan et al., 2016).

552 While the ability to replicate empirical evidence is often seen as the only truly decisive criterion
553 for the quality of an ABM model, it has been suggested by Bert et al. (2014) that the ABM
554 testing should also rely on the validation of model processes and components during the model
555 development. This is because most ABM models are applied to non-observable scenarios such
556 as the implementation of hypothetical adaptation policies. As a result, there are no
557 observational data available for the testing. The model should show theoretical validity, agent-
558 behavioural validity, validity under extreme conditions and structural validity (Damgaard et al.,
559 2009). A number of approaches may be used for the model process validation, such as the
560 TAPAS (Take A Previous Model and Add Something) (Polhill et al., 2010), “modelling for a
561 purpose” (Takama and Cartwright, 2007), POM (Grimm et al., 2005), and the participatory
562 modelling (Voinov and Bousquet, 2010). Clearly, such approaches are beneficial for both
563 model development and testing. For the empirical testing, it is not only to assess how good the
564 model can reproduce the reality, but also for the simultaneous calibration, tuning and further
565 development of the model (Bert et al., 2014). For the latter, methods such as the “Post-hoc
566 POM” could be used (Topping et al., 2012). To find the balance between empirical validation
567 and process validation, the “invariant-variant” method proposed by Brown et al. (2005) could
568 be a useful guide which has been applied in the land-use field to help modellers to understand

569 the situations with good model results, and the instances with poor model results due to either
570 path dependence (Arthur, 1988) or stochastic uncertainty.

571 When dealing with complex models especially these with a large number of different
572 adaptation options and a large group of heterogeneous agents, the computational requirements
573 could explode to infeasible levels that certainly cannot be handled by desktop PCs. With the
574 rapid development of supercomputing facilities, this issue could be addressed through
575 implementation in cluster environments as well as the application of surrogate models and
576 design experiments with a minimal amount of simulations (Löwe et al., 2017), for instance,
577 sequential setups proposed by Kleijnen (2015).

578 **Model documentation**

579 Documentation for ABMs is often incomplete, opaque and difficult to understand, which
580 hamper their applications and further developments by the community. Without a standard
581 protocol, it would be difficult to understand, compare and duplicate the ABM models that have
582 been developed. Grimm et al. (2006) has proposed a standard protocol called ODD (Overview,
583 Design concepts, and Details) for describing ABMs, which has been widely received in the
584 scientific community. First, the ‘Overview’ provides the purpose and main processes of the
585 model with three subcomponents of purpose, state variables and scales, and process overview
586 and scheduling; second, the ‘Design concepts’ describes the general concepts underlying the
587 model design; and third, the ‘Details’ shows all the necessary information for the
588 reimplementation of the model with three subcomponents of initialization, input, and
589 submodels. A more recent version of the protocol (ODD + Decision) has been presented in
590 Müller et al. (2013), which is added with a new component for human decision-making. The
591 new version is more useful for documenting ABMs in general when human decisions are
592 included which is more suitable for flood-risk related ABM models. The ODD and its extension

593 have been used widely for documenting ABMs including in flood-related studies (Tesfatsion
594 et al., 2017;Noël and Cai, 2017). It is also expected if developed ABM models/frameworks
595 could be shared and reused such as through open-source software platforms (e.g.,
596 <http://www.comses.net>, and <https://github.com/>), it might allow more researchers to focus on
597 exploring the choices of appropriate decision models (Bell et al., 2015).

598 **5. Conclusions**

599 The utilisation of ABM to tackle flood-related challenges is becoming more popular in recent
600 years. The variety of identified topic areas illustrates that, on one hand, there is a continuing
601 prominence of real-time flood emergency management and planning focused studies; and on
602 the other hand, there is a significant rise of studies interested in the application of ABM to
603 flood adaptation policy and strategy planning support in recent years. A particularly valuable
604 area might be the latter. This is based on two reasons. First, studies in this area have significant
605 potential to contribute to practically driving flood resilience by guiding and improving multi-
606 shareholder decision-making. Second, such a topic could tackle interdisciplinary issues and
607 encourage cross-disciplinary collaborations more directly than other topics. As increasing
608 flood resilience is high on the agenda of policy-makers and academics alike in many countries,
609 it is expected that the importance of this topic in the context of flood risk management studies
610 will remain.

611 While technical comparisons of the ABM models are not the focus of this paper, the review
612 however reveals the limitation of ad hoc implementations of decision-making and behaviour
613 in the models, and lack of a consistent format of presentation and documentation. This, as a
614 result, makes the model comparison difficult across the studies and is challenging to summarize
615 a common framework for ABM applications in flood risk management. Future ABM
616 development in the field will be influenced by the continuing development and refinement of

617 modelling framework and theoretical foundations, and enhancement of model testing and
618 documenting capabilities. While the review has identified the limitations and potential areas
619 for future improvement of ABM applications in the field, it would be the most efficient to
620 develop across disciplines to include all actors in ABM systems. For instance, it would benefit
621 from the interactive involvement of environmental scientists, social scientists, economists, and
622 psychologists in the development process. Especially, for adaptation and mitigation planning,
623 models that encourage collaboration between disciplines and sectors, will more likely promote
624 knowledge sharing and allow easier acceptance by wider audiences/users naturally (Hansen et
625 al., 2019).

626 Based on the review, although ABM has shown valuable advancements for flood risk
627 management studies, its application is still in a state of infancy, especially its contribution to
628 the understanding of how human decisions and behaviours affect the whole human-flood
629 systems has yet to be fully exploited.

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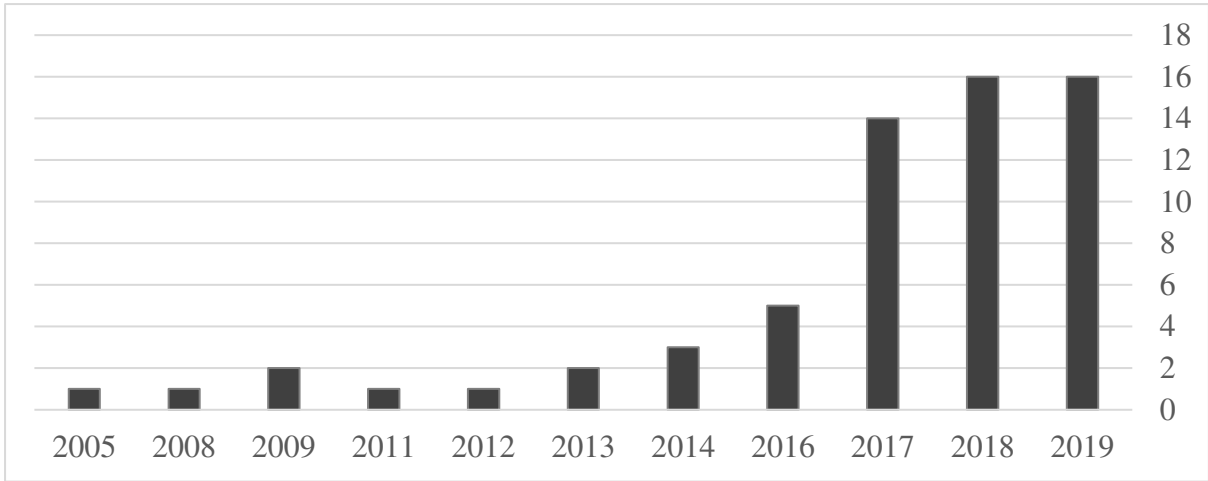
1035

1036 **Table 1.** Comparisons of Netlogo, Repast and MASON. Source (Salgado and Gilbert, 2013).

	Netlogo	Repast	MASON
Licence	Free, but not open source	General Public Licence	General Public Licence
Documentation	Good	Limited	Improving, but limited
User Base	Large	Large	Increasing
Modelling Language(s)	NetLogo	Java, Python	Java
Speed of Execution	Moderate	Fast	Fastest
Support for graphical user interface development	Very easy to create using 'point and click'	Good	Good
Built-in ability to create movies and animations	Yes	Yes	Yes
Support for systematic experimentation	Yes	Yes	Yes
Easy of learning and programming	Good	Moderate	Moderate
Easy of Installation	Good	Moderate	Moderate
Link to geographical information system	Yes	Yes	Yes

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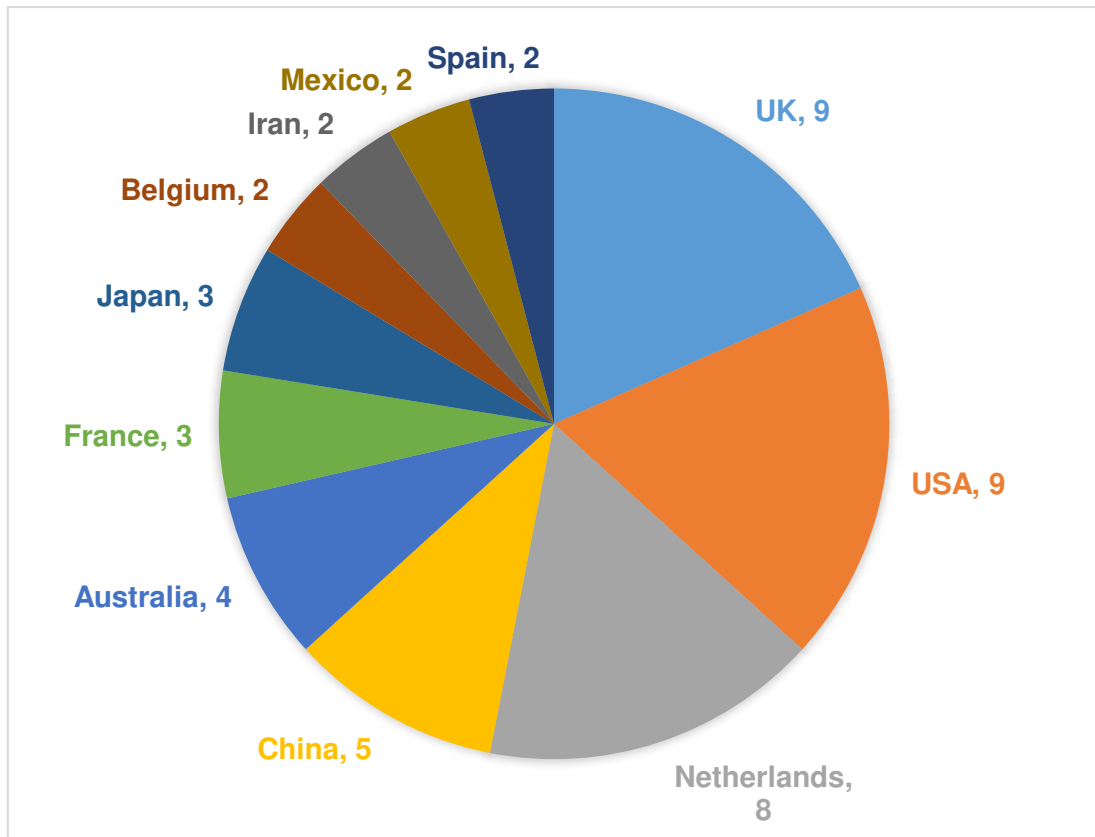


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1040 **Figure 1.** Annual distribution of the identified articles.

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1044 **Figure 2.** The global distribution of ABM applications in flood risk management (by their case
 1045 study areas). Only countries appeared more than once are listed (49 papers). Additional seven
 1046 papers have one case study carried out in Bangladesh, Chile, Ethiopia, Germany, Ghana, Italy
 1047 and Pakistan, respectively. The remaining five papers are based on synthetic scenarios (four)
 1048 and the whole European Union (one), respectively.

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