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Flood Evacuation in Informal Settlements: Application of an Agent-Based Model to Kibera Using Open Data

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Abstract: Flood incident management involves taking actions to save lives and reduce damages during a flood. Agent-based modelling tools have recently been developed to simulate the dynamic interactions between people and floodwater as a flood event unfolds. To date, these have only been applied in locations with a wealth of data, relying upon bespoke local or national datasets. Although informal settlements have a concentration of vulnerable people and are often more exposed to natural hazards, data availability is often limited, posing challenges for planning and implementing flood incident management actions. In this study, a model that was first applied in the UK is adapted and applied to simulate flood evacuations in Kibera, a densely populated informal settlement in Nairobi. Although data quality limits some of the model's potential, the results reproduce patterns of observed behaviour. Evacuation shelters in the Northwest, North, and Northeast are shown to perform best. A major exit route to the South, a bridge crossing, and a river path are shown to be especially prone to congestion during evacuations. This paper reports on the first application of an agent-based model to an informal settlement, Kibera. The demonstration is an important step towards an operational tool for flood incident management planning in informal settlements around the world.

Keywords: flooding; risk analysis; agent-based model; evacuation; data availability; global south

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1. Introduction

Understanding the impacts of flooding events is a complex issue that varies from place to place with regard to both their effects on the economy and the responses of the local populations. Data show exposure to 1-in-100-year floods to be as high as 23% of the global population (1.81 billion people), with 89% of these people living in low–middle-income countries [1]. This higher vulnerability is primarily attributable to high rates of population growth and poverty, coupled with economic constraints limiting the capacity to adapt to current and future flood risks.

In many developed countries, flood incident management (FIM) plans have been established to help reduce the consequences of flooding in towns and communities [2,3], whilst limited resources and a lack of awareness limit the ability of developing countries to create effective FIM plans [4]. These plans typically set out numerous measures, including hard engineering and soft engineering actions to reduce the likelihood of a flood, as well as policy change and emergency response plans to reduce the social and economic impacts of a flood that does occur. However, numerous events over the past decade have shown how poor FIM can have devastating impacts on both human life and infrastructure. Poor FIM can result from underestimating the magnitude or intensity of a flood event or through ill-conceived plans that are impractical to implement. An example of both was seen during the 2022 floods in Pakistan, when July and August received 180% and 243% excess rainfall, respectively, across the whole country [5]. Over 1600 people were killed, 33 million people were affected, and 7.9 million were displaced [6], highlighting the need to implement a mix of structural and non-structural flood management measures [7].

Such events prompted the need to develop methods that consider the interaction between human and technological systems in order to better understand flooding events and the actions that can be implemented to reduce their impacts [8]. Understanding crowd dynamics in a region prone to flooding, prior to and during an event, can help develop an understanding of how important networks, such as transport routes, can be affected. This can help engineers and planners develop schemes to reduce the number of deaths that occur from flooding [9]. However, due to the large spatial variation in both flooding events and responses to flooding globally, the application of an FIM scheme in one location cannot be translated directly to another. Historical events should always be used as opportunities to learn and understand what has happened. However, it is crucial to take proactive measures to prepare. To address this, we present an agent-based model that can simulate flood incidents and human evacuation. This model, first developed by Dawson et al. [10], has been applied to urban areas in the UK and other data-rich locations. Here, we adapt the model and test its utility in an informal settlement where data are typically less readily available, and the capacity to develop FIM plans is typically lower than in wealthier urban areas.

Kibera, an informal settlement located outside of Nairobi, Kenya, was chosen as our case study (Figure 1). Kibera lies 5 km southwest of the capital city of Kenya, Nairobi, spanning an area of approximately 2.38 km^2. It comprises 13 villages, with population estimates ranging from 137,000 to 500,000 and even up to 1 million [11–15]. The official census report from 2019, conducted by the government of Kenya, counted the official population to be 185,777 [16]. The informal settlement is strategically placed to allow access for labourers to find work in the industrial regions of Nairobi [17]. Propped up along the banks of the Ngong River, illegally built houses lay tightly strewn across a slope, creating significant flood risk [18]. The area is also intersected by streams, so the bridges and accessways become inaccessible during flooding events [19]. The poorest among the population have been forced to build along the banks of the river, which regularly overflows its banks during the wet season, exacerbated by poor management of solid waste clogging the already limited drains [20]. Studies show that at least 30,000 of the population of Kibera live within 30 m of the river and streams [20]. For much of the slum, physical access is navigable only by foot, and during the wet season, the pathways can become inaccessible, making evacuation difficult. Despite many years of mapping activity and engagement in flood resilience [21,22], there is limited understanding of the most effective routes for people to take during a flood event to get to safety, making this a priority that we address here [23–26].

A number of simulation approaches have been developed to simulate urban evacuations. One of the earliest used a cellular automata (CA) approach to mimic local interactions and behaviours within an environment by implementing simple rules at incremental time steps across a grid or lattice [27–29]. However, CA's simplicity restricts the ability to represent movements over complex networks and capture different types of communications between people and organisations [30]. For example, a diverse range of behaviours during flood events has been observed, including knocking down barriers, returning home to save pets, refusing to evacuate, etc., that cannot be incorporated into a CA model.

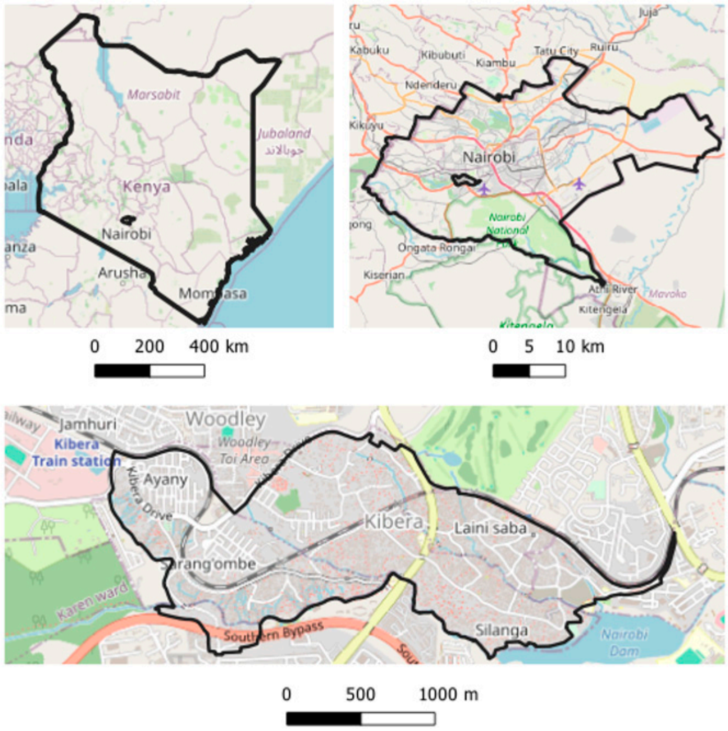

Figure 1. Location of Kibera. Basemap source: OpenStreetMap.

An agent-based model (ABM) enables more realistic movements to be represented, and simulated agents behave more flexibly and act autonomously [31]. Interactions in space and time can be enabled between individuals, organisations, and their virtual environment [10,32]. In contrast to physically based models, e.g., models of hydrodynamics, an ABM of a flood evacuation cannot be truly validated [33]. Even when we simulate and successfully replicate human response during a historical event, people learn and do not behave in the same way should the same flood happen again [34]. However, ABMs are useful for understanding possible outcomes and interactions between social, technological, and environmental systems [35]. In spatially complex and densely populated urban environments, like Kibera, an ABM offers the unique potential to test a range of different FIM plans and population responses that would not be possible in workshops or full-scale field exercises.

Following this introduction, we introduce the method and how the ABM was adapted to an informal settlement, then present and discuss the results from our analysis before drawing conclusions on the utility of the model, how it compares to previous applications in the UK, and the requirements for operationalising the ABM to support FIM in settlements around the world.

2. Materials and Methods

This study applies the Flood Infrastructure Resilience Model (FIRM) developed by Dawson et al. [10]. The model is coded in NetLogo (v4.0.4), a well-established ABM language that has been applied to a range of applications [32]. It provides a visual interface in which the programmer can watch an event unfold, as well as a scenario manager written in Python that can be used to simulate batch runs with differing scenarios. The original application studied the impacts of coastal flooding in Towyn, North Wales [10].

The ABM couples hydrodynamic and agent simulations to explore the impact of rising stream levels and FIM responses used, such as evacuation to preassigned shelters. A 2D dynamic flow is represented over a raster grid, with flow between cells defined as a function of the free surface height difference between those cells [36,37]. In this study, the raster grid is defined by the resolution of the digital elevation model. Spatial inputs (buildings, pathways, and roads) form the environmental setup of the model, whilst behavioural rules define how agents interact with each other, the environment, and response mechanisms to FIM strategies. Risk analysis defined by vulnerability information (economic or physical risk) is the primary focus of the work, with a scenario manager enabling the batch running of FIM simulations (Figure 2). The model is summarised in detail in [10], but the most salient aspects are summarised below, as well as the data used and the model developments required to implement the FIRM in a different context.

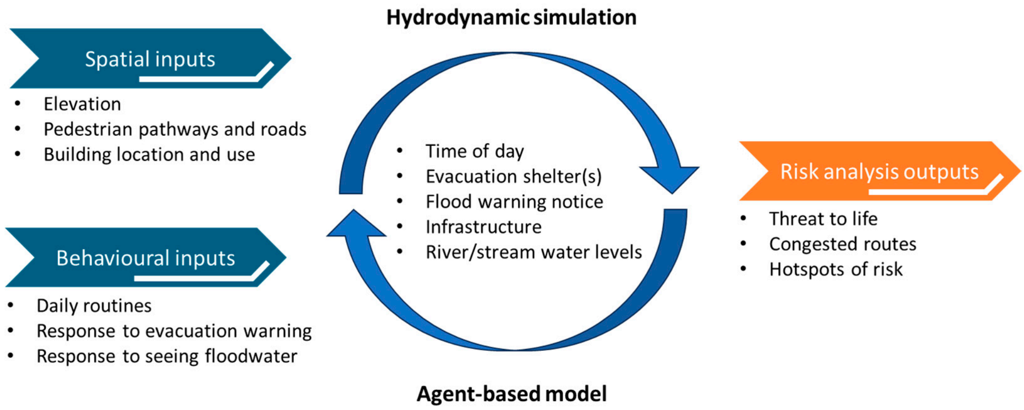

Figure 2. Model schematic for FIM.

2.1. Model Setup

2.1.1. Road Network

The road network was constructed using open-source shape files of all the major pathways and roads throughout the settlement. The data were co-produced by the Map Kibera project [21] (led by community members and residents of the slum) and made available through OpenStreetMap [38]. With no centralised planning, roads of varying hierarchy emerged from use, strongly influenced by the topography of the region [39]. The complex network of roads and pathways provides challenges for evacuation planning. Some routes are designed for and dominated by vehicle use, some are predominantly used by pedestrians and too narrow for cars, whilst many are mixed-use. Additionally, spaces between buildings can be used as access routes, a railway running through the centre of the domain also serves as a pedestrian highway, and in the dry season, creeks and sewers can also be used by pedestrians. Data were tidied up to ensure the correct connectivity of roads and paths (Figure 3a). Subsequently, each road or pathway segment and junction was assigned a unique ID to enable agent movements to be tracked (Figure 3b).

2.1.2. Buildings

Geospatial building data for the whole of Kibera are incomplete. For the village of Kisumu Ndogo, a comprehensive mapping survey was conducted of all structures for the Map Kibera project. As with previous applications of the ABM, these buildings were added directly to the model. For the remaining villages, the number of buildings was generated synthetically based on population density and the number of structures from the 2009 census data [40]. The location of buildings was assigned randomly using a uniform spatial distribution onto areas designated as built-up in OpenStreetMap (Table 1) [40].

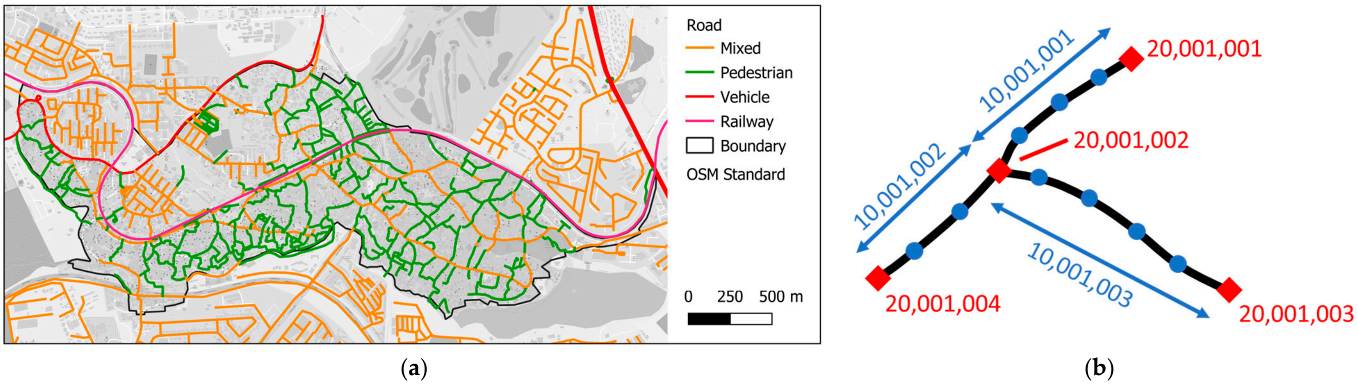

Figure 3. (**a**) Road and pathway networks in Kibera [1]. (**b**) An example of the unique identifiers assigned to each node (diamond markers) and road (series of links that connect two nodes). Basemap source: OpenStreetMap.

Table 1. Population densities according to the government census [39].

Village	Gatwkera	Kanbimuru	Kianda	Kisumu Ndogo	Laini Saba	Lindi
Area (km^2)	0.2782	0.0754	0.1629	0.1668	0.2591	0.253
number of structures	1978	446	1304	886	2193	1931
number of inhabitants	23,053	3367	17,356	16,437	11,342	18,666
Village	**Makina**	**Mashimoni**	**Raila**	**Silanga**	**Soweto East**	**Soweto West**
Area (km^2)	0.4355	0.124	0.0813	0.2076	0.2307	0.0685
number of structures	2496	825	883	1574	1939	590
number of inhabitants	31,602	12,375	6644	15,569	23,566	10,360

How a building is used, whether for residential, business, education, or other public use, influences how and where agents move during the day. In the UK, a bespoke database (the National Property Database) provides information on the type of each building, including houses, schools, museums, etc. In contrast, building use data for Kibera are limited, can change quickly, and are difficult to categorise, as buildings often serve multiple purposes and market shops are built along the side of the streets. The results from a Map Kibera assessment in Kianda captured generic statistics of building uses: Household Units (91.2%), Business Units (4.6%), Service Units (0.6%), Empty Units (1.94%) and Other (1.66%) [41]. Whilst not very granular, the figures provided an overall picture of building usage and were representative of the whole modelling domain for the purposes of this study. Building use was assigned at the same time as building location, according to this distribution.

2.1.3. Inundation Modelling

A digital elevation model (DEM) [42] is a fundamental requirement for flood risk management in order to understand key flow paths and the magnitude and spatial variability of flood risk. Here, a globally available product, the Shuttle Radar Topography Mission (SRTM) DEM, was used. With a 30 m resolution, this is much lower than the 1 m DEM typically available for flood risk studies in the UK. However, it has a higher resolution than many other freely available global products and has been shown to perform as well as, or better than, many other products, especially outside of steep valleys [43,44].

High intensity rainfall in Kibera during the two wet seasons is the main cause of pluvial and fluvial flooding events [45]. Flood events in Kibera are usually a combination of an influx of water through rivers and streams, combined with sewage and open drainage that flows through the area. Water was introduced to the simulation at the upstream river boundary. A reduced complexity hydrodynamic model (described in [10]) is used to simulate flood flows and accumulation, with flood volumes approximating to the 1 in 50-year event [25].

2.2. Agent Behaviour

Incorporating pedestrian-based evacuation required adapting the original model to reflect new routes the agents could use, the speed at which they travel, and their vulnerability to high flood waters. The original UK version considered only a vehicle simulation; in Kibera, it is crucial to capture pedestrian movements, as most people cannot afford motorized transport options [46].

2.2.1. Agent Demographics

Results from a public [47] survey showed that approximately 33% of the population of Kibera is under the age of 15, 10% lower than the results from other studies [48]. With discrepancies in the available data for Kibera, the ability to characterise different agent types and update modelling parameters as new data become available is imperative. Selected for the age and gender breakdown, Figure 4 shows the demographics considered in the simulations, based on the data provided by the APHRC survey.

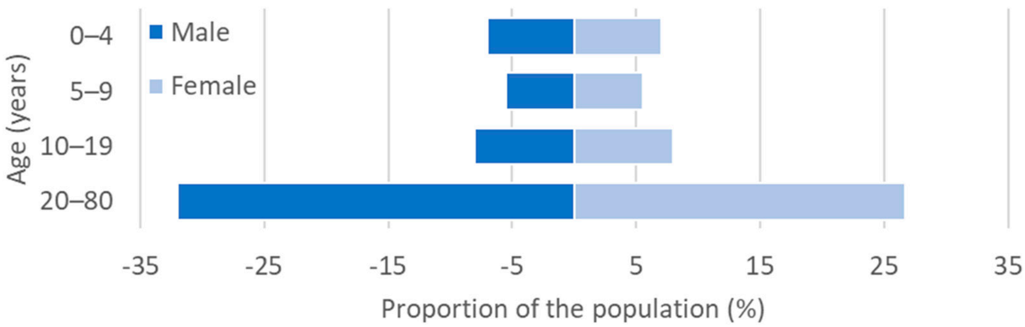

Figure 4. Population age distribution in Kibera.

With little form of local employment, surveys identify that many inhabitants rise early in the morning in search of manual labour and often travel to other parts of the city in search of work [46,49]. Due to the sheer volume of youths and men searching for work, local employment opportunities are slim, and as many as 50% of those able to work remain unemployed [41]. In order to account for this influx of men into the city centre in search of work, locations representing external employment were added at the model boundaries [50]. In contrast, the majority of women remain in the slum during the day, performing tasks such as washing clothes and collecting water or running small businesses, such as selling charcoal and groceries [46].

2.2.2. Agent Routines

Assimilating the information above enabled us to infer some representative daily routines of residents in Kibera based on gender and age; schematics of these routines are shown in Figure 5. In the event of a flood warning, these daily routines are interrupted. Depending on the time of day, the location of agents can vary substantially depending on the time at which the evacuation is called, which in turn can affect the relative success of evacuation strategies. When an agent receives an evacuation order, the probability that they act on it is selected by the user; for agents that act, they are assumed to make their way to the nearest evacuation shelter.

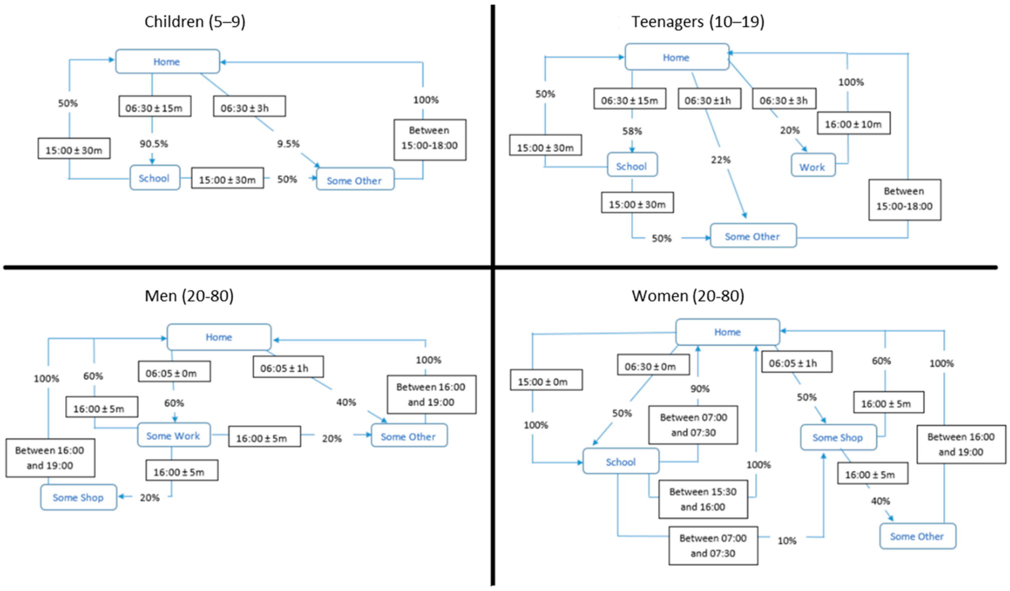

Figure 5. Daily routines inferred for different demographic groups. Decisions to move between schools, homes, shops, places of work (curved boxes), are taken by a proportion of each demographic group (indicated by the percentages on each arrow), at a specific time of day with a given variance (square boxes).

2.2.3. Agent Movement

At the start of the simulation, all agents are assigned randomly to a residential building. Throughout the day, agents can be within their assigned residence or visiting a non-residential building for work or to access other services. If an agent leaves a building, they move onto the nearest road/path segment. Their destination is defined according to their daily routine (Section 2.2.1) or a shelter if evacuating. Agents are routed according to Djikstra's A* shortest path algorithm [51]. Vehicles can move up to the speed limit. If the road network is congested, they slow down. The maximum speed at which a pedestrian agent can travel is determined by their age; for example, children travel at half the speed of an adult. The maximum adult walking speed is assumed to be 4 km/h [52]; as with the road network, when paths are congested, agents slow down and are limited by the physical capacity of the space.

2.2.4. Agent Vulnerability

Factors such as the height, age, and fitness of an individual are key to determining people's vulnerability and capacity to evacuate and move through flood water. A threshold relationship, derived from physical experiments, was applied, whereby children (under 12 years old) are considered to be 'in harm's way' for depths $\geq$30 cm, whilst adults are 'in harm's way' for depths $\geq$70 cm. Water levels below this are considered to be walkable [53]. At each timestep, the ABM counts and reports the number of child and adult agents in flooded buildings or outside in flood water that exceeds these thresholds.

2.3. Evacuation Sites

There are no formal, pre-determined evacuation shelters or routes for the residents of Kibera. With a total population of over 200,000 people, several shelters would be needed. Using satellite imagery, five non-residential buildings were identified as appropriate evacuation sites. These included places of worship, schools, and marketplaces, distributed around the area (Figure 6). Testing different potential locations for, and combinations of, evacuation shelters can help planners examine likely areas of congestion and identify locations for shelters that perform best under different flood event scenarios.

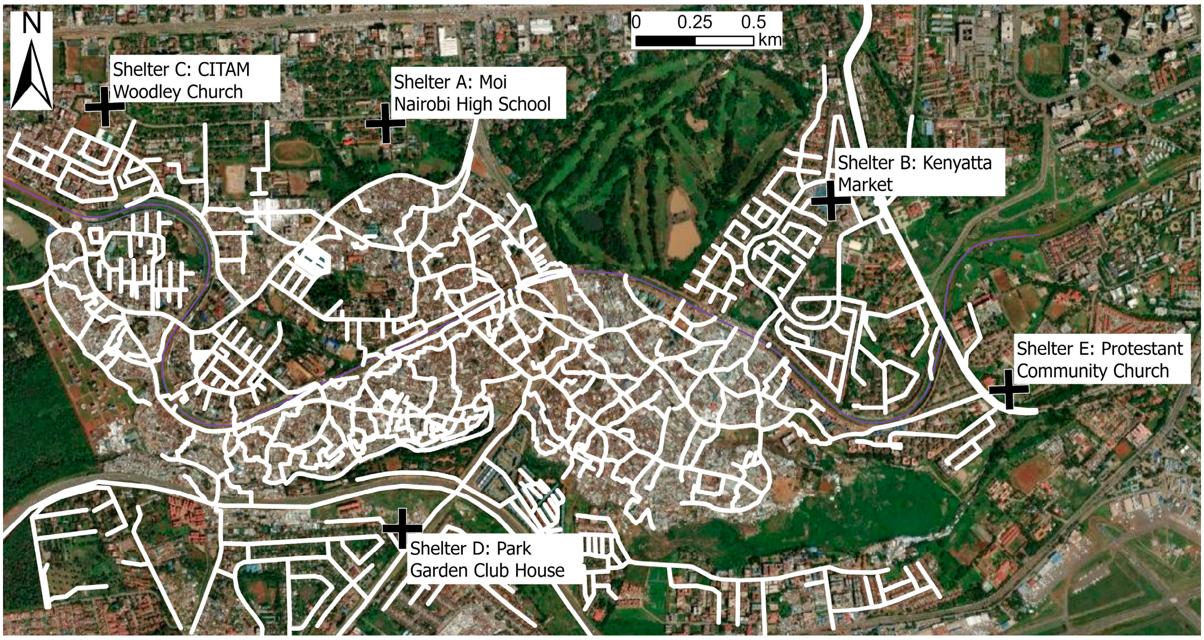

Figure 6. Evacuation shelters (+ symbols) tested in the scenarios. Basemap source: ArcGIS World Imagery.

3. Results

Different evacuation plans and responses are tested. A random seed alters how agents are distributed spatially across the domain when the model is initialised. The computational expense of simulating the full population required only a proportion of the population to be represented in the simulations. There is typically a non-linear increase in computational time for increases in the number of agents as the number of possible interactions increases exponentially [54]. Simulating only 1% of the population meant that outcomes were very sensitive to the initial conditions of the agents, with results ranging from 0–2% of agents at risk. The sample was so small that many simulations returned no risk to people because the random distribution of the agents (Section 2.2.3) allocated them all to buildings far from the flood risk area, and interactions between agents were too limited. However, reducing the number of agents in a simulation by one order of magnitude typically has a limited impact on model output [55]. Simulating 10% of the population (20,000 agents) provided a range of 1.1–1.6% agents at risk. For this number of agents, three hours of time required approximately 20 min of computational time (using a Dell Intel Xeon Gold 6134 @ 3.2 GHz server with 256 GB RAM). This was considered an acceptable balance to enable multiple simulations whilst capturing key evacuation behaviours. In total, 335 simulations were run, comprising various sensitivity tests and evacuation scenarios.

3.1. Evacuation Shelters

Each simulation began at 6:00 a.m. (based on average daylight hour records for Nairobi) and ended at 9:00 a.m. In each simulation, 90% of the population is assumed to respond to a call to evacuate, starting at 6:45 a.m. In the first instance, only one evacuation shelter is assumed to be available. Table 2 shows the number of agents, averaged over 10 simulations with different random seeds, at risk from high levels of flood water. Located near the Nairobi dam, nearly five times more people were at risk attempting to reach the evacuation centre at the Protestant church than would have been the case if no evacuation had been called. This is over 10% of the total number of simulated agents; therefore, this shelter was discarded from further analysis.

Table 2. The number of people exposed to dangerous flood levels for each evacuation scenario averaged over 10 simulations and modelling 10% of the total estimated population of Kibera.

Shelter	Location	Agents at Risk
-	No shelters or evacuation order	245
A	Moi Nairobi High School	155
B	Kenyatta Market	188
C	CITAM Woodley Church	92
D	Park Garden Estate Club House	235
E	Protestant Community Church	1161

The performance of the shelters can be assessed in terms of the number of people exposed to dangerous levels of flood water, and the number of people successfully evacuated. Simulations that consider two shelters do not always substantially improve on the results of individual shelters (Table 2, Figures 7 and 8). In individual simulations (Table 2) Shelter D leads to more people being exposed to dangerous flood levels. However, when Shelter D is used in combination with other shelters (Figure 7) fewer people are exposed to dangerous flood levels compared with other combinations where all the shelters are to the North. Overall, combination A&D leads to the most people reaching a shelter within 2 h and fewest being exposed to dangerous flood levels, whilst combination B&C leads to the fewest reaching a shelter within 2 h and the most people exposed to dangerous flood levels. However, whilst the combination of A&C leads to a good evacuation rate, it also exposes the second highest number of people to dangerous flood levels.

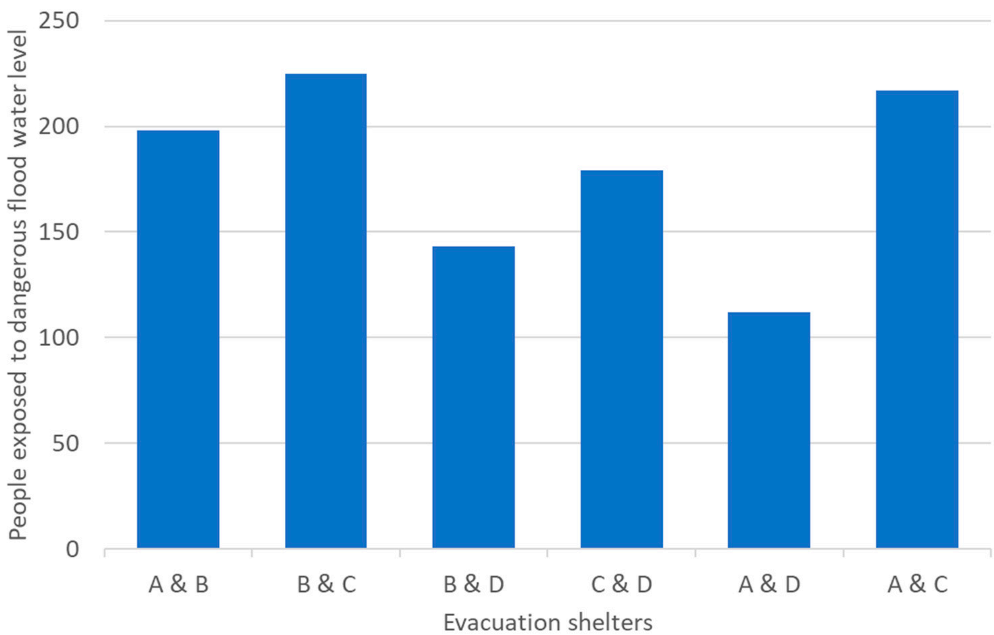

Figure 7. The total number of people exposed (averaged over 10 simulations) to dangerous flood water levels for each pairing of evacuation shelters.

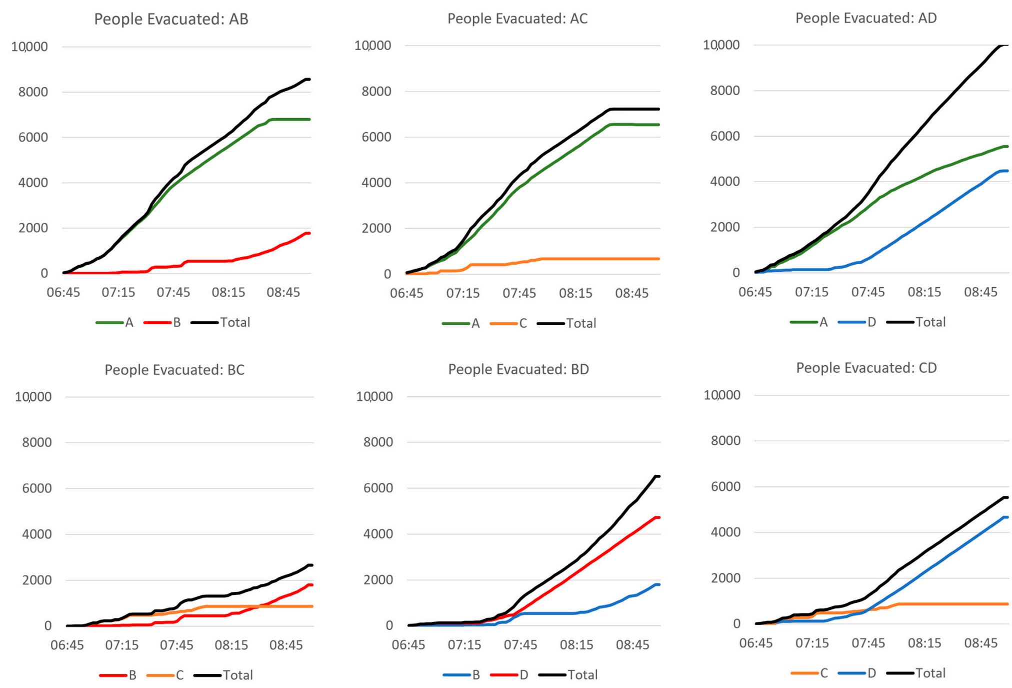

Figure 8. The number of people reaching evacuation shelters over time, where for each scenario two shelters are operating.

The effectiveness of shelters is influenced by a combination of factors. Analysis of the timeseries of Shelter C (Figure 8) shows a slow but steady arrival of evacuees at the shelter, with the numbers flattening off towards the middle of the simulations. Agents in the model are automatically assigned their nearest evacuation shelter, with agents living near the shelter arriving unhindered by flood water. However, for agents coming from farther afield, paths and access routes can become blocked, causing agents to divert to avoid the flood water and hindering (or entirely blocking) access to Shelter C.

Proximity to streams and rivers flowing through the domain influences the timing of evacuees arriving at the shelters. Shelter A is located on higher ground away from major streams and rivers. Evacuees start to arrive relatively quickly from the outset of an evacuation. In contrast, it takes some time for people to start arriving at Shelter D, with an acceleration in arrivals an hour into the evacuation. To reach Shelter D, the majority of agents must cross the Ngong River. Walking to a safe crossing point delays the arrival of agents at the shelter and results in high levels of congestion at crossings, which act as 'pinch points' (Figure 9 and Section 3.2).

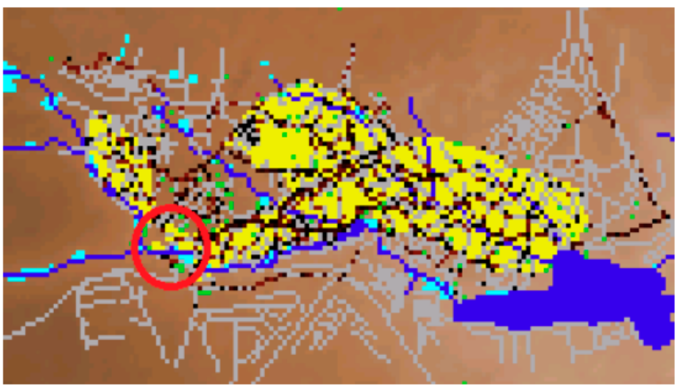

Figure 9. Screenshot of the model simulation. The circle highlights a crossing point over the Ngong River.

For the most part, more evacuation options enable more agents to reach shelters compared to individual shelter scenarios (Table 3). However, this is not always the case, and some combinations do not lead to an increase in the number of agents evacuated safely or reduce the number of agents at risk. For example, whilst simulations involving Shelters A and D consistently perform better, when either of those shelters is operational in combination, a smaller proportion of agents reach either Shelter B or C. However, the model assumes the shelters do not have capacity constraints that might obligate agents to move to another shelter or gather in different, possibly ad-hoc, locations.

Table 3. Percentage of people using each evacuation shelter during multiple scenarios, with the averages taken across 5 simulations for each.

Scenarios	A	B	C	D	Agents Evacuated	Agents at Risk
Scenario ABC	71%	21%	8%		6430	199
Scenario BCD		22%	9%	68%	5992	181
Scenario ABD	48%	14%		38%	9369	129
Scenario ACD	52%		7%	41%	8576	152

This highlights a challenge of evacuation planning. In these simulations, the model assumes agents will try to reach their nearest shelter. A crow-flies analysis of where to place evacuation shelters might assume that people can, and would choose to, reach the nearest shelter. However, this analysis has shown how the success of these strategies is mediated by interactions between people, pathways, river crossings, and floodwater influencing the accessibility of shelters.

3.2. Congestion Maps

Information on agent movements is extracted from the simulations above to show which roads are more prone to congestion during a flood event. This is measured by the maximum density of evacuees on each road within any two-minute period during the simulation. There is no standard definition of congestion, but observations have shown that a pedestrian density of six people/m^2 or more is typically associated with accidents [56], and walking speed can start to reduce at pedestrian densities above 1 person/m^2 [57], which is the threshold reported here. A composite of all the evacuation shelter scenarios was obtained and is shown in Figure 10. This shows routes that are crowded for only one evacuation shelter (green) and consistently crowded regardless of the evacuation shelters considered (red).

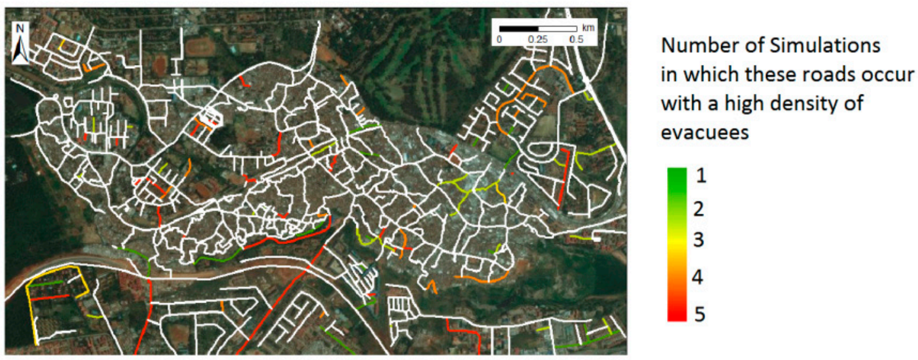

Figure 10. Roads suffering from congestion for one or more evacuation shelter scenarios. Roads with a density of less than 1 person per m length of road were removed. Basemap source: ArcGIS World Imagery.

Figure 11 shows road congestion for Scenario ABD when three evacuation shelters are modelled simultaneously. Located north, northeast and south of Kibera, these three shelters give agents multiple options for evacuation. As might be expected, there is a general increase in congestion near Shelters B and D. In contrast, despite receiving a higher proportion of evacuees, the roads leading up to the school maintain a density of less than one person/m^2 throughout the event because people are able to approach via routes from the east, south and west.

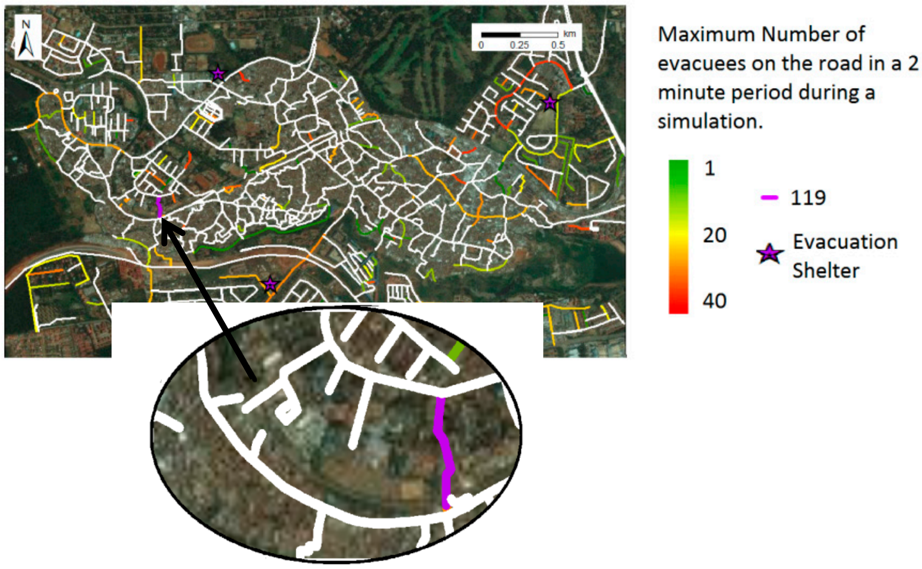

Figure 11. The maximum density of agents recorded in Scenario ABD. Only roads where the density per square meter is greater than 1 are considered. Basemap source: ArcGIS World Imagery.

In Figure 11, the enlarged detail shows discontinuities in the road network. These discontinuities restrict agents in the simulation to using fewer roads, resulting in very high densities of evacuees in some places. In some instances this could be an error in the data, but the approach enables planners to identify points of significant congestion in Kibera.

4. Discussion

The results presented in this study explore potential strategies for FIM in Kibera. An agent-based model initially developed for application in the UK was applied and adapted to consider the potential value and utility of a social simulation approach in a region considered to be data-poor. The results, limitations, and potential future work are discussed based on this context.

4.1. Utility of Agent-Based Modelling in Data-Poor Areas

An ABM is not modelling physical processes and is therefore not a predictive tool in the same sense. Model validation by comparison with empirical data is therefore not possible. There are no detailed observations of exactly where and how people moved during a flood event. However, even if observations of evacuations existed for one event, it is widely observed that people learn from their experience of a flood and would behave differently during a subsequent flood [58]. Alternatively, we can have confidence that the model represents some key emergent behaviours by looking at other sources of information. For example, climate adaptation studies of Kibera have identified the limited bridge crossings as vulnerable to overcrowding, as was the case in the simulations above (Figure 10 and Section 3.2) [21]. Furthermore, flood modelling has demonstrated areas near the Nairobi Dam to be at high risk, reinforcing our results that warn against the danger of placing an evacuation shelter near this area [25,45]. Insights from the residents highlight that they tend to evacuate northwards during a flood event, reinforcing the findings that these provide more robust options [59]. Despite the data limitations, at an aggregate level, the model achieves representative behaviours.

Considering social responses to floods is not a new concept for disaster risk managers. One approach is to explore a few scenarios or storylines, perhaps through role-play of a mock incident or a desk-based exercise [60]. An ABM should not replace those sorts of activities because they can elicit an important understanding, especially about the nature of stakeholder interactions. However, this work has shown how, even in a data-poor region, an ABM can test a range of flood evacuation strategies and provide important information on areas more likely to lead to fatalities, roads and paths prone to overcrowding, and the relative merits of different evacuation locations—insights obtained only partially, or not at all, from other approaches. Moreover, as model parameter choices are made transparent, their appropriateness and implications can be debated amongst stakeholders. By exploring a range of values for key parameters, the sensitivity of model outcomes can be understood.

4.2. Quality and Availability of Data

Several adaptations were required to apply the ABM, previously developed for a UK context, to Kibera. The primary addition was to include pedestrian agents along with vehicles. This was essential to capture a dominant mode of movement but also required a vulnerability function to reflect human stability in floodwater. The majority of the alterations reflected the lower granularity of the available data, including flood modelling, building use, and behaviour rules.

Although a 5 m DEM has recently become available, flood mapping with this model did not pick up many locations observed to flood, highlighting the difficulty of urban flood modelling. The decision was therefore made to use globally available datasets as the focus of this work to explore the utility of this approach in data-poor regions. The coarse DEM used here is likely to have impacted the timing of the flood wave; although this does not adversely impact the spatial insights from the model, such as congestion, it will increase the uncertainty associated with timings. Consistent with other studies that use global flood datasets, this highlights the importance of very high-resolution spatial data [43], as well as knowledge of the location of channels, drainage features, and other overland features that disrupt flow, to accurately predict inundation [61].

Only summary information on building use within Kibera was available. The building generator assigned building use and location, and agents were initially assigned to residential buildings. In this application, the very high density of buildings and the dominance of residential use mean that this had limited influence on the variance of model results. Less compact areas with a greater diversity of building types would be more sensitive to this data uncertainty. Although the number of building use categories is very small, they were sufficient for the ABM to capture the key daily behaviour patterns that connect people between their houses, schools, shops, and places of employment. Understanding that major sources of employment were outside Kibera allowed the ABM to capture key commuting dynamics; whilst the proportion of commuting journeys in each direction was unknown, the model can still represent these key daily flows of people.

A more significant uncertainty was incomplete data on paths. Knowing the location and connectivity of roads and paths is paramount to understanding how people move through Kibera. This is made more difficult as people are not restricted to official roads and pathways; alleyways between buildings, areas of wasteland, etc. provide additional route options for agents. The purple lines in Figure 12 show additional routes not captured in the source data, whilst the red polygon shows an area of wasteland. The results in Section 3.2

still provide important insights into likely choke points, especially given the importance of personal interaction communication mechanisms in Kibera [62]. Moreover, studies have shown good modelling performance can be achieved with as much as 25% of roads and paths missing [63].

Figure 12. The blue (darker) lines show the official mapped roads, whilst the purple (lighter) lines represent potential pathways between buildings mapped by the Map Kibera project. The red area shows an area of wasteland. Basemap source: ArcGIS World Imagery.

4.3. Further Development

Despite the changes needed to adapt the model to operate with less data, it has still provided useful insights for FIM. This pilot demonstration has highlighted several areas for further development.

It is a priority in Kibera and many other parts of the world to populate global datasets with more accurate information. For example, the Missing Maps initiative hosts mapathons to manually add to datasets in OpenStreetMap to improve access and the quality of spatial data [64]. Such approaches can now be augmented by machine learning [65]. These initiatives understandably often focus on the major routes and structures, but to support flood management, they should also identify smaller drainage infrastructure and features that disrupt surface water movements. Other data, such as building use, employment, demographics, commuting, and travel patterns, augment the accuracy and capabilities of the ABM and are typically gathered by government agencies.

Agent decision-making can be improved in many ways. This can include, for example, inherent knowledge of evacuation routes or routes prone to congestion. Furthermore, whilst agents can adjust their routes to account for roads being blocked by floods, they are not yet able to respond reflexively to other information and make more substantial changes, such as altering which evacuation shelter is their destination. Similarly, evacuation shelters always have a finite capacity that should be considered in further model development.

A flood communication system has been established to issue flood warnings to Kibera residents. Red and green flags mounted by the river indicate the likelihood of flooding, whilst local radio channels are used to disseminate weather information [66]. An improved agent decision-making algorithm would enable other communication strategies for flood warnings to be explored, recognising the important and often dynamic role of social interactions during an emergency [67,68]. Optimisation algorithms could subsequently be applied to the ABM results to identify the best locations for communication infrastructure [9].

The model can be further extended by incorporating different types of agents. These could include community leaders, emergency services, and representatives of other organisations who can support flood resilience. This would greatly increase the flexibility and scope of the model to identify and test different flood incident management responses. These might be expected to reduce risks, but ABMs can expose unintuitive outcomes from the complex interactions of many people. However, any increase in the number and type of agents simulated could increase computational expense, which may require deployment of the model on cloud or high-performance computing platforms.

5. Conclusions

This paper has demonstrated how a data-intensive agent-based model, previously developed to support flood incident management in the UK, can be adapted and applied to an informal settlement in Kenya. This required some further development of the model, most notably, to reflect the importance of pedestrian movement. Agent behaviour rules were also updated to reflect local circumstances. The methodology predominantly uses global datasets, with national census data on population. Mapping data in Kibera have been augmented by local community action but made available in the OpenStreetMap global database. Key priorities for data improvement are a higher-resolution global DEM and a complete network of pathways. Further model development has been identified to enable more incident management responses to be explored, ranging from emergency service support to alternative approaches to communication.

Despite some data gaps and lower-resolution datasets, the model has sufficient input to provide useful insights into risks to people during flood events. The results of an ABM must be interpreted with care, and while the interpretation of individual agents is not appropriate, the model can reproduce reported behaviours at the scale of the whole settlement. Notably, in Kibera, it highlights the importance of having a diversity of evacuation routes, the importance of shelters that are close to the northern boundary of the settlement and the potential for congestion during evacuation in a number of important places, including exit roads and paths along the river. This is the first instance of an agent-based model being applied for flood incident management in an informal settlement. The demonstration offers a first step towards developing an operational tool to enable improved flood incident management planning in informal settlements around the world.

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