Modelling urban sewer flooding and quantitative microbial risk assessment: A critical review

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Abstract
Modelling urban inundation and its associated health implications is numerous in its many applications. Flood modelling research contains a broad wealth of material, and microbial risk assessment has gained more popularity over the last decade. However, there is still a relative lack of understanding of how the microbial risk can be quantified from urban sewer flooding. This article intends to review the literature encompassing contemporary urban flood modelling approaches. Hydrodynamic and microbial models that can be applied for quantitative microbial risk assessment will be discussed. Consequently, urban sewer flooding will be the focus. This review found that the literature contains a variety of different hazards posed by urban flooding. Yet, far fewer examples encompass microbial risk from sewer system exceedance. To date, there is no evidence of a perfect model or technique, to carry out a quantitative microbial risk assessment from hydrodynamic simulations. The literature details many different methods. We intend to detail the advantages and limitations of each method. Along similar lines, hydraulic data constitutes a large part of the uncertainty which is inherent to this research field. Many studies in the literature detail data paucity and uncertainty in input data. As such, any advancement in this discipline will very likely aid future research.

KEYWORDS
flood mitigation, storm sewerage, urban drainage, water quality

1 INTRODUCTION

1.1 Urbanisation and climate

For the majority of our history, humankind has lived across the globe in relatively modest populace. Over the last century, and particularly in the last few decades, global populations have increased drastically due to improved medical and health care (McKeown et al., 1972) and agricultural productivity (Armelagos et al., 1991). More than 50% of the world’s population now lives in cities, with over 500 of them inhabiting over 1 million citizens (Lee et al., 2007). As an unprecedented amount of the world’s population now live in
urban areas, the need to understand the interaction between humans and urban hydrology has never been more apparent than in recent times. Urban drainage is a necessity, providing a quality living environment, whilst maintaining essential urban function without being affected by frequent rainfall events. Contemporary flood management faces a number of very daunting future challenges. Climate change and urbanisation intensify the complexity of management strategies and create many uncertainties (Milly et al., 2008). Flooding within urban regions is prominent in the literature, with many suggesting that it is one of the greatest threats to human health and uninterrupted economic growth (Miller & Hutchins, 2017).

In a nonurban environment rain would fall onto a natural surface (e.g. forest cover or grassland). Under these circumstances a number of things will proceed. Namely, interception by vegetation (which increases roughness and causes evapotranspiration), depression storage and infiltration. As such, only a relatively small amount will comprise of overland flow. And this is subject to the infiltration rate upon the surface (e.g. the infiltration rate of a clay soil is very slow) and rainfall intensity. In an urban environment the natural hydrological cycle is disrupted due to the increase of impermeable surfaces. For example, roads and pavements, driveways and car parks and roofs from buildings (Pazwash, 2016). These new artificial surfaces will increase the runoff due to infiltration capacity decreasing to such an extent, very little or no rainfall is likely to percolate through the ground. Under these conditions runoff will increase, which can have severe consequences as a faster flow will reduce the time of concentration (Chadwick, 2012). As surface runoff travels faster over urban surfaces than natural ones, peak flows will magnify across urban landscapes and within drainage networks. Similarly, precipitation has been predicted to intensify at an unprecedented rate in many parts of the world, though this is a complicated process, which is dependent on spatial and temporal scales. For example, mean precipitation is expected to increase in low and high altitudes and to decrease in the subtropics, due to an increase of greenhouse gas concentrations in the atmosphere. This will very likely affect numerous facets of the global climate by the end of the century. Likewise, extreme weather events are predicted to occur more often and violently in the future such that persistent wet and dry spells could last for days, weeks or months (May, 2008). With respect to Europe for example, severe storms are increasing in frequency and duration. As such, weather variability has been predicted to seriously disrupt urban flood management in this region (Butler et al., 2007).

### 1.2 Sewer systems

Many drainage systems rely on combined sewers to convey sewage and storm water away from urban sources towards treatment plants. Alongside controlling the volume of water that would accumulate on urban surfaces (reducing flood risk), another main function of combined collection systems is to reduce pollution levels of storm water. Water quality issues from storm water have been extensively acknowledged (Li et al., 2019; Xu et al., 2018). Therefore, it is beneficial to convey storm water away from urban surfaces and treat the water as necessary. Yet, there is one drawback to this arrangement. Combined systems have not been designed to cope with both sewage and storm water during high precipitation periods (Rathnayake & Faisal Anwar, 2019). During times of dry weather, the collection system will only carry domestic effluent. When it rains, sewer flow amalgamates with storm water. As such, storm water will dominate the pipe flow, even in relatively light precipitation. Butler et al. (2018) show that in heavy storms, runoff produced by extreme rainfall could be up to 100 times greater than the mean dry weather flow of domestic wastewater. This signifies that it cannot always be possible to convey the entire combined flow to treatment. To avoid flooding on urban surfaces, combined sewer overflow (CSO) may discharge untreated sewer flow into a receiving water as a safety measure. Though poor maintenance and unpredictable pipe pressures cannot always permit safety. Pipes are also prone to leakages and infiltration of groundwater. Along similar lines, wastewater can still come into contact with people, as CSO’s can empty into recreational water (Butler et al., 2018). Extreme precipitation will therefore heighten combined sewer flooding, with combined sewer overflows creating health risks to humans. A good example of this problem is highlighted by Thames Water (located in southern England). They manage over 68,000 miles of sewers, with the vast majority being combined. In 2021 Thames Water was fined 6 million pounds for releasing raw sewage into surface waters, as they could not cope with the amount of sewage (Environment Agency, 2021).

### 1.3 Surcharge

An intricate concept of urban flooding is the interaction between the piped sub-system and ground surface system, as it is a two-way process. Physically speaking, surface runoff within an urban catchment is captured by inlets, which is then conveyed to the piped system via gullies. During heavy precipitation and floods, flow exchange between manholes and gullies can reverse in
flow direction. These alternate flows can either be free, partially or fully submerged outflows. Although the changes in surface flows do not occur rapidly, pressure changes in piped systems can. Sometimes manhole covers can be removed partly or completely depending on how much pressure is evident from surcharge (Chen et al., 2016).

The term surcharge is reference to a pipe that has been designed to run full or part full, and that is carrying flow under pressure. This phenomenon occurs when the flow exceeds the pipes design capacity. Pipe capacity is a function of diameter, roughness and hydraulic gradient. If a conveyance system carries maximum flows a new hydraulic gradient is reached. This will lead to pipe surcharge, as water levels rise above the crown level of the pipe. If this new gradient rises above ground level it is possible for the water to flood past the manhole cover, leading to manhole surcharge. Under surcharge conditions wastewater from human sources can be introduced to the surface (Djordjevic et al., 2013). In a combined system sewage may also be introduced to storm water by unlawful connections, poor plumbing between sewer and storm water pipes, and leakages from cracked pipes or joints (Ahmed et al., 2019). Raw untreated sewage contains many pathogens including bacteria, viruses, and protozoa; with a variety of transmission pathways increasing health problems (Brouwer et al., 2018). This poses a huge threat to the very young and old, or people with underlying health issues. Nonetheless, even a very healthy individual is at risk of diarrhoea, nausea and infections from untreated sewage (Cherqui et al., 2015).

1.4 | Coliforms

Coliforms are the classical indicators of faecally contaminated water. They belong to a single taxonomic family of Enterobacteriaceae and can grow both aerobic and anaerobically. Although coliforms are not correlated with waterborne pathogens (Wu et al., 2011), some of them can be favourable indicators of faecal contamination (Iqbal & Hofstra, 2019). Faecal coliforms (FC’s) are a subgroup of coliform originating from faecal sources. Though, they are not completely reliable for identifying the presence of faecal material, due to free-living environmental FC’s occurring. Other types of coliforms can be found in soils and plants (Klebsiella, Enterobacter aerogenes and Enterobacter cloacae), not all coliforms are correlated with faecal contamination. Escherichia coli (E. coli) are Gram negative and non-spore forming bacilli. WHO (Dufour, 2013) argue that E. coli is the only coliform that is exclusive to faecal contamination. Similarly, when found within the gut of warm-blooded mammals, E. coli are in much greater abundance than other coliforms (Rodrigues & Cunha, 2017). The available evidence therefore suggests that E. coli are the best faecal indicator bacteria (FIB) when analysing faecal contamination. Gastroenteritis and E. coli are significantly correlated, leading to bloody diarrhoea, stomach cramps, nausea and vomiting.

1.5 | Review outline

The intention of this critical review is to present contemporary state-of-the-art literature investigating human health exposure induced by pathogens and faecal indicator bacteria resulted from combined sewer flooding via hydrodynamic modelling. Section 2 will begin by discussing how the papers were selected. Section 3 will then present state-of-the art computational urban flood modelling, paying close attention to the different types of models currently available. 1D-1D and 1D-2D models will be critically discussed, detailing advantages and limitations of both. Section 4 introduces flooding and human health, which leads into pathogenic microorganisms and the spread of illnesses. How contemporary research has used hydrodynamic-microbial transport modelling will also be discussed. Section 4.2 describes quantitative microbial risk assessment (QMRA) and how they can be used alongside hydrodynamic modelling. Known limitations of QMRA are also detailed. Hydraulic and microbial data paucity will be covered in Section 5. Finally, Section 6 concludes the review with research gaps and future challenges of using QMRA alongside hydrodynamic modelling of sewer systems.

2 | METHOD

2.1 | Selection of review papers

We conducted our review process during March 2020 using the Web of Science (WoS) database. Before a rigorous screening process that removed many titles, a Boolean search string was conducted in WoS. This search included—“(urban flooding” OR “urban flood” OR “storm water” OR “urban drainage” OR “pluvial flood” OR “pluvial flooding” OR “urban inundation” OR “hydrodynamic”) AND (“modelling” OR “model” OR “dual drainage”). All titles that were directly related to the topic were selected. The keywords such as “microbial” and “pathogen” were manually applied to narrow down the selection of papers related to human health topic. The search was restricted to English over time periods 2000–2020; this meant that only the most up-to-
date state-of-the-art papers were considered. Since the search was conducted, other key works were added (e.g. Rubinato et al. 2022). The geographic location (country) was not important to the search. In some cases, we used review papers to find other relevant works. For example, Ahmed et al. (Ahmed et al. 2019) and Brouwer et al. (2018). The search only targeted referenced journal articles, however some book chapters (e.g. Butler et al., 2018) were later added when discussing more theoretical aspects. Online manuals were also referenced when discussing some of the commercial models (e.g. Roberts et al., 2019 and Deltaires, 2019). Papers that included key words but did not fit into the scope of the study were removed. For example, if a study included pollutants that were out of the study reach, such as heavy metals. The screening process also involved removing studies that did not fit the scope of health risks associated to flooding and how they are quantified. This meant that studies were removed if they were not specific to the spread of pathogenic microorganisms under flood inundation. After the screening process 190 titles were used in this review paper.

3 | URBAN FLOOD MODELLING

Urban flood models play a crucial role in flood risk management, as they aid in the geospatial analysis of flood hazards. From hydraulic parameters, such as velocity and flood depths, the probability and severity of a flood occurring in an urban area can be investigated (Rosenzweig et al., 2021). Hydrodynamic models are dual drainage models that simulate sub-surface (minor system) along with surface (major system) water flows (see Figure 1). They try to replicate the motion of fluid in both systems, by computationally solving mathematical continuity and dynamic equations (Teng et al., 2017). Approaches in flood modelling can be defined as one dimensional (1D) sewer flows, and/or 1D, two dimensional (2D) overland flows. A combination of both the subsurface and surface modelling approaches can be applied as 1D-1D or 1D-2D (Hammond et al., 2015). Sewer-surface models allow for the interaction of both systems to be investigated. In a 1D-1D model, the interplay is connected by 1D overland flow and 1D sewer flows. Whereas in a 1D-2D model, overland flows are 2D. Similarly, complex 3D Computational Fluid Dynamic (CDF) numerical models are also available for pipe flow simulations (Djordjevic et al., 2013), pollutant exchange between the major and minor system (Beg et al., 2020) and overland flows (Andersen et al., 2013).

Modelling approaches of urban flooding are complicated because of the temporal and spatial sensitivity of rainfall, topography and proficiency of drainage systems. Moreover, the characteristics that influence local run-off and sewer flows are heavily influenced by human activity. In contemporary urban pluvial flood modelling, there are generally three fundamental practices. That is, topographic index analysis (TIA), overland flow routing and sub-drainage pipe simulations (Glenis et al., 2018). Yet, it has been usefully explained in other research that TIA utilises digital elevation models (DEM’s) from remotely sensed data. This tool combines flat areas with areas close to drainage pathways and local depressions, and identifies them as high flood risk regions. Thus, TIA measures the extent of flow accumulation at any given point of a topographic surface. So, this approach is considered to be an assessment tool and not a flow modelling tool. This can be used instead of topographic wetness index (TWI); which quantifies topographic controls on hydrological processes. TWI measures the effect of the local topography on runoff by demonstrating long-term moisture availability on a surface (Pourali et al., 2016). Though with any flow modelling tool, high resolution topographic data is a fundamental step, as it identifies the physical properties of a modelled system. Advances in remote sensing techniques has increased the performance of overland flow modelling. This is notable from airborne LiDAR and Synthetic Aperture Radar data. Improved computing capacity can also claim some of this responsibility (Nkwunonwo et al., 2020).

3.1 | Popular hydrodynamic models

There are many methods available for the modeller to utilise, to calculate the subsurface and surface interactions and flow paths. Although there are many examples of research, which have offered rapid and accurate flood modelling, many challenges continuously face hydrological studies. The complex and somewhat unstable nature of flooding followed by its uncertainty are proof of this. There is a wealth of literature describing, comparing and measuring the performance of various models and algorithms that encompass 1D, 2D and 1D + 2D models. Some previous studies have detailed these models, for example Teng et al. (2017) and Néelz and Pender (2013). Table 1 lists contemporary flood inundation models and Table 2 illustrates 2D computational features.

Hunter et al. (2008) presented a review of 2D models: TUFLOW Classic 2D, DIVAST, DIVAST TVD, JFLOW, TRENt and LISFLOOD-FP. They concluded that the models produced plausible simulations from their case study. Though, from the investigated flood event, there was slight differences between flood depths and extents between all the models. Similar research conducted by
Cheng et al. (2017) used an Infoworks 2D hydrodynamic model to simulate historical and designed precipitation events to highlight flood risk zones. Along similar lines, they found this 2D model to be a plausible method once verified to the observed flood monitoring records. Though, there were also slight discrepancies with some simulated water depths once compared with observed values. The evidence appears to suggest that minor discrepancies can occur in simulations, which is understandable due to the complexity of urban flooding studies.

A relatively new approach of 2D flood modelling comprises of smoothed particle hydrodynamics (SPH). Since its development (Monaghan, 1994) improvements have been made; this particularly apparent to SPH’s long computational times. For example, Liang et al. (2015)
| Model       | Model name                        | Software developer                        | Reference                  |
|-------------|-----------------------------------|-------------------------------------------|----------------------------|
| 1D          | FASTER                            | Cardiff University                        | Gao et al. (2011)          |
|             | Flood Modeller Pro 1D solvers     | CH2M Hill                                 | Jacobs (2018)              |
|             | Infoworks RS                       | Innovyz                                   | Wallingford (2008)         |
|             | MASCARET                           | Electricité de France                     | Gouta and Maurel (2001)    |
|             | SIPSON                             | University of Exeter                      | Chen et al. (2007)         |
|             | SOBEK Suite                        | DELTARES                                  | Deltas (2019)              |
|             | SWMM                               | U.S Environmental Protection Agency       | Rossman (2015)             |
| 2D          | ANUGA Hydro                        | Geoscience Australia                      | ANGUA (2019)               |
|             | BreZe                              | University of California                  | Brett and Begnudelli (2019) |
|             | CaMa-Flood                         | Tokyo University                          | CaMa (2021)                |
|             | CityCAT                            | Newcastle University                      | Glenis et al. (2018)       |
|             | DELFT2D                            | DELTARES                                  | Deltas (2019)              |
|             | DIVAST                             | Cardiff University                        | Falconer (1986)            |
|             | DIVAST TVD                         | Cardiff University                        | Liang et al. (2006)        |
|             | FINEL2D                            | Svašek Hydraulics                         | Svašek (2020)              |
|             | Flood Modeller Pro 2D ADI          | CH2M Hill                                 | Jacobs (2018)              |
|             | Flood Modeller Pro 2D TVD          | CH2M Hill                                 | Jacobs (2018)              |
|             | Flowroute-i                        | Ambiental                                 | Ambiental (2020)           |
|             | Infoworks 2D                        | Innovyz                                   | Wallingford (2008)         |
|             | Itzi                                | Mexican Institute of Water Technology     | Courty et al. (2017)       |
|             | JFLOW                              | JBA                                       | Bradbrook (2006)           |
|             | LISFLOOD-FP                        | University of Bristol                    | Hunter et al. (2005)       |
|             | MIKE 21                            | DHI                                       | DHI (2020)                 |
|             | RFSM EDA                           | HR Wallingford and HeriotWatt University  | Jamieson et al. (2012)     |
|             | SOBEK Suite                        | DELTARES                                  | Deltas (2019)              |
|             | SPH                                | Monash University                         | Vacondio et al. (2011)     |
|             | TELEMAC 2D                         | Electricité de France                     | Gouta and Maurel (2001)    |
|             | TRENT                              | Nottingham University                     | Villanueva and Wright (2006)|
|             | TUFLOW GPU                         | BMT                                       | Syme (1991)                |
|             | TUFLOW FV                          | BMT                                       | Syme (1991)                |
|             | UIM                                | University of Exeter                      | Chen et al. (2007)         |
|             | XP3D                               | XP Solutions/LaGa Systems                 | LaGa (2020)                |
|             | Flood Modeller Pro                 | CH2M Hill                                 | Jacobs (2018)              |
| 1D-2D       | HYSTEM EXTRAN 2D                   | itwh                                      | Itwh GmbH (2010)           |
|             | InfoWorks                          | Innovyz                                   | Wallingford (2008)         |
|             | Itzi + SWMM                        | Mexican Institute of Water Technology     | Courty et al. (2017)       |
|             | LISFLOOD-FP                        | University of Bristol                    | Hunter et al. (2005)       |
|             | MIKE Flood                         | DHI                                       | DHI (2020)                 |
|             | RFSM EDA                           | HR Wallingford and HeriotWatt University  | Jamieson et al. (2012)     |
|             | SOBEK Suite                        | DELTARES                                  | Deltas (2019)              |
|             | TRENT                              | Nottingham University                     | Villanueva and Wright (2006)|
|             | TUFLOW Classic                     | BMT                                       | Syme (1991)                |
|             | UIM + SIPSON                       | University of Exeter                      | Chen et al. (2007)         |
|             | UIM + SWMM                         | National Taiwan University                | Hsu et al. (2002)          |
|             | XPSWMM                             | XP Solutions                              | LaGa (2020)                |
|             | XPSTORM                            | XP Solutions                              | LaGa (2020)                |
increased simulation run times by using modern graphic processing units. When using high resolution simulations, this method demonstrated high accuracy. The authors did this by investigating hypothetical experimental and field-scale urban flood events. CityCAT is another example of other novel and unique 2D models which have been discussed in previous literature. Glenis et al. (2018) validated CityCAT with three analytical and laboratory-based experiments in their study. Although each test increased in complexity, they concluded that CityCAT is efficient at solving complex flow simulations in urban areas. The model was able to model convoluted dam breaks along with shocks around objects.

It is appropriate to point out here, for argument’s sake, that there is no such thing as a perfect model. As the statement first coined by British Statistician George Box states—“All models are approximations; essentially all models are wrong, but some are useful. However, the approximate nature of the model must always be borne in mind” (Box & Draper, 1987, p. 424). From all the different types of models that have been identified (Tables 1 and 2), it has not been the intention to regard any one as the best model. There are many reasons why this is the case. Choosing the best one for the job requires the researcher to think about the requirements of the end user, computational demands, investment in data.

| 2D model      | Governing equations | Numerical scheme | Temporal discretisation | Spatial discretisation | Shock capturing          |
|---------------|---------------------|------------------|-------------------------|------------------------|--------------------------|
| ANUGA Hydro   | Shallow water       | Finite volume    | Explicit                | Flexible               | Riemann solver           |
| BreZo         | Shallow water       | Finite volume    | Explicit                | Unstructured           | Riemann solver           |
| CaMa-Flood    | Diffusive wave      | Finite difference| Explicit                | Structured             | Not available            |
| CityCAT       | Shallow water       | Finite volume    | Explicit                | Structured             | Total variation diminishing |
| DELFT3D       | Navier Stokes       | Finite difference| Implicit                | Flexible               | Available                |
| DIVAST        | Shallow water       | Finite difference| Implicit                | Structured             | Not available            |
| DIVAST TVD    | Shallow water       | Finite difference| Explicit                | Structured             | Total variation diminishing |
| FINEL2D       | Shallow water       | Finite element   | Explicit                | Flexible               | Riemann solver           |
| Flood Modeller Pro 2D ADI | Shallow water | Finite difference | Implicit | Structured | Not available |
| Flood Modeller Pro 2D TVD | Shallow water | Finite difference | Explicit | Structured | Total variation diminishing |
| Flowroute-i   | Shallow water       | Finite volume    | Explicit                | Structured             | Not available            |
| Infoworks 2D  | Shallow water       | Finite volume    | Explicit                | Flexible               | Riemann solver           |
| Itzi          | Shallow water       | Finite difference| Explicit                | Structured             | Not available            |
| JFLOW         | Diffusive wave      | Finite volume    | Explicit                | Structured             | Riemann solver           |
| LISFLOOD-FP   | Dynamic wave        | Finite difference| Explicit                | Structured             | Not available            |
| MIKE21        | Shallow water       | Finite volume    | Explicit                | Flexible               | Available                |
| RFSM          | Shallow water       | Finite difference/finite volume | Explicit | Flexible | Not available |
| SOBEK Suite   | Shallow water       | Finite difference| Implicit                | Structured             | Available                |
| SPH           | Shallow water       | Particle simulation| Explicit | Mesh free | Available |
| TELEMAC 2D    | Shallow water       | Finite element/finite volume | Implicit/explicit | Unstructured | Available |
| TUFLOW GPU    | Shallow water       | Finite volume    | Explicit                | Structured             | Not available            |
| TUFLOW FV     | Shallow water       | Finite volume    | Explicit                | Flexible               | Available                |
| TUFLOW Classic 2D | Shallow water | Finite difference | Implicit | Structured | Not available |
| TRENT         | Shallow water       | Finite volume    | Explicit                | Structured             | Riemann solver           |
| UIM           | Diffusive wave      | Finite difference| Explicit                | Structured             | Not available            |
| XP3D          | Shallow water       | Finite difference| Implicit                | Structured             | Not available            |
collection and model set up. The main aim is to therefore create a model that is as realistic as possible in defiance of the many constraints a modeller may have (Chadwick, 2012). Existing urban flood models fluctuate in complexity, differing from terrain-based routing models to more complex hydrodynamic models, which utilise fluid motion equations. As such there are many technical limitations associated with each modelling approach. For example, models that are simpler will have fewer input requirements, and are usually computationally faster. Though this will reduce their accuracy. On the other hand, complex models can be limited by the availability of data for parameterisation (Rosenzweig et al., 2021).

An advantage of the commercial packaged models is that they are integrated with common geographical information systems (GIS) software. For example, MIKE Flood and Info Works are fully integrated with ESRI ArcGIS products. This means that adding DEMs, network of sewers, land use layers and socio-economic data is relatively straightforward if the user has an ESRI licence. Although some licences are expensive, open-source GIS software packages are available (QGIS, 2020). GIS and its many functions accounts for more than 80% of modelling approaches (including ArcView, ArcGIS, ArcInfo, ArcGIS-Python, and GRASS). A good example of an open-source model built upon GRASS and Python is the Itzi model (Courty et al., 2017); rainfall/runoff and 2D surface flows can be calculated on a regular raster grid, whilst SWMM calculates 1D drainage flows. Data management, utilising map algebra, geographical visualisation and the delineation of watersheds from DEM’s to estimate model parameters are some of the examples of why GIS is so popular (Salvadore et al., 2015). These computer packages tend to be less demanding with regards to simulations and data requirements, than the physically based deterministic models like UIM + SIPSON, MIKE Flood, and InfoWorks, which algorithms are established on mathematical relationships among physical parameters. The values for the dependant variables in a deterministic model are completely driven by the parameters of the model (Rey, 2015). One sequence of input data will give the same output every time. Meaning randomness is non-existent. On the other hand, a stochastic or probabilistic model introduces randomness to the outcomes of the model, which are probability distributions, rather than unique values (Rey, 2015). Outputs from stochastic models will therefore give a range of possible answers and not give the same answer every time. Stochastic models are very interesting due to these probabilistic outcomes, with some arguing that urban drainage models should always have some element of probability due to their complexity (Butler et al., 2018).

### 3.2 Stochastic approaches

Evidence of probabilistic modelling is observed in the works of Li and Willems (2019). A 1D sewer model (Infoworks RS) was used in conjunction with a probabilistic logistic regression model. The authors used this hybrid, to optimise flooding records, predicting the probability of flooding in two urban sub-catchments. They found that the probabilistic approach allowed for better flood prediction. Yet, they found model predictions were lumped. Meaning no information was available on the spatial distribution of flood probabilities. Though a better understanding of prevailing physical mechanism governing flooding in urban catchment was reached.

Many notable stochastic approaches have been developed to reduce model uncertainty. Including constraints in input data, model structure and parameters. Del Giudice et al. (2013) created a Bayesian framework in their study. They were able to obtain more reliable hydrological simulations, as flow predictions can sometimes be overconfident and biased in many deterministic models. This is mainly due to input errors, structural deficits and systematic error in flow measurements. Muleta et al. (2013) tested the effectiveness of Markov-chain Monte Carlo for parameter uncertainty in SWMM (Storm Water Management Model). They found that parameter uncertainty and total predictive uncertainty was appropriately evaluated with this method. Yu et al. (2013) combined Monte Carlo and fuzzy possibilistic simulations for flood risk assessment. A number of methods were combined, which included flood inundation modelling, Monte Carlo simulation, depth damage function derivation and fuzzy vertex analysis. This meant that the authors could understand better the various types of uncertainty associated with flood inundation modelling and damage assessment. They established that total direct damage was 2.4 times higher using this method than when using standard deterministic approaches. Tehrany et al. (2015) analysed and verified flood susceptibility by combining support vector machine and frequency ratio. They provide strong evidence that by combining two machine learning methods together, flood susceptibility assessment had a higher accuracy than a simple decision tree method. Löwe et al. (2014) analysed the quality of multi-step ahead forecasts of runoff volumes. The authors considered new estimation methods based on scoring rules for k-step-ahead predictions. The results showed that they were able to identify noisy in-sewer observations in hydraulic models by using a score-based method. Dotto et al. (2012) compared several uncertainty assessment techniques of hydrodynamic model parameters. The methods included the Generalised Likelihood Uncertainty Estimation, the Shuffled Complex Evolution
Metropolis algorithm, a genetically adaptive multi-objective algorithm and a Bayesian approach based on a simplified Markov Chain Monte Carlo method. Each approach provided similar posterior parameter distributions and predictions' uncertainty. Though the modeller should select the method which is most suited to the modelled system (number of parameters), as this can affect the results. Leitão et al. (2017) used Monte Carlo simulations to evaluate sewer inlet clogging to reduce flood risk. They found that their stochastic approach was efficient in dealing with uncertainty in inlet operational conditions. They showed that fluctuations of inlet capacity did affect the occurrence of flooding. Flood prone areas were identified better than traditional deterministic methods. Although Monte Carlo simulations can become very computationally exhausting for long time series analysis (Torres-Matallana et al. 2018).

### 3.3 | 1D-1D models

1D models are based on the premise that runoff is treated as 1D flow, and that they can be unified to administer an assumed hydrograph at the catchment outlet. Flows are simulated on the surface in discretized set of linked nodes, which represent linear flow pathways. Nodes demonstrate ponds and junctions, whereby the storage capacity is defined. Unsteady open channel flow can be interpreted as propagation of shallow water waves over the channel flow. This can be simulated using the full Saint Venant equations (dynamic wave), or their simplified approximations as kinematic, non-inertia wave or diffusive wave.

1D-1D sewer and surface models are relatively low in complexity, hence are frequently used in many applications (Chen et al., 2016). A very popular freeware 1D-1D model is SWMM, which has been developed by the US Environment Protection Agency (Rossman, 2015). The research conducted by Nanfa et al. (2015), shows that SWMM was a suitable tool to identify critical zones of urban flooding, within their study catchment. For example, once validated their model explained appropriate water depths and flow velocities. In addition, SWMM has been used successfully in many other urban hydrological studies. Stuti et al. (2018) analysed the water balance based on a number of rainfall return periods using SWMM in Indonesia. Cipolla et al. (2016) compared the hydrological behaviour of a green and traditional roof over a 15 month period with SWMM 5.1. Whereas Arjennaki et al. (2021) explored the effects of low impact development on urban drainage and runoff.

However, its 1D-1D approach for urban drainage systems has been discredited by some, for example in the works of Mark et al. (2004), Chen et al. (2016) and Kourtis et al. (2017). The main theoretic premises behind this dispute is centred on the fact that 1D-1D models fail to accurately show overland flow from a surcharged system. This is because this type of dual drainage model stores the water above the surcharged manhole within a water storage curve. During rainfall events 1D-1D models are unable to simulate inundation depths in urban areas, so the flood extent is underrepresented. Kourtis et al. (2017) presented the findings after comparing 1D-1D SWMM with 1D-2D MIKE Flood. They argue the fact that 1D-1D models do however accurately represent flows in the subsurface sewer system. 1D-1D models also are computationally simpler. They generally have larger time steps and require less spatial data than a 1D-2D model, which means simulation speeds are much faster and are computationally less demanding. Further evidence for advantages in 1D-1D modelling are apparent in works by Maksimovic et al. (2009). The authors suggested that 1D-1D modelling is more suitable for real-time representation or rapid calculations of flood monitoring. This is due to less computational times needed.

### 3.4 | 1D-2D models

There is rapidly growing literature on approaches that have joined 1D and 2D models together, to investigate the major and minor systems. Many studies have applied a variety of different hydrodynamic applications. Since its early development (Akan et al., 1982; Djordjevic et al., 1999; Nasello & Tucciarelli, 2005; Price and Howard, 1978; Thompson & Lupton, 1978; Wisner et al., 1981) many advances have been adopted. Chen et al. (2007) combined two distinct models together for simulating the flows within both the major and minor system. Namely SIPSON (a 1D sewer model) and UIM (a 2D urban inundation model). SIPSON was used to calculate the rainfall-runoff hydrographs plus the minor system flow conditions. Whereas the UIM was chosen to calculate the overland flow routes. Both models are run separately using different time steps. Geographic locations and times are linked to couple the results. When applied to a case study, they found that their model simulated the intricate process of overland pluvial flooding well, although moderately simplified the process. One main issue with the coupled models is synchronising the time accordingly. If not done correctly errors in the simulations will occur. Similarly other problems can arise with regards to spatial resolutions. A coarse resolution may prove to be unrealistic, as urban surfaces are not represented clearly enough, or ponds not draining properly. Whereas if the resolution is too small computational
times may be unsatisfactory (Chen et al., 2007). Hsu et al. (2000) used the surcharge hydrographs at manholes calculated by SWMM as a single directional input to UIM. Hsu et al. (2002) next introduced a bidirectional coupling method to link UIM and SWMM. Chang et al. (2015) further developed a novel approach to model dynamic flow interactions between UIM and SWMM for different land covers in urban areas. Furthermore, Chang et al. (2018) included the effect of the flow processes in gullies in the coupled UIM and SWMM modelling.

Similar research (Chen et al., 2016) led to the 1D SIPSON model being coupled with a P-DWave (2D Parallel Diffusive Wave) model. The two models were linked together through manhole discharge and inlets at each time step. Based on diffusive wave equations the P-DWave neglects the inertial terms in 2D shallow water equations. This means that all acceleration and pressure terms are ignored. The authors constructed this new model linkage to simulate the interplay between the major and minor system, including discharges from associated inlets and raised manhole covers. Two case studies are explored, revealing that the new model simulates surcharge appropriately when the manhole cover impedes inflow and outflows. They found that their improved dual drainage model could force overflow via inlets, which gave it a more realistic result.

Other works by Martins et al. (2017) compared the SIPSON and P-DWave model to two other dual drainage models. The comparison first included a fully dynamic model using shallow water equations and the second was a local inertia model. Both models were also coupled to SIPSON. The simulation results showed that the three different models did not vary too much with each other and had a close agreement. This was with regards to the extent, depth and exchanges of volumes. However, the P-DWave model had slightly less agreement than the other two models, as it estimated a higher flood depth and a slower flood propagation than the models using shallow water and a local inertia equations.

There are some limitations to 1D-2D modelling approaches, be it discrepancies in flood depths or synchronising time steps accordingly (Leitão et al., 2010). Yet, 1D-2D models usefully represent the complex system well, and offer some important insight to the physical system, if calibrated and validated appropriately. (Vojinovic & Tutulic, 2009) explored the variation of 1D and 1D-2D modelling approaches of urban flooding across uneven terrain. The authors conclude that in their case study, which had steep and irregular terrain, a 1D flood model would require very careful consideration in GIS analysis. This is due to 1D models not having a 2D spatial framework. Thus, a 1D model could introduce errors. Although long simulation times would not allow for real time analysis, their 2D model was better suited to represent more detailed analysis of flooding over this type of urban surface than a 1D model.

4 FLOODING AND RISKS TO HUMAN HEALTH

During the 10-year period of 2009–2019, flooding has affected the health of approximately 697 million people worldwide (EM-DAT, 2019). Existing literature displays a variety of diverse health effects from urban flooding, which can be both physical and mental in nature (Hajat et al., 2003). The health implications are convoluted and include drownings, injuries, and microbiological illnesses and diseases (Jonkman et al., 2008). Further consensus from medical literature reveals the impact flooding has on mental health (Philippe & Houle, 2020). Anxiety and depression are likely, as the consequences of floods can last many months. Mort et al. (2018) identified children’s heightened anxiety and stress from subsequent flooding. Similarly, Haq (2019) summarise how the elderly are afflicted, as many underlying physical and mental health problems can be exacerbated by flood waters.

Another main issue from flooding is the presence of pathogenic microorganisms and the spread of infectious diseases. As such, flood conditions will intensify the spread of illnesses through a variety of intricate pathways (Scoullos, Lopez Vazquez, et al., 2019a). Infectious diseases attributable to sewer flooding is very high in developing countries. This is due to several complicated socio-political reasons, including poor water sanitation, hygiene and poor health care. This is exacerbated by meagre infrastructure and poor maintenance. (Cissé, 2019). However, sewer flooding and infectious diseases are not restricted to any one area; there is evidence of this phenomena occurring all over the world, including developed western regions. Notable events illustrate faecal indicator bacteria being present after urban floods; for example in the U.S (Bradbury et al., 2013; Sinigalliano et al., 2007), Canada (Hrudey et al., 2003), Germany (Abraham & Wenderoth, 2005), the U.K (Fewtrell et al., 2011; Reacher et al., 2004), Hungary (Dura et al., 2010), Switzerland (Veronesi et al., 2014) and the Netherlands (Sales-Ortells & Medema, 2015). Therefore, the spread of pathogenic microorganisms in flood waters is an acute problem worldwide (Scoullos, Vazquez, et al., 2019b). These results provide confirmatory evidence that there is room within this research field for further debate, analysis and conclusions based on empirical evidence.

Similarly CSO’s pose health risks, conceding that humans come into direct contact with the outfalls
fewtrell et al., 2011; fewtrell & kay, 2008; huynh et al., 2019; katukiza et al., 2014). Though high flows can reduce concentrations due to dilution (Kay et al., 2008), which reduces exposures. Further evidence demonstrating CSO’s and human exposure to harmful microorganisms lie in the findings of Palazón et al. (2017), who built a predictive model to investigate microbial contamination in bathing waters. Further evidence demonstrating CSO’s and human exposure to harmful microorganisms lie in the findings of Palazón et al. (2017), who built a predictive model to investigate microbial contamination in bathing waters. Yet, from the available evidence, there seems to be relatively less conducted studies that have researched microbial risks from sewer exceedance. Though some do occur. For example, ten Veldhuis et al. (2010) evaluated the risk associated from combined sewer flooding in the Netherlands. Large concentrations of E. coli, intestinal enterococci and Campylobacter were found in their samples from three sewer flooding incidents. Although this study does contribute to the literature, the authors did not adopt hydrological modelling in their methods.

Some other works have identified the need of further research in this area. Collender et al. (2016) review knowledge gaps in microbial transport models and concluded quantitative research on microbiological risks associated with floods is limited. Kolahi et al. (2009) further support this notion after their work focuses on the link between urban sewerage and diarrhoea in Tehran. This suggests that there is a lack of understanding whereby untreated faecally contaminated domestic effluent is conveyed into urban landscapes, causing health risk to human populations (Asano et al., 2007). Enteric diseases and associated waterborne pathogens are highly correlated with urban inundation. With many studies arguing that flood water being a major source of infection to humans. Huynh et al. (2019) agree with this statement after they found high concentrations of E. coli and Rotavirus in flood waters in Can Tho city, Vietnam. Along similar lines, Fewtrell et al. (2011) conclude that a considerable number of people are at risk from viral gastroenteritis during the clean-up process of flooding.

4.1 Hydrodynamic-microbial transport models

The current literature details many examples, where microbiological modelling has been coupled to hydrodynamic simulations (See Table 3). The works usefully

| Application         | Model name                                      | Reference                                      |
|---------------------|-------------------------------------------------|------------------------------------------------|
| Catchment scale     | Hydrological simulation program Fortran         | Brannan et al. (2002); Pachepsky et al. (2006); Benham et al. (2006). |
|                     | SIMHYD                                          | Haydon and Deletic (2006).                    |
|                     | Watershed assessment model                      | Collins and Rutherford (2004).                |
| CSO’s               | GEMSS-WQM                                       | Erengo et al. (2016)                          |
| Drinking water supply | Hydrosim via Modeleur with Dispersim         | Heniche et al. (1999); Secretan and Roy (1999); Secretan et al. (2000); Jalliffier-Verne et al. (2017); Jalliffier-Verne et al. (2016). |
|                     | Pathogen catchment model                       | Ferguson et al. (2007).                       |
|                     | WATFLOOD                                        | Dorner et al. (2006).                         |
| River systems       | EcoLab                                          | Islam et al. (2018)                           |
|                     | RiverStrahler                                   | Servais et al. (2007); Nguyen et al. (2016).  |
|                     | Soil Water Assessment Tool                      | Iqbal et al. (2019); (2019).                 |
| Saline environments | GEMSS                                           | Kolluru et al. (2014)                         |
|                     | Telemac 2D + 3D                                 | Abu-Bakar et al. (2017)                       |
|                     | Telemac 3D                                      | Garcia et al. (2018)                          |
|                     | DIVAST                                          | Gao et al. (2011)                             |
|                     | FASTER                                          | Gao et al. (2011)                             |
| Flooded buildings   | Heat Air and Moisture Model                    | Taylor et al. (2011, 2013).                  |
| Storm water         | Hairsine-Rose pollutant model                   | Jiang et al. (2021); Liang and Smith (2015); Wang et al. (2017) |
| Sewer networks      | CFD Reynolds Averaged Navier–Stokes Equations   | Beg et al. (2020)                             |
|                     | HYSYSTEM EXTRAN 2D                              | Sàmann et al. (2019)                          |
|                     | SIMDEUM - WW                                    | Bailey et al. (2019, 2020)                     |
highlight how both types of modelling approaches can be applied to research. One common factor that many studies share is the simulation of pathogen fate and transport through water, though quantifying the probability of infections to humans have not always been within their aims and objectives. Many previous studies have just looked at the transport and not identified health risks. Along similar lines there seem to be a research gap in sewer-surface modelling approaches. This review of literature therefore highlights the need for further research in identifying human health risks from the transport of microbes from sewer networks to surface flows during urban flood events. Figure 2 illustrates the microbial modelling framework. From the water quality models, output quantification of the health risks is possible. This quantification will be shown in Section 5.

Evidence regarding the effectiveness of hydrodynamic models being applied in conjunction with microbial models is seen in the works of Eregno et al. (2016). The authors investigated the impact of bacteria fate and transport from CSO’s to receiving waters. A combination of GEMSS-HDM hydrodynamic model and GEMSS-WQM water quality/transport model was used in their study. They simulated CSO outflow, documenting the movement and decay of E. coli based on a number of reference pathogens on six Norwegian beaches after heavy rainfall. They successfully identified spatio-temporal patterns of microbial pathogens. Though in some instances the model goodness of fit was low and E. coli concentrations were higher than expected. This was possibly due to bird faeces and other storm water discharges that were not within the boundary conditions. Nevertheless, this study usefully highlights hydrodynamic-microbial modelling techniques.

Liang and Smith (2015) developed a high performance integrated hydrodynamic modelling system (HiPIMS); 2D shallow water equations, utilising first order Godunov-type shock capturing schemes were implemented. This hydrodynamic model is carried out on multiple GPU’s to increase computational efficiency. Jiang et al. (2021) further developed this model by coupling it to a wash off model, known as Hairsine-Rose pollutant model (H-R). The H-R washoff model was used to simulate diffuse pollutants derived from urban flooding events. The validated particle tracking model was able to simulate the hydrodynamics of overland flow, whilst accurately trace pollutant dynamics. Though further work is needed to model different types of sustainable urban drainage (SuDS). Although Jiang et al. (2021) investigated particulate pollutants, others have used the H-R washoff model to simulate the transfer of E. coli from soil to overland flows (Wang et al., 2017). Their research analysed the transfer of microorganisms from soil into overland flow under rain-splash conditions. The H-R model was insensitive to E. coli (per colony-forming units) if the assumed initial mass concentration of E. coli was very small in comparison to soil particle classes. This illustrates that the H-R model is acceptable when considering the transfer of E. coli from soil to runoff. Though little work has been conducted regarding the transfer of E. coli from soil to runoff in urban environments.

Sàmann et al. (2019) developed a solute transport model. They used a 1D-2D model, associated with a pollution load system (HYSYSTEM EXTRAN 2D), to simulate velocity fields over a surface and pipe flow. Next the authors used a Langrangean approach to model contaminant transport from a point source spill. A high-resolution Eulerian transport model was used as a comparison for model verification. The simulation outcome was strongly influenced by rainfall. A high temporal resolution of velocity fields is necessary to capture short duration path changes. Hence the accuracy of modelling velocity fields is related to temporal and spatial resolution of rainfall input data. Although more work is needed on the leakage of pollutant into the soil, this model can be applied to many other useful applications.

Bailey et al. (2019) developed a stochastic sewer model (SIMDEUM-WW) based on household discharge patterns to investigate water conservation under future scenarios. The output is derived from a probability function of household appliance usage and occupancy, using Monte Carlo simulations. This led to SIMDEUM-WW (Bailey et al., 2020) being used to investigate flow, nutrient and temperature changes in a Dutch case study. SIMDEUM-WW was validated using measured field data from a sewer system from 418 households in Amsterdam. The output from SIMMDEUM was loaded into a InfoWorks model. Wastewater concentrations of total suspended solids (TSS), chemical oxygen demand (COD), total Kjeldahl nitrogen (TKN) and total phosphorus (TPH) were modelled against the field measurements. The InfoWorks model predicted the mass flow of pollutants well (R-values 0.69, 0.72 and 0.75 for COD, TKN and TPH, respectively). Though, the prediction for wastewater concentration parameters was less robust. This was due to the lack of a time-varying solids transport model within InfoWorks. Nevertheless, the model was still considered capable of analysing the effects of three water conservation strategies (greywater reuse, rainwater harvesting and water-saving appliances) on flow, nutrient concentrations, and temperature in sewer networks. In future research it is possible for SIMDEUM-WW to be used to model E. coli.

After an extensive search in the literature, it seems that there are far fewer studies, where 1D-1D or 1D-2D hydrodynamic models have been used in conjunction
FIGURE 2 Microbial modelling framework used in conjunction with hydrodynamic models
with microbial transport models. Though examples do exist. Evidence of research supporting hydrodynamic models combined with microbial transport models lie in the findings of Pathirana et al. (2011). Although no risks were quantified the authors simulated both the hydrodynamic and pollutant transport from sewer exeedance in the U.K. and Vietnam. 1D SWMM model and 2D BreZo hydrodynamic model were coupled together and applied to both case studies. Pollutant transport in Brezo was implemented through advection-dispersion exchange at cell boundaries. After validation, the results confirm that the interaction between 1D sewer flows and the 2D pollutant model were suitable. Surcharge and overland flow was simulated accordingly, including flood depths in the U.K. catchment. Unsurprisingly the accuracy of the 2D pollutant transport was subject to spatial resolution. This was illustrated by poorer topographic data in Vietnam, which produced uncertainty.

Based on the evidence currently available, a wide variety of methods have been developed to analyse microbial spreading in hydrological environments. From the literature reviewed, there does not seem to be an explicit approach. There is a wealth of literature that have applied modelling techniques to the origin of faecal contamination and its fate and transport. Understanding this physical process has undoubtedly helped in the advancement of this research field. The proceeding studies (in Table 3) have done this accordingly. Though they have not identified the probability of infections or quantified health risks. With regards to future microbial studies, the importance of identifying risk is great as exposure to pathogens can be very high if the pollution source is in close contact to humans. This notion is supported in the works of O’Flaherty et al. (2019), who used a human exposure assessment model to predict microbial risk in bathing waters; and Donovan et al. (2008) who quantified health risks in bathing waters attributable to CSO outfall after rainfall events. Therefore, it could be suggested that identifying the probability of infection is important for mitigation and adaptation strategies (Whelan et al., 2014). Another important point is that there are very few studies that have used sewer-surface models to simulate pathogen transport; hence the need for future work in this ever-growing field of study.

4.2 Quantitative microbial risk assessment

Estimating infections presented by urban flooding exposures cannot be simply done by the measurement of pathogen concentration and modelling their transportation. Once models have been successfully applied for the simulation of pathogen transport, a framework should be applied to identify the risk through a QMRA. This measures the probability of infection and disease from human exposure to pathogens and microorganisms. It is based on an identification and the content of the pathogen, what the level of exposure is, and the dose-response based on concentrations (Jorgensen et al., 2016). The quantification to risk of infection and illness when a population is exposed to microorganisms in the environment can then be estimated. From a QMRA output decision makers can use the information to help with mitigation strategies, where mitigation solutions maybe based on multi-criteria analysis.

There are four main steps necessary for a QMRA. These are as follows:

1. Hazard identification. This simply involves choosing the infectious pathogens that are present in faecal contamination. Common examples in wastewater include Campylobacter, Cryptosporidium spp., Giardia spp., E. coli., Salmonella spp., Vibrio cholerae (V. cholerae), rotavirus, norovirus, poliovirus, and hepatitis A. (Brouwer et al., 2018), enterovirus (de Man et al., 2014) and enterococci (ten Veldhuis et al., 2010). There are many different pathogens resulting from faecal contamination, therefore no study will try to quantify every infection known. Similarly microbial data is usually sparse (Collender et al., 2016; Huynh et al., 2019). So, studies need to be fastidious about which pathogens to quantify. Reference pathogens, of bacterial, viral and protozoan are commonly used, presented in a worst-case scenario of high incidence (Fewtrell et al., 2011).

2. Exposure assessment. Potential routes of exposure are defined by oral, dermal and inhalation. Exposure assessment takes this into account whilst identifying the potential concentration of the pathogen ingested (Fewtrell et al., 2011). There are many ways to assess exposures. This can be computationally modelled (Eregno et al., 2016), collected from concise interviews from residents (Mark et al., 2018) or based on past research outcomes (Katukiza et al., 2014). Constraints and uncertainties will undoubtedly arise from any method, as water ingestion rates can differ. Literature values can be useful to determine concentrations in urban sewer flooding in the absence of microbial data. Maximum values can be used for strict estimates. Some typical values in wastewater can be seen in Table 4; here pathogen concentrations, pollution source and location of study are shown. In Table 4 units of the concentrations are expressed as pdu (per detection unit), gc (genomic copies), ge (genomic equivalents), efu (colony forming unit) and mpn (most
| Organism          | Country       | Source of pollution                        | Concentrations                                      | Reference                  |
|------------------|---------------|--------------------------------------------|------------------------------------------------------|----------------------------|
| Adenovirus F&G   | Indonesia     | Fluvial with sewage inflow                 | 51 to $60 \times 10^3$ pdu/L                       | Phanuwan et al. (2006)     |
|                  | Uganda        | Open grey water tertiary drain             | 1.35 $\times 10^{-1}$ to 1.9 $\times 10^{-3}$ gc/ml | Katukiza et al. (2014)     |
|                  | Uganda        | Open storm drainage channel                | 4.8 $\times 10^{-2}$ to 1.53 gc/ml                 | Katukiza et al. (2014)     |
| Campylobacter    | Netherlands   | Sewer flooding                             | 14 to $10^3$ mpn/L                                 | de Man et al. (2014)       |
| Coliforms—Faecal | United Kingdom| Sewer flooding                             | 1.7 $\times 10^7$ to 2.8 $\times 10^6$ cfu/100 ml  | Kay et al. (2008)          |
|                  | United Kingdom| Sewer flooding                             | 7.2 $\times 10^5$ cfu/100 ml                       | Kay et al. (2008)          |
|                  | United Kingdom| Fluvial with sewage inflow                 | 0.1 to 1 oocysts/L                                 | Fewtrell et al. (2011)     |
|                  | Netherlands   | Sewer flooding                             | 10 to 15 oocysts/L                                 | ten Veldhuis et al. (2010) |
|                  | Netherlands   | Sewer flooding                             | 0.1 to 10 oocysts/L                                | de Man et al. (2014)       |
|                  | Bangladesh    | Sewer and pluvial flooding                 | $10^6$ to $10^8/100$ mpn/ml                        | Mark et al. (2018)         |
|                  | Netherlands   | Sewer flooding                             | 8.7 $\times 10^4$ to 1.08 $\times 10^7$ cfu/100 ml | ten Veldhuis et al. (2010) |
|                  | Uganda        | Open storm drainage channel                | 6.6 to 6.9 log_{10} cfu/100 ml                     | Katukiza et al. (2014)     |
|                  | Uganda        | Open grey water tertiary drain             | 6.1 to 6.9 log_{10} cfu/100 ml                     | Katukiza et al. (2014)     |
| Ecoli            | Bangladesh    | Sewer and pluvial flooding                 | $10^9 / 10^{100}$ mpn/ml                           | Mark et al. (2018)         |
|                  | Netherlands   | Sewer flooding                             | 5.0 $\times 10^4$ to 3.7 $\times 10^5$ cfu/100 ml  | ten Veldhuis et al. (2010) |
|                  | United Kingdom| Sewer flooding                             | 1.9 $\times 10^6$ to 4.9 $\times 10^5$ cfu 100 ml  | Kay et al. (2008)          |
|                  | Indonesia     | Fluvial with sewage inflow                 | 1.84 $\times 10^4$ mpn/100 ml                      | Nguyen et al. (2016)       |
|                  | Netherlands   | Sewer flooding                             | 12 to $72 \times 10^3$ pdu/L                       | Phanuwan et al. (2006)     |
|                  | Netherlands   | Sewer flooding                             | 1.6 to $40 \times 10^3$ pdu/l/L                    | de Man et al. (2014)       |
|                  | Netherlands   | Sewer flooding                             | 0.1 to 142 cysts/L                                 | de Man et al. (2014)       |
|                  | United Kingdom| Fluvial with sewage inflow                 | 0.1 to 204 cysts/L                                 | ten Veldhuis et al. (2010) |
|                  | United Kingdom| Fluvial with sewage inflow                 | 7.1 to $8.7 \times 10^3$ pdu/L                     | Phanuwan et al. (2006)     |
|                  | Brazil        | Sewage                                    | $2.1 \log_{10} \text{ to } 2.4 \log_{10} \text{ gc/ml}$ | Casanovas-Massana et al. (2018) |
|                  | Brazil        | Standing water                             | $2.2 \log_{10} \text{ to } 2.3 \log_{10} \text{ gc/ml}$ | Casanovas-Massana et al. (2018) |
| Norovirus        | Netherlands   | Sewer flooding                             | $10^2/10^4$ pdu/L                                 | de Man et al. (2014)       |
| Norovirus GI     | Indonesia     | Fluvial with sewage inflow                 | 200 pdu/L                                         | Phanuwan et al. (2006)     |
|                  | Indonesia     | Fluvial with sewage inflow                 | 2.2 to $3 \times 10^4$ pdu/L                      | Phanuwan et al. (2006)     |
|                  | Netherlands   | Sewer flooding                             | 530 to $4 \times 10^5$ pdu/L                      | de Man et al. (2014)       |
| Rotavirus        | Uganda        | Open storm drainage channel                | 2.48 to $2.98 \times 10^3$ Gc/ml                   | Katukiza et al. (2014)     |
|                  | Uganda        | Open grey water tertiary drains            | $3.44 \times 10^{-1}$ to 8.85 Gc/ml                | Katukiza et al. (2014)     |
| Salmonella       | Uganda        | Open storm drainage channel                | 4.6 to $5.3 \log_{10} \text{ cfu}/100 \text{ ml}$ | Katukiza et al. (2014)     |
|                  | Uganda        | Open grey water tertiary drains            | 4.6 to $5.1 \log_{10} \text{ cfu}/100 \text{ ml}$ | Katukiza et al. (2014)     |

(Continues)
probable number). A cyst is a dormant stage of bacteria or protozoa, whereas an oocysts refers to a sporozoan zygote undergoing sporogenous development.

3. Dose-response relationships. These relationships are mathematical functions that measure the infection probability for a given dose. They are regression models where the independent variable is referred to as the dose or concentration. The dependant variable is the response or effect (Ritz et al., 2015). The literature illustrates two main dose response curves used in QMRA for determining risk to human health as a consequence of exposure to the microbial pathogens in water. These are the Beta-Poisson and Exponential Dose-Response Models. These response models vary when considering different pathogens. For example, Eregno et al. (2016) and ten Veldhuis et al. (2010) used Beta-Poisson models for Campylobacter, Salmonella and Norovirus, whereas they used exponential models for Cryptosporidium and Giardia. This means that each model has an assumption based on the distribution of organism among replicated doses and how capable the organism is of producing an infection (Teunis & Havelaar, 2000).

4. Risk characterisation. The final step calculates the detrimental human health risk as a consequence of exposure to the microbial pathogens. This is the probability of infection and has been previously assessed per single exposure (de Man et al., 2014; Eregno et al., 2016) or annually (Katukiza et al., 2014). Many assumptions are placed on the characterisation of risk. In order to comprehend the many uncertainties of risk characterisation, conditions need to be declared clearly (Eregno et al., 2016). As identified by Caradot et al. (2011), risk can be estimated from a number of components, which include the probability of the hazard occurring, the intensity of the hazard, the vulnerability of the associated risk, and the elements at risk, or unit/system at exposure.

Vulnerability is also important to consider as it defines the susceptibility of a person (Caradot et al., 2011). Though a more stringent definition could be used. Hajat et al. (2003) includes the capacity to cope, resist and recover from an impact. This means that vulnerable groups (children, disabled and elderly people) are more likely to feel the adverse effects of illness. The vulnerable are therefore less likely to recover as quickly, than the non-vulnerable. Fazil (2005) argue that the assessment of risk should be able to answer at least one of the following:

- What is the nature and magnitude of the risk?
- Which individuals or groups are at risk?
- How severe are the adverse impacts or effects at likely exposures?
- What is the evidence and how strong is it?
- What is uncertain about the nature of the risk?
- What is the range of informed views about the nature and probability of the risk?
- How confident are the risk assessors about their prediction?

The literature has many examples of QMRA detailed from the aftermath of urban sewer flooding. For example, de Man et al. (2014) quantified the health risk of infection from waterborne pathogens Campylobacter, Cryptosporidium spp, Giardia spp, norovirus and enterovirus, and E. coli. They were present in urban floodwaters, originating from combined sewers, storm sewers and surface runoff. The determination of exposure to floodwaters were collected using questionnaires. Ingestion volumes were presented and the probability of infection risk was calculated from pathogen and exposure data. A dose response relationship was assigned to the probability of infection per exposure event. Dilution and inactivation caused lower concentrations of pathogens than other studies (Lodder & de Roda Husman, 2005), but as expected sewers caused a greater risk to public health than storm sewers and runoff. The mean risk of infection of exposure for children was much higher than adults, which is consistent with other works (Hajat et al., 2003). Though as a limitation to their study all questionnaires were assumed to be correct for the ingestion volume. This illustrates uncertainty due to children taking part. Although uncertainty was recognised, a sensitivity analysis was not considered.

ten Veldhuis et al. (2010) found very high levels of E. coli, intestinal enterococci, Campylobacter, Cryptosporidium
ridium spp. and Giardia spp. in their samples proceeding the after-math of a combined sewer system surcharging. The sediment samples from the same study showed concentrations of E. coli at 100 times higher than flood water, which is consistent with other works (Gao et al., 2011). Ingestion volumes for the exposure scenarios (pedestrian: 10 ml per incident and children playing in water: 30 ml per incident) were based on other works (Donovan et al., 2008; Schets et al., 2008), respectively. They conducted a screening level QMRA using an Exponential Dose-Response Model for the analysis of Cryptosporidium spp. and Giardia spp., whereas they used a Beta-Poisson dose response for Campylobacter. The results highlight that single exposure to pedestrians varied from $5 \times 10^{-5}$ for Cryptosporidium spp. and $1 \times 10^{-2}$ for Giardia spp. and $2 \times 10^{-1}$ for Campylobacter. The single exposure risk was larger for playing children, as expected. Though some limitations should be noted. Their research only analyses a very small number of samples from three sewer flooding incidents, which may increase the uncertainty in their results. Similarly, the infection probabilities for children were based lower than—due to the dose-response being calculate for healthy adults. Further to this WHO (2016) explain that screening level QMRA’s can be crude and may not give an in-depth understanding of the drivers of the risk. A sensitivity analysis could have increased the robustness of their results by reducing uncertainty in the inputs. Though, their study does give satisfactory insight regarding the dangers to exposure of combined sewer flooding. Katukiza et al. (2014) developed an approach for QMRA caused by waterborne viruses in a slum environment. E. coli, Salmonella spp., total coliforms, rotavirus and adenoviruses F and G were identified as the hazards in their catchment. Hazard pathways were chosen, including ingestion, dermal and inhalation. The volume of the pathogen consumed via the hazard pathways was assumed from the literature. The volume was then multiplied by the pathogen concentration to calculate the dose for each sampling location. Beta-Poisson models were chosen for the dose-response for rotavirus, E. coli and Salmonella spp. Exponential models were created for adenoviruses F and G. Risk characterisation was then distinguished through disability—adjusted life years (DALY). One DALY is equal to one lost year of healthy life. Across a population the DALY is the gap between current health and ideal health (WHO, 2020). The burden of disease was calculated by the probability of illness outcome from an infection. The results illustrate that the highest disease burden was 680 DALY’s per 1000 persons annually. Surface water contributed to the highest disease burden and the highest mean estimation of infection was resultant of E. coli. One main limitation to their study is the lack of credible data. As such, the estimation of disease burden introduced uncertainty. Although the foregoing studies illustrate some examples of uncertainty and limitations with exposure and ingestion assessment, they do usefully highlight how there are many approaches to QMRA.

QMRA is an important framework to quantify risks posed by pathogens to humans. This method is very well suited to sewer flooding in urban regions. There are four main steps necessary for a QMRA analysis. Several different approaches can be taken for each step, depending on the study. For example, exposure and ingestion volumes vary between research. Though this can introduce errors and uncertainty in the analysis. The studies under review agree that children are more vulnerable than adults from many exposure scenarios. So infection probabilities tend to be higher. Though they did not consider other vulnerable groups, like the elderly or disabled. The next section of this review will introduce examples in the literature that has combined QMRA with hydrodynamic-microbial simulations.

### 4.3 Hydrodynamic-microbial simulations and QMRA

The literature shows many examples of hydrological modelling approaches and QMRA. van Bijnen et al. (2018) details a methodology for QMRA of combined sewer conditions on health risk. Their methodology includes in-sewer defects which are attributable to sewer floods. A calibrated Infoworks 1D-1D model was used to simulate the interplay between the major and minor systems from historical storm events. The probability of flooding was evaluated through Monte Carlo simulations. The average annual infection probability was calculated from the overall probability of infection per exposure incident and the prevalence of flooding. They found that the infection probability for both adults and children increases with sedimentation of sewer pipes. Though, the average probability for infection was 10 times higher for children. Similarly, the probability of infection increases for both adult and children as the flooded area decreases. This was due to higher probability for more frequent but less severe flood events. Although the authors state that flood duration may impact infection probabilities in their study, this was not actually included.

Andersen et al. (2014) quantified the health to residents exposed to flood waters during a clean-up procedure. MIKE Urban was applied to an advection-dispersion model to simulate E. coli, Campylobacter and Enterococci. The models were validated from dry weather flows and CSO data within the catchment. Ingestion volumes were taken from the literature (Donovan et al., 2008; Schets et al., 2008). They conducted a screening level QMRA using an Exponential Dose-Response Model for the analysis of Cryptosporidium spp. and Giardia spp., whereas they used a Beta-Poisson dose response for Campylobacter. The results highlight that single exposure to pedestrians varied from $5 \times 10^{-5}$ for Cryptosporidium spp. and $1 \times 10^{-2}$ for Giardia spp. and $2 \times 10^{-1}$ for Campylobacter. The single exposure risk was larger for playing children, as expected. Though some limitations should be noted. Their research only analyses a very small number of samples from three sewer flooding incidents, which may increase the uncertainty in their results. Similarly, the infection probabilities for children were based lower than—due to the dose-response being calculate for healthy adults. Further to this WHO (2016) explain that screening level QMRA’s can be crude and may not give an in-depth understanding of the drivers of the risk. A sensitivity analysis could have increased the robustness of their results by reducing uncertainty in the inputs. Though, their study does give satisfactory insight regarding the dangers to exposure of combined sewer flooding. Katukiza et al. (2014) developed an approach for QMRA caused by waterborne viruses in a slum environment. E. coli, Salmonella spp., total coliforms, rotavirus and adenoviruses F and G were identified as the hazards in their catchment. Hazard pathways were chosen, including ingestion, dermal and inhalation. The volume of the pathogen consumed via the hazard pathways was assumed from the literature. The volume was then multiplied by the pathogen concentration to calculate the dose for each sampling location. Beta-Poisson models were chosen for the dose-response for rotavirus, E. coli and Salmonella spp. Exponential models were created for adenoviruses F and G. Risk characterisation was then distinguished through disability—adjusted life years (DALY). One DALY is equal to one lost year of healthy life. Across a population the DALY is the gap between current health and ideal health (WHO, 2020). The burden of disease was calculated by the probability of illness outcome from an infection. The results illustrate that the highest disease burden was 680 DALY’s per 1000 persons annually. Surface water contributed to the highest disease burden and the highest mean estimation of infection was resultant of E. coli. One main limitation to their study is the lack of credible data. As such, the estimation of disease burden introduced uncertainty. Although the foregoing studies illustrate some examples of uncertainty and limitations with exposure and ingestion assessment, they do usefully highlight how there are many approaches to QMRA.

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et al., 2008), which were based on accidental contact (10 ml per incident). The authors were able to quantify a single exposure risk of 0.49 (e.g. 49% infection risk); and 0.15 for a single risk of illness (e.g. 15% illness risk) for Campylobacter. Their research included dilution factors from hydraulic modelling, which reduced uncertainty in concentrations. They could clearly identify higher concentrations in flood waters and CSO discharge than storm water, due to the dilution factor. Their study did not consider vulnerable groups, as it was assumed that the clean-up was carried out by healthy adults.

Andersen et al. (2013) incorporated a QMRA to an extreme rainfall event, which led to CSO in recreational waters. A 1D sewer model (MOUSE TRAP) and a hydrodynamic model (MIKE 3FM) was coupled to a bacterial model (MIKE ECOLab). ECOLab simulated the decay of *E. coli* and intestinal enterococci based on forcing factors (irradiance, temperature and salinity). Maximum literature values of pathogen concentrations were applied. Incident rates were single exposures of accidental ingestion for healthy male and female swimmers during an Iron Man Competition. Ingestion volumes were assumed to be 0.60 ml/min for men and 0.44 ml/min for women. Dilution rates were also considered during simulations. Both Beta-Poisson and Exponential Dose-response models were used. The authors conclude that during the Iron Man Competition, 55% of the competitors were at risk of gastrointestinal disease. Though there was still uncertainty about the pathogen concentrations, even though dilution was considered. This was due to the concentration values coming from the literature.

Eregno et al. (2016) proposed a method for estimating public health with a QMRA at recreational beaches. Five pathogens were analysed from CSO’s. Exponential Dose-Responses Models were applied to Cryptosporidium spp. and Giardia spp. Beta-Poisson models were employed for Campylobacter, Salmonella spp. and norovirus. Ingestion assessment consisted of concentration results from their GEMSS-HDM hydrodynamic model and GEMSS-WQM water quality/transport model. The risk of infection was calculated as a single infection exposure based on adults and children. As expected, ingestion of contaminated water was higher for children. The probability of infection from Cryptosporidium spp., Campylobacter, Salmonella spp. and Giardia spp. was 1.9%. Which is considered an acceptable value for recreational beaches. Norovirus was exceptionally high as it was estimated that all particles were infectious. A sensitivity analysis was carried out, which helped reduce the uncertainty in the input values. One constraint is considering the infection of children using the minimum, maximum and average concentrations of Cryptosporidium spp. from their study. If the maximum concentration was administered to their study the probability level would result in beaches being unsafe for children after rainfall.

Mark et al. (2018) applied MOUSE TRAP (DHI), an advection-dispersion microbial transport model to simulate pathogen concentrations in an urban drainage system. This was used in conjunction with MIKE FLOOD (DHI), a coupled 1D-2D hydrodynamic model to simulate Enterococci, *E. coli*, and *V. cholerae*. Their flood model showed good agreement with observed flood maps. However the maps did not contain flood depths. This created some uncertainty in calibration. This research usefully highlights that this combination of model could be utilised to analyse the transport of several different pathogens in a variety of locations with better calibration data sets. The exposure to humans from flood water was estimated by a field study. This included structured interviews on how residents behave during flood inundation. Water samples were taken from three locations. The risk of exposure was then quantified by the authors with Monte Carlo simulations. Dose responses were implemented via a Beta-Poisson model. The results suggest that the greatest estimated risk of *V. cholerae* was $5.6 \times 10^{-3}$ per day for children from poor families, which was greater than for middle class families. The estimated risk of *V. cholerae* for adults in the same area was lower, which was estimated to be $5.5 \times 10^{-4}$. A constraint of their study was an inaccurate sewer network map, as it came from old engineering plans. Sewer connections were difficult to assign, though they mitigated some of the uncertainty by setting up a number of different connection scenarios. A sensitivity analysis strengthened their research. However, it could be suggested that interviews from the field study increased uncertainty of exposure volumes. This is due to some interviews being either biased towards a particular answer, or uncertain if answered by children. Nevertheless, the results did confirm that low-income families were at higher risk, as were children compared with adults.

There is a wealth of material in contemporary literature detailing the advancement of QMRA. Exposure and ingestion volumes have been estimated by many novel approaches, though this does introduce many uncertainties. This is particularly apparent when studies have constructed questionnaires on possible ingestion volumes or assumed the exposed are healthy adults. The advancement in computational simulations has allowed spatial representation of the risks. However, there is a need for credible data. Poor data will only weaken simulation results. When combining hydraulic simulations with microbial assessment, pathogen data is a well-known constraint (Collender et al., 2016; Huynh et al., 2019). In accordance with this review, we present a hydrodynamic-microbial-QMRA framework (see Figure 3). The framework identifies the key objectives in...
Figure 3: QMRA modelling framework used in conjunction with hydrodynamic microbial modelling.
QMRA from dual drainage modelling and pathogen transport. Figure 3 also illustrates that decision support mechanisms can be used in conjunction with the QMRA output.

5 | DATA PAUCITY

5.1 | Hydraulic data

One key debate that crops up continuously within the literature is the lack of empirical data that is needed for robust hydraulic simulations. This is particularly prominent with regards to hydrologic and hydraulic flood inundation data. In the major system these include flood depths and extents, inundation times and flow velocities over a surface. Known pipe flows and depths, and roughness values also offer obstacles when modelling the minor system (Nkwunonwo et al., 2020). The accuracy of any flood model is therefore directly related to the possession of high-quality data. Challenges take many forms, when regarding data availability. Storm drains maybe centuries old, or drainage maps may not be digitised accordingly (Rosenzweig et al., 2021). Though stochastic techniques are available to estimate parameters in data sparse drainage networks as explained previously. A good example of this is using Bayesian inference for parameter estimation (Egger et al., 2013). Another barrier to data acquisition may also arise in the form of institutional impediment. For example, fragmented water governance in the U.S has presented challenges for receiving funding and obtaining trans-jurisdictional data (Rosenzweig et al., 2021). Molinari et al. (2019) discuss the validation of flood risk models and current practices. They also argue that the main model validation method compares observed data and predictions. Therefore, adequate observational data is paramount for accurate simulations. The authors suggest that after flooding events the collection of high-quality data should be encouraged, and freely shared.

For the sake of discussion, one could argue that some data is better than no data. Certain errors and limitations will naturally arise in data collection, due to locality, budget and time (Hammond et al., 2015). For example, Mignot et al. (2006) and Hammond et al. (2015) suggest that the assessment of urban flood impacts are made more difficult due to data paucity. Both authors recognise and detail the sparseness of data in their research. Along similar lines, Hunter et al. (2008) and Collender et al. (2016) argue the importance of using experimental data sets for the calibration and validation of numerical models. Observed data should be withheld for this analysis. Therefore, the studies in question explain that with better empirical data, model uncertainty will be reduced. This is crucial for robust research. However, in many situations field-based studies may not be efficient enough for appropriate data acquisition. Another important point is the use of uncertainty and sensitivity analysis, as this also can improve model outputs alongside model calibration (Liu et al., 2020; Petterson & Ashbolt, 2016; Savage et al., 2016; Thorndahl et al., 2008; Wong et al., 2021).

Urban flooding is uncertain temporally and spatially, hence obtaining credible data to calibrate and validate computational models is very challenging. A number of studies in the literature have detailed how water laboratories can be used to investigate hydraulic behaviour of the major and minor systems. Despite this, there is still further need for future research utilising water laboratory techniques. This is due to the fact that many more numerical hydraulic scenarios can be validated against real-scale or part-scale physical models. As such, water laboratories aid in the potential quantification of errors and allows researchers to examine hydraulic advancement. For example knowledge on velocity fields and discharge partitions are necessary to increase understanding in multi-directional flow pathways. These flows are extremely complicated in urban environments due to raised streets and buildings and convoluted drainage networks (Mignot et al., 2019).

Rubinato et al. (2013) compared a fully calibrated Info Works 1D model with a water laboratory. The water facility represented a section of sewer network from a case study site at one-sixth of full scale. The hydraulic model was descaled, to serve the same location. Fifteen historic rainfall events were simulated through both models. It was concluded that the physical model duplicated authentic rainfall episodes that were simulated through the software. Although this study does not include the major system, it does usefully highlight that water laboratories are sufficient in replicating data to use for model calibration and validations for 1D modelling approaches. Martins et al. (2018) tested and validated a fully dynamic model using 2D shallow water equations adjacent to a manhole. Several different grate inlets were studied. Experimental and numerical results of velocity fields around the manhole were compared. The authors were able to improve the understanding of previous knowledge on velocity field behaviour. The numerical model was able to predict velocities well, though was more accurate in areas of more longitudinal flows than transversal. Similarly, errors increased nearer the manhole.

Other works in the literature have detailed this complex interaction and researched the major and minor system (Djordjevic et al., 2013). The author’s present results following a replicated full scale gully system and representative urban surface, with a piped system below. A complex CFD model simulated the process.
surface slopes and a variety of different gratings were defined to investigate the interplay of surface and pipe flow. The results suggest that the observed and simulated steady flow depths on the surface agreed, though inflow was represented slightly better than outflow. Unsteady surcharged conditions were simulated in the numerical model, though this was not demonstrated in the experimental laboratory. This pioneering study usefully highlighted how a full-scale gully system would be suitable for calibrating and validating any sewer model in many applications.

Fraga et al. (2017) explain how they validated a 1D-2D dual drainage model under different hydraulic conditions with an experimental laboratory. They quantified rainfall-runoff processes. The results were satisfactory, though the model overestimated mean surcharge flow rates. Similarly, Martins et al. (2017) verified two finite volume models against an experiment data set. The authors found that their study contributed to the understanding of shock capturing finite volume flood models. Nonetheless, the sensitivity of the models were corresponded to the surcharge–surface inflow ratio. Therefore, further calibration is needed to fully verify localised modelling of sewer-to-floodplain flows.

The importance of modelling small scale obstacles in urban flooding has also been considered within experimental datasets. Mignot et al. (2013) simulated flow in a three-branch bifurcation with several pieces of urban furniture. From the nine obstacles they could determine very different flow patterns. Bazin (2013) agrees to this conclusion. In the same experimental laboratory as Mignot et al. (2013), Bazin (2013) added a pavement to the facility in a three-branch bifurcation with subcritical flow. They compared the experimental dataset with a 2D model and found that bias in the average ground elevation leads to errors in the approximation of discharge partition in the street profile.

Sewer flooding is a three-dimensional process, in which the interaction of flow with the major and minor system is highly complex, and interchangeable. As such, pressurised and free surface flows can change rapidly, with directional flows also alternating. Obtaining calibration and validation data, although necessary for robust simulations, can be very difficult to come by. Water laboratories can aid in this procurement of valuable data.

previously mentioned, a number of studies investigated sewer to surface hydraulic flow rates through manholes and gullies during flooding events. Yet, the literature on validation of a hydrodynamic-microbial model are still limited. Beg et al. (2020) created a 3D CFD numerical model in Open Foam to simulate flow and soluble transport through a manhole during surface flooding scenarios. The model was compared with hydraulic and solute transport experimental dataset. As a result, the authors were able to offer a better understanding of manhole exchanges under steady state flows. Their results show that flow rates were very accurate in the CFD model (<1.7% difference). Concentration profiles in the sewer pipes also had very low error (RMSE was between 1.25*10⁻⁸ and 4.46*10⁻⁸ mg/L). The model was able to accurately replicate solute mixing. However, this project used a simplified piped system; therefore, further work is needed to understand a change in geometry and pipe shape.

More recently (Rubinato et al., 2022) estimated the exchange of soluble pollutants between sewer pipe and floodplain using a physical model. Five different street profiles were investigated, which determined how differing geometries affected flow and pollutant transport. All geometries presented significant pollutant exchange from the piped system to the street (in the range of 28–39%). They found that when the manhole was closer to the edge of the street the mass of pollutants being exchanged to the surface increased. Similarly, the existence of parking spaces alone did not appear to affect the mass of pollutant exchanged. Limitations in this research include all tests only being conducted under steady state conditions and the manhole covers being removed for simplicity.

Zhang et al. (2020) ran a series of laboratory experiments in a rainfall–simulation hall; they validated a numerical model that simulated overland flow, using shallow water equations and a pollutant transport model using advection–diffusion equations. Two building layouts were investigated. Their results showed that the dissolved pollutant runoff process was correctly predicted by their model. Similarly, buildings slowed down the pollutant transport process. Although a real urban area would have been more complex. As such, their study did not identify sewage networks, spatial and temporal varying ground features and rainfall intensity.

5.2 Water quality data

Understanding how contaminant is move from sewer networks to surface flows is critical to quantifying health risks posed by urban floods. As this allows water engineers/managers to design mitigating measures.

5.3 Surveillance cameras and crowdsourcing

As high-resolution rainfall and flood data is of the utmost importance for urban inundation modelling, and hard to collect, novel data acquisition methods have also
been applied to previous studies. For example, obtaining velocity measurements for shallow urban overland run off from consumer-grade surveillance cameras (Leitão et al., 2018). Large scale particle image velocimetry (LSPIV) was used in their study. It was noted that artificial light is important when assessing velocity measurements, as poor light can affect results. Similarly, Le Boursicaud et al. (2016) used the LSPIV technique with crowdsourced YouTube videos, to estimate flash-flood volumes. Corrections for lens distortion and camera movement were applied; as such error was very low. Testing diverse image resolution indicated that the difference in time-averaged longitudinal velocity was <5% compared with full resolution. A limited number of GRPs (usually 10) is necessary, but they must be adequately distributed around the area of interest. Water levels are the main source of uncertainty in the results, usually much more than errors because of the longitudinal slope and waviness of the free surface of the flow. Boller et al. (2019) used Google Street View to automatically identify and locate drain inlets and manhole covers. This approach shows good performance and an enhancement over other image-based urban drainage infrastructure component detection. While the geographical localisation of the detected objects still contains errors, the accuracy achieved is nevertheless sufficient for flood risk assessment.

de Vitry and Leitão (2020) used a novel method known as static observer flood index (SOFI). This method is useful as it does not correspond to a single flooded variable; it analyses information on how the water level changes over time. SOFI tests the hypothesis that the quantity of visible water in the images of a static surveillance camera is related with the actual flooded level of water. SOFI uses a deep convolutional neural network (DCNN) to intermittently segment water in images from a static surveillance camera. The area covered by water in each image is expressed as a fraction of the whole image. de Vitry and Leitão (2020) found that when using SWMM the SOFI increased model performance by 70% compared with normal sensor data. Nevertheless, image-based proxy data does contain complex correlated errors. Model performance can therefore be effected due to the complex nature of image-based proxy data. Twitter was used by Holderness and Turpin (2015) to collect flood information in Jakarta. The authors used this social media platform in a project named PetaJakarta. This method meant that flood locations could be shared with residents and the emergency management agency. Decision support options could be easily assessed from the real-time flood conditions.

6 | RESEARCH GAPS AND FUTURE CHALLENGES

The literature strongly suggests that further research, including robust data collection and analysis, is needed with regards to combining hydrodynamic-microbial transport models with QMRA. Based on this review of literature, some significant research gaps and challenges were identified. They are categorised as the following:

- A lack of credible data for hydrodynamic and microbial simulations

A key area of future work is reducing uncertainty in hydrodynamic and microbial simulations. This can be very likely reduced with vigorous hydraulic calibration and validation, along with a higher quality of pathogen data. A comprehensive approach will also enable the analysis of hydrodynamic and microbial risks. Water laboratories are an ideal method for decreasing uncertainty in hydrodynamic computations. It is suggested that using a water facility, which can model the interaction of the minor and major systems, can aid forthcoming QMRA research projects. The collection of parameters such as flow rates, water depths and velocity fields can be used to validate a variety of numerical simulations. In doing so, the hydraulic behaviour within an urban catchment can be improved. This will reduce uncertainty in the hydraulic performance of any computational model. As such, modelling the movement and decay of pathogens will also be enhanced. Though, this comes at a cost as water laboratories are expensive to build and run, plus take up a large space.

Paucity of microbial data is also an area that needs further research. Previous studies have detailed how collecting water samples from flood water is very challenging due to the unpredictable nature of floods. Local sensors can have a poor spatial resolution, and sampling teams are expensive to coordinate (ten Veldhuis et al., 2010). Additional sampling during flood events are needed to aid in estimating the severity and health impacts using risk assessment methodologies. Collaborating between practitioners and academics has also been debated as being an important step in the future of flood modelling. This will establish better model methods and guidelines along with data sharing (Jia et al., 2021).

- There is room for improvement regarding QMRA exposure assessment

The literature illustrates many examples of different exposure assessment methods. Each approach has limitations. For example, it would seem that questionnaires
from the public increases the scepticism of exposure assessments. This is especially apparent when children are involved. Exposures base on preceding works maybe a better alternative, yet they too have limitations. The diversity of every incident and geographic location is one such drawback of using pathogen concentrations from previous works. Reference pathogens, of bacterial, viral and protozoan presented in a worst-case scenario of high incidence is another known method. Yet, this may overestimate concentrations in flood waters. Future work may then investigate floodwater quality based on several methods (literature values and experimental data) then present the results and limitations for both.

- Socio-economics should be further explored when assessing human exposure to flood water

Some previous studies have identified the increase and decrease of pathogen concentrations with regards to socio-economic changes of an urban catchment. Yet there is paucity when quantifying the risk posed to humans. Future work should include identifying the likelihood of exposure based on socio-economic data of the area and not just solely identifying the differences between adults and children, as many works have done. Addressing the risk to other demographics, including the elderly and disabled is also necessary.

7 | CONCLUSION

Population growth and climate change exacerbates the issue of urban flooding, especially in regions where the frequency of intense rainfall events has been predicted to increase; and where urbanisation is rapidly altering natural hydrological flows and pathways. The changes will escalate the risk of flooding as the design capacity of sewer systems are more likely to be exceeded. To study the interaction between the minor and major system, along with the transport of pathogens on the surface, a number of modelling steps need to be executed. If any step is under performed, model uncertainty increases. Despite no model can perfectly predict all possible future scenarios, an improved modelling approach that can better describe the physical processes and associated uncertainties could provide more reliable analyses. The contemporary literature had an abundance of methods that are available for engineers and researchers to utilise individually.

From the available evidence, it seems that the methodology to combine 1D-1D or 1D-2D hydrodynamic models to the application of microbial and transport for QMRA is sparse and not well understood. Moreover, there is still much uncertainty with regards to data acquisition for robust model calibration and validation. A limiting factor of QMRA is that exposure assessment creates uncertainty. Some methods covered in this review used less reliable methods for obtaining exposures than others. Calculating ingestion volumes from sparse measurement data and applying to dose-response models also are limiting factors.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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