

Research papers

Drainage representation in flood models: Application and analysis of capacity assessment framework

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ABSTRACT

Drainage systems are an integral part of urban infrastructure to help transport and treat wastewater as well as manage flooding during extreme rainfall events. Although there is a significant cost associated with the creation, operation and maintenance of drainage systems, the representation of these systems in flood models is overly simplified. This simplification is due to data protection regulations, and the complexities associated with drainage network modelling. A new framework developed by Water UK in collaboration with the Environmental Agency and sewerage undertakers for UK Drainage Water Management Plans provides data on the capacity and performance of the drainage system. The output from this framework provides a new method of incorporating a more explicit representation of spatially varied drainage capacity in flood models.

This study presents the first application of the UK's capacity assessment framework (CAF) for drainage representation in flood models. We develop a method of using the CAF outputs to represent spatially varied drainage losses across a catchment and assess its impact on flood risk. Three catchments in Leeds are used to quantify the difference generated in flooding when using a national average removal rate (NARR, e.g., 12 mm/hr) and our CAF-derived rainfall removal rates. Although there is variance across catchments, the results show the CAF removal rates increase flood depths, velocities, and flood hazards when compared to the national average due to a more realistic representation of the real system drainage capacity. With the pressures of climate change and continued urban development, a better representation of real drainage systems capacities will become more important and will make local solutions more resilient and relevant to the realities on the ground.

1. Introduction

Drainage systems are a key infrastructure to convey, collect and store water. Increases in population and hence urbanisation have led to the replacement of natural processes of drainage, such as infiltration, with infrastructures such as pipes, and culverts, as well as forms of sustainable urban drainage systems (SUDs) (Bisht et al., 2016; Booth, 1991; Butler et al., 2018). Over time, drainage systems developed from a simple ditch or gully on the side of a path into a complex network of underground pipe systems. These pipe systems are often designed to convey and treat either: (i) foul water, i.e., waste produced at homes; or (ii) stormwater, i.e., excess water because of extreme rain; or (iii) a combination of both, through combined systems (Smedema et al., 2004; Butler et al., 2018).

Pipes that make up a drainage system vary in material, size, length, diameter, and thus capacity. The stormwater drainage capacity for urban areas in the UK is usually designed to accept flows of either a 1-in-10 or 1-in-30-year return period (Butler et al., 2018; Environment Agency, 2018; Ochoa-Rodríguez, 2013; Zoppou, 2001). Therefore, a storm event of a greater magnitude than the system design capacity will often result in surcharge and excess runoff (Dawson et al., 2020; Djordjević et al., 2005; Guerreiro et al., 2017; Houston et al., 2011; Leitão et al., 2017; Mark et al., 2004; Ochoa-Rodríguez, 2013). In many cases, the capacity of a system is reduced due to operational malfunctions such as blockages, ageing infrastructure and lack of capacity in pipes, particularly in extreme rainfall events (Palla et al., 2018; Schmitt et al., 2004).

Although the challenges associated with representing drainage

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capacity are known, the effective capacity of these systems is still misrepresented in models used for flood risk management (Ferguson & Fenner, 2020; Palla et al., 2018). Flood models (e.g., built using Flood Modeller Pro, TuFlow or HEC-RAS etc.) are used to assess the rainfall response of a catchment and are used to answer questions about where and when flooding will occur. These models are therefore key tools in the planning and implementation of flood-mitigating interventions (Rehman et al., 2019; Teng et al., 2017). While natural characteristics of catchments such as elevation, land use and rainfall are represented explicitly, the capacity and performance of the systems are often assumed and/or oversimplified. (Chang et al., 2015; Palla et al., 2018; Singh et al., 2021; Yu et al., 2016).

The key elements driving the oversimplification of drainage networks in flood models are the lack of data availability, complexities associated with drainage network modelling, and shortage of skill required for drainage network modelling (Fenner, 2000; Freni et al., 2009; Vercruyssen et al., 2019; Yu et al., 2016). Of these elements, data availability has been a particular challenge for the study of drainage systems and flood modelling, as explicit drainage network data can be commercially sensitive and extensive to model explicitly.

The most common method of drainage capacity representation in flood modelling is using a rainfall removal rate, where a constant rate of rainfall is subtracted from that falling from the sky, with the assumption that this is handled by the drainage system and therefore does not need to be explicitly included in the overland flood model (Chang et al., 2015; Wang et al., 2018). The rainfall reduction approach was also applied to produce the national Risk of Surface Water Flooding (RoSWF) map for England and Wales (Chang et al., 2015; Environment Agency, 2013; Ferguson & Fenner, 2020). Wang et al. (2018) and Chen et al. (2009) also implemented the national average removal rates (NARR) and applied a fixed reduction of 12 mm/hr to the design rainfall to represent the function of the stormwater systems. Vercruyssen et al. (2019) applied a drainage capacity estimate when modelling a 1-in-50-year flood event for Newcastle-upon-Tyne and produced flood risk maps that identified source areas that contributed significantly to flood hazards in an urban domain. Assuming and estimating the capacity of drainage systems in pluvial flood modelling consequentially leads to the oversimplification of the source of the hazard itself such as blockage in gullies and inlets or surcharging manholes (Maksimović, 2009; ten Veldhuis et al., 2015; Walsh et al., 2012).

Other methods of estimating drainage capacity include the use of surcharge hydrographs at manholes, however, this assumes water can only move from the sewer system to the surface (Hsu et al., 2000). More technical approaches, such as combining sewer flow models with overland flow models (flow of water over the land surface in two dimensions) have also been used (Adeogun et al., 2015; Martins et al., 2018; Teng et al., 2017). However, these models are computationally demanding, and require information regarding the network. Lastly, generating synthetic drains to include in the models has also been explored, however, this faces significant challenges associated with validating large-scale synthetic drainage models (Bertsch et al., 2017; Möderl et al., 2009).

The Drainage Wastewater Management Plans (DWMP) enable water companies to work together and improve the robustness of drainage infrastructure for its customers and the environment. The DWMP also addresses requirements associated with improving transparency and long term resilience outlined in the UK government's Strategic Policy Statement (Defra, 2017; Jenkins, 2020; Ofwat, 2017; Water UK, 2019). One of the key tools developed as part of the DWMP to improve transparency and long-term planning is the capacity assessment framework (CAF). The CAF is a tool that provides information on the capacity of the drainage system. The outputs from this framework show the change in available capacity within the drainage system over time.

This paper utilises the outputs generated by the newly available CAF to represent drainage systems more explicitly in flood models. (Water UK, 2019). Specifically, the goal is to gain insight into the value of using

spatially varied drainage losses and to investigate if this makes a difference in the modelling results. Achieving this goal aids in demonstrating a methodology for using the CAF data outputs for drainage representation and evaluate the impact of this data in comparison with the existing method of drainage representation (e.g., NARR). This paper is the first-ever comparison and evaluation of drainage representation and subsequent flood risk using this sector-provided data. To achieve this, flood models of three flood-prone catchments in Leeds are used to develop and demonstrate the method of using the CAF outputs to evaluate the subsequent impact on flood hazard.

2. Data and methods

2.1. Study areas

Flood modelling was conducted for three catchments within Leeds, these are Holbeck, Wyke Beck and Lin Dyke shown in the map in Fig. 1. The Holbeck catchment in the southwest of Leeds covers an area of 62.56 km² (Fig. 1). The upstream end of the catchment is mostly rural, comprising mainly arable land, whereas the downstream reaches of the catchment are heavily urbanised consisting of residential areas, industrial buildings, and major transport links. In total, green space comprises 68% of the catchment and grey areas such as buildings, paved and unpaved roads make up 28% of the area. Flood risk in the Holbeck catchment is a combination of fluvial and pluvial flooding. Fluvial flooding is caused due to exceeded capacity in rivers. Pluvial flooding is surface water flooding caused by high-intensity rainfall in urban areas, this can be a result of artificial drainage systems capacity being exceeded. Wyke Beck covers 38.87 km² of Leeds, 63.13% of the catchment is made up of buildings, paved and unpaved roads, whereas 36.87% is composed of green spaces such as parks and gardens. Wyke Beck is predominantly a residential catchment, with a significant number of businesses. Flooding within the catchment is a combination of fluvial and pluvial mechanisms. The total area of Lin Dyke is 22.19 km² and has two main urban towns, Garforth located upstream, and Kippax located midstream. The downstream area of the catchment is mostly wetland, which drains into the river Aire. Green space makes up 78% of the catchment and grey areas cover 22% of the catchment. Flooding within the catchment is primarily pluvial.

2.2. Capacity assessment framework data

The outputs of CAF used in this paper were derived from water companies detailed hydraulic modelling of the combined drainage networks. Key inputs of drainage models used to generate the CAF outputs are network data and ancillary structures specified in Table 1 (Gorton et al., 2017a; Udale-clarke, 2018; Water UK, 2019). The outputs are presented by assigning a score for the capacity of the network system (explained in Section 2.3).

The CAF data provided by Yorkshire Water were in GIS shapefile format and processed using QGIS. A set of capacity hexagons clipped for the study areas is presented in Fig. 2. Each hexagon has a diameter of 0.5 km² and a score of 0 to 5, where 0 represents no data and scores of 1 to 5 represent the percentage length of pipes in that hexagon that are likely to surcharge in (Table 2). The CAF data set provides the hexagon score, the total length of pipes modelled per hexagon and the total length of pipes that will exceed capacity for a specified return period (also known as red-length).

To assign an aggregate score to each hexagon first, the scoring of drainage system performance is assessed by establishing a capacity metric for pipes and CSOs individually. Individual scoring is identified using the surcharge return period for pipes, the average number of spills per year for CSOs and the average number of spills per summer for CSOs. Additional factors used to generate the individual scores are specified in Table 1S ('S' denotes Supplementary material). Using this information, an aggregate score is assigned to each hexagon by calculating the

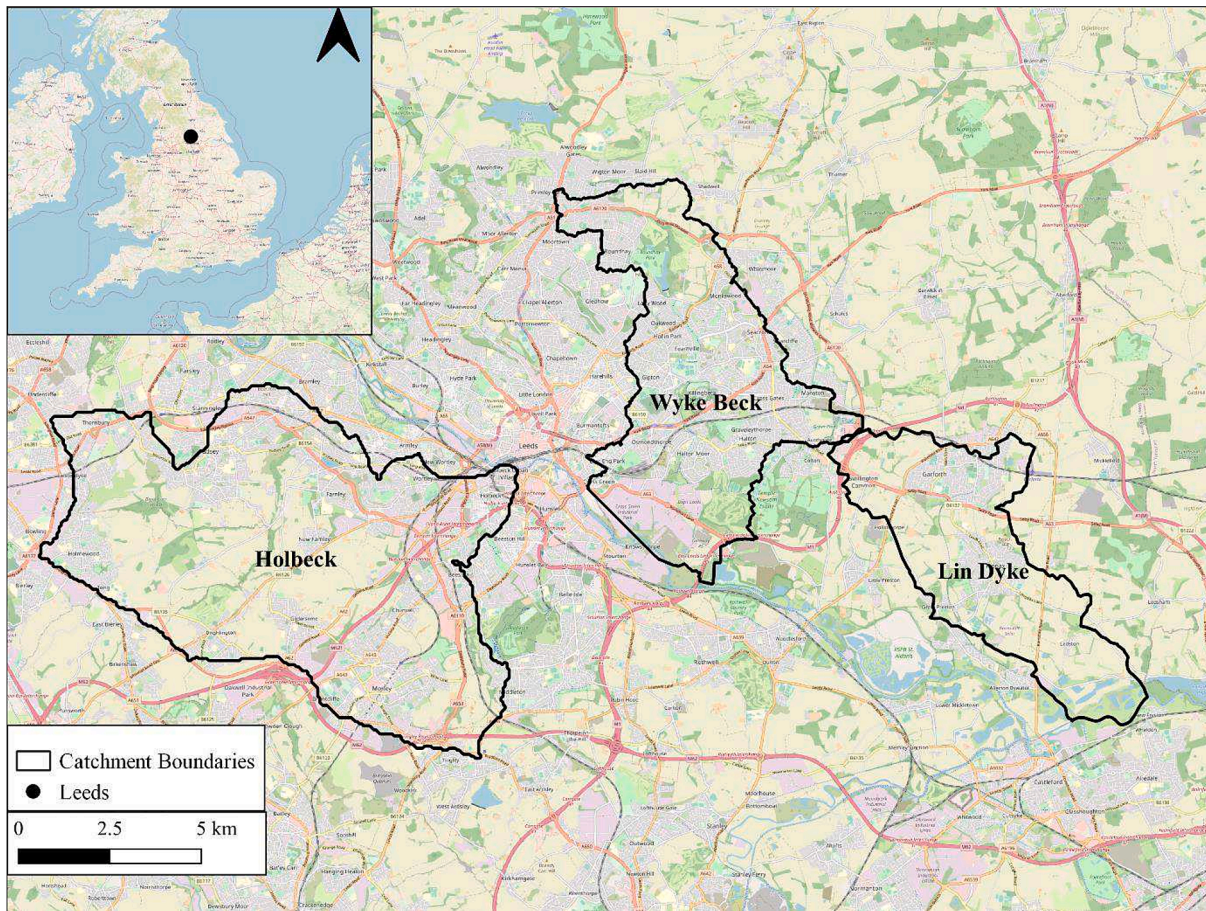


Fig. 1. Three study area catchments located in Leeds, north of England in the United Kingdom.

Table 1
Key urban drainage components used to derive the CAF outputs.

Input Category	Description
Network Data	<ul style="list-style-type: none"> • Manhole locations, cover levels and chamber floor levels • Pipe locations, dimensions, and invert levels • Network connectivity such as gradient, bifurcation
Ancillary structures	<ul style="list-style-type: none"> • Combined Sewer Overflows (CSOs) • Pumping stations • Wastewater treatment works • Storage tanks • Control structures (including weirs, sluice gates, orifices, flap valves, outfalls etc.)

percent length of individual pipes classified as red pipes per hexagon. Red pipes are defined as pipes that surcharge in a given storm event. There are three methods in which aggregate scores can be calculated and applied for pipes and CSOs. These are:

$$Lengthofpipe = \frac{TotalLengthofpipeswithaREDindividualscore \times 100}{TotalLengthofallpipes} \quad (1)$$

$$Populationequivalent = \frac{Populationequivalentupstreamofallredpipes \times 100}{populationequivalentupstreamofallpipes} \quad (2)$$

$$CSOScoring = \frac{TotalnumberofpointsscoredbycsOs \times 100}{TotalnumberofcsOs \times 2} \quad (3)$$

The CAF outputs include representation of drivers that affect drainage network performance. Parameters that affect system performance and capacity are population change, decrease of permeability in

urban areas due to increase in urbanisation, and climate change.

2.3. Flood modelling

HEC-RAS 6.1 was used for modelling flooding in each of our catchments. The inputs used for the modelling (Table 3) were a digital elevation model (DEM), land use and net hyetograph after the removal of representative losses due to the physical characteristics of the catchment (infiltration, evapotranspiration etc.).

All models use a bare earth LiDAR DEM at a resolution of 2 m for Holbeck, Wyke Beck and Lin Dyke (Environmental Agency, 2019). The DEM was adjusted to represent buildings by identifying the cells that overlapped with building vectors defined by OS Mastermaps, these building footprints were raised in elevation by 5 m to ensure that water flows around these structures, additionally, kerbs were inserted by assuming a uniform kerb height of 10 cm to realistically represent urban morphology. Design storm periods for a 1-in-10 year, 1-in-30 year and 1-in-100-year return period for each catchment were generated using the Revitalised Flood Hydrograph model (ReFH2). The ReFH2 uses the physical attributes of a catchment to estimate rainfall depth for a required frequency and duration (Kjeldsen et al., 2013; Wallingford Solutions, 2016).

Two methods were used to represent drainage losses:

1. The National Average Removal Rate (NARR) of 12 mm/hr was applied uniformly across the whole catchment.
2. The CAF outputs were used to generate unique removal rates per risk score hexagon, which we will refer to as the CAF removal rates from here on.

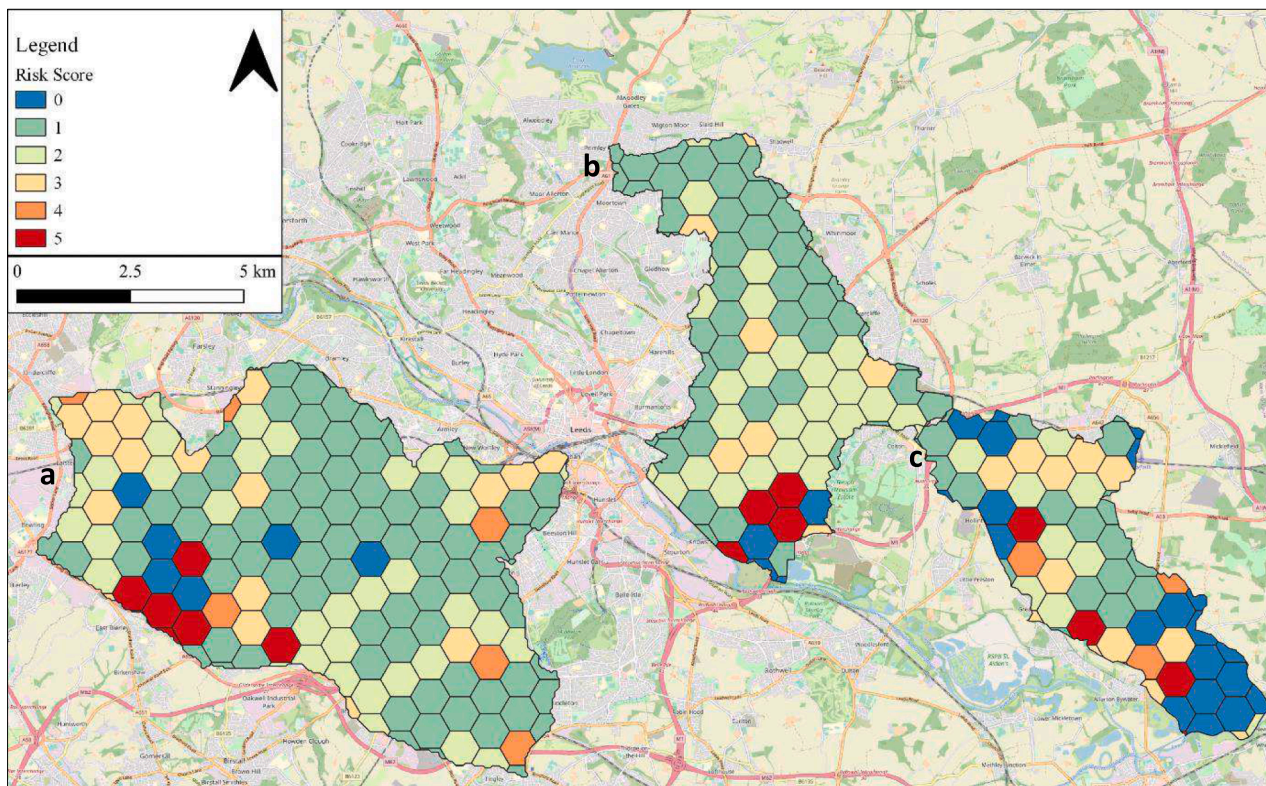


Fig. 2. The CAF outputs showing the capacity i.e., percent of pipes likely to flood based on the hexagon risk score for a) Holbeck b) Wyke Beck and c) Lin Dyke.

Table 2

Hexagon score and % length of pipes likely to surcharge for a specified return period.

Risk Score	Percentage length of pipes flooding
0	No data
1	0–15
2	15–30
3	30–45
4	45–60
5	60–100

Table 3

Data sets used for model build for the three study areas.

Dataset	Source	Format	Description
DEM	Environmental Agency	Raster	LiDAR composite DTM
Catchment Boundary	UK Centre for Ecology and Hydrology	Vector	Outlines the boundary for the catchment obtained from the FEH web service
Land Use	OS Mastermap	Vector	Details of various land-use types within the study area
Rainfall Input	REFH2	CSV	Design storm profiles for various return periods.

The CAF-based removal rate uses the method detailed in Section 2.3.1 below, the CAF data set provided was for a 1 in 30-year return period. In summary, the CAF outputs have been used to interpolate drainage loss removal rate values to create a unique hyetograph for each hexagon risk score resulting in spatially varied hyetographs applied across each catchment. The red length per risk score for a 1 in 30-year return period was averaged and utilised to provide a more realistic representation of the capacity of the drainage system within the area.

2.3.1. Linear interpolation of CAF data

The CAF was used to interpolate drainage removal rate values that should be applied based on the average percentage of red-length pipes per hexagon score. The national average removal rate of 12 mm/hr was used as the upper threshold to ensure that the removal rate is not higher than 12 mm/hr because this is the typical value for drainage removal rates across catchments in England and Wales. In areas of known low drainage capacity, Lead Local Flood Authorities (LLFAs) have been guided to substitute alternative values of 6 mm/hr hence this was chosen to represent areas that have a risk score of 5 (Environment Agency, 2013).

To interpolate drainage removal rate values, the average percentage of red length per hexagon score was calculated for each study area and each risk score. The average red length of pipes per hexagon score is therefore assumed to be a relevant proxy for capacity and therefore loss removal rate, as it indicates on average the length of pipes that will have their capacity exceeded. Equation 4 was used to calculate the slope of a line (m) and Equation 5 was used to calculate the drainage removal rates (y).

$$m = \frac{(y_2 - y_1)}{(x_2 - x_1)} \tag{4}$$

$$y = y_1 + m(x - x_1) \tag{5}$$

where, y_1 denotes the minimum removal rate and y_2 denotes the maximum removal rate (i.e., 6 mm/hr and 12 mm/hr), x denotes the percentage of pipes at red-length x_1 is 0 i.e., the minimum % of pipes at red-length and x_2 is the maximum percentage of red-length pipes i.e., 100 %.

2.3.2. Postprocessing of model outputs

All results were processed to analyse the hazard measures i.e., depth, velocity and extent posed by the scenario that uses the NARR and the scenario that uses CAF removal rates within each catchment. To identify

the flooded area, all cells with a water depth greater than 0.1 m and velocity greater than 0.25 m/s were used. The flood hazard maps were further processed to assess the U.K. Hazard Rating, as recommended in the flood risks to people guidance using Equation (6) (DEFRA, 2006; Hunt, 2009).

$$Hazard = D*(V + 0.5) + DF \tag{6}$$

where, *D* = depth (m), *V* = velocity (m/s) and *DF* = debris factor. Where the debris factor is either 0, 0.5 or 1 depending on the depth, velocity, and land use. The most recent guidance states to use a depth-varying debris factor with a non-zero value at low flood depths. The depth and velocity used to calculate the flood hazard rating as per the U.K. Hazard Rating are presented in Table 4.

3. Results

3.1. CAF scores

To generate the hyetograph inputs for rainfall-runoff modelling for each of the study areas, the average length of red-length pipes per risk score was calculated. Table 5 presents the average length of red length pipes for the whole of each catchment modelled. The ratio of red-length pipes to total pipes modelled per risk score is presented in Fig. 2. For all three catchments, the ratio of total pipes modelled and the average % of red-length pipes increase as the risk score increases. This means that although the length of pipes for hexagons that are classified as a risk score of five is small, most of the length of those pipes will surcharge in a 1-in-30-year return period event. This trend is observed across the three catchments as seen in Fig. 2, where all three catchments have values over 70% for the average percent length of red-length pipes. This trend is reversed for pipes modelled under hexagons classified as a risk score of 1, where the average percentage of red-length pipes is below 10% for each of the catchments. Overall, 12.45% of the total pipes in the Holbeck catchment are red-length pipes. In Wyke Beck, 14.91% of the total pipes modelled are red-length, and for the catchment of Lin Dyke 21.80% of the pipes modelled are red-length.

The total length of pipes modelled is 3,410,905 km, 1,906,096, km, and 931,128 km, for the Holbeck, Wyke Beck and Lin Dyke catchment respectively. The total length of pipes at red length is 423,606.94 km, 284,229.91 km, and 203,026.40 km, for the Holbeck, Wyke Beck and Lin Dyke catchment, respectively. Red length pipes, irrespective of score make up 12.41 %, 14.91 % and 21.80 % of total length of pipes modelled within the Holbeck, Wyke Beck and Lin Dyke catchment. The total

Table 4
Depth and velocity classifications for the UK hazard ratings (Defra, 2006; Hunt 2009).

Hazard	Rating	Depth (m)	Velocity (m/s)	Description
Low	< 0.75	0.1 – 0.3	< 0.25	Considered safe, depth is likely to exceed the height of the kerb. Velocity is that of still waters.
Moderate	0.75 – 1.25	0.3 – 0.6	0.25 – 0.5	Hazard to some such as children and elderly, likely to cause some property flooding and damage to vehicles
Significant	1.25 – 2.0	0.6 – 1.2	0.5 – 2.0	Hazard and danger to most, unsafe for vehicles, most likely to cause property damage and breach flood resilience measures
Extreme	>2	> 1.2	> 2	Unsafe for all including emergency services, likely to cause building failure

Lastly, any figures with a suffix of ‘S’ have been presented in the supplementary material.

Table 5
Average length of red-length pipes per risk score for each catchment.

Risk Score	The average length of red-length pipes per catchment (km)		
	Holbeck	Wyke Beck	Lin Dyke
1	5.78	6.65	4.24
2	22.08	20.17	20.19
3	35.27	32.50	36.60
4	49.48	52.30	49.07
5	71.33	87.04	81.61

length of pipes modelled for hexagons that score one is considerably higher for each catchment. For example, 26.27%, 32.01 and 22.05% for Holbeck, Wyke Beck and Lin Dyke when compared to the total length modelled for hexagons that score 5, i.e., 4.33%, 1.63% and 11.46% for each of the catchment respectively (Table 6, and Fig. 1S).

3.2. Rainfall inputs

Based on the average percent of red-length pipes per risk score for each catchment, a drainage removal rate was interpolated to estimate the capacity of pipes (Table 7). The newly calculated capacity estimates were used instead of the 12 mm/hr national average. The drainage removal rates were calculated using the methodology outlined in Section 2.3.1 and have been presented in Table 5 for each catchment. These values were then utilised to generate a unique net-hyetograph for each hexagon, for the return periods of 1-in-10-year, 1-in-30-year, and 1-in-100-year per catchment (Fig. 3). For any hexagons that score a zero, i.e., no data available, the default NARR of 12 mm/hr has been used.

Common between the net-hyetographs of all the catchments is the increase in peak net-rainfall and total net-rainfall when using the CAF-derived removal rates for the return periods of 1-in-30-year and 1-in-100-year. When compared to the peak net-rainfall of the NARR, net-peak rainfall in the Holbeck catchment increases by 24.51%, 10.06% and 14.84%, for the return periods of 1-in-10-year, 1-in-30-year and 1-in-100-year, respectively. Similarly, for Wyke Beck, the increase is 8.01%, 4.45% and 6.09%, for the return periods of 1-in-10-year, 1-in-30-year and 1-in-100-year.

The catchment of Lin Dyke, however, only experiences an increase in peak and total net-rainfall for the return periods of 1-in-30-year and 1-in-100-year. The net-hyetographs for the 1-in-10-year event, have no difference when compared to that of the NARR. Additionally, Holbeck and Wyke Beck have a unique net-hyetograph for each hexagon score for each return period, however, Lin Dyke only has a unique hyetograph for each risk score for a 1-in-100-year return period. Furthermore, the hyetographs for a 1-in-30-year return period, are only different for hexagons that are classified as a risk score of five.

Other differences are observed in the hyetographs of the Holbeck catchment which demonstrates the greatest difference in rainfall depth values when approaching the peak, however, for Wyke Beck, a more pronounced difference between the hyetographs for each risk score is observed in the rising and falling limbs of the hyetographs. Fig. 4 shows the percent difference in total rainfall when compared to the total net-rainfall of the NARR.

Table 6
Percent of red length pipes and percent of total pipes modelled per risk score and per catchment.

Score	Total length of red length per score risk score (%)			Total length of pipes modelled (%)		
	Holbeck	Holbeck	Lin Dyke	Holbeck	Wyke Beck	Lin Dyke
1	1.54	14.49	20.78	26.27	32.015	22.05
2	15.883	14.17	21.55	23.23	32.25	23.45
3	16.43	14.33	22.25	23.86	32.46	21.58
4	16.31	31.41	21.664	22.28	1.62	21.43
5	17.65	32.73	23.68	4.33	1.63	11.46

Table 7
Peak drainage removal rate (mm/hr) for each study area and related hexagon risk score.

CAF Risk Score	Holbeck	Wyke Beck	Lin Dyke
No Data	12	12	12
1	11.65	11.60	11.74
2	10.67	10.78	10.78
3	9.88	10.04	9.80
4	9.03	8.86	9.05
5	7.72	6.77	7.10

Holbeck and Wyke Beck show the greatest difference in the rainfall totals for each risk score when compared to the NARR net-rainfall total. Both Holbeck and Wyke Beck also show that the difference in net-rainfall total decreases as return period increases, for instance, the difference between NARR and CAF removal rates net-rainfall totals for Holbeck decreases from 17.38% to 14.14% for risk score five hexagons from the return periods of 1-in-10-year, 1-in-30-year, 1-in-100-year. Similarly, for Wyke Beck the difference in net-rainfall totals when compared to NARR decreased from 21.66 % to 15.89%. Like the net-hyetographs, Lin Dyke has no difference in the rainfall totals for a 1-in-10-year event. A small difference of 0.23% and 2.31% is observed for hexagons that score four and five for the 1-in-30-year return period when compared to the totals of the NARR. The 1-in-100-year return period shows a difference in the net-rainfall totals for risk score three to five. The net-rainfall totals increase by 0.35%, 2.79%, and 7.58%, respectively, when compared to the totals of NARR.

3.3. Flood modelling

For all catchments, CAF-derived outputs generate an increase in flood depths and velocities. The total area of each catchment flooded for the three return periods and the two drainage removal rates scenarios (i. e., CAF vs NARR) are presented in Table 8. The total area of the Holbeck catchment that is flooded when using the NARR is 6.17 km², 6.80 km², and 7.56 km² for the return periods 1-in-10-year to 1-in-100 years, respectively. When using the CAF-derived removal rates, this total area flooded is increased to 6.24 km², 6.85 km², and 7.61 km². When compared to the flooded area predicted by the NARR, the CAF removal rates results increase the flooded area by, 1.11%, 0.79% and 0.61%, for 1-in-10-year, 1-in-30-year and 1-in-100-year return periods. Similarly, for the Wyke Beck catchment, the difference in total area flooded area is less than 1% when comparing the NARR and CAF removal rates for all return periods. The total flooded area for the Lin Dyke catchment for a 1-in-10-year and a 1-in-30-year return period shows no difference between NARR and the CAF removal rates scenarios. However, for a 1-in-100-year return period, there is an 8.36 % difference in the total area flooded within the Lin Dyke catchment. The total area flooded when using the NARR is 10.75 km², this increases to 11.65 km² when using the CAF removal rates. Additionally, this increase of 12.05% and 4.52% due to the CAF removal rates is mostly observed at shallow depths of 0 to 0.15 m and 0.15 m to 0.30 m.

Like the depth ranges, the results for the velocity ranges also indicate small differences between the two drainage removal rate scenarios for all return periods. Most of the flooded area within the Holbeck catchment for each of the return periods is exposed to a velocity of 0 to 0.25 m/s which is considered safe for all. All differences in velocities between

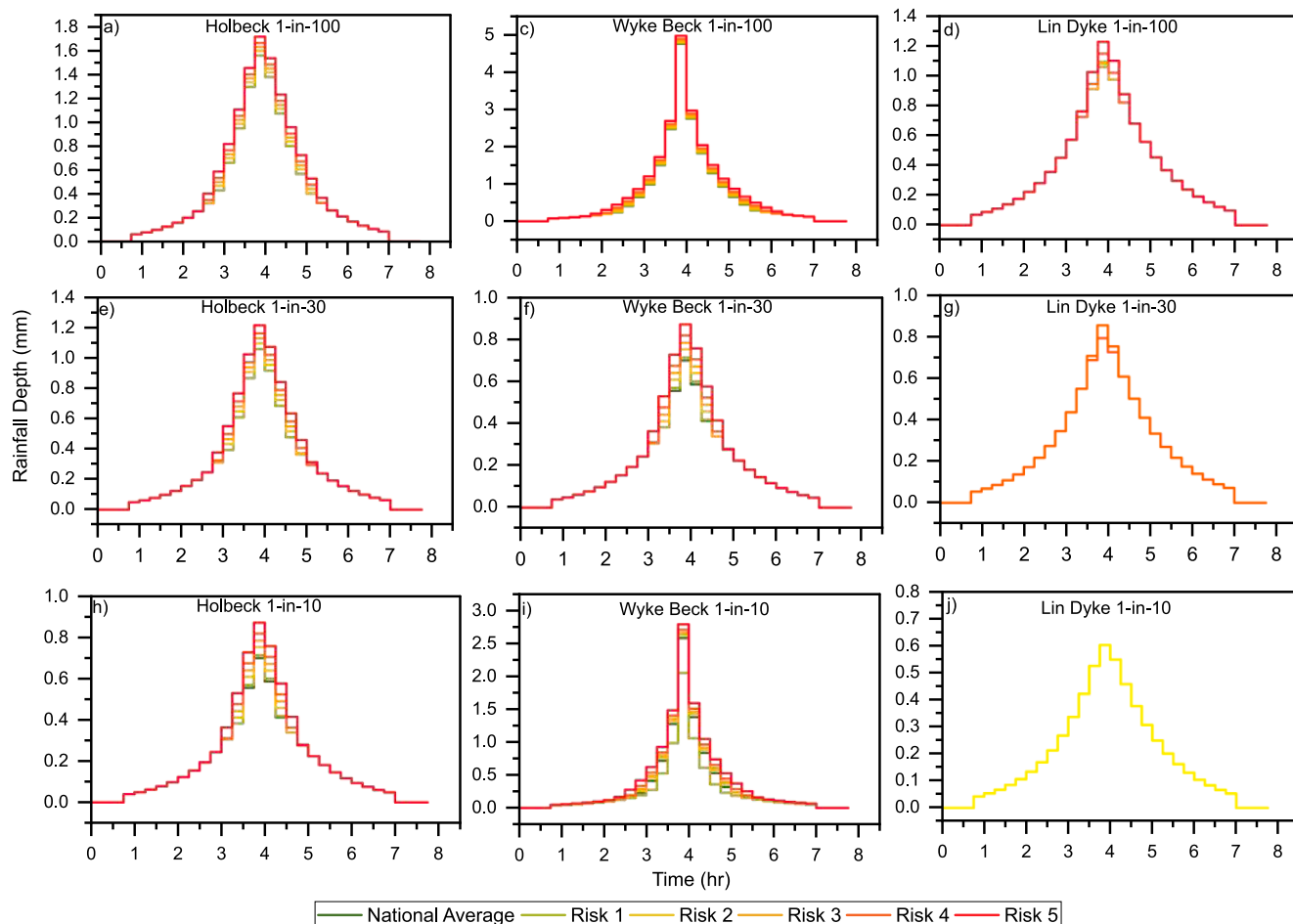


Fig. 3. Net-hyetograph inputs for Holbeck (a, e, h), Wyke Beck (c, f, i) and Lin Dyke (d, g, j) for a 1-in-10-year, 1-in-30-year, and 1-in-100-year return period.

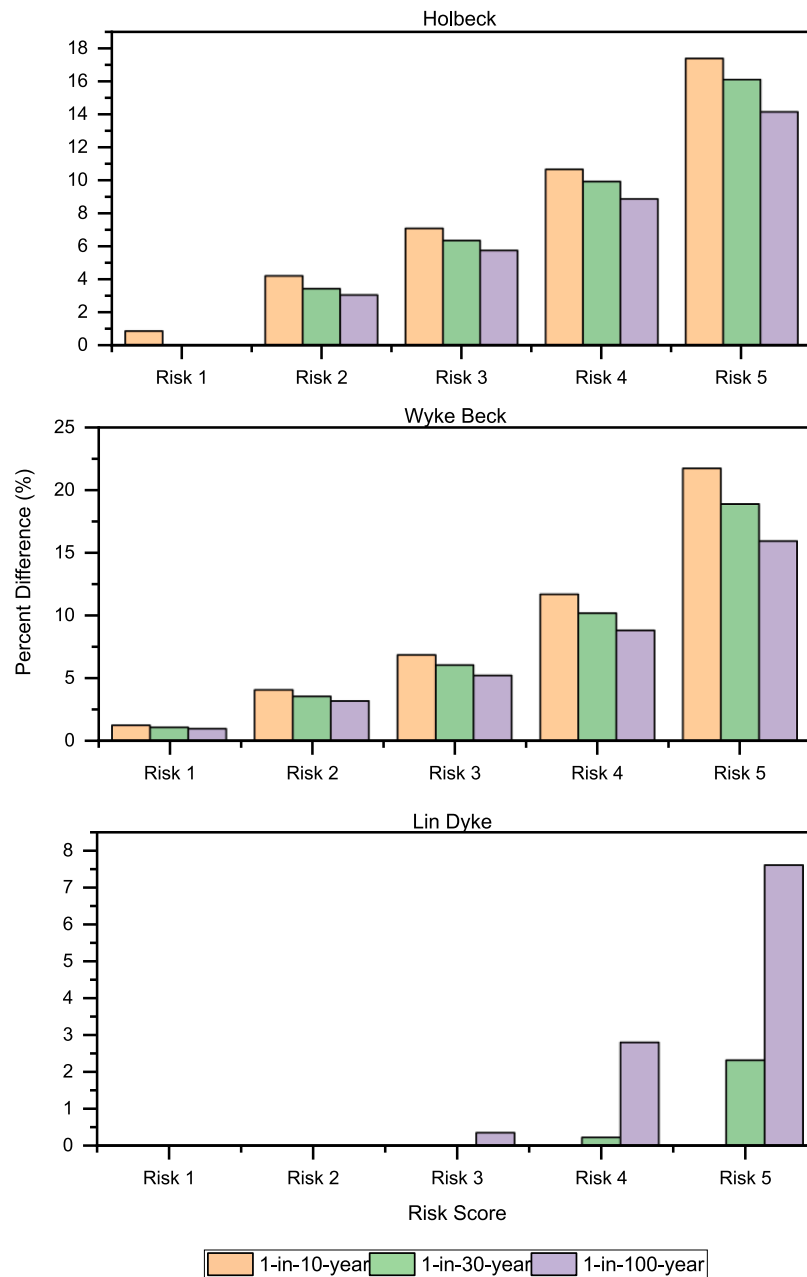


Fig. 4. Difference in net-rainfall totals when compared to the net-rainfall total of the NARR scenario for all return periods for the catchments of (a) Holbeck (b) Wyke Beck (c) Lin Dyke.

the NARR results and CAF removal rates results are no greater than 1.12% for the Holbeck catchment, with the maximum difference observed for a 1-in-10-year return period. Similarly, the velocities within the flooded area for Wyke Beck remain similar between the two scenarios where the differences in the results are less than 1%. The velocity results for Lin Dyke show that there is a difference in velocity ranges experienced by the total flooded area for a 1-in-100-year return period. The largest difference between the NARR and the CAF removal rates is observed at the velocity range of 0.25 m/s to 0.50 m/s. The CAF removal rates predict a 26.56% increase in the total flooded area exposed to this velocity range when compared to the NARR. This velocity range is expected to be dangerous for the elderly and children and causes damage to vehicles and some property flooding. Furthermore, there is a 7.45% increase in areas subjected to 0 to 0.25 m/s velocity.

The results for the hazard rating classifications show a greater percentage difference when comparing the NARR and CAF removal rates

scenarios. The Holbeck catchment shows a 3.75 %, 2.43% and 1.07 % increase in overall hazard rating for a 1-in-10-year to 1-in-100-year return period. Moreover, moderate, and significant hazards when using the CAF removal rates are increased by 9.04 % and 7.21 % for a 1-in-10-year return period. For a 1-in-30-year and 1-in-100-year return period, the CAF removal rates predict a 1.78 % and 1.34 % increase in moderate hazard. Unlike Holbeck, Wyke Beck shows the greatest difference in hazard ratings for a 1-in-30-year return period when comparing the NARR and CAF removal rates. Moderate hazard is increased by 13.52 % and significant hazard is increased by 6.99 %. There is no difference in the hazard results for a 1-in-10-year event for the Lin Dyke catchment when comparing the NARR and CAF removal rates. Furthermore, the 1-in-30-year predicts less than a 1 % increase in overall risk within the two scenarios. However, for a 1-in-100-year event, the CAF removal rates predict a 15.29% increase in low hazard, but an 11.80% decrease in moderate hazard. This pattern of change matches that of the depth

Table 8

Total flooded area and hazard extent for each catchment, across the three return periods and flood modelling scenarios that use the NARR and CAF removal rates.

Catchment	1-in-10-year					
	Holbeck		Wyke Beck		Lin Dyke	
	Total Flooded Area (km ²)	Hazard extent (km ²)	Total Flooded Area (km ²)	Hazard extent (km ²)	Total Flooded Area (km ²)	Hazard extent (km ²)
NARR	6.17	1.31	5.02	1.21	9.70	1.58
CAF removal rates	6.24	1.36	5.06	1.26	9.70	1.58
Difference	0.07	0.06	0.04	0.05	0	0
	1-in-30-year					
NARR	6.80	1.80	5.55	1.62	9.86	2.11
CAF removal rates	6.85	1.85	5.59	1.65	9.86	2.12
Difference	0.05	0.05	0.04	0.03	0	0.01
	1-in-100-year					
NARR	7.56	2.45	6.17	2.08	10.75	2.78
CAF removal rates	7.61	2.48	6.21	2.12	11.65	2.86
Difference	0.05	0.04	0.04	0.04	0.10	0.08

results for Lin Dyke where the CAF removal rates increase shallow flooding.

Fig. 5 marks the four key locations in which the difference between the NARR and CAF removal rates can be observed for the hazard ratings of a 1-in-100-year event. All the key locations are situated in the two urban areas of Lin Dyke, Location 1 (Fig. 6, Fig. 2S) and Location 2 (Figs. 2S and 5S) located in Garforth showing how the hazard rating has increased between the two scenarios. For instance, Location 1 shows a 100% increase in the extent that is a classified extreme hazard when using the CAF removal rates for drainage representation. Moreover, the significant hazard is increased by 21.37%, and low and moderate hazards have decreased by 7.92 % and 6.80 %, respectively at Location 1 when compared to the NARR hazard outputs. Additionally, Location 2 indicates a decrease in low, significant, and extreme hazards, however, moderate hazards at the location increase by 10.12% when using the

CAF removal rates. In Location 3 (Fig. 3S, Fig. 6S) moderate, significant, and extreme hazard has increased by 9.54%, 17.05% and 11.68%. Extreme hazard increase by 100% in Location 3 when using the CAF removal rates scenario. Location 4 (Fig. 7, Fig. 7S) shows that when using the CAF removal rates, low hazard decreased by 6.43% however, moderate and significant hazard increased by 23.97 %, and 5.05 %.

4. Discussion

The results indicated that the CAF outputs when used to estimate drainage capacity make a tangible difference to the net-hyetographs used as inputs in to the models for each catchment. These differences are in the range of 0 to 24 % for the Holbeck catchment, 0 to 8 % for the Wyke Beck catchment and 0 to 8 % for the catchment of Lin Dyke. Although there are significant differences in the rainfall inputs, this

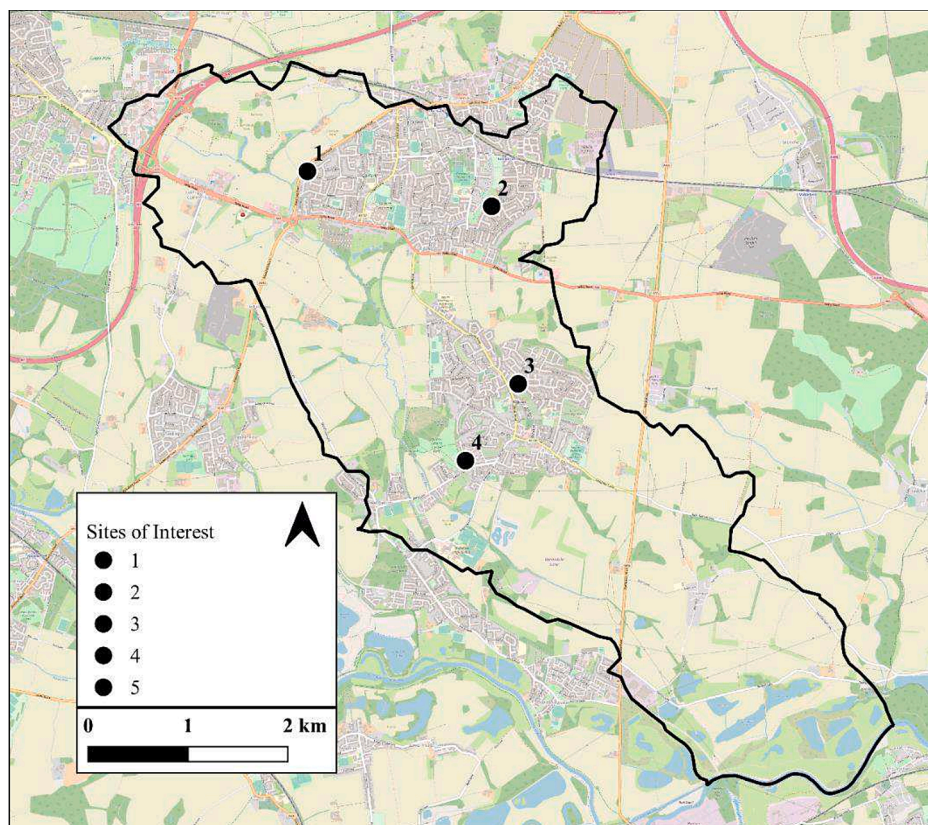


Fig. 5. Key locations in the catchment of Lin Dyke where the difference in flood hazard category can be identified between NARR and CAF removal rates scenario for a 1-in-100-year return period.

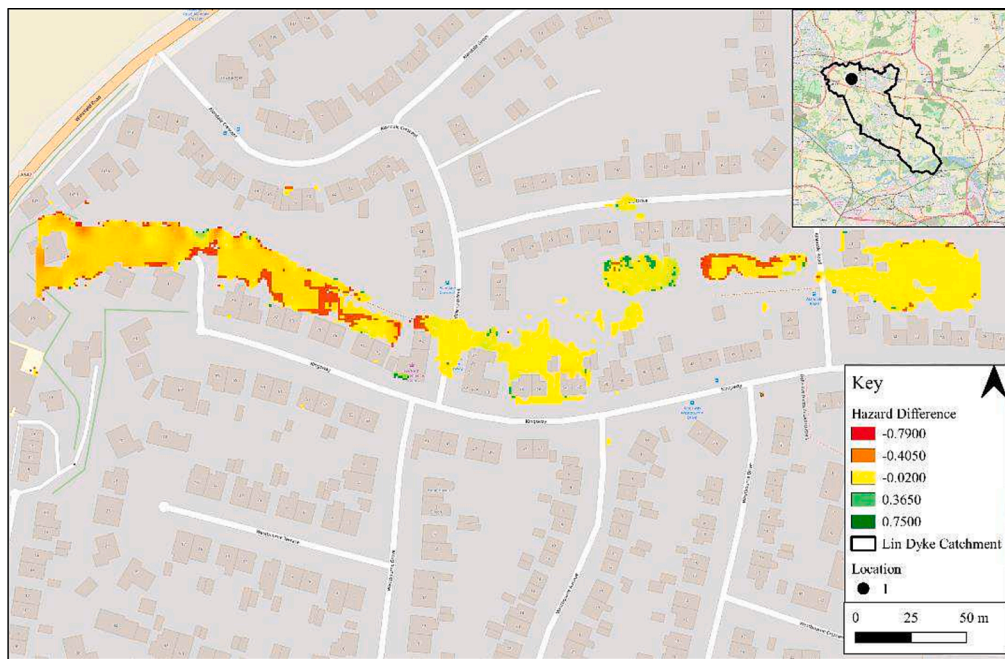


Fig. 6. Location 1 of 4 in Lin Dyke showing the difference in the extent of hazard rating between the NARR and CAF removal rates (i.e., NARR-CAF) scenarios.

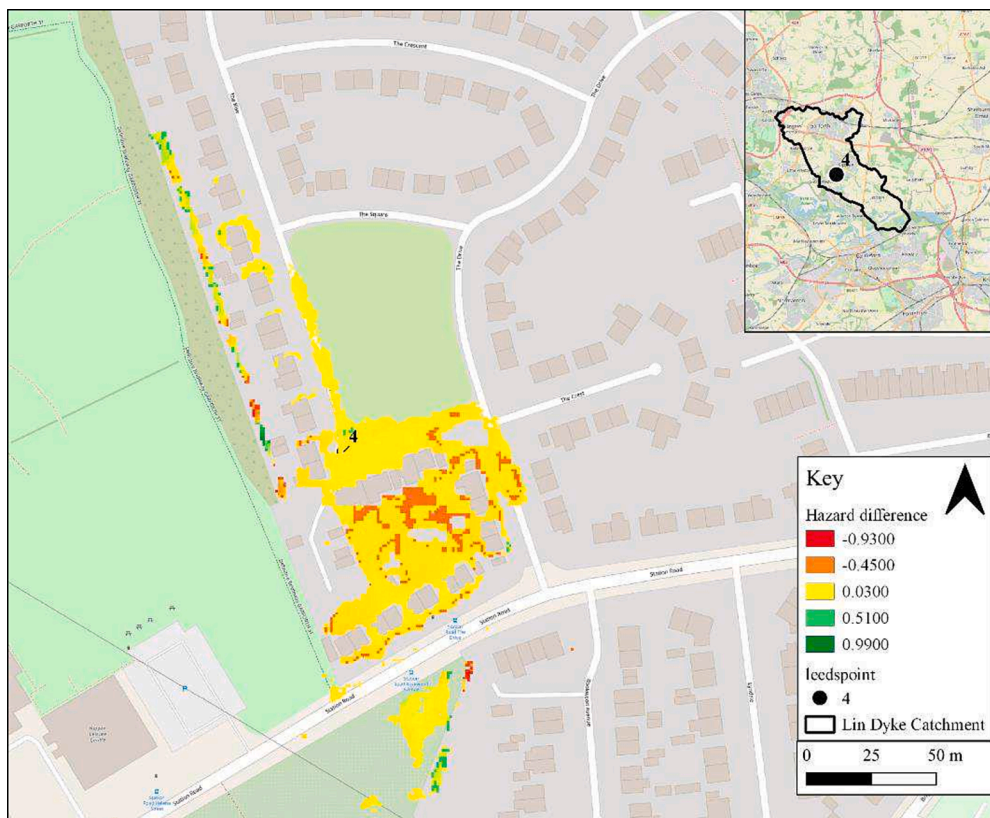


Fig. 7. Location 4 of 4 in Lin Dyke showing the difference in the extent of hazard rating between the NARR and CAF removal rates scenarios.

difference, does not always translate to a major flood risk increase. Based on the results, using the CAF-derived drainage removal rates results in less than a 2 % increase in flood risk overall within the Holbeck and Wyke Beck catchment when compared to outputs generated using the NARR of 12 mm/hr. These differences are consistent across flood depths, velocity, hazard and return periods.

The simulated results for the Lin Dyke catchment, however, show a larger variation in flood risk when comparing the NARR and CAF removal rates results. The results indicate that although there is minimal difference between the outputs for the 1-in-10-year and 1-in-30-year events, there is a larger difference of 8.36 % in the outputs of the 1-in-100-year event. The results indicate that the CAF-derived inputs

increased the catchment area exposed to shallow flooding, but decreased the area exposed to deeper flooding. Locations 1 to 4 present where the differences in flood extent and hazard pose a significant risk to properties. On a large scale an 8.36% difference in flood extent may seem small, this difference is important at a local scale for stakeholders concerned with funding flood defences, housing, and any future infrastructure projects.

When using the CAF removal rates scenarios as inputs, volume of rainfall received by each catchment was increased. However, this increase in rainfall inputs did not translate to an increase in overall flood risk within the catchments, indicating a non-linear system that is governed by thresholds. Even though the difference is generally small, the CAF removal rates produce a slightly larger flood extent in all three case studies. The results also show that the value in the use of the CAF for drainage representation in models will vary based on the catchment itself and the local parameters. For instance, smaller catchments such as Lin Dyke may be more reactive to changes in rainfall. The open channel watercourse in the town of Garforth located in the north of Lin Dyke has been culverted in a piecemeal fashion and new drainage infrastructure has been connected, seemingly without regard to capacity limitations. Since the drainage system is already a problem, Lin Dyke is more susceptible to changes in the inputs. Furthermore, even though the drainage system hasn't been explicitly represented, any representation of the system draws even more attention to the fundamental issue. Additionally, larger storm events in large catchments likely overwhelm the catchment, i.e., once flooding has passed the out-of-bank threshold and has filled the floodplain, the increase in rainfall only marginally increases the flood extent.

Each catchment contains less than 5 percent of the hexagons that are classified as a risk score of five, this likely has a small influence on the overall flood risk. Especially if these hexagons are in rural areas, or where the pipes are not directly or closely linked to the larger systems or hydraulic structures. The CAF data presented in this paper also provides an incomplete picture of the sewer capacity and performance of the drainage system, this is highlighted by the hexagons identified as no data. Despite that, significant areas in each of the catchments have complete data sets, therefore the data presented can still be used to design interventions at a high level. For instance, CAF data can aid in the analysis of potential estimation of the impact of increasing sustainable urban drainage systems (SUDs) in hexagons that have high-risk levels and estimate the costs and benefits of increasing green space in selected hexagons. It must be noted that the interpolation method used to derive CAF removal rates uses 12 mm/hr (as the upper threshold), and this was based on the NARR. However, different catchments will have different NARRs, as specified by the RoSWF (Environment Agency, 2013). Hence potentially, catchments that have higher NARR will show greater differences. Nonetheless, the interpolation method used to derive the CAF removal rates for the CAF risk scores is adaptable and can be amended to any given threshold, thus making it applicable to any location.

The subject of the absence of sewer modelling data however is not limited to this paper, to date, only 25% of the surface water sewers in England and Wales have been modelled. For Yorkshire, the total percentage of surface water sewers currently modelled is only 30% (Udale-Clarke, 2018). Therefore, an obvious effort needs to be made to improve the coverage of models to generate complete CAF datasets. It is also important to note that some pipes are designed to surcharge significantly (without causing flooding), and the CAF does not omit these pipes from the red-length modelled, therefore some hexagons identified as high-moderate to high risk may be at a lower risk level. Additionally, it is unknown if the risk in a specified hexagon is due to the foul, combined or storm drainage system. Hence, when applying engineering interventions, it is important to consider the unknowns and uncertainty associated with the CAF inputs and outputs.

The method presented in this paper was also created to reflect current practice, so that it is easier to adopt and implement. Therefore we use REFH2 to adjust the hydrographs to allow for drainage capacity

based on the risk score and the interpolated values. Hence, the expertise required for this method is similar to the expertise that would be required for a normal modelling study with no significant additional budget being required to implement the methodology (Petrucci & Tassin, 2015; Teng et al., 2017). Although the removal rates for NARR and CAF have been compared, a detailed uncertainty analysis has not been done. Uncertainties also include characteristics such as varying rates of urbanisation, lack of model validation and rainfall variability and therefore should be considered for any further work associated with using the NARR and the CAF.

The results presented in this paper do not include the impacts of climate change on the rainfall inputs or a future increase in population, however, the CAF datasets do include these in aggregate scores for the epoch of 2030, 2050 and 2080. Under future scenarios, the capacity and performance of drainage systems are likely to deteriorate. Moreover, the frequency of extreme events is projected to increase, the Environment Agency guidance for rainfall uplifts for the region of Leeds is 20% central allowance and 35% upper-end allowance for the epoch 2050. For epoch 2070 the uplift allowance changes to 25% for the central allowance and 40% for the upper-end allowance (Met Office Hadley Center, 2019). The combination of ageing infrastructure with an increase in extreme events suggests that a better representation of real drainage systems capacities is becoming more important and will make local solutions more resilient and relevant to the realities on the ground.

5. Conclusions

In this paper, a methodology to use the CAF outputs for the representation of spatially varied drainage capacity was successfully implemented in flood models for the first time for three catchments in Leeds. The availability of the CAF data provides insights into the current state of the drainage system within catchments in the form of red-length pipes and aggregate scores. Using the information provided by the CAF dataset, a novel approach is developed to translate CAF risk scores into spatially varied drainage removal rates that can be used in flood models to better represent real drainage systems. The proposed approach improves on the simplified use of the 12 mm/hr national average drainage removal rate that is normally used to represent drainage systems uniformly across a catchment.

The developed methodology for converting CAF risk scores to drainage removal rates was applied to three urban catchments in Leeds, UK, namely, Holbeck, Wyke Beck and Lin Dyke. The three catchments have a long history of flooding and are key locations of current and future flood risk management. Three return periods and two scenarios for each return period were used to demonstrate the use of the CAF data set and the impact it has on flood risk. For two out of three catchments, flood risk only moderately increases, however, the catchment of Lin Dyke showed important local differences in the flood risk when using the CAF-derived rainfall removal rates for drainage representation.

The results show that the CAF dataset produced an increase in the rainfall inputs that are used for flood modelling, however, the increase in rainfall inputs did not always translate to an increase in flood extent. The difference in the extent and magnitude of flood risk is a function of the individual characteristics of the catchment. These characteristics include but are not limited to, urban extent, topography and the number of hexagons that have a high-risk score. Additionally, the analysis showed that the model results were not, at an average scale, largely affected by a variable representation of drainage removal rates derived using the CAF for the catchments. However, these small differences may still be of great importance when implementing flood risk management strategies, future developments, and investments.

In this case, three case studies were used which responded differently to the use of CAF-derived drainage representation. This indicates that drainage representation is valuable in flood models, however, the importance is a function of the catchment, location, and scale. Therefore, applying the CAF dataset and the methodology outlined in this

study to other catchments in the UK is important to understand the wider implication of this dataset and methodology. Doing this will enable us to understand and quantify the implications of using variable drainage representation in flood models. Additionally, case studies are also necessary to determine how catchments with certain parameters are more sensitive to drainage representation. Further work should also focus on quantifying the value of using the CAF dataset and the methodology presented in this paper under climate change projection scenarios. Although the removal rates for NARR and CAF have been compared, a detailed uncertainty analysis has not been done, but would be useful in future work.

CRedit authorship contribution statement

Amrie Singh: Conceptualization, Methodology, Investigation, Visualization, Writing – original draft, Writing – review & editing, Formal analysis. **David Dawson:** Supervision, Writing – review & editing. **Mark A. Trigg:** Supervision, Writing – review & editing. **Nigel Wright:** Supervision, Writing – review & editing. **Claire Seymour:** Writing – review & editing. **Luke Ferriday:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jhydrol.2023.129718>.

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