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A Subgrid Modelling Approach to Nature-Based Solutions (NbS): Enhancing Flood Risk Management in Riseley, UK

Amrie Singh[1,2] | Harry Mansfield[2] | Maria Pregnolato[3] | Nigel Wright[4]

[1]University of Leeds, School of Civil Engineering, Leeds, UK | [2]Create Consulting Engineers, Norwich, UK | [3]TU Delft, Faculty of Civil Engineering and Geosciences, Delft, the Netherlands | [4]University of Birmingham, School of Engineering, Birmingham, UK

Correspondence: Amrie Singh (cenasi@leeds.ac.uk)

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ABSTRACT

Subgrid sampling (SGS) has been increasingly integrated into hydraulic modelling to refine terrain representation without excessively increasing computational demands. This study investigates the effects of SGS and nature-based solutions (NbS), focusing on flow velocities, storage volumes and mass balance stability. Using a rain-on-grid TUFLOW model, we simulate a 1-in-30-year flood event across different NbS interventions, including leaky dams, floodplain planting and bunds with floodable depressions. Results demonstrate that higher SGS frequencies of 11 significantly enhance terrain resolution, improving the representation of flow paths and floodplain activation. However, a lower SGS frequency of three introduces notable numerical artefacts, leading to persistent negative cumulative volume errors and misrepresenting water retention within the system. NbS interventions generally minimise peak flow rates, with bunds and depressions (Option 3) proving the most effective, achieving a storage volume increase of up to 162.83% compared to the baseline scenario. Mass balance assessments show that models without SGS overestimate flood storage, potentially misguiding NbS implementation and compliance with flood storage regulations such as the UK Reservoirs Act (1975).

1 | Introduction

Climate change is progressing rapidly and is characterised by rising sea levels, retreating glaciers, changes in precipitation patterns and a rise in extreme weather events (Calvin et al. 2023; Miller and Hutchins 2017; Tao et al. 2004; Turner and Annamalai 2012). The impacts of climate change, including both short-term variability and long-term trends, highlight the need for solutions that include mitigation and adaptation (Owen 2020; Turek-Hankins et al. 2021). Adaptation efforts focus on minimising vulnerability to natural hazards like floods and strengthening the resilience of communities (Carter 2011; Eriksen et al. 2015; Mertz et al. 2009; Owen 2020). Local flood risk is influenced directly by hydroclimatic changes and by factors such as land use changes and modifications to river channels due to anthropogenic activities (Sietsma et al. 2021; Werritty 2006).

Historically, flood management has relied on engineering solutions aimed at safeguarding infrastructure. Whilst traditional flood management methods have effectively protected infrastructure, they have adverse effects on the natural hydrological processes (Sörensen et al. 2016; Wilby and Keenan 2012). These impacts include disrupted flow of water, reduced groundwater recharge, habitat loss and impaired ecosystem services. Additionally, engineered defences, typically designed to handle specific flood magnitudes, require continuous updates to maintain effectiveness under evolving climate conditions, leading to substantial economic costs (Chatterton et al. 2013; Perry and Nawaz 2008). Consequently, there is a demand for adaptation strategies that use sustainable natural resources and promote flood management practices to improve resilience against the increasing frequency of extreme weather events (Frame et al. 2020; Heller and Zavaleta 2009; Wilby and Keenan 2012).

Nature-based solutions (NbS) offer a more sustainable approach by working with natural processes to mitigate flood risks and enhance ecosystem health (Collins et al. 2023; Schanze 2017; Ungvári and Kis 2022). NbS utilize the inherent properties of landscapes—such as wetlands, forests and rivers—to reduce flood impacts, enhance biodiversity, improve water quality and strengthen long-term environmental health (Gijsman et al. 2021; Huang et al. 2020; Lane 2017; Müller et al. 2021; Short et al. 2019; UNDRR and UNU-EHS 2023; Van Coppenolle and Temmerman 2019). To fully understand and quantify the flood reduction benefits of NbS, hydrological and hydraulic modelling is used to analyse how NbS implementation can reduce flood hazard and risk (Hankin et al. 2020; Hill et al. 2023). However, the models often require high-resolution topographic, hydrological and meteorological data, alongside detailed information on both structural and non-structural hydraulic elements of the river and floodplains (Allitt 2009; Cea and Costabile 2022; Novak 2018; Teng et al. 2017). This demands substantial computational resources, forcing modellers to compromise between high data accuracy and manageable computation times (Guo et al. 2021; Jodhani et al. 2023; Teng et al. 2017).

To address the challenge of computation time whilst maintaining accuracy, several methods have been developed, including the use of Graphical Processing Units (GPUs) to accelerate computation, applying machine learning (ML) techniques to improve prediction accuracy and reduce model complexity and simplifying the representation of channels and floodplains with 1D models and subgrid sampling (SGS) techniques (Fernández-Pato and García-Navarro 2021; Hosseiny et al. 2023; Hou et al. 2020; Liang et al. 2016; Mark et al. 2004; Mosavi et al. 2018; Reshma et al. 2024; Rizeei et al. 2019; Vojinovic and Tutulic 2009). Each approach helps balance the need for detailed modelling against the practical limitations of computational resources for effective implementation and analysis of NbS. GPUs for simulations use parallel processing to manage the high-resolution DEM efficiently, handling extensive datasets without increasing computational times. GPUs are efficient but a less popular option in practical engineering due to their cost and the high specification of computational hardware required (Fernández-Pato and García-Navarro 2021; Neal et al. 2012). Similarly, ML techniques, such as Artificial Neural Networks, integrate with hydraulic models to speed up processing times; however, the effectiveness of ML models relies on the availability of substantial, event-specific data, which is often lacking, thus limiting their applicability (Grenier et al. 2024; Hosseiny et al. 2023; Mosavi et al. 2018; Schmidt et al. 2020). Simplified hydraulic models speed up calculations by omitting certain terms from the shallow water equations, expediting the computational process significantly compared to more comprehensive 2D models (Ghimire et al. 2014; Horritt and Bates 2002; Hunter et al. 2008; Lin et al. 2005). Although a simplified approximation of the equation in models reduces processing time, it compromises the granularity of data, such as flow velocities critical for accurate flood hazard mapping.

In contrast, SGS techniques offer a balanced approach that retains high-resolution detail without the substantial computational overhead of full-scale models (Begmohammadi et al. 2024; Casulli 2019; Neal et al. 2012). SGS methods refine the modelling within larger grid cells, capturing essential topographical details for accurate hydrodynamic modelling. This process of refinement makes them suited for detailed flood risk modelling where precision is key, but resource constraints limit the feasibility of high-resolution modelling. This feature is now widespread in software packages such as HEC-RAS, LISFLOOD-FP and TUFLOW (Bryant et al. 2023; Huxley and Syme 2020; Neal et al. 2012; Reshma et al. 2024).

Several studies have explored the application of SGS in flood modelling, covering a range of topics from real-time urban flood simulation and integration of topographic effects in urban settings to coupling hillslope hydrology with hydraulic models for watershed management (Hankin et al. 2020; Reshma et al. 2024). Specialised models for large-scale storm surges and detailed inundation mapping during significant events like Hurricane Sandy have also been developed (Loftis 2014; Woodruff et al. 2023). NbS strategies, such as wetland restoration or green infrastructure implementation, require nuanced consideration of the hydrology of the area. Integrating SGS into NbS modelling enhances spatial detail, improves predictive accuracy and supports better decision-making in flood risk management. By refining terrain representation, SGS allows NbS interventions to optimise flood mitigation (Kitts et al. 2020; Néelz and Pender 2007). Whilst SGS has been widely applied in urban and riverine flood modelling (Li et al. 2023; Neal et al. 2012; Rizeei et al. 2019), its impact on NbS performance remains underexplored. This study addresses this gap by demonstrating how hydrodynamic modelling can be applied to evaluate NbS interventions, ensuring their effectiveness particularly in flood risk contexts.

This study focuses on the village of Riseley (UK), a flood-prone area that serves as an ideal case study. Three NbS strategies—leaky dams, riparian plantings and offline storage are—tested under four SGS frequencies to quantify their effects on runoff reduction, volume storage and peak flow attenuation. These NbS measures are selected for their dual role in enhancing river morphology and providing sustainable flood relief (Ferguson and Fenner 2020; O'Donnell et al. 2019). The key objectives of this study are:

- To evaluate the impact of SGS resolution on NbS performance in flood modelling.
- To compare different NbS strategies under varying SGS frequencies.
- To assess the broader implications of SGS refinement in NbS implementation for flood resilience.

This research advances the understanding of how SGS influences NbS modelling accuracy and effectiveness, helping bridge the gap between hydrodynamic modelling and practical flood risk management.

2 | Methods

2.1 | Study Area

The study area is the catchment containing the village of Riseley (Figure 1), located in Bedfordshire (UK). The village has a long history of flooding during the winter due to intense and prolonged rainfall on saturated ground, causing rapid and high runoff volumes. Properties have often reported flooding from water overtopping Riseley Brook; in December 2020, there was standing water up to 500 mm deep on the ground floor of some properties (Bedford Borough Council 2021). The banks of the Riseley Brook also partially collapsed, and High Street in Riseley became impassable. Infrastructure located to the south of High Street and outside the river flood zones was impacted by overland surface water flow during this event. The Flood Risk from Surface Water Mapping indicated that overland flow routes formed in the fields to the south, encroaching on the property and surrounding areas (Environment Agency 2019). Several ditches originating in these fields discharge into Riseley Brook to the southwest of the affected properties (Balboni and Tandy 2021). Whilst some ditches are culverted beneath the road, others overtop onto High Street, following the topography towards Riseley Brook. High river levels in the Brook prevented these ditches from discharging freely, causing water to back up. Table 1 provides a brief overview of the notable flood events in the village.

The site selection for implementing NbS options, as highlighted in Figure 1, is strategically justified for several reasons related to the characteristics of Riseley Brook and the surrounding area. Firstly, the chosen NbS site is positioned immediately upstream of the village, so this location is ideal for interventions to reduce flood risk downstream. By implementing NbS measures

TABLE 1 | Historic flood events in Riseley Village (Bedford Borough Council 2021).

Date	Event
1968	Summer flood event
1987	Winter flood event
1992	Flooding of 800 mm in the autumn in the high street
1998	Spring floods
2001–2002	Winter flooding across two consecutive years
2020	Winter floods made the high street impassable
2023	High water levels and partial flooding through the village

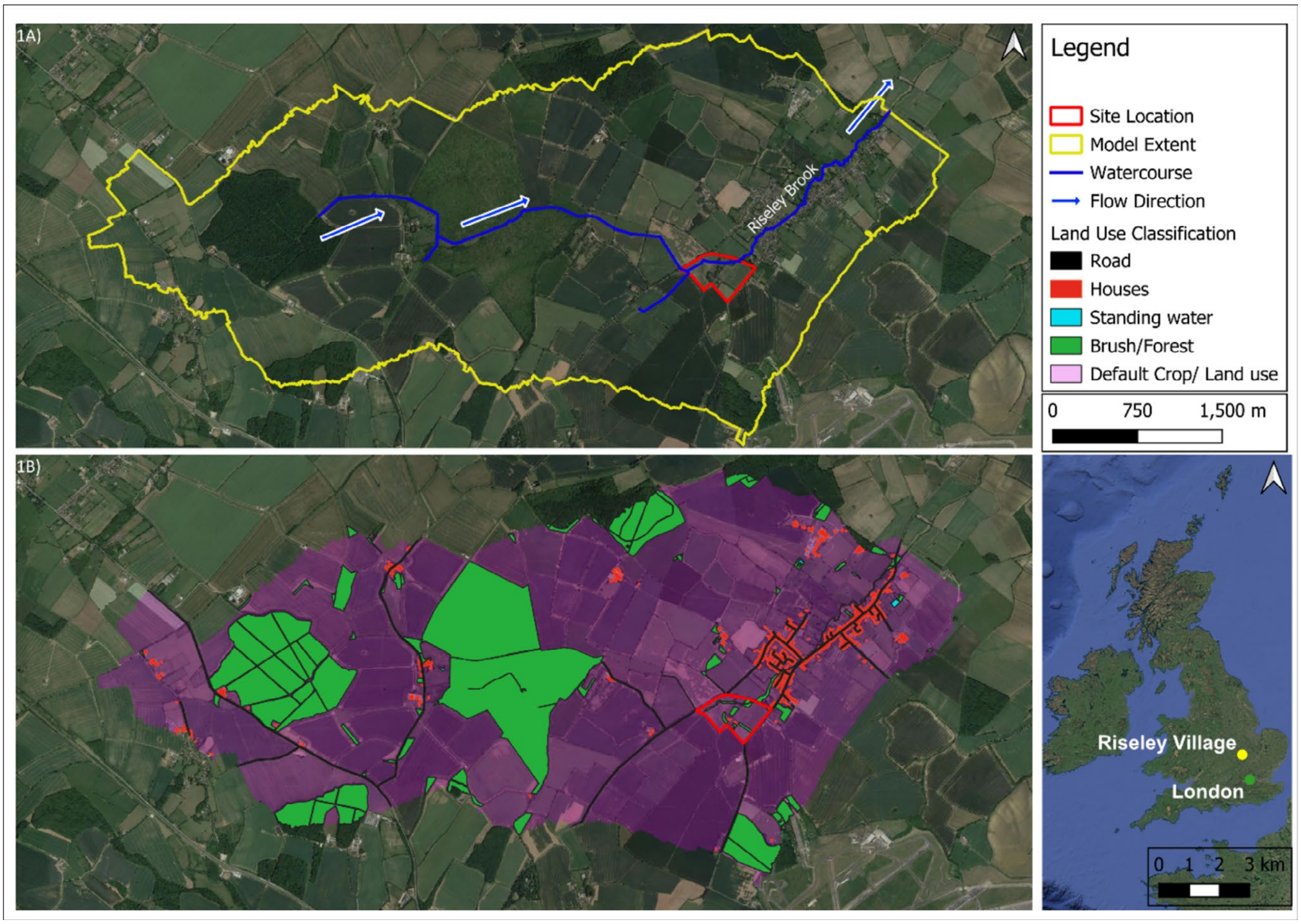

FIGURE 1 | (A) Location of Risely Village, the extent of the study area and the NbS site within the model extent and (B) types of land use in the study area.

upstream, the site can effectively moderate the flow of water entering Riseley Village, thereby mitigating the risk of flooding in populated areas.

Additionally, Riseley Brook flows west to east through the site, entering via a culvert under Riseley Road near Knotting Lane and exiting near the High Street intersection; hence, the site along this flow path allows for strategic placement of NbS measures to slow down and store floodwaters. The topographical features of the site are conducive to a range of NbS interventions. The river channel is deeply incised at both the western and eastern ends, shallower in the centre and deepens again before exiting. This varied topography offers opportunities for implementing different NbS tailored to the specific channel characteristics, such as creating pools and riffles in the shallower sections to enhance water retention and slow the flow. Additionally, the presence of three field drains feeding into Riseley Brook within this area presents additional opportunities for flood management. Managing these drains through NbS options can help control the flow of water entering Riseley Brook, reducing the volume and speed of runoff during heavy rainfall events.

2.2 | Model Description

2.2.1 | Build Type

The approach was a rain-on-grid model built within ESTRY TUFLOW. Reviewing the Environment Agency (EA) surface water modelling shows that the village of Riseley has a greater risk of surface water flooding than fluvial flooding; hence, capturing this rain-on-grid modelling was deemed appropriate. Most of the models, including major flow channels and culverts, are represented in 2D. The TUFLOW Engine version TUFLOW.2023-03-AA (released March 2023) was used for modelling. Figure 1 shows the modelled extent, including the study area where various NbS measures will be implemented, the village of Riseley and all contributing hydrological catchment areas. The model outflow is set to an unnamed road culvert downstream of Riseley. The total catchment area is 16.16 km^2.

EA-available LiDAR digital terrain models (DTM) were used for model topography at a 1-m resolution. The catchment includes a network of field drains and smaller channels, often culverted under farm tracks and roadways. Manual adjustments were made to ensure flows pass through these culverts, following the procedure for surface water modelling outlined by the Environment Agency (Environment Agency 2019). This procedure involves using shape files in TUFLOW to smooth over roadways and maintain flow path slopes. Figure 1B shows land uses within the catchment and is instrumental in setting the roughness and infiltration parameters of the model. The assigned values are presented in Table 2. Houses were represented using variable roughness to mimic the impact of low-flow drainage systems around the buildings and the inability of the systems to deal with incoming flows as water depth increases. Hence, for depth values < 0.03 m, a roughness of 0.02 is used, and for depths of > 0.1 m, a roughness value of 1 is used; for depths between 0.03 and 1 m, values are interpolated by TUFLOW.

TABLE 2 | Roughness coefficient and infiltration losses applied to the 2D model.

Land use	Roughness	Infiltration (initial losses/cumulative losses mm/h)
Default cultivated, no crop	0.05	0.2
Roads	0.022	0.2
Houses	0.03, 0.02, 0.10, 1.0	0.12
Standing water	0.03	0.2
Brush/forest	0.06	0.2

2.2.2 | Subgrid Sampling (SGS)

SGS, introduced in the February 2022 release of TUFLOW, improves the ability of the model to use high-resolution LiDAR data, even with grid cell sizes larger than the DTM (BMT 2020). This feature integrates additional elevation points along the boundaries of each TUFLOW grid cell, assigned from the DTM, allowing for more refined flow paths than those defined by the grid size. This enhancement improves the spatial accuracy of simulations without increasing computational time. This study implemented SGS with 3-, 7- and 11-point configurations on a 10-m grid size.

2.2.3 | Hydrology

This analysis uses a rain-on-grid model to include rainfall across the entire modelled extent. This method assigns a specific rainfall hyetograph to each cell within the modelled area, ensuring that rainfall intensity is uniformly distributed. Rainfall frequency and depth data for the catchment were obtained from the Flood Estimation Handbook (FEH) Web Service, utilising the latest FEH22 rainfall depth duration frequency model (Vesuviano 2022). Additionally, FEH Catchment descriptors were critical for defining catchment characteristics and were sourced from the FEH Web Service. The critical storm duration for the catchment is 11.6 h, rounded to 12 h; this duration was calculated using Equation (1) established by the Flood Studies Report (FSR)/FEH (Kjeldsen 2007)

$$\boldsymbol{D = Tp\left(1 + \frac{\mathrm{SAAR}}{1000}\right)} \tag{1}$$

where D is the design storm duration, Tp is the catchment time to peak and SAAR is the standard average annual rainfall.

The time to the peak was determined to be 7.15 h using a flood modeller REFH2. SAAR is taken directly from the FEH Catchment Descriptors and equals 622 for the catchment. Rainfall Storm Distribution is set to the FSR Summer profile, which was chosen due to its higher peak intensities compared to other seasonal profiles, aligning with the focus on assessing the model under more severe storm conditions. Areal reduction factor (ARF) converts the FEH-derived design rainfall into an areal rainfall (Kjeldsen 2007). This process replicates the non-uniform rainfall over a catchment area. The ARF is calculated using Equation (2) (Faulkner 1999; Kjeldsen 2007)

$$\boldsymbol{ARF = 1 - bD^{-a}} \tag{2}$$

where D is the duration in hours, and a and b are functions of area A in km^2. Therefore, for a catchment area of 16.16km^2, Equation (3) gives the ARF for 12 h, yielding 0.96 ARF:

$$\mathbf{1 - 0.1056 * \left((12)^{-0.387602}\right)} \tag{3}$$

The modelling will focus on the lower-order rainfall of 1 in 30-year events. The derived hyetograph for this event is presented in Figure 2.

2.3 | NbS Development

NbS processes target rainfall events of lower magnitude and higher frequency (Huang et al. 2020; Short et al. 2019). Three options are developed and tested for this study (Table 3).

Option 1 involves installing leaky dams within the main river channel, as shown in Figure 3. The dams are designed to slow water flows, create pooling and elevate water levels, facilitating the reconnection of the river with its floodplain (van Leeuwen et al. 2024). Leaky dams feature a 100 mm gap at the base to accommodate low flows and ensure fish passage (Müller et al. 2021). Eight leaky dams are used, and the location of the dams has been determined to ensure an even spread of storage, to take advantage of in-channel pooling and to take advantage of floodplain pooling. In TUFLOW, these interventions are modelled as structures that partially block water flow, increasing the likelihood of water spilling over the banks. Each barrier includes a 1D "culvert" element representing the 100 mm gap, matching the width needed to handle the baseflow of the channel.

Option 2 uses a combination of leaky dams and riparian and floodplain planting. A total of six leaky dams are used and spaced along the centre and lower portions of the NbS site. This option also uses floodplain bunding to interrupt and slow floodplain flows and floodplain planting. The schematisation of these features in the model is shown in Figure 3. The land use within the site shows the area already features significant vegetation along the riverbanks. Additional plantings that extend from the riverbank to the edges of the flood zone will enhance this existing vegetative growth. This increase in woodland cover is designed to improve soil infiltration capacities, reduce surface runoff and decelerate water flows across the landscape (Frantzeskaki 2019; UNDRR and UNU-EHS 2023). The enhanced vegetation cover stabilises the riverbanks and acts as a natural buffer, absorbing excess water during flood events. This newly introduced woodland has been represented in the hydraulic model as a new category of land use, with an associated Manning's roughness value and infiltration mm/h value of 0.1 and 0.2, respectively.

Option 3 uses offline storage areas and is implemented through low earthen bunds schematised across the floodplain and excavating floodable depression, as shown in Figure 3. The bunds act as additional blockages, enhancing water retention and ponding upstream, thereby increasing the floodplain storage capacity during peak flow events. The floodable depression (Figure 3) is contoured to blend with the existing topography, with shallower side slopes than a 1:3 gradient for stability and safety. The depression is engineered to fill during flood events via a spillway that connects the river channel to the depression, creating a temporary water storage area.

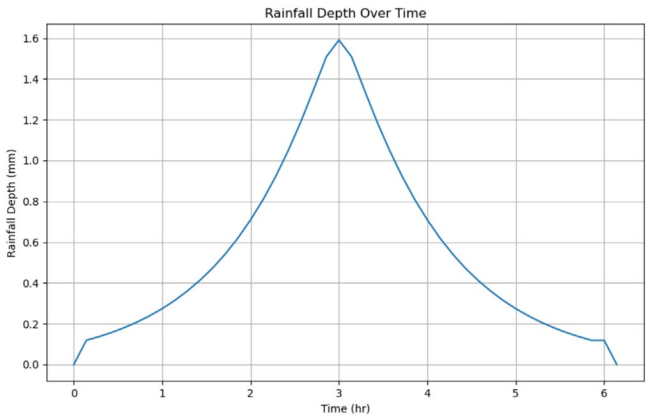

FIGURE 2 | Hyetograph for a 1 in 30-year return period applied to the model extent.

2.4 | Output Processing

The results are evaluated using two sets of metrics: primary and secondary. The primary metrics analyse the depth, velocity

TABLE 3 | List of NBS techniques (UNDRR and UNU-EHS 2023).

NBS technique	Description	Ecological benefits
Leaky dams	Dams (logs or wooden structures) should be installed across watercourses to slow water flow, promote storage and enhance sediment deposition	It creates diverse aquatic habitats, promotes and supports fish spawning and increases biodiversity
Offline storage areas	Creating areas adjacent to rivers for temporary floodwater storage during high flows reduces flood peaks and provides additional storage	Enhances habitats, supports amphibians and wading birds, promotes nutrient cycling and reduces soil erosion
Riparian woodlands	Planting trees along riverbanks to stabilise banks, reduce erosion, increase water uptake, provide shade and improve aquatic habitats	Improves water quality pollutants, increases biodiversity and reduces thermal stress on fish

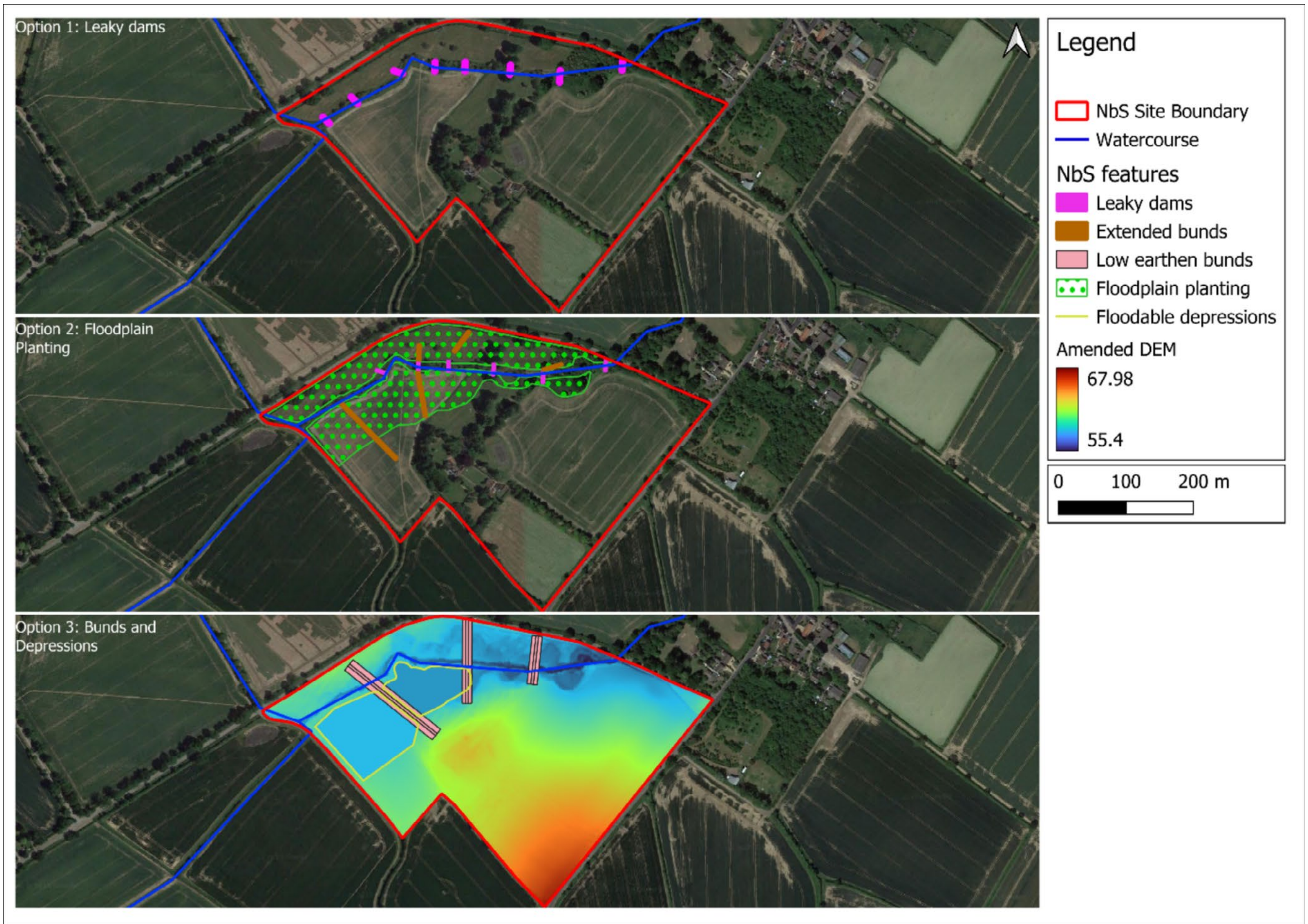

FIGURE 3 | Schematisation of Option 1, 2 and 3 NbS interventions within the model.

and flow rates. The secondary metric calculates the total volume of water stored within the NbS site during the simulated flood events. The storage volume at the site was calculated using the depth raster data obtained from the flood modelling results. The depth raster files, which provide water depth at each grid cell within the study area, were utilised. Only the cells within the defined NbS site boundary were considered for the storage volume calculation. A depth threshold of 0.1 m was applied to exclude shallow depths that do not significantly contribute to storage. For each relevant cell, the water volume was calculated by multiplying the cell area by the maximum recorded water depth; the volume for each cell was determined by Equation (4).

$$\textbf{Volume} = \textbf{Cell Area} \times \textbf{Depth} \tag{4}$$

The total storage volume at the NbS site was then obtained by summing the volumes of all relevant cells within the site.

3 | Results and Discussion

The primary objective of the NbS measures in this study is to enhance flood resilience by maximising flood storage whilst minimising peak flow rates. This balance is crucial for ensuring effective flood attenuation without causing excessive water retention in areas where flooding is undesirable. Each NbS measure is evaluated based on its ability to increase storage capacity, reduce peak discharge and promote floodplain reconnection. The SGS is assessed in this context, examining how different SGS configurations influence these outcomes. Hence, these objectives frame the results to provide a clear basis for interpreting which NbS strategies and SGS configurations are most effective. Table 4 provides a summary of the scenarios run and the naming convention which will be used to discuss the results.

3.1 | Impact of SGS on Primary Metrics

The results indicate that the inundated area, velocity and peak flow rate are the largest in scenarios where no SGS is applied (denoted by 00). For instance, under the BSLN_00 scenario compared to scenarios with SGS frequencies (BSLN_03, BSLN_07 and BSLN_011) (Figure 4), higher SGS frequencies consistently show lower inundated areas than BSLN_00. This is because SGS refines the floodplain representation and reduces the extent of flooding, except within the channels. Higher SGS values capture more detailed landscape features, allowing the model to represent small channels, minor elevation changes and natural dams influencing water flow. For instance, the BSLN_03 scenario shows a 46.25% reduction in inundated areas compared to BSLN_00. However, the differences in regions inundated amongst BSLN_03, BSLN_07 and BSLN_011 are relatively small.

TABLE 4 | Summary list of simulation options and SGS sampling frequency.

Scenario name	NbS intervention	SGS configuration
BSLN_00	Baseline (No NbS)	No SGS
BSLN_03		SGS (3 points)
BSLN_07		SGS (7 points)
BSLN_011		SGS (11 points)
OP1_LD_00	Leaky dams	NoSGS
OP1_LD_03		SGS (3 points)
OP2_LD_07		SGS (7 points)
OP1_LD_011		SGS (11 points)
OP2_FP_00	Floodplain planting	NoSGS
OP2_FP_03		SGS (3 points)
OP2_FP_07		SGS (7 points)
OP2_FP_011		SGS (11 points)
OP3_BD_00	Bunds and depressions	NoSGS
OP3_BD_03		SGS (3 points)
OP3_BD_07		SGS (7 points)
OP3_BD_011		SGS (11 points)

FIGURE 4 | Flood depth within Risely under the simulated SGS frequencies.

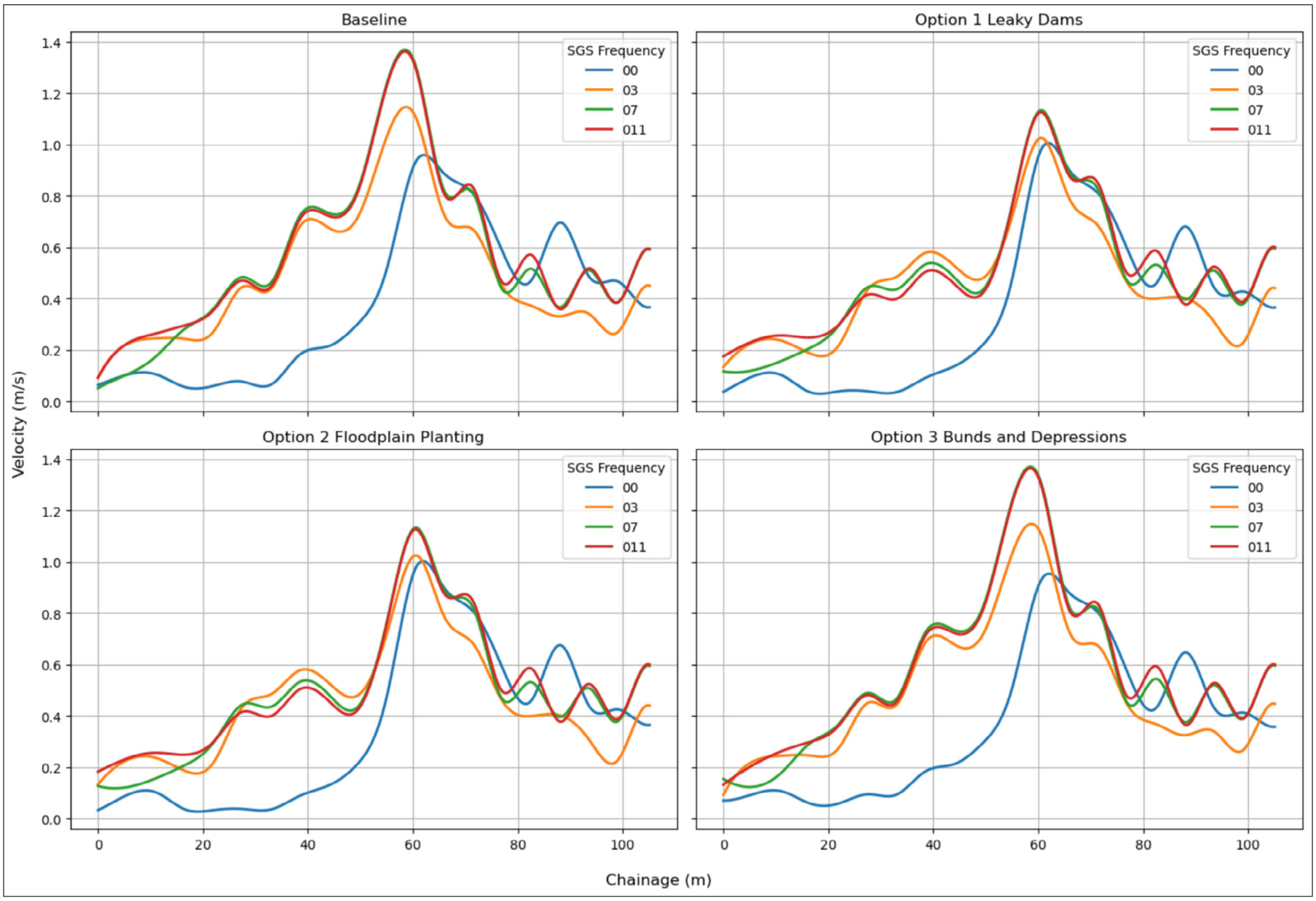

FIGURE 5 | Velocity profiles at the outlet for each NbS option under different SGS frequencies.

The plots in Figure 5 illustrate the influence of SGS on velocity distribution under different NbS scenarios. Higher SGS frequencies (BSLN_07, BSLN_011) result in sharper velocity gradients due to improved representation of flow paths and drainage networks. In contrast, lower-resolution terrain (BSLN_00) leads to a more uniform velocity distribution, as smaller-scale topographic variations are not captured, causing artificial water storage, slower movement and excessive floodplain diffusion.

BSLN_03 exhibits lower velocities than higher SGS scenarios. This is likely due to the following:

1. Terrain smoothing effects reduce flow turbulence (Polcher et al. 2023; Ryan et al. 2022).
2. Underrepresentation of small-scale dams and conduits prevents an accurate depiction of terrain-induced velocity fluctuations (Ryan et al. 2022).

Whilst SGS parameters allow water to flow between lower points within a grid cell, an insufficient resolution fails to capture finer drainage variations, affecting the accuracy of velocity predictions.

Higher SGS frequencies refine velocity distributions, simulating more realistic flow acceleration and turbulence patterns. With a more detailed terrain representation, water is directed into specific flow paths, reducing widespread floodplain storage and increasing flow efficiency (Polcher et al. 2023; Sehili et al. 2014). BSLN_011 exhibits the highest velocity increase, with a 16.85% rise from BSLN_00.

Amongst the NbS interventions:

- OP1_LD (leaky dams) slightly reduces velocity peaks, indicating that these structures partially slow and disperse flow energy. However, turbulence remains high in SGS scenarios, suggesting they delay rather than fully dissipate flow energy.
- OP2_FP (floodplain planting) smooths velocity distributions, especially in SGS03 and SGS07, but higher SGS settings still produce sharper peaks.
- OP3_BD (bunds and depressions) exhibits the highest velocity peaks, indicating temporary water retention followed by dynamic release, leading to strong, localised flow acceleration.

At higher SGS frequencies, post-peak velocities remain elevated, suggesting that it is efficiently channelled downstream once water is released. Table 5 and Figure 6 highlight that SGS increases peak flow rates across all scenarios compared to scenarios where no SGS is applied. For example, in the baseline scenario (BSLN_00), peak flow increases from 9.22 to 17.65 m^3/s,

TABLE 5 | Comparison of peak flow rates under different NbS options and SGS scenarios.

NbS option	Scenario	Peak flow rate (m^3/s)	Difference (%)
Baseline	BSLN_00	9.22	—
	BSLN_03	17.65	—
	BSLN_07	19.03	—
	BSLN_011	19.01	—
Option 1: Leaky dams	OP1_LD_00	8.98	2.62
	OP1_LD_03	17.28	2.09
	OP1_LD_07	18.59	2.33
	OP1_LD_011	18.55	2.41
Option 2: Floodplain planting	OP2_FP_00	8.98	2.66
	OP2_FP_03	17.23	2.39
	OP2_FP_07	18.59	2.29
	OP2_FP_011	18.57	2.36
Option 3: Bunds and depressions	OP3_BD_00	8.31	9.91
	OP3_BD_03	16.79	4.86
	OP3_BD_07	18.48	2.91
	OP3_BD_011	18.46	2.93

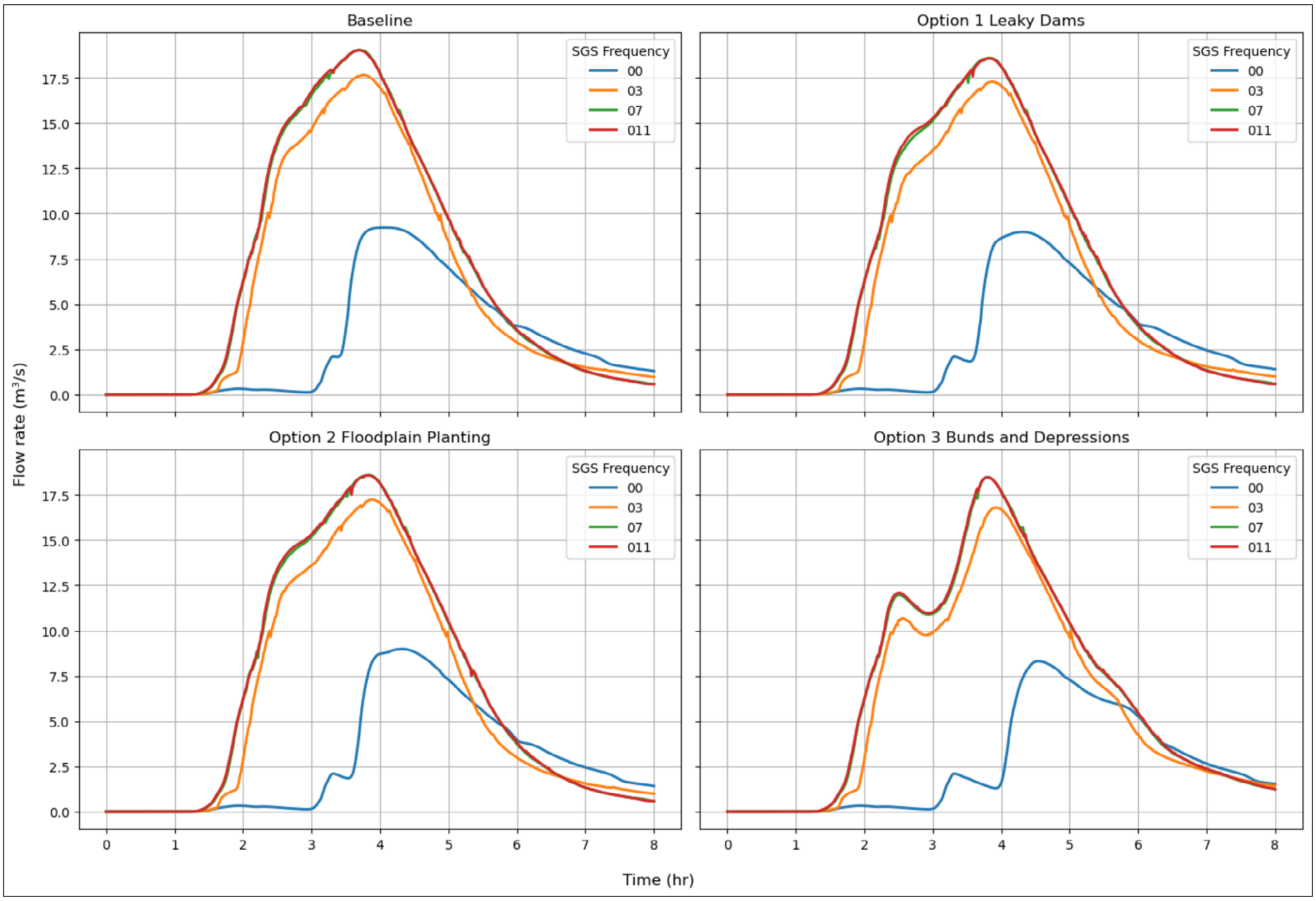

FIGURE 6 | Flow rate over time for different SGS configurations under baseline and NbS options.

19.03 and 19.01 m^3/s under SGS frequencies 03, 07 and 011, respectively. This is due to improved terrain resolution, which reduces artificial flood storage and allows water to drain more efficiently. Despite the increase in peak flows, NbS interventions remain effective in attenuating flood peaks. OP3_BD shows the most significant reduction, lowering peak flow by 9.91% under all SGS frequencies. For example, OP3_BD_00 reduces peak flow to 8.31 m^3/s, a 9.91% reduction from the baseline. Even under OP3_BD_03, OP3_BD_07 and OP3_BD_011, Option 3 maintains the lowest peak flow rates, confirming its ability to divert water into offline storage areas and delay peak flow arrival.

3.2 | SGS Performance and Model Stability

A key concern in applying SGS is whether observed changes in model outputs, such as increased peak velocities and more concentrated flow pathways, stem from improved terrain representation or numerical artefacts. To investigate this, cumulative volume errors across different SGS frequencies were analysed (Figure 7). The results indicate that the lower SGS frequencies exchange significantly higher volume errors over an extended period, indicating that lower SGS frequencies may introduce numerical inconsistencies due to terrain smoothing effects that misrepresent small-scale flow features. The higher SGS frequencies appear to converge on similar behaviours, implying a minimum threshold beyond which additional refinement yields diminishing returns. Further evidence comes from the velocity profiles at the site outlet. The lower SGS frequencies (03) produce underrepresented peak velocities and a more diffusive floodplain response. In contrast, SGS 07 and 011 capture sharper flow acceleration, indicating that terrain representation, rather than numerical instability, drives the observed changes in model behaviour. Nonetheless, it remains essential to balance SGS refinement with computational efficiency and numerical stability. Overly delicate SGS settings could lead to excessive velocity fluctuations or artificial flow concentrations. The results indicate that SGS 07 provides a suitable balance, effectively refining terrain-driven flow paths without introducing excessive numerical artefacts.

3.3 | Impact of NbS Development

Across all development types (BSLN, OP3_BD, OP1_LD and OP2_FP), the scenario with no SGS consistently results in the highest storage volumes (Figure 8). The absence of SGS means the model fails to capture finer-scale drainage pathways, which could result in water being trapped in artificial depressions rather than moving efficiently across the landscape. For example, in the baseline scenario (BSLN):

- SGS 03: 58.08% reduction in stored volume compared to no SGS settings.
- SGS 07: −50.07% reduction.
- SGS 11: −49.38% reduction.

This pattern is also evident in NbS interventions, where higher SGS configurations result in lower storage volume estimates. Under high SGS scenarios, water is distributed more efficiently than artificially accumulates in modelled depressions. This leads to overestimated flood storage volumes and unrealistic water retention within the model. With higher SGS frequencies, the artificial depressions are smoothed out, allowing water to follow natural flow paths and drain more efficiently across the floodplain. In models with no or low SGS frequency, the limited terrain resolution can cause premature or excessive floodplain inundation due to an inability to distinguish between channelised and overbank flow. When higher SGS frequencies are used, floodplain activation occurs only when natural overflow thresholds are reached. This leads to a more realistic representation of flood progression and storage. Amongst the NbS interventions, OP3_BD consistently demonstrates the highest flood storage capacity across all SGS settings. However, SGS refinement significantly reduces estimated storage volume, with OP3_BD storage decreasing from 49,208.14 to 32,192.77 m^3 under SGS

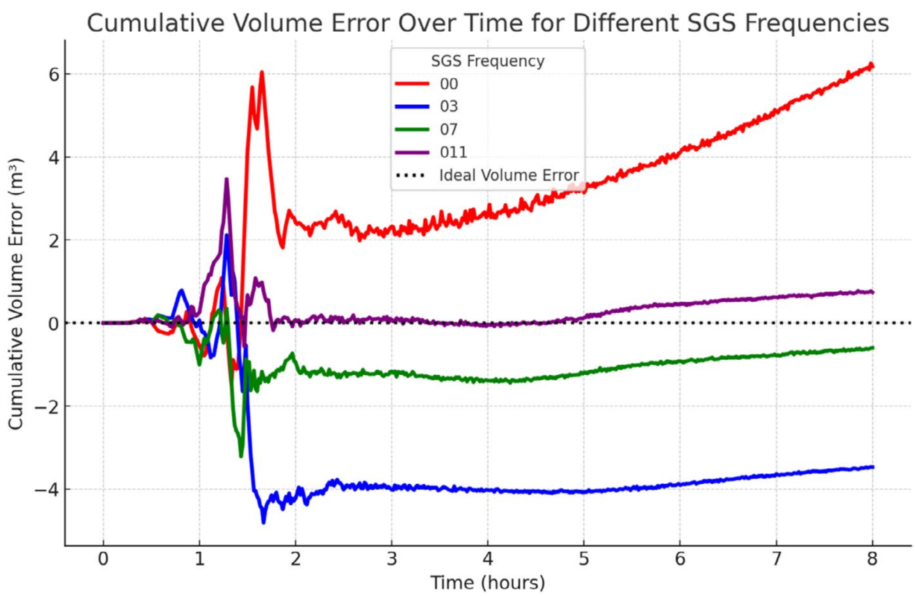

FIGURE 7 | Cumulative volume error of the simulated SGS frequencies for the BSLN development scenario.

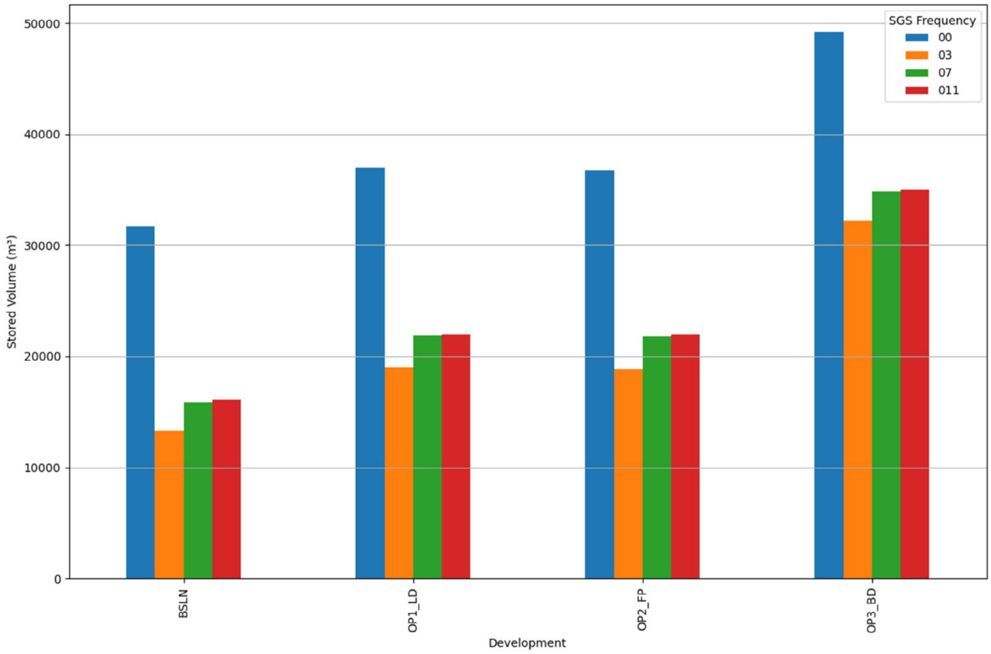

FIGURE 8 | Storage volume for the baseline, each NbS Option and the SGS frequency configuration.

03. A similar trend is observed in OP1_LD and OP2_FP, where storage volumes decline by approximately 40%–50% as SGS frequency increases. This reduction is attributed to improved terrain representation, which prevents artificial water retention in modelled depressions. Whilst this does not imply that NbS interventions are less effective, models without SGS may overestimate their retention capacities due to unresolved small-scale drainage pathways. Higher SGS frequencies enable a more accurate simulation of flood dynamics, reducing unrealistic ponding and providing a more realistic assessment of NbS performance.

Based on the calculated storage volumes and peak flow rates:

- Option 3 consistently shows the highest stored volumes across all scenarios (Figure 9) and a significant reduction in peak flow rates, indicating its effectiveness in enhancing local storage. The increases range from 105.72% to 162.83% compared to the baseline condition.
- Option 1 shows considerable increases in storage volume, ranging from 31.73% to 49.51% compared to the baseline scenario.
- Option 2 also shows significant storage capacity improvements, with increases ranging from 30.54% to 47.90% compared to the baseline scenario.

3.4 | Implications for Flood Risk Management

The findings from this study have significant implications for flood risk management, particularly in terms of how SGS influences flood modelling accuracy and the assessment of NbS. As demonstrated, SGS significantly impacts flow velocity, floodplain storage and the effectiveness of NbS interventions. Flood risk assessments relying on low-resolution terrain models (No SGS) may misrepresent flood behaviour. This has consequences for both flood mitigation planning and regulatory compliance.

The results confirm that terrain resolution and flow path representation critically affect predicted flood processes. In models without SGS, the terrain is oversimplified, leading to artificial floodwater retention and lower estimated velocities. This suggests that relying solely on models with no SGS may underestimate flood hazard intensity, resulting in poorly informed flood mitigation strategies. By contrast, higher SGS frequencies (SGS 07, SGS 011) provide a more accurate representation of drainage pathways, improving the prediction of floodwater movement and peak discharge timing. This is particularly crucial in urban planning and infrastructure resilience, where accurate flood extent and velocity estimates are essential for designing effective flood defences.

The study highlights that NbS interventions (e.g., leaky dams, floodplain planting and bunds and depressions) interact differently with flow conditions depending on SGS resolution. When SGS is not applied, NbS measures appear to store significantly more water than they likely do, leading to the overestimation of their retention capacity. This could result in over-reliance on NbS for flood mitigation, potentially underestimating residual flood risks and insufficient downstream flood protection. Higher SGS resolutions provide a more realistic assessment of NbS measures function under different flood scenarios. For instance:

- Leaky dams (OP1_LD) help slow down peak flows. Still, higher SGS frequencies reveal that flow turbulence and post-peak velocity remain significant, meaning these structures alone may not be sufficient for long-term flood mitigation.
- Floodplain planting (OP2_FP) enhances roughness and delays peak flows, but higher SGS settings suggest that its

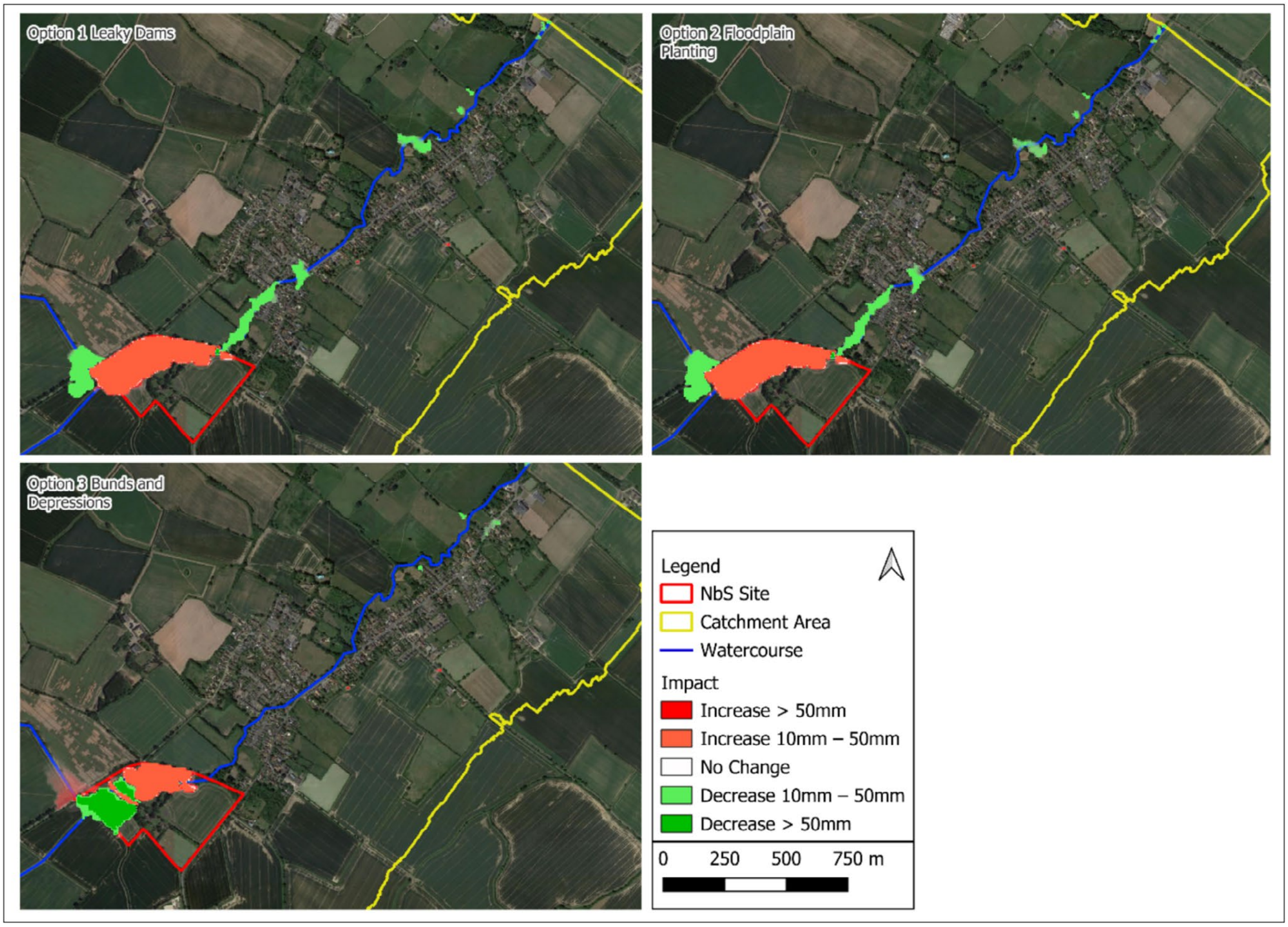

FIGURE 9 | NbS option shows varying degrees of flood depth reduction within the site boundary compared to the baseline, with Option 3 showing the most significant reduction.

impact on absolute storage capacity is less than previously estimated under NoSGS scenarios.

- Bunds and depressions (OP3_BD) provide the highest storage, yet when modelled with SGS, it becomes evident that these features function more dynamically than expected, with faster water release post-storage.

Integrating SGS-enhanced modelling into flood risk management allows decision-makers to assess the effectiveness of NbS more accurately and optimise their implementation within catchment-scale flood mitigation strategies. One key regulatory challenge identified is the discrepancy in storage volume estimates between models with and without SGS. Higher SGS resolutions produce lower, more realistic storage volumes, which may influence regulatory thresholds for flood storage classification. In the UK, the Reservoirs Act (1975) applies to reservoirs exceeding 10,000 m^3 of retained water, imposing strict safety regulations, inspections and maintenance requirements. The results indicate that without SGS, NbS interventions exceed this regulatory threshold due to overestimated storage volumes. However, when SGS is introduced, many NbS measures may fall below the regulatory definition of a reservoir.

If hydraulic models do not incorporate SGS, NbS measures may be incorrectly classified as reservoirs, subjecting them to unnecessary regulatory oversight under the Reservoirs Act (1975). This could lead to delayed approvals, increased engineering and monitoring costs and administrative burdens, ultimately discouraging the widespread adoption of NbS as a viable flood mitigation strategy. Conversely, SGS-refined models ensure that only large-scale retention features requiring regulation are classified as reservoirs, avoiding unnecessary restrictions on NbS implementation. Since NbS solutions such as bunds, depressions and floodplain planting offer cost-effective and environmentally sustainable flood mitigation benefits, reducing regulatory barriers through SGS-corrected models can accelerate their uptake. Additionally, relying on low-resolution models that overestimate storage could result in under-preparedness for extreme flood events, as actual retention capacity may be lower than predicted. Therefore, ensuring regulatory frameworks account for SGS-based modelling refinements will be essential for advancing NbS strategies whilst maintaining regulatory compliance.

Whilst this study focused on a localised site, the findings have broader implications for catchment-wide flood risk management. NbS measures are most effective when implemented across a larger watershed, gradually reducing runoff, slowing flows and distributing floodwater storage throughout the landscape. Integrating SGS-based modelling in larger-scale flood planning could enhance decision-making in catchment-scale flood resilience programmes. By accurately simulating how flow paths interact with different NbS interventions, planners can identify optimal locations for interventions to maximise their cumulative impact. Additionally, SGS-enabled models could support climate adaptation strategies, ensuring that flood defences and NbS solutions remain effective under future climate conditions, where more intense rainfall events and higher runoff volumes are expected. Whilst higher SGS frequencies improve flood modelling accuracy, they also introduce higher computational costs. This means that decision-makers must balance the need for high-resolution simulations with practical constraints on processing power and modelling efficiency. Fine-resolution SGS settings (07, 011) for smaller urban catchments are ideal as they provide accurate local flow predictions. However, in large-scale catchments, coarser base grids combined with optimised SGS settings (e.g., SGS 03 or SGS 07) may offer a practical compromise, capturing key terrain features whilst maintaining computational efficiency.

4 | Conclusions

This study highlights the critical role of SGS in improving flood modelling accuracy and NbS performance assessments. By refining terrain representation, higher SGS frequencies (07, 011) provide a more realistic depiction of flow paths, velocities and storage capacities, leading to more reliable flood risk assessments. However, this comes at the cost of increased computational demand. Option 3 (bunds and floodable depressions) consistently demonstrated the highest flood storage potential, reinforcing the effectiveness of NbS in mitigating peak flows when strategically implemented.

From a policy and planning perspective, these findings stress the need for regulatory frameworks and flood modelling guidelines to integrate SGS as a standard practice. Without SGS, NbS storage volumes may be overestimated, leading to misclassification under reservoir regulations and potential dams to NbS adoption. The study also highlights the trade-off between model accuracy and computational feasibility, urging planners to strike a balance that ensures practical and data-driven flood management strategies.

Finally, whilst this study focused on a localised site in Riseley, NbS interventions are most effective when applied at a catchment scale. Future research should also explore how integrating NbS across entire watersheds can enhance flood resilience and improve floodplain connectivity. A key area for future research is conducting a sensitivity analysis to assess how variations in SGS frequency, model grid resolution and NbS design parameters influence flood modelling outcomes. Sensitivity analysis would help determine how different SGS settings impact peak flow estimates, storage capacity calculations and flow velocities. Additionally, investigating the sensitivity of NbS performance to factors such as soil infiltration rates, vegetation roughness and structural failure scenarios (e.g., partial blockage of leaky dams) would enhance the predictive reliability of flood models. Such an approach would strengthen confidence in model predictions, improving flood risk management decision-making and NbS planning at regional and national scales.

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Data Availability Statement

Data presented in this study are available from the corresponding author upon reasonable request.

References

Allitt, R. 2009. "Coupled 1D - 2D Modelling in Urban Areas." *WaPUG User Note* 40: 1–20.

Balboni, N., and M. Tandy. 2021. "Section 19 Flood Investigation Report: Riseley."

Bedford Borough Council. 2021. "Flood Investigation Report."

Begmohammadi, A., D. Wirasaet, N. Lin, J. C. Dietrich, D. Bolster, and A. B. Kennedy. 2024. "Subgrid Modeling for Compound Flooding in Coastal Systems." *Coastal Engineering Journal* 66: 434–451. https://doi.org/10.1080/21664250.2024.2373482.

BMT. 2020. "TUFLOW Release Notes (2020–01)."

Bryant, S., H. Kreibich, and B. Merz. 2023. "Bias in Flood Hazard Grid Aggregation." *Water Resources Research* 59, no. 9: 35100. https://doi.org/10.1029/2023WR035100.

Calvin, K., D. Dasgupta, G. Krinner, et al. 2023. "Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change." (Core Writing Team, H. Lee and J. Romero (eds.)). IPCC, Geneva, Switzerland. (P. Arias, M. Bustamante, I. Elgizouli, G. Flato, M. Howden, C. Méndez-Vallejo, J. J. Pereira, R. Pichs-Madruga, S. K. Rose, Y. Saheb, R. Sánchez Rodríguez, D. Ürge-Vorsatz, C. Xiao, N. Yassaa, J. Romero, J. Kim, E. F. Haites, Y. Jung, R. Stavins, C. Péan, Eds.). In *IPCC, 2023: Climate Change 2023: Synthesis Report*, Intergovernmental Panel on Climate Change (IPCC). https://doi.org/10.59327/IPCC/AR6-9789291691647.

Carter, J. G. 2011. "Climate Change Adaptation in European Cities." *Current Opinion in Environmental Sustainability* 3, no. 3: 193–198. https://doi.org/10.1016/j.cosust.2010.12.015.

Casulli, V. 2019. "Computational Grid, Subgrid, and Pixels." *International Journal for Numerical Methods in Fluids* 90, no. 3: 140–155. https://doi.org/10.1002/fld.4715.

Cea, L., and P. Costabile. 2022. "Flood Risk in Urban Areas: Modelling, Management and Adaptation to Climate Change. A Review." *Hydrology* 9, no. 3: 50. https://doi.org/10.3390/HYDROLOGY9030050.

Chatterton, J., C. Clarke, and E. Daley. 2013. "The Costs and Impacts of the Winter 2013 to 2014 Floods." *Project Summary* 28: 18–29. https://doi.org/10.1016/j.apergo.2015.03.019.

Collins, S. L., A. Verhoef, M. Mansour, C. R. Jackson, C. Short, and D. M. J. Macdonald. 2023. "Modelling the Effectiveness of Land-Based Natural Flood Management in a Large, Permeable Catchment." *Journal of Flood Risk Management* 16, no. 2: 12896. https://doi.org/10.1111/jfr3.12896.

Environment Agency. 2019. "What Is the Risk of Flooding From Surface Water Map?" http://publications.environmen.

Eriksen, S. H., A. J. Nightingale, and H. Eakin. 2015. "Reframing Adaptation: The Political Nature of Climate Change Adaptation."

Global Environmental Change 35: 523–533. https://doi.org/10.1016/j.gloenvcha.2015.09.014.

Faulkner, D. 1999. *Flood Estimation Handbook Volume 2: Rainfall Frequency Estimation*. UK Centre for Ecology and Hydrology.

Ferguson, C., and R. Fenner. 2020. "The Impact of Natural Flood Management on the Performance of Surface Drainage Systems: A Case Study in the Calder Valley." *Journal of Hydrology* 590: 125354. https://doi.org/10.1016/j.jhydrol.2020.125354.

Fernández-Pato, J., and P. García-Navarro. 2021. "An Efficient Gpu Implementation of a Coupled Overland-Sewer Hydraulic Model With Pollutant Transport." *Hydrology* 8, no. 4: 146. https://doi.org/10.3390/hydrology8040146.

Frame, D. J., S. M. Rosier, I. Noy, et al. 2020. "Climate Change Attribution and the Economic Costs of Extreme Weather Events: A Study on Damages From Extreme Rainfall and Drought." *Climatic Change* 162, no. 2: 781–797. https://doi.org/10.1007/s10584-020-02729-y.

Frantzeskaki, N. 2019. "Seven Lessons for Planning Nature-Based Solutions in Cities." *Environmental Science and Policy* 93: 101–111. https://doi.org/10.1016/j.envsci.2018.12.033.

Ghimire, S., M. Wilkinson, and G. Donaldson-Selby. 2014. "Application of 1D and 2D Numerical Models for Assessing and Visualizing Effectiveness of Natural Flood Management (NFM) Measures." *11th International Conference on Hydroinformatics*. https://academicworks.cuny.edu/cc_conf_hic/189.

Gijsman, R., E. M. Horstman, D. van der Wal, D. A. Friess, A. Swales, and K. M. Wijnberg. 2021. "Nature-Based Engineering: A Review on Reducing Coastal Flood Risk With Mangroves." *Frontiers in Marine Science* 8: 702412. https://doi.org/10.3389/fmars.2021.702412.

Grenier, M., J. Boudreault, S. Raymond, and M. Boudreault. 2024. "Projected Seasonal Flooding in Canada Under Climate Change With Statistical and Machine Learning." *Journal of Hydrology: Regional Studies* 53: 101754. https://doi.org/10.1016/j.ejrh.2024.101754.

Guo, K., M. Guan, and D. Yu. 2021. "Urban Surface Water Flood Modelling–A Comprehensive Review of Current Models and Future Challenges." *Hydrology and Earth System Sciences* 25, no. 5: 2843–2860. https://doi.org/10.5194/hess-25-2843-2021.

Hankin, B., P. Metcalfe, K. Beven, and N. A. Chappell. 2020. "Integration of Hillslope Hydrology and 2D Hydraulic Modelling for Natural Flood Management." In *Hydrology: Advances in Theory and Practice*, 73–86. IWA Publishing. https://doi.org/10.2166/nh.2019.150.

Heller, N. E., and E. S. Zavaleta. 2009. "Biodiversity Management in the Face of Climate Change: A Review of 22 Years of Recommendations." *Biological Conservation* 142, no. 1: 14–32. https://doi.org/10.1016/j.biocon.2008.10.006.

Hill, B., Q. Liang, L. Bosher, H. Chen, and A. Nicholson. 2023. "A Systematic Review of Natural Flood Management Modelling: Approaches, Limitations, and Potential Solutions." *Journal of Flood Risk Management* 16, no. 3: e12899. https://doi.org/10.1111/jfr3.12899.

Horritt, M. S., and P. D. Bates. 2002. "Evaluation of 1D and 2D Numerical Models for Prediting River Flood Inundation." *Journal of Hydrology* 268, no. 876: 87–99. https://reader.elsevier.com/reader/sd/pii/S002216940200121X?token=EEF8925393FE9CC48B8FE1F5363908CA07B2102C224FF788E03ECE0435EF7E02E8BBFF692DBBFF5082A1B9335D1041E3.

Hosseiny, H., C. C. Masteller, J. E. Dale, and C. B. Phillips. 2023. "Development of a Machine Learning Model for River Bed Load." *Earth Surface Dynamics* 11, no. 4: 681–693. https://doi.org/10.5194/esurf-11-681-2023.

Hou, J., Y. Kang, C. Hu, Y. Tong, B. Pan, and J. Xia. 2020. "A GPU-Based Numerical Model Coupling Hydrodynamical and Morphological Processes." *International Journal of Sediment Research* 35, no. 4: 386–394. https://doi.org/10.1016/j.ijsrc.2020.02.005.

Huang, Y., Z. Tian, Q. Ke, et al. 2020. "Nature-Based Solutions for Urban Pluvial Flood Risk Management." *Wiley Interdisciplinary Reviews: Water* 7, no. 3: 1–17. https://doi.org/10.1002/WAT2.1421.

Hunter, N. M., P. D. Bates, S. Neelz, et al. 2008. "Benchmarking 2D Hydraulic Models for Urban Flooding." *Proceedings of the Institution of Civil Engineers: Water Management* 161, no. 1: 13–30. https://doi.org/10.1680/wama.2008.161.1.13.

Huxley, C., and B. Syme. 2020. *Next Generation Urban Surface Water Modelling Capabilities*, 1–12. Stormwater Australia National Conference.

Jodhani, K. H., D. Patel, and N. Madhavan. 2023. "A Review on Analysis of Flood Modelling Using Different Numerical Models." *Materials Today Proceedings* 80: 3867–3876. https://doi.org/10.1016/j.matpr.2021.07.405.

Kitts, D., W. Syme, S. Gao, G. Collecutt, and P. Ryan. 2020. "Mesh Orientation and Cell Size Sensitivity in 2D SWE Solvers." *Submitted Paper for the IAHR 10th Conference on Fluvial Hydraulics, River Flow.*

Kjeldsen, T. R. 2007. *The Revitalised FSR / FEH Rainfall-Runoff Method. Centre for Ecology and Hydrology*, Centre for Ecology & Hydrology (CEH).

Lane, S. N. 2017. "Natural Flood Management." *Wiley Interdisciplinary Reviews: Water* 4, no. 3: e1211. https://doi.org/10.1002/WAT2.1211.

Li, C., N. Sun, Y. Lu, et al. 2023. "Review on Urban Flood Risk Assessment." *Sustainability* 15, no. 1: 10765. https://doi.org/10.3390/su15010765.

Liang, Q., X. Xia, and J. Hou. 2016. "Catchment-Scale High-Resolution Flash Flood Simulation Using the GPU-Based Technology." *Procedia Engineering* 154: 975–981. https://doi.org/10.1016/j.proeng.2016.07.585.

Lin, B., J. M. Wicks, R. A. Falconer Dsc, and K. Adams. 2005. "Integrating 1D and 2D Hydrodynamic Models for Flood Simulation." *Water Management* 159: 19–25.

Loftis, J. D. 2014. "Development of a Large-Scale Storm Surge and High-Resolution Sub-Grid Inundation Model for Coastal Flooding Applications: A Case Study During Hurricane Sandy." https://doi.org/10.25773/v5-15yy-8z84.

Mark, O., S. Weesakul, C. Apirumanekul, S. B. Aroonnet, and S. Djordjević. 2004. "Potential and Limitations of 1D Modelling of Urban Flooding." *Journal of Hydrology* 299, no. 3–4: 284–299. https://doi.org/10.1016/j.jhydrol.2004.08.014.

Mertz, O., K. Halsnæs, J. E. Olesen, and K. Rasmussen. 2009. "Adaptation to Climate Change in Developing Countries." *Environmental Management* 43, no. 5: 743–752. https://doi.org/10.1007/s00267-008-9259-3.

Miller, J. D., and M. Hutchins. 2017. "The Impacts of Urbanisation and Climate Change on Urban Flooding and Urban Water Quality: A Review of the Evidence Concerning the United Kingdom." *Journal of Hydrology: Regional Studies* 12: 345–362. https://doi.org/10.1016/j.ejrh.2017.06.006.

Mosavi, A., P. Ozturk, and K. W. Chau. 2018. "Flood Prediction Using Machine Learning Models: Literature Review." *Water* 10, no. 11: 1536. https://doi.org/10.3390/w10111536.

Müller, S., C. A. M. E. Wilson, P. Ouro, and J. Cable. 2021. "Leaky Barriers: Leaky Enough for Fish to Pass?" *Royal Society Open Science* 8, no. 3: 201843. https://doi.org/10.1098/rsos.201843.

Neal, J., G. Schumann, and P. Bates. 2012. "A Subgrid Channel Model for Simulating River Hydraulics and Floodplain Inundation Over Large and Data Sparse Areas." *Water Resources Research* 48, no. 11: 12514. https://doi.org/10.1029/2012WR012514.

Néelz, S., and G. Pender. 2007. "Sub-Grid Scale Parameterisation of 2D Hydrodynamic Models of Inundation in the Urban Area." *Acta Geophysica* 55, no. 1: 65–72. https://doi.org/10.2478/s11600-006-0039-2.

Novak, P. 2018. "Hydraulic Modelling–An Introduction." In *Hydraulic Modelling–An Introduction*, CRC Press, an imprint of Taylor & Francis Group. https://doi.org/10.1201/9781315272498.

O'Donnell, E., C. Thorne, S. Ahilan, et al. 2019. "The Blue-Green Path to Urban Flood Resilience." *Blue-Green Systems* 2, no. 1: 28–45. https://doi.org/10.2166/bgs.2019.199.

Owen, G. 2020. "What Makes Climate Change Adaptation Effective? A Systematic Review of the Literature." *Global Environmental Change* 62: 102071. https://doi.org/10.1016/j.gloenvcha.2020.102071.

Perry, T., and R. Nawaz. 2008. "An Investigation Into the Extent and Impacts of Hard Surfacing of Domestic Gardens in an Area of Leeds, United Kingdom." *Landscape and Urban Planning* 86, no. 1: 1–13. https://doi.org/10.1016/j.landurbplan.2007.12.004.

Polcher, J., A. Schrapffer, E. Dupont, et al. 2023. "Hydrological Modelling on Atmospheric Grids: Using Graphs of Sub-Grid Elements to Transport Energy and Water." *Geoscientific Model Development* 16, no. 9: 2583–2606. https://doi.org/10.5194/gmd-16-2583-2023.

Reshma, R., N. N. Devi, and S. N. Kuiry. 2024. "Real-Time Urban Flood Modeling: Exploring the Sub-Grid Approach for Accurate Simulation and Hazard Analysis." *Natural Hazards* 120: 9609–9647. https://doi.org/10.1007/s11069-024-06579-0.

Rizeei, H. M., B. Pradhan, and M. A. Saharkhiz. 2019. "An Integrated Fluvial and Flash Pluvial Model Using 2D High-Resolution Sub-Grid and Particle Swarm Optimization-Based Random Forest Approaches in GIS." *Complex and Intelligent Systems* 5, no. 3: 283–302. https://doi.org/10.1007/s40747-018-0078-8.

Ryan, P., B. Syme, S. Gao, G. Collecutt, and B. PhillipRyan. 2022. "Direct Rainfall Hydraulic Model Validation." *Hydrology and Water Resources Symposium*.

Schanze, J. 2017. "Nature-Based Solutions in Flood Risk Management–Buzzword or Innovation?" *Journal of Flood Risk Management* 10, no. 3: 281–282. https://doi.org/10.1111/jfr3.12318.

Schmidt, L., F. Heße, S. Attinger, and R. Kumar. 2020. "Challenges in Applying Machine Learning Models for Hydrological Inference: A Case Study for Flooding Events Across Germany." *Water Resources Research* 56, no. 5: 25924. https://doi.org/10.1029/2019WR025924.

Sehili, A., G. Lang, and C. Lippert. 2014. "High-Resolution Subgrid Models: Background, Grid Generation, and Implementation." *Ocean Dynamics* 64, no. 4: 519–535. https://doi.org/10.1007/s10236-014-0693-x.

Short, C., L. Clarke, F. Carnelli, C. Uttley, and B. Smith. 2019. "Capturing the Multiple Benefits Associated With Nature-Based Solutions: Lessons From a Natural Flood Management Project in the Cotswolds, UK." *Land Degradation and Development* 30, no. 3: 241–252. https://doi.org/10.1002/ldr.3205.

Sietsma, A. J., J. D. Ford, M. W. Callaghan, and J. C. Minx. 2021. "Progress in Climate Change Adaptation Research." *Environmental Research Letters* 16, no. 5: 054038. https://doi.org/10.1088/1748-9326/abf7f3.

Sörensen, J., A. Persson, C. Sternudd, et al. 2016. "Water." In *Re-Thinking Urban Flood Management-Time for a Regime Shift*, MDPI. https://doi.org/10.3390/w8080332.

Tao, N., C. Longxun, and Z. Zijiang. 2004. "The Characteristics of Climate Change Over the Tibetan Plateau in the Last 40 Years and the Detection of Climatic Jumps." *Advances in Atmospheric Sciences* 21, no. 2: 193–203.

Teng, J., A. J. Jakeman, J. Vaze, B. F. W. Croke, D. Dutta, and S. Kim. 2017. "Flood Inundation Modelling: A Review of Methods, Recent Advances and Uncertainty Analysis." *Environmental Modelling and Software* 90: 201–216. https://doi.org/10.1016/j.envsoft.2017.01.006.

Turek-Hankins, L. L., E. Coughlan De Perez, G. Scarpa, et al. 2021. "Climate Change Adaptation to Extreme Heat: A Global Systematic Review of Implemented Action." In *Oxford Open Climate Change*, vol. 1. Oxford University Press. https://doi.org/10.1093/oxfclm/kgab005.

Turner, A. G., and H. Annamalai. 2012. "Climate Change and the South Asian Summer Monsoon." *Nature Climate Change* 2, no. 8: 587–595.

UNDRR, and UNU-EHS. 2023. "Nature-Based Solutions for Comprehensive Disaster and Climate Risk Management: UN Office for Disaster Risk Reduction Toolkit for Integrated Planning and Implementation of Disaster Risk Reduction and Climate Change Adaptation." https://www.undrr.org/contact-us.

Ungvári, G., and A. Kis. 2022. "Reducing Flood Risk by Effective Use of Flood-Peak Polders: A Case Study of the Tisza River." *Journal of Flood Risk Management* 15, no. 3: 12823. https://doi.org/10.1111/jfr3.12823.

Van Coppenolle, R., and S. Temmerman. 2019. "A Global Exploration of Tidal Wetland Creation for Nature-Based Flood Risk Mitigation in Coastal Cities." *Estuarine, Coastal and Shelf Science* 226: 106262. https://doi.org/10.1016/j.ecss.2019.106262.

van Leeuwen, Z. R., M. J. Klaar, M. W. Smith, and L. E. Brown. 2024. "Quantifying the Natural Flood Management Potential of Leaky Dams in Upland Catchments, Part II: Leaky Dam Impacts on Flood Peak Magnitude." *Journal of Hydrology* 628: 130449. https://doi.org/10.1016/j.jhydrol.2023.130449.

Vesuviano, G. 2022. "The FEH22 Rainfall Depth-Duration-Frequency (DDF) Model."

Vojinovic, Z., and D. Tutulic. 2009. "On the Use of 1d and Coupled 1d-2d Modelling Approaches for Assessment of Flood Damage in Urban Areas." *Urban Water Journal* 6, no. 3: 183–199. https://doi.org/10.1080/15730620802566877.

Werritty, A. 2006. "Sustainable Flood Management: Oxymoron or New Paradigm?" *Area* 38, no. 1: 16–23. https://doi.org/10.1111/j.1475-4762.2006.00658.x.

Wilby, R. L., and R. Keenan. 2012. "Adapting to Flood Risk Under Climate Change." *Progress in Physical Geography* 36, no. 3: 348–378. https://doi.org/10.1177/0309133312438908.

Woodruff, J., J. C. Dietrich, D. Wirasaet, A. B. Kennedy, and D. Bolster. 2023. "Storm Surge Predictions From Ocean to Subgrid Scales." *Natural Hazards* 117, no. 3: 2989–3019. https://doi.org/10.1007/s11069-023-05975-2.