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Impact Of Remote Sensed Soil Moisture and Infiltration on Flood Dynamics Under Extreme Rainfall Events

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Abstract.

As climate change leads to heavier and more frequent rainfall, flooding, one of the most destructive natural hazards worldwide, is becoming an increasing concern in the United Kingdom. These changes elevate the risk of both flash floods and river flooding, placing pressure on communities, emergency planning, and infrastructure design. Reliable flood models are therefore essential for early warning and resilience planning. Flood behaviour depends on several interacting factors, including rainfall intensity, river flows, coastal levels, and infiltration, which strongly controls the proportion of rainfall converted into surface runoff. However, many traditional shallow-water-equation-based models neglect infiltration, potentially leading to unrealistic flood responses. This study introduces an improved modelling framework (DIVAST-TVD-GA) that integrates the Green–Ampt infiltration approach into a shallow-water hydrodynamic model and dynamically updates infiltration processes using satellite-derived soil moisture via a Kalman filter. A sensitivity analysis study conducted in York, UK, shows that including infiltration reduces simulated flood depths, volumes, and extent, while soil moisture data assimilation further influences runoff generation under varying antecedent conditions. While the framework was evaluated on a single case study, it is applicable to other catchments when calibration and validation data is available. Overall, the framework provides a basis for improving the representation of hydrological processes in flood modelling.

Keywords: Remote-sensed soil moisture, Green Ampt infiltration, Kalman Filter, flooding.

1 Introduction

Floods are one of the most damaging natural hazards globally and in the UK. In 2022, there were 176 floods worldwide, with direct economic losses of \$44.9 billion, affecting 57,100,000 people and causing 7,954 deaths [1]. In 2023, the Association of British Insurers estimated the annual cost of flooding in the UK at £700 million [2]. Climate change is expected to increase extreme rainfall intensity by 20–30% for England and Wales over the next 20–30 years [3]. As a result, major flood events such as flash flooding and large-scale river flooding will occur more frequently [4]. Floods are driven by a myriad of mechanisms, including rainfall, streamflows, coastal water levels, and infiltration [6]. Infiltration plays a vital role in flood modelling as it governs the amount of rainfall translated into surface runoff. The infiltration rate is highly sensitive to soil

moisture. Large areas of saturated soil often lead to higher runoff, particularly in metropolitan areas or regions with rich clay soils and low infiltration rates, thereby increasing the likelihood of floods [7].

Flood modelling helps us understand and predict how floods form, move, and impact people and places, allowing us to estimate where and when floodwater will spread and how severe the consequences may be [5]. Although soil moisture content is important for accurate flood modelling [4], most urban-scale flood models (e.g., [8, 9]) do not account for infiltration or dynamically evolving soil moisture. Even in models that consider infiltration, soil moisture is often estimated using simplified water-balance approaches and is not dynamically updated during simulation [4]. While data assimilation techniques such as the Kalman filter have been widely applied to hydrological modelling, they have been rarely applied to hydraulic and shallow-water models and flood map applications [4, 9, 10, 12]. Despite the nonlinearity of soil moisture processes, the standard Kalman filter remains a computationally efficient and stable first-order approximation for updating soil moisture, making it suitable for large-scale hydrodynamic applications [11].

The study develops a flood modelling framework that accounts for infiltration, assimilates remote-sensed soil moisture data, and dynamically updates soil moisture over time. The proposed framework integrates the Green-Ampt infiltration model, satellite-derived soil moisture data, and a data assimilation scheme into a shallow-water hydrodynamic model. The framework will be an essential tool in investigating the effects of soil moisture in future flooding scenarios.

2 Methodology

We developed the flooding framework by incorporating remotely sensed soil moisture data into the Green-Ampt infiltration model and into the DIVAST-TVD (Depth Integrated Velocity and Solute Transport - total variation diminishing) full shallow-water equation-based flood model [7]. The DIVAST model, Green-Ampt model, remote sensing of soil moisture and Kalman filter data assimilation are introduced in this section.

2.1 The DIVAST-TVD-GA model

The Green-Ampt and the data assimilation models are incorporated in the DIVAST-TVD model developed at Cardiff University [7] solves the Shallow Water Equations, resulting in the DIVAST-TVD-GA model. The DIVAST-TVD numerical solution scheme combines the traditional MacCormack scheme with a symmetric five-point total variation diminishing (TVD) term that employs a shock-capturing technique to maintain crisp gradients and prevent numerical oscillations. Infiltration was incorporated as a source term into the mass balance equation, yielding Eq (1).

$$\frac{\partial \zeta}{\partial t} + \frac{\partial q_x}{\partial x} + \frac{\partial q_y}{\partial y} = i - f \quad (1)$$

where t is time, ζ is water surface elevation above datum, q_x and q_y is discharge per unit width in the x and y directions, f is infiltration rate, and i is rainfall intensity. The infiltration process, modelled by the Green-Ampt equation [13], is incorporated into the DIVAST-TVD model.

2.2 Satellite data assimilation and Kalman filter

Accurate soil moisture assessment is critical for understanding how land reacts to extreme events [12]. While the Green-Ampt model captures crucial infiltration processes, its simplified subsurface dynamics may give inaccurate results with time. To improve modelling accuracy, data assimilation was utilised to blend modelled and measured soil moisture. In this investigation, a sequential Kalman Filter [15] was used. The model was initiated by soil moisture data and then regularly updated by comparing forecasts to observations. This method reduces uncertainty, corrects for model drift, and eliminates unrealistic infiltration during extended rainfall events. In this study, soil moisture data from the NASA Soil Moisture Active Passive (SMAP) project, which provides 9 km-resolution soil moisture estimates at three-hour intervals, were extracted from NSIDC [14]. The model domain ($8.5 \text{ km} \times 6.25 \text{ km}$) is comparable to the spatial resolution of a single SMAP pixel. Soil moisture was assumed to be uniform across the region and utilised as the initial conditions.

3 Case studies – York City in the United Kingdom

The DIVAST-TVD-GA modelling framework was applied to two flood cases in the city of York, UK (Fig. 1). The city of York is in East England, situated at the confluence of the Ouse and Foss rivers. The city is prone to flooding, e.g., in 2000, 2014, and 2015 [16; 17], thus modelling and preventing flooding at the location are critical for residents. York presents a challenging hydrodynamic and hydro-informatic environment because the area comprises a river confluence, dense urban housing, tightly spaced commercial blocks, key transport corridors, large green spaces, and river embankments, making flood pathways highly sensitive to infiltration, obstruction effects, and the representation of buildings in information and models.

Two case studies, namely Storm Eva (SE) and Storm Desmond (SD), both from 2015, were simulated. Storm Eva occurred on December 25, 2015, in the City of York. Hourly rainfall data taken from the National River Flow Archive at the Skelton station, showed a daily rainfall record of 50 mm on December 25, 2015, with the storm lasting 12 hours [18]. Storm Eva delivered torrential rain and rising river levels to York, flooding around 500 homes and prompting the evacuation of 250 people. River Ouse rose to 5.4 m during the storm. The second case, Storm Desmond (SD), recorded 341.4 mm of rainfall in 24 hours up to 1800 GMT on 5 December 2015 at Honister Pass in Cumbria, setting a new UK rainfall record. Storm Desmond was a significantly more intense rainfall event than Storm Eva and was used to test the effects of data-assimilated soil moisture under extreme rainfall conditions.

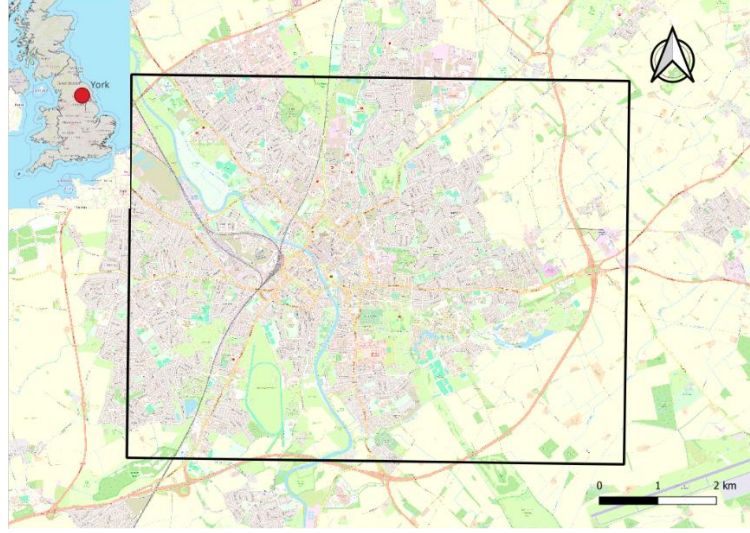


Fig 1: York City location within the UK

The study area covers approximately 55 km². Topographic data were obtained from 1 m-resolution LiDAR data provided by the UK government's Environment Agency. River cross-section data were obtained from an Environment Agency report [19]. A rectilinear mesh with a grid size of 10 m $\times$ 10 m was used, resulting in $850 \times 652 = 554,200$ grid points. The simulations depict combined rainfall-runoff (pluvial) and river (fluvial) flooding processes. The flow rate at Skelton station was imposed as the upstream inflow boundary condition, while the water level at Middlethorpe was used as the downstream boundary condition. The inflow boundary condition for the River Foss was based on measured flow rates at Huntington station. Rainfall was applied through a source term, i in Equation 1, throughout the domain. York is predominantly characterised by clay loam soils [20], and the Green-Ampt parameters used in this study were derived from Rawls et al. [21]. York's urban environment comprises dense built-up areas and extensive surrounding pervious green spaces, including floodplains, parks, and open land. In this study, Green-Ampt infiltration is applied solely to pervious surfaces, while impervious surfaces such as buildings and roads are specifically excluded from infiltration calculations using GIS masking. To represent the impact of urban features on flow dynamics, two building representation methods were applied. The Building Block (BB) method retains buildings within the computational grid but raises their elevation by 5 m, preventing water from flowing through them [22]. The Building Hole (BH) method treats buildings as voids that are removed entirely from the computational domain, following the approach described by Iliadis et al. [23]. Both approaches effectively handle impermeable areas as non-infiltrating surfaces, ensuring that hydraulic representation and infiltration models are consistent.

Table 1: The simulations that were carried out.

No	Case		Description
	SE	SD	
1.	1	7	Building Block No Green Ampt (No GA)
2.	2	8	Building Block Green Ampt, No Data Assimilation (GA and No DA)
3.	3	9	Building Block Green Ampt and Data Assimilation (GA and DA)
4.	4	10	Building Hole No Green Ampt (No GA)
5.	5	11	Building Hole Green Ampt, No Data Assimilation (GA and No DA)
6.	6	12	Building Hole Green Ampt and Data Assimilation (GA and DA)

4 Results

The total volume results in Figs. 2 and 3 show how infiltration and soil moisture data assimilation affect flood storage during the storms. When Green-Ampt infiltration is absent (No GA), all rainfall becomes surface runoff, leading to rapid increases in flood volumes. In Storm Eva, the simulated volume jumped from approximately 420,000 m³ to roughly 1,050,000 m³, indicating neglecting infiltration can dramatically exaggerate flooding. The GA model reduced flood volume to around 750,000-800,000 m³ by allowing some rainfall to infiltrate into the soil. When GA with Data Assimilation (GA and DA) was used, infiltration increases further because assimilated soil moisture raises the soil moisture deficit for these storms. As a result, more rainfall seeps into the ground and slightly diminishing surface storage.

4.1 Infiltration Rate

The infiltration curves in Fig. 4 show how infiltration changes during the two storms under data-assimilation (DA) and no-data-assimilation (No-DA) scenarios. Infiltration was at its maximum in both storms at first, then gradually decreased as the soil becomes wetter and its infiltration capacity decreases. For Storm Eva, DA resulted in somewhat higher infiltration than No-DA, especially at the beginning, indicating that soil moisture assimilation causes a greater moisture deficit. In Storm Desmond, the difference between DA and No-DA is minimal, implying that heavy rainfall limits infiltration.

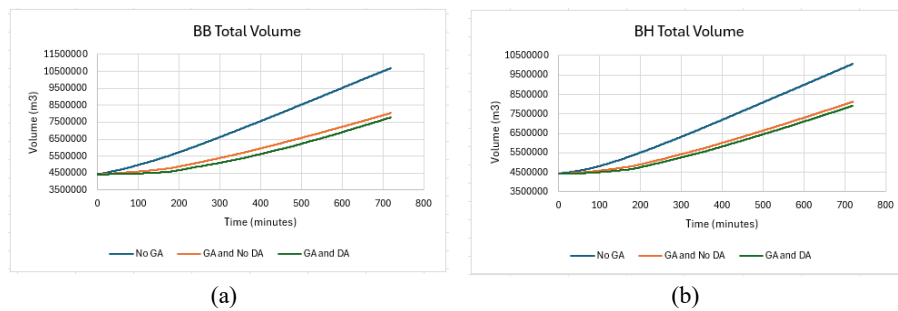


Fig 2: Total Volume graphs for Storm Eva on 25/12/2015 for (a) the BB method; and (b) the BH method

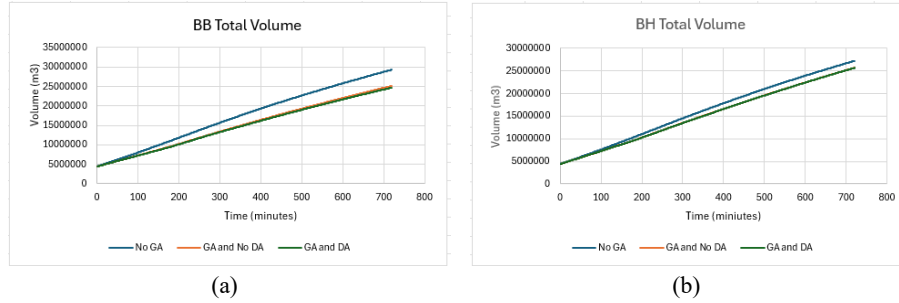


Fig 3: Total Volume graphs for Storm Desmond on 05/12/2015 for (a) the BB method, and (b) the BH method

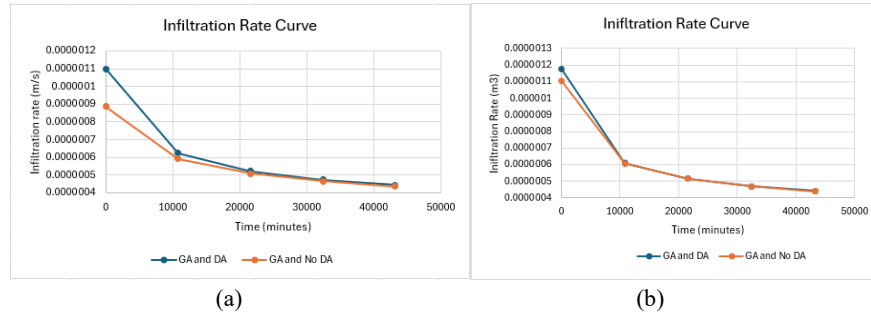


Fig 4: Infiltration rate curves for (a) Storm Eva and (b) Storm Desmond for both BB and BH scenarios

4.2 Soil Moisture

Figure 5 shows how soil conditions change during Storm Eva and Desmond. The initial SM and the observed SM have the same value of $0.40 \text{ m}^3/\text{m}^3$, since the initial satellite-observed SM is taken as the initial SM at the time the storm starts. As the downpour continues, the simulated soil moisture rapidly increases, approaching near-saturation levels. The assimilated soil moisture gradually adjusts to the observed values, enabling the model to depict soil conditions over time better. However, during both storms, the earth quickly became saturated and ceased to increase.

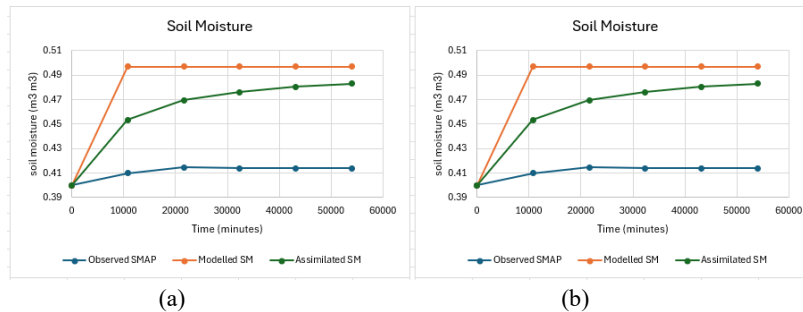


Fig 5: Soil Moisture curves for (a) Storm Eva, (b) Storm Desmond, for both BB and BH cases.

4.3 Flood Extent and Depth

Figures 6 and 7 show that the highest flood depth and extents were resulted in the No GA situations (Cases 1 and 7), particularly along river systems and in low-lying urban areas. When GA infiltration was used without data assimilation (GA and No DA) (Cases 2 and 8), some rainwater infiltrates into the soil, lowering both flood depth and total inundated area. The GA and DA in Figs 6(c) and 7(c) have the smallest flood extent and depth because the assimilation of soil moisture enhanced infiltration capacity, reducing surface water accumulation.

4.4 Water Depth at Monitoring Points

Figure 8 shows Storm Eva's water depth increases gradually throughout the simulation. Without infiltration (no GA), depths reach around 0.50 m at point (487,118) and 0.85 m at point (756,463) after 720 minutes. When infiltration is considered, depths fall, with GA and No DA providing lower values of approximately 0.38-0.40 m and 0.60-0.65 m, respectively. Figure 9 shows Storm Desmond caused significantly deeper flooding due to the heavy rains. Without infiltration, the depth at point (487,118) reaches about 2.6 m, but GA and DA reduce it to approximately 2.3 m, with comparable reductions at point (756,463).

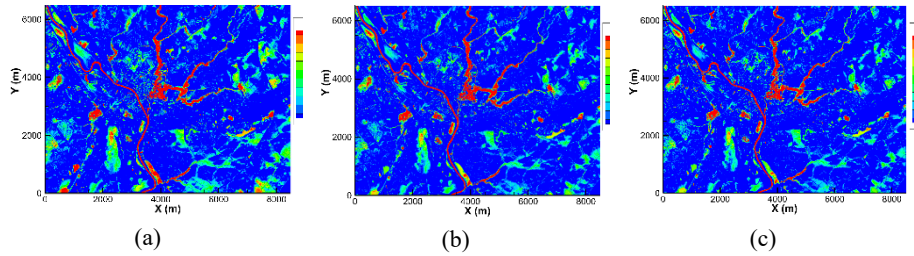


Fig 6: Flood extent during Storm Eva at 720 minutes. (a) Case 1; (b) Case 2; (c) Case 3.

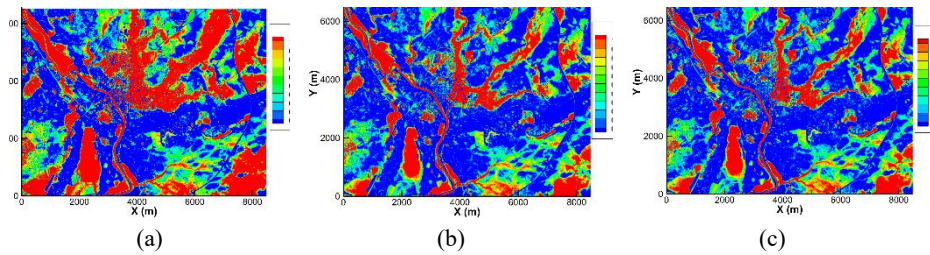


Fig 7: Flood extent during Storm Desmond at 720 minutes. (a) Case 7; (b) Case 8; (c) Case 9.

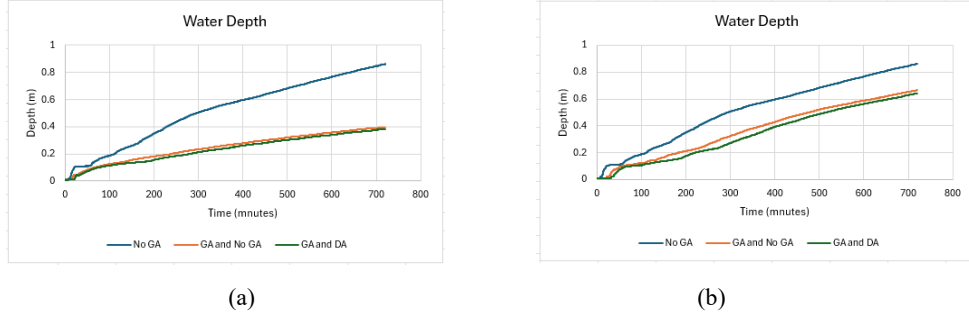


Fig 8: Water depth during Storm Eva, Case 1-3 at (a) point (487,118) and (b) point (756,463)

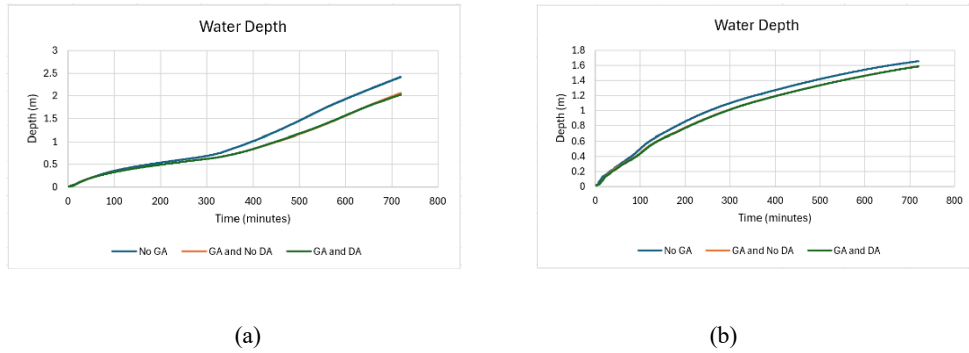


Fig 9: Water depth during Storm Desmond, Case 7-9 at (a) point (487,118) and (b) point (756,463)

5 Discussion

The framework's representation of actual flood behaviour was significantly enhanced with the addition of the Green-Ampt (GA) infiltration method. GA delayed the rise in water levels and reduced overall flood volumes in both building-block and building-hole configurations, as shown in Figure 8. This is because, rather than all the water turning into surface runoff, initially unsaturated soils absorb some of the rainfall due to moisture deficiency and capillary suction. The impact is most noticeable in Storm Eva, where flooding is greatly reduced by infiltration. Infiltration's ability to lower peak depths, even during the more powerful Storm Desmond, demonstrates its value in extreme circumstances (Figures 6 and 7). Results compared to GA-only simulations indicate somewhat larger flood depths and volumes when data assimilation (DA) is included (Figures 8 and 9). Once saturation is achieved, soil moisture values become similar across both storms, as shown in Figure 5, since the ground's ability to absorb rainfall has greatly reduced. This study highlighted the sensitivity of including infiltration and accurate data and knowledge of soil properties in flood modelling. While most severe floods are still managed by surface hydrology, infiltration primarily lessens flood peaks during flash floods. Once validated with real flood data, this will demonstrate that proper flood modelling requires the combination of surface flow and subsurface dynamics.

6 Conclusion

This study investigated how infiltration and soil moisture conditions influence flood modelling outcomes using a coupled DIVAST-TVD-GA framework. Three approaches were compared: models without infiltration, with Green–Ampt (GA), and with GA combined with data assimilation (DA). Across both Storm Eva and Storm Desmond, results consistently showed that excluding infiltration leads to higher simulated flood volumes, depths, and extent, as rainfall is fully converted into surface runoff. Incorporating Green–Ampt infiltration reduces these values by allowing water to infiltrate into the soil, whereas data assimilation modifies infiltration behaviour by dynamically updating soil moisture conditions. The results presented a sensitivity analysis of model behaviour, showing the effect of data-assimilated remote-sensed soil moisture on flood dynamics. Furthermore, the analysis is based on a single case study, so the findings will be transferable to other areas after validation with real-life flood data. Future work will focus on validating the sensitivity analysis results using real-life storm data for storms Eva and Desmond. Also, more work should focus on incorporating spatially variable soil properties, multi-layer soil moisture representation, additional remote sensing datasets, and testing the framework across multiple catchments, alongside uncertainty analysis to improve model robustness and applicability.

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