A Framework and Data Visualisation Approach to Grid-Asset Flood-Risk Prioritisation

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***Abstract*—Climate change is increasing the frequency of extreme weather, making substation flooding more likely, which causes severe cost to both equipment and communities. Given the volume of Distributed Energy Resources (DER) managed by organisations like Northern Powergrid, the time and cost of running advanced simulations and models on all of them is infeasible. This study investigates the combination of flood, terrain and energy-asset data to map the exposure of substations, in order to develop a framework for a reproducible data and visualisation workflow to identify priority targets for further assessment. The framework combines Northern Powergrid Open Data (substation locations, customer counts), Environment Agency Flood Maps (both coastal and surface water flooding), 10m LiDAR Digital Terrain Models (DTM), and UKCEH Land cover data. Risk is evaluated across physical hazard, terrain, vulnerability and consequence. These criteria are weighted into a single prioritisation score, by the flood data's 30, 100, and 1,000-year return periods. In a case study of the proposed framework, of Northern Powergrid substations in the County Durham area, 249 of the 4166 substations were identified as being exposed to some level of flood risk. 2 are high risk (score > 0.75), 21 are medium risk (score > 0.50), and 226 are low risk. The outcome is an efficient, reproducible framework and tool for evaluating an entire network of DERs for flood risk. This will allow operators to prioritise which substations require other, more high-fidelity surveys to improve their physical flood defences.**

***Keywords*—Distributed Energy Resources (DER), Flooding, Power Grid Resilience**

I. Introduction and Related Work

Flooding poses a significant hazard to electricity distribution networks, mainly through direct inundation of electrical components within ground-mounted substations [1], or through the structural failure of pole-mounted substations [2]. Climate change is expected to increase the frequency and severity of extreme rainfall and associated flooding [3], subsequently increasing the exposure of energy infrastructure to flood-related risks. Electricity supply infrastructure, including generation, storage, and distribution systems, is classified as 'Essential Infrastructure' under the National Planning Policy Framework (NPPF) [4], highlighting its importance to communities and the wider economy. According to the NPPF, the location of electricity assets is often constrained by operational requirements, making relocation often impractical. This creates a need to identify which assets are most vulnerable to flood hazards and where further assessment should be prioritised. Furthermore, recent UK heatwaves and associated periods of drought can increase the potential for flash flooding when followed by intense rainfall, as dry and hardened soils reduce infiltration and promote surface runoff [5]. The increasing occurrence of these extremes highlights the need for approaches to support flood-risk planning for critical energy infrastructure.

Existing approaches to assessing flood risk to infrastructure operate at contrasting spatial and computational scales. Detailed asset-scale studies can provide valuable insight into the complex consequences of flooding at individual sites. Methods aligned with the SAT-Guard project demonstrate this: 3D Computational Fluid Dynamics (CFD) paired with Deep Reinforcement Learning (DRL) evaluate hydrodynamic forces and control operations during floods, [6], while predictive control methods aim to keep substations running during storms [7]. Frameworks mainly target single-site resilience, such as formal verification approaches which assess long-term weather degradation of DERs [8], and digital twin approaches [9] offer valuable insight. However, these methods all require detailed, site-specific data, including the local physical properties of a site to train physics-informed machine learning models [10]. The associated computational requirements can make their application across an entire distribution network impractical, suggesting that deploying such intensive models across the thousands of substations managed at a county scale is infeasible without an initial screening stage to first identify the assets of greatest concern.

In contrast, network-wide screening approaches often prioritise scalability over granularity. County Durham's Strategic Flood Risk Assessment (SFRA) [11], for example, provides relevant local context, but considers flood exposure as a binary model, offering no differentiation between individual flood characteristics, such as flood depths, velocities, or probabilities. Existing overview methods for macro flood risk analysis have been used to calculate the cost of a flood [12], but are limited to pluvial (surface water) flood risk in urban areas – and therefore have a broader focus on resources at risk than DERs. Existing work across the initial review presents a significant trade-off: asset-scale methods retain hazard detail but do not scale, while network-wide methods scale but discard hazard detail. There is therefore a need for an intermediate approach that is scalable for network-wide assessment, while retaining greater information about a flood hazard's characteristics.

This study aims to address this gap through the development

of a reproducible, data-driven framework for prioritising flood risk across energy networks. The framework combines physical flood hazard, terrain susceptibility, asset vulnerability, and network consequence into an adjustable prioritisation score for individual substations. Rather than replacing more detailed modelling approaches, the framework is intended to identify which assets would benefit from such further assessment, acting as an informative network-wide screening stage. The study addresses two main questions:

1) Does combining flood hazard, terrain susceptibility, and network criticality produce a more informative prioritisation ranking than considering physical flood hazard alone?
2) Which factors contribute the most to infrastructure exposure, and can a reproducible framework based solely on open-access data support improved planning and prioritisation?

The framework is tested through a regional case study of Northern Powergrid substations across County Durham, with the intention of informing network operators of priority assets which may require further assessment. The use of openly available datasets and adjustable parameters supports repeatable assessment under alternative scenarios, while remaining computationally efficient to apply to the entire network.

II. Methodology

The framework used combines physical flood hazard (depth, velocity, and probability) with terrain susceptibility (terrain indices), asset vulnerability (substation type), and consequence (criticality to network) into a weighted prioritisation score, which is summarised in Fig. 1. Each flood risk component was retained independently before being aggregated into a combined score.

A. Physical Flood Hazard Characterisation

To quantify the physical hazard posed by floods at exposed locations, a flood hazard rating was derived which combines multiple hazard criteria as defined by the UK Flood Risks to People Methodology (FD2321) [13], including flood depth, flow velocity, and debris potential. This corresponds to the Physical Flood Hazard Rating within Fig. 1, which feeds directly into the Hazard Score used within the weighted aggregation. The hazard rating's original use was intended to be to assess danger to people, rather than infrastructure, therefore its application within this study relies on the assumption that depth, velocity, and debris loading also act as mechanisms for structural failure.

Flood depth was characterised using probabilistic flood-risk datasets that cover both fluvial/tidal and surface water flood sources. A series of maximum mapped depth thresholds were derived for each asset, across High, Medium, and Low likelihood tiers (Table I). To preserve the ordinal relationship between likelihoods, maximum depth was defined as the deepest threshold exceeded while a site remained within, or above, that specific tier.

TABLE I: Risk of Flooding Likelihood Categories [14], [15]

Likelihood	Annual Probability	Return Period
High	$\geq 3.3\%$	≥ 1 in 30
Medium	$1\% - 3.3\%$	1 in 30–100
Low	$0.1\% - 1\%$	1 in 100–1,000

As exposure from fluvial/tidal and surface water flooding may occur independently or simultaneously, the depth was derived separately for each scenario, before taking the maximum of the two sources as a combined maximum exceeded depth threshold. This represents a worst-case scenario across flooding mechanisms, consistent with UK planning guidance to consider all sources of flood risk [4].

Where primary flow velocity data was unavailable, velocity was estimated using Manning's equation for shallow overland flow [16]:

$$v = \frac{1}{n} R^{2/3} S^{1/2} \tag{1}$$

where R is hydraulic radius, S is slope, and n is Manning's roughness coefficient. This method approximates hydraulic radius to the combined depth, which is considered appropriate for shallow sheet flow. Slope was derived from a digital terrain model, and converted to a dimensionless gradient. Roughness coefficients were assigned based on the land-cover class associated with exposed asset locations, using published roughness coefficients [17].

Debris potential was incorporated following the FD2321 [13] which classifies Debris Factor (DF) based on flood severity and three broad land use categories (Table II). The final hazard rating was calculated through the combination of depth, velocity, and debris factor, using the standard FD2321 formula:

$$HR = d \times (v + 0.5) + DF \tag{2}$$

TABLE II: Debris Factor Classification [13]

Depths	Pasture/Arable	Woodland	Urban
0–0.25 m	0	0	0
0.25–0.75 m	0	0.5	1
$d > 0.75$ m and/or $v > 2$ m/s	0.5	1	1

Each resulting hazard rating was classified into one of four categories: Low (<0.75), Moderate (0.75-1.25), Significant (1.25-2.5), Extreme (>2.5) [13], ultimately generating a flood severity classification for each asset at each likelihood tiers.

B. Terrain Susceptibility

Local topography can have a significant influence on the severity of a flood hazard. To acknowledge this, two terrain-derived indices were calculated to assess distinct failure mechanisms: the Topographic Wetness Index (TWI) and the Stream

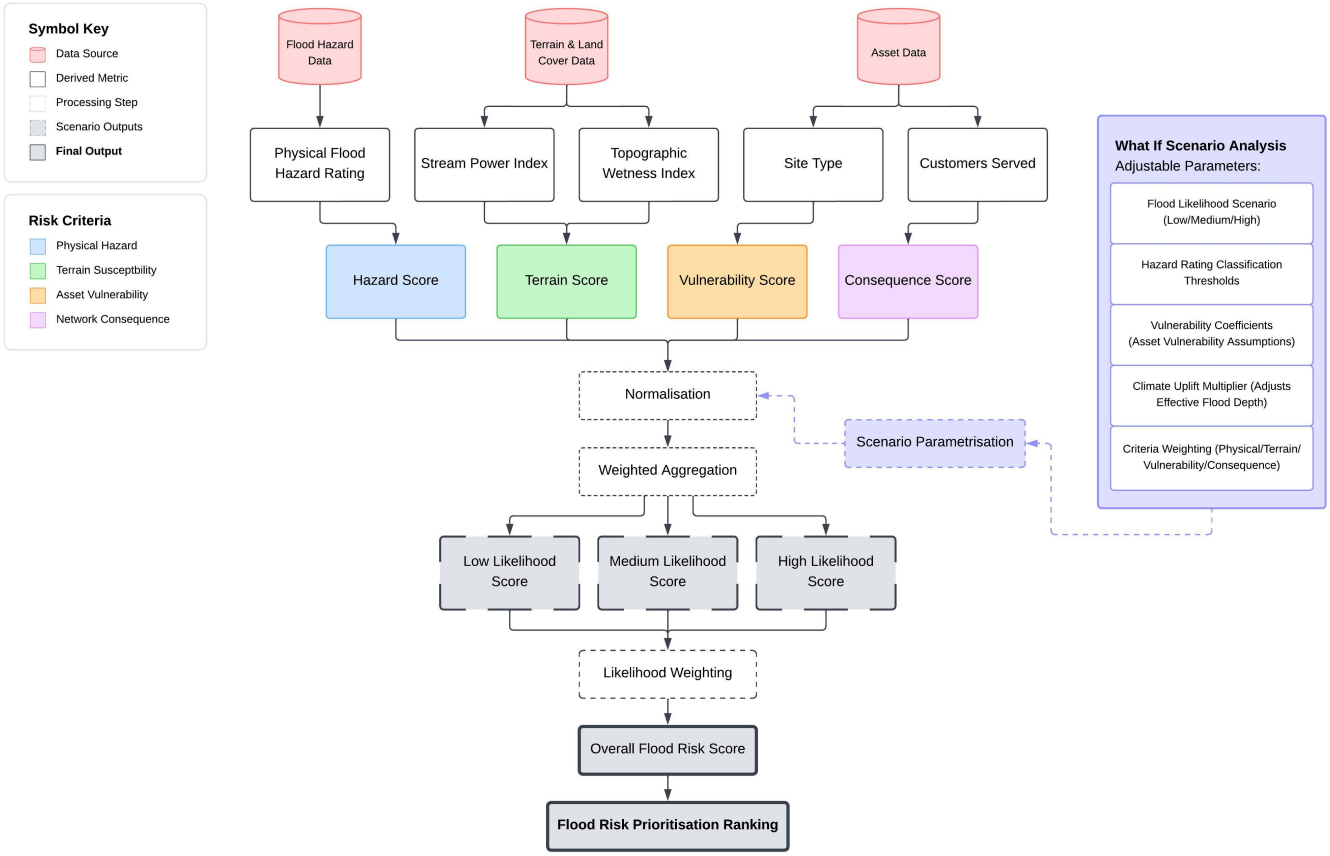


Fig. 1: Conceptual framework for asset flood-risk prioritisation. For visual clarity, the scenario parametrisation is integrated centrally, however, specific parameters intervene at their relevant stages (e.g. climate multiplier adjusts the input for the FD2321 Hazard Rating).

Power Index (SPI). Together these form the two terrain inputs which are combined into the Terrain Score (Fig. 1). Both required a hydrologically conditioned digital terrain model to eliminate artificial sinks [18].

TWI represents the likeliness of an area to accumulate surface and retain surface water, and was calculated as [19]:

$$TWI = \ln\left(\frac{A}{\tan\beta}\right) \tag{3}$$

where A is the catchment area (approximated by flow accumulation scaled by cell size), and β is local slope.

SPI represents the erosive power of surface flow, and was calculated using the same inputs [20]:

$$SPI = A \times \tan\beta \tag{4}$$

Higher values of TWI represent areas where water is more likely to pool due to a combination of high upslope contributing area and low local slope, therefore relevant to inundation-driven failure mechanisms. Higher SPI values indicate areas where higher upslope flow and steep gradients produce high erosive energy, relevant to structural failure mechanisms such as foundation scour [2].

C. Asset Vulnerability

The structural configuration of each substation was used as an indicator of asset vulnerability, corresponding to the Site Type input which feeds the Vulnerability Score in Fig. 1, to reflect distinct flood failure mechanisms associated with each configuration. Vulnerability was treated as a structural trait rather than a hazard response, to avoid the duplication of the physical hazard variables such as depth and debris. Each configuration was therefore assigned a vulnerability 'coefficient', to represent inherent structural fragility.

D. Network Consequence

The consequence to the network was approximated using the number of customers supplied by each asset, corresponding to the Customers Served input which feeds the Consequence Score in Fig. 1. Data sensitivity limitations meant that sites serving very low customer counts are often redacted. These were assigned the lowest consequence class, while the remaining numerical distribution was classified into four further classes using the 25th, 50th, and 75th percentiles.

E. Prioritisation Scoring

Physical hazard, terrain susceptibility, asset vulnerability, and network consequence were each independently classified and normalised to a common scale (Normalisation stage within Fig. 1), before being combined into a single prioritisation score for each asset.

1) Classification:

- Physical Hazard: The four categories derived in Section II-A were assigned numerical values from 1 (Low) to 4 (Extreme). This was done separately for each likelihood tier.
- Terrain Susceptibility: TWI and SPI were both classified into five classes using the 20th, 40th, 60th, and 80th percentiles of the entire distribution of extracted values across the dataset. Terrain susceptibility was assigned one value per substation (rather than per likelihood tier), as it is a fixed property of each site.
- Asset Vulnerability: Vulnerability coefficients were assigned on a common 0-1 scale, where 0 would assume complete protection from the failure mechanism, and 1 would assume extreme risk to the failure mechanism. The vulnerability coefficient was evaluated across the three different likelihood scenarios, and was only applied if the substation was at risk of flooding at that specific likelihood tier.
- Network Consequence: Consequence took a single fixed value (from Classes 1-5) following the redacted-grouping and percentile distribution rules outlined in Section II-D. As with terrain susceptibility, network consequence took a single, fixed value per substation.

2) Combined Score: As each risk indicator relies on a different categorical scale, each were normalised to a common 0-1 scale:

$$x_{\text{normalised}} = \frac{x - x_{\text{minimum}}}{x_{\text{maximum}} - x_{\text{minimum}}} \tag{5}$$

where x is classification. The normalised TWI and SPI indices were combined into a single index for terrain susceptibility, through simple averaging.

Each substation obtained three separate prioritisation scores for each likelihood scenario, S_{tier}, which were calculated as a weighted linear combination of the four normalised scores:

$$S_{\text{tier}} = w_H x_{H,\text{tier}} + w_T x_T + w_V x_{V,\text{tier}} + w_C x_C \tag{6}$$

where $x_{H,\text{tier}}$ and $x_{V,\text{tier}}$ are the likelihood-specific normalised hazard and vulnerability scores, and x_T and x_C are the fixed normalised terrain and consequence scores. Weights (w_H, w_T, w_V, w_C) were implemented as adjustable parameters to allow for direct testing of the sensitivity of the resulting prioritisation ranking to weighting choices, forming part of the Scenario Parametrisation in Fig. 1. Substations with no mapped flood exposure at a given likelihood tier were assigned a score of 0.

It is important to note that, for the final baseline prioritisation ranking, vulnerability was assigned a weighting of 0%. The physical, terrain, and consequence weightings were redistributed equally. This was because, in the absence of further structural information, all exposed assets were assigned a uniform vulnerability coefficient of 0.5. Applying a non-zero weight to this uniform coefficient would provide no differentiation between assets, and may introduce an unintentional influence on prioritisation across likelihood tiers. Vulnerability was therefore excluded from the baseline ranking, but retained within the framework to allow its influence to be explored through a sensitivity analysis, and to support future structural data.

To combine the three scores into a single Flood Risk Prioritisation Ranking, an Overall Risk Score, S (Fig. 1), was calculated, weighting each score by a representative Annual Exceedance Probability (AEP) corresponding to its likelihood tier:

$$S = \frac{(S_{\text{low}} \times 0.55) + (S_{\text{medium}} \times 1.54) + (S_{\text{high}} \times 3.33)}{5.42} \tag{7}$$

The High tier was weighted at its 3.33% threshold (1 in 30 AEP) (Section II-A), corresponding to its upper threshold. The Medium and Low tiers were weighted using the midpoint probabilities of their respective ranges (1.54% and 0.55%), to avoid disproportionately favouring a particular scenario.

F. Scenario Analysis and Parametrisation

To develop a framework suitable for energy stakeholders and to account for potential changes in future flood risk due to climate change, a series of adjustable parameters were adopted to create a dynamic prioritisation environment rather than a static ranking. These parameters are listed within What-If Scenario Analysis panel within the Scenario Parametrisation stage of Fig. 1. The adjustable weights (Section II-E2) inherently account for investigating the influence of individual flood risk criteria. In addition, two further domains were parametrised:

- Classification Thresholds: The boundaries defining the hazard severity classes, originally defined by the FD2321 (Extreme, Significant, Moderate, Low), and the vulnerability coefficients can be adjusted to analyse their influence on ranking stability.
- Climate Intensification: A dedicated climate multiplier can be applied to the maximum flood depth thresholds to simulate the intensification of physical hazard across exposed sites, to observe how future climate scenarios may exacerbate existing vulnerabilities.

These parameters enable a what-if scenario analysis that can be used examine how various assumptions affect the identification and ranking of priority assets.

III. Case Study: County Durham Northern Powergrid Substations

A. Study Area

The framework was applied to County Durham, specifically the administrative area of Durham County Council, which covers a total area of 2,232 km^2 [11]. County Durham falls

within three main river catchments: the Wear, Tees, and Tyne, with the majority of the county falling within the Wear and Tees [11]. These provide exposure to fluvial flooding, which is considered in this study alongside surface water flooding. The county exhibits substantial topographic variation, from low-lying terrain across the east, including the coast and reaches of the Wear and Tees, to substantially increased elevations towards the west [11]. This variation in topography, as well as the presence of major watercourses, provides a diverse setting to assess the spatial variation in flood risk, and the vulnerability of the exposed assets.

B. Northern Powergrid Substations

The energy assets evaluated within this study include all sites and substations within the Northern Powergrid (NPg) distribution licence, of which approximately 7% fall within the administrative boundary of Durham County Council. Attributes such as transformer ratings, maximum demand, and customer numbers were obtained from the NPg Open Data Portal [21] (Table III).

C. Data Sources

TABLE III: Summary of Data Sources and Preprocessing Steps (All spatial layers projected to EPSG:27700).

Product / Source	Res.	Preprocessing & Notes
Substation Sites List NPg (2026)[a]	Point	Filtered to include only sites within study area
Live Power Cut Data NPg[a]	Point	Baseline outage tracking
RoFRS (Rivers & Sea) EA (2026)[b]	2 m	Extracted each of five depth thresholds
RoFSW (Surface Water) EA (2025)[b]	2 m	Extracted each of five depth thresholds
Land Cover Map UKCEH (2024)[c]	10 m	Extracted band 1; reclassified for FD2321 debris factor
MapIt mySociety	Vector	Extracted Durham County Council boundary
LIDAR Composite DTM EA (2023)[b]	10 m	Sink-filled for hydrological analysis

[a]NPg Open Data Licence v1.0 [b]OGL v3.0 [c]Non-Commercial

Flood hazard information was obtained from the Environment Agency's Risk of Flooding from Rivers and Sea (RoFRS) and Risk of Flooding from Surface Water (RoFSW) datasets (Table III), both of which report a categorical likelihood of the exceedance of five fixed depth thresholds. These are therefore probabilistic representations of flood risk, and were used to approximate flood conditions affecting substation sites. Each of the five depth thresholds (0.2m, 0.3m, 0.6m, 0.9m, and 1.2m) were spatially intersected with the point asset locations to extract the maximum depth thresholds for each site at each likelihood tier. Where both sources of flooding were reported at a single location, the maximum depth value was retained.

Slope and terrain indices were derived through ArcGIS, using the LiDAR Digital Terrain Model (DTM) (Table III). Land cover information was obtained at each substation from the UKCEH Land Cover Map, which classifies land use into 21 categories. These were therefore reclassified into the broader categories required for FD2321 debris-factor classification.

The original NPg substation sites dataset provided the information required to represent network consequence. Customer numbers were classified according to the percentile-based approach described in Section II-D. As NPg redacts sensitive data for sites serving five or fewer customers (accounting for approximately 56% of County Durham sites), these sites were retained as the separate, lowest consequence category.

D. Software Implementation and Reproducibility

The entire data processing and visualisation workflow is open source and reproducible (available at https://github.com/Oscar-Ryley/Flood-Risk).

The Python pipeline is run via `scripts/main.py`, which executes all processing scripts sequentially and outputs results to different files in `public/data/`. In the pipeline, `scripts/process_substations.py` clips the substation list (`substation_sites_list.geojson`) to the County Durham boundary (`county_durham.geojson`, MapIt ID 2223) and combines substation fact data with the 10 m LiDAR Composite DTM and Environment Agency RoFRS and RoFSW depth layers (0.2 m, 0.3 m, 0.6 m, 0.9 m, and 1.2 m) to produce full raw data for each substation in `substation_sites_processed.geojson`. Next, `scripts/export_risk_substations.py` exports the classified substations sorted by final risk score to `classified_risk_substations.txt`, and `scripts/sensitivity_analysis.py` outputs `sensitivity_results.txt` for different scenarios, namely the sensitivity analysis, which can be found in section V.

For dynamic data, a GitHub Action runs `scripts/archive_powercuts.py` every 30 minutes. It fetches live power cut data from Northern Powergrid's OpenDataSoft API and active flood warnings from the Environment Agency, adding each timestamped snapshot to the end of `powercut_archive.geojson` as a new line.

An interactive map is hosted at https://floodrisk.oryley.com. It visualises substations classified by risk level as High (star), Medium (triangle), Low (circle), coloured in gradient from green to red, least to most at risk; as well as the Not at Risk substations (blue circle). Live Power Cuts (black lightning bolt) and the Environment Agency's live RoFSW WMS layer can also be visualised on this map.

To reproduce the workflow locally, clone the repository, download and place the un-tracked big data files (LiDAR DTM, and the RoFRS/ RoFSW folders) into `public/data/` (links can be found in `README.md`), and run:

```
git clone https://github.com/Oscar-Ryley/Flood-Risk.git
cd Flood-Risk
python public/scripts/main.py
```

IV. Results and Evaluation

There are 249 total substation assets in County Durham exposed to flood risk, of those 2 are of high risk (score > 0.75), 21 are of medium risk (score > 0.5), and 226 are of low risk (any level of exposure). The substations identified by the framework in the case study as having the ten highest level of flood risk exposure can be found in Table IV.

The most at risk substation is Durham Sutton (fig 2a). It serves 226 customers with a maximum recorded demand of 241.0 kVA through a $11/0.4$ kV, 500 kVA ground-mounted transformer. In sensitivity analysis (Table V) Durham Sutton is the top ranked across three of the four dominant weighting scenarios (w_H, w_V, and $w_C = 0.7$) and places second under the terrain-dominant scenario ($w_T = 0.7$).



(a) The Durham Sutton Northern Powergrid Substation.



(b) The Durham Sutton Substation is located on a sloped hill lower than ground level, under the historic Durham viaduct.



(c) Existing rain (surface) water flood defences, extra rainwater guttering on the roof of the Durham Sutton Substation.

Fig. 2: Photos of Durham Sutton Substation.

With a slope of $4.75°$ caused by its position on a hillside below road level, and an elevation of 49.54 m (with a Topographic Wetness Index of 5.11), the site is beneath the historic Durham railway viaduct (fig 2b).

Durham Sutton gains a final flood risk prioritisation score of 0.8350, ranking it first among all assessed assets in the county. Surface water inundation depth of 0.9 m under a high-probability (30-year) storm event, rising to 1.2 m in both medium (100-year) and low (1000-year) return period scenarios. Combined with the steep slope of the area, this produces very high flood hazard ratings ($HR = 7.86$ to 12.26).

Due to its geographic positioning, the dominant source of Durham Sutton's flood risk is surface water. Visiting the site confirmed existing flood defence measures, such as extensive roof guttering that drain away from the roof (fig 2c), confirming that flooding from rainwater has been an issue at this site in the past and that the framework's analysis was effective.

Placed over the geographic map of County Durham, the classified substations can be quickly identified and reviewed by stakeholders interested in strengthening defences for improving general powergrid resilience to flooding (fig 3). High risk assets are visibly clustered around areas with more substations, arguably due to higher concentration of DERs; however the higher customer counts, and therefore consequence scores, of urbanised areas do cause higher risk scores.

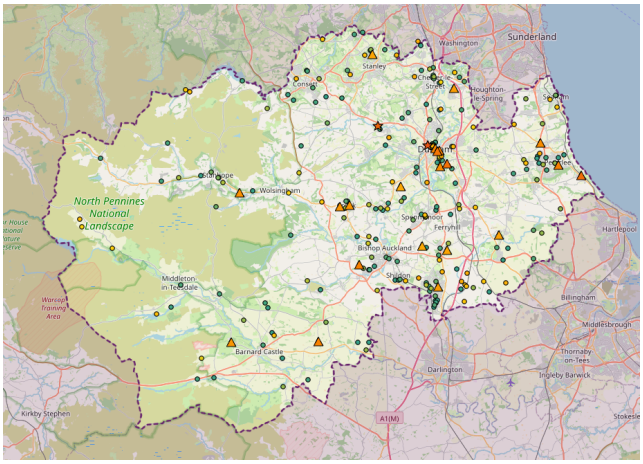


Fig. 3: Classified substations mapped onto geographic points. Low risk are circles, medium are triangles, and high are stars. Colours are a green to red gradient based on final risk severity score. Visualisation from the live site: https://floodrisk.oryley.com

A K-means clustering, with 4 clusters over all substations' slope and elevation, then mapped back over the geographic distribution, reveals different types of terrain across County Durham. When mapping the different classified levels of risk back onto this analysis, it shows that lowland areas are more likely to classify as at risk due to the larger impact of surface water flooding in the study.

TABLE IV: Top 10 Highest Risk County Durham Substations When Ranked by Final Flood Risk Score

			Electrical Specs			Terrain & Hydrology					Inundation Depth, d (m)			Hazard Score, HR			Final
#	Substation Name	Type[a]	kV[b]	kVA	Cust.	Dem.[c]	Elev. (m)	Slope (°)	TWI	Source[d]	High	Med	Low	High	Med	Low	Score
1	DURHAM SUTTON	GM	11/0.4	500	226	241.0	49.54	4.75	5.11	SW	0.9	1.2	1.2	7.86	12.26	12.26	**0.8350**
2	LANGLEY PARK WEST	GM	20/0.4	500	351	193.5	98.73	1.85	5.87	SW	0.3	0.6	0.6	1.34	2.99	2.99	**0.7672**
3	BLACKHALL EAST	GM	20/0.4	500	294	159.1	54.74	2.36	5.59	SW	0.3	0.3	0.6	1.43	1.43	3.28	**0.7364**
4	SHINCLIFFE WEST	GM	11/0.4	315	114	175.0	37.48	3.58	5.26	RS	0.3	0.6	1.2	1.61	3.85	10.78	**0.7235**
5	NEW ELVET NORTH	GM	11/0.4	1000	75	350.0	33.16	2.36	5.87	RS	1.2	1.2	1.2	8.96	8.96	8.96	**0.7063**
6	ELVET	GM	11/0.4	500	28	120.9	34.56	1.66	6.06	RS	0.6	1.2	1.2	2.88	7.69	7.69	**0.6650**
7	ETHERLEY LEAZES	PM	20/0.4	50	24	33.7	147.85	7.25	4.66	SW	0.6	0.6	0.9	5.15	5.15	9.50	**0.6650**
8	YODEN	GM	11/0.4	1000	67	539.9	94.14	1.82	5.98	SW	0.6	0.9	1.2	2.97	5.22	8.00	**0.6650**
9	LITTLE NEWSHAM	PM	20/0.4	50	12	20.4	115.65	4.40	5.33	SW	0.9	1.2	1.2	7.60	11.84	11.84	**0.6625**
10	FREEMANS REACH SOUTH	GM	11/0.4	800	36	131.3	32.20	2.16	6.04	RS	0.3	0.6	1.2	1.40	3.17	8.62	**0.6385**

[a] GM: Ground-Mounted; PM: Pole-Mounted. [b] Primary / Secondary operating voltages (kV). [c] Maximum recorded demand. [d] Dominant pathway: SW = Surface Water (Pluvial); RS = Rivers and Sea (Fluvial/Tidal).
[*] High, Med, and Low indicate return periods (30-year, 100-year, and 1000-year events). TWI: Topographic Wetness Index; HR: Flood Hazard Rating.

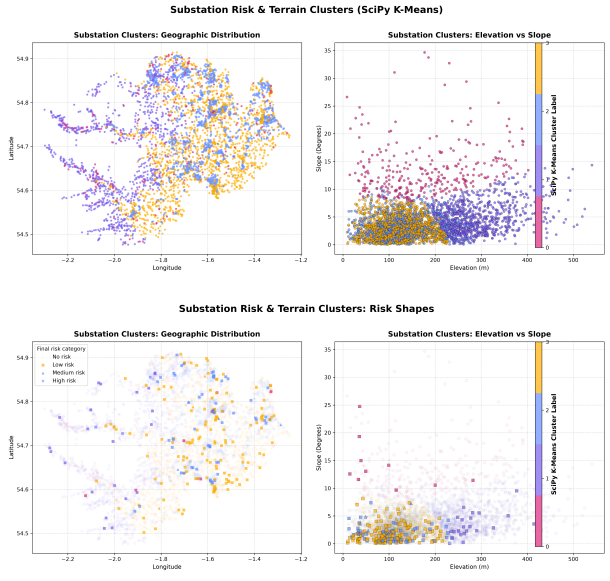


Fig. 4: K-means clustering of Durham county substations based on Slope and Elevation scores, mapped onto geographic positions (left) and filtered by those classified in the study (bottom).

The clustering partitioned the terrain dataset into three distinct geographic terrain types across County Durham. Cluster 1 is defined by high slope values ($> 8°$, up to $35°$) across variable elevations. Cluster 2 is defined by high elevations ($>$ 220 m up to 550 m) Clusters 3 and 4 represent low-lying elevations ($<$ 220 m) with predominantly flat terrain (slope $< 8°$).

Projecting the prioritised assets onto these clusters shows that a majority of flood-exposed (classified) substations fall within Clusters 3 and 4 (lowland plains and urban valleys). This demonstrates that surface water pooling in flat, densely developed areas is the primary cause of grid asset exposure in the region.

A. Sensitivity Analysis

To evaluate the stability of the final prioritisation ranking, the top ten substations identified under the equally weighted baseline were tracked across scenarios in which the weightings of individual parameters were adjusted. For each scenario, one parameter was assigned a dominant weighting of 70%, while the remaining three were each weighted at 10%. These results were then compared with the baseline prioritisation ranking. The analysis reveals that the top-priority group is broadly stable across weighting scenarios. Spearman's rank correlation against the equally weighted baseline remained high across all four dominant-weighting scenarios (Table V), showing that the overall ranking is not highly sensitive to the specific weights.

TABLE V: Sensitivity Analysis: Substation Ranks Across Dominant Weighting Scenarios (70% Target Parameter, 10% Others)

Substation Name	Baseline (33/33/0/34)	Hazard ($w_H = 0.7$)	Terrain ($w_T = 0.7$)	Vuln. ($w_V = 0.7$)	Conseq. ($w_C = 0.7$)
DURHAM SUTTON	1	1	2	1	1
LANGLEY PARK WEST	2	10	9	5	2
BLACKHALL EAST	3	14	16	12	3
SHINCLIFFE WEST	4	11	4	6	6
NEW ELVET NORTH	5	2	1	2	8
ELVET	6	3	7	3	9
ETHERLEY LEAZES	6	5	20	15	14
YODEN	6	3	7	3	9
LITTLE NEWSHAM	7	5	2	15	20
FREEMANS REACH SOUTH	8	12	6	7	13
Spearman's Rank ρ	—	**0.926**	**0.979**	**0.966**	**0.918**

V. Discussion

A. Overall Performance

The final framework was able to successfully identify and differentiate priority substations according to their combined flood-risk characteristics. The comparison of the top ten substations at baseline weightings (Table IV) indicates that prioritisation is not determined solely by physical hazard, with sites displaying different combinations of hazard severity, terrain, and network characteristics. The Shincliffe West site provides a clear example of this, ranking 4th despite having a relatively low customer demand and a high return period depth of only 0.3m. Its hazard scores increase substantially under the medium and low likelihood scenarios (3.85 and 10.78 respectively) therefore contributing to its overall prioritisation ranking.

This directly addresses the first research question outlined in Section I, by demonstrating that a combination of risk criteria produces a more informative ranking than hazard alone. Under a hazard-dominant ranking, Shincliffe West would place outside the top ten. Its combined score is therefore elevated by other risk criteria. The hazard-dominant weighting scenario

within Table V demonstrates that a physical hazard-driven ranking would substantially rerank several baseline top ten sites, notably Langley West falling from 2nd to 10th and Blackhall East from 3rd to 14th.

B. Sensitivity and Robustness

Several assets retained a consistently high-priority ranking regardless of weighting. Durham Sutton ranked first under baseline conditions, and remained the top- or second-ranked substation across all weighting scenarios. However, other rankings within the top ten were considerably more sensitive to assigned weights than the correlation values suggest. For example, Etherley Leazes ranked 6th under the baseline, but fell to 20th under the terrain-dominated scenario, while Little Newsham fell from 7th to 20th under the consequence-dominated scenario. It can therefore be interpreted that a site's ranking can depend substantially on which criteria are assumed to be most significant, even when the overall ranking correlation remains high.

Despite vulnerability being excluded from the baseline ranking, a vulnerability-dominated scenario was tested to investigate how the ranking would respond to more robust vulnerability data (discussed further in Section V-D). The results suggest that the choice of weighting can influence the relative ranking of sites at the margin of the top-ten priority group. By presenting weights as adjustable parameters, stakeholders can examine how their own priorities would reshape the output.

These results also help address the second research question outlined in Section I: which factors contribute the most to substation exposure and prioritisation. The Spearman's rank correlations in Table V provide a useful indication of the relative influence of each factor on the overall ranking. The terrain-dominant scenario has the highest correlation against the baseline (ρ = 0.979), indicating that an increased terrain susceptibility weight modifies the overall prioritisation ranking the least. Contrastingly, the consequence-dominant scenario has the lowest correlation (ρ = 0.918) and produces the largest rank shifts, indicating that it has the greatest influence on the prioritisation ranking when weighted more heavily. The hazard- and vulnerability-dominated scenarios produce intermediate correlations of ρ = 0.926 and ρ = 0.966 respectively. Overall, the prioritisation is most sensitive to consequence, followed by hazard and vulnerability, while terrain susceptibility has the least influence on the rankings.

C. Methodological Uncertainties

The representation of flood-risk criteria was subject to constraints derived from the underlying datasets. Firstly, the estimation of shallow overland flow velocity using Manning's equation is a significant uncertainty, as localised artefacts within the DTM generated unrealistic slope gradients and therefore physically implausible flow velocities exceeding 44 m/s. The terrain indicators, also derived purely from topographic characteristics, are similarly sensitive to artefacts within the DTM and the deterministic flow-routing method used. While the method favours reproducibility, it has been demonstrated that more sophisticated flow-routing methods, such as Multiple Flow Direction and iterative-catchment area estimation, significantly improve spatial accuracy, particularly in low-gradient areas [18].

D. Limitations and Assumptions

While the proposed framework successfully produces a regional screening tool for network operators, several methodological and data-driven limitations must be acknowledged:

- The reliance on probabilistic flood datasets means that physical hazard is evaluated as a maximum exceeded depth threshold rather than a precise continuous measurement. The 1.2m threshold cap acts as a lower bound for extreme events, therefore sites mapped at this threshold could be exposed to significantly greater flood depths in reality.
- As noted in Section V-C, the velocity component is sensitive to small-scale DTM artefacts, and should be interpreted cautiously. It may be reasonable to exclude velocity from the hazard rating calculation, and retain it as an exploratory sensitivity parameter.
- The framework does not account for existing flood defences. The Risk of Flooding datasets used represent undefended flood extents in some cases, and defended risk in others, therefore assets situated behind flood defences may therefore be assigned a physical hazard rating that overestimates their true exposure. The site visit to Durham Sutton confirmed existing rainwater drainage measures, suggesting that its current risk may be lower than its score implies.
- The climate parametrisation successfully models vertical hazard intensification by applying adjustable depth thresholds, however it fails to account for the associated horizontal spatial expansion. In reality, an increase in flood volume would also propagate laterally across terrain, potentially exposing previously unaffected substations. Simulating this would require dedicated hydrodynamic modelling, which is beyond the scope of this point-based screening study.
- Asset vulnerability is constrained by the lack of individual asset data. The absence of factors such as asset age, maintenance history, and structural condition means that the vulnerability coefficient is only assigned based on structural type. The sensitivity analysis highlights the need for further asset information to meaningfully represent vulnerability.
- Network consequence is similarly constrained, represented solely by the number of customers supplied, ignoring additional factors such as network topology, or the type of customer. For example, substations supplying critical infrastructure are treated equivalently to those supplying residential customers with the same number of customers.

VI. Conclusion and Future Work

This study presented a reproducible, data-driven framework for prioritising flood risk across a distribution network, explicitly designed as a broad, point-based screening tool for Distribution Network Operators (DNOs). It provides an initial prioritisation stage, rather than serving as a deterministic prediction of asset failure. Applied to County Durham, the framework successfully identified exposed substations within the Northern Powergrid network, demonstrating the potential use as a practical approach for identifying assets that warrant more detailed investigation and resilience planning.

The results demonstrate that combining multiple flood risk criteria (physical hazard, terrain susceptibility, and network criticality) produces a more informative ranking than considering physical flood hazard alone, and that network consequence and physical hazard have the strongest influence on prioritisation ranking sensitivity. More broadly, these findings demonstrate that open-access data and an adjustable, multi-criteria scoring approach can produce a network-wide flood-risk screening without the computational demand of site-specific modelling.

Limitations of the framework have been discussed in section V-D. Future work to reduce these limitations could include an extended screening method that takes into account flood defences, and can be updated when work is done to the system or other dynamic factors change levels of flood risk to certain substations.

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