Social Impact and Spatial Inequalities

INCLUSION BY DESIGN: ADVANCING GIS METHODS IN CLIMATE SERVICES FOR EQUITABLE DISASTER RISK REDUCTION

FINAL REPORT

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Abstract

Climate change is intensifying hazards and amplifying unequal impacts, especially in data-scarce regions where social vulnerability is poorly captured. Monetary loss alone underestimates harm when natural hazards disrupt access to essential services. Consultancy workflows increasingly rely on GIS to compress time and cost. Yet, thin inputs, single-layer or static outputs, and interpretation gaps risk overlooking vulnerable groups and keeping results non-actionable. The target is to enhance GIS tools such as SPIN to show who loses access, why it happens, and what to do next, balancing speed with accuracy and equity. Three solution concepts are considered: (1) addressing data scarcity through long-term, community-based fieldwork; (2) a comprehensive, multi-layer analysis to enhance SPIN; (3) interpreting analyses "from maps to actions". Using PPP/TBL, strategic fit, technical feasibility, and ethics, Concept (2) ranked highest and was selected as the lead pathway, with valuable elements from (1) and (3) incorporated. The final solution is a single operational package spanning three threads: embedding a spatial social-vulnerability index within SPIN's pipeline (combining accessibility, hazard exposure, built environment, and where applicable, post-disaster accessibility loss with context-specific weights); a community-scale Flood-ABM to incorporate demographic data; and a planning/advisory layer linking hotspots to candidate measures and confidence cues. Outputs include a reproducible spatial SoVI map, a curated planning/measures knowledge base, and a prototype advisory that reduces interpretation bias and nudges decisions toward equitable options. Current limits include incomplete coupling between ABM and SPIN network dynamics, narrow built-environment detail, and qualitative/context layers needing further validation. Near-term development prioritises the hazaprioritises layer, with a phased 24-month plan: integrate refined flood-exposure datasets; pilot within institutional projects while testing private-sector utility (e.g., insurers); and complete full platform integration with subscription-based commercialisation to sustain continued tool development. The project is delivered by a 10-member interdisciplinary team, structured into Social Vulnerability, Spatial Planning, and Hacking SPIN clusters. Weekly cross-cluster exchanges, stakeholder interviews, surveys, and two Ishikawa workshops underpinned integration and guided the final design.

Contents

1 Introduction

Climate-related disasters are increasing globally, and the impacts on populations are uneven. This is because exposure to climate-related disasters does not solely determine the impact (Donatti et al., 2024). Highly developed countries experience fewer adverse effects despite comparable event frequencies. This is in stark contrast with, for example, several African nations that have seen rising numbers of people affected even as the event counts decline (Donatti et al., 2024). The highest impact densities occur across the Global South (Central America and the Caribbean, Eastern Africa and Madagascar, Southern and Eastern China, India and Southeast Asia), with Eastern North America the only high-impact area outside this group (Donatti et al., 2024). This disparity in the Global South is rooted in long-standing socio-economic and political inequalities and in weak or absent climate adaptation and mitigation interventions (Ngcamu, 2023). Vulnerable populations are frequently overlooked in social programmes and risk-reduction measures, and local governments often diverge from established international frameworks when designing interventions. (Ngcamu, 2023).

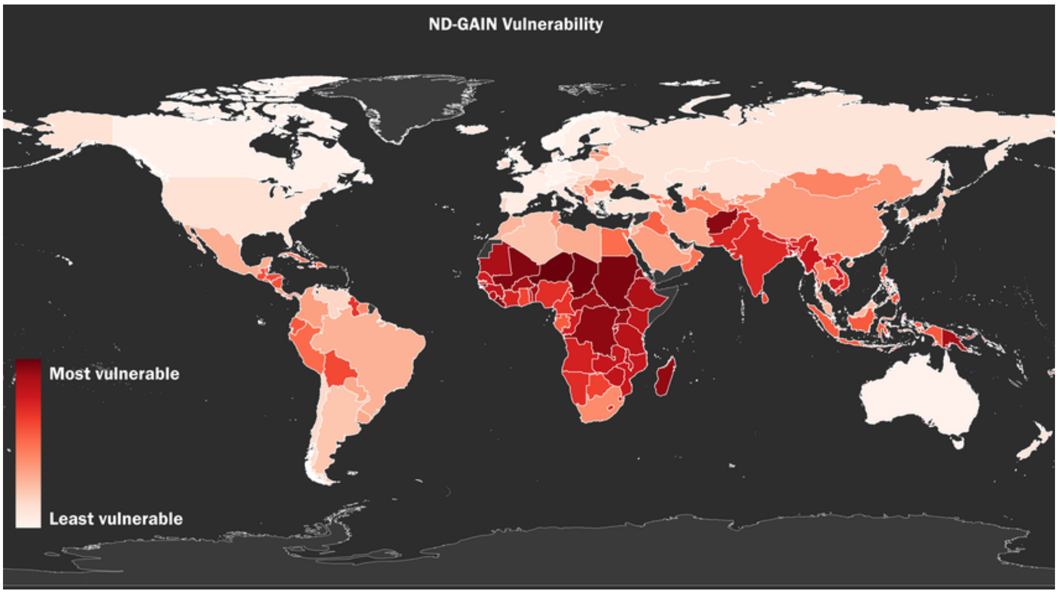


Figure 1: The global distribution of climate impacts risk (Marcantonio et al., 2021)

In response, third-party advisors, particularly consultancies, have become embedded in adaptation governance, supplying governments and institutions with programme and measure design and implementation support (Keele, 2017). This shift reflects growing demand for timely, actionable climate intelligence and has driven the demand for consultancy climate services for decision-makers (Keele, 2019). However, concerns persist that a client-driven, profit-oriented model can weaken the knowledge base required for adequate responses (Keele, 2019), thereby risking recommendations that fail to address the structural inequities amplifying disproportionate impacts. The context, therefore, requires methods that balance efficiency and accuracy in decision support and a critical reappraisal of how consultancies and other intermediaries assemble evidence and formulate advice for decision-makers in the Global South.

Consultancy organisations assemble and legitimise their advice by mobilising practical knowledge, calculative practices, expert authority, instruments and inscriptions to configure governmental interventions under climate uncertainty (Keele, 2017). To reduce time and cost in this advisory cycle, Geographic Information Systems (GIS) is widely used to conduct methodological analysis that support evidence gathering in the formulation of options (Gibas-Tracy, 1996). GIS enables interactive queries, spatial analysis, data editing and visual communication (Pandey et al., 2013).

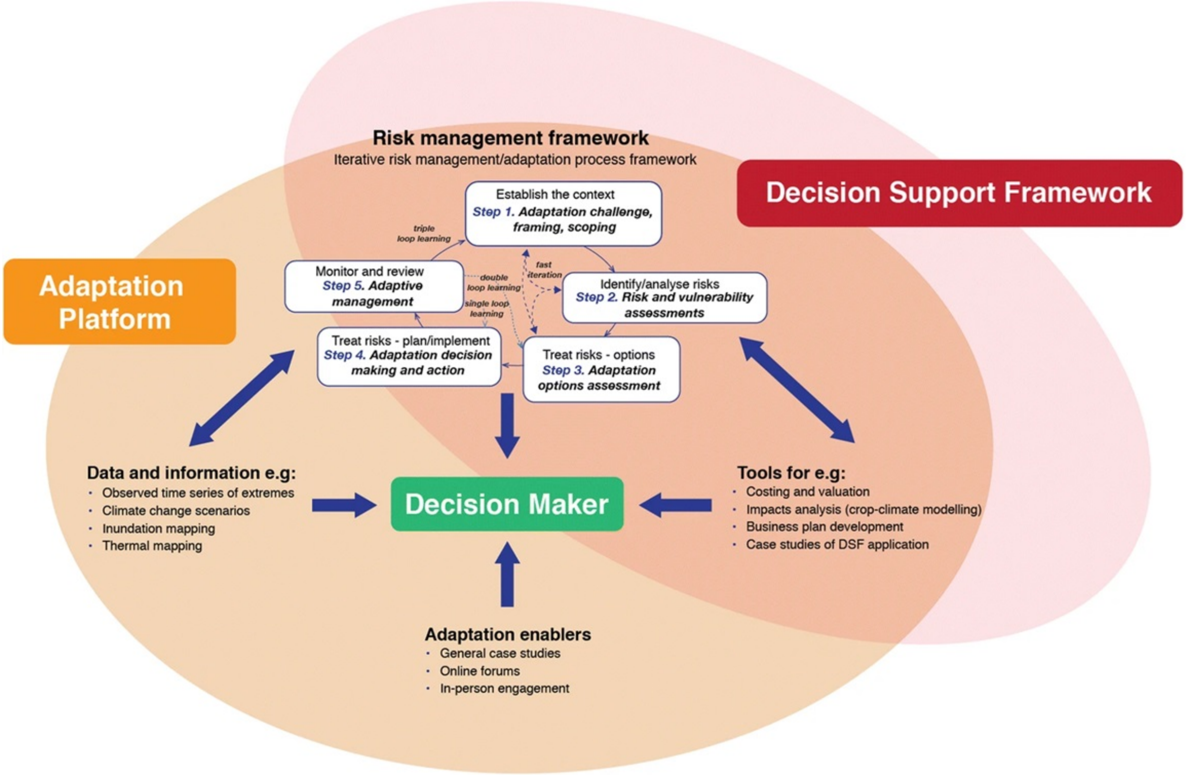


Figure 2: Typical structure of a climate adaptation platform with decision support (Palutikof et al., 2019)

1.1 Objective of Research

This report, conducted in close collaboration with Haskoning, examines how recommendations in decision-making can more accurately include socially vulnerable populations and reduce spatial inequality by improving **the use of GIS tools**, specifically the firm's SPIN tool (Haskoning, 2025), while balancing responsiveness and accuracy.

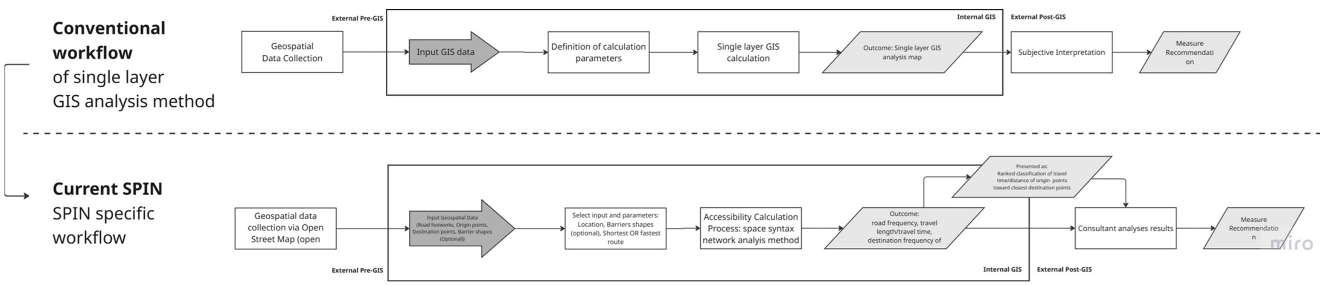


Figure 3: Outline of a generic GIS workflow (Pandey et al., 2013) and how, through a tool like SPIN, it informs consulting practices

Haskoning's SPIN tool already offers a foundation for exploring equity-driven strategies by including vulnerability though the mapping of accessibility to critical infrastructure. Haskoning uses this to identify communities that are less connected and/or cut-off in the case of flooding. This information is then utilised to do pre-emptive measures or locate and aid isolated communities in the face of a disaster (Haskoning, 2025). For this, the tool calculates road frequency, travel length/travel time, destinations frequency of usage and disruptions through the use of departure points (communities), arrival points (critical infrastructure), networks (roads) and barriers (flood-shapes) collected from Open Street Map (OSM) (Figure 3). However, accessibility represents only one dimension of social vulnerability. This alongside other factors (Figure 4) asks for further exploration. **For this, the guiding research question is:**

"How can the use of GIS analysis methods such as SPIN be improved to promote the inclusion of socially vulnerable groups in climate-disaster decision-making?"

Four methodological concerns, identified in the workflow of GIS-tools like SPIN, motivate the work:

1. GIS pipelines depend on geospatial datasets (Al-Yadumi et al., 2021) that in many parts of the Global South are incomplete or unreliable (Vasantha Kumaran et al., 2025), precisely where adaptation needs are highest (Donatti et al., 2024). Such gaps risk excluding vulnerable communities and degrading planning, preparedness and resource allocation (Al-Yadumi et al., 2021).

2. Many GIS outputs remain single-perspective, static layers derived solely from quantitative inputs; without systematic multi-view analysis, decision-makers can develop tunnel vision, and persistent critiques call for more reflexive and qualitative integrations (Leszczynski, 2009).

3. Actionability is often deferred to the human interpreter; recommendations are generated outside the tool, amplifying possible bias in decision making, further addressed in the following item. Furthermore, this process makes outcomes dependent on specialist availability, which in multi-team systems can lead to a decrease in effectiveness (Waring et al., 2020). Furthermore, whilst room for interpretation, expert opinions and local knowledge can improve the effectiveness of advise and measures, you can't always count on it being qualitatively sound (Elbroch et al., 2011).

4. Subjective interpretation introduces cognitive biases, wishful and confirmatory (Méndez-Sánchez et al., 2022), which can skew judgements that influence decisions (Kunkler and Roy, 2023).

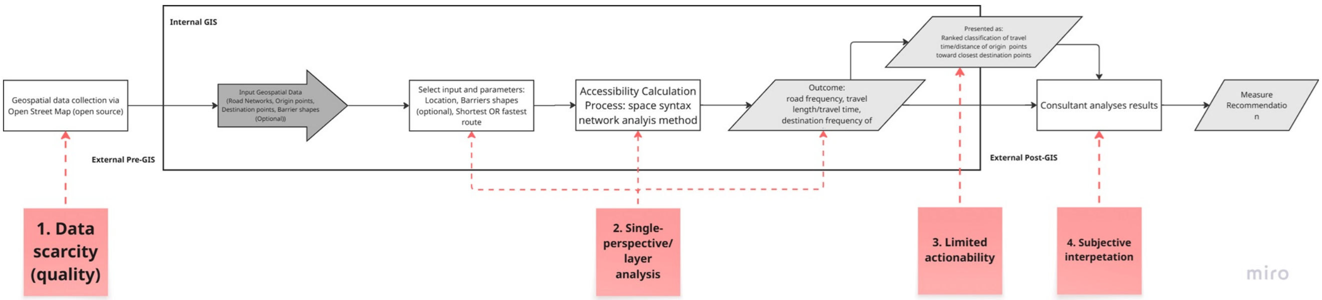


Figure 4: Identified concerns located in the workflow of Haskoning's GIS-tool SPIN

Accordingly, the main research question was broadened for the study to additionally address these **four sub-questions:**

1. How can data quantity and quality be improved to increase geospatial analytical accuracy?

2. How can GIS tools be expanded to include multiple analytical perspectives?

3. How can the interpretation and use of geospatial results be enhanced to minimise cognitive bias?

4. How can GIS tools produce curated, transparent and actionable recommendations which can be easily deployed by decision-makers?

1.2 Structure of the Report

To address the research question and its subsidiary questions, the report is organised as follows. The Introduction (section 1) establishes the context and states the aim. Within section 2 on methodology, details about the research design from question formulation to results are specified to ensure transparency, replicability and justification. Multiple candidate approaches that could answer the research question are set out in section 3. These are tested and compared in the selection process (section 4) using a multi-criteria method. The final solution (section 5) then integrates the evaluation findings into a final solution pathway. A subsequent product evaluation (section 6) assesses the selected solution's feasibility, risks and societal impact, and discusses strengths and limitations. Finally, in section 7 on business recommendations, the findings are translated into a proposal and implementation timeline to demonstrate viability. The report closes with a group reflection (section 8), reviewing collaboration and lessons for future work.

2 Methodology

In this chapter, the processes through which evidence is collected, organised, and transformed into conceptual solutions are delineated, along with the subsequent testing, synthesis, and evaluation of these concepts. The purpose is to ensure that the research pathway is transparent, traceable, and reproducible, thereby demonstrating the progression from data sources and stakeholder input to the formulation of design options, their comparative assessment, and the selection of the final solution.

This report is conducted by an independent and interdisciplinary team of ten researchers divided, on their expertise, into three research clusters (Figure 5): **(I)** Spatial Planning, with the focus on actionability and spatial measures **(II)** Hacking SPIN, with the focus on workflow improvement and optimisation and **(III)** Social Vulnerability, with the focus on defining, including and mapping social vulnerability. Each cluster offers a different perspective on the research questions. To address the project from a business and economic perspective, one student of the Rotterdam School of Management (RSM) at Erasmus University was added to the research team. Through weekly exchanges and discussions, the cluster-internal research was combined into integrated and holistic findings and results. All research is approached through a "feasibility lens," translating research-based improvements into solutions and recommendations that Haskoning can implement and sustain, effectively transforming academic insights into practical impact.

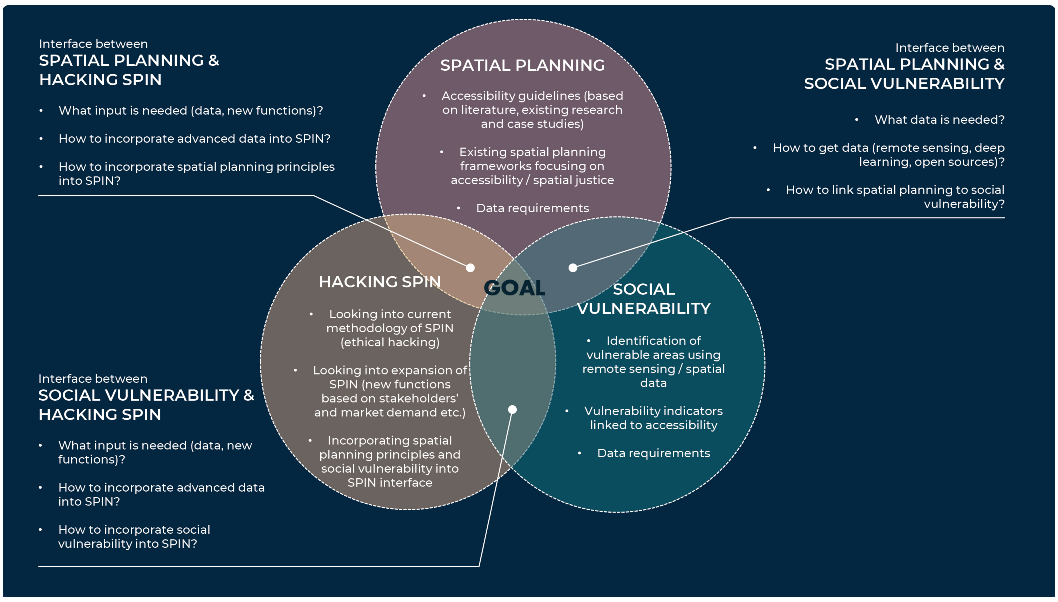


Figure 5: Research clusters

All the research inputs (peer-reviewed literature, interview notes, and workshop artefacts) done by each cluster are stored in a shared repository (Miro and Microsoft Teams) with standard metadata (source, date, cluster, theme). Interview notes are transcribed and thematically sorted by weekly rotating researchers; discrepancies are resolved in short meetings. Weekly cross-cluster sessions produced concise "definition boxes" to harmonise terms and avoid drift across disciplines.

Stakeholders were identified and mapped on a power–interest matrix to set engagement intensity (Figure 6). Semi-structured interview protocols, developed in alignment with the research themes and conducted with both internal (Haskoning) experts and end-users (The Netherlands Red Cross). Discussions were recorded when consent was granted, or alternatively, detailed notes were taken to ensure accurate documentation. Additionally, research and interviews resulted in a questionnaire, which was deployed to Haskoning employees to quantify academic results. Furthermore, research findings were pitched and discussed with independent master students of the RSM during a speed dating event. From this new perspectives on the research and topic were gathered, which led to different research directions.

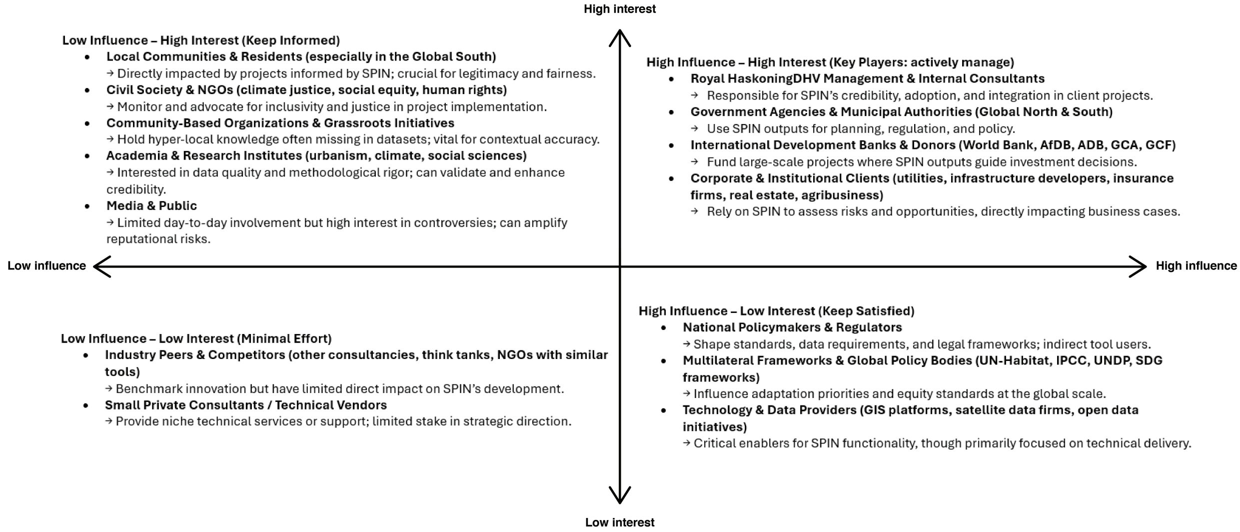


Figure 6: Stakeholder Analysis

Problem structuring commenced with a facilitated Ishikawa (fishbone) analysis. Each disciplinary cluster contributed domain-specific drivers to the diagram, after which overlaps were reconciled to generate a consolidated causal map and a concise set of problem statements. Research questions were subsequently derived by translating each statement into an actionable inquiry, with these artefacts constituting the foundation for the subsequent design phase.

Concept construction used a second workshop that inverted the fishbone from causes to remedies. For each driver, candidate interventions are mapped to the analysis scope (**input**, **tool**/**engine**, and **interpretation**/**action**) and assembled into three coherent solution concepts. Comparative evaluation followed a multi-criteria framework aligned to the triple bottom line (People, Planet, Profit) and an additional feasibility lens. Criteria were scored on a 1–5 scale with short, cited justifications. To reduce single-rater effects, at least two assessors scored each concept.

3 Solution concepts

This chapter presents the candidate approaches developed to address the research question. As outlined in the Methodology, evidence from literature and interviews was organised through the lenses of three clusters. Two fishbone workshops first distilled the root problems that motivated the research question and then inverted them to derive remedy pathways. In combination with a workflow analysis (Figure 3 & Figure 4). This process identified three intervention categories that structure the chapter: **(1) Pre-GIS input**: measures that improve data availability and quality before analysis; **(2) In-tool enhancement**: improvements to the GIS engine itself (here: Haskoning's SPIN) to enable richer, multi-perspective outputs; and **(3) Post-GIS interpretation**: measures that reduce interpretive bias and translate results into concrete actions. Given that each category reflects a distinct perspective on the research question, three solution concepts are formulated and placed in the process accordingly: Concept 1 (external, pre-tool inputs), Concept 2 (internal, tool improvements), and Concept 3 (external, post-tool interpretation and action).

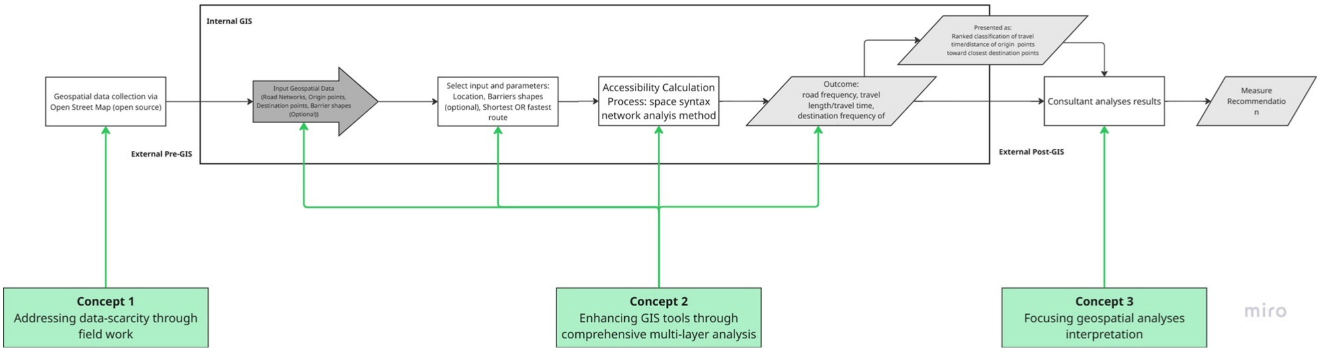


Figure 7: Solution concepts within SPIN's GIS workflow

3.1 Concept 1: Addressing Data Scarcity Through Fieldwork

As mentioned on the first methodological concern, one of the key barriers to equitable climate adaptation is the scarcity of locally specific data, a critical input for SPIN. Limited access to accurate, high-resolution data hinders the ability to effectively and justly plan for and respond to climate hazards (Al-Yadumi et al., 2021). A focus could be set on improving data availability and accuracy through long-term, community-based fieldwork combined with technological implementation. By enhancing the quality of local data, decision-makers can better identify at-risk populations and tailor adaptation strategies to their specific contexts (510 Global, 2024; UNICEF, 2024).

To achieve this, a combination of field visits, installation of monitoring equipment, and training of local actors needs to be conducted (Turnbull and Turvill, 2012). For instance, in Malawi, projects have installed monitoring stations equipped with rain gauges and water-level sensors that continuously collect and process real-time hydrological data (UNICEF, 2024). Additionally, the use of drones provides high-resolution spatial data that surpasses the precision of many publicly available satellite datasets (UNICEF Venture Fund, 2023). The establishment of the African Drone and Data Academy (ADDA), supported by UNICEF, ensures local expertise is available to operate, maintain, and interpret these systems. Through local training programs, ADDA supports the continuity and independence of data collection beyond the project phase (UNICEF Venture Fund, 2023).

To ensure the quality and reliability of the data collected, collaboration with local experts and community networks is necessary. Local experts, volunteers, and village protection committees can validate data and help communicate early warnings through trusted channels such as WhatsApp groups and local languages (510 Global, 2024; Partners for Water, 2024). This participatory approach promotes a sense of ownership and accountability within the community (Turnbull and Turvill, 2012). More importantly, it transforms data collection into a sustained process which requires field visits, regular maintenance, and continuous communication. By integrating these, Malawi's approach demonstrates how addressing data scarcity can create a foundation for equitable and context-specific climate adaptation strategies.

(a) Drone footage showing extent of floods in Malawi, December 2022 (Globhe, 2022)

(b) Engaging with the community in Malawi, October 2023 (UNICEF Venture Fund, 2023)

Figure 8: Malawi Project

3.2 Concept 2: Enhancing GIS tools through comprehensive multi-layer analysis

The second concept addresses in-tool enhancements. Currently, GIS methods like SPIN tend to focus on only single-perspective physical geospatial data. In the case of SPIN this results in emphasising hazard exposure and infrastructure distribution while under-representing the social and systematic dimensions of vulnerability. This limitation can skew outcomes toward physical risk assessment, omitting indirect social impacts that emerge before, during, and after hazard events (Koldasbayeva et al., 2024).

To address this imbalance, the concept introduces a multi-layer analytical framework that integrates spatial, social and temporal dimensions of vulnerability. Through synthesising different dimensions, the completeness of the analysis of the available data can be enhanced (Shay et al., 2016). Part of the deliverable will be a spatial measure matrix, which will systematically link with the causes and effects of climate hazards. The matrix goes beyond direct effects, such as lives lost and destruction of infrastructure, and also lists indirect effects, such as lowered access to education or food scarcity (United Nations Office for Disaster Risk Reduction (UNDRR), 2025). This helps include the information that is not visible in the geospatial data and takes into account vulnerable groups that may not be considered otherwise. Each identified cause-effect pair is associated with a catalogue of measures that are phase-specific, distinguishing between pre-emptive measures, immediate response measures, and recovery measures (Singh, 2024). This classification supports a structured workflow for users, allowing decision-makers and consultants to contextualise interventions according to both hazard types and disaster phases and centralise pre-existing knowledge. This integration facilitates a more comprehensive understanding of the available options applicable to the current analysis context (Singh, 2024).

To further improve depth, a Social Vulnerability Index (SoVI) (McCullagh et al., 2023) focused on spatial equality will be integrated into the framework. This SoVI will map the social vulnerability based on access to key infrastructure, the risk of being exposed to natural hazards, and the built environment. This approach gives more information on the physical surroundings where people live, the land use, and the number of people living in the area and expands the GIS's analytical scope from a static asset impact to a multi-dimensional vulnerability assessment, and thus counteracts some of the bias introduced through geospatial data (Sung and Liaw, 2020). The relative weights between the different criteria are determined in collaboration with experts within Haskoning.

To complement the structured quantitative analysis, a qualitative data integration layer is introduced within SPIN. Utilising web-scraped data from credible sources such as scientific reports, governmental publications, and verified news outlets provides localised, recent contextual insights. The qualitative data is then processed through filtering and geoparsing techniques, ensuring only relevant, location specific information is retained. The processed information is subsequently visualised through a dedicated contextual interface. By embedding these insights directly into the user interface, the GIS at hand can present users with a richer and more grounded understanding of the realities, bridging the gap between geospatial analysis and lived experiences and counteracting internal biases ("Mapping Out Disaster Preparedness: The Role of GIS Applications in Effective Disaster Management – Precision Eco-Landscaping", 2024).

A qualitative integration allows decision-makers and consultants to interpret spatial outputs within their broader societal and environmental context, improving situational awareness and supporting locally sensitive decision-making. Therefore, SPIN could evolve into a comprehensive multi-layer analysis platform, uniting spatial data, social vulnerability indicators, and qualitative context to inform more equitable and context-aware climate adaptation strategies.

3.3 Concept 3: Focusing of geospatial analyses interpretation

This concept targets the “last mile” of geospatial analysis: translating accessibility (risk) maps into just location-specific actions. This doesn’t result in changes to the inputs or the core architecture of the tool. Moreover, this solution’s focus lies on the interpretation and analysis of geospatial maps that GIS tools like SPIN produce. With this focus, a cross-sector issue is addressed: cognitive/interpretation bias. Such biases involve systematic distortions in judgment that occur outside conscious awareness (Kunkler and Roy, 2023).

Two recurrent cognitive drivers are *wish bias* — the tendency to interpret evidence in line with one’s hopes or beliefs — and *confirmation bias* — the inclination to interpret evidence in accordance with prior expectations (Méndez-Sánchez et al., 2022). These biases can produce errors without carelessness or misconduct, which makes them hard to control (Kunkler and Roy, 2023). Mitigation strategies are available to address these biases. These involve the appointment of case managers to filter and validate information, the adoption of structured data pipelines that deliver only analysis-relevant content with explicit justification for why and when items appear, and the application of objective weighting to evaluation parameters (e.g., biasing power, objectivity, relevance) following the Linear Sequential Unmasking-Expanded (LSU-e) protocol (Kunkler and Roy, 2023). Additional safeguards include blind verifications to reduce expectation effects (Kunkler and Roy, 2023). However, most counter-bias measures rely on formal organisational adoption and protocol change, which are often slow and resource-intensive solutions (Kunkler and Roy, 2023). Solution concept 3, therefore, embeds these principles within the tools interface, making it widely adaptable after a one-time development investment.

Each critical accessibility hotspot identified by the GIS analysis method, whether an isolated link, facility, or area, is automatically matched to a curated contextual database that includes hazard type and phase, local governance constraints, and contextual social-vulnerability profiles. Each hotspot is then linked to a curated measure library aligned with the Dutch multi-layer safety framework, encompassing **(1) protective and defensive works**, **(2) spatial-planning measures** that reduce exposure and enhance accessibility and **(3) disaster-management interventions** for preparedness and response (Bosoni et al., 2023). This matching process is facilitated by geospatial semantics, which integrates top-down, theory-informed methodologies with bottom-up, data-driven approaches, connecting geospatial data points to Geospatial Knowledge Graphs (GeoKGs) (Mai et al., 2025).

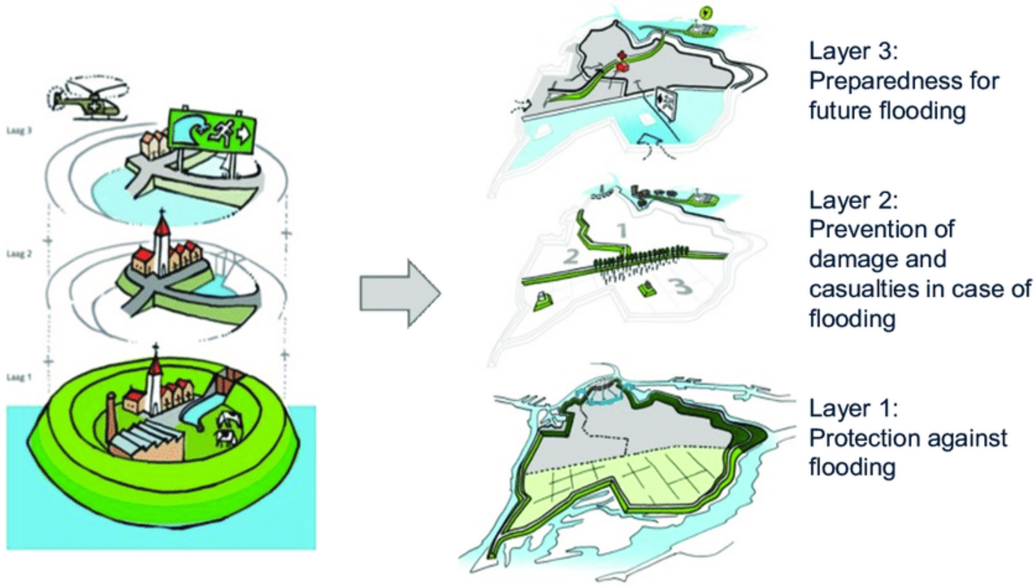


Figure 9: The Dutch multi-layer safety approach to flood risk management Bosoni et al., 2023

A lightweight AI advisory model is trained to recognise the data points of accessibility hotspots from geospatial data analyses. It thereby ’reads’ the analysis map and links it to the GeoKGs, containing the contextual information and the measures library. The generative component of the AI model is operationalised as a plain-language *why-card*, a one-screen explanation that tells a non-expert *why* a hotspot appears and *who* is affected. A ranked set of measures for pre-, during- and post-disaster phases with cost and lead-time bands and equity notes, and optional what-if prompts is provided by the AI model.

The approach replaces subjective map reading with traceable explanations and action menus, directly addressing interpretation bias (Kunkler and Roy, 2023). The system is kept simple, while actionability and accountability are added. Therefore, every map becomes a curated shortlist of measures tied to place and phase. Finally, it embeds uncertainty and verification by attaching confidence cues, based on similar evaluation parameters as in LSU-E (Kunkler and Roy, 2023), to each recommendation and suggesting a quick check (call, photo, or site note) before commitment.

4 Selection Process

Within the Introduction (section 1), four core challenges within geospatial analysis were identified: the prevalence of limited and unreliable datasets, reliance on single-static analyses, limited actionability and the influence of analyst decision biases. The proposed solution concepts each address these pain points and can be expanded to promote inclusion of marginalised groups in climate-disaster decision-making processes. However, in the interest of time due to the urgency of climate change impacts, it is imperative to invest in the most effective, feasible, and sustainable options to maximise long-term resilience that aligns with performance, cost, and stakeholder needs and reduces the risk of costly redesign later (Yahya et al., 2021).

In 2015, the United Nations (UN) established 17 Sustainable Development Goals (SDGs) (United Nations General Assembly, 2015), to be achieved by 2030, providing a global framework for governments and organisations to guide their sustainability efforts. Although the SDGs have achieved broad international endorsement, their complexity and interdependence pose significant challenges for effective implementation and progress monitoring (van Tulder and van Mil, 2018). To address these challenges, the Triple Bottom Line (TBL) framework provides an integrated approach for evaluating organisational performance through the three dimensions of People, Planet, and Profit (PPP), ensuring the alignment of ecological, economic, and social values (Alhaddi et al., 2015).

The three solution concepts at hand were thus evaluated with the Triple Bottom Line framework to select the concept to be taken forward. To strengthen the decision-making process, the strategic fit of the solution concept with long-term goals and urgency, technical feasibility, and ethical considerations to support just and inclusive climate adaptation measures were considered as three additional criteria.

4.1 People - Social Analysis

Incorporating accessibility and social vulnerability into geospatial analysis is central to impact assessment, shifting the focus from traditional asset-based loss metrics to metrics that capture who experiences loss of access, for how long, and under which hazard conditions. Concept 2 integrates a **Social Vulnerability Index (SoVI)** calibrated to local exposure, sensitivity, and adaptive capacity indicators (Cutter, 2024). Within SPIN, these SoVI scores are combined with accessibility modelling and linked to a structured **causes–effects–measures database**, enabling planners to determine which population groups experience isolation, the underlying causes (e.g., road failure or service disruption), and the corresponding pre-, during-, and post-event interventions that are most relevant.

Relative to concept 1, which increases local accuracy but scales slowly and unevenly, concept 2 delivers **methodological efficiency and repeatability** by relying on existing spatial datasets and structured weighting using established decision-support techniques such as Multi-Criteria Decision Analysis (MCDA) (Dodgson and Spackman, 2009). In contrast to Concept 3, which improves narrative clarity after the analyses but does not strengthen the underlying evidence base, Concept 2 keeps assumptions, indicator weights, and data lineage transparent and reviewable. That supports procedural justice by allowing both internal experts and external stakeholders to challenge or adjust how vulnerability is defined, rather than accepting an opaque model output (Adger, 2006).

Solution concept 2 operationalises principles from vulnerability and resilience research (Markkanen and Anger-Kraavi, 2019). Climate impacts are unevenly distributed, and adaptation planning that overlooks disparities in access can inadvertently reproduce existing inequalities. By linking SoVI scores to accessibility, SPIN can generate equity-oriented performance indicators. These insights align with SDG 10 (reduced inequality) and SDG 11 (resilient and inclusive cities) (United Nations Office for Disaster Risk Reduction (UNDRR), 2025), while also providing an auditable foundation for allocating funding and prioritising interventions in a manner that is defensible to both clients and affected communities.

4.2 Planet - Environmental Analysis

The main objectives of SPIN align with building resilient infrastructure (SDG 9), reducing inequalities (SDG 10), and strengthening sustainable cities and communities (SDG 11), however, taking climate action and mitigating its impacts (SDG 13) (United Nations General Assembly, 2015) represents one of SPIN's central goals and forms the core of this environmental analysis. Inclusive climate risk mitigation strategies that account for socially vulnerable groups can generate wide-ranging co-benefits (Markkanen and Anger-Kraavi, 2019). For example, resilient infrastructure not only supports ecosystem preservation but also provides socioeconomic advantages for local communities (United Nations Office for Disaster Risk Reduction (UNDRR), 2025).

Among the proposed solution concepts, concept 1 relies primarily on manual processes to improve SPIN, whereas concepts 2 and 3 integrate Artificial Intelligence (AI) to broaden SPIN's analytical capacity. The rapid expansion and increasing complexity of Machine Learning (ML) models lead to significant energy consumption, water use, and carbon emissions (Patterson et al., 2021). As per the study, although ongoing advances in algorithms, processors, and data centres continue to improve energy efficiency, training a single Natural Language Processing (NLP) model can still require between 24 MWh and 232 MWh of electricity, equivalent to as much as 110.4 tons of CO_2 emissions in the Netherlands (van Cappellen et al., 2021). These emissions can be reduced by approximately 20% through algorithmic optimisation (Wu et al., 2022) and further lowered by adopting renewable energy sources.

Therefore, AI should be implemented only in contexts where its contribution to mitigating climate risks clearly outweighs the emissions it generates. When appropriately applied, integrating AI as a validation and optimisation tool can enhance the precision and effectiveness of sustainability initiatives, helping to offset its own environmental footprint and contributing to SPIN's broader sustainability objectives (Wu et al., 2022).

4.3 Profit - Economic Analysis

The economic perspective assesses cost-efficiency, market scalability, and long-term economic viability. Within concept 2, SPIN as a tool is expanded into a multi-layer analytical platform, which creates new value propositions for both public and private clients. The added analytical depth allows SPIN to diversify its client base beyond institutional partners toward commercial insurance and ESG risk-assessment sectors (Royal HaskoningDHV, 2025). This scalability is supported by the modular architecture of Concept 2, which enables the reuse of existing geospatial datasets, lowering marginal costs and enhancing project profitability. Furthermore, its methodological transparency and decision-support relevance can attract co-financing from international adaptation funds, which increasingly prioritise equity-based analytics aligned with SDG 10 and 13 (United Nations Office for Disaster Risk Reduction (UNDRR), 2025).

Solution Concept 1 provides moderate profitability, as community-based fieldwork strengthens SPIN's reputation for data accuracy and inclusiveness, potentially attracting grant-based funding from NGOs and development agencies. However, its dependence on site-specific operations, equipment installation, and long-term maintenance significantly raises fixed costs, making it less viable for rapid expansion (510 Global, 2024). Financially, its return on investment is slower due to high labour intensity and low scalability.

The use of AI to support interpretation and decision-making processes can enhance automation and improve operational efficiency. Moreover, a user-friendly interface facilitates client interaction with SPIN, creating opportunities for premium service models. Nevertheless, the heavy reliance on advanced AI training and maintenance incurs substantial upfront costs, energy consumption and data-processing expenses (Mai et al., 2022; Strubell et al., 2019). Furthermore, clients in the humanitarian or public sectors may perceive such a high-tech model as less accessible or cost-effective, potentially limiting its short-term profitability.

4.4 Strategic Fit

Strategic fit encompasses both internal and external factors and their alignment with an organisation's overarching strategy (Scholz, 1987), necessitating stakeholder analysis and the adoption of international climate adaptation frameworks. As noted by the UNFCCC (UNFCCC, 2018), effective climate adaptation requires consideration of diverse, interconnected risks, addressing not only the direct impacts of climate hazards but also their indirect and cascading effects. In line with the UNFCCC's focus on managing complex, interrelated climate risks, the BECCA criteria (Weiland et al., 2016): Effectiveness, Efficiency, Equity, Acceptability, and Robustness, serve as a comprehensive framework for evaluating strategic fit.

All proposed solution concepts promote **equity** through an inclusive design approach that integrates diverse stakeholder perspectives and supports socially responsive decision-making. Concept 1 ranks highest in equity, as it includes in-depth, ground-based surveys that reduce data scarcity and foster community participation. Concept 2 achieves a high level of equity by contextualising social vulnerability through a refined, multi-dimensional index. In contrast, concept 3, while incorporating AI for data interpretation, attains only a moderate equity score, as algorithmic processes may reduce but not fully eliminate underlying biases.

Ground-based data acquisition in Concept 1 also yields high **effectiveness**, enabling precise identification of vulnerable groups and, consequently, more targeted and impactful adaptation measures. Concept 2 demonstrates moderate to high effectiveness through its contextualised Social Vulnerability Index, which captures multi-dimensional insights despite some data limitations. Conversely, Concept 3 exhibits low effectiveness, as restricted and secondary data sources limit the depth and accuracy of vulnerability assessments.

Both Concept 1 and Concept 2 perform well on **acceptability**. Their qualitative (Concept 1) and quantitative (Concept 2) approaches to identifying socially vulnerable groups are transparent and accessible to stakeholders. In contrast, Concept 3 faces low acceptability challenges, as AI-driven outputs may lack interpretability for non-technical users, potentially reducing trust and adoption among key stakeholders.

Concept 3 achieves high **efficiency** by leveraging automation and web-scraping to synthesise insights from publicly available data sources such as reports, news articles, and academic publications. This approach significantly reduces the time and effort required for manual research and data processing. Concept 2 demonstrates moderate to high efficiency, as it integrates established spatial technologies, such as multi-criteria decision analysis (MCDA) (Weinberg and Smith, 2020)—to optimise analytical workflows and avoid development redundancies. However, Concept 1 scores low in efficiency, since converting ground-based data into geospatial formats requires substantial logistical resources and limits scalability.

Concept 2 ranks highest in **robustness**, as it employs multi-hazard, multi-regional indicators that extend analytical reliability beyond the limitations of field-based or AI-only methods. This approach aligns closely with global climate adaptation frameworks, enhancing the salience, credibility, and legitimacy of outcomes (Cash et al., 2003). Concept 1 shows lower robustness as concept 1 only relies on a localised scope.

The proposed solution concept 2 thus addresses urgent climate adaptation needs, especially for vulnerable groups, by aligning with effective knowledge systems. It enhances salience, credibility, and legitimacy (Cash et al., 2003), ensuring technically robust, socially responsive, and widely accepted strategies within the global climate adaptation framework, particularly as disasters disproportionately affect vulnerable populations (United Nations Office for Disaster Risk Reduction (UNDRR), 2025).

4.5 Technical Feasibility

The technical feasibility of acquiring relevant data, conducting analysis, and recommending adaptation measures is significantly improved by strengthening the architecture, intelligence, and output capabilities of geospatial analysis tools like SPIN. Traditional fieldwork methods in Concept 1, such as drone surveys, are labour-intensive, expensive, and difficult to scale, particularly in resource-constrained regions. Deploying large language models (LLMs) or AI in Concept 3 for map interpretation requires highly specialised expertise and extensive model training, which limits operational efficiency (Pierdicca et al., 2025).

The proposed Concept 2 builds on existing, validated technologies such as spatial analysis software and embedded decision-support frameworks to construct a refined Social Vulnerability Index and structured analytical matrices for assessing causes, effects, and adaptation strategies (Esri, 2025; Weinberg and Smith, 2020), further validated by qualitative data analysis using web scraping techniques and NLP techniques such as sentiment tagging and topic modelling to extract qualitative insights from the text data. Furthermore, taking a case study, for instance, in Mombasa, and evaluating the impacts of flooding in the African cultural context can be scaled to other African regions with similar characteristics, and even beyond the continent. This contextualises indicators across hazards and geographies, enabling scalable, stakeholder-inclusive, maintainable, and globally applicable operations.

4.6 Scoring the Solution Concepts

The three solution concepts were evaluated based on five key criteria (Figure 10): People, Planet, Profit, Strategic Fit, and Technical Feasibility. Each concept offers unique strengths and limitations in enhancing geospatial analysis tools (Appendix A shows detailed scoring). Concept 2, however, achieves the highest overall performance, indicating it offers a strong balance across all sustainability dimensions. It performs particularly well in terms of social impact (People) by identifying socially vulnerable communities and providing measures that are both qualitatively and quantitatively defined. This aligns with the strategic goals, making it a well-rounded and feasible option for implementation.

Concept 1 also performs relatively well, especially on environmental (Planet) and social (People) aspects, suggesting that it is a sustainable and community-oriented approach, but it scores lower in identifying socially vulnerable communities and long-term financial sustainability. However, due to its relatively less reliance on technology development, its environmental footprint is lower, making it sustainable. With the inclusion of diverse stakeholders in all phases of the disaster, Concept 1's aspects of data acquisition can be incorporated into the analysis stages by qualitative data and in preparing contextualised disaster management measures.

Concept 3 focuses on interpretation bias and translating maps into actionable insights. It introduces a lightweight AI model and contextual databases, enhancing usability and decision-making. While it lacks strong stakeholder engagement compared to Concept 1 and 2, its clarity and accountability features are crucial. From Concept 3, the biases in interpreting results can be reduced, which can help with clear actionable points for the user and facilitate a just decision-making process. Consequently, Concept 2 represents the most feasible, sustainable, and impactful pathway for further integration within the geospatial analysis. It can integrate Concept 3's interpretive clarity, supported by Concept 1's inclusive data acquisition approach.

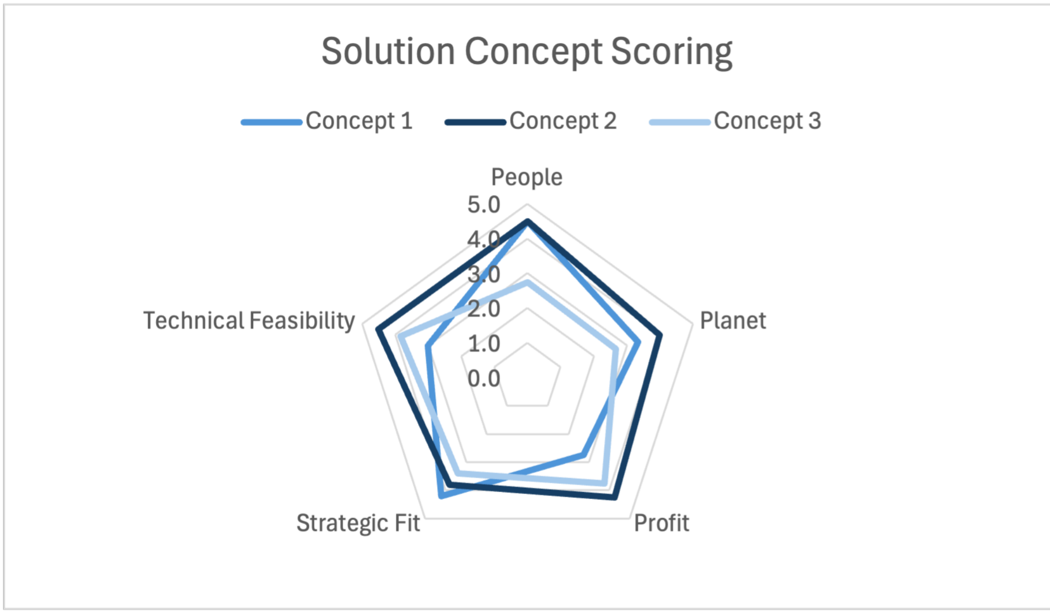


Figure 10: Solution concept scoring

5 Final Solution

The final solution is compiled from the best-scoring aspects of the solution concept, defined in section 4. Combined, the focus lies on improving tools that are used in knowledge acquisition and decision-making processes within climate services. The result is a new framework for the use of GIS-based tools, wherein the findings of each cluster-specific research perspective contribute to an interdisciplinary result. This chapter dives into the findings and results of each perspective. Whereafter, these results are synthesised into a final framework and workflow recommendation.

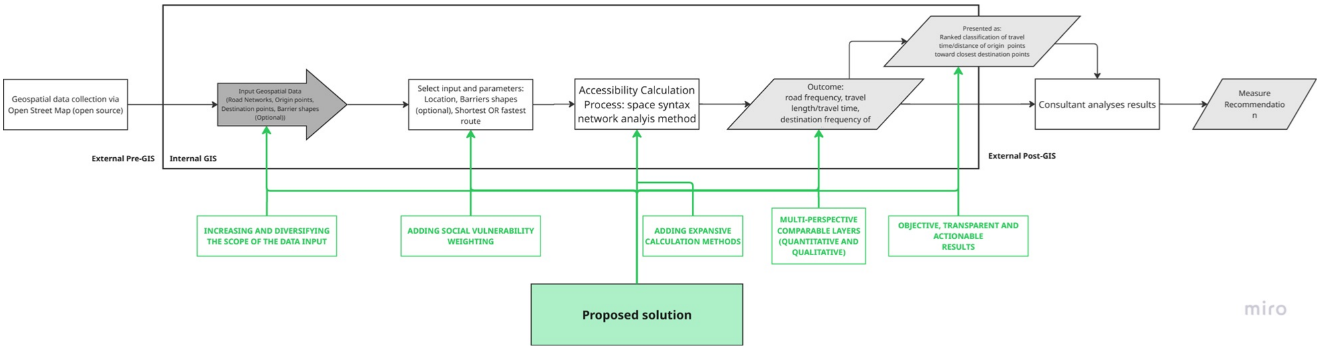


Figure 11: Final solution proposition within SPIN's GIS workflow

5.1 Social Vulnerability

Social vulnerability is defined as the potential for harm and loss, describing the sensitivity of a population to natural hazards, the level of exposure to them, and its corresponding ability to respond to and recover from those impacts (McCullagh et al., 2025). The concept roots through diverse disciplines, from sociology, public health, to the economy. Social Vulnerability is primarily understood as being partially derived from inherent social inequalities–factors that influence susceptibility to harm and ability to respond–and place inequalities—characteristics of the built environment or community economic vitality (Cutter, 2024).

As vulnerability varies geographically and socially, incorporating it into spatial analysis is highly significant. Tools like the *Social Vulnerability Index (SoVI)* enable mapping and visualisation of these disparities, highlighting the uneven capacities for preparedness, response, and recovery across different communities (Cutter, 2024). This spatial understanding is critical for supporting just spatial planning and climate adaptation. Socially integrated spatial analysis translates theory into effective operational practice in disaster management, enabling geospatial targeting of spatial measures to the most vulnerable populations throughout disaster phases (Cutter, 2024).

5.1.1 Integrating Social Vulnerability in Spatial Analysis

Despite the importance of social vulnerability in spatial planning, socially constructed vulnerabilities are often overlooked due to challenges in quantification, resulting in frequent exclusion of social losses from post-disaster cost and impact analyses (Cutter et al., 2003). Considering these challenges and the fact that SPIN is a spatial tool, this study focuses on spatially related indicators to ensure methodological alignment. Measurable spatial indices derived from SoVI are employed so that, even in regions lacking detailed socio-economic data, social vulnerability is not entirely disregarded.

SoVI remains one of the most influential frameworks in vulnerability science, providing a foundation for quantitative social vulnerability analysis (Cutter, 2024). Building on this, a spatial-focused SoVI formula is developed by integrating multiple indicators weighted through the Best-Worst Method (BWM), wherein experts help to identify the most and least critical indicators, and compare them to each other (Rezaei, 2015). This structured weight-assigning approach ensures that the resulting aggregated score reflects context-specific priorities.

SoVI Formula

The proposed Social Vulnerability Index (SoVI) incorporates both baseline and post-disaster conditions to capture variations in community vulnerability resulting from changes in accessibility. The corresponding formulations are expressed as follows:

$$SoVI_{\text{baseline}} = W_1 \cdot A + W_2 \cdot E + W_3 \cdot B \tag{1}$$

$$SoVI_{\text{post-disaster}} = W_1 \cdot A + W_2 \cdot E + W_3 \cdot B + W_4 \cdot \Delta A \tag{2}$$

In these equations, A (Accessibility) measures access to key infrastructure such as hospitals, emergency shelters, schools, and food markets. E (Exposure) captures the risk of encountering natural hazards. B (Built environment) characterises the physical and structural attributes of a location. In urban contexts, high building density may correspond to poorer living conditions and greater vulnerability, whereas in rural settings, moderate clustering of structures can enhance access to shared resources and reduce vulnerability. W_i denotes the weights derived from BWM and $\sum_{i=1}^{n} W_i = 1$. Finally, ΔA (changes in accessibility), represents the loss of access to key infrastructures following a disaster.

$$\Delta A = A_{\text{baseline}} - A_{\text{post-disaster}} \tag{3}$$

The selected dimensions are designed to capture the multifaceted nature of social vulnerability. Together, they encompass both spatial exposure and social conditions, allowing vulnerability to be represented even when detailed demographic data are unavailable.

1. **Accessibility**: Limited accessibility often amplifies vulnerability during disasters (Wee, 2022), as communities with poor transport connectivity face delayed emergency responses and reduced adaptive capacity.
2. **Natural Hazard Exposure**: This factor quantifies the degree to which populations and assets are located in hazard-prone areas. The direct spatial overlap between human settlements and environmental risks is captured, serving as the foundation of physical vulnerability.
3. **Built Environment**: This dimension serves as an indirect indicator of socio-economic conditions in data-scarce contexts. Characteristics of the built environment, such as housing density and building quality, often reflect the socio-economic status (Smith et al., 2017) and therefore influence social vulnerability.

The overall aim of the SoVI formula is to generate a synthesised map that serves as an additional analytic layer for the SPIN output, introducing social vulnerability nuances and enabling more geo-targeted measure recommendations.

Assigning Weights

The identified criteria (Accessibility, Hazard exposure and Built environment) are assigned different weights as indicated in Equation 1. The Bayesian Best–Worst Method (BWM) (Mohammadi and Rezaei, 2020) was employed to determine criterion weights using fewer pairwise comparisons, thereby reducing inconsistency and improving reliability. In BWM (Rezaei, 2015) for multi-criteria decision making (MCDM), the most important (best) and least important (worst) criteria are identifiedd; the best criterion is then compared against all others, and all criteria are compared against the worst using a consistent preference scale. In this project, four experts from Haskoning and from TU Delft provided these ratings through a questionnaire (Appendix D). This system is promising in providing a probabilistic representation of group preferences that is more robust than simple averaging.

Data construction

The aggregation of expert judgments in the Best–Worst Method (BWM) framework is formalized using a Bayesian hierarchical model. Let C denote the total number of indicators. Each expert $i \in \{1, 2, 3, 4\}$ first identified the most and least important indicators and provided preference ratios ranging from 1 to 9 for two vectors of pairwise comparisons:

- Best-to-Others ratios a^i_{Bj} for all j: how much more important is the best indicator compared to j ($1 =$ equal, $9 =$ absolutely more).
- Others-to-Worst ratios a^i_{jW}: how much more important is indicator j compared to the worst.

The expert-provided preference ratios are first converted into a probability distribution over the indicators, which is then used to model the observed selection counts as draws from a multinomial distribution.

$$p_{ij}^{AB} = \frac{(a_{Bj}^{(i)})^{-1}}{\sum_{k=1}^{C}(a_{Bk}^{(i)})^{-1}}, \quad AB_j^{(i)} = \mathrm{round}(\underbrace{\sum_{k=1}^{C} a_{Bk}^{(i)}}_{N_B^{(i)}} \cdot p_{ij}^{AB}).$$

$$p_{ij}^{AW} = \frac{a_{jW}^{(i)}}{\sum_{k=1}^{C} a_{kW}^{(i)}}, \quad AW_j^{(i)} = \mathrm{round}(\underbrace{\sum_{k=1}^{C} a_{kW}^{(i)}}_{N_W^{(i)}} \cdot p_{ij}^{AB}).$$

Model

Given the $(C-1)$-simplex: $\Delta^{C-1} = \left\{ w \in \mathbb{R}_+^C : \sum_{j=1}^{C} w_j = 1 \right\}$, let $w^{(i)} \in \Delta^{C-1}$ denote the individual weight vector for expert i and let $w^{\mathrm{agg}} \in \Delta^{C-1}$ be the aggregated weight vector across experts. The individual and aggregated weights are modeled hierarchically:

$$w^{(i)} \mid w^{\mathrm{agg}}, \gamma \sim \mathrm{Dirichlet}(\gamma \cdot w^{\mathrm{agg}}), \quad w^{\mathrm{agg}} \sim \mathrm{Dirichlet}(0.01 \cdot \mathbf{1}), \quad \gamma \sim \mathrm{Gamma}(0.001, 0.01), \tag{4}$$

where $\gamma > 0$ is a concentration parameter; larger values of γ shrink $w^{(i)}$ more tightly toward w^{agg} and the Dirichlet prior with 0.01 in $\mathrm{Dirichlet}(0.01 \cdot \mathbf{1})$ is weakly informative, reflecting minimal prior assumptions.

The observed BWM data are incorporated through multinomial likelihoods, where the normalization ensures probabilities sum to one:

$$\text{Others-to worst counts: } \mathbf{AW}^{(i)} \sim Multinomial(N_W^{(i)}, w^{(i)}), \tag{5}$$

$$\text{Best-to others counts: } \mathbf{AB}^{(i)} \sim Multinomial(N_B^{(i)}, normalize((w^{(i)})^{-1})). \tag{6}$$

Combining the hierarchical prior (4) and the likelihoods (5), (6) yields the joint posterior distribution of the aggregated and individual weights given the observed data:

$$\begin{aligned} P\left(w^{agg}, w^{1:K} | AB^{1:K}, AW^{1:K}\right) &\propto P\left(AB^{1:K}, AW^{1:K} | w^{agg}, w^{1:K}\right) P\left(w^{agg}, w^{1:K}\right) \\ &= P(w^{agg}) \prod_{k=1}^{K} P\left(AW^{(k)} | w^{(k)}\right) P\left(AB^{(k)} | w^{(k)}\right) P\left(w^{(k)} | w^{agg}\right). \end{aligned} \tag{7}$$

Samples from this posterior are drawn using Markov Chain Monte Carlo (MCMC) methods (Speagle, 2020), producing a set of aggregated weight draws $\{w_s^{agg}\}_{s=1}^{10000}$. The final aggregated weights are estimated by the posterior mean:

$$\widehat{w}^{agg} = \frac{1}{10000} \sum_{s=1}^{10000} w_s^{agg}. \tag{8}$$

This approach provides a robust representation of the consensus across experts, while simultaneously accounting for individual variability and the inherent uncertainty in the BWM data.

5.1.2 Case Study: Implementation Test

To demonstrate the effectiveness of the SoVI formula, a case study approach was adopted. The chosen region is Mombasa County and natural hazard type is a flood scenario. Mombasa County, located in southeastern Kenya, covers an area of approximately 229.7 km² and has a population of around 1.19 million. The county was chosen for the following reasons:

1. **Severe flash flooding:** Due to its low-lying coastal landscape, inadequate flood-mitigation infrastructure, and the increasing impacts of climate change (Oluchiri, 2025), Mombasa County experiences recurring flash floods. This makes it an ideal case study area to test the natural hazard exposure component of the SoVI model.

2. **Availability of geospatial data:** Kenya is recognised for its relatively well-developed national spatial data infrastructure among Global South countries (Mwange et al., 2018). Together with other open data sources, this enables sufficient data collection and reliable datasets, particularly for the accessibility and built environment indicators.
3. **High socio-economic diversity:** From Mombasa's demographic survey, it exhibits significant spatial variation in income levels, urban density, and access to public services. This diversity allows for a more nuanced validation of how the SoVI model captures differences in vulnerability across socio-economic groups.

The data sources of the case study can be found in Appendix B.

Maps Generation and Result Interpretation

To address the limitation that many GIS assessments are single-layered, this set of maps combined multiple spatial dimensions, which provides a more comprehensive basis for identifying and mitigating social vulnerability.

To generate the accessibility map, the output of the current SPIN model was adapted. SPIN requires origins, destinations, and a road network as inputs. Origins were derived from the population density map, with each point representing 1,000 individuals. The road network was pre-processed to satisfy SPIN's input requirements by adding a speed attribute. Destinations were selected as points of interest during natural hazard events, including medical facilities, schools, and hotels (used as proxies for shelters). The shortest-path method was then applied, with a 2 km threshold from origins to the nearest roads to prevent miscalculations. Due to limitations in data availability, only the baseline SoVI formula was tested.

To facilitate subsequent analysis, the CSV file containing each origin's minimum travel time to the nearest destination was selected for post-processing. As the SPIN output initially consists of discrete points, while the intended outcome is a continuous surface reflecting regional accessibility patterns, spatial interpolation was performed at a 100 m resolution to produce the final accessibility map (Figure 12a). This accessibility map reflects the population's ability to reach critical services under hazards conditions, representing the communities' abilities to recover from hazards.

To represent the most common natural hazard and its impact on local communities, the analysis focused on floods, following a methodology adapted from a flood assessment study in Mombasa (Omanga, 2024). According to the study, nine contributing factors were selected: slope, elevation, profile curvature, flow accumulation, total wetness index, distance to rivers, soil composition, land cover, and projected rainfall for 2050. By assigning weights to these key variables, a composite flood risk map was generated in raster format at a 100 m resolution (Figure 12b).

For the built environment, building density was selected as a proxy, based on data availability (Wang et al., 2024). A 100-metre resolution fishnet grid was generated, and building density was calculated as the ratio of total building footprint area to the grid cell area. The resulting values were rasterized for further processing (Figure 12c). Built environment serves as a proxy for socio-economic conditions in data-scarce contexts, characteristics such as building density often reflect socio-economic status(Smith et al., 2017). In this sense, the built environment acts as a spatial manifestation of economic inequality—areas with dense construction quality or inadequate infrastructure often correspond to lower-income populations, who are less capable of coping with and recovering from hazard impacts.

As described in item 5.1.1, the Bayesian BWM (Mohammadi and Rezaei, 2020) was applied to determine the weights in the SoVI formula. The resulting weights were 0.336 for accessibility, 0.426 for Natural Hazard Exposure 0.426 and 0.238 for Built Environment. Before generating the synthesized vulnerability map, all three component layers were normalized to a common scale between 0 and 1 using the min–max normalization method. Since Accessibility is an inverse indicator (higher accessibility implies lower vulnerability), it was normalized using the formula

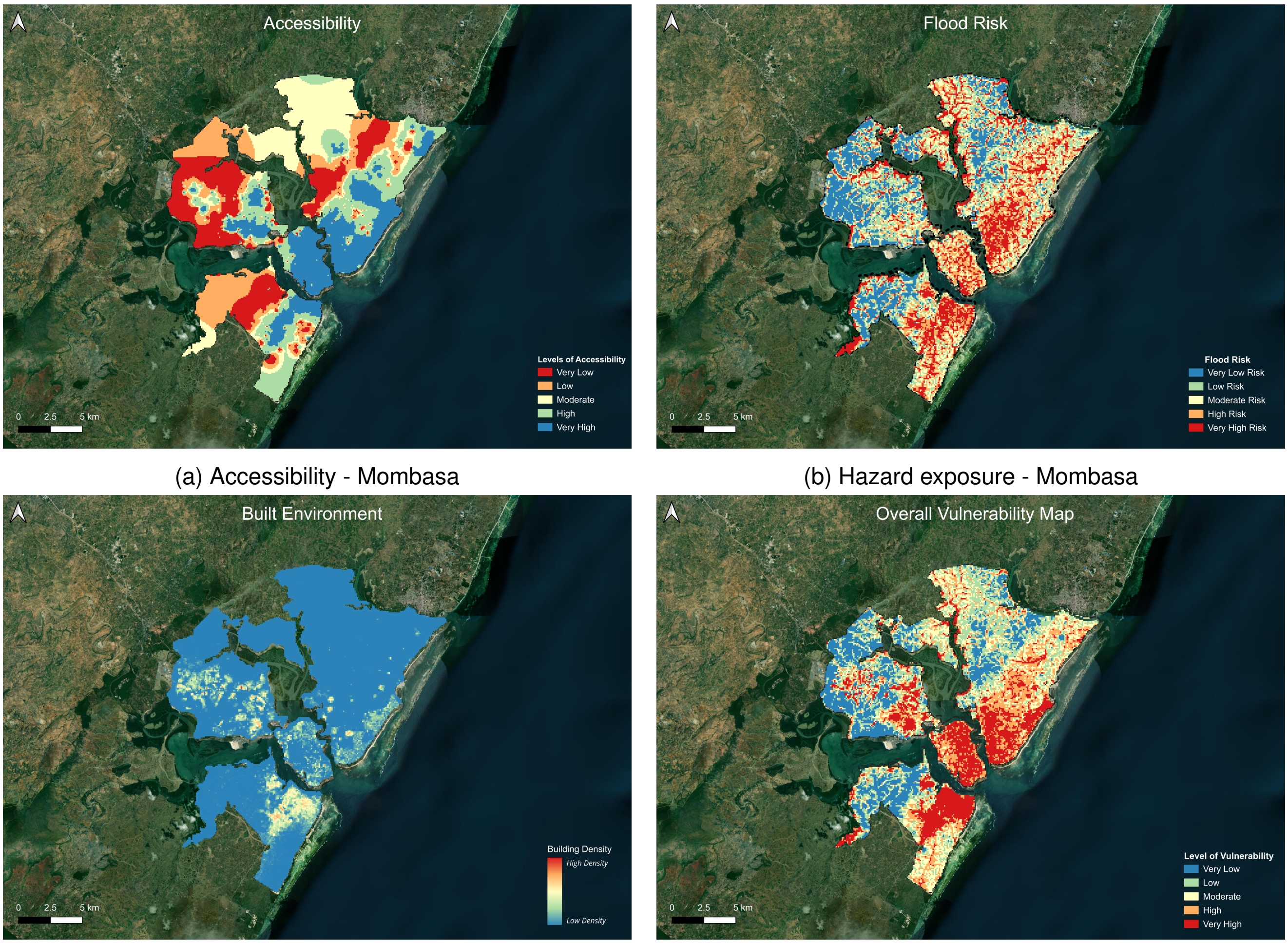
$$X' = \frac{X_{\max} - X}{X_{\max} - X_{\min}}. \tag{9}$$

In contrast, Natural Hazard Exposure and Built Environment were normalized as

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{10}$$

The normalized layers were then combined in the raster calculator through a weighted overlay to produce the final synthesized vulnerability map(Figure 12d).

Figure 12 illustrates the spatial results of the three main components contributing to the Social Vulnerability Index (SoVI) and the final synthesized vulnerability map for Mombasa County. The accessibility map shows that inland areas have lower accessibility to essential services, whereas central urban zones near the coast demonstrate much higher accessibility levels. The flood hazard exposure map reveals that coastal and low-lying zones are more prone to flooding, reflecting their proximity to waterways and the Indian Ocean. The built environment map highlights higher building densities in the coastal and central areas, indicating concentrated urban settlements. The overall social vulnerability demonstrates that coastal areas face higher vulnerability mainly driven by natural hazard exposure(flood in this case study), while inland areas with poor accessibility also demonstrate high vulnerability despite low hazard exposure risk.



(a) Accessibility - Mombasa

(b) Hazard exposure - Mombasa

(c) Built environment - Mombasa

(d) Social Vulnerability - Mombasa

Figure 12: Case study maps

Value Added

In the case of Mombasa, without incorporating additional layers of flood exposure and building density on the accessibility analysis, coastal communities would not appear as vulnerable in the analysis (Figure 12a), risking their exclusion from the decision-making process despite facing significant exposure to flood and relatively densely built (Figure 12b & Figure 12c). However, it is important to note that the accessibility map generated with SPIN in this study did not include any flood barrier component, as static flood shapefiles are not not easily accessible. SPIN only allows the use of a binary (0 or 1) static hazard map rather than a continuous hazard probability map, which reduces accuracy. Nevertheless, the results might differ if such barriers were initially incorporated.

The current version of SPIN primarily measures accessibility, which only captures the ability of people to reach essential services during hazard events. Integrating the proposed SoVI formulation adds nuance to the SPIN output: the SoVI maps serve as overlays to highlight communities that also fall within other vulnerability criteria, such as flood exposure or poorly built environments, and might reveal additional vulnerable areas that may be overlooked by accessibility analysis alone.

Social vulnerability is a complex and multi-dimensional concept that is often difficult to quantify. This multi-layered approach enables a more comprehensive, context-specific assessment and helps prioritise areas and/or select measures based on the underlying causes of vulnerability.

5.1.3 Implementing Flood-ABM on a Vulnerable Community

This study also experiments with incorporating socially induced SoVI into the analysis by implementing Agent-based Modelling (ABM) in the case of Mombasa. ABM represents individuals or households as autonomous agents endowed with attributes and decision rules, interacting with one another and with their environment over discrete time (Macal and North, 2009). Flood-ABM differentiates population groups using a socio-economic index to examine how resource and vulnerability disparities affect flood impacts. It simulates individual and collective behaviours across pre-, during-, and post-flood phases (Addai et al., 2025). The model can be used to reveal which groups are most affected and whether disparities stem from economic thresholds, mobility constraints, or service bottlenecks rather than exposure alone. This approach allows the incorporation of socio-economic attributes into the spatial-focused social vulnerability analysis, serving as a complement to the developed SoVI map presented in Figure 12.

The detailed demographic and socioeconomic inputs, data sources, and fitted distribution parameters are listed in Table 8; the simulation setup and components development can be found in Appendix C.

The simulation is currently a stand-alone process – not yet coupled to SPIN workflow –and, due to time and computing constraints, is applied at a certain community level in Mombasa (land cover shown in Figure 21). It follows the same model structure and rules as in (Addai et al., 2025), with the context-specific inputs replaced by Mombasa or Kenya data. Given the modular agent initialisation and parallelizable updates, scaling to a citywide extent is feasible when conditions permit (Liu and Lim, 2018).

To complement the spatial SoVI map, which relies on accessibility, natural hazard exposure, and the built environment, the Flood-ABM assigns socioeconomic attributes to household or individual agents, including gender, age and their distributions, education level, income and wealth distributions, mobility, and identity status (local or refugee). With these attributes, the simulation can compare outcomes across socioeconomic strata under the same hazard event. It tracks, by day t (pre-, during, and post-flood), the proportions of people evacuated, stranded, hospitalised, sheltered, injured, or deceased, contrasted between low and high socioeconomic status (SES), labeled as low-SES and high-SES.

$$\mathrm{SES} = \frac{\mathrm{Age}_{\mathrm{SES}} + \mathrm{Edu}_{\mathrm{SES}} + \mathrm{Gen}_{\mathrm{SES}} + \mathrm{Id}_{\mathrm{SES}} + \mathrm{Wth}_{\mathrm{SES}}}{5}, \tag{11}$$

The SES is a social vulnerability index that integrates only socio-economic attributes: age, education, gender, identity, and wealth class(Addai et al., 2025), where $\mathrm{Age}_{\mathrm{SES}}, \mathrm{Edu}_{\mathrm{SES}}, \mathrm{Gen}_{\mathrm{SES}}, \mathrm{Id}_{\mathrm{SES}}, \mathrm{Wth}_{\mathrm{SES}} \in [0,1]$ are disadvantage-oriented transforms (e.g., low education, low income/wealth class), with higher SES indicating higher vulnerability. Thresholds (e.g., $\mathrm{SES} \leq 0.3$ for low-SES vs. ≥ 0.7 for high-SES) are then used for outcome comparisons. By comparing the proportions of residents, such as those stranded or hospitalised during the flood, between low-SES and high-SES agent groups, the analysis quantifies the extent to which socially vulnerable populations are more severely affected by natural hazards. The output comparison graphs tested for the Mombasa case are shown in Figure 22.

Furthermore, the model includes residential savings, business agents, government, hospitals, and local taxation, allowing incomes, cash buffers, and commercial activity to evolve before, during, and after the flood. This enables resilience trajectories analysis, such as resident asset loss, business downtime and recovery, and local revenue gaps, and enables decision-makers to test budget allocations for critical infrastructure across hazard phases. The tested outputs are shown in Figure 23.

Hospital capacity, shelter capacity, and disaster funds are implemented as tunable parameters, allowing scenario simulations to adjust these levers and information latency to test plausible interventions (e.g., surge beds, temporary shelters). This enables estimation of marginal benefits, such as reduced stranded or hospitalised shares among high-SES groups, from capacity expansion or targeted subsidies, aligning measures with subgroup-specific constraints.

Value Added

The model supports more targeted, hence effective, disaster management strategies. The significance of ABM lies in its ability to incorporate demographic or social vulnerability data into the analysis and test intervention effectiveness in scenarios. It helps tailor measures to the specific needs of different community groups.

5.1.4 Limitation and Future Study

One limitation of the current study is that building density is the only built environment indicator incorporated into the SoVI-based map, though the formula is flexible and can accommodate additional indicators. The expanded formula is as follows, where S_i is other social vulnerability indicators.

$$SoVI = W_1 \cdot A + W_2 \cdot E + W_3 \cdot B + W_4 \cdot \Delta A + \sum_{i=5}^{n}(W_i \cdot AS_i) \tag{12}$$

Future work could expand the built environment dimension with other variables, such as age of building, drainage network density or green space (Wang et al., 2024). Other building datasets are also available, like Google's Open Buildings. Alternative methods for assigning weights, such as multi-criteria decision analysis (MCDA), could also be explored to reflect context-specific priorities and improve the robustness of the synthesised map. Last but not least, the BMW method for assigning weights could be further refined by including broader expert review to enhance the robustness and accuracy of the results, particularly local stakeholders.

The limitation of the built environment map lies in the variation of data sources and their resolution. High-resolution imagery and volunteer-maintained maps can capture individual buildings but may be inconsistent or incomplete, while coarser land cover maps provide broader coverage suitable for large-area analysis. Moreover, accessibility and natural hazard maps can be developed in multiple ways. Accessibility can be measured using more advanced methods; for example, the two-step floating catchment area (2SFCA) method considers both population demand and the supply capacity of infrastructures. Meanwhile, natural hazard maps can be generated with software such as HEC-RAS or SOBEK. Ultimately, the developed map is highly sensitive to the data source, processing method, and resolution.

Regarding the ABM component, its integration with the SPIN workflow is currently limited, as the model constrains agent movement using land cover rather than realistic road networks. Expanding the ABM to incorporate road-based mobility would allow more detailed testing of interventions, which might include formalising the behaviour of floods under specific measures in the area or implementing a partial barrier to roads as opposed to SPIN's total road blockage. This modular approach could provide more nuanced insights into targeted disaster management measures and strengthen the applicability of SPIN outputs.

5.2 Spatial Planning

As outlined in the case study subsection 5.1.2, Mombasa was considered for a case study due to the availability of geospatial data, high socio-economic diversity, and its flood-prone region as an ideal case for evaluating with the SoVI model. A general literature review was thus conducted with the following key words: disaster risk assessment, accessibility during disasters, social vulnerability, Mombasa, and flooding. The team identified that the predominant issue in spatial planning is the insufficient accounting of the vulnerable communities that are most dependent on accessibility in various phases pertaining to disasters ("Sendai Framework for Disaster Risk Reduction 2015-2030 | PreventionWeb", 2015). The underlying causes for these are a knowledge gap that impedes preventive strategies and unclear prioritisation of spatial measures during different phases of the disaster (Hussainzad and Gou, 2024; Omanga, 2024).

With the identification of socially vulnerable communities and areas in a nuanced and more inclusive manner with the redefined SoVI, the consequent step is to evaluate the measures one can take for disaster mitigation. A toolkit in the form of a matrix that links the causes, effects, and corresponding measures of flood vulnerability can address the identified knowledge gap and improve prioritisation of spatial measures across different disaster phases (K'oyoo et al., 2024). This approach allows for systematic analysis and clear identification of actionable interventions based on a research of best practices and community knowledge gathered from literature review and interviews with experts. By organising information in a scalable and adaptable format, the matrix can facilitate targeted decision-making for Mombasa, but also provides a framework that can be replicated in other regions facing similar challenges (Mulligan et al., 2016). Hence, a structured review of existing toolkits was conducted to create a database that can be embedded in the SPIN tool.

5.2.1 Content of the database

Disasters are caused by various hydrogeological conditions, and their intensity and frequency are due to varying climatic conditions (Pisarello and Jawitz, 2021). The first step is to identify the climate classification as per the

Köppen-Geiger climate classification system (Peel et al., 2007) for the region. The SPIN tool should be embedded with a list of regions and corresponding climate classifications. Furthermore, the user should define the hazard type, which, for this case study, was 'Flooding'. Thus, the user can select the Phase type. For each of the permutations and combinations of these two categories, the contains identifying causes, effects, and measures for all phases of the disaster.

For this case study, the climate type of Mombasa is tropical wet and dry, which makes it prone to floods and droughts. Upon selecting the hazard type as flooding, three tables were thus developed: 1) Causes, 2) Effects, and 3) Measures. They offer a structured way to understand flood-related challenges and plan appropriate responses across different types of settlements. The 'Causes' table outlines a range of flood triggers, each with a cause ID from C1 to C10. These triggers include events like heavy rainfall, blocked drains, dam mismanagement, and sedimentation in upstream channels. Each cause results in various effects, which are detailed further in the second table, 'Effects', which includes instances such as overtopping embankments, reverse hydraulic gradients, or lateral erosion. These are further distinguished between direct and indirect impacts. Direct impacts are those that occur immediately, like road submergence or emergency response delays, while indirect impacts emerge through secondary disruptions, such as overcrowded shelters due to increased evacuation and impact on education. An important thing to consider is that each cause can have multiple effects, and each effect may in turn result in other effects (indirect).

Subsequently, the Measures table complements this by listing interventions that can be applied before, during, or after flood events. Each measure is categorised under one of three phases (Leskens et al., 2013): Prevention, Protection, or Preparedness. The table includes the name of the measure, corresponding with the type of settlement to which it applies: urban, rural, peri-urban, or non-inhabited, and the nature of the intervention, whether it is structural, nature-based, policy-driven, or community-based. This classification is as per Haskoning's standardised terminologies. Further, the table also highlights co-benefits such as improved biodiversity, groundwater recharge, or recreational space, alongside trade-offs like high costs, land use conflicts, or maintenance needs. These are included to give the users and the stakeholders involved the ability to make decisions on prioritising actions, beginning with low-hanging fruit, and the collaborations that would entail.

These measures are linked directly to specific effects from the second table, which are in turn linked to specific causes from the first table, ensuring that interventions are targeted and relevant (refer to the Appendix E for the relations between Causes, Effects, and Measures). This database draws from urban planning, environmental science, and infrastructure resilience practices, and a comprehensive literature review (refer to the references for the tables subsection E.1), offering a comprehensive toolkit for flood management. Together, Table 1, Table 2, and Table 3 provide a clear and actionable framework for understanding flood risks and designing context-sensitive solutions that account for technical feasibility with social and ecological considerations.

Cause ID	**Cause: Flooding (pluvial + fluvial)**
C1	Upstream discharge + blocked drains/solid waste
C2	Intense cloudbursts
C3	Wetland loss + sealed surfaces
C4	Overtopped causeway / low bridge
C5	Heavy rainfall
C6	River meander shift + bank erosion
C7	Backflow from river tributaries
C8	Dam/spillway mismanagement during storm peaks
C9	Floodplain encroachment
C10	Sedimentation in upstream channels

Table 1: Causes

Effect ID	Mechanism	Impact Type
E1	Overtops embankments	Direct
E2	Deeper, longer floods	Direct
E3	Damaged road and bridge infrastructure	Direct
E4	Culvert backwater	Direct
E5	>X% households beyond clinic threshold	Direct
E6	Market access time doubles	Direct
E7	Micro-floods	Direct
E8	Emergency response speed loss	Direct
E9	School days lost	Indirect
E10	Reduced infiltration/retention	Indirect
E11	Higher peaks downstream	Direct
E12	Single point failure	Indirect
E13	Corridor cut	Direct
E14	Whole catchment left with 1 or 0 egress routes	Direct
E15	Flash flood	Direct
E16	Urban ponding	Direct
E17	Lateral erosion undermines structures	Indirect
E18	Embankment toe failure	Direct
E19	Detours increase >30% travel time	Indirect
E20	Isolation of rural settlements	Direct
E21	Reverse hydraulic gradient	Direct
E22	Flooding of secondary roads and farmlands	Direct
E23	Household relocation	Indirect
E24	Economic loss	Indirect
E25	Sudden controlled releases	Direct
E26	Downstream bridge piers and levees overstressed	Direct
E27	Emergency evacuations	Direct
E28	Livestock loss	Direct
E29	Food supply disruption: Local markets/service centers cut off	Direct
E30	Obstructed flow paths	Direct
E31	Drainage blockage	Direct
E32	Embankment stress points	Direct
E33	Shelters overcrowded	Indirect
E34	Reduced channel capacity	Direct

Table 2: Effects

Measure ID	Disaster Phase	Measure Name	Settlement Area Type	Type of measure	Co-benefits	Trade-offs
M1	Prevention	Culvert/bridge right-sizing & debris racks	Peri-Urban	Structural (Infrastructure)	Improved drainage, reduced road flooding, enhanced safety	High capital cost, possible construction disruption
M2	Prevention	Mangrove protection and restoration	Rural / Coastal	Nature-based	Coastal protection, fisheries, carbon sequestration	Long-term maintenance, enforcement needs
M3	Prevention	Blue-green corridors	Urban	Structural + Nature-based	Habitat connectivity, flood absorption, recreation	Land allocation, maintenance cost
M4	Prevention	Bioswales	Urban	Structural + Nature-based	Stormwater filtration, groundwater recharge	Requires maintenance, limited capacity
M5	Prevention	Resilient informal settlement upgrades	Urban	Structural + Planning	Health improvement, community safety, reduced losses	Relocation and cost challenges
M6	Prevention	Larger culverts	Urban / Rural	Structural	Increases flow capacity, reduces local flooding	Costly, may need redesign of adjacent infrastructure
M7	Prevention	Convert recurrent inundation zones to wetlands/parks	Urban / Peri-urban	Structural + Planning	Flood storage, biodiversity, recreation	Land use conflict, resettlement
M8	Protection	Raise or armor critical road segments; modular flood barriers	Transitional space / Network	Structural (Infrastructure)	Maintains access during floods, reduces infrastructure downtime	May alter local drainage patterns, costly
M9	Protection	Solid-waste capture at inlets + community campaigns	Urban	Non-structural + Community-based	Reduces blockage, improves health, promotes local stewardship	Requires behavior change, consistent engagement
M10	Protection	Sediment management through reforestation	Rural	Nature-based	Reduced siltation, improved water quality, erosion control	High initial investment, delayed benefits
M11	Protection	Riparian setbacks (greater than 6m and less than 30 m)	Urban , Peri-urban	Planning , Policy	Water quality, ecosystem buffers, recreation	Reduces developable land, enforcement needed
M12	Protection	Floodable parks	Urban	Structural + Nature-based	Recreation, cooling, biodiversity, flood storage	Requires land, seasonal usability limits
M13	Protection	Detention/retention basins	Urban / Peri-urban	Structural	Peak flow reduction, groundwater recharge	High land demand, sediment buildup
M14	Protection	Raised/retrofitted critical links	Urban / Rural	Structural	Maintains mobility, protects critical routes	Expensive, alters drainage flow
M15	Protection	Upstream storage coordination	Rural / Peri-urban	Structural + Policy	Downstream flood reduction, water supply co-benefit	Requires inter-jurisdictional coordination
M16	Protection	Debris booms at culverts	Urban	Structural	Prevents blockages, reduces infrastructure damage	Needs regular maintenance, risk of overflow
M17	Protection	Raised roads	Urban / Rural	Structural	Maintains connectivity, reduces isolation	Expensive, may redirect floodwaters
M18	Preparedness	Temporary/portable bridges (Bailey), boat staging points	Transitional space / Network	Structural (temporary)	Maintains connectivity during floods, rapid emergency deployment	Requires training and logistics capacity
M19	Preparedness	Floodplain restoration & set-back levees	Rural	Structural + Nature-based	Ecosystem restoration, biodiversity, groundwater recharge	Land acquisition, resettlement challenges
M20	Preparedness	Wetland restoration	Rural / Urban fringe	Nature-based	Flood mitigation, biodiversity recovery, water quality improvement	Land use conflicts, long-term restoration period
M21	Preparedness	Drainage asset management (desilt, trash screens, smart gates)	Urban	Structural + Operational	Improves drainage efficiency, reduces blockages	Requires regular maintenance and monitoring
M22	Preparedness	Temporary levees/sandbag berms	Non-inhabited	Structural (temporary)	Rapid flood protection, community preparedness	Labor-intensive, short lifespan
M23	Preparedness	Pop-up bridges	Peri-urban	Structural (temporary)	Ensures access during flood, supports evacuation	Requires logistics and training
M24	Preparedness	Contraflow traffic	Regional	Non-structural	Efficient evacuation, traffic safety	Requires pre-planning and signage
M25	Preparedness	Safe hubs/shelters on flood-safe parcels	Regional	Structural + Planning	Protects vulnerable populations, enables quick sheltering	Land allocation, O&M costs
M26	Preparedness	Relocation packages	Rural	Non-structural + Policy	Reduced human exposure, long-term resilience	Social resistance, cost, livelihood loss

Table 3: Measures

5.2.2 Database Development: Decisions and Technical Background

When designing the database that would host this information, a top-down design approach was used, beginning with the identification and organisation of the required data. Through expert interviews and individual research, the following key attributes were determined to be essential for filtering:

- **Climate Type:** To provide nuance regarding environmental factors that may impact the measures required, the user should be able to filter over different climate types.
- **Hazard:** To specify which hazard is being analysed or monitored
- **Phase:** To distinguish between pre-hazard (prevention), during-hazard (response and mitigation) and post-hazard (recovery and evaluation) stages.

From a technical perspective, it was important to maintain one of the strengths identified by the coaches at Haskoning, namely its simplicity. The system is intuitive for users, especially those familiar with GIS and Haskoning systems. It also performs efficiently with minimal loading time. These qualities should be maintained, meaning data retrieval and storage remain efficient and do not significantly increase runtime.

Another important quality to ensure the sustainability of the tool is its data integrity and scalability (Elmasri and Navathe, 2016). The database is intended to be a living document capable of incorporating future research and knowledge. At the same time, data must remain accurate and consistent to prevent confusion or misinformation. To uphold these properties, common best-practice guidelines and normalisation techniques were applied. Normalisation minimises redundancy, improving both data integration and space efficiency. It also ensures that any given value only needs to be updated once, reducing the risk of conflicting or outdated information(Elmasri and Navathe, 2016).

However, during the design process, it became apparent that two of the selected attributes did not strictly conform to the First Normal Form (1NF), that is, they could contain multiple values within a single field. Those categories belong to the Measures table, namely Co-benefits and Trade-offs. This decision was deliberate: these fields are strictly output and not used for filtering. Preserving these fields in a non-atomic form supports the tool's flexibility and reflects the complex, multi-dimensional nature of the data being modelled. Normalisation is best where data integrity is a priority. Denormalisation is best for read-heavy applications, where performance and query speed are more important(Elmasri and Navathe, 2016). This design still adheres to the broader goals of normalisation by limiting redundancy and maintaining internal consistency, while allowing for a more nuanced data representation within these descriptive fields.

Normalisation also helps to make sure that the database is in accordance with the ACID principles: Atomicity, Consistency, Isolation and Durability(Muppala, 2025).

- **Atomicity** ensures that every transaction only entails a singular operation, so if either fails completely or succeeds completely. This is beneficial since we do not have a value that is 'half-proceeded'.
- **Consistency** is in line with that, since it ensures that a database is in a valid stage both before and after a transaction, and does not break any constraints or contain any corrupted data.
- **Isolation**, similar to atomicity, means that one transaction does not impact another. It runs in isolation and will not be visible before it is committed.
- And finally, **Durability** ensures that changes made in the database are persistent and stay even when there is failure

Once the information was sorted into feature classes and tables accordingly. In Figure 13 and Figure 14, the division becomes clear.

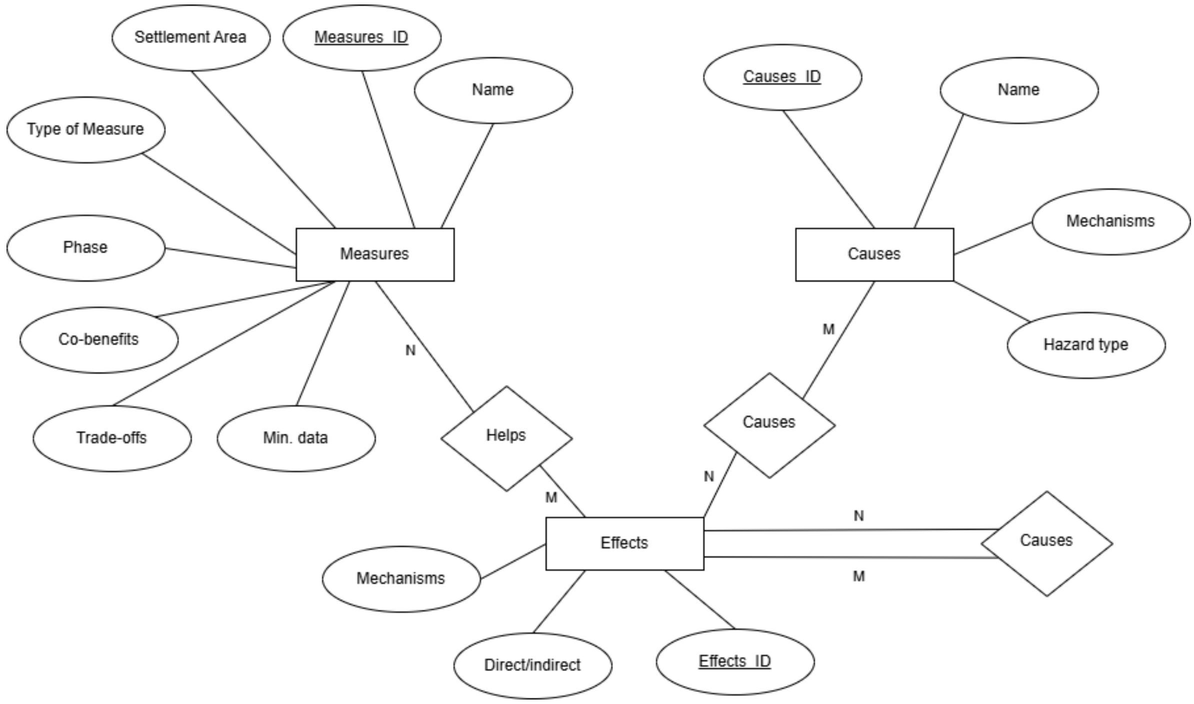


Figure 13: Entity-Relationship model, which depicts relevant entities as well as their relationship

Figure 14: Relational database schema for the Cause-Effect-Measure database storing the spatial intervention matrix

5.2.3 Limitations and further study

Currently, the database requires the User to query the data manually. One possible research field that is worth exploring is to link the simple textual data to geospatial data. There is a precedent of tools that can map the climate types of a region(Koppen.Earth, 2025), meaning the user could choose a region and it would link to the corresponding causes, effects and measures.

Furthermore, the database can further include weightage derived during the Social Vulnerability Index calculation. Weighing the effects of flooding enables prioritisation of spatial measures by linking physical impacts to social vulnerability. Further research is needed to refine weighting methods through local data calibration and participatory validation to improve decision accuracy and equity.

Another factor that would be interesting to include in the database, but has not been included due to the complexity it adds, is cultural aspects and how they affect the success or trajectory of measures. Currently, the database was intended to keep a level of simplicity, to minimise runtime and prevent redundancy. Further research would need to be done to evaluate whether mapping culture and its impact on specific measures could be feasible, or whether it is exceeding the capabilities of the database.

5.3 Hacking SPIN

While the multi-criteria spatial analysis proposed in subsection 5.1 enhances SPIN's capacity to identify vulnerable groups, data scarcity may still result in certain populations being overlooked, as informal settlements, local place names, and lived experiences are seldom captured in quantitative datasets. To address this limitation, qualitative data are integrated into the SPIN framework through the development of a Qualitative Information Layer (QIL), designed to strengthen both analytical depth and interpretive accuracy. This supplementary layer systematically compiles and analyses qualitative materials, including reports and news articles, relevant to the area of interest and the specific hazard theme. The collected texts are geo-parsed to extract entities corresponding to who, what, where, and when, and subsequently normalised to align with SPIN's ontology encompassing hazard types, causes, effects, social profiles, and institutions. Each identified hotspot is then parsed with ranked, confidence-scored contextual information. This qualitative information layer not only reveals existing knowledge gaps but also enhances transparency and mitigates potential biases in spatial inequality assessments.

The qualitative information layer is conceptually designed to complement SPIN's quantitative analysis by providing grounded, narrative context for each identified hotspot. While SPIN can calculate where access is limited under a given hazard, it cannot independently describe which population groups were most affected, or what coping and response mechanisms were in place. The information layer aims to bridge this gap by sourcing recent, location-specific textual evidence and linking the resulting insights to the corresponding hotspot within SPIN. Instead of conducting this retrieval internally, SPIN only passes out two already existing parameters, the *Area of Interest (AOI)* and the *hazard scenario*. All subsequent data retrieval, extraction, and processing steps are executed externally, allowing SPIN to maintain its core analytical function while benefiting from an enriched, context-aware information layer (Lewis et al., 2020, United Nations Office for the Coordination of Humanitarian Affairs (OCHA), 2024).

After receiving AOI and hazard from SPIN, the external module initiates a four-step workflow that corresponds to the "Processed Outside SPIN / Added external data acquisition capabilities" lane in the integrated architecture.

1. **LLM Corpus & Web-scrapping:** The module uses the AOI-hazard pair as a strict filter to retrieve recent documents that specifically describe that hazard within the AOI, assembling these documents into a focused corpus.

2. **Geo-parsing & Information Extraction:** Spatial references within the qualitative data are resolved to administrative units or coordinates. Additionally, key attributes are extracted, such as which infrastructure failed, which population groups were affected, and when the events occurred.

3. **Confidence Scoring:** Information extracted from that corpus are evaluated based on their direct relevance to to the AOI, hazard, timeliness and their reliability.

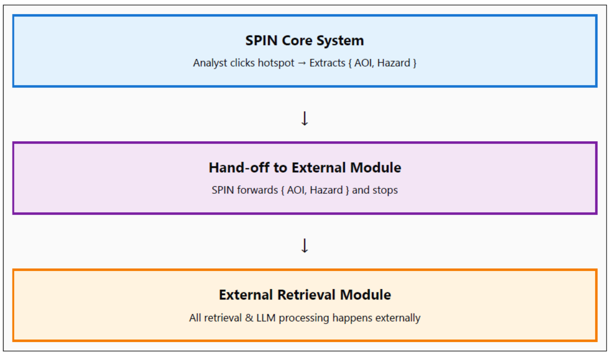
4. **Text to Context:** The geolocated and confidence-scored information is normalised according to SPIN's ontology, capturing hazard, social vulnerability, and local cultural or institutional contexts. The resulting contextual data is then returned to SPIN to be visualised alongside the corresponding hotspot.

This modular workflow enables SPIN to maintain its internal network and accessibility analysis while the external module enriches the analysis with AOI-specific, evidence-based narrative context, processed entirely outside SPIN (Lewis et al., 2020, United Nations Office for the Coordination of Humanitarian Affairs (OCHA), 2024).

5.3.1 LLM Corpus & Web-scrapping

From that point onward, {AOI, hazard} is treated as a hard filter that governs every downstream action.

The first step is initiated as the hotspot is manually opened in SPIN. At this stage, SPIN only provides two pieces of information: the Area of Interest (AOI) and the hazard under consideration. Here, AOI refers to *the smallest stable, named administrative area containing the clicked hotspot*, such as “neighbourhood/district/municipality/county”, rather than a hand-drawn polygon. No additional AOI selection is required for the qualitative layer, the same AOI as in SPIN’s quantitative assessment is used. SPIN then transmits the {AOI, hazard} pair to an external module and ceases further processing, leaving all document retrieval and language-model operations to be executed outside SPIN.



The external module converts the AOI (e.g., “Kisauni, Mombasa, Kenya”) into a single authoritative record, including a stable identifier, official name, administrative hierarchy, geometry and curated aliases, a process referred to as canonicalisation. This ensures that alternative spellings, diacritics, and language variants all map to the same location. From this point onward, the {AOI, hazard} pair works as a hard filter for downstream processing. The module enforces this filter in two stages: **Gate 1 (Query)** builds locality-constrained searches using the canonical AOI together with the hazard term (and near synonyms); **Gate 2 (Accept)** only keeps documents, whose body text explicitly mentions the same AOI and hazard. This two-gate approach enables the use of broad source endpoints while still ensuring that the final corpus is strictly AOI- and hazard-specific.

Corpus construction and retrieval methodology:

Under the hard {AOI, hazard} filter, the external module assembles a focused, auditable corpus from four families of sources that carry clear dates, publishers, and locations:

1. **Newspaper articles** that explicitly mention the AOI and describe the hazard
2. **Governmental reports** which include incident updates, and assessments from municipal, provincial, and national portals
3. **NGO reports** curated through ReliefWeb (The United Nations OCHA platform that aggregates vetted updates from UN agencies, governments, and NGOs) including the familiar “OCHA-style” situation reports (SITREPs) used operationally in emergencies (these are source formats, not AI modules) (United Nations Office for the Coordination of Humanitarian Affairs, 2024)
4. **Scientific reports** that document service disruption, isolation of communities, or transport/health/education access issues inside the AOI.

Queries are generated from the canonical AOI name and its frequent variants (including local-language forms) combined with the active hazard label and near-synonyms. The retrieval includes the following domains:

- **Locality-scoped news queries**
  Issues Google news queries with geographic scoping (Google, 2024)
- **ReliefWeb Humanitarian Database**
  Queries to ReliefWeb by country or subregion using the hazard topic, prioritising the official API when available to retrieve UN/NGO reports and assessments(United Nations Office for the Coordination of Humanitarian Affairs, 2024)
- **Domain-restricted authority searches**
  Performs site- or domain-restricted searches targeting public-authority portals, such as ministries, municipalities, and relevant agencies to capture official bulletins and circulars

Returned candidates are accepted only when the body text explicitly ties the described event to the same AOI and the same hazard within the relevant time window; otherwise, they are rejected as generic or out-of-scope.

The collector adheres to each website’s access rules (robots.txt) and applies rate limiting to control the frequency of requests to individual sites. Links are normalised (removing tracking parameters and resolving redirects) and near-duplicate items are merged or removed based on URL equality and text similarity, ensuring each report appears only once. Retained items are stored with provenance (publisher name, publication date, and URL) and converted into plain text. The model handles both HTML and PDF files. Scanned documents are transformed using optical character recognition (OCR). Language detection and machine translation are applied as needed to produce a uniform, comparable text stream. The recency window is hazard-dependent, with shorter windows for rapid-onset events (e.g., floods, landslides) and longer windows for slow-onset hazards (e.g., drought, infrastructure decay). A temporary cache prevents repeated retrieval of the same AOI–hazard pair during iterative runs. The resulting output is a retrieval-augmented evidence set: documents are first retrieved under strict constraints and only filtered, relevant evidence is passed forward (Lewis et al., 2020). These engineering safeguards and ethical constraints, summarized in Table 4, ensure that the retrieval pipeline operates reliably, transparently, and in compliance with website access rules.

Dimension	Implementation
Rate Limiting	Respects website's access directives and implements conservative rate limits per domain
Deduplication	Canonicalizes URLs and removes near-duplicates via URL and text similarity analysis
Provenance Tracking	Stamps each retained item with publisher, publication date, and URL metadata
Text Extraction	Handles HTML and PDF formats; employs OCR fallback for scanned municipal documents
Language Processing	Performs language detection and machine translation for local-language reporting
Temporal Tuning	Recency window adapted to hazard profile (short for floods, longer for drought)
Caching	Short-lived cache prevents re-fetching during iterative AOI hazard analysis

Table 4: Engineering safeguards and ethical constraints in retrieval pipeline

The large language model processes exclusively the AOI- and hazard-filtered corpus. This scope is intentionally narrow and verifiable, to extract and summarize only those passages that directly address the event's impacts within the AOI. The output is a deduplicated (duplicates are eliminated, retaining a single canonical version) evidence set, enriched with provenance details (publisher, publication date, and URL). This set consists of concise summaries, each tied to its original source metadata and limited strictly to the AOI. Subsequently, this evidence set undergoes geo-parsing and confidence scoring to enable targeted operations.

5.3.2 Geo-parsing & Information Extraction

Geo-parsing is the process of detecting place names in text and resolving them to coordinates (Bobadilla et al., 2020). This process is the bridge between the texts ingested (reports, news, assessments) and the maps SPIN produces. Geo-parsing detects place names, disambiguates them, and anchors each fact to coordinates and admin codes. A standard toponym recognition and resolution pipeline is used:

1. **Named-Entity Recognition:** place mentions in each passage (e.g., "Mombasa", "Kenya") is detected using Named Entity Recognition (NER) model;
2. **Candidate Lookup:** for each mention, a gazetteer (a geographic dictionary of place names) is queried to retrieve candidate places with coordinates (Bobadilla et al., 2020);
3. **Toponym resolution:** a detected place name is linked to the correct real-world feature (e.g., "Likoni" is the sub-county in Mombasa, not another Likoni). Open-source toolkits such as Mordecai illustrate this pipeline: detect place mentions, generate candidate coordinates from a gazetteer, then choose the best candidate using contextual rules (prefer places inside area of interest, match nearby co-mentioned places) (Halterman, 2020);

5.3.3 Confidence Scoring

Data scarcity poses a significant challenge for spatial inequality analysis in the Global South, where quantitative datasets are often limited or unavailable. To address these data gaps and enhance geospatial analyses, qualitative data can provide valuable contextual insights. However, not all qualitative sources are suitable for examining hazards, social vulnerability, or local cultural contexts.

After discussions with Haskoning experts, Social media data, NGO reports, Haskoning internal reports, governmental reports and newspaper articles were identified as qualitative datasets with potential. Further research revealed that, in the Global South, the most widely used social media platforms are often direct messaging applications such as WhatsApp and Telegram (Badrinathan and Chauchard, 2024). These platforms typically lack fact-checking and labelling mechanisms, making it difficult to manage the spread of misinformation

(Badrinathan and Chauchard, 2024). Consequently, social media data were excluded from the qualitative data analysis.

This decision left reports from various organisations and newspaper articles as qualitative data sources. To ensure the reliability and relevance of this information, a ranking system was developed. One key criterion is the publication date, which affects the credibility of digital information (Bojić et al., 2024). Systematic reviews have shown that within two years, approximately 23% of studies require updates, though reports generally remain relevant for longer periods (Shojania et al., 2007). Therefore, a two-year timeframe is considered a reasonable threshold for identifying current and relevant information. The median survival time of research signals has been estimated at 5.5 years (Shojania et al., 2007), while modelling of literature obsolescence suggests a median half-life of 5 to 10 years, with many references becoming obsolete after 10 to 15 years (Dorta-González et al., 2022). This resulted in the criteria for publication date displayed in Table 5.

A second ranking criterion is geographical relevance, defined by the spatial distance between the information source and the target location. Spatial proximity is a primary indicator of contextual significance (Reichenbacher, 2005), and users tend to value geographically closer information more highly (Jones, 2008). Therefore, a ranking level was established. A "division level" with the highest relevance and direct spatial correspondence with the location, a "county level" with medium relevance referring to the same administrative region. The last level is the "regional level" with lower relevance and weaker spatial association (Hu et al., 2018).

The final ranking criterion considers the type of data source. Haskoning internal reports are assigned the highest confidence level due to the company's rigorous data acquisition and processing standards. NGO reports are also regarded as credible sources, as NGOs often act as "information subsidies" by providing journalists with ready-made data and narratives (McPherson, 2016). Although newspapers are valued for editorial independence, they frequently rely on NGO outputs, creating an interdependent relationship between advocacy and journalism (Wright, 2018). For this reason, NGO reports are ranked above newspaper articles in terms of reliability. Governmental reports are also included in the qualitative dataset. However, in many parts of the Global South, limited state capacity constrains governments' ability to deliver accurate information to citizens (Badrinathan and Chauchard, 2024). Moreover, misinformation often interacts with low state capacity (Badrinathan and Chauchard, 2024), which justifies ranking governmental reports at the same level as NGO reports within the proposed system.

	Publication date	**Distance**	**Type of data source**
High relevance	0 - 2 years	"Division level"	Haskoning reports, Scientific reports
Moderate relevance	2 - 5.5 years	"County level"	NGO reports, Governmental reports
Low relevance	5.5 - 10 years	"Region level"	Newspaper articles
Not considered	>10 years	"Country level"	Social media data

Table 5: Confidence ranking

Conceptually, the confidence scoring system provides a structured framework to balance the reliability, spatial relevance, and timeliness of qualitative data sources. In subsequent steps, a quantitative scoring approach could be developed to assign weights to each criterion, potentially using the Best–Worst Method (BWM) described in subsubsection 5.1.1. The confidence ranking can also be adjusted dynamically depending on the context and the availability of qualitative data sources, allowing for flexibility in data-scarce environments. This adaptive framework enhances analytical transparency and consistency, enabling users to systematically integrate and compare qualitative evidence in geospatial assessments with greater confidence.

5.3.4 Text to Context

After a passage is geolocated, detailed information is then extracted and normalized to SPIN's ontology. The chosen features will then be stored with attached ISO/admin codes (e.g., KE-28 for Mombasa, Kenya (on Geographical Name, 2025) and geometry (e.g., point shapefile). In the Qualitative Information Layer, the text that has been filtered, geoparsed, and normalized is returned as three information blocks:

1. **Hazard context:** *hazard_type* (e.g., river flood, flash flood), *hazard_phase* (pre/during/post), *duration / timeline*, *causes* (e.g., blocked drainage, excess rainfall), *effects* (e.g., flooded road, bridge damage), and *successful_measures*. These labels come from the same ingested sources, which typically describe impacts and measures.

2. **Social vulnerability context:** short snippets tagged to *sv_profiles_general* (e.g., low-income households, people with disabilities, informal settlements), and *sv_profiles_hazard_specific* (e.g., communities that were neglected in previous hazard events).
3. **Local cultural context:** concise evidence on *norms / values*, *institutions / procedures* (how decisions are made, formal and informal), and *demography / social structure* (roles of women / youth). These are extracted from the text and presented as short and auditable bullet points or short paragraphs.

Each item that has been stored with ISO/admin codes will be written to a **Geospatial Knowledge Graph** (a network of real-world entities with a geographical context) (Zhu, 2024), so SPIN can quickly fetch the most relevant (highest ranked) facts by location and topic. This information layer will be shown beside SPIN's maps as location-specific and confidence-scored context for interpretation and decision support.

5.3.5 Limitations and Future Study

The qualitative information layer presented remains a conceptual framework rather than a fully operational system. While the required data inputs, the analytical logic and the integration pints are specified, several technical components still need to be defined. The current design does not yet determine the concrete artificial intelligence stack or outline the precise methods for interfacing with SPIN's API and user interface. Consequently, the workflow has not yet been performance-tested or evaluated for computational efficiency, data latency, or accuracy under real-world conditions.

Future development should begin with the creation of quantitative weighting schemes for the confidence model and the refinement of geo-parsing and normalisation processes. Additionally, evaluation benchmarks should be established to ensure precision, recall, and interpretive reliability. Attention should also be given to technical interoperability and data governance, including the definition of standardised data exchange formats between SPIN and the external retrieval module, compatibility with existing APIs, and the enforcement of metadata standards for provenance and traceability. Further research should address ethical considerations such as source licensing, data protection, and bias auditing to maintain transparency and accountability. These steps should be included, before operationalising the framework end-to-end and implementing a prototype that connects the modules.

Once these components are integrated and validated, the qualitative information layer can evolve from a conceptual workflow into an operational layer that systematically enriches SPIN's spatial inequality assessments with grounded, transparent, and verifiable qualitative evidence.

5.4 Integrated Solution

To avoid unsystematic outputs and turn analysis into action, solutions from all three clusters will be integrated into a single coherent system architecture for SPIN. Spatial Planning contributes to causes-effects-measures database; Social Vulnerability provides the Social Vulnerability Index formula with defined indicators and weights; and Hacking SPIN binds these together into the SPIN tool. Integration ensures every hotspot (accessibility failure location) is evaluated under the same area of interest, hazard, and time window, enriched by the Qualitative Information Layer for context, and linked to a curated measures database. The result is an end-to-end auditable pipeline beginning from access impact to who is affected, then to why it happens, and ending with what to do next. Therefore, it will be consistent enough to support equitable and defensible decisions.

5.4.1 SPIN's System Architecture

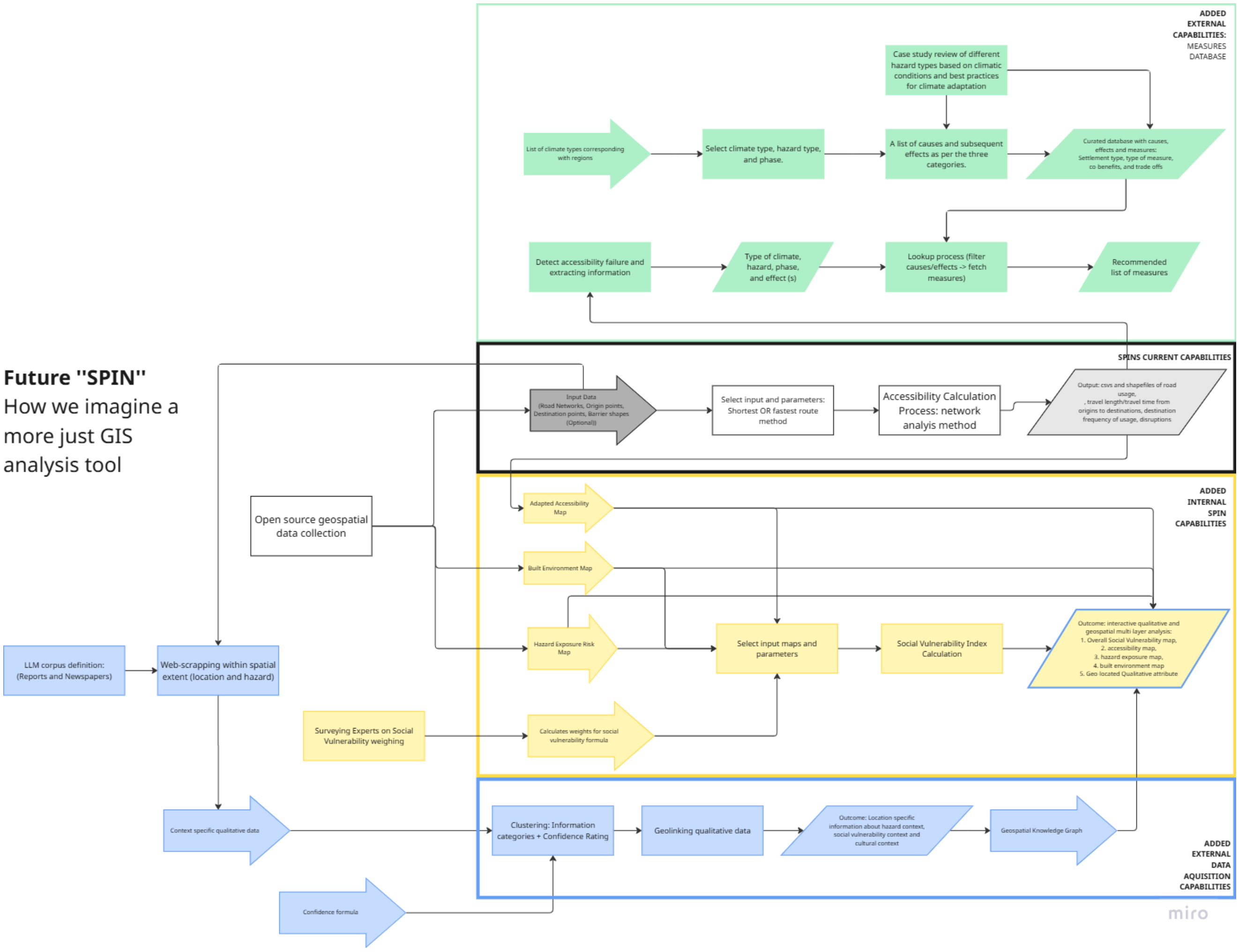


Figure 15: SPIN's Prospective System Architecture

5.4.1.1 Processed Inside SPIN

1. **Input:** Prepared geospatial layers are loaded into SPIN: road network, origins, destinations, barrier layers, risk exposure of hazard map, and built environment map. Determined weight set for the Social Vulnerability Index (SoVI) components also inputted. Details about what type of data required and their sources is in Appendix B.
2. **Process:** SPIN's existing engine performs road network analysis to derive baseline accessibility and road usage patterns. The added internal module then synthesized accessibility score, risk exposure of hazard, and built environment map using applied SoVI formula with the weights. Then it assembles layer stack (accessibility, exposure, built environment, SoVI).
3. **Output:** Within SPIN the user sees:
   - accessibility (time/distance) maps,
   - road-segment frequency and destination-usage maps,
   - hazard-exposure and built environment maps,
   - synthesized Social Vulnerability Index map.

5.4.1.2 Processed Outside SPIN

(a) **Added External Data Acquisition (Qualitative Information Layer)**

- **Input:** The area of interest and hazard type used in SPIN are passed outward as filters. This constrains the web-scraping/ingestion process to relevant reports, assessments, and trusted news covering the area and hazard.
- **Process:** Documents are collected and cleaned, passages are extracted. A geo-parsing pipeline detects place names and resolves them to coordinate units. Event/entity fields are extracted and normalised to a schema with three main interests: *hazard context* (types, phases, causes, effects, measures), *social vulnerability context* (profiles, neglected groups), and *local cultural context* (norms/values, institution procedures, social structure). Confidence scores are assigned to the output and stored with provenance in a geospatial knowledge store.
- **Output:** The output shown will be geo-linked snippets with confidence scores and sources. Organised into three different contexts. SPIN simply displays these items next to the maps (e.g., in a different panel next to the map), giving users an auditable qualitative context.

(b) **Measures Database**

- **Input:** The measures database contained a structured "cause-effect-measure" matrix that is keyed by climate type, hazard type, and phase. For each (climate–hazard–phase) combination, it stores normalised IDs for Causes (e.g., blocked drainage, overtopping), their linked Effects (e.g., road submergence, bridge approach scouring) and a catalogue of Measures associated with those effects.
- **Process:** After SPIN runs its network analysis and an accessibility failure is detected, the context needed is inferred from the map to query the measures database. Then the lookup process is performed by:
  (a) Filtering the "cause-effect-measure" table based on climate-hazard-phase,
  (b) Fetching candidate measures from Effect-Measure relation.
- **Output:** The database returns as a list of measures. This gives users an explainable list that is grounded in the cause-effect context supporting transparent and auditable recommendation.

6 Product evaluation

6.1 Societal Impact - Responsible Research & Innovation

The selected solution concept framed under the Responsible Research & Innovation to make innovation socially responsible and in the public interest by using the AREA approach (Anticipate, Reflect, Engage, Act) (Research and Innovation, 2023). Using the AREA framework for SPIN matters because the tool influences real-world adaptation choices. It will ensure that SPIN's development aligns with societal needs, protects rights, and is auditable.

Anticipate

Anticipation focused on the impacts of pairing an internal Social Vulnerability Index with a spatial-measures dataset and an additional qualitative evidence layer. Concretely, access loss is calculated and explicitly weighted for vulnerable communities, reducing the risk that communities are overlooked when hazards disrupt reachability. At the same time, there are other risks, such as qualitative sources and geospatial layers may be incomplete or biased, along with the problem of advisory features may be over-trusted if uncertainty is hidden. Anticipatory safeguards, therefore, include data minimisation and confidence scores shown to users so that the outputs remain explainable rather than prescriptive (OCHA Centre for Humanitarian Data, 2025, Abhayaratnar, 2021).

Reflect

Reflecting asks who stands to benefit or be harmed if access loss is misestimated, which groups are most likely to be under-represented in the data, and how those risks change in data-scarce settings. It also clarifies who has an interest (local communities, government, emergency responders, NGOs) and what alternative could reduce risk. Because SoVI indicators and thresholds are context-dependent and qualitative sources can be biased, SPIN is positioned strictly as a decision support tool, not a replacement for consultation or authority. To keep this visible, the UI and documentation retain traceable methods, sources, and limitations, so decisions can be explained, challenged, and improved (Alfred, 2025).

Engage

Engagement for SPIN should open up design choices to those affected and those who will use the tool. Stakeholders are identified and prioritised across scales (community groups, local authorities, national agencies, humanitarian actors, data providers) (Figure 6). Co-design activities focus on selecting SoVI indicators, setting weights/thresholds, and interpreting the qualitative layer (hazard context, social vulnerability context, local cultural context). The inclusive practices help ensure under-represented groups are included and that engagement quality can be reviewed over time.

Act

Acting means adjusting aims, processes, and outputs in response to what is learned through the first three stages (Research and Innovation, 2023). The selected concept is implemented with:

- Explicit criteria and documented assumptions for SoVI and the spatial-measures dataset
- Qualitative information layer that surfaces hazard, social vulnerability, and cultural context with confidence ratings
- An advisory layer that selects the region's climate type, hazard type, and phase; uses case-study evidence to list typical causes and effects; and compiles these into a curated measures database to give specific recommendations.

Together, these will make the tool auditable and adjustable. Therefore, users can trace each output to sources and assumptions, review items, and adjust weights.

6.2 Risk Analysis

6.2.1 Data quality and data scarcity risk

The enhanced SPIN workflow depends on multiple heterogeneous inputs (road networks, facility locations, disruption layers, and the Social Vulnerability Index, plus scraped qualitative intelligence). In many Global South contexts, these inputs are incomplete, outdated, or inconsistent across sources. If poor-quality inputs are ingested without clear confidence scoring, the tool can misrank who is “cut off,” understate exposure for informal or undocumented communities, or overstate the usefulness of certain routes or measures. This creates the risk that decisions appear evidence-based but still reproduce the historic blind spots we are trying to correct. For example, informal settlements or migrant groups being structurally undercounted in official datasets is widely documented in accessibility and vulnerability mapping literature (Humanitarian Data Exchange (HDX) and OCHA, 2020; Cutter et al., 2003).

6.2.2 Interpretation and misuse risk

SPIN now goes beyond a static map and produces a structured "causes–effects–measures" storyline: what happened; who lost access; which pre-, during-, and post-measures are relevant. That narrative layer is intentionally designed to help non-experts and funders understand the situation, but it also creates a new risk: people may treat the output as a prescriptive answer instead of as decision support. If users lift the recommended measures out of context, for example, applying "bridge reinforcement" from Mombasa to a drought context elsewhere, without checking assumptions such as hazard type, phase, or local governance capacity, they could invest money in technically plausible but socially unworkable interventions. This "automation bias" and over-trust in decision-support tools have been raised repeatedly in climate-risk planning and resilience investment guidance (OECD, 2024a; Adger, 2006; OECD, 2024b).

6.2.3 Equity and legitimacy risk

A central claim of the solution is that we shift from "how many assets are hit" to "who loses access, how fast, and for how long," explicitly surfacing socially vulnerable groups. That creates reputational and ethical exposure. If the SoVI weights and access thresholds are not transparently explained and co-signed by domain experts and local stakeholders, planners and donors can challenge the legitimacy of the prioritisation ("why is this neighbourhood classed 'critical' and not mine?"). Worse, communities labelled as "highly vulnerable" can be politically stigmatised or blamed for "dragging resources," something already criticised in the vulnerability-index literature when indicators are not properly contextualised (Cutter et al., 2003; United Nations Office for Disaster Risk Reduction, 2017). The tool therefore carries the risk that, instead of empowering ignored groups, it triggers pushback or reinforces harmful narratives about them.

6.2.4 Temporal / maintenance risk

The proposed workflow assumes that SPIN is not a one-off map but a living system: it stores past events (which areas actually became isolated, which roads actually failed), and uses that history as a baseline validation layer so that future analyses don't repeat the same blind spots. That creates an obligation. If Haskoning or the client does not resource the continuous update of that event memory, or if the update routine is handed to non-specialists after project delivery, the validation layer will drift. Out-of-date "lessons learned" can become misleading "evidence," and the credibility of the tool in procurement / donor processes will erode. This maintenance burden and model-drift risk is well known in AI-augmented decision systems and climate analytics platforms (OECD, n.d.; Luo et al., 2021).

6.2.5 Compliance and accountability risk

SPIN proposes to integrate qualitative intelligence (local news, NGO situation reports, emergency responder notes, etc.) and tag it to geography, hazard phase, and affected service. Even when no personal data are stored, those sources can still contain politically sensitive statements (e.g. "this informal settlement was ignored in evacuation") that point indirectly to specific groups, authorities, or operators. If such statements are surfaced in a donor-facing dashboard without a clear provenance trail (source type, publication date, confidence level), Haskoning could be held accountable for claims it did not generate, or could expose local partners to political pressure. Similar concerns about traceability, duty of care, and do-no-harm are highlighted in humanitarian data management standards (Humanitarian Data Exchange (HDX) and OCHA, 2020; OCHA, 2021).

6.2.6 Profitability risk and associated costs

A key risk associated with improving the GIS system SPIN is that the improvements may not generate sufficient value to justify their cost. Because there is no standardised method of calculating return on investment (ROI) in

GIS projects(Maguire et al., 2008), it can be difficult to demonstrate the profitability of the proposed improvements.

Other major risks include technical incompatibility, cost escalation and user resistance. Stakeholder interviews with employees in Haskoning made clear that the current GIS tool is intentionally designed to resemble tools already existing in Haskoning. Although the suggested improvements could enhance the user experience as analysed, an organisational resistance to change within Haskoning might lead to the new features being underutilised or disregarded over time(Keating et al., 2009).

6.2.7 Adoption and delivery risk for Haskoning

The final product positions SPIN as an auditable decision-support workflow that donors and public authorities can "defend": needs are shown as loss of essential access for defined vulnerable groups, and candidate measures are linked to clearly stated assumptions and phases (prevention/immediate response/recovery). That is commercially attractive, because it matches the current demand for resilience masterplans and for investment cases that prove both social impact and value-for-money (OECD, n.d.; UK HM Treasury, 2022). But that also raises expectations. If the company offers SPIN as part of bids without a clear statement of scope (what the tool can and cannot conclude without on-the-ground validation, what confidence bands mean, how local buy-in is secured), clients may treat it as a turnkey guarantee of impact rather than as structured expert support. The risk is reputational (overselling), legal (perceived liability if measures fail), and operational (teams in future tenders may feel forced to reproduce our workflow under tighter budgets and timelines).

7 Final Recommendation

7.1 Business recommendations

At present, SPIN is used mainly through institutional clients such as the Global Center on Adaptation (GCA), the World Bank, and the Asian Development Bank (ADB). After 10 months of developing to now, SPIN remains under the budget threshold, with total operational costs standing 57% higher than the potential demand value. In other words, the platform will requires 1.57 times more project volume to reach its break-even point, requiring an additional €208,133 to achieve full cost recovery.

In the future, SPIN will follow a project-based development strategy, as confirmed by the project team. This means that further development will only occur through externally funded projects, with an additional €30,000 anticipated to be financed from the profits of future projects.

Under the best-case scenario, assuming the highest feasible number of funded vulnerability projects within one year, SPIN is projected to reach its break-even point by Q2 2027. In a normal-case scenario, with approximately 20% fewer projects (21 small, 14 medium, and 7 large projects over three years), break-even would be achieved by Q3 2028. However, even then, the current strategy allows SPIN to cover its costs but not to invest in future tool development.

Best Case Break-Even Scenario			
Type of Project	Revenue	2026	2027
Small	£4,000	15	7
Medium	£6,000	10	5
Large	£8,000	5	
Total		£160,000	£58,000
		Q2 2027	£218,000

Bad Case Break-Even Scenario				
Type of	Revenue	2026	2027	2028
Small	£4,000	10	8	3
Medium	£6,000	7	5	2
Large	£8,000	4	2	1
Total		£114,000	£78,000	£32,000
			Q4 2028	£224,000

Figure 16: Determining the Annual Project Volume Required for Break-Even Using Excel Solver

While institutional partnerships remain essential, the SPIN team has improved the tool with Social Vulnerability Index, creating opportunities beyond traditional vulnerability projects. The enhanced SPIN model can now support commercial insurance activities, helping insurers evaluate social exposure, loss potential, and ESG-related risks. According to our analysis, global insurers collectively spend over €80 million annually on catastrophe and natural hazard. If SPIN were to capture even 0.1 of this global market, annual revenues could rise to €130,000, cutting the break-even horizon from 3.7 years to just 1.6 years.

INSURANCE MARKET OPPORTUNITY - SUMMARY	
CURRENT SITUATION	
Break-even Cost Required	€349,800
Money Still Needed	€208,133
Current Model Timeline	3 years (by 2028)
Current Monthly Cost	€26,650
INSURANCE MARKET OPPORTUNITY	
Global Insurance Market Size 2025	$7620.0B
Annual Climate Risk Tool Budget	$114.3B
Natural Hazard Losses 2024	$137.0B
Protection Gap (Uninsured)	$181.0B
NEW TIMELINE WITH INSURANCE REVENUE	
Conservative Scenario	1.6 years (by mid-2027)
Moderate Scenario	1.2 years (by Q1 2027)
Aggressive Scenario	0.8 years (by Q3 2026)

Figure 17: Using Excel Solver and Various Scenario Analysis Annual Project Planning in the Insurance Market

7.2 Launching Timeline

The implementation process will proceed through different phases over 24 months. In the first eight months, the project team will integrate flood-related geospatial datasets and refine the exposure layer using around €20,000 generated from upcoming project profits in 2026. As the workflow becomes standardised, team involvement is expected to decline from 20% to 15% of total project time, improving cost efficiency and freeing resources for model enhancement. Phase 2 will pilot the flood exposure map within an ongoing institutional project while testing its utility with selected insurers. A single insurer partnership worth €250,000 annually could make SPIN immediately profitable, while even conservative estimates show break-even in 2.7 years—38% faster than relying solely on public clients. In the final phase (months 17–24), the validated flood exposure model will be fully integrated into SPIN's operational platform and commercialised through a subscription-based service, enabling recurring revenue generation for both private and public clients.

7.3 Next steps for Haskoning

This section sets a clear sequence of next steps for Haskoning to integrate social vulnerability into SPIN's practice. It is organised by timeline prioritization: **immediate (0–3 months), near-term (3–9 months), and longer-term (9–18 months)**. This is to move from low-friction actions that can start today, through standardisation and data backbone work, to targeted innovation pilots. The goal is a practical path from quick wins to scalable capability.

Immediate (0–3 months): Haskoning can start by making SPIN inclusion-ready without heavy rework. Configure projects around the accessibility-first default so that every simulation reports who loses access, where, and for how long across pre-event, during, and post-event conditions. Use this to prioritise upgrades for communities at highest isolation risk. At the same time, build a "community input" framework into project kick-offs to capture local knowledge. Use quick interviews and site notes for groups under-represented in datasets and reflect this in explicit assumptions and confidence flags. Afterwards, set up an internally shared Cause–Effect–Measure (CEM) library/database that links common climates to common hazard drivers to pre/during/post measures. Give items persistent IDs (coherent database management) so it can be easily used in future projects. This database is to be compiled of the existing Haskoning case repository, using existing databases and documents. Simultaneously, integrate social vulnerability consideration into SPIN's workflow by embedding the SoVI as an additional analytical layer alongside SPIN accessibility outputs. This ensures that SPIN's outputs reflect not only mobility and accessibility but also hazard exposure and socio-economic sensitivity. The process should begin with the more accessible spatial datasets (e.g., population density, flood maps, building footprints).

Near-term (3–9 months): Standardise methods and widen data so inclusion becomes repeatable across projects. Define a relevant SoVI set and a weighting protocol with internal experts. In parallel, progressively integrate additional indicators such as building age, drainage network, or healthcare capacity, as data availability improves. Haskoning should engage local experts to assist with selecting context-specific SoVI, calibrating indicator weights, and expanding data inputs. This could mean establishing a data acquisition plan that harvests internal project datasets and secures partnerships with trusted external sources, with clear refresh cycles and licensing. This will provide stable input for SPIN's upgraded calculation capacity added in the previous phase. Introduce a company wide uniform confidence rubric (source quality, cross-source agreement, geo-specificity) to evaluate incoming quantitative and qualitative data. Expand and govern the CEM library, assign ownership for database management and regional variants. Package readiness playbooks that, adjacent to SPIN, generates correlated input (county/region and hazard type) into pre/during/post checklists.

Longer-term (9–18 months): In this phase, pilot advanced analytics to extend capability, using scoped trials and external experts where this accelerates delivery. Test the proposed agent-based models during events in pilot project/cities, and calibrate against observed results. Develop or procure, with the help of third parties, an LLM geoparsing and web-scraping pipeline that (I) harvests vetted reports and news,(II) tags hazard and cultural/vulnerability context, (II) links items to locations with confidence scores, and (IV) supplies geolocated equity notes back into SPIN. Finally and optionally, move SPIN toward a service-oriented architecture with APIs for layers, measures, SoVI and scenarios to speed reuse across regions and clients.

8 Group reflection

To fully utilise academic expertise and demonstrate personal interests, three research clusters were formed: Spatial Planning, Social Vulnerability, and Hacking SPIN (Figure 5). This structure promised effective research and focused development, however, substantial communication was required to ensure effective collaboration.

- **Spatial Planning:** With backgrounds in urbanism and technology management, this cluster focused on exploring the existing spatial planning framework and identifying accessibility goals.
- **Social Vulnerability:** Comprising individuals with expertise in geomatics, applied mathematics, and policy analysis, this cluster concentrated on geographic and demographic data collection, defining vulnerability indicators, and establishing standards for vulnerability assessment.
- **Hacking SPIN:** With expertise in environmental engineering, policy analysis, business, and sustainable energy, this cluster analysed the current functionality of SPIN, identified its limitations, and proposed extended features.The inclusion of the business perspective is important for the project, as it complements the technical development by assessing the financial feasibility and practical viability of improvements. Even the most innovative ideas require evaluation against resource availability and budget constrains to ensure sustainable implementation.

During the ten-week project, several challenges shaped the workflow and highlighted the complexities of interdisciplinary collaboration:

- **Scope and direction:** The initial research topic "Social Impact and Spatial Inequalities" was broad and included areas from emergency response to responsible spatial planning. This made it difficult to clearly define research problems and potential deliverables.
- **Interdisciplinary communication:** Participants' diverse academic and cultural backgrounds sometimes resulted in key concepts being framed differently across disciplines, leading to occasional misalignment and slower decision-making.

To address these challenges, the following measures were implemented:

- **Regular online and in-person working sessions:** During these sessions, open issues, proposed possible solutions and integrated intermediate results were identified and aligned as interdisciplinary concepts across clusters.
- **Expert consultation:** Consultation sessions with domain experts, supported by company coaches, helped refine the understanding of research problems and assess the feasibility of potential solutions. Additionally, meetings with academic supervisors from TU Delft were conducted to recalibrate focus and ensure alignment of ideas.

There are several aspects the team would improve in a future iteration:

- **Earlier definition of scope and deliverable:** While exploring the problem space is valuable, delaying commitment to a core deliverable reduced the time available for research depth and result validation. Problem definition and subsequently defining the intended final product in an earlier stage,would allow for more time for research depth and result validation, rather than only convergence in the later stages.
- **Clearer data requirements:** Data availability and quality, especially in data-scarce regions in the Global South, were a structural constraint. Establishing a baseline for datasets, including sources, resolution, and data confidence, early in the project can help determine feasible and reliable outputs.
- **More structured cross-cluster integration:** The clusters work well in deepening expertise in their own domains. However, sometimes the integration checkpoints were ad hoc. In the future, formalising integration checkpoints, especially in written formats, to align each cluster provides intermediate results and explanations. This would reduce delays and minimise misunderstandings.

Each person's reflection can be found in the Appendix F

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A Selection Process

Criteria	Concept 1	Concept 2	Concept 3
People	**4.5**	**4.5**	**2.8**
Stakeholder engagement & co-design	5.0	5.0	3.0
In-depth identification of socially vulnerable communities	5.0	4.0	3.0
Methodological transparency	4.0	5.0	2.0
Capacity building & usability	4.0	4.0	3.0
Planet	**3.3**	**4.0**	**2.7**
Environmental footprint (energy, emissions)	4.0	3.0	2.0
Contribution to climate adaptation goals	2.0	5.0	4.0
Use of sustainable and existing data resources	4.0	4.0	2.0
Profit	**2.8**	**4.3**	**3.8**
Cost efficiency and break-even potential	2.0	4.0	4.0
Market scalability and diversification	2.0	5.0	4.0
Accessibility to clients (public/private)	4.0	3.0	3.0
Long-term financial sustainability	3.0	5.0	4.0
Strategic Fit	**4.2**	**3.8**	**3.4**
Effectiveness	5.0	4.0	3.0
Efficiency	2.0	4.0	4.0
Equity	5.0	4.0	3.0
Acceptability	5.0	4.0	3.0
Robustness	4.0	3.0	4.0
Technical Feasibility	**3.0**	**4.5**	**3.8**
Scalability	2.0	5.0	4.0
Integration capability	3.0	5.0	4.0
Data quality and accuracy	5.0	4.0	4.0
Maintainability & update frequency	3.0	4.0	3.0
Disaster resilience of system infrastructure	3.0	4.0	4.0
Reproducibility	2.0	5.0	4.0
Total score	**3.7**	**4.2**	**3.3**

Table 6: Concept solution scoring matrix ranking (5 = very high; 4 = high, 3 = moderate, 2 = low; 1 = very low)

B Data Sources & Input

Dataset	Website	Purpose
Land Cover	https://esa-worldcover.org/en	Natural Hazards
DEM, Slope, Total Wetness Index, Flow Accumulation, Profile Curvature	https://portal.opentopography.org/raster?opentopoID=OTSDEM.032021.4326.3	Natural Hazards
Percipitation Estimation in 2050	https://www.chelsa-climate.org/	Natural Hazards
Distance to River	https://www.openstreetmap.org/ https://www.geofabrik.de/	Natural Hazards
Soil Composition	https://soilgrids.org/	Natural Hazards
Soil Composition	https://soilgrids.org/	Natural Hazards
Built-up Area	https://www.openstreetmap.org/ https://www.geofabrik.de/	Built Environment
Degree of Urbanisation stage	https://human-settlement.emergency.copernicus.eu/datasets.php	Built Environment
Population Density	https://www.worldpop.org/	Accessibility
Point of Interest	https://www.openstreetmap.org/ https://www.geofabrik.de/	Accessibility
Road Networks	https://www.openstreetmap.org/ https://www.geofabrik.de/	Accessibility

Table 7: Data Sources

	Data	Description	Source Recommendation	Data Type	Readiness	Purpose
1	Origin Points	Represent starting point of each communities. From population density data -> define area boundaries for each communities -> transform the square area into point containing (population and centroid of the communities)	OSM, User's data	Shapefile (Points)	Need processing	Accessibility, Road Frequency
2	Destination Points	Represent target location (hospital, school, water). From shapefile point containing information of public building (school, hospital, park, etc.) select only relevant bulding -> eliminate the rest -> point of interest.	HDX, OSM Point of Interest, User's data	Shapefile (Points)	Need processing	Accessibility, Road Frequency
3	Road Network	Road map, contain attribute field for speed limit of each segments.	OSM, Google Maps, SPIN has a function to download the roadnetwork	Shapefile (Lines)	Ready to use	Accessibility, Road Frequency
4	Barrier (Disaster)	Represent disrupted area during disaster. Shapefile containing barrier shape (i.e. flood extent, road blocks, wildfire hotspots).	User's data	Shapefile (Polygons)	Need processing	Accessibility, Road Frequency
5	Built Environment	Raster map providing information about built environment score. Indicators use to calculate built environment score will be varied for different regions.	Analysis	Raster	Generated Outside SPIN	Social Vulnerability Index
6	Exposure Risk to Natural Hazards	Raster map providing information about risk score to certain hazard (i.e. flood, wildfire).	Analysis	Raster	Generated Outside SPIN	Social Vulnerability Index
7	Accessibility Score	Generated from SPIN's output (travel time to facilities). Normalize travel time to 0 - 1 scale, then interpolate these points into raster grids using Inverse Distance Weighted (IDW) method.	Analysis	Raster	Generated Outside SPIN	Social Vulnerability Index

Figure 18: Data Input for SPIN

	Data	Description	Source...	Data Type	Readiness	Purpose
1	Land Cover	Raster map providing information about classified land cover area	ESA WorldCover	Raster	Use & Calculate Outside SPIN	Exposure to Hazard
2	DEM	Digital Elevation Map will be used to calculate Slope, Total Wetness Index, Flow Accumulation, Profile Curvature	Copernicus DEM	Raster	Use & Calculate Outside SPIN	Exposure to Hazard
3	Slope	Raster map providing information about slope degree calculated from DEM using GIS tool	Analysis	Raster	Use & Calculate Outside SPIN	Exposure to Hazard
4	Flow Accumulation	Raster map providing information about flow accumulation index which derived based on slope and aspect of elevation data. This map identifies stream channels and ridges.	Analysis	Raster	Use & Calculate Outside SPIN	Exposure to Hazard
5	Profile Curvature	Raster map providing information about profile curvature in degrees based on calculation process in GIS tool using DEM data.	Analysis	Raster	Use & Calculate Outside SPIN	Exposure to Hazard
6	Total Wetness Index	Raster map showing index of drainage area based on terrain profile (DEM).	Analysis	Raster	Use & Calculate Outside SPIN	Exposure to Hazard
7	Precipitation	Raster map providing information about mean annual rainfall in mm/yr.	Chelsa Climate	Raster	Use & Calculate Outside SPIN	Exposure to Hazard
8	Distance to Rivers	Raster map providing information about the distance of certain area from a river/waterways (based on river map).	OSM Waterways + Analysis	Raster	Use & Calculate Outside SPIN	Exposure to Hazard
	Soil Map	Raster map providing information about classification of soil type, linking to soil water saturation value.	Soilgrids	Raster	Use & Calculate Outside SPIN	Exposure to Hazard

Figure 19: Input for Exposure to Hazard Map (Flood Case)

	Data	Description	Source...	Data Type	Readiness	Purpose
1	Built-Up Area	Shapefile map showing location of buildings in polygon shape.	OSM Building, Open Buildings	Shapefile	Use & Calculate Outside SPIN	Built Environment
2	Degree of Urbanisation Stage	Raster map providing information about urban/peri-urban/rural classification area.	GHS-SMOD Copernicus	Raster	Use & Calculate Outside SPIN	Built Environment

Figure 20: Input for Built Environment Map

C Flood-ABM Community Level Study

The land cover, flood map and buildings—Business, School, House, Government, Shelter, and Healthcare—are developed using open-sourced data (United Nations Office for the Coordination of Humanitarian Affairs (OCHA), 2024) and manually labeled based on information derived from Google Maps through QGIS (Figure 21). The land cover area was selected based on the natural flood map (Figure 12b), focusing on regions with complete building data, relatively high flood risk, and a size comparable to the Calgary case (Addai et al., 2025). Flood map dynamics consist of three phases, developed according to flood risk probability. These components are separated into different polygon layers, each exported from QGIS as shapefiles compatible with Mesa-Geo and MESA(Projectmesa, 2025a, 2025b). Finally, the simulation is conducted using Python programming language for 10 iterations to ensure robustness—which should be increased in the future.

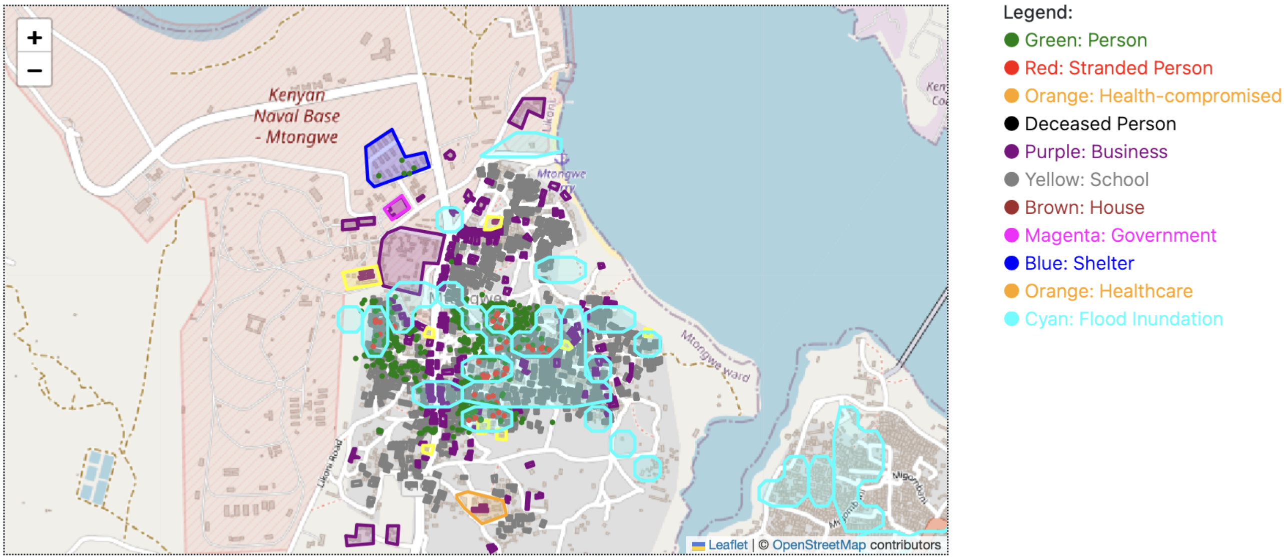
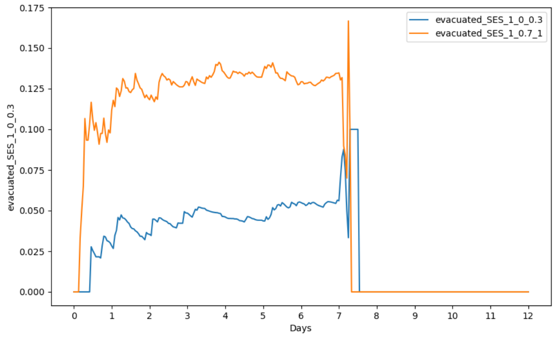


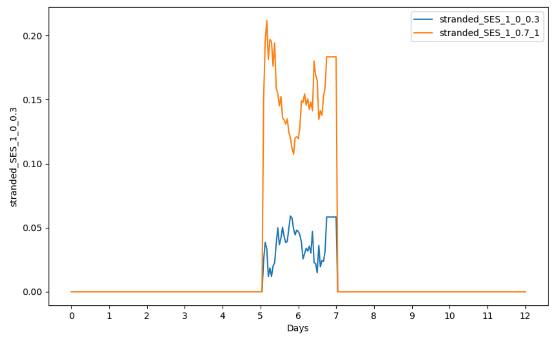
Figure 21: Flood-ABM Community Map

Description	Parameter	Value	Dimension	Reference
Wealth class distribution	Upper class percentage Middle class percentage Lower middle class percentage Lower class percentage	3.5 27 37 32.5	% of population % of population % of population % of population	Computed from World Bank, 2022 and Gini coefficient, inspired by Darkwah et al., 2016
Identity distribution	Locals (Kenyan) Refugee (Kenyan-Somali)	98.5 1.5	% of population % of population	Adan and Duncan, 2020
Age group distribution	Age 0–14 percentage Age 15–64 percentage Age 65–100 percentage	33 65 2	% of population % of population % of population	Kenya National Bureau of Statistics, 2019, Data downloaded from: http://data.knbs.or.ke/pages/themes
Gender distribution	Male Female	49.8 50.2	% of population % of population	Kenya National Bureau of Statistics, 2019, http://data.knbs.or.ke/pages/themes
Determines the understanding of flood risk	Educated people percentage	50	% of population	http://data.knbs.or.ke/pages/themes
Income range	Upper class yearly income Middle class yearly income Lower middle class yearly income Lower class yearly income	(5000–10000] (2000–5000] (1000–2000] (0–1000]	USD USD USD USD	Computed from World Bank, 2022 and Gini coefficient, inspired by Darkwah et al., 2016
Taxation	Tax rate (person) Tax rate (healthcare) Tax rate (business)	lower: 0 lower middle: (0,0.01] middle: (0.01,0.18] upper: (0.18,0.24] (0,0.05) (0,0.3)	% of income % of income % of income	Inspired by Kenya Revenue Authority, 2023
Tunable parameters	Population Shelter capacity Healthcare capacity Shelter funding Healthcare funding	500 1 5 50000 100000	Number of agents % of population % of population USD USD	Manually defined

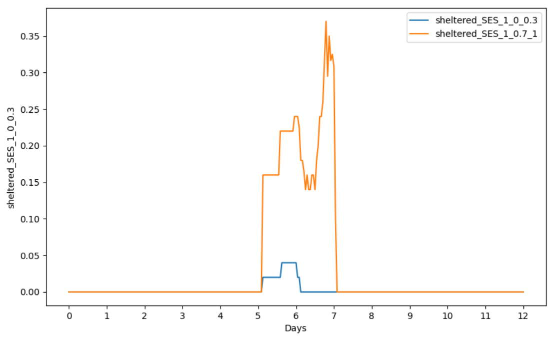
Table 8: Socioeconomic and model parameters for the Mombasa community case



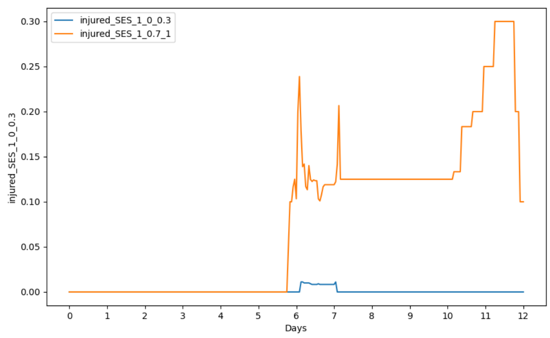
(a) Proportion of evacuated agents



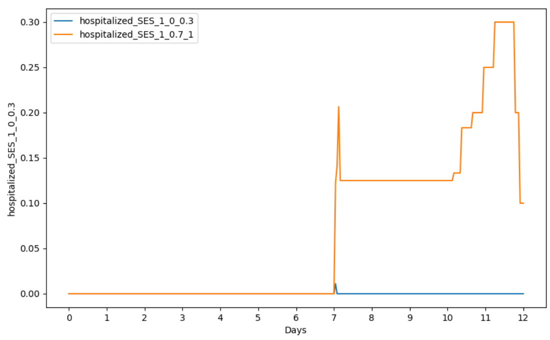
(b) Proportion of stranded agents



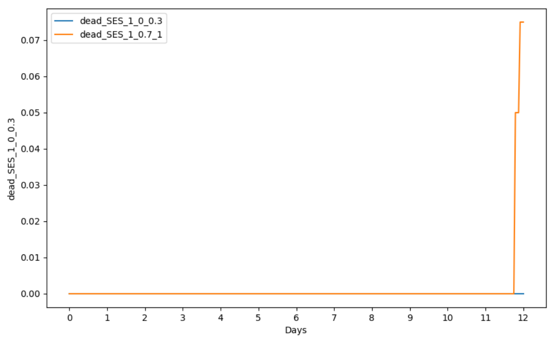
(c) Proportion of sheltered agents



(d) Proportion of injured agents

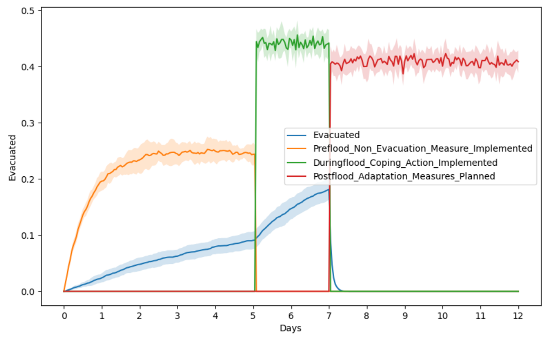


(e) Proportion of hospitalized agents

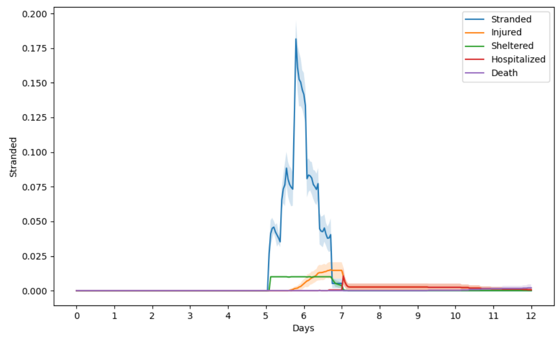


(f) Proportion of deceased agents

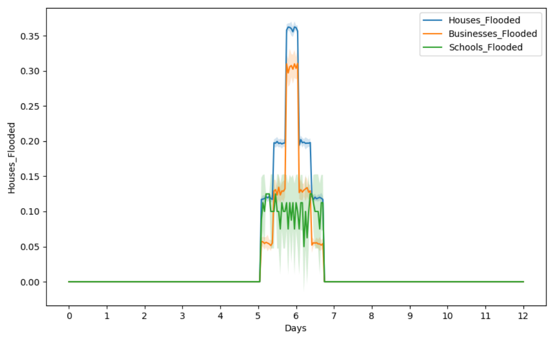
Figure 22: Differential impacts among SES groups of flood-affected population groups



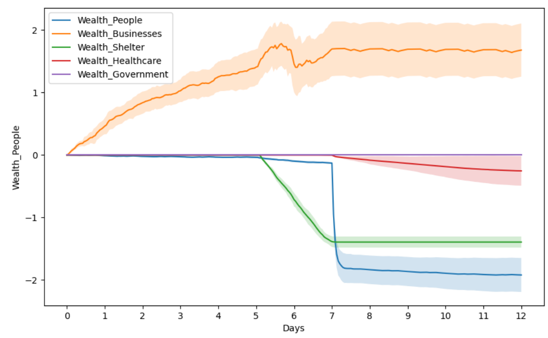
(a) Flood effects on person agent actions



(b) Flood effects on person agents



(c) Flood effects on buildings

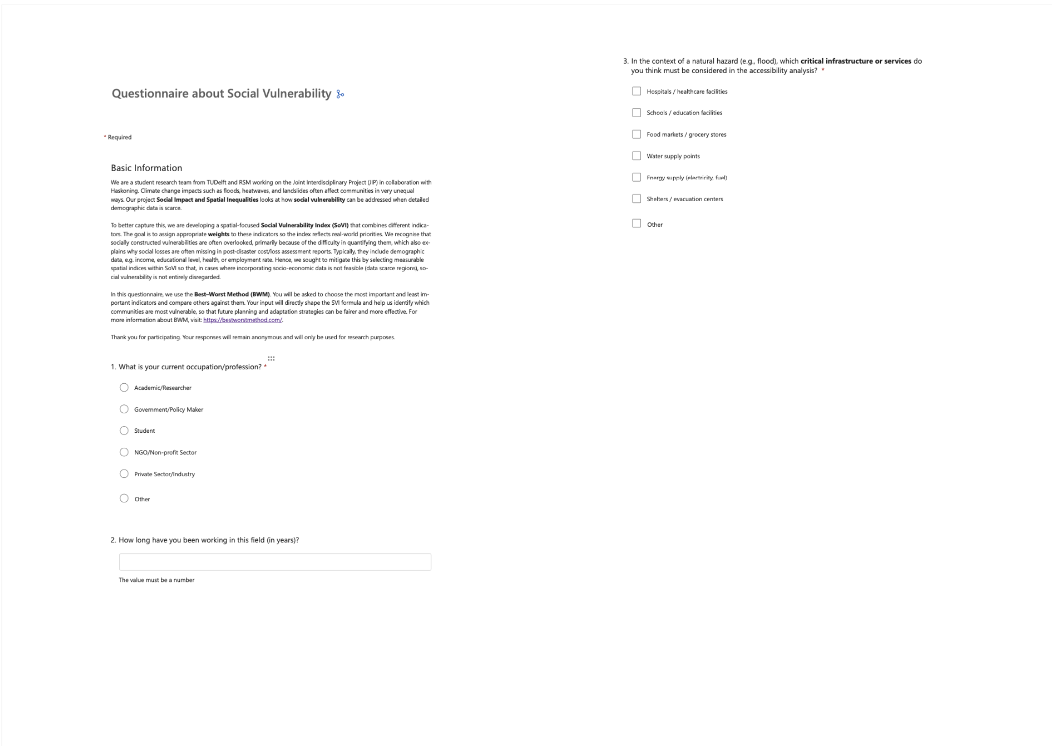


(d) Flood effects on relative wealth

Figure 23: An overview of the effects of the flood simulation across four dimensions

D Best-Worst Method Questionnaire

The weight assigning questions are branching questions. The content of the whole questionnaire is as follows.



Questionnaire about Social Vulnerability

* Required

Basic Information

We are a student research team from TUDelft and RSM working on the Joint Interdisciplinary Project (JIP) in collaboration with Haskoning. Climate change impacts such as floods, heatwaves, and landslides often affect communities in very unequal ways. Our project **Social Impact and Spatial Inequalities** looks at how **social vulnerability** can be addressed when detailed demographic data is scarce.

To better capture this, we are developing a spatial-focused **Social Vulnerability Index (SoVI)** that combines different indicators. The goal is to assign appropriate **weights** to these indicators so the index reflects real-world priorities. We recognise that socially constructed vulnerabilities are often overlooked, primarily because of the difficulty in quantifying them, which also explains why social losses are often missing in post-disaster cost/loss assessment reports. Typically, they include demographic data, e.g. income, educational level, health, or employment rate. Hence, we sought to mitigate this by selecting measurable spatial indices within SoVI so that, in cases where incorporating socio-economic data is not feasible (data scarce regions), social vulnerability is not entirely disregarded.

In this questionnaire, we use the **Best–Worst Method (BWM)**. You will be asked to choose the most important and least important indicators and compare others against them. Your input will directly shape the SVI formula and help us identify which communities are most vulnerable, so that future planning and adaptation strategies can be fairer and more effective. For more information about BWM, visit: https://bestworstmethod.com/.

Thank you for participating. Your responses will remain anonymous and will only be used for research purposes.

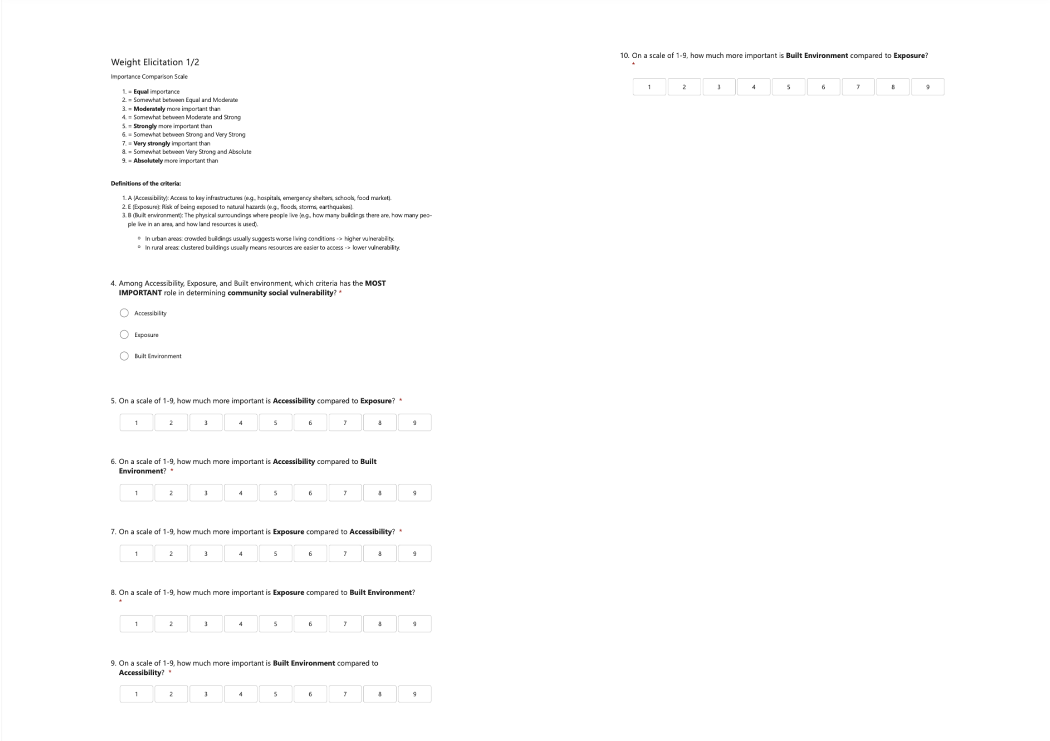
1. What is your current occupation/profession? *
   - Academic/Researcher
   - Government/Policy Maker
   - Student
   - NGO/Non-profit Sector
   - Private Sector/Industry
   - Other

2. How long have you been working in this field (in years)?

   The value must be a number

3. In the context of a natural hazard (e.g., flood), which **critical infrastructure or services** do you think must be considered in the accessibility analysis? *
   - Hospitals / healthcare facilities
   - Schools / education facilities
   - Food markets / grocery stores
   - Water supply points
   - Energy supply (electricity, fuel)
   - Shelters / evacuation centers
   - Other

Figure 24: Questionnaire first page



Weight Elicitation 1/2

Importance Comparison Scale

1. = **Equal** importance
2. = Somewhat between Equal and Moderate
3. = **Moderately** more important than
4. = Somewhat between Moderate and Strong
5. = **Strongly** more important than
6. = Somewhat between Strong and Very Strong
7. = **Very strongly** important than
8. = Somewhat between Very Strong and Absolute
9. = **Absolutely** more important than

Definitions of the criteria:

1. A (Accessibility): Access to key infrastructures (e.g., hospitals, emergency shelters, schools, food market).
2. E (Exposure): Risk of being exposed to natural hazards (e.g., floods, storms, earthquakes).
3. B (Built environment): The physical surroundings where people live (e.g., how many buildings there are, how many people live in an area, and how land resources is used).
   - In urban areas: crowded buildings usually suggests worse living conditions -> higher vulnerability.
   - In rural areas: clustered buildings usually means resources are easier to access -> lower vulnerability.

4. Among Accessibility, Exposure, and Built environment, which criteria has the **MOST IMPORTANT** role in determining **community social vulnerability**? *

- Accessibility
- Exposure
- Built Environment

5. On a scale of 1-9, how much more important is **Accessibility** compared to **Exposure**? *

1 2 3 4 5 6 7 8 9

6. On a scale of 1-9, how much more important is **Accessibility** compared to **Built Environment**? *

1 2 3 4 5 6 7 8 9

7. On a scale of 1-9, how much more important is **Exposure** compared to **Accessibility**? *

1 2 3 4 5 6 7 8 9

8. On a scale of 1-9, how much more important is **Exposure** compared to **Built Environment**? *

1 2 3 4 5 6 7 8 9

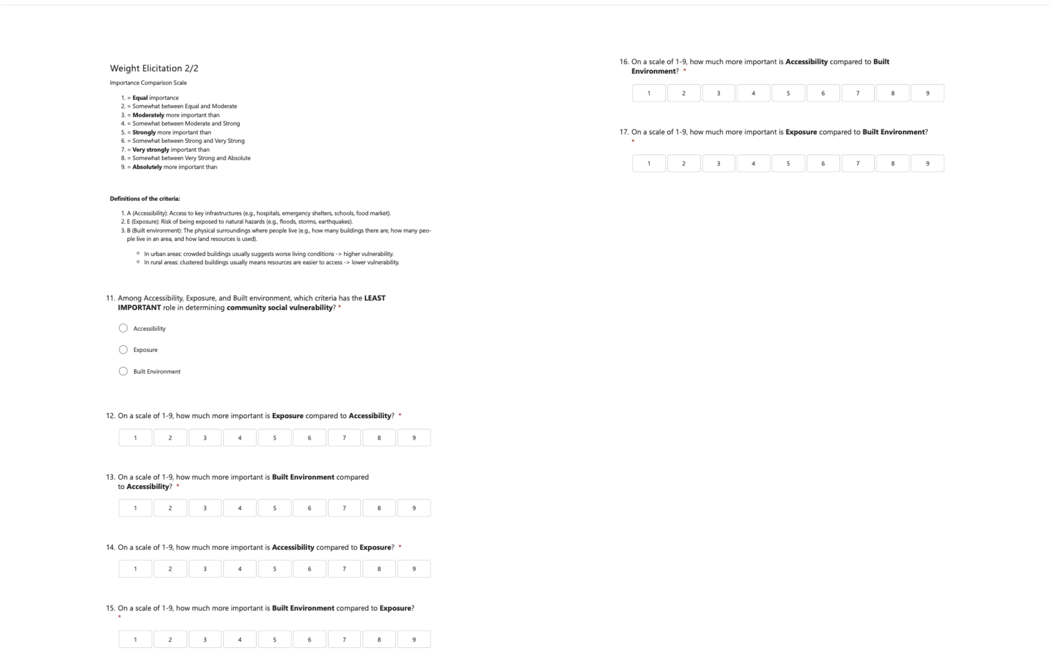
9. On a scale of 1-9, how much more important is **Built Environment** compared to **Accessibility**? *

1 2 3 4 5 6 7 8 9

10. On a scale of 1-9, how much more important is **Built Environment** compared to **Exposure**? *

1 2 3 4 5 6 7 8 9

Figure 25: Questionnaire second page



Weight Elicitation 2/2

Importance Comparison Scale

1. = **Equal** importance
2. = Somewhat between Equal and Moderate
3. = **Moderately** more important than
4. = Somewhat between Moderate and Strong
5. = **Strongly** more important than
6. = Somewhat between Strong and Very Strong
7. = **Very strongly** important than
8. = Somewhat between Very Strong and Absolute
9. = **Absolutely** more important than

Definitions of the criteria:

1. A (Accessibility): Access to key infrastructures (e.g., hospitals, emergency shelters, schools, food market).
2. E (Exposure): Risk of being exposed to natural hazards (e.g., floods, storms, earthquakes).
3. B (Built environment): The physical surroundings where people live (e.g., how many buildings there are, how many people live in an area, and how land resources is used).
   - In urban areas: crowded buildings usually suggests worse living conditions -> higher vulnerability.
   - In rural areas: clustered buildings usually means resources are easier to access -> lower vulnerability.

11. Among Accessibility, Exposure, and Built environment, which criteria has the **LEAST IMPORTANT** role in determining **community social vulnerability**? *

- Accessibility
- Exposure
- Built Environment

12. On a scale of 1-9, how much more important is **Exposure** compared to **Accessibility**? *

1 2 3 4 5 6 7 8 9

13. On a scale of 1-9, how much more important is **Built Environment** compared to **Accessibility**? *

1 2 3 4 5 6 7 8 9

14. On a scale of 1-9, how much more important is **Accessibility** compared to **Exposure**? *

1 2 3 4 5 6 7 8 9

15. On a scale of 1-9, how much more important is **Built Environment** compared to **Exposure**? *

1 2 3 4 5 6 7 8 9

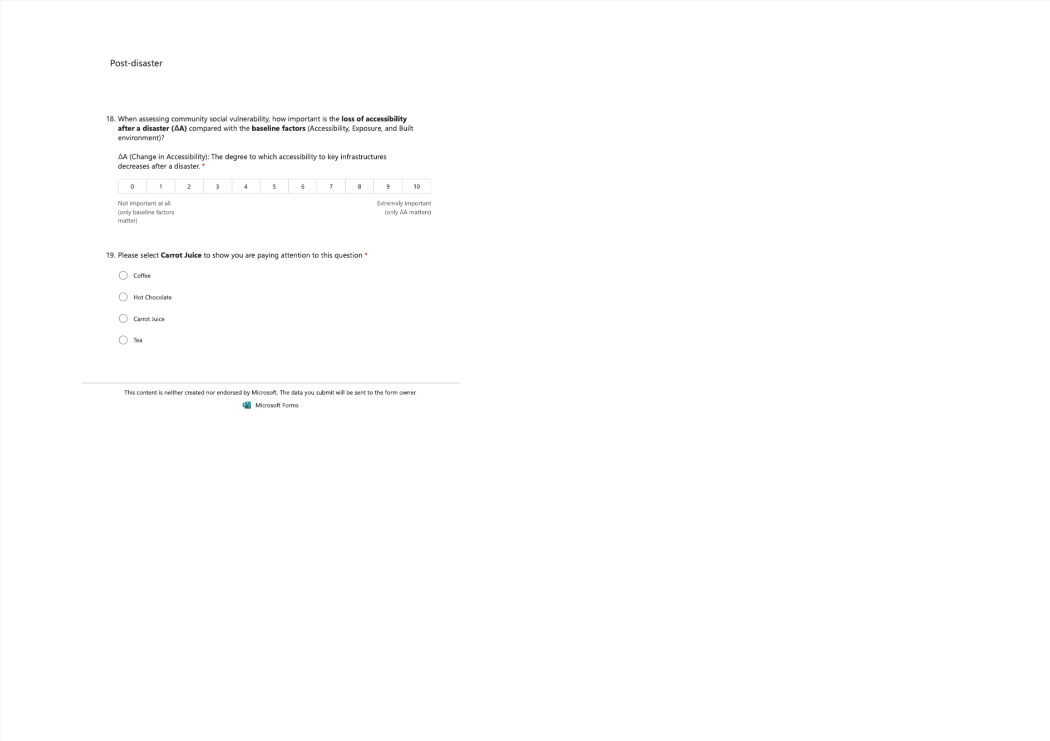
16. On a scale of 1-9, how much more important is **Accessibility** compared to **Built Environment**? *

1 2 3 4 5 6 7 8 9

17. On a scale of 1-9, how much more important is **Exposure** compared to **Built Environment**? *

1 2 3 4 5 6 7 8 9

Figure 26: Questionnaire third page



Post-disaster

18. When assessing community social vulnerability, how important is the **loss of accessibility after a disaster (ΔA)** compared with the **baseline factors** (Accessibility, Exposure, and Built environment)?

ΔA (Change in Accessibility): The degree to which accessibility to key infrastructures decreases after a disaster. *

0	1	2	3	4	5	6	7	8	9	10

Not important at all (only baseline factors matter)

Extremely important (only ΔA matters)

19. Please select **Carrot Juice** to show you are paying attention to this question *

- Coffee
- Hot Chocolate
- Carrot Juice
- Tea

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Microsoft Forms

Figure 27: Questionnaire fourth page

E Spatial Planning Database

Cause ID	Effect ID
C1	E3, E14, E28, E29
C2	E1, E5, E16, E23
C3	E3, E9, E10, E11, E14
C4	E1, E2, E19, E28
C5	E1, E5, E16, E23, E24, E25
C6	E6, E7, E15, E19
C7	E6, E7, E15, E19
C8	E1, E15, E22, E24, E25
C9	E16, E17, E18, E20
C10	E1, E8, E19, E30

Table 9: Causes-Effects

Effect ID	Effect ID
E1	E15, E16, E24, E25
E2	E19, E26, E27
E3	E12, E13, E14, E25
E4	E16, E17, E18, E27
E5	E16, E23, E24
E6	E7, E15, E20
E7	E6, E15, E24
E8	E19, E20, E30
E9	E3, E11, E12
E10	E9, E11
E11	E3, E9, E10
E12	E3, E13, E25
E13	E3, E12, E27
E14	E3, E28, E29
E15	E1, E6, E7, E24
E16	E1, E4, E5, E24, E25
E17	E4, E18, E20
E18	E4, E17, E27
E19	E2, E8, E20
E20	E6, E8, E17, E19
E21	E24, E25, E26, E27
E22	E1, E15, E24
E23	E1, E5, E16, E24
E24	E1, E5, E15, E16, E21
E25	E1, E3, E16, E21
E26	E2, E21, E27
E27	E2, E4, E13, E18, E21, E26
E28	E1, E14, E29
E29	E14, E28, E3
E30	E1, E8, E19
E31	E1, E14, E28, E29
E32	E1, E15, E6, E7
E33	E4, E18, E27, E13
E34	E1, E8, E19

Table 10: Effects-Effects

Measure ID	Effect IDs
M1	E3, E14, E28, E29
M2	E1, E15, E16, E24
M3	E3, E9, E11, E12
M4	E5, E16, E23
M5	E6, E7, E15
M6	E8, E30, E19
M7	E3, E14, E25
M8	E4, E18, E27
M9	E2, E19, E26
M10	E13, E12, E3
M11	E16, E17, E20
M12	E1, E22, E24
M13	E21, E25, E26
M14	E6, E8, E20
M15	E9, E11, E3
M16	E10, E9, E11
M17	E1, E15, E6
M18	E3, E14, E29
M19	E4, E18, E27
M20	E1, E8, E30
M21	E1, E15, E6
M22	E21, E25, E26
M23	E6, E8, E20
M24	E9, E11, E3
M25	E10, E9, E11
M26	E1, E8, E30

Table 11: Measures-Effects

E.1 References for causes, effects, and measures

- Omanga, A., County Government of Mombasa, Kenya Marine and Fisheries Research Institute, & MDF Training and Consultancy. (2024). *Flood risk assessment of Mombasa County, Kenya*. In *Technical Report: Flood Risk Assessment Using Multi-influencing Factors Technique Coupled With Community Participatory Mapping*. Covenant of Mayors for Sub-Saharan Africa (CoM SSA) c/o Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ). https://comssa.org/download/qbkGc8npDQF7WsexEoMVYjfrgRPH05C1/Mombasa-Flood-Risk-Assessment-Technical-
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- Kenya Forest Service. (2021). *Coastal Ecosystem Report*.

F What did we learn

Figure 28: 3.4.1 Haskoning JIP Team

F.1 Aparnaa

As an urbanist with a Bachelor's in Urban Design and currently pursuing a Master's in Urbanism at TU Delft, I have previously collaborated with professionals from various backgrounds, although mostly within the design disciplines. However, this JIP project was truly interdisciplinary, introducing me to new perspectives beyond the spatial and qualitative approaches I usually employ. I learned how mathematics can be applied to develop an index for assessing social vulnerability and how AI can support data interpretation and pattern recognition, expanding my understanding of analytical tools in urban research and planning. Working within a team of ten required clear organisation, distribution of tasks, and regular synthesis of ideas. The fishbone exercise proved particularly useful in structuring our collaboration. I also realised that people from different fields may use similar terminology differently, reinforcing the importance of clear communication. Overall, these nine weeks have been a rewarding experience that broadened my outlook on interdisciplinary urban practice.

F.2 Ayoub

As an Engineering and Policy Analysis student in the Hacking SPIN track, my main lesson was that improving SPIN is as much about product thinking as it is about code. We learned to keep the tool simple for analysts and to move complexity into quiet, testable components. That meant setting small interfaces, writing clear "definition of done" notes, logging what the system does, and making every run reproducible. When we treated SPIN like a product with users, rather than a demo, the work clicked: shorter iterations, early demos, and quick hallway tests revealed more than long debates.

A second lesson was governance. SPIN influences decisions, budgets, and priorities, so its claims need to be traceable and its limits visible. We chose to show sources, dates, and methods next to results, to write down thresholds and assumptions, and to plan for maintenance rather than hoping someone will remember later. This mindset reduced risk: fewer hidden choices, clearer handovers, and a tool that teams can trust and improve.

Finally, I learned to balance speed and rigor. We cut features when they did not earn their keep, shipped thin slices that worked end to end, and added runbooks so others can operate the tool without us. The craft here was not a fancy algorithm, but the discipline to make SPIN reliable, explainable, and ready for the next team to build on.

F.3 Defasha

Through this project, I gained valuable insight into how vulnerability can be measured, visualized, and integrated into software. I learned that identifying vulnerable communities is not only a data or modelling exercise but also a matter of understanding context and behaviour. Coming from a water resources engineering background, I was accustomed to addressing disasters through technical and infrastructural solutions. However, discussions with Haskoning experts and exposure to interdisciplinary perspectives helped me see that the societal dimension is also important. Working in a multidisciplinary and multicultural team was an intense experience, it sometimes took effort to align ten different perspectives, but the process taught me to listen and negotiate with others. On the technical side, I also learned new things such as software development, particularly about system architecture of a tool. Overall, this project has expanded both my professional competence and my worldview, helping me grow from an engineer who only focused on technical systems, to someone who understands that resilience begins with people.

F.4 Lorenz

The project was titled “Social Impact and Spatial Inequalities”, two topics I was not familiar with when applying for this JIP case. However, they were subjects I had long been interested in and wanted to explore further. My academic background is in Sustainable Energy Technology, where I had not previously encountered Spatial Analysis. Through this project, I realized that even when your expertise lies in a different field, you can still make valuable contributions and offer an interdisciplinary perspective. I had worked in international and interdisciplinary teams before, but usually within a well-defined structure. In this project, establishing that structure, organising workflows, maintaining clear communication, and adapting to diverse working styles, turned out to be a challenge I had initially underestimated. I developed a stronger understanding of team organisation, the importance of transparent communication, and the value of effective collaboration tools. In summary, this project not only introduced me to a previously unfamiliar topic but also reinforced my confidence in quickly adapting to new subjects and taught me a lot about interdisciplinary teamwork.

F.5 Nam

Working on the SPIN project has been a very meaningful learning experience for me, both academically and personally. Going into the project, I was interested in understanding how data-driven tools can support climate adaptation and reduce inequalities. Throughout this process, I realized that building such tools is not only about technical accuracy but also about ethics, and responsibility. I learned that when tools like SPIN are used in real-world decision-making, sustainable business model are just as important as the data itself.

Another key learning was the value of collaboration. Working across clusters—spatial planning, vulnerability, and business perspective—showed me how multidisciplinary adaptation really is. It strengthened my ability to coordinate with others, adapt to feedback, and approach challenges from difference perspective.

F.6 Nina

I study Management of Technology with a background in Computer Science. One of the major takeaways is how to manage the balance between converging and diverging. We are a pretty large team full of creativity, but that also means making compromises, staying organised, being diligent about what information gets stored and communicated where. To move the shared creativity forward, it was really important to set explicit deadlines, make responsibility clear and hold each other accountable. I am also really grateful for my group mates who have helped majorly in shaping the product as it is now. I am not a topic expert in Urbanism and Spatial Planning, but many of my group members had experience with working with geospatial data and geospatial analysis, which led to many very insightful contributions, discussions and conversations. Within the last nine weeks, I felt like I learned a lot about this otherwise unfamiliar topic.

F.7 Rachel

I have always been fascinated by the quantification of human behavior and socio-economic factors, though I often felt this approach reduces complexity to numbers and loses nuance. This tension led me to study Engineering and Policy Analysis. Joining the social vulnerability cluster allowed me to explore it further through meaningful research with teammates skilled in geomatics and mathematics. Working with them broadened my knowledge, especially in geospatial data processing through hands-on learning with QGIS. Beyond the cluster, I also gained insights into flood map generation, spatial measures for different flood phases, and system architecture. Collaborating with a large team has been inspiring, yet challenging. Ensuring everyone was on the same page was not easy. It taught me the importance of clear, continuous communication—something I'm still improving. Overall, I'm proud of our work and grateful for my resilient teammates and supportive coaches, as well as the guest lecturers they provided whose real-world experience motivated my learning.

F.8 Valdemarr

I joined this project because, in architecture and urbanism, the data behind our plans often feel less certain than the designs that follow. Spatial design can create opportunity and improve livelihoods when evidence is sound and processes are fair, but it can also reinforce inequality when blind spots go unchecked. This JIP project made that tension tangible. Working with patchy datasets across unfamiliar contexts, cultures, and capacities revealed how difficult it is to turn analysis into just outcomes. It also highlighted the ethics of method: the speed–accuracy trade-off, the limits of single-layer maps, and how interpretation shapes who gets seen. These insights will guide my future work, making me more aware of the complexities of my profession and the world.

From a teamwork perspective, my background in architecture makes me comfortable sketching structure quickly and driving projects forward. In a group of ten students from diverse fields, this strength sometimes over-showed. Early on, I pushed frameworks before we had a shared language, which taught me to pause, clarify, and collaborate more deliberately. I learned to check definitions, ask questions before proposing structures, and keep early outputs provisional. The simple sounding practices taught me a lot in making my decisions sturdier.

The midterm critique was a turning point in the project. Afterwards I joined the Hacking SPIN cluster, in combination with Spatial Planning, as this cluster was struggling to turn research into results I helped them organise their work and define a clearer path. It was a valuable experience, but it also showed me that facilitation can come at a cost. The more I facilitated, the less time I had to do my own research and deepen my own understanding. Balancing both will take effort in the future.

F.9 Xinya

I study Geomatics and hold a bachelor's degree in Urban Planning with an emphasis on economics. My bachelor's thesis researched a similar field, which focused on social equity and justice in the distribution of urban green and blue spaces. I've always been fascinated by spatial analysis. During the JIP project, I sometimes found myself immersed in technical details rather than focusing on designing and building a feasible solution. However, working with people from different backgrounds greatly broadened my vision and inspired me to explore the possibility of integrating AI into geospatial analysis.

F.10 Yufan

This project gave me a real taste of QGIS, with practical work on new geospatial datasets and geometry types outside my field. I was also shown an eye-opening early-warning case by Haskoning, illustrating how flood alerts and interventions for refugee settlements in parts of Africa are designed. Working in a team of ten, I learned from each interaction, solved shared problems through clear communication and efficient handovers, and saw how a large group runs and why a well organized schedule matters.