

multi-Risk sciEnce for resilienT commUnities undeR a changiNgclimate

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2. ABSTRACT

The first part of this report presents a conceptual structure for the analysis of uncertainty propagation along the modelling chain for flood risk evaluations. After a literature review, also based on previous deliverables (from VS1 but also from other spokes), a limited number of papers have been selected (see bibliography) as basis for the conceptualization.

The second part of the report presents and briefly discusses the same topic based on the PoC developed within VS1, through schematic forms aimed at defining the uncertainty chains within each PoC, along the conceptual structure defined in the first part of the report.

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4. Section 1: literature review

4.1 Introduction

Flood risk assessment is a cornerstone of modern water management and climate adaptation planning, providing critical information for infrastructure design, emergency response, and policy-making. However, the predictions underpinning these assessments are not deterministic truths but rather uncertain estimates shaped by a complex chain of models and data. The first part of this report explores the concept of uncertainty propagation along the modelling chain in flood risk assessment, examining how errors and knowledge gaps at each stage amplify or interact as they move through the system, ultimately affecting the reliability and usefulness of final flood predictions.

At its core, flood risk assessment involves a linked sequence of models and data that transform meteorological inputs into estimates of flood impacts and, therefore, risk. The full modelling chain ideally starts with climate and meteorological models that simulate rainfall and other atmospheric conditions. These outputs serve as inputs to hydrological models that translate rainfall into river flows, which in turn inform hydraulic models that simulate water levels and inundation patterns across landscapes. Finally, these hydraulic results feed into risk models that estimate economic damages, social impacts, and other consequences of flooding. Each stage in this chain introduces its own sources of uncertainty, and these uncertainties do not remain isolate, they propagate and accumulate through the system in ways that are often non-linear and difficult to predict.

Uncertainty propagation in this context refers to the process by which the errors and unknowns in earlier stages of the modelling chain influence the results of later stages. This propagation can occur through various mechanisms, including input data errors, model structural simplifications, parameter choices, and the mathematical relationships between different variables. For example, errors in rainfall estimates can be magnified through the rainfall-runoff transformation process, leading to larger errors in predicted river flows. Similarly, uncertainties in topographic data can dramatically affect hydraulic model predictions of inundation extent and depth, which in turn influence damage estimates and cost-benefit analyses.

The sources of uncertainty in flood risk modelling chains are diverse and can be broadly categorized into several groups. Input data uncertainty arises from measurement errors, spatial and temporal sampling limitations, and the use of imperfect observations to calibrate models. Model structural uncertainty stems from the simplifications and approximations that are necessary to represent complex physical processes in mathematical form. Parameter uncertainty reflects the difficulty of precisely estimating the values of model parameters that control how the system responds to different inputs. Finally, there is epistemic uncertainty associated with our incomplete understanding of the underlying processes themselves.

The implications of uncertainty propagation for flood risk management are profound. Decision-makers rely on flood risk assessments to prioritize investments in flood protection infrastructure, develop emergency response plans, and evaluate the costs and benefits of different adaptation strategies. If the uncertainties in these assessments are not properly understood and communicated, there is a risk of either over-investing in protection measures that may not be necessary or under-investing in measures that could prevent significant damage and loss of life.

Understanding uncertainty propagation is therefore essential for developing robust flood risk management strategies that are resilient to the inherent uncertainties in the modelling process. This requires not only technical approaches to quantify and characterize uncertainties at each stage of the modelling chain but also methods for effectively communicating these uncertainties to decision-makers and stakeholders. It also necessitates a shift in how we think about flood risk assessment results, moving from a focus on single "best estimate" predictions to a more nuanced understanding of the range of possible outcomes and their associated likelihoods.

The study of uncertainty propagation in flood risk modelling chains has gained increasing attention in recent years, driven by the growing recognition of the limitations of traditional deterministic approaches and the need for more robust decision-making in the face of climate change. Researchers have developed a range of methods

for analyzing and quantifying uncertainty propagation, from sensitivity analysis techniques that identify the most influential sources of uncertainty to probabilistic modelling approaches that explicitly represent uncertainty in model inputs and parameters.

Despite these advances, significant challenges remain. The complexity of flood risk modelling chains makes it difficult to fully characterize all sources of uncertainty and their interactions. The computational demands of running large numbers of simulations to explore uncertainty space can be prohibitive, particularly for high-resolution models of large regions. There is also a need for better methods to integrate different types of uncertainty, including aleatory uncertainty (inherent randomness) and epistemic uncertainty (lack of knowledge), and to communicate these uncertainties effectively to non-technical stakeholders.

This report will explore these issues in more detail, examining the specific mechanisms of uncertainty propagation in flood risk modelling chains, the methods used to analyze and quantify uncertainty, and the implications of uncertainty for flood risk management decision-making. By providing a comprehensive overview of this important topic, the report aims to contribute to a more nuanced and robust understanding of flood risk assessment that acknowledges and addresses the inherent uncertainties in the modelling process.

4.2 Sources of Uncertainty in the Flood Risk Modelling Chain

Flood risk assessment relies on a sequence of models and data that transform uncertain inputs into estimates of hazard, exposure, and vulnerability. At each step of this modelling chain, various types of uncertainty emerge, and understanding their origins is essential for interpreting results and improving model reliability. Broadly, these sources can be grouped into input data uncertainty, model structure uncertainty, parameter uncertainty, and epistemic or knowledge-based uncertainty. Each of these categories manifests differently across meteorological, hydrological, hydraulic, and socio-economic components of a typical flood-risk chain, and their interplay often governs the overall uncertainty in the final risk estimates.

Following discussion is focused on the typical flood chain; however, there are relevant scenarios involving further and more complex modelling chains, like small mountain basins, where sediment transport and morphological changes should be modelled jointly with hydrologic and hydraulic processes, or like pluvial flooding which requires model of the urban drainage network, or like coastal flooding, where hazard is related to marine forcing terms.

4.2.1 Input Data Uncertainty

Input data uncertainty arises from the limitations of observations, measurements, and surrogate datasets used to drive flood-risk models. In a standard modelling chain, inputs may include rainfall fields, temperature and pressure data, river discharge measurements, topographic and bathymetric datasets, land-use maps, exposure data (e.g., building footprints and population distribution), and socio-economic information such as asset values. All of these quantities are measured or inferred with finite resolution, imperfect instruments, incomplete spatial coverage, and varying temporal sampling, which collectively introduce uncertainty into the modelling process.

Rainfall data, for example, are often obtained from rain gauges, weather radars, or satellite products, each with distinct error characteristics. Rain gauges provide point measurements that may not represent the spatial variability of rainfall over a catchment, particularly in mountainous regions or areas with complex terrain. Radar and satellite products, while covering larger areas, suffer from calibration errors, beam-blockage effects, and difficulties in distinguishing between different types of precipitation. When these data are used to force hydrological models, interpolation and merging techniques introduce additional uncertainty, as do assumptions about temporal aggregation (e.g., hourly vs. daily rainfall). Studies have shown that differences between observed and model-derived rainfall fields can lead to substantial variability in simulated hydrographs, particularly for extreme events where small errors in rainfall intensity or timing can be amplified through the rainfall-runoff transformation.

River discharge data used for model calibration and evaluation are also subject to measurement uncertainty. Stream-gauge readings depend on water-level stage measurements converted to discharge via rating curves, which themselves are empirical and often extrapolated beyond the range of observed conditions. Gauge instability, sedimentation, and changes in channel geometry can shift these curves over time, adding further uncertainty. When such data are used to calibrate hydrological or hydraulic models, the propagated uncertainty affects not only the accuracy of simulated flows but also the estimation of return levels for flood frequency analysis.

Topographic and bathymetric data, on which hydraulic models are heavily dependent, are another major source of input uncertainty. Digital elevation models derived from LiDAR, satellite altimetry, or photogrammetry are subject to vertical accuracy errors, missing features, and artefacts caused by vegetation or buildings. In river channels and coastal areas, the resolution of these datasets may be insufficient to capture critical features such as levees, culverts, or small embankments that strongly influence flood pathways. When these minor elevation errors are propagated through 2D hydraulic models, they can significantly alter predicted inundation extents, water depths, and flow velocities, particularly in low-gradient floodplains where small elevation differences determine whether an area floods or remains dry.

Land-use and exposure data add another layer of uncertainty. Land-use maps are often derived from satellite imagery and may not capture recent changes, such as new developments or cleared vegetation. Building footprints and population distributions may be based on outdated census data or administrative records, leading to misrepresentation of exposure in rapidly urbanizing areas. Socio-economic data, such as asset values or replacement costs, are often estimated at coarse spatial scales and may not reflect local variability. When these data are combined with inundation maps to estimate flood damage, the resulting uncertainty can be comparable to or even exceed the uncertainty originating from hydrological and hydraulic components.

More in general, all system parameters are evaluated on past or present conditions, while risk estimates are inevitably referred to the future; therefore, all parameters are affected by uncertainty with regard to possible evolutions, first of all because of direct and indirect effects of climatic changes, but also related to any kind of changes in society and anthropic activities.

4.2.2 Model Structure Uncertainty

Model structure uncertainty reflects the fact that all flood-risk models are simplified representations of real physical, social, and economic systems. No model can capture every process, interaction, or scale of variability, and the choice of which processes to include, how to parameterize them, and at what spatial and temporal resolution to represent them introduces structural uncertainty. This uncertainty is often difficult to quantify because it stems from the underlying conceptualization of the system rather than from measurable errors in input data.

In the meteorological and climate-modeling component, structural uncertainty arises from the choice of physical parameterizations, grid resolution, and numerical schemes used to simulate atmospheric processes. Climate models, for instance, must represent complex interactions between radiation, cloud microphysics, convection, and large-scale circulation, often using simplified closures that may not behave realistically under future climate conditions. When such models are used to generate rainfall scenarios for flood-risk assessment, their structural biases can propagate through the entire chain, affecting the frequency and intensity of simulated extreme events.

Hydrological models, which translate rainfall into river flows, are also subject to structural uncertainty. Different hydrological frameworks (such as lumped conceptual models, semi-distributed models, and fully distributed physically-based models) make different assumptions about how water moves through a catchment. Some models assume that all rainfall reaches the river channel instantaneously, while others represent overland flow, subsurface flow, and routing through channels and reservoirs. The choice of model structure influences how the catchment responds to different rainfall patterns, particularly under extreme conditions. In many cases, available observations are insufficient to uniquely identify the “best” model structure, leading to multiple competing representations of the same system, each with different weaknesses and strengths.

Hydraulic models are further constrained by their assumptions about friction, roughness, and flow dynamics. Simplifications such as neglecting 3D turbulence, ignoring sediment transport, or assuming steady flow can introduce systematic biases, especially in complex urban environments or coastal zones where vertical mixing and wave interactions are important. When these structural limitations propagate through the model, they can lead to systematic overestimation or underestimation of flood depths and velocities, which in turn affects damage estimates and risk-based decision-making.

Risk and damage models introduce additional structural uncertainty through their functional forms and assumptions about vulnerability. Many flood-damage models use empirical relationships linking water depth to damage ratios, often derived from past flood events or expert judgment. These relationships may not capture non-linearities, threshold effects, or behavioral responses such as evacuations or flood-proofing measures. Furthermore, different models may define damage differently (e.g., direct vs. indirect, tangible vs. intangible), leading to inconsistent results even when driven by the same inundation maps. Furthermore, for some categories of exposed elements impact models are not sufficiently developed, or their application requires data that are not available (example: many lifelines, productive sectors). When impact evaluations are embedded in a chain fed by uncertain hydrological and hydraulic outputs, the compounded structural uncertainty can significantly affect the reliability of cost-benefit analyses and other evaluations of flood-risk management options.

4.2.3 Parameter Uncertainty

Parameter uncertainty arises from the difficulty of precisely estimating the numerical values that govern how a model behaves. All models contain parameters that must be calibrated or inferred from data, and these parameters seldom represent directly measurable quantities. Instead, they often act as “effective” parameters that lump together multiple processes, such as infiltration rates, storage capacities, or routing times. The estimation of these parameters is typically constrained by limited and noisy observations, leading to uncertainty in their true values.

In hydrological modelling, parameter uncertainty is a well-known issue. Many rainfall-runoff models have several parameters that cannot be uniquely identified from available data, particularly in ungauged or poorly gauged catchments. Calibration to a limited set of flood events may produce a good fit for those events but may not generalize well to other conditions, especially to extreme or future events that differ from the calibration sample. This leads to uncertainty in predicted flow magnitudes, timing, and shapes of hydrographs, which can propagate through the hydraulic and risk components of the chain. Ensemble calibration approaches and Bayesian methods have been proposed to quantify this parameter uncertainty, but they often require substantial computational resources and may still be limited by the quality and quantity of available data.

Hydraulic models also depend on parameters such as Manning’s roughness coefficients, weir and gate coefficients, and boundary conditions. These parameters are often estimated from field observations, empirical tables, or expert judgment, but their true spatial variability is rarely known. In complex urban environments, for example, the effective roughness of a street network can depend on the density and height of buildings, the presence of parked vehicles, and other temporary obstructions that are difficult to capture systematically. When such parameters are uncertain, the resulting uncertainty in predicted water depths and flow velocities can be substantial, particularly in low-gradient areas where small changes in resistance can alter the flow path.

Risk and damage models introduce further parameter uncertainty through their damage-depth functions, discount rates, and other coefficients used to translate inundation into economic or social impacts. Damage-depth curves are often derived from limited datasets of past floods and may not capture the full range of possible responses, particularly for rare or unprecedented events. Discount rates used in cost-benefit analyses are inherently uncertain, as they depend on future economic conditions and societal preferences. When these parameters are combined with uncertain hydrological and hydraulic outputs, the propagated uncertainty can strongly influence decision-making about flood-risk management investments.

4.2.4 Epistemic and Knowledge-Based Uncertainty

Beyond data, structure, and parameter uncertainty, flood-risk modelling chains are also subject to epistemic uncertainty, which stems from incomplete or imperfect knowledge about the system being modelled. This type of uncertainty is particularly challenging because it cannot always be reduced by collecting more data or improving observational networks. Instead, it reflects fundamental limitations in our understanding of the processes at play, the interactions between different components of the system, and the appropriate ways to represent them mathematically.

In the context of climate change, epistemic uncertainty arises from the difficulty of projecting future climate conditions, particularly for extreme events. Climate models disagree on the magnitude and spatial patterns of future changes in precipitation, temperature, and sea level, and these disagreements are not fully captured by the current generation of climate simulations. When these uncertain climate projections are used to drive flood-risk models, the resulting uncertainty in future flood hazard is often large and difficult to quantify with confidence. This epistemic uncertainty is compounded by the fact that many of the processes at play, such as convective rainfall, compound events, and feedbacks between climate and land-use change, are not fully understood.

Another source of epistemic uncertainty is the representation of human behavior and land-use change in flood-risk models. Human responses to flood risk, such as investments in flood protection, changes in land use, or migration, can significantly alter the evolution of risk over time. However, these responses are difficult to model accurately, as they depend on a wide range of social, economic, and political factors that are not well captured by current modelling frameworks. Similarly, future land-use change and urban development patterns are inherently uncertain, but they can strongly influence flood exposure and vulnerability. When these uncertain human and land-use dynamics are combined with uncertain hydrological and hydraulic outputs, the overall uncertainty in future flood-risk estimates can be substantial.

Epistemic uncertainty also arises from the integration of different models and disciplines within a single flood-risk assessment. Hydrologists, hydraulic engineers, geomorphologists, economists, and social scientists each bring different perspectives and assumptions to the modelling process, and reconciling these perspectives into a coherent framework is challenging. Different disciplines may use different definitions of risk, different scales of analysis, and different methods for quantifying uncertainty, leading to inconsistencies and potential conflicts in the final assessment. This disciplinary uncertainty is often difficult to quantify, but it can have a significant impact on the robustness and credibility of flood-risk estimates.

4.3 Mitigation and Best Practices in Handling Uncertainty Propagation

Reducing the impact of uncertainty along the flood-risk modelling chain is not about eliminating uncertainty entirely - this is often impossible - but about controlling, quantifying, and communicating it in a way that supports robust, transparent, and defensible decision-making. Best practices in uncertainty mitigation span technical modelling choices, methodological strategies, and the way results are presented to stakeholders. When applied systematically, these practices help decision-makers understand the reliability of flood-risk estimates, avoid overconfidence in single “best” scenarios, and design adaptive strategies that remain effective across a range of plausible futures.

4.3.1 Quantification and Representation of Uncertainty

A foundational step in mitigating uncertainty propagation is to explicitly represent uncertainty mathematically rather than treating model inputs and outputs as deterministic values. This usually involves moving from a single “design” scenario to a probabilistic framework in which key inputs, such as rainfall intensities, climate projections, or extreme-value distributions, are characterized by probability distributions or ensembles. For example, rainfall inputs can be sampled from distributions fitted to observed data, or from multi-model climate

ensembles, while hydrological and hydraulic parameters can be varied according to prior or calibrated distributions.

Monte Carlo simulation is one of the most widely used techniques for propagating these probabilistic inputs through a modelling chain. In this approach, many runs are performed with randomly sampled parameter sets and input realizations, producing a distribution of outputs (e.g., flood depths, inundation extents, or damage estimates) rather than a single point estimate. From this ensemble, one can compute statistics such as mean, variance, confidence intervals, or return-level curves, which help convey the range of possible outcomes and their likelihoods. Such probabilistic outputs are particularly valuable for risk-based decision-making, where understanding the tails of the distribution (e.g., worst-case low-probability events) is as important as the central tendencies.

Another important practice is to propagate uncertainty across disciplines, linking hydrological, hydraulic, and economic models through shared probabilistic frameworks. For instance, instead of calibrating a hydrological model once and using its “best” parameters as fixed inputs to a hydraulic model, one can carry forward the full posterior distribution of hydrological parameters and propagate them into the hydraulic component. This avoids underestimating uncertainty by treating mid-range estimates as truth and allows for a more realistic assessment of how parameter and structural uncertainty interact across scales and components.

Finally, engineering common practices often embed safe-side evaluations for uncertain parameters; if such practice may be appropriate for design purposes, it leads to biased intermediate results along the chain, thus biasing the probabilistic representation of the scenarios. In such cases it is, therefore, fundamental to differentiate design-aimed modelling from risk assessment-aimed modelling approaches.

4.3.2 Sensitivity and Interaction Analysis

Once uncertainty is quantified, the next best practice is to identify which sources contribute most to the overall uncertainty in the final outputs. Sensitivity analysis is a key tool for this purpose. Local sensitivity methods (e.g., one-at-a-time parameter variations) can quickly reveal how outputs change in response to small perturbations in individual parameters or inputs. However, they are limited when interactions between sources are strong, as they often miss higher-order dependencies and non-linear effects.

Global sensitivity analysis (GSA) methods, such as variance-based techniques, are better suited for complex flood-risk chains. These methods decompose the total output variance into contributions from individual inputs and their interactions, allowing analysts to rank sources of uncertainty and identify which ones should be prioritized for reduction. For example, in coastal flood-risk chains, wave overtopping and sea-level components often dominate uncertainty budgets, whereas in some river basins climate-model choice, bias-correction method, and flood-frequency distribution fitting may be more influential. Identifying these “hot-spots” of uncertainty helps focus resources: improved wave-gauge networks, more refined overtopping formulae, or better observational data for specific catchments can have a disproportionate impact on the reliability of final risk estimates.

Sensitivity analysis also supports the design of emulators or surrogate models: simpler, faster models that approximate the behavior of computationally intensive hydraulic or climate models. These emulators can be used to run large numbers of Monte Carlo simulations at low cost, enabling high-resolution uncertainty and sensitivity analysis without the prohibitive run-times of full-scale models. Emulators are particularly useful when the full chain includes computationally expensive 2D hydraulic simulations or multi-model climate ensembles, as they make probabilistic exploration of uncertainty more feasible.

4.3.3 Model Selection, Calibration, and Validation

Careful model selection and calibration are central to reducing uncertainty propagation. Choosing an appropriate model structure, that is, one that balances complexity with available data and computational resources, is critical. Overly simplistic models may miss important physical or socio-economic processes, while overly complex models may be difficult to parameterize and validate, increasing structural and parameter uncertainty. In practice, this often means selecting models whose complexity is justified by the purpose of the analysis and the quality of available data.

Calibration should be performed with an awareness of equifinality (the fact that many different parameter sets can produce similarly good fits to observed data). Techniques such as multi-objective calibration, ensemble calibration, or Bayesian parameter estimation help characterize this equifinality explicitly and provide a distribution of parameter sets rather than a single “optimal” solution. These distributions can then be propagated through the rest of the chain, preserving the uncertainty associated with parameter estimation rather than freezing it at a single point.

Validation is equally important. Models should be tested not only against historical events used for calibration but also against independent datasets or events that differ in magnitude, timing, or spatial extent. This helps reveal structural biases that might not be evident during calibration (e.g., consistent underestimation of large floods) and provides a more realistic assessment of model performance under uncertainty. When validation datasets are scarce, cross-validation or split-sample testing can be used to approximate performance while still acknowledging the limitations of the validation evidence.

4.3.4 Communicating Uncertainty to Decision-Makers

Quantifying uncertainty is necessary but not sufficient; effective communication is essential for translating complex uncertainty analyses into actionable insights. Decision-makers often prefer simple, deterministic narratives, but flood-risk assessments should instead present a rich picture of possible outcomes, including central estimates, confidence ranges, and worst-case scenarios. Visual tools such as probabilistic inundation maps, risk curves, and cost-benefit profiles that show how outcomes vary with different assumptions can help stakeholders grasp the implications of uncertainty without requiring deep technical expertise.

A best practice is to explicitly report uncertainty sources and their contributions alongside numerical results. For instance, a coastal flood-risk assessment might state that wave overtopping and sea-level projections account for the majority of variance in economic damage estimates, whereas hydrological uncertainty plays a smaller role. This allows stakeholders to judge which aspects of the analysis are most robust and which may be sensitive to future improvements in data or modelling. It also supports adaptive planning, where measures are designed to perform well across a range of plausible futures rather than being optimized for a single, uncertain scenario.

Finally, uncertainty communication should be framed in terms of risk management trade-offs. For example, decision-makers can be shown the probability of exceeding a given damage threshold under different protection strategies, or the expected annual damage as a function of different investment levels. This risk-based perspective helps move the discussion away from “Is this model accurate?” to “What level of risk are we willing to accept, given the uncertainties?” and encourages more explicit consideration of residual risk even after protection measures are implemented.

5. Section 2: Uncertainty analysis along PoC modelling

5.1 PoC Arno

5.1.1 Brief description of the PoC

Arno River basin: Long term changes in flood quantiles from the continuous hydrological modelling of bias-corrected Convection Permitting Model (CPM) projections.

The PoC will allow us to compare different scenarios and methodologies to determine which is best suited to identifying changes in the flood frequency curve of the Arno River, potentially providing recommendations/guidelines applicable to other river basins. The results can also be transferred to the Northern Basin District Authority, which is directly responsible for managing the Arno River's flood risk.

5.1.2 PoC modelling chain

Component	yes	no
Meteorology		x
Hydrology	x	
Hydraulics		x
Impacts		x

5.1.3 Evaluation of uncertainties

Hydrologic model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 3
- parameters 3
- input data 1
- epistemic uncertainty 2

Comments

The uncertainty of the SWAT+ semi distributed process based model is valuated based on governing and detailed parameterized water balance model.

Average NSE is 0.6;

Average MAE ~ 10%.

The uncertainty of the input data is reduced thanks to the bias correction performed and the verification done by Mazzoglio et al. 2025.

5.2 PoC Cervinara

5.2.1 Brief description of the PoC

Study area Cornito Stream, Cervinara (province of Avellino, Campania).

A small mountain basin, characterized by slopes covered with pyroclastic layers subject to sudden collapse during intense and prolonged weather events. The mobilized material spreads downstream at high speed in the form of rapid mudflows and debris flows, impacting the residential areas below. The PoC aims to: numerically reconstruct the catastrophic flow of December 19, 1999, which destroyed several buildings and caused six deaths; validate the models using surveys conducted immediately after the event and available cartographic information on the characteristics of the pyroclastic materials; illustrate the entire analysis chain—from rainfall infiltration into the slopes to the simulation of flow along the stream channels—as a practical example that can be replicated in similar contexts.

5.2.2 PoC modelling chain

Component	yes	no
Meteorology		x
Hydrology	x	
Hydraulics	x	
Impacts		x

5.2.3 Evaluation of uncertainties

Hydrologic model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 2
- parameters 3
- input data 3
- epistemic uncertainty 2

Comments

Hydrological modelling has been carried out to assess the liquid discharge that flows through the stream where the debris flow, triggered by the failure of a slope, is channelized. This evaluation is required when the hydraulic model used for the flow routing is based on a two-phase approach. The highest uncertainty came from the parameters describing the infiltration capacity of the soils, as well as from the rainfall input data, that were taken from a rain gauge installed around two kilometers far from the catchment. However, owing to the high porosity and hydraulic conductivity of the pyroclastic deposits covering the slopes of the studied catchment, the predicted liquid discharge is in any case much smaller than the mud discharge coming from the slope failure, thus only slightly affecting the subsequent hydraulic modelling.

Hydraulic (+sediment transport) model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 3
- parameters 4

- input data 2
- epistemic uncertainty 3

Comments

Hydraulic modelling had twofold objectives: predicting the infiltration and drainage processes in the pyroclastic soil deposits, required for the assessment of slope failure; simulating the runoff of the mixture of mud, debris and water through the stream running at the foot of the failed slope, that carried the debris flow to the nearby hamlet of Ioffredo, where big damage and victims were reported.

To model the flow through the unsaturated soil deposit, estimates of the soil water characteristic curves are needed. The spatial variability of soil properties, and the limited information that could be derived from laboratory measurements on soil samples and field measurements taken near the studied catchment, introduces uncertainty in the parameters of the model. This uncertainty also affects the structure of the model, where a single soil layer was introduced in place of the actual layered soil profile. Furthermore, the knowledge of the physical behavior of the system was limited (epistemic uncertainty) as regards the hydraulic behavior of the soil-bedrock interface, which controls the gravitational drainage of the soil deposit. A simplified hydraulic coupling of the unsaturated soil column with the underlying shallow aquifer developing in the fractured bedrock is introduced, with the aquifer conceptualized as a linear reservoir, the parameters of which were estimated based on field observations in similar contexts. In any case, the obtained results show that uncertainty mostly affected the identification of the position of the failed slope portions, while the estimated mobilized mud volume could be satisfactorily predicted.

The flow routing of the debris through the stream was simulated with several models, either commercial or self-developed. Although the models were all based on the integration of the 2D Saint-Venant equations, different approaches and hypotheses were adopted: single-phase flow with various rheological equations (i.e., Voellmy-Salm, O'Brien and Julien, etc...), in some cases considering the effect on rheological parameters of the variability of sediment concentration along the path; double-phase flow; fixed or erodible bed. This multi-model approach, that reflects the epistemic uncertainty on the physical behaviour of the mixture, also magnified the effects of the uncertainty on model parameters, either rheological or related to the material constituting the stream bed.

5.3 PoC Misa

5.3.1 Brief description of the PoC

Misa River basin, Marche Region, with particular reference to the municipalities of Ostra, Senigallia, and Trecastelli, affected by the flooding of September 15, 2022. Research Objectives: collect, structure, and make available empirical datasets at the micro-scale (i.e., single building) on flood damage suffered by residential buildings and businesses; fill the gap in detailed observational data, which is essential for calibrating predictive flood damage models and guiding mitigation strategies.

5.3.2 PoC modelling chain

Component	yes	no
Meteorology		x
Hydrology		x
Hydraulics	x	
Impacts		x
Coastal circulation	x	

5.3.3 Evaluation of uncertainties

Hydraulic model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 3
- parameters 3
- input data 3
- epistemic uncertainty 3

Comments

Different hydraulic models have been used. Here only the river flow HEC-RAS hydraulic model is evaluated here.

Coastal model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 1
- parameters 2
- input data 2
- epistemic uncertainty 2

Comments

The circulation models used for this POC are the Delft3D-FM FLOW and the SWAN models. Both have a long history of application and use; thus, the uncertainties are generally small and typically related to the input data.

5.4 PoC Adda

5.4.1 Brief description of the PoC

Research Objectives Implement and test the NatFIM tool for integrated flood damage assessment in an area, demonstrating its operational potential; demonstrate the effectiveness and versatility of NatFIM as a national-scale model for estimating tangible impacts (quantitative and qualitative) related to flood scenarios.

5.4.2 PoC modelling chain

Component	yes	no
Meteorology		x
Hydrology		x
Hydraulics	x	
Impacts	x	

5.4.3 Evaluation of uncertainties

Hydraulic model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 2
- parameters 2
- input data 3
- epistemic uncertainty 3

Comments

The hydraulic component of the PoC relied on a well-established 2D modelling approach for the simulation of flood inundation scenarios. Such models are widely used in flood risk assessments and their structural uncertainty is relatively limited. Model parameter uncertainty was also moderate, as detailed data and ancillary information were available and supported model calibration. The main sources of uncertainty were related to input data (e.g., boundary conditions) and to residual epistemic uncertainty associated with the simplifications required to represent complex hydraulic processes and local features within the model domain.

Impact model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 4
- parameters 3/4
- input data 4
- epistemic uncertainty 4

Comments

Impact modelling was affected by relatively high uncertainty due to the heterogeneous complexity of modelling approaches across different exposure categories. Monetary damage estimates can differ significantly depending on the assumptions embedded in the adopted damage models. Moreover, the spatial granularity, completeness and representativeness of input exposure datasets vary across sectors, further contributing to uncertainty in the estimation of potential damages.

5.5 PoC Granelli

5.4.1 Brief description of the PoC

Objectives: to evaluate the effectiveness and long-term durability of fully natural and hybrid (traditional + natural) interventions for flood risk mitigation in coastal areas, estuaries, and lagoons, in light of climate change; to understand how interventions will perform over time and under different climate conditions, to predict the effects of climate change on coastal flooding and erosion processes and on the ecosystem services that habitats provide. The PoC will enable the development of practical planning tools capable of adapting (adaptive planning) and design to provide decision-making support to local managers of coastal sites vulnerable to changing climate conditions.

5.4.2 PoC modelling chain

Component	yes	no
Meteorology	x	
Hydrology	x	
Hydraulics	x	
Impacts		x
Morphodynamics	x	

5.4.3 Evaluation of uncertainties

Meteorologic model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 2
- parameters 2
- input data 2
- epistemic uncertainty 2

Comments

The PoC relied on data derived from modelling products, specifically wind forcing and sea level information. The main source of uncertainty is associated with the climate models used as input for the Mediterranean-scale sea level variation model. However, in situ historical sea level time series are available at the site and provide a valuable basis for calibration and validation. Overall, the adopted modelling framework is able to reproduce the main processes related to sea level variability with a satisfactory level of accuracy, which helps contain the overall uncertainty associated with this component. Moreover, being a microtidal environment in which sea level excursions are limited even during extremes ($O(10^1-10^2)$ cm), impact of uncertainty on levels is limited.

Hydrologic model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 3
- parameters 4
- input data 4
- epistemic uncertainty 4

Comments

River discharges used as input to the model were estimated through a rainfall-runoff model applied to the main watershed feeding the lagoon system. The main uncertainties are related to the representation of infiltration processes, soil moisture conditions, and vegetation effects on runoff generation and retention. In particular, the spatial and temporal variability of land cover and vegetation can significantly influence the partitioning between infiltration and surface runoff. Additional uncertainty also arises from the limited availability of detailed observations for calibration and validation of hydrological response during extreme events.

Hydraulic model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 2

- parameters 4
- input data 3
- epistemic uncertainty 4

Comments

The hydro-morphodynamic modelling framework adopted within the PoC includes several sources of uncertainty related to hydraulic processes. Uncertainty is associated with the confidence range of the input forcing data, including sea level rise scenarios and related percentile-based projections. Another relevant source concerns the available topographic and bathymetric datasets, which are not fully homogeneous in time: lagoon topography refers to a 2013 survey, the coastline representation is more recent, and bathymetry derives from a combination of nautical charts and bathymetric surveys carried out in 2025. In addition, the vegetation dissipation module introduces further uncertainty, since the model does not explicitly reproduce flexible vegetation and local morphological and biomechanical properties of the vegetation are not known in detail. Instead, simplified and spatially uniform vegetation characteristics, e.g. stem height/stem density, were adopted. Nevertheless, a sensitivity analysis on vegetation height was performed during calibration in order to evaluate the influence of this assumption on model results. Water levels in the lagoons are measured by hydrometers, which provide a basis for calibration/validation.

Morphologic model: how do evaluate the weight of following model uncertainties (1= min, 5 = max)

- model structure 5
- parameters 5
- input data 3
- epistemic uncertainty 5

Comments

A morphodynamic model was used to simulate beach sediment changes, shoreline erosion, and the potential breaching of the inlet barrier. This component is affected by substantial uncertainty and requires an extensive calibration phase. Model structure plays a crucial role, as results can be strongly influenced by grid resolution, grid orientation, and the overall numerical set-up. From a parametric perspective, the calibration of sediment transport parameters is particularly critical, much more than in purely hydrodynamic applications, because small changes in cross-shore transport parameter values may produce significant differences in predicted erosion and morphological evolution. Input data also contribute to uncertainty, although to a lesser extent than model structure and parameterization. Overall, epistemic uncertainty remains high because morphodynamic processes are intrinsically complex, strongly non-linear, and difficult to constrain with limited field observations. Despite that, we obtained good results on the calibration of the model based on satellite image analysis of shoreline change. Influence of input data is mainly related to topographic data uncertainty.

6. References

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