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# Linking urban structure types and Bayesian network modelling for an integrated flood risk assessment in data-scarce mega-cities

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ABSTRACT

Urban flood risk increases under rapid urbanization and climate change. Thus, it becomes crucial to assess current and future risk and potential adaptation strategies to minimize the consequences for society, ecology and economy, especially in the Global South where urbanization and vulnerabilities are particularly high. However, current assessment tools oftentimes struggle to perform integrated assessments of flood risk due to reasons like data scarcity, complexity of cities or the integration of different domains. Hence, current approaches usually apply a reduced perspective, e.g. in terms of the urban extent covered or the domains included. Here we propose an approach using urban structure types in combination with Bayesian networks to represent different environmental and socio-economic conditions throughout a city. The approach facilitates integrative flood risk assessments and allows to address questions of uncertainty, variability and explainability in complex and data-scare urban areas. The implementation of this new approach is presented and discussed. Results from our pilot in Mumbai, show that the approach is suitable for scenario evaluation in data-scarce contexts. The flexibility offered by the approach makes it relevant for policy and urban planning since different key drivers of urban flood risk can be integrated in assessments of adaptation strategies and decision-making.

## 1. Introduction

Climate change and urbanization are two of the key drivers of increasing risk of natural hazards (Dodman et al., 2022; Garschagen and Romero-Lankao, 2015). Thus, it is crucial to adapt to and manage this risk. Measures and strategies which help to minimize risk should be evaluated by assessments and simulations, ideally before implementation, in order to steer decision making (Cea and Costabile, 2022; Kreibich and Sairam, 2022; Nkwunonwo et al., 2020). Simulations show the optimal strategy given a certain scenario and potentially prevent the implementation of measures which lead to maladaptation (Chi et al., 2021). Nevertheless, to run simulations we largely depend on data and methods which allow a straightforward representation of complex and dynamic systems. While the development of methods is needed for assessments, data availability is a particular problem, especially in risk hotspots of the Global South (Zapata-Caldas et al., 2022). Adaptation is of high urgency and importance in these highly affected areas which will in future hold large shares of the planet's people and economy (Dodman et al., 2022; Martin, 2019). Thus, it is crucial to develop methods which are on the one hand able to integrate various complex systems, and on the other hand can be applied to data-scarce environments (Vincent and Cundill, 2022).

Flood risk continues to rise particularly in rapidly growing mega-cities with high rates of land use change and population growth

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(Alfieri et al., 2017; Dodman et al., 2022; Fowler et al., 2021; Hallegatte et al., 2013; Tellman et al., 2021). Yet, simulating the current flood risk, as well as scenarios of future situations in mega-cities, is especially challenging due to multiple reasons (Cea and Costabile, 2022). Five key challenges are discussed in Zwirglmaier et al. (2024):

A major challenge is data scarcity. Commonly applied urban flood models require various high resolution data which are oftentimes not available, especially in countries of the Global South (Nkwunonwo et al., 2020). Furthermore, with the rapid (re-)development within the city and the continuous growth of the city's extent, existing local data can become soon obsolete. This impedes the assessment of the current flood risk status let alone how it will change in future.

The second major challenge, dynamics, is also closely connected to the (re-)development of the urban area. The everchanging dynamic interactions between the natural environment (e.g., a coastal setting), climatic changes, humans and their needs, as well as political systems which influence flood risk, pose a nearly impossible contexts to capture in a model (Wetzel et al., 2022). This problem increases when future dynamics and scenarios are included in the model. Thus, new methods have to be developed to ease the analysis of interactions and scenarios (Kreibich and Sairam, 2022).

Thirdly, to capture the interactions which form flood risk, the challenging task of integrating various domains has to be addressed by simulation methods (Vojinović, 2015). However, modelling principles are usually tailored to specific tasks, like the physical assessment of flood hazards, and do not allow the integration of other domains addressing flood exposure or vulnerability within the same method (Duespohl et al., 2012).

The fourth challenge, complexity, is related to the inherently complex nature of large urban agglomerations, especially those developed in an unplanned way, like many megacities in the global south (Rangari et al., 2019). Models are a representation and simplification of the real world, and some components of the real-world system must be neglected in order to perform simulations. Yet, it is crucial to determine which components can be neglected for the specific site of assessment. This flexibility in model structure is oftentimes not given in urban flood models or existing methods to assess flood risk.

The final challenge addressed in Zwirglmaier et al. (2024) is uncertainty. All the previously mentioned points add to the challenge of uncertainty and thus, it is important to use a method for scenario analyses which can capture the various kinds of uncertainty, i.e. in model structure or uncertainty arising from input data (Bates et al., 2014; Halsnæs and Kaspersen, 2018; Reinstaller et al., 2022). The communication of uncertainty in assessments of natural hazards, however, is oftentimes neglected because it is not straightforward (Doyle et al., 2019).

Driven by those challenges, we present a novel approach to perform integrated urban flood risk assessments under different future socio-economic pathways and climate change. With this approach, we offer a solution for achieving spatially distributed assessments of flood hazard, exposure and vulnerability in data-scarce environments, and provide a more detailed representation of future urbanization scenarios beyond the typical focus on urban sprawl (Zwirglmaier et al., 2024). We construct a Bayesian Network (BN) and use mixed data sources (qualitative and quantitative) to overcome data-scarcity. Furthermore, we link relevant variables to Urban Structure Types (USTs) to get a spatial representation of flood risk, while having almost no spatially distributed observations of flood related variables. Bayesian networks make it further possible to address the challenges of uncertainty, integration and complexity. As BNs are built on causal links between variables, they have a high explanatory power and flexibility, which makes it a suitable method scenario analysis (Sperotto et al., 2019).

To our knowledge, no previous research has combined BNs and USTs to parameterize and spatially distribute results in regions with limited data. USTs have typically been applied in data-rich environments (Beckers et al., 2013; Shan et al., 2022; Xu et al., 2020; L. Xu et al., 2021). We now extend their application for parameters derivation in data-scarce settings. Also, while USTs have primarily been used to estimate vulnerability in flood risk contexts (Shan et al., 2022; Tam et al., 2018; Wurm et al., 2009), they have not been applied to model flood hazard processes and enable a comprehensive assessment of the total risk chain.

In this paper, we integrate Bayesian Networks and Urban Structure Types to assess the flood hazard probability in the pilot city Mumbai, India, and present the implementation and first results.

## 2. Key elements and concepts for the integrated modelling approach

### 2.1. Urban structure types

#### 2.1.1. Definition

Within urban studies, classifying a city into Urban Structure Types (UST) is a common approach to understand the internal heterogeneity of cities across various scales (Heiden et al., 2012; Wang et al., 2023a; Zhu et al., 2022). USTs are used to describe the physical appearance of a city, often also referred to as urban morphologies or urban forms. Lehner and Blaschke (2019) define a generic classification scheme for USTs based on all natural and artificial surfaces, like the composition of open spaces, buildings and roads. If this composition is homogeneous in an area, then it belongs to one UST. In later steps, one can integrate different activities associated with an UST. This could be compared to describing land use versus describing land cover (Meyer and Turner, 1994; Taubenböck et al., 2008). Additionally, processes or characteristics like socio-economic features or hydrological processes can be related to USTs (Heiden et al., 2012; Lehner and Blaschke, 2019).

#### 2.1.2. Application

USTs are used a wide range of urban sustainability research and practice, and their application becomes increasingly popular. One group of recently published studies focuses on how to derive USTs in a city (Zhang et al., 2017; Zhao et al., 2023b; Zhu et al., 2022), estimating changes observed in a city (Xu et al., 2015; Zhao et al., 2023a) or how to model USTs (Xiao and Liu, 2023; Yang et al., 2023c). The second group of publications focuses on making assessments of various topics based on USTs, ranging from studies estimating land surface temperature and ventilation in cities (Drach et al., 2018; Mo and Liu, 2023; Nagel et al., 2023; Palusci et al., 2022; Pan, 2023; Shao et al., 2023; Wang et al., 2023b; Yang et al., 2023b; Yang et al., 2023a; Zhang et al., 2023a; Zhao et al., 2023c; Zheng et al., 2023; Zhou et al., 2023b), criminality rates (Yue et al., 2023), Covid transmission (El Samaty et al., 2023), energy consumption (Song et al., 2022; Xie et al., 2023; Zhang et al., 2023b; Zhou et al., 2023a), the potential of USTs for installing facilities for energy, food and water production (An et al., 2023; Lau et al., 2017; Toboso-Chavero et al., 2023; B. Wang et al., 2017) up to estimating the inequality of accessible open spaces (Silva and Pafka, 2023). Studies considering USTs in the context of flooding typically use them as proxy to estimate economic damages (Beckers et al., 2013; Shan et al., 2022) or to estimate the roughness of USTs for runoff estimation (C. Xu et al., 2020).

#### 2.1.3. *Potential for application within flood risk assessment*

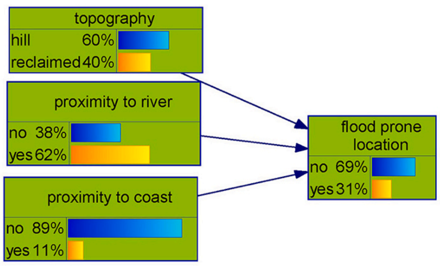
We see the potential in applying USTs to make more realistic assessments of flood risk in data-scarce urban environments. With the assumption that in similar USTs we have similar hydrological processes and functions, we estimate and include parameters which are unobserved or not measurable, but crucial not only for flood hazard assessments but for total integrated flood risk. Furthermore, new products and frameworks which map the USTs and are derived from remote sensing data or modelling are become increasingly available and more precise (Braun et al., 2023; Xiao and Liu, 2023; Yang et al., 2023c; Zhang et al., 2017; Zhao et al., 2023b; Zhu et al., 2022). With these products we get an increased spatial coverage and resolution of USTs. Oftentimes in flood risk assessments under data-scarce conditions, single estimates of relevant unobserved parameters are made for the total urban area (Scheiber et al., 2023). By relating these unobserved parameters to USTs, we can get more distributed estimates of the relevant parameters to make city-wide flood risk assessments. Besides the potential to approximate parameters, USTs are policy relevant, as they can be used as urban planning unit (Debray et al., 2023; Follmann et al., 2023; C. Xu et al., 2022). In addition, we see great potential to use USTs in order to capture and model different profiles of socio-economic vulnerability, exposure and adaptive capacity to flooding across the city since different USTs typically represent different socio-economic groups with different characteristics in this respect (Reimuth et al., 2024).

### 2.2. *Bayesian networks*

#### 2.2.1. *Definition*

Bayesian Networks, also called probabilistic causal models, are statistical tools to model the qualitative and quantitative aspects of complex multivariate problems (including feedback loops), and can be used for diagnostics, classification and prediction (Puga et al., 2015). Bayesian Networks are based on Bayesian statistics and they consist of a qualitative part, i.e. the directed acyclic graph, (Fig. 1 a) and a quantitative part, i.e. the conditional probability tables, (Fig. 1 b) (Koski and Noble, 2009). The qualitative graphical part comprises the nodes of a BN which represent the network's variables and arcs which define the causal relationship between the nodes (Scutari, 2010; Yang, 2019). The arcs have to be directed and acyclic (DAG), meaning that no loops can be generated within an BN (Scutari, 2010). The quantitative part are the conditional probability tables (CPTs) of each node of the network. The CPTs define the probability of a node to take a state given the states of its influencing parent nodes. In Fig. 1 the parent nodes *topography*, *proximity to river* and *proximity to coast* are influencing the child node *flood prone location*. All three nodes have two states: *topography* has the states *hill* and *reclaimed*; *proximity to river* and *proximity to coast* have the states *no* and *yes,* and *flood prone location* has the states *no* and *yes*. Thus, the CPT (Fig. 1 b) for *Pr(flood prone location*| nodes *topography*, *proximity to river*, *proximity to coast)*, i.e. the probability of *flood prone location* taking one of its states given the parent nodes *topography*, *proximity to river* and *proximity to coast* are in one of their states, is defined for all these states. Compared to frequentist statistics which estimate the outcome based on observed data samples, Bayesian

a)




b)

| | topography | hill | | | | reclaimed | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **proximity to river** | *no* | | *yes* | | *no* | | *yes* | |
| | **proximity to coast** | *no* | *yes* | *no* | *yes* | *no* | *yes* | *no* | *yes* |
| **flood prone location** | *no* | 0.9999 | 0.9947 | 0.9947 | 0.7000 | 0.7000 | 0.0280 | 0.0280 | 0.0004 |
| | *yes* | 0.0001 | 0.0053 | 0.0053 | 0.3000 | 0.3000 | 0.9720 | 0.9720 | 0.9996 |

**Fig. 1.** Example of a BN with the graphical part (a) and the conditional probability table of the node flood prone location (b).

statistics include prior information from literature or experts which is particularly beneficial when the data availability is limited, as they help to get initial probability distributions before new evidence becomes available (Fornacon-Wood et al., 2022; Tschirk, 2014).

### 2.2.2. Application

Bayesian Networks are applied in various disciplines. The application domains range from medical sciences (Cook et al., 2018; Jin et al., 2021; Kalet et al., 2015; Lin et al., 2022; Piao, 2011; D. Wang et al., 2020; T. Zhang et al., 2021), psychology (Briganti et al., 2022; Eizirik et al., 1993; Moret-Tatay et al., 2016; Song et al., 2018), agriculture (Kocian et al., 2020) to business and economy (Cao et al., 2022; Chong and Klüppelberg, 2018; Ekici and Ekici, 2016; Haned et al., 2006; Hou, 2015; Jia, 2008; Jian and Liu, 2008; Moreno et al., 2009) or engineering (Ayra et al., 2019; Bae et al., 2017; Kim et al., 2018; Ren et al., 2020; Straub and Der Kiureghian, 2010; J. Xie and Thomas Ng, 2013). Also in environmental studies BNs are a popular tool to make assessments, e.g., in modelling species distribution (Aguilera et al., 2010), habitat suitability (Hamilton et al., 2015), ecosystem services (Stritih et al., 2020), pollution (Bonotto et al., 2018; Cheng et al., 2018; Nguyen et al., 2023) as well as in the context of flood risk (Abebe et al., 2018; D'Addabbo et al., 2016; Huang et al., 2021; Wu et al., 2020).

### 2.2.3. Potential for application within flood risk assessment

BNs can be trained with incomplete data, which is crucial when working in highly data-scarce environments. Under these conditions, it is possible to build BNs solely based on expert knowledge (alpha-level model) and update the model as soon as other data or information becomes available (beta-level model) (Frank, 2015; Marcot et al., 2006). With this feature, we do not have to exclude crucial parameters from our analysis due to a lack of data. Furthermore, compared to other modelling techniques, like numerical models or statistical methods, Bayesian Networks are interpretable and have a high explanatory power, as they are based on causal relations (Hozumi and Shimizu, 2022; Mihaljević et al., 2021; Pearl, 2009). This makes them particularly policy relevant. The relevance for policy and decision-making is further supported by the fact that BNs can integrate assessments of multiple disciplines, such as social, natural and economic, due to the causal process description and because they do not depend on quantitative data (Chen and Pollino, 2012; Duespohl et al., 2012; Johnson and Mengersen, 2012). We argue that a simultaneous assessment of domains and dimensions is necessary for proper decision-making because these dimensions are codependent. In addition, not only current states can be assessed but BNs can also be used to assess future change scenarios and adaptation options by changing the parameters.

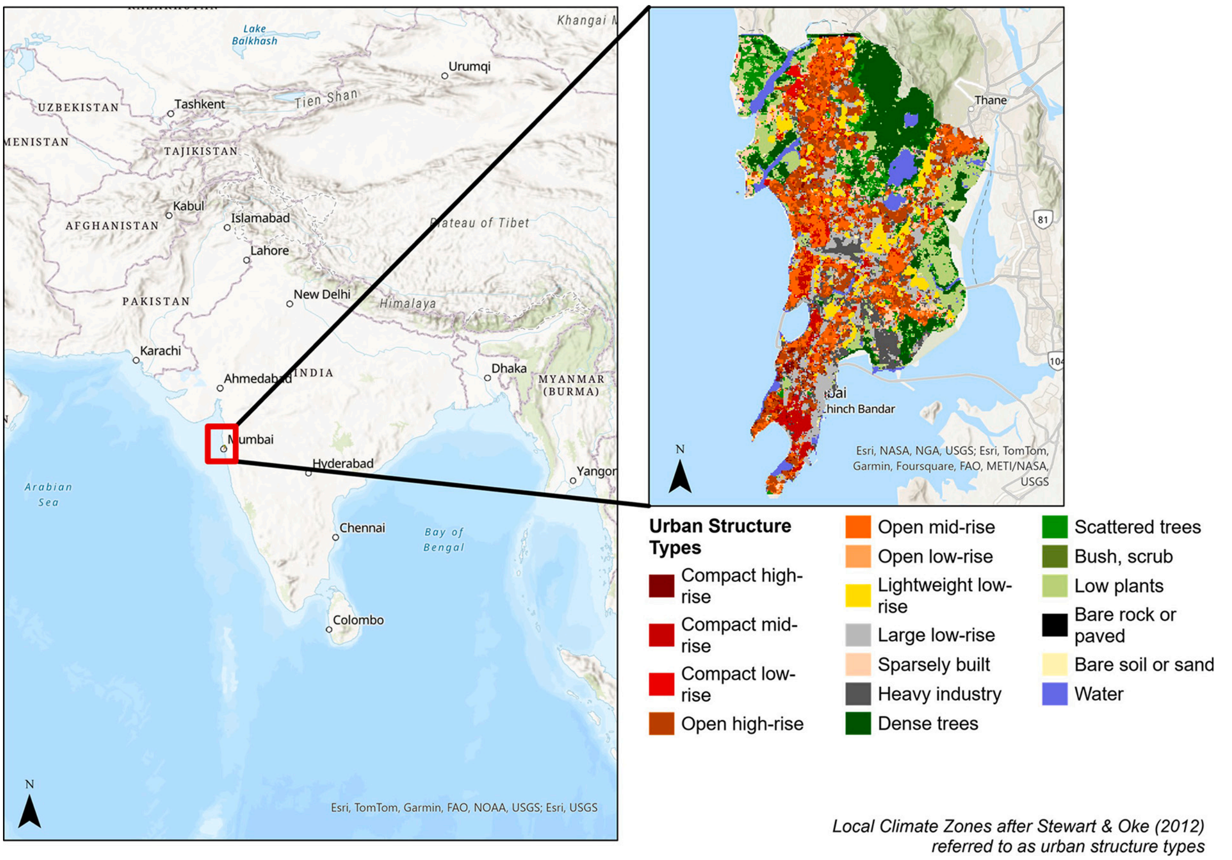



**Fig. 2.** Location of Mumbai and the distribution of Urban Structure Types (Source: Zhu et al. (2022)).

## 3. Case study

### 3.1. Study area - Mumbai

Mumbai is a coastal megacity in India consisting of the Mumbai City and the Mumbai Suburban districts. It extends between 18.00°-19.20°N and 72.00°-73.00°E (Fig. 2) and has an approximate population of 20 million people (Tripathy et al., 2024). Mumbai is the financial capital of India and faces rapid development and growth (Vaz et al., 2021). Its climatic conditions, geographical location and anthropogenic activities make it highly susceptible to flooding (Dhiman et al., 2019). The meteorological conditions in Mumbai are determined by the monsoon occurring from June to September with extreme rainfall larger than 204.5 mm/day (Mohanty et al., 2023). The rainfall patterns are very complex as they are influenced not only by the monsoon conditions, but also largely interact with the urbanized area on a small-scale (Kishtawal et al., 2010). While the area currently making Mumbai was previously an archipelago of seven islands, it was formed to one mainland by land reclamation (Riding, 2018). Thus, most of the land lays below the high-tide level (Dhiman et al., 2019). Furthermore, rapid and unplanned urbanization results in a high flood hazard probability on multiple levels.

### 3.2. Examples of urban strcuture types in Mumbai

The urban area of Mumbai is very heterogeneous and complex in its form and in the socio-economic, but as well as in the hydrological and hydraulic profiles. Urban structure types can be used to capture this heterogeneity. In this study, local climate zones (Stewart and Oke, 2012) are referred to as Urban Structure Types and used to classify the city of Mumbai. Therefore, we used the open-source dataset of Zhu et al. (2022) (Fig. 2). Based on expert consultation with local partners, the Urban Structure Types in Mumbai represent different settlement types. So-called compact low-rise settlements and lightweight low-rise areas can be seen as indicators for slum areas (Fig. 3, right), whereas open high-rise areas correspond to high income areas, often gated communities (Fig. 3, left). Other Urban Structure Types (physical characteristics) are less associated with special settlements. Thus, further indicators besides physical characteristics, such as income and formality status, are used to associate the Urban Structure Types with variables relevant for flood risk (e.g. service provision). This is supported by expert insights and secondary data sources, including household surveys, open-source slum cluster data, and formality status listings from the Slum Rehabilitation Authority of Mumbai. However, purely physical variables, such as roughness or the percentage of pervious area, are very closely associated with different Urban Structure Types and can hence be used directly for the modelling.

### 3.3. Floods in Mumbai

Mumbai's heightened susceptibility to flooding is attributable to various factors like its geographical location and subjected to intense monsoon precipitation, while compounded by human-induced factors, such as extensive urbanization and insufficient water management infrastructure, and solid waste management (Dhiman et al., 2019). In 2005, Mumbai experienced its most severe flooding incident in the recent history with 1493 reported fatalities and an estimated damage of 1.7 billion USD (Doshi and Garschagen, 2023). Until 2070, the flood exposed population in Mumbai is estimated to increase from 2,787,000 to 11,418,00, and the exposed assets from 46.2 billion to 1598.05 billion USD compared to 2005, showing a clear need for adaptation (Hallegatte et al., 2010; Nicholls et al., 2007).

## 4. Introducing a new modelling approach to link Bayesian networks and urban structure types

Within this study we want to bring all the factors which influence flood hazard probability and the heterogeneity of Mumbai together and propose a novel approach to assess flood susceptibility changes under different urbanization and climate futures despite

**Fig. 3.** Examples of Urban Structure Types in Mumbai, the left picture shows dense tree vegetation with the UST class open high-rise (LCZ4) in the background. The picture on the right shows LCZ7 (lightweight low-rise) in the front and LCZ1 (compact high-rise) under construction in the back.

data scarcity.

We construct a BN linked with Urban Structure Types to assess flood hazard probability under different future development (SSP) and climate scenarios (RCP). The SSP (socio-economic pathway) scenarios presented in O'Neill et al. (2017) were downscaled for Mumbai in several stakeholder meetings with representatives from civil society, academia and local authorities (Petzold et al., 2024). The change of rainfall intensity according to the RCP scenarios was taken from existing downscaling studies (Rana et al., 2014).

The basic idea behind coupling USTs with BNs for assessing flood risk in data-scarce urban environments is to use the unit of homogeneous physical structures (represented by USTs) to derive distributions of relevant flood risk parameters. Fig. 4 shows the general concept. First, we use a spatially distributed map of pre-defined USTs to characterize our study area (Fig. 4, left). In parallel we define the sub-model BNs for our target variables of interest (Fig. 4, centre) and learn the nodes (parameters) of the BN per UST. The UST map from step 1 is then used as input to get a spatial representation of the target variable (Fig. 4, right). The main model is defined in step 2. Here, we build on the assumption that within an Urban Structure Type, parameters and processes are similar (Heiden et al., 2012), however they are not equal. To account for this inherent variability, we use the probabilistic approach of BNs. For example, let us assume we want to include drainage infrastructure in the flood assessment, but within the study area data is limited on drainage infrastructure. However, as drainage infrastructure is highly influencing the flood processes, we do not want to exclude it from our assessment. To still include drainage infrastructure, we can learn a proxy distribution over likely capacity. To differentiate spatial variability, we use USTs as proxy unit to obtain information. We have three different cases on data availability to learn BNs with the help of USTs as proxies:

1. Data is available for some USTs across the whole extent of the study area
2. Data is available for all USTs but not for the complete extent of the study area
3. A mixed scenario from 1. and 2

For the first case we can use the data and learn a fully informed proxy prior distribution for the USTs where data is available. For the USTs where no data is available, other methods like expert knowledge can be applied to get the information on the prior distribution. In the second case, the available data is used to learn partially informed prior distributions for all USTs. Therefore, the prior distribution learned for an UST in the areas where data is available is transferred to the areas where no data is available. After learning the CPTs of the BNs with the proxy prior distributions we can make inferences of our target nodes, in this case the flood hazard probability or the flood risk category. The target node also has a distribution over different risk categories (Fig. 4, right). When evidence on a parameter becomes available the value of that parameter can be updated for the total UST or only a single pixel. This will make the result more robust, and the target node distribution will show less uncertainty.

## 5. Illustrating the implementation of the modelling approach in the pilot city

During the implementation of the approach, we followed a predefined workflow (Fig. 5).

Furthermore, we used different information sources for identifying relevant influencing factors, the derivation of the causal relationship between them and the learning of the respective probabilities (Table 1).

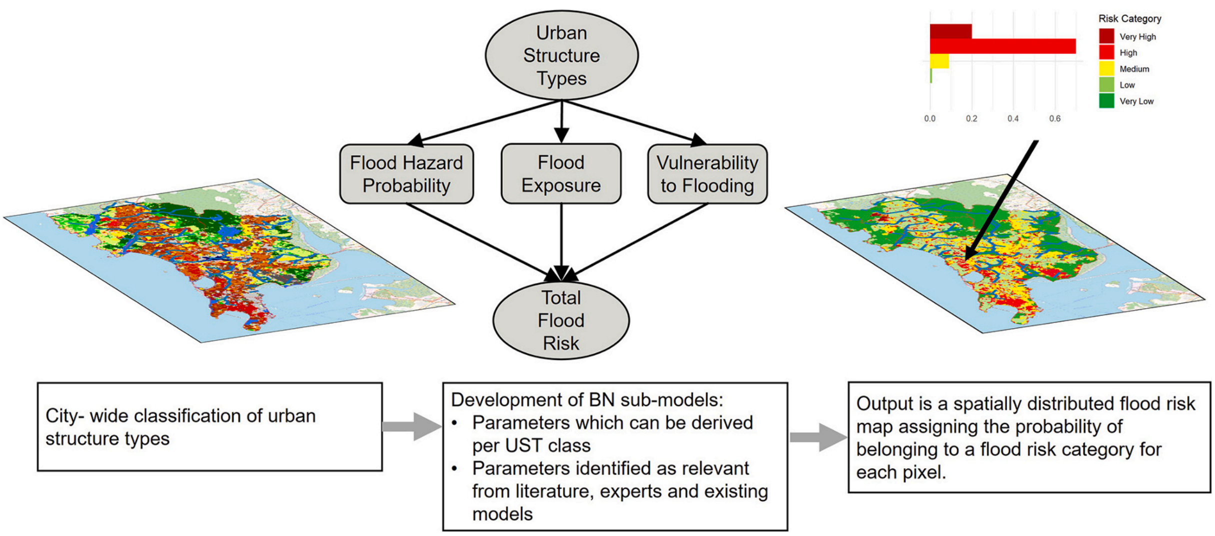



**Fig. 4.** Conceptual framework of the approach. The Urban Structure Type classification is used to develop Bayesian Network (BN) sub-models for flood hazard probability (presented in this study), flood exposure and vulnerability to flooding. Therefore, proxies are derived from the Urban Structure Types which are used to build and parameterize the BNs. The outcome will be a spatially distributed map with the likelihood of an area belonging to a certain category of overall risk.

For the data preprocessing and the implementation of the BN-UST approach we used three different software (Table 2).

### 5.1. *Identifying relevant variables and nodes for the Bayesian network*

We used literature and expert knowledge to identify the relevant variables which are included as nodes in the BN.

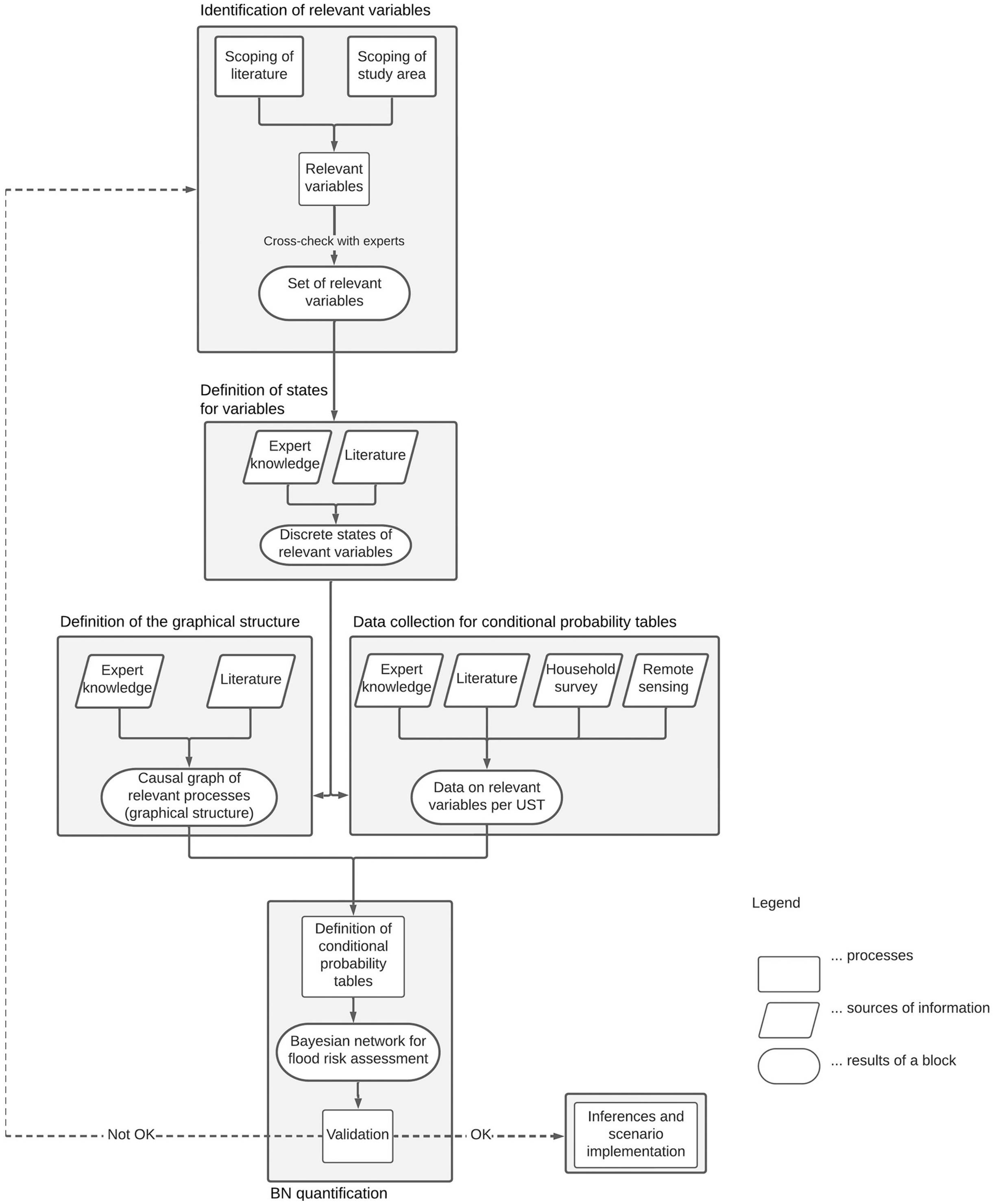



**Fig. 5.** Workflow followed during the implementation for the BN-UST approach in Mumbai, India.

**Table 1**
Overview of the information sources used for the implementation of the BN-UST approach.

| Source of information | Description |
|---|---|
| Literature | • Academic literature: scientific papers, conference contributions, scientific books<br>• Grey literature: technical reports, governmental documents, publications of NGOs |
| Expert knowledge | • Interviews with local experts from academia<br>• Local partners<br>• Various actor groups during project workshops to derive SSP scenarios |
| Household survey | Data collected during a structured household survey ($n = 1106$) |
| Remote sensing | Data products derived from satellite missions which are publicly available:<br><br>• DeltaDTM (Pronk et al., 2024)<br>• UST classification (Zhu et al., 2022)<br>• HAND analysis (Donchyts et al., 2016) |
| Climatic data | • Rainfall data from research articles (Rana et al., 2014; Tripathy et al., 2024; Zope et al., 2015)<br>• Open-source rainfall products (India Meteorological Department, 2022)<br>• Downscaled climate products (Fick and Hijmans, 2017) |

Urban flooding is a well-researched phenomenon and countless studies have been published on flooding in Mumbai or comparable cities. As a first step, literature served as information source to identify key parameters which influence flood hazards in rapidly developing coastal mega-cities of the global south (Chitra, 2022; Darabi et al., 2019; Gupta, 2007; Li et al., 2023; Parthasarathy, 2016; Qi et al., 2022; Sakijege and Dakyaga, 2022; Seleem et al., 2022; Y. Wang et al., 2022).

After the first set of relevant variables was identified through literature analysis, five key local experts from academia and civil society were identified and interviewed online or in-persona. In bilateral semi-structured interviews, we identified further variables which influence flood hazards in the context of Mumbai. Semi-structured interviews are a qualitative research method which use open end questions to elicit information from the interviewee. As they follow a semi-structured interview guide, important topics and questions are covered, however enough space is given to the respondent to contribute their full knowledge (Jamshed, 2014). A bilateral interview setting was used in order avoid biases (Cain, 2001). A list of the included nodes is given in the Supplementary Material.

### 5.2. Defining the states of Bayesian network nodes

In a next step we defined the discrete states of the influencing variables, i.e. the nodes of the BN. The states of a node are mutually exclusive and cover all possible values the respective parameter can take. For example, if we consider the node *flood prone location* the states are binary (yes, no) as it is either flood prone or not. Defining the states of the nodes is a crucial step as the number of states can largely influence the results. The goal is to have the smallest possible number of states to reduce the CPT. The states of the nodes should represent the current state as well as possible future states under different scenarios (Chen and Pollino, 2012). We defined the states of the nodes with help of literature and expert domain knowledge. For example, from the expert interviews it became clear that urban areas located on a hill were less flood-prone whereas areas in previously reclaimed land were very flood-prone. Thus, for simplicity, the topography node was assigned the states *hill* and *reclaimed.* A full list of the states assigned to the nodes and the description can be found in the Supplementary Material.

### 5.3. Definition of the graphical structure of the Bayesian network

The set of parameters identified by using literature was then used to design a first graphical structure of a BN for flood hazard assessment in Mumbai.

After finalizing the set of relevant parameters, we set up the graphical structure of the BN models. The relevant parameters function as nodes in the BN. Combining them with arcs which represent the causal relationships between the nodes built the graphical structure. We defined the relationships between the nodes in with the help of expert knowledge of the scientific flood risk community and local experts. Furthermore, process descriptions of urban flooding in literature and model descriptions gave us additional validation of the set arcs. We used the method of parent divorcing to reduce the complexity of the BN. Parent divorcing implies that intermediate variables are introduced between the cause variables (parents) and the effect variable (child). This is relevant if many parents are associated with one child because the size of the CPTs grow exponentially with the number of parents per child (Kjærulff and Madsen, 2013). In Fig. 6 this method is illustrated on an excerpt of the BN of this study.

**Table 2**
Overview of the software used for implementation.

| Software | Version | Description |
|---|---|---|
| ArcGIS Pro | 3.0.2 | Commercial software for geospatial data analyses |
| GeNIE | 3.0.6518.0 (32-bit) | Commercial software for the construction of Bayesian Networks |
| RStudio | 2023.03.0 + 386 with R version 4.2.3 | Open-source programming software |

As a result, we obtained the graphical structure of our BN which builds the basis of our assessment model (Fig. 7). For this step we use the GeNIE software .

### 5.4. Data collection for conditional probability definition

Before we started to define the quantitative part of the BN, i.e. the CPTs, we collected data on the selected nodes. As we wanted to apply this approach in data-scarce contexts, we used and triangulated different data sources (Fig. 5). The parallelogram boxes list the information sources we used. Nevertheless, other sources of information can be used, and this list is not exclusive. In the following we describe how the different data sources were used to obtain information required to build the CPTs of the BN. We differentiated between quantitative information (remote sensing data and household survey data) and qualitative information (literature and expert knowledge).

To preprocess the quantitative information, we considered two cases:

1. The data itself has a complete spatial coverage (e.g. raster files) and observations for the total study area (remote sensing data).
2. We have observations for some locations in the study area and relate them to USTs, however for the other USTs, qualitative expert knowledge and literature are used to elicit the information (household survey data).

For the included variables *proximity to large-scale green infrastructure*, *proximity to river*, *proximity to coast* and *topography,* remote-sensing products were used, and preprocessing of raster files in ArcGIS Pro was performed. The node *topography* is based on a reclassification of the DeltaDTM (Pronk et al., 2024) where all areas above 5 m were classified as hill area and all below as reclaimed. The threshold 5 m was used based on the high-tide level in Mumbai. The nodes, *proximity to river* and *proximity to coast* are based on creating buffers of 1 km around river and coastline. These were taken from Open Street Map. For the node *proximity to river,* the global HAND (height above nearest drainage) (Donchyts et al., 2016) was used to assess if a location is close to a river or the coast. For the node *proximity to large-scale green infrastructure* buffers around the USTs *dense trees, scattered trees, bush/scrub and low plants* were created and locations within these pixels were classified as ‘yes’.

Household survey data was collected in collaboration with our local partners in Mumbai during a survey campaign in the year 2023

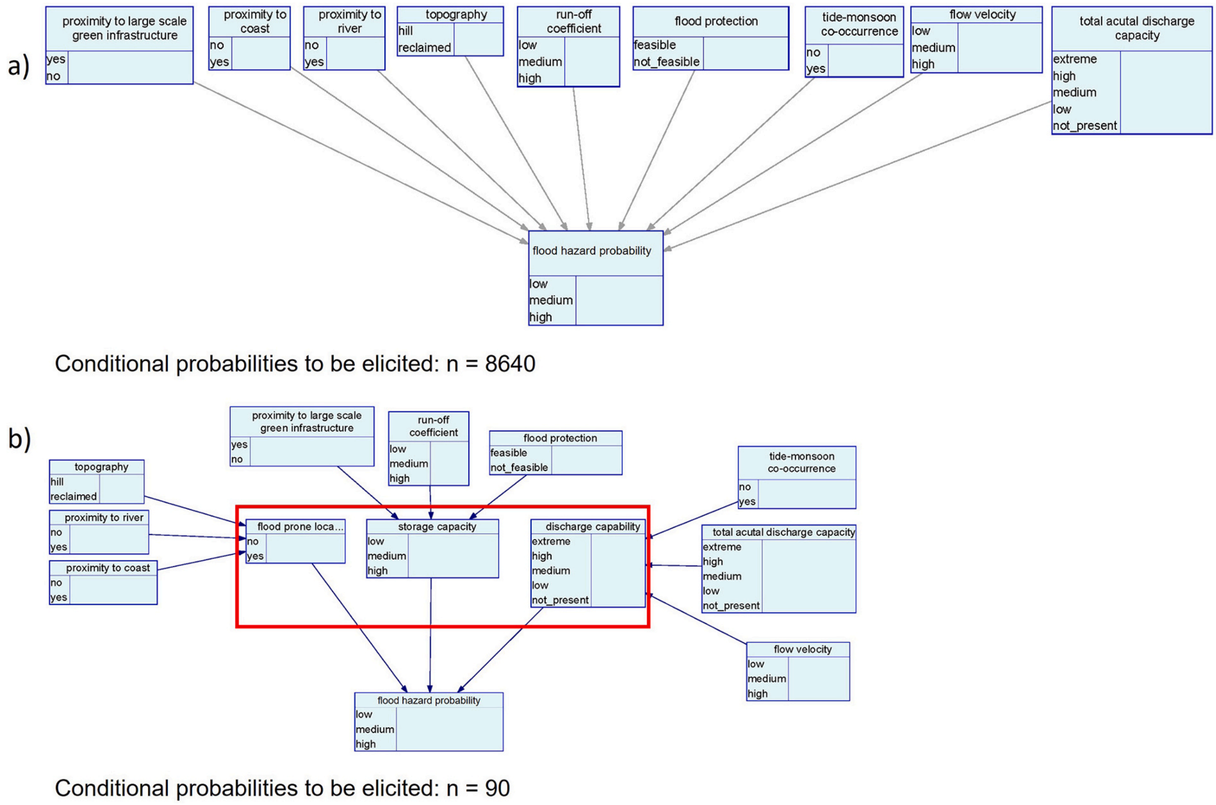



**Fig. 6.** Illustration of the parent divorcing method. a) shows a graphical structure without the intermediate values. The number of probabilities which have to be elicited to populate the CPT for this network is 8640. b) shows the same network with intermediate nodes (red box) ‘flood prone location’, ‘storage capacity’ and ‘discharge capability’. Here the number of probabilities necessary to populate the CPT is decreased to 90. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

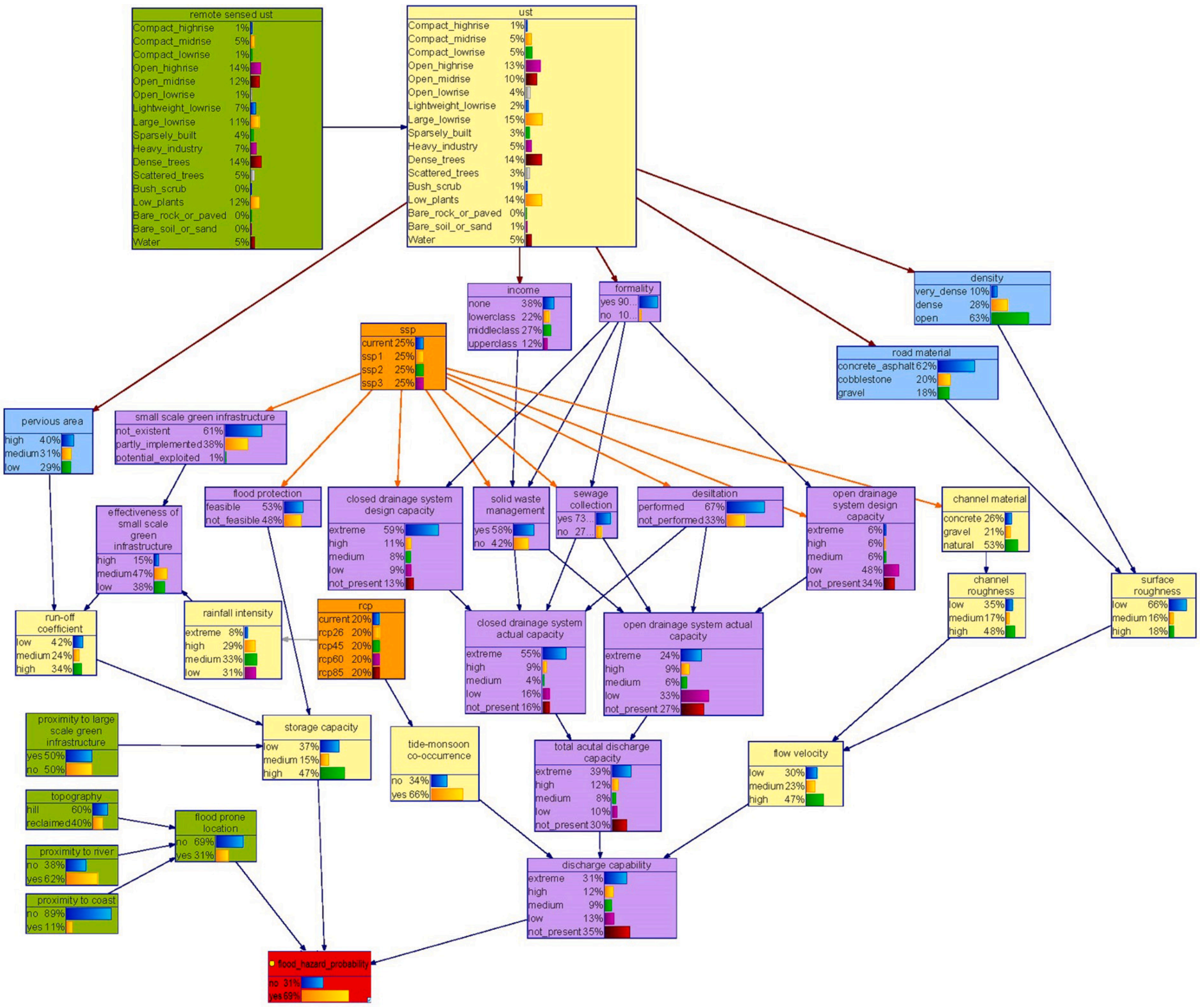



**Fig. 7.** The graphical structure of the BN with the states of the nodes. The colours of the nodes indicate the spatial nodes (green), the scenario nodes (orange), the nodes mainly derived from expert knowledge (purple), the nodes from literature (yellow), the physical variables derived from the LCZ description (blue), and the target node (red). The orange arcs indicate the connection between the SSP scenario and the nodes directly influenced by the scenarios. The dark red arrows indicate the nodes associated with the USTs (LCZ). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

collecting 1100 samples randomly selected across the city covering different USTs and locations which were recently affected by flooding. The data was later used to define the CPTs for reported nodes.

We considered literature and expert knowledge as qualitative data sources to define the CPTs. Regarding the literature, we used various literature sources, like government reports, technical documentations of implemented projects, and project reports from different civil society organizations active in Mumbai. These sources were used to derive qualitative information for nodes where no quantitative information was available.

Furthermore, we elicited information for the CPTs from five experts performing semi-structured interviews. These experts were all from academia or civil society and employed at different institutions in Mumbai. All the experts work on flooding in Mumbai with different perspectives, ranging from flood modelling to on ground research of flood hazard in Mumbai's slum areas. During the semi-structured interviews, we asked questions to obtain the effect of individual parent states on the child states, the relative weight of each parent, and a prior distribution over the states of the child. The procedure we followed is described by Whitney et al. (2018). It was difficult to assess the quantitative effects directly from the experts as they were unfamiliar with the concept of BNs. Thus, qualitative questions were used to elicit the required information. For example, the size of the effect of individual parent states on the child states were asked for: "*Do you think an extreme rainfall of 200mm/hr influences the effectiveness of small-scale green infrastructure and will it be less or more effective under this condition?*" The answer given was converted into pluses and minuses representing the effects of the parent state on the state of the child with:

- +++ effect of a parent state means that this state is highly associated with higher states of the child.

- — effect of a parent state means that this state is highly associated with lower states of the child.
- 0 effect means that this state has no specific effect on the child state.

Fig. 8 shows an example data sheet of how the qualitative expert knowledge was documented.

Furthermore, experts within dedicated workshops were consulted on how the variables will change under future conditions (Petzold et al., 2024).

To quantify the qualitative data (Fig. 8), the pluses and minuses were replaced by values ranging from −1 to 1 divided in three negative and three positive values (Table 3). To construct the total information required to derive the CPT the effect values were averaged between the individual data sheets.

Furthermore, we derived the changes in variables under the SSP scenarios through expert interviews. For this purpose, we presented the experts with narratives of the downscaled SSP scenarios. Subsequently, we asked the experts which variables of the BN structure they thought were impacted by the SSP scenarios and which effects they expected from the SSP1, SSP2, and SSP3, respectively. The SSP1 scenario projects a shift towards sustainability, characterized by strong environmental governance and reduced socio-economic inequality. SSP2 depicts a trajectory of moderate socio-economic development, following current trends. SSP3 describes a scenario of geopolitical fragmentation, resulting in hindered economic development and adaptation. The quantification again followed the adapted procedure by Whitney et al. (2018).

### 5.5. Quantifying the conditional probability tables of the Bayesian network

Depending on the data type, the quantification of the conditional probability tables followed different procedures.

Within this study, spatial flood hazard probability maps are produced. To represent the spatial coverage, we use spatial data as input to the Bayesian network. This spatial data has a coverage over the total study area, has no parents and a marginal probability table. The nodes with spatial coverage are *UST*, *proximity to large-scale green infrastructure*, *proximity to river*, *proximity to coast* and *topography*. The states of the nodes are categorical and a frequency analysis over the total study area is performed to initialize the probabilities. However, the spatial data is available from open-source data (DEM, global datasets), and for inferences of the scenario analyses, the spatial data was be used as evidence.

For some nodes we have quantitative data from the household survey. The household survey data is geolocated and thus a UST can be assigned to the individual data points from the global dataset used within this study (Zhu et al., 2022). For UST classes with available data, we used a two-way frequency table to compute probabilities of the nodes categories per UST. For example, *road material* is a reported variable in the household survey data and in the BN, it is dependent on the UST and the SSP scenario. For the current status of the node *road material,* we computed the observations of the mutual exclusive categories per UST class and divided them by the total number of observations for this UST class. These values are used to populate the CPT. For the quantification of the CPTs for unobserved UST classes and to estimate the future development of the node under different SSP scenarios, the qualitative information from the downscaled SSP narratives for Mumbai (Petzold et al., 2024) were used.

For the qualitative data, we used the *make_CPT* function from the R package *decisionSupport* to generate the final CPTs (Luedeling et al., 2022). The preprocessed qualitative information as describe above was used as input.

### 5.6. Inferences with the Bayesian network

To assess how the spatial flood hazard probability of Mumbai changes under different SSP and RCP scenarios, we exported the final BN from GeNIE as a .net file and import it to R with the package bnspatial (Masante, 2017). This package allows to give spatially distributed raster inputs to a predefined BN and gives spatially distributed outputs for the target node. The spatial inputs are the geospatial nodes (*UST*, *proximity to large-scale green infrastructure*, *proximity to river*, *proximity to coast* and *topography)*. Furthermore, we set evidence on the SSP and RCP scenarios to assess the change for different scenario combinations. The target node of the BN is *flood hazard probability*, which means the predisposition of a location to flooding, and no spatial interactions are represented.

| Parent 1 | | |
|---|---|---|
| Parent Node: lcz | | |
| *Description* | Node states | Effect |
| *Compact high-rise* | LCZ1 | + |
| *Compact mid-rise* | LCZ2 | + + |
| *Compact low-rise* | LCZ3 | - |
| *Open high-rise* | LCZ4 | + |
| *Open mid-rise* | LCZ5 | + |
| *Open low-rise* | LCZ6 | + |
| *Lightweight low-rise* | LCZ7 | - |
| *Large low-rise* | LCZ8 | - |
| *Sparsely built* | LCZ9 | + + |
| *Heavy industry* | LCZ10 | - - |

| Child Node: small scale green infrastructure | | |
|---|---|---|
| Parent Node: lcz, ssp | | |
| Relative Influence of Parents | | |
| Parent 1 | 1 | |
| Parent 2 | 1 | |
| Prior distribution | | |
| *Description* | Node states | |
| No small-scale green infrastructure is implemented | Not existent | 0.6 |
| Small-scale green infrastructure is partly implemented | Partly implemented | 0.3 |
| The potential for small-scale green infrastructure is exploited | Potential exploited | 0.1 |

| Parent 2 | | |
|---|---|---|
| Parent Node: ssp | | |
| *Description* | Node states | Effect |
| Sustainable pathway | Ssp1 | + |
| Current trends | Ssp2 | 0 |
| Increasing barriers | Ssp3 | - - |

**Fig. 8.** Example of a data sheet elicited from the qualitative expert knowledge and qualitative information derived for the node from literature.

**Table 3**
Quantitative replacement values for the pluses and minuses derived from the qualitative expert information.

| --- | -- | - | 0 | + | ++ | ++ |
|---|---|---|---|---|---|---|
| -1 | -0.66 | -0.33 | 0 | 0.33 | 0.66 | 1 |

## 6. Flood hazard probability in Mumbai under SSP and RCP scenarios: Learning from the results of the pilot study

Fig. 9 shows how flood hazard probability in Mumbai changes across the city under different SSP and RCP scenario combinations. Changes in flood hazards between the scenario combinations can be observed. Fig. 9 a), b) and c) illustrate the three considered SSP scenarios under a medium climate change scenario. The green area represents areas where flood hazard probability was reduced. Under both SSP1 and SSP2 scenarios, respectively a sustainable development and the development following current trends, the flood hazard probability is reduced. However, the decrease in flood-prone area is higher under SSP1. Under the SSP3 scenario (Fig. 9 c), i.e. a

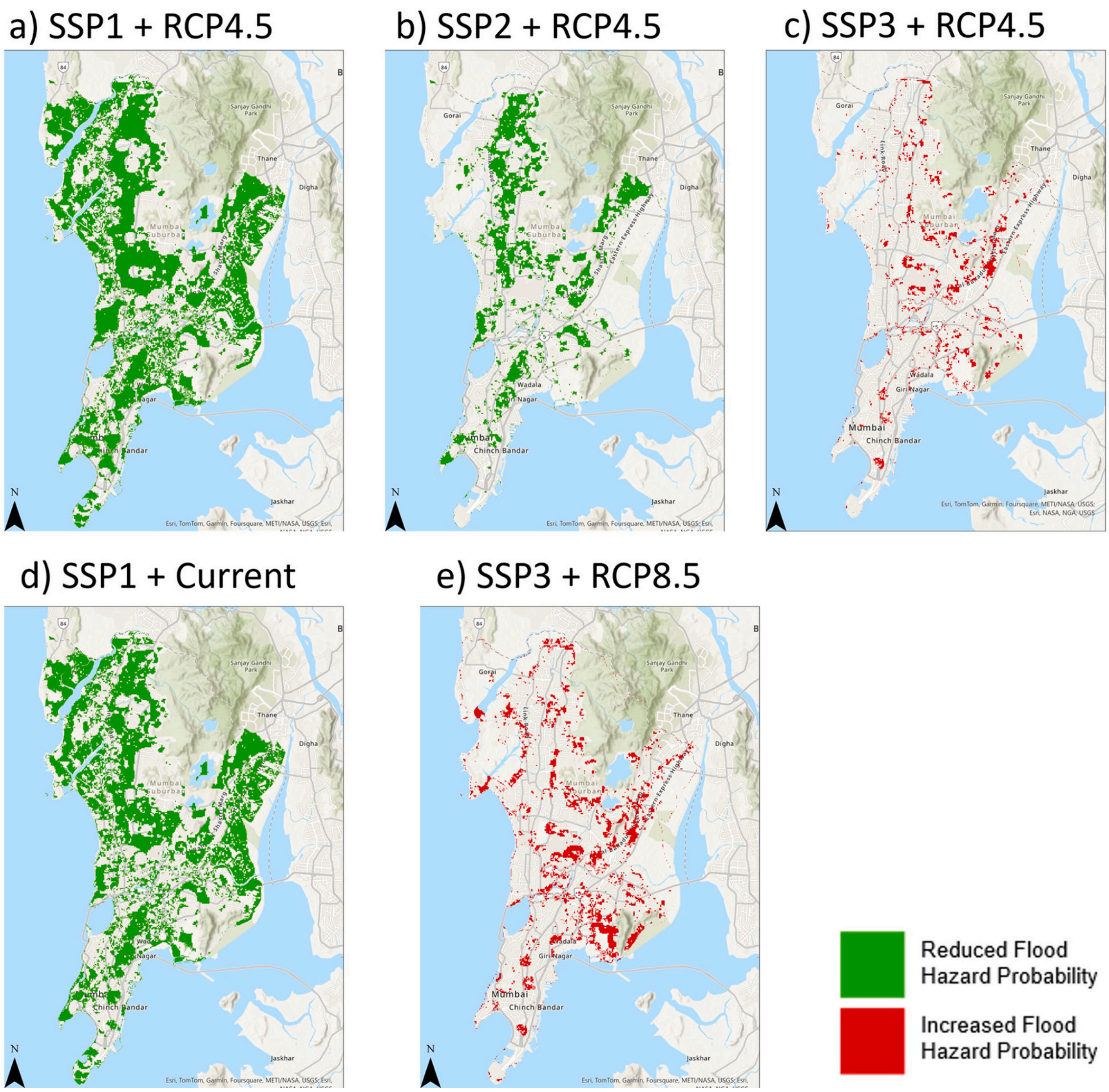



**Fig. 9.** Differences of flood hazard probability compared to the baseline scenario (current socio-economic conditions and current climate) where green stands for area with reduced and red for increased flood hazard probability, respectively. The combination of the RCP 4.5 represents a mid-way climate change scenario, combined with a sustainable development pathway (SSP1) (a), a development pathway which follows current trends (SSP2) (b) and a development pathway where additional barriers for adaptation are introduced through regional rivalry and gaps (SSP3) (c). d) depicts the best-case scenario (sustainable development scenario SSP1 with no additional climate change) and e) the worst-case scenario combining high-end climate change (RCP 8.5) and SSP3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

development with increased barriers and increasing inequalities, flood-prone areas increase. Fig. 9 d) shows the change in flood hazard probability under sustainable development with no climate change. This scenario combination represents the best-case scenario. The worst-case scenario is depicted in Fig. 9 e), i.e. the combination of SSP3 and a high-end climate change scenario RCP 8.5. The flood-prone area increases under these conditions.

## 7. Discussion

### 7.1. Scenario analysis of flood hazard probability in Mumbai

The results produced by the BN show that the model is in general able to produce consistent changes between the scenarios. However, experts included in the study were often hesitant to give information on the effect of future change on the nodes, while they were able to adequately discuss the current status of the nodes. The development of the variables under future scenarios is complex and many conflicting interests are present which are yet unclear how they will be resolved in the future. For example, during the expert interviews, one of the points discussed was the implementation of small-scale green infrastructure to increase the capacity to store rainfall and to decrease the amount of rainfall turning into runoff (runoff coefficient). Under the sustainable development pathway SSP1 it would be reasonable that the potential of small-scale green infrastructure like green roofs could be exploited. However, in the development of Mumbai under the SSP1 scenario, rooftops are rather used for solar energy production. This clearly shows that different domains and interests must be considered in the development of the assessments. To get a realistic representation of the developments, an additional participatory expert elicitation with actors representing different domains must be considered and the assumptions made within the scenarios have to be documented thoroughly. Under the SSP2 scenarios, i.e. following current trends, developments were mainly appraised as very positive and presented as sufficient to tackle climate change when implemented. This results in the reduction of flood hazard probability within SSP2 scenarios. Even though a more thorough estimation of the parameter dependencies under future scenarios could improve the results, the future remain uncertain. Thus, while making assessments of future scenarios, it is crucial to document the assumptions made during the process. Yet, the suitability of the BN for flood hazard probability assessments under SSP and RCP scenarios is shown. The reported trends in flood hazard probability are reasonable and the model is inherently consistent.

### 7.2. Challenges during the implementation

#### 7.2.1. Uncertainty in remote sensing data

Multiple nodes within the presented BN rely on remote sensing data. Yet the remote sensing data is often highly uncertain due to measurement errors or errors occurring during its processing (e.g. classification). It is important to be aware of the uncertainty which is introduced and propagated through the model by using remote sensing data (Stritih et al., 2019). This is especially true for the use of remote sensing data in urban agglomerations. In this environment a very high resolution (e.g. LIDAR data) is required to capture the variability and complexity of the city (Yu and Fang, 2023). Yet in this study only open-source data was used and this is not available in reasonable resolution. For example, the used DTM, DeltaDTM, is 30 m horizontal resolution with a mean error of 0.45 m in vertical direction (Pronk et al., 2024). While the vertical resolution is good the horizontal resolution is very coarse for applying it to flood assessments cities as the topography can be very heterogeneous on a small scale. Yet this heterogeneity in topography greatly impacts the flow direction and the connectivity of low-lying coastal flow areas (Fereshtehpour and Karamouz, 2018). If higher resolution data would be available, we could determine subbasins within Mumbai and determine which infrastructure influences which area.

Another source of uncertainty is introduced by the classification of Urban Structure Types from remote sensing data. With our field visits and the structured household survey conducted in the case study city Mumbai, it became clear that an unconditional application of the UST dataset is problematic, as the reported UST in Zhu et al. (2022) is not always consistent with observations on the ground. One explanation is the datasets coarse resolution of 100 m. In Mumbai, oftentimes inhomogeneous structure types can be found within a one-hectare area or re-development in a previously homogeneous UST area takes place. Stritih et al. (2019) reported the high uncertainty in classification of land cover datasets even if high resolution earth observation data would be available and suggested methods to account for this spatially distributed uncertainty. Zhu et al. (2022) reported the uncertainty of their UST dataset, which is used in this study, by giving a confusion matrix derived from ground truthing data. We use the confusion matrix to derive a CPT of how likely a pixel is the specific UST given the UST classified from remote sensing data.

#### 7.2.2. Challenges of urban structure types for parameter derivation

Besides the uncertainty introduced by using remote sensed UST data, the suitability of USTs, in specific local climate zones as UST representation, was heavily debated during the expert elicitation exercises. In some local climate zones (especially LCZ 1 – Compact High Rise) we can find a high variability of the parameters we want to derive. For example, solid waste management and related clogging potential is related to the socio-economic status of the residents. LCZ1 areas, however, represent slum resettlement areas whose residents are associated with low-income groups, but it also represents residential areas, whose residents belong to middleclass-income groups. Thus, the service is rather related to the income than the LCZ type and we introduced an income node to the BN. Yet, no spatial dataset of income is available, and we must derive income as child node from the UST (LCZ) data. Urban structure type classifications might also not be suitable for some nodes where it was initially assumed that they are related to USTs experts did not confirm the association (e.g. that LCZs associated with wealthier residents are more likely to get flood protection infrastructure). Yet, for physical variables like density, roughness, pervious area the usage of LCZ classification is suitable. Also, it is an appropriate way to represent divergent or convergent developments under the different SSP scenarios.

#### 7.2.3. Challenges in expert knowledge elicitation

Expert knowledge is a key information source for the set-up of the flood hazard BN and used for the identification of influencing variables, the definition of variable states and the derivation of CPTs. Wherever observed data on these steps is unavailable, the utilization of expert knowledge is the only feasible way to derive this information (Bühler et al., 2013). Within our case study, observational data is not existent due to data-scarcity and because we want to predict changes under future scenarios. Yet, using information derived from expert knowledge is prone to uncertainty and the process has to be designed and integrated carefully (Cain, 2001). Especially if experts are not familiar with probabilistic thinking the derivation of CPTs is challenging (Duespohl et al., 2012). As the experts we addressed for this study are not related to probabilistic methods, we decided to use semi-structured interviews to elicit the information. This also prevents the bias which could be introduced by asking too specific questions and forcing the expert to answer even though they are unsure. By using semi-structured interviews, the chance of introducing subjectivity is given while transferring the qualitative information to the quantitative information necessary to derive CPTs after Whitney et al. (2018). Thus, it is crucial to follow a structured procedure like the association of qualitative information to pluses and minuses and then averaging between the experts. Yet, further methods should be tested of how to use qualitative information to populate CPTs and a higher number of experts should be interviewed to increase the sample size and thus the robustness of the process.

#### 7.2.4. Validation

Within this study we want to showcase the applicability of the methodology to simulate future scenarios of flood hazard probability in data-scarce contexts. As measured validation data is not available for future scenarios, we validate the model structure and its quantification with local experts. However, the next steps must include the validation of current flood probability with current data, which will enhance the outcomes to get not only relative changes but absolute values.

### 7.3. Potentials and limitations of the modelling approach

In Table 4 we give an overview of potentials and limitations of the proposed BN-UST approach for flood risk assessments in data-scarce urban environments and further discussion of potentials and limitations is given in Duespohl et al. (2012). The approach is especially suitable for contexts in which rapid (re-)development outdates data and measurements obtained in large-scale field campaigns. The use of BNs linked with USTs allows us to make assessments of flood risk even if measurements, data or other types of information are incomplete. Furthermore, as we use units of USTs, it becomes possible to depict inner-urban redevelopment by changing the UST of a certain area and extra-urban development by increasing the boundaries of the study area. Thus, simulating changes under urbanization scenarios is not limited to representing urban sprawl. A further potential is that we describe the flooding situation and related processes in the causal nature of BNs. This can be done for any other discipline, context or process where process understanding is available as BNs are also not dependant of quantitative data. The BNs developed for different domains can then be directly linked by shared nodes, where usually, each discipline has own methods to assess a specific context and thus only results can be combined. For example, flood hazard, exposure and vulnerabilities can be defined in BNs and, by linking then through shared nodes, they can influence each other as in reality they are also codependent. Nevertheless, feedback loops cannot be implemented due to the DAG requirement (Kjærulff and Madsen, 2013). Dynamic BNs can account for temporal dynamics by introducing time steps and thus it is possible to indirectly implement feedback. However, the feasibility is limited by the increasing size of the CPTs and the complexity of the model (Norton, 2010; Wetzel et al., 2022). Moreover, when applying the BN-UST approach the users need to be aware of the fact that it is only suitable for performing rough assessments. The approach is designed to identify flood risk hotspots in data-scarce environments under different configurations of urbanization scenarios and adaptation options while considering flood hazard, exposure and vulnerability. Thus, it is suitable to identify hotspots and to relocate resources before making costly and more detailed assessments. While we do not cover the assessment of exposure and vulnerability within this study, the same approach can be followed for it. Therefore, it is relevant to identify relevant variables influencing exposure and vulnerability from literature and expert knowledge, define the relationship between these variables and estimate the effect sizes of the parent variables to its child variable.

**Table 4**
Potentials and limitations of the BN-UST approach.

| Potentials | Limitations |
|---|---|
| • Assessment of complex urban environments with incomplete data<br>• Possibility to include relevant components and domains even if no quantitative measurements are available<br>• Inclusion of more detail in urbanization changes than solely representing urban sprawl<br>• Integration of various domains for a full big picture assessment by using the same approach<br>• Powerful and explanatory tool to inform city planning<br>• Potential for updating when new information becomes available<br>• Intuitive integration and evaluation of scenarios | • Feedback implementation would require complex dynamic BN modelling<br>• Rough estimates to identify flood hotspots without detailed flood modelling<br>• Sensitive to UST classifications and its resolution<br>• Dependent of expert knowledge and estimates of parameters<br>• No representation of actual spatial interactions like water flow |

### 7.4. Outlook

We present a detailed workflow and first results of constructing a BN with mixed data for scenario analysis. To achieve higher robustness of the network, further validation of the current flood situation with independent experts and observed data must be done. Furthermore, additional experts on future developments shall be consulted to improve and concretize the development of the variables under the SSP scenarios. After completing the final validation, adaptation and urbanization scenarios can be implemented. The scenario implementation is intuitive and can be performed on several scales. We use USTs as main assessment unit for urbanization and adaptation scenarios. Thus, we can include urbanization scenarios and adaptation strategies in three different scales:

1. Changing urbanization types within the existing boundaries of the city (e.g., to simulate the impact of gentrification)
2. Expanding the boundaries of a city by adding units of UST to the existing boundaries
3. Internally changing a specific UST to include adaptation (e.g., to assess what is the impact of introducing a working solid waste management in slum areas or also only in certain slum areas)

Additionally, further efforts should be invested in fine tuning of the BN and the development of BNs for flood exposure and vulnerability to assess the total flood risk (Fig. 4) following the same workflow (Fig. 5). To increase the relevance of the approach to policy makers, it is also important to facilitate the application of the scenario analysis tool by introducing a graphical user interface. The readily available online platform for spatial BN inferences gBay, developed by Stritih et al. (2020), could be used for this.

## 8. Conclusion

Within this publication we propose an approach which helps to perform integrated flood risk assessments under various scenarios in data-scarce megacity regions, by combining Bayesian Networks (BN) with Urban Structure Types (UST). With this approach we overcome challenges currently faced by popular flood risk assessment tools. We address data scarcity by using mixed data sources, qualitative and quantitative, and USTs as proxy unit to estimate relevant parameters where no data is available, while representing their spatial variability and associated uncertainty with BNs. Due to the causal structure of BNs, we make the complex urban environment and situations forming flood risk understandable and explainable. Furthermore, as BNs are not based on physical descriptions of the flood processes but on causal relationships of influencing factors, we enable the integration of various domains (e.g., social sciences, ecology) in the assessment, and effects of soft and hard adaptation options can be simulated. These properties of the BN-UST approach give us good indications to believe that the approach will greatly contribute to the development of flood risk assessment methodologies. We present a modelling approach and a detailed workflow of how to construct the BN under data-scarce conditions. Even though several uncertainties and limitations should still be addressed in our study, the value of the results of how flood hazard probability changes under future scenarios in data-scarce urban areas is shown. As the approach is promising to assess changes in various domains under future scenarios, we would like to encourage further testing of the feasibility and transferability. Therefore, we open the debate and invite the research community to apply the approach to their specific case studies. The approach can be applied to facilitate the assessment of flood impacts on humans and other systems under current but especially under future urbanization and climate change scenarios. This flexibility and multi-dimensionality are, up to now, uncommon in flood assessment approaches. We think that policy as well as urban planning can greatly benefit from the application of the BN-UST approach since different key drivers of urban flood risk can be integrated in assessments of adaptation strategies and decision-making.

## CRediT authorship contribution statement

**Veronika Zwirglmaier:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Matthias Garschagen:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

## Declaration of competing interest

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## Data availability

Data will be made available on request.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.uclim.2024.102034.

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