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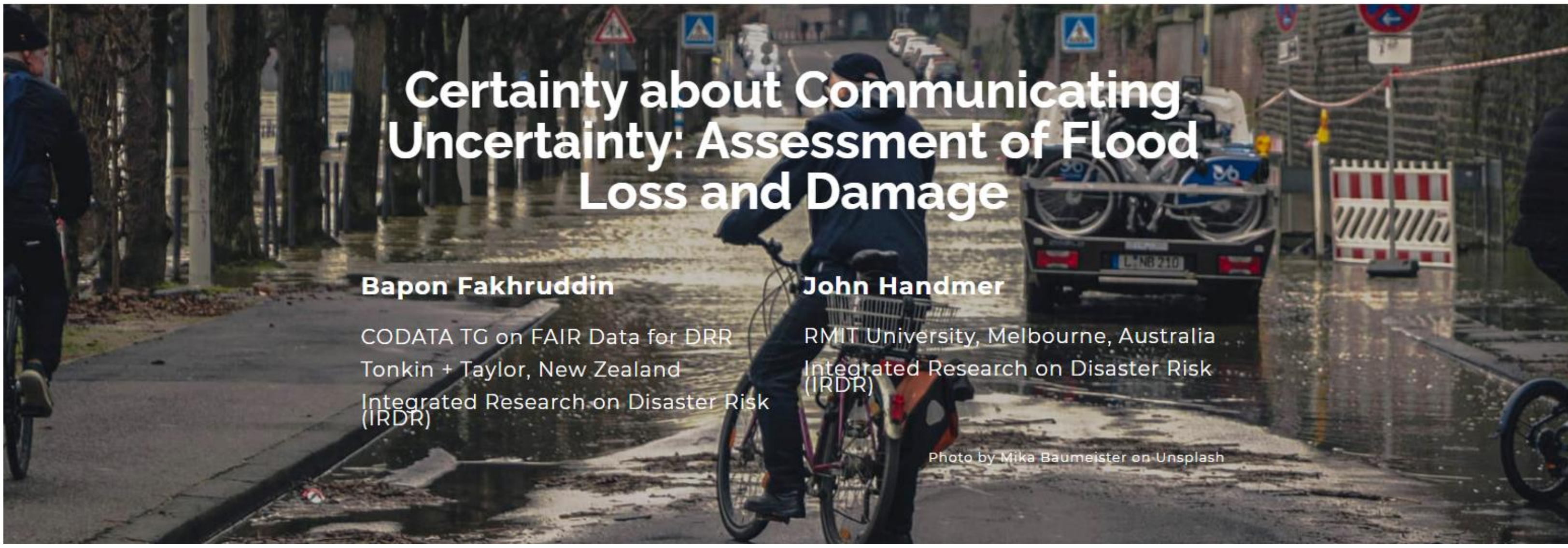

Introduction

Uncertainty in flood loss and damage assessment is inevitable due to the flaws in data accuracy and reflecting the simplification of a complex system that is inherent to any assessment. Understanding the level of uncertainty in flood loss and damage assessment would help decision makers to understand the overall loss in future events, improve planning and allocation of their resources to protect from and respond to a flood event.

Statistical information on uncertainty may be difficult to interpret and hence it may not be used when making decisions related with flood risk management at many levels, including by insurance companies and farmers (Poortvliet et al., 2019). If uncertainties are known and communicated properly, flood loss and damage assessment would improve effectiveness and efficacy of decision making, and in turn reduce the actual flood loss and damage.

A common framework and standardized techniques for communicating uncertainty to decision makers are not readily available. This research has developed a framework for communicating uncertainty for flood loss and damage assessment to the end users based on the floods in Thailand.

Uncertainty in Flood Loss and Damage Assessment

Flood impacts (losses and damages) are calculated through flood risk assessment. The flood risk assessment provides information about the vulnerability and exposure to floods and what measures can be taken to reduce the risk. It has inbuilt uncertainty, which may be aleatory or stochastic (natural variability) and epistemic (deficiencies by a lack of knowledge or information). Aleatory uncertainty may be quantified using statistical methods.

To understand the uncertainty and its implications, uncertainties in data used for hazard, exposure and vulnerability calculation needs to be holistically analysed. Natural variability can occur due to temporal variability, spatial variability and individual heterogeneity. Knowledge uncertainty focuses on the model development factors, parametric breadth and numerical accuracy of available data, and the type of model used in relation to decision making needs (De Groeve at. al., 2014).

Hazard assessments derived with parametric approaches have a high level of uncertainty. Higher degrees of accuracy may be achieved with data-intensive physically based flood models, however uncertainties are still associated with each step of the process (Morrs et. al., 2005).

Exposure and vulnerability data contain uncertain quantities. The relevance of spatial and time scales is critical for baseline data selection. Data collected in each phase of disaster risk management could reflect different variabilities and uncertainties, such as incomplete knowledge about each phase and timelines. The flood impact would be significantly varied at various timelines for disaster management (Figure 1). This uncertainty is also confounded by the effects of land use changes (Kundzewicz, 2013), population growth, and urbanization (Salman & Li, 2018), etc.

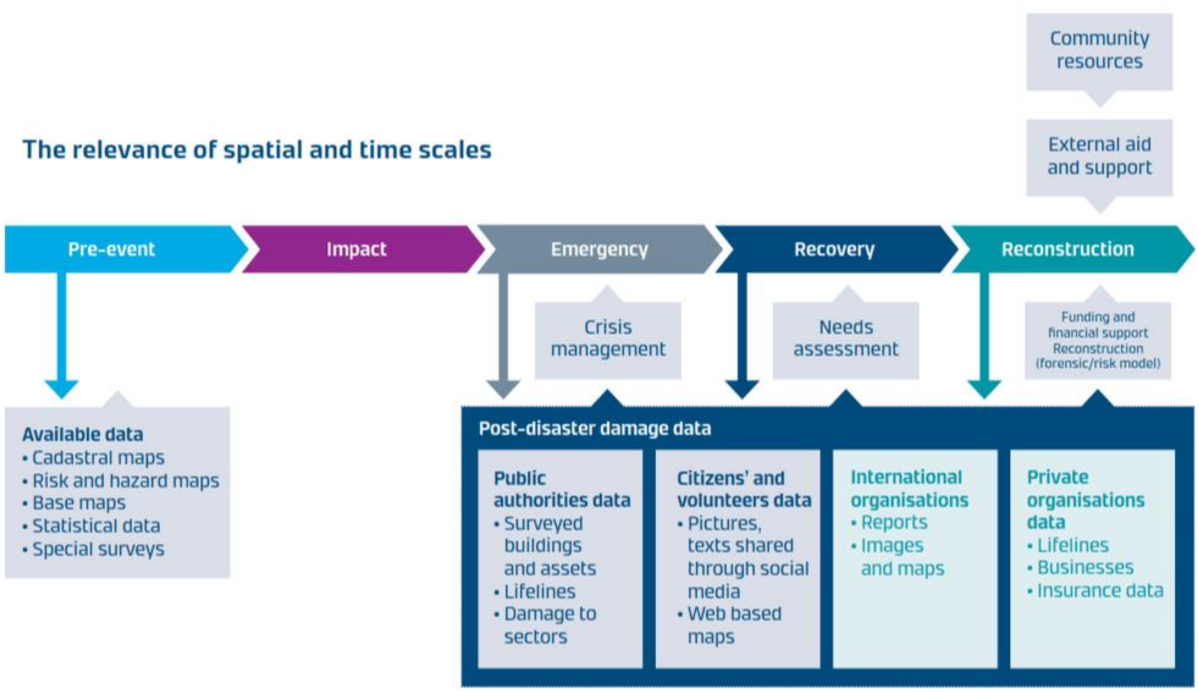

Figure 1: The relevance of spatial and time scales data for disaster management

Updated Uncertainty Classification Framework

We used the *updated uncertainty classification framework* proposed by Romão and Paupério (2014), that was built based on the uncertainty classification framework described by Skeels et al. (2010) and the Pedigree Parameter of the Numeral Unit Spread Assessment Pedigree (NUSAP) method described by Funtowicz and Ravetz (2006). Survey and focus group discussion were used for primary data collection and literature review for secondary data collection for the case study to test the framework.

Uncertainty Classification Framework

The original framework (by Skeels et al., 2010) was developed based on a movement away from a generalized treatment of aleatory and epistemic uncertainties. The updated framework is established on a (modified) hierarchy and connectivity among six types of differentiated uncertainties including measurement, completeness, inferences, disagreement, credibility and human error. Romão and Paupério (2014) identified the inability to account for a human error and proposed additional consideration for this type of uncertainty in the updated framework (Figure 2).

Typically the process used to solve a problem can be described in three stages, where each stage has a more advanced state of data processing and one of the six types of uncertainties expressed in the stages. Uncertainties relating to disagreement, credibility, and human error are considered at all three stages (Figure 2).

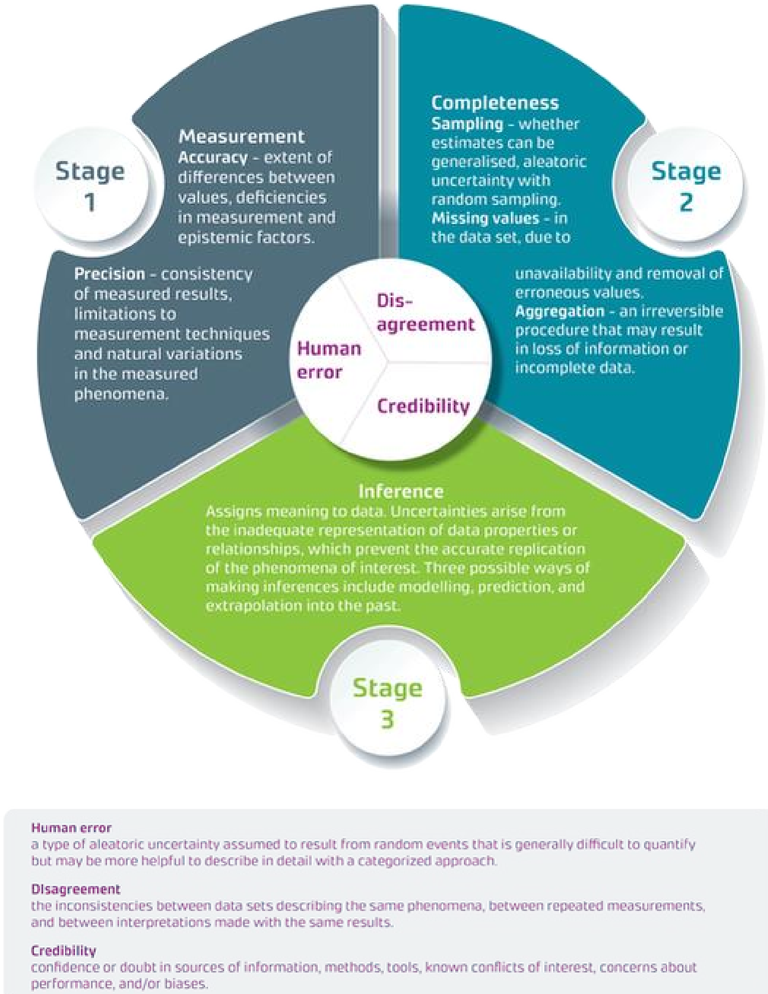

Figure 2: Six Types of Uncertainty and their relationships (Source: Fakhruddin 2017, Romão and Paupério, 2014)

The Pedigree Parameter of the Numeral Unit Spread Assessment Pedigree

The Pedigree parameter is a matrix where problem-specific criteria are assigned scores based on a customizable numerical scale (De Groeve et al., 2014). For each stage, uncertainty scores range from 1.0 (high uncertainty) to 5.0 (low uncertainty). In all three stages, human error is consistently identified as the most significant evaluation criteria contributing to uncertainty in the flood damage assessment process. The matrix structure does not have any formal requirements; the rating scale, number and type of criteria are selected to reflect the needs of each problem.

The Numeral Unit Spread Assessment Pedigree (NUSAP) method provides a systematic framework for synthesizing qualitative and quantitative uncertainty assessments and the information is organized in a coherent and easily understandable way. Consequently, it can be applied to complex models of natural phenomena. The Pedigree parameter specifically evaluates the strength of relevant values by considering both the background by which it was produced and the status of the value following processing. This helps to focus research efforts on the most problematic or weakest model components. By providing an in-depth and comprehensive overview of the sources and nature of the uncertainties, the method serves as an effective way for all participants (i.e. scientists, stakeholders, policy and decision makers) to become more aware of their interaction with the data at different stages, thereby supporting a transparent and extended peer review process. The main disadvantage, however, is that it can be a time intensive procedure. The NUSAP method to flood loss and damage assessments can be applied at multiple stages:

- the initial examination of uncertainties and assumptions
- decision to perform expert or stakeholder elicitation
- the selection of experts
- the choice of pedigree criteria
- problem visualization with diagnostic diagrams
- reporting and communicating findings
- interpreting results and integration in the decision-making process.

To determine disaster losses, data acquired at the first stage can either be used as an indicator to represent actual loss or be applied as input for further processing (Romão and Paupério, 2014). Therefore, the degree of uncertainty is dependent on the extent of processing per stage.

Case Study: Thailand Flood Damages

A limited sample size (*n* = 10) was chosen to gather preliminary data about the flood impacts on farmers in the study area of Banghpa Inn and Wangnoi districts in Bangkok, Thailand. Respondents included farmers who worked on their properties or rented land. The respondents' ages ranged from 29 to 67 years old, with an average of 49 years. All participants received at least primary level education. Most participants lived on the farm since birth, with the shortest length of residence of 8 years. Based on the ages and farming experience, it may be assumed that they have sufficient experience to make decisions to safeguard and optimize the returns of their labour. However, due to the partial or limited ownership of the farms and/or differential education levels, certain participants may not have the ability or adequate knowledge to make significant changes related to the uncertainties facing agricultural production in the future. However, the complexity of the system might make this impossible in practice, within a reasonable time. As well we could find that our increased knowledge tells us that the system becomes chaotic and unpredictable at a certain point. These require an evolving process to enhance knowledge.

The range of average score varies for each stage. Scores at Stage 3 were lowest, implying that the levels of uncertainty associated with relating data processes to realizing project objectives are notably higher than at the first two stages- stage 1: 3.3 to 4.0; stage 2: 3.3 to 4.0 and stage 3: 3.0 to 3.7.

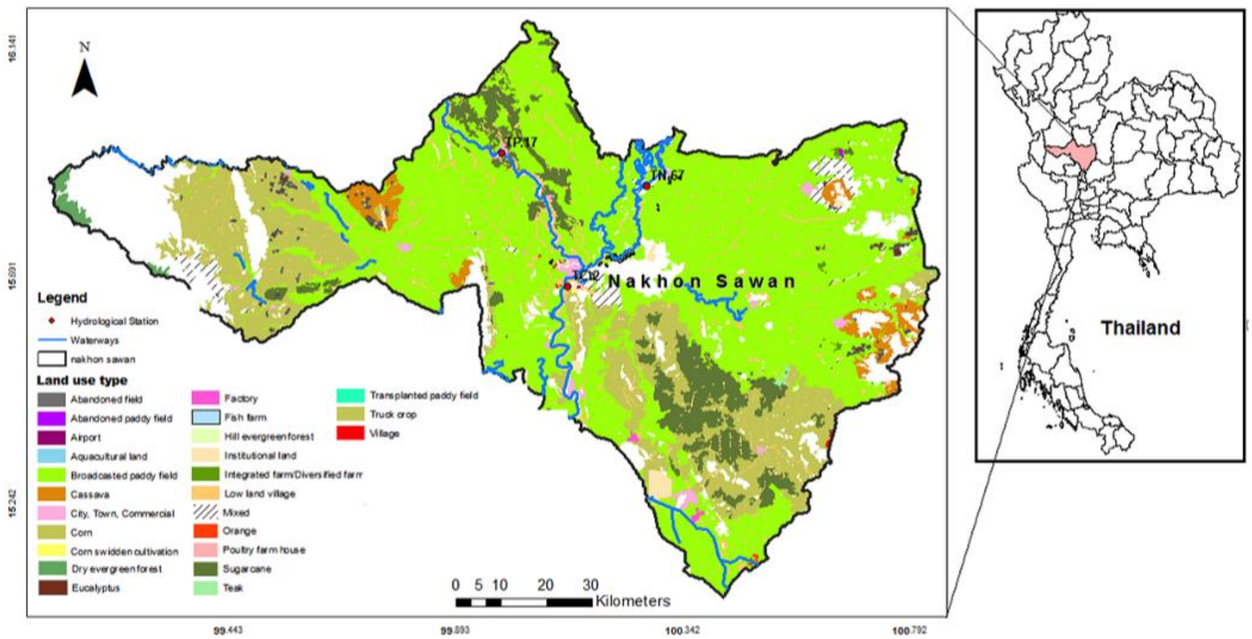

Figure 3: Case study area in Thailand

This assessment reveals that the uncertainties associated with the first three stages of data acquisition, processing, and inference are consistently attributed to human error. Furthermore, the interpretation of the modelled data at the final stage should also be re-examined to ensure that all assumptions and generalizations are valid. Elimination of these two sources of uncertainty would improve the credibility of the information presented to decision makers.

Conclusion

The *communicating uncertainty framework* was applied to the case study in a basic way to provide an impression about the relative uncertainty of key areas within the flood loss and damage assessment and results communication processes. The findings demonstrated how the proposed uncertainty framework could be used to identify areas within data management and transformation process that could benefit from improvements.

Uncertainties due to human errors and inferences were identified as the most significant contributors to flood loss and damage data calculation. Subsequent decisions based on flood exposure and vulnerability information could be improved if uncertainties from these areas are minimized and the insights provided by end users are addressed. The other general type of uncertainty was irreducible, at least through science. This includes some human behaviour, including negligence, corruption, other priorities, politics and so on. The importance here is that a lot of effort goes into trying to reduce the uncertainty that is not amenable to reduction through standard science.

A formal procedure could be developed to select key experts to perform the uncertainty assessments. Selection criteria could include educational background, impartiality and scope of involvement in the project. It would be beneficial to consider developing criteria for evaluation matrices with groups or experts and stakeholders, so that the areas of concern are clearly represented and can be directly addressed.

In addition to communicating uncertainty information, it may be useful to investigate different risk elements and their consequences to reduce known uncertainties (i.e. whether the prediction of loss and damages by physical modelling is the best approach). The results from the survey and focus group discussions can be integrated to better communicate scientific results to end users.

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