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REVIEW ARTICLE

Decision making under deep uncertainty for adapting urban drainage systems to change

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ABSTRACT
Urbanisation and climate change are augmenting the uncertainty surrounding the future state of the world's water resource and are resulting in cities experiencing growing levels of risk of pluvial flooding. Drainage infrastructure is generally built using the paradigm of 'predict and optimise'; however, this approach fails to account for erroneous predictions. This can result in drainage systems delivering insufficient levels of flood protection. Irrespective of these uncertainties new drainage systems must be built, and existing ones adapted in such a way that they remain reliable. This work presents a critical analysis of the drivers of change of urban pluvial flooding and the uncertainties surrounding urban flood planning; thereby highlighting the shortcomings of current planning methodologies. Different Decision Making Under Deep Uncertainty (DMDU) frameworks are then explored and it is shown that they offer an improved ability to design reliable urban flood systems regardless of highly uncertain future conditions.

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Introduction

The world is undergoing a rate of change more rapid than ever witnessed before (Friedman 2008). The global population is growing, with increasingly significant portions of this growth occurring within urban agglomerations (Geltner and de Neufville 2012). Simultaneously, climate change continues to augment the uncertainty surrounding the future state of the world's hydrological system. The confluence of these factors results in urban areas experiencing an increased level of risk of pluvial flooding due to climatological and socio-economic hazards.

A significant subset of these hazards are related to water, encompassing issues such as water supply, flood protection, and coastal defence (Jha, Miner, and Stanton-Geddes 2013). Due to the dynamic nature of urban systems, their economic importance, and the multiple stresses acting upon them, there is a need to anticipate and develop long-term strategies for these challenges. The current planning paradigm of 'predict and optimise' is insufficient for an increasingly uncertain future as it fails to account for errors in predictions (McInerney, Lempert, and Keller 2012). Irrespective of these uncertainties, new infrastructure systems must be built, and existing ones adapted in such a way that they remain reliable in the future despite the potential changes in land use and climate that may occur.

This article explores the applicability of new methodologies for planning under uncertainty to deliver protection against urban pluvial flooding. First, the drivers of change and their related uncertainties are discussed. Then an overview of decision-making under deep uncertainty (DMDU) methodologies is presented and recommendations made on the selection of the most suitable DMDU approach in relation to urban flooding.

Changing urban flood risk

The two main strands of global change that are increasing urban flood risk are 1) climate change and 2) changes in human settlement patterns.

Socio-demographic change

In recent decades there has been a movement of wealth from the Western world to the rest of the globe, particularly Asia (Friedman 2008). The increased size and wealth of the world's population has resulted in the development of a new middle class with increased demands for water, food, transport and other commodities. As a part of this transition certain populations are urbanising rapidly, thus concentrating assets and increasing the potential impact of climate hazards.

Urbanisation is defined as 'the process of transition from a rural to a more urban society' (UNFPA 2008, 6). The UNPD (2014, 1) states that few factors will influence the globe's development to the same extent as 'the size, structure and spatial distribution of the world's population'. In 2007, for the first time, half of the world's population resided in urban areas; this represents a rise from 746 million people in 1950 to 3.9 billion people in 2014. By 2050, it is estimated that 61% of the world's total population will be urbanised. The United Nations Department of Economic and Social Affairs Population Division (2014) provides an in-depth investigation into changing global demographic shifts. The migration of people from rural areas to cities stretches the capacity of existing infrastructure systems. In low-income countries migrants generally arrive on the fringes of cities and form ad-hoc settlements with little or no-centralised control (UNPD 2014). In the context of urban flooding these settlements are unlikely to have

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appropriate flood defence infrastructure and adhere to policy measures meant to reduce exposure to flood risk.

Projections of future population size and urbanisation should be treated cautiously as they are estimated by extrapolating the past behaviour of these populations and are sensitive to various uncertainties (UNPD 2014). Furthermore, these historic behaviours may not be indicative of future growth dynamics. Growth predictions are sensitive to differences in fertility rates which are in turn affected by a number of highly unpredictable factors such as access to birth control, women's education, and opportunities for women to work (UNPD 2014). These uncertainties have resulted in a history of imprecise projections of population growth; Satterthwaite et al. (2007) have noted that the world is notably less urbanised than what was predicted in the past. This is true with respect to the proportion of the global population urbanised, the size of urban areas, and the total urban population.

Climate change

Climate change can affect the statistical distribution of weather parameters by altering the mean, variance or skewness of their distributions (IPCC 2012). These changes in the frequency, intensity, and spatial extent of weather events can result in increasingly likely extreme events (IPCC 2012). To address climate change, actions must be taken immediately to reduce the quantity of greenhouse gases being released into the atmosphere despite the continued growth of the global middle class. The problem of climate change is compounded by thermal inertia, which suggests that excess heat will be stored within the atmosphere even if levels of greenhouse gases were to fall rapidly (Jenkins 2010). Due to this, climate change adaptation is necessary as the effects of climate change will be observed at some level even with aggressive mitigation measures.

Climate change has the potential to significantly affect pluvial flood risk. The IPCC's Fifth Assessment Report's Working Group II concluded that it was likely that there had been increases in the number of heavy precipitation events over the second half of the twentieth century (Trenberth et al. 2007). Increases in heavy precipitation events have been observed even in places where total precipitation depths have decreased, implying an increase in precipitation intensity (IPCC 2008). These changes in intensity have lead to an increase in the risk of pluvial flooding in some regions (IPCC 2012). This has been observed within the Midwest of the United States where an increase in the frequency of heavy rainfall days has been observed despite overall rainfall depths remaining constant, suggesting that changes in the magnitude and frequency of floods are occurring at regional scales (Mallakpour and Villarini 2015).

These trends suggests that the frequency of heavy precipitation or the proportion of total rainfall from heavy rainfalls will increase in the twenty-first century over many areas of the globe. Over the same timeframe, global land use forecasts predict that urban areas will continue to grow (Güneralp and Seto 2013; Seto, Guneralp, and Hutyra 2012). The combined effect of climate and land use change is likely to exacerbate the risk of urban pluvial flooding through increased runoff volumes and more rapid responses due to the growth in impermeable land surfaces (McGranahan, Balk, and Anderson 2007).

Changing risks

The climate challenges experienced across the globe include heat stress (Trenberth et al. 2007), extreme precipitation (Trenberth, Fasullo, and Shepherd 2015), coastal flooding (Jha, Miner, and Stanton-Geddes 2013) and water scarcity (Revi et al. 2014); many of these risks are concentrated in urban areas (Field et al. 2014). In 2011 sixty per cent of urban areas with populations greater than a million people were living in areas at high risk of exposure to at least one type of a natural disaster (UNPD 2014). Within Latin America, the Caribbean, North America and Asia between one-half and two-thirds of the cities with 1 million inhabitants are exposed to at least one form of natural disaster (UNPD 2014). In the context of water risks, the World Economic Forum's Global Risks Report placed four water related impacts on the top ten most likely to occur with 'water crises' listed as the event with the highest potential impact (World Economic Forum 2015).

Flooding can incur major economic costs, through direct damage, disruption to affected systems and costs of recovery (IPCC 2014). As noted earlier, the impacts of global change are being observed, and cities have begun to adapt to these new water-related risks. These adaptations aim to defend against increased hydrological variability and challenges to the efficacy of existing water systems. These changes in system performance may occur gradually or in an unexpected manner (IPCC 2012). To protect cities from growing risks it is necessary to develop adaptive capacity (Habitat 2014). The need for new or reformed urban infrastructure has been highlighted by numerous sources (Geltner and Richard 2012; Habitat 2014). The American Society of Engineers has described the state of American infrastructure as requiring major redevelopment (American Society of Civil Engineers 2013), while the UK's Institution of Civil Engineers described the state of Britain's flood infrastructure as in need of significant investment. It has been estimated that 57 trillion US dollars will be required to meet global infrastructure demand worldwide by 2030, with over two-fifths of this amount needed for power and water infrastructures (Dobbs et al. 2013). However, the planning and design of appropriate flood defences is complicated by many sources of uncertainty interacting with one another.

Uncertainty propagation

Changes in the structure, development, and location of global populations are key drivers of greenhouse gas emissions, which in turn dictate the level of climate change that will be experienced (Kjeldsen and Rosbjerg 2004; Stainforth et al. 2007). These societal developments are affected by implementing environmental regulations, economic investment in clean technologies, and population growth. However, these factors are extremely difficult to accurately predict due to their complex and non-quantitative nature.

The effects of these greenhouse gas emissions are translated to potential changes in the climate through the use of

Global Circulation Models (GCMs). The IPCC recognises three main sources of uncertainty in GCM projections: uncertainties in identifying and replicating natural variability in the climate; uncertainties in climate model parameterisation and structure; and uncertainty in future carbon dioxide concentrations (Kirtman et al. 2013). The outputs of Global Circulation Models can diverge considerably due to how they identify climate change from noisy climate data. Due to this, GCMs are not extremely sensitive to different emissions scenarios in the near future. However, GCM results concerning the end of the twenty-first century are dominated by model and emissions uncertainties (IPCC 2012). Lastly, there remain a number of unknowns in climate modelling, Knutti and Sedláček (2012) found that despite better process understanding, there is little evidence from the Coupled Model Intercomparison Project (CMIP5) that the ability to model large-scale climate feedbacks has improved significantly from CMIP4.

Despite this, GCM projections are broadly in agreement on how global averages will change. At regional scales there is disagreement between GCMs on the magnitude and in some cases the direction of change that may occur (García et al. 2014). This is particularly true with regards to precipitation patterns (Schewe et al. 2014). Probabilities of potential future events can be generated by running ensembles of these models; however the accuracy of these probabilities are dependent on their ability to accurately reflect real life dynamics. Despite their shortcomings, GCMs remain the best class of models on which we can rely to predict future climatic change. Other models allow for a more integrated assessment of climate change impacts, but these models are still reliant on GCMs for climate projections (Carter et al. 2007).

Global Circulation Models generate outputs at coarse temporal and spatial resolutions (Collins et al. 2013). One grid cell may encapsulate several countries or regions while the temporal resolution may be on an annual scale. Urban flood models however perform best with input data at sub-hourly resolutions and at a local scale (IPCC 2012). Urban rainfall runoff models therefore rely on downscaling to increase the spatial and temporal resolution of results from the large-scale climate models. However, both statistical and dynamical downscaling methods are limited in their ability to deliver useful information if the GCMs are not in agreement. The downscaling procedure itself adds a further level of uncertainty. Downscaling utilises historically observed relationships to transform global or regional projections to information relevant for a specific location (Kirtman et al. 2013). In the context of climatic non-stationarity it is not clear whether this predictor-predictand relationship will remain valid in the future (Milly et al. 2008).

Deep uncertainty

Infrastructure systems have design lives which can extend to two hundred years in length, the presence of uncertainty greatly hampers the planning and design of these systems (Hallegatte 2009). Due to the length of such design lives there is a high degree of uncertainty surrounding the future conditions under which these systems will operate and whether infrastructure decisions will remain relevant in the future. These long term decisions are undertaken within a context of *deep uncertainty* (Hallegatte et al. 2012). Generally speaking, decision makers are either unaware of the presence of deep uncertainty or are not familiar with how to manage it. This has resulted in DMDU not entering the mainstream of climate change adaptation.

Deep uncertainty is defined as 'when the parties to a decision do not know – or agree on – the best model for relating actions to consequences or the likelihood of future events' (Lempert 2003, 3). This may result in a situation where the direction or magnitude of change may be unknown (Regos 2012). Walker, Haasnoot, and Kwakkel (2013) built further on this definition by stating that deep uncertainty occurs when decision makers cannot agree upon the appropriate framework to model the system including the statistical distributions of key parameters, the sources of uncertainty and how to rank the possible strategies generated.

Hallegatte, Shah, Brown, et al. (2012) stated that there are three factors that need to be addressed in the context of making decisions under deep uncertainty: Knightian uncertainty (Knight 1921); multiple valid potential futures; and decisions must be considered with path dependence in mind, meaning that the order in which solutions are implemented has an effect on system performance.

It is critical to note that deep uncertainty does not reflect a state of complete ignorance about the future. It is possible to generate plausible states of the world and potentially rank them in order of likelihood (Kwakkel and Pruyt 2013). However it is extremely difficult to explore all possible uncertainties and futures (Herman et al. 2014a).

In the context of urban flooding multiple sources of uncertainty are introduced through climate change, land use change, population growth and the availability of future capital to maintain systems as highlighted in the previous section. Given the uncertainties surrounding projections there can be only limited confidence in the ability to predict the future state of these systems. Therefore, planning methodologies must account for these uncertainties as traditional optimum design is not appropriate to address decision challenges with the characteristics of climate change (Groves and Lempert 2007). Strategies designed to improve the reliability, robustness, or resilience of drainage systems must therefore account for uncertainties in order to be effective.

Adaptation to future change

Current methodology and limitations

The standard method of designing infrastructure is to utilise models to predict the most likely future and generate infrastructure design to operate in this future (de Neufville and Scholtes 2011). In the context of urban flooding, this approach generates a flood defence scheme tailored to what the forecast predicts is the 'most likely' future. This methodology is generally referred to as 'predict then act' and is usually reliant upon historical data.

There are two main issues with this approach. Generally, future projections are based upon or to a great extent utilise historical data with the assumption that the future will continue to look significantly like the past (Rahman, Walker, and

Marchau 2008). However, the effects of climate change are such that Milly et al. (2008) declared the death of meteorological stationarity. Due to this non-stationarity, Brown (2010) noted that many of the assumptions made about infrastructure have been made void or will be made void in the future, leading to the end of reliability.

In addition predictions of the probability distributions of future variables may have high variances and 'fat tails' (Taleb 2012). The presence of fat tails denotes a high probability of extreme events occurring. Given that the effectiveness of flood defence plans can deteriorate rapidly if small deviations occur from the projected climatic conditions, errors in prediction can lead to systems that deliver inadequate levels of flood protection. Traditional, optimised systems perform well across a narrow band of conditions. McInerney, Lempert, and Keller (2012, 549) noted that this was similar to 'dancing on the top of a needle', as such systems tend to experience very rapid declines in performance when conditions are outside of this narrow range of conditions.

Within the predict-then-act paradigm there is only limited recognition of uncertainty caused by overconfidence in projections of the future (Slovic, Fischhoff, and Roe 1981). These methods are effective when uncertainties about the future are small and well characterised. However they are generally inadequate for the long term planning of open systems such as urban drainage systems. The limitations of static, highly optimised plans are already being exhibited. Climatic uncertainty, coupled with growing urban demands from consumers and legislation, poses challenges to the success of water agencies' plans (Groves et al. 2008). For example, the 2001 master plan to mitigate flooding in Ho Chi Minh City had to contend with higher than expected increases in peak rainfall that occurred between the design and final implementation phase of the master plan (Jha, Bloch, and Lamond 2012).

In the past, to overcome these shortcomings the designed solutions were made more robust. This can be achieved by adding factors of safety; however, this can impose a large financial cost and raises the additional question of how large this factor of safety should be. This is especially true if the adaptation strategy is for an entire city or district as opposed to an individual dwelling. Furthermore, solutions can be designed to a probability level such that there is only a remote change that this design event can be exceeded. However, as noted earlier, such estimations are prone to errors, and only a limited degree of confidence can be placed in them.

System attributes

It is becoming increasingly evident that the use of optimal, but otherwise fragile strategies is not appropriate for an uncertain future. Strategies for the future must be robust, there are two variations of this: static and dynamic. Static robustness defines the range of possible futures within which a system can deliver a desired level of reliability (Matalas and Fiering 1997). More simply, this is the ability to withstand a wide range of shocks, usually developed by utilising factors of safety and layers of redundancy. However, this strategy can quickly become prohibitively expensive. This is especially true if a conservative factor of safety is utilised as it is not known how large these factors of safety should be.

Alternatively, dynamic robustness can be utilised which represents a system's ability to adapt to changing conditions. However this form of robustness requires a high degree of pro-active management of the system (Herman et al. 2014a). A dynamically robust approach emphasises learning and iterative decision-making in order to develop improved system understanding and re-evaluation of the system.

In the context of adaptation planning, it is critical to make a distinction between reliability and robustness. Reliability revolves around the expected performance level of a system such as design return periods or system thresholds. Robustness is centred around the range of potential futures that a strategy is able to deliver reliability.

Decision Making Under Deep Uncertainty methodologies

Decision Making under Deep Uncertainty (DMDU) techniques offer insights on how to manage the potential impacts of change as opposed to predicting future conditions (Walker, Haasnoot, and Kwakkel 2013). DMDU can be thought of answering 'What if?' questions as opposed to 'What will happen?' questions. The approach acknowledges that there are many potential futures and that a given standard of reliability must be achievable for all of them (IPCC 2014). DMDU techniques tend to result in strategies which result in multiple adaptation pathways (Haasnoot et al. 2012), the postponement of decisions until more knowledge is available (Zhang and Babovic 2012), emphasise maintaining system flexibility (Deng et al. 2013), and iterative risk-based decision-making to achieve these goals. DMDU techniques have been applied to water supply issues in the past (Matrosov, Woods, and Harou 2013); however, they have not been widely used in flood management.

Generally speaking, DMDU techniques utilise exploratory modelling to facilitate the identification of robust strategies. In exploratory modelling the effects of variation on key parameters are investigated. This results in large number of computational experiments with each one representing a hypothesis about what may occur in the future. From this ensemble of potential futures it is possible to ascertain which policies perform well across multiple futures. Exploratory modelling is useful in identifying behaviours which are general and which are specific to combinations of parameters, the validity of key parameters, and modellers' biases (Mackay and Mckiernan 2004). There are a number of methods to perform exploratory modelling, generally speaking, the more expansive and through the exploration the greater the computational power required.

Within the context of urban flooding, there are a number of DMDU techniques that can be applied. Walker, Haasnoot, and Kwakkel (2013) provides a comprehensive summary of decision-making under deep uncertainty approaches. A brief summary of the relevant model-based methodologies applicable to urban flooding problems is presented in more detail below.

Robust Decision Making

Robust Decision Making (RDM) can be thought of as stress testing a given strategy through the use of many model runs (RAND 2013). In a RDM analysis the current system is modelled and its performance evaluated across numerous potential futures. A meta-analysis can then be performed on these scenarios in order to identify which are the key parameters that result in failure. Once these vulnerabilities are known, potential vulnerability reducing measures can be suggested, delivering a solution that performs adequately across all or most futures (Lempert, Groves, and Fischbach 2013). The process can then be repeated on the more robust system; this iterative process 'enables systematic quantitative reasoning about the consequences of and trade-offs among alternative decision options using multiple values and multiple expectations about the future' (Lempert, Groves, and Fischbach 2013, 10). As such, RDM seeks strategies whose performance is insensitive to the most significant uncertainties.

Robust Decision Making eliminates the need to identify a set of scenarios which are felt to describe all potential futures before performing the analysis (Herman et al. 2014b). Robust Decision Making may be computationally expensive depending upon the computational cost to simulate a single future and the number of futures explored; the load is exacerbated by the number of policies evaluated and the number of iterations of analysis undertaken. Scenario discovery allows for the identification of which range and combination of variables policies experience failure (Groves and Lempert 2007; Lempert, Groves, and Fischbach 2013; Lempert et al. 2006). This can be achieved through the use of Classification and Regression Tree (CART) (Agusdinata 2008) or the Patient Rule Induction Method (PRIM) (Matrosov, Woods, and Harou 2013). This results in a small number of discrete scenarios which together should adequately represent all potential futures. A global optimisation evolutionary algorithm may be used if there are many trade-offs between planning alternatives, this is known as Many-Objective Robust Decision Making (Kasprzyk et al. 2013).

Within the context of urban flood risk management a RDM analysis was performed for the urban drainage system of Ho Chi Minh City (Lempert et al. 2013). The city relies on a significant amount of legacy infrastructure and there was a need to investigate the system's ability to handle future population change. The system was stress tested using the Storm Water Management Model (SWMM), against 1000 potential futures based upon six uncertain parameters. Six potential strategies were assessed with success measured by the economic losses caused by a design storm.

Adaptation Tipping Point and Adaptation Pathways

Adaptation Tipping Points (ATP) is a method of adaptation planning in which a system is modelled and then placed under increasingly large stresses in order identify when the system will no longer be able to deliver a desired level of reliability. This level of stress is known as an Adaptation Tipping Point. The desired reliability level is generally defined through the use of national standards and legislation. Adaptation Pathways builds upon the Adaptation Tipping Points approach by identifying when the current system will fail, identifying potential adaptations to the system, and re-performing the ATP methodology on the adapted system (Kwadijk et al. (2010). This results in a set of potential adaptation pathways. The conditions under which an ATP will occur may be transformed into an estimate of when it is likely to occur, known as a 'sell by date' through climate projections. In doing so, the effects of forecasting errors are secondary to the physical processes that might occur in the catchment.

The benefit of the ATP methodology is that it is virtually independent of climate change scenarios, and the probabilities of climate change. The method is based on potential changes and their effects on the system; the probability associated with a certain level of climate change occurring is secondary to the impact it may have. Combining the ATPs with information from projections provides information about the robustness of systems by giving an indication of how quickly an ATP may be reached. Adaptation pathways allows for path-dependence to be considered as earlier decisions influence potential adaptation strategies of the future thereby facilitating low-regret decision-making. Additionally, the solutions developed will be area-specific, allowing for a high degree of stakeholder engagement. The analysis is most easily applied to changes resulting from a single driver, however, in actuality there are likely to be a combination of drivers of change.

The ATP method was used by Gersonius, Nasruddin, Ashley, et al. (2012) who applied it to analyse a storm drainage system in Dordrecht, the Netherlands. The design storm's rainfall intensity for the drainage system was increased until the system failed to perform to national standards. The performance of Dordrecht's existing drainage system was found to remain acceptable for up to a 30% increase in rainfall intensity. When compared to the worst-case climate change scenario generated by the Dutch climate office, this ATP was not expected to be exceeded until after 2100. Another prominent example of the application of ATP method is the Thames 2100 study (Ranger, Reeder, and Lowe 2013), which was utilised to identify potential flood defence measures along the Thames estuary. The Thames estuary was modelled and the sea level incrementally raised to identify when to implement new coastal defence measures. This resulted in a stepwise strategy to protect against sea level rise.

Dynamic Adaptive Policy Pathways

Dynamic Adaptive Policy Pathways (DAPP) is an amalgamation of the Adaptations Tipping Points methodology and Adaptive Policy Making, a high-level framework for decision-making (Kwakkel, Walker, and Marchau 2010). DAPP is an emerging planning paradigm that aims to develop dynamic plans, thereby allowing systems to adapt over time (Swanson et al. 2010; Walker, Rahman, and Cave 2001; Hallegatte 2009). This methodology is particularly useful for systems that experience large uncertainties and where highly divergent futures are possible.

The DAPP method identifies gaps in reliability that may occur and actions which address these gaps in a manner not dissimilar to the ATP approach. These gaps are utilised to develop potential adaptation pathways and preferred pathways. These pathways can be evaluated and their robustness assessed through the use of many computational experiments. The analysis of plausible actions is complicated by the fact that plans should be adapted over time. This entails analysing potential adaption options across a planning horizon rather than one moment; this allows for staged decision processes to be replicated within the framework (Haasnoot et al. 2013). Once the planning is completed, a Dynamic Adaptive Plan is then put into place with the objective of monitoring the system under study and maintaining flexibility of choice between pathways for as long as possible.

DAPP requires the generation of many simulations to identify gaps in reliability, how to address those gaps and how to assess the pathways. As most hydrological models are too computationally intense to be applied in this context, it is recommended that simple and faster models are utilised when under taking a DAPP analysis (Kwakkel, Haasnoot, and Walker 2014).

Within the context of flooding the DAPP method was used to model a flood defence scheme in the lower Rhine (Haasnoot et al. 2013). The final output of this approach was a set of robust candidate pathways. By providing a set of potential pathways and through integrated local monitoring, decision-making processes can focus upon choosing and updating appropriate plans of action such that options remain open to future developments.

Discussion and recommendations

As discussed earlier urban drainage systems are exposed to many interacting, cascading and accumulating uncertainties. The resulting deep uncertainty leads to a state of ambiguity regarding future conditions. Traditional methods of infrastructure design such as 'predict then act' also known as 'top-down' approaches revolve around making decisions based on accurate forecasts. However, limited trust can be given to forecasts regarding systems such as cities or the climate as they are both open and complex adaptive systems. In order to improve urban pluvial flood planning and build future-proof infrastructure designers and engineers should focus on how drainage systems or potential adaptations will react to potential changes. This is a fundamental shift in the way infrastructure is designed. The decision-making under uncertainty paradigms analysed all acknowledge this and utilise a 'bottom up' approach, but perform their analysis in slightly different ways.

The choice of which DMDU framework to use should be decided by how pro-active the urban drainage system's management body is. Robust Decision Making has a tendency to generate solutions that are more statically robust than the other frameworks presented. This has the benefit that solutions can be implemented with minimal management. In this approach there might be a larger capital cost initially but little operational management is needed. Alternatively, Adaptation Tipping Points and Dynamic Adaptive Policy Pathways place a greater deal of emphasis on monitoring the drainage system and performing iterative decision-making. In such a framework solutions are implemented only when needed and the individual adaptations would be more incremental than in the RDM. This would result in a need for a more pro-active system of management but with less emphasis on constructing infrastructure. The choice between ATP and DAPP should be made after formulating the problem. If a problem involves many different or diverging stakeholders or influencing factors then DAPP is more applicable as it is more adept at resolving these contradicting factors.

Regardless of the selected approach, the application of a DMDU framework requires a larger computational investment than typical design paradigms in order to assess how the modelled system may react to potential changes. To better manage these large ensembles of simulations the urban drainage community requires an improved understanding of how to utilise the emerging developments in high performance computing, cloud computing, and parallelisation to their advantage. To reduce the computation load on these systems tradeoffs may be made between model run time and the degree to which physical processes are replicated within the model. What is the appropriate tradeoff between these factors remains an open question and there is much to investigate specifically with regards to model choice.

With respect to modelling, existing urban flood tools are, in theory, appropriate for use within DMDU applications. Many models can deliver varying levels of fidelity with regards to mesh size, semi or fully distributed physics, and one/two dimensional surface flows. However, for the purposes of DMDU analyses they will require improved interfacing with control functions to better manage the results of hundreds of model runs. Depending on the scope of the urban drainage problem, these models will also need appropriate Application Program Interfaces (API) to interact with external modules such as land-use or economic models. These additions will greatly improve the speed with which these analyses can take place. The computational load and organisation of these computational experiments will greatly add to the workload of the engineering team that generates the design of the urban adaptation. This workload is further exacerbated by the need to engage with stakeholders

DMDU frameworks are most effective when there is broad stakeholder engagement. This is especially critical at the beginning of the assessment when trying to structure the problem. Perhaps most importantly it is critical that the stakeholders come to a definition of success or failure. Within an urban drainage problem, the specific stakeholders that should be involved in the planning process will differ depending on the division of ownership and responsibilities for each locality's drainage system. However it would be safe to assume that the local governmental authority, the local drainage authority, and local residents or businesses would be consulted in the vast majority of cases. The coordination of these stakeholders would best be undertaken by whoever is responsible for the design of infrastructure so that these views can be taken into account during the analyses phase. Upon the completion of the DMDU analysis the design team would then re-convene the stakeholders in order to effectively communicate the costs and benefits of the potential strategies that may be implemented. Based upon these stakeholder consultations a strategy would be chosen and constructed.

Conclusion

The application of Decision Making under Deep Uncertainty frameworks and techniques to the realm of urban flooding offers the potential for great practical benefits. This is especially true given the highly dynamic urban climate era that is currently taking place. DMDU will allow for the continued ability to have reliable systems despite the highly uncertain future. The need for strategies to cope with deep uncertainty is clear and can be championed by many parties such as the government or the local community. However, the responsibility with applying these techniques resides with the practitioners of the urban drainage community. The intersection between urban drainage planning and Decision Making under Deep Uncertainty is a young field and there remain many open questions and opportunities for further work. These include questions regarding model structure, problem formulation, stakeholder engagement, the investigation of how to couple multiple models and the applicability of blue-green infrastructure to situations of deep uncertainty. By addressing these issues and building a body of knowledge in this domain the urban drainage community can ensure a greater level of robustness to climate stresses in the future.

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