Development trajectory of an integrated framework for the mitigation of future flood risk: results from the FloodLand project

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Development trajectory of an integrated framework for the mitigation of future flood risk: results from the FloodLand project

In this paper, the development trajectory of an integrated framework for the mitigation of future flood risk of the Ourthe river basin in Belgium is discussed. The paper contributes to the state-of-the-art by presenting an integrated multidisciplinary framework capable of making long-term projections (time horizon 2050 and 2100) with the objective of mitigating future flood risk by proposing alternative land-use scenarios. It bridges numerous different fields, including urban planning, transport engineering, hydrology, geology, environmental engineering and economics. The overall design and validation results of the different sub-modules of the framework are presented, and ongoing and future enhancements are highlighted.

Keywords: river floods, development trajectory, land-use transport interaction model, hydrologic model, hydraulic model

1. Introduction

Worldwide, floods are the most frequent natural disasters and cause over one-third of overall economic losses due to natural hazards (Munich RE; He et al. 2011). For many river basins, studies show that the flood risk will further increase during the 21st century as a result of climate change. However, climatological changes will not be the only increasing factor of future flood risk. Societal changes, induced by economic development and exhibited by changes in land-use, can affect future flood risk through multiple pathways, including climate (e.g., modified evapotranspiration), run-off in the catchment (reduced infiltration), inundation flows (obstruction by buildings) and flood exposure (higher value of elements-at-risk in the floodplains).

Compared to the vast body of literature regarding the influence of climate change on hydrological extremes, less research has addressed the influence of land-use changes on flood risk (Beckers et al. 2013; Thieken et al. 2014). Among the few existing studies, some suggest that land-use change, in the form of urban sprawl, could be the overwhelming contribution to future rises in flood risk (Poelmans, Van Rompaey, and Batelaan 2010; Elmer et al. 2012). Nonetheless, the impact of land-use change on flood exposure and vulnerability has not yet been studied at a sufficiently fine spatial scale to capture the relevant process governing future flood risk in urbanized floodplains.

Thus far, no study has combined future land-use modeling with building-scale inundation modeling, exposure analysis and damage assessment. This is especially true when interactions between land-use and transportation are also explicitly taken into account. The latter interactions are important, as disruptions in the transportation infrastructure cause severe strains on society. Failures and disruptions in the transportation system negatively affect activity-travel patterns and business operations (Jenelius and Mattsson 2015; Sohn 2006; Suarez et al. 2005).

This paper contributes to the state-of-the-art by presenting the development trajectory of an integrated multidisciplinary framework that is capable of making long-term projections (time horizon 2030 and 2100) with the objective of mitigating future flood risk by proposing alternative land-use scenarios. It bridges numerous different fields, including urban planning, transport engineering, hydrology, geology, environmental engineering and economics. The study area for this development is the river basin of the Ourthe in Belgium (displayed in Figure 1). However, note that, for the development of different submodules of the framework, a larger geographical scope is envisaged. This is particularly the case for sub-models that assess effects surpassing the boundaries of the study area, such as the estimation of reduced business activities in the occurrence of river floods.

Figure 1. Map of the study area.

The remainder of the paper is organized as follows. In Section 2, an overview of this framework is provided, and the already developed sub-models and their validation results are presented. Further enhancements and future developments are discussed in Section 3, and finally, a wrap-up of the most important findings is provided in Section 4.

2. Integrated framework

2.1. Design

An overview of the integrated framework is displayed in Figure 2. The framework consists of five primary modules that are strongly connected. Note that the arrows in this scheme represent the most important flows of the modeling process.

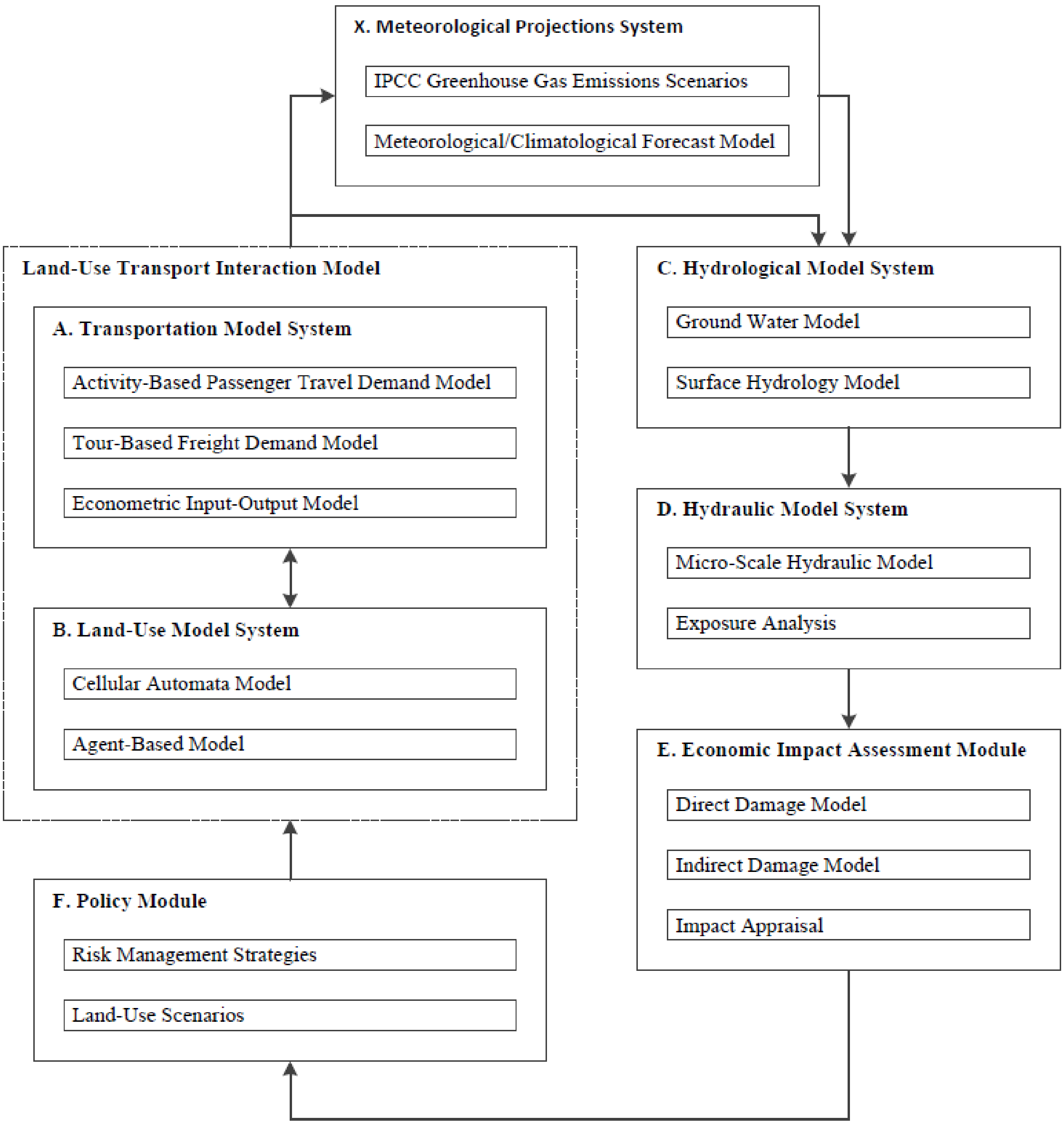

Figure 2. Integrated flood-risk mitigation framework.

The starting point for the long-term forecasts is the meteorological projection system [X], which uses the greenhouse gas emission scenarios defined by the intergovernmental panel on climate change (IPCC) as an exogenous input to direct the climatological forecasts in terms of future precipitation levels and temperatures. The potential of using the climate scenarios provided by IPCC in the context of the quantification of hydrological impacts of climate change has been underlined in the literature (Drogue et al. 2004; Kundzewicz et al. 2005; van Pelt et al. 2009; Vansteenkiste et al. 2013; Jun et al. 2013). The climatological/meteorological forecasts are obtained by global circulation models (GCM) and regional climate models (RCM).

The forecasts concerning future precipitation levels and temperatures are used as an input for the hydrological model system [C]. The water transfers at the catchment level are modeled with a physically based and spatially distributed model, which couples surface and groundwater flows. The main results of these simulations are series of calculated river discharges at different locations in the watershed. They are further used to establish flood-frequency curves.

These flood-frequency curves are then used as an input to the hydraulic model system [D] that estimates the inundation extent and depth, and this enables an exposure analysis to estimate the elements at risk.

Once the elements at risk are determined, the cascade of economic damages is valued by separating the direct economic damage (e.g., economic damage related to business interruption) and the cascade of indirect effects (e.g., loss of connectivity within the broader economic region) in the economic impact assessment module [E]. To this end, input-output models provide an adequate methodology to capture the workings of an economic system and the influence of disturbances therein (Jonkman et al. 2008). An overview of input-output models, which make the direct linkage with land-use transport interaction models, is provided by Bachmann, Kennedy, and Roorda (2014).

The appraisal of the total economic impact will then allow for the development of policy scenarios [F] that can mitigate this impact. Policy scenarios can be separated in specific spatial planning scenarios, as can policy measures that focus on policy engagement in the context of water resource management. The effect of the land-use scenarios will then be evaluated by the land-use transport interaction model, which consists of a land-use model system [B] and a transportation model system [A]. In turn, the altered land-use and transport patterns will be used as an input to the hydrological model system, as well as for the meteorological projections.

2.2. Sub-model development

2.2.1. Land-Use Transport Interaction Model

A key element in the development of the mitigation forecasting framework is the land-use transport interaction (LUTI) model, as it provides the forecasts for changes in land-use and transport infrastructure. The explicit choice to opt for the development of an LUTI model is motivated by the crucial aspect of transport infrastructure in future land-use development, e.g., the significance of proximity to road infrastructure in future constructions (Mustafa et al. 2015a), and the impact of land-use in terms of activity opportunities on the transport pattern. In the current state of development of the LUTI model, the "transport → land-use" feedback is already fully incorporated, whereas the "land-use → transport" feedback is not yet fully incorporated.

2.2.1.1. Transportation Model System. The implementations with regard to the development of the transport model system can be broadly categorized into (*i*) the development of a travel demand model for freight transport, which will become integrated with the input-output model, and (*ii*) the development of an activity-based travel demand model.

The development of the travel demand model for freight transport is especially important in the context of the chain of higher-order effects when different production facilities are affected. Current developments have thus far focused primarily on the development of a four-step model, as it is reasonably adopted for goods transport modeling (Holguín-Veras et al. 2014). With respect to the first step, i.e., trip generation, the challenge mainly lies within the collection of sufficiently detailed data to make sure that perhaps the most import step of the four-step model is calibrated with acceptable precision. In this regard, recommendations, formulated in the 2012 dedicated NCFRP report (Lawson et al. 2012), were taken into account. To perform the model estimation, data stemming from a detailed survey of retail activities (Devillet, Jaspard, and Vazquez Parras 2014) were used. In particular, location information and industrial sector information (NACE code), as well as the value of assets in the trade sector, were used as inputs. Moreover, statistics provided by the Belgian federal ministry for economy were adopted to increase the model accuracy. Regarding the second step, i.e., trip distribution, we opted for a gravity model, as the properties facilitate integration with an input-output analysis. Concerning modal choice, the current model focuses mainly on truck transport, which is further assigned to the road network in the fourth step using a deterministic user-optimal equilibrium assignment.

With respect to the development of the activity-based travel demand model, research efforts have focused on the development of a large-scale agent-based micro-simulation model. The purpose of this agent-based micro-simulation approach is the prediction of travel patterns of a given population on the transportation network. The disaggregated nature of agent-based micro-simulation models allows for higher temporal and spatial resolutions compared to more conventional models (Rasouli and Timmermans 2014; Henson et al. 2009).

Running agent-based models requires a base year population. In this context, a synthetic population is generated as a key input. Afterward, agents are assigned activity chains through an activity-based generation process. Finally, the synthetic population, along with the network, is integrated into a dynamic traffic assignment simulator.

Concerning the generation of synthetic populations, many methodologies have been developed during the last few decades, such as Iterative Proportional Fitting (IPF) (Beckman, Baggerly, and McKay 1996; Guo and Bhat 2007; Pritchard and Miller 2012) and Iterative Proportional Updating (IPU) (Ye et al. 2009; Pendyala et al. 2012). More recently, an original technique based on a Markov Chain Monte Carlo (MCMC) algorithm (Gibbs sampler) was presented as an alternative to the standard approaches (Farooq et al. 2013). According to Farooq et al.'s results, the MCMC method clearly outperforms the previous ones. Therefore, this methodology has been preferred here for its higher accuracy. To perform the population synthesis, data from the Belgian national household travel survey (BELDAM) (Cornelis et al. 2012) were used. As a first attempt, the most relevant variables related to households (income, household size, number of cars, and dwelling type) were extracted. When applying the simulation-based technique, results show a strong match between real and predicted population attributes, as illustrated by Figure 3 and documented in Saadi et al. (2016d).

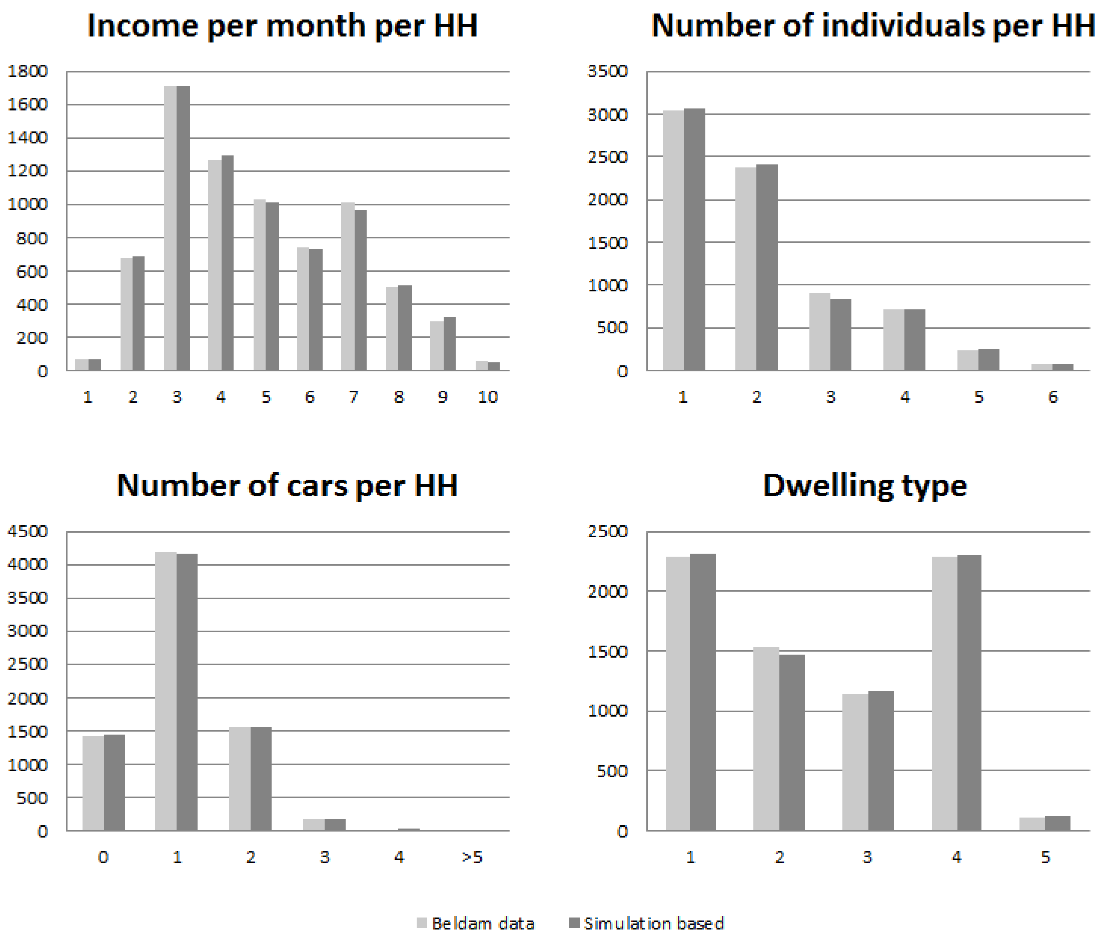

Figure 3. Comparison between the simulation-based population synthesis approach and BELDAM.

Regarding the prediction of activity-travel patterns, several improvements have been realized during the last few decades, but these prediction models still need to be further enhanced (Rasouli and Timmermans 2014; Auld and Mohammadian 2009). In this context, we opted for the approach suggested by Liu et al. (2015) using the profile Hidden Markov Model (pHMM). This technique learns the structure of pre-established activity chains extracted from activity-travel diaries. Consequently, agent activity chains can be randomly generated from the pHMM model. This technique is particularly flexible since it characterizes both short and long activity chains. Moreover, it is capable of identifying regular and irregular activities within each cluster, as well as their sequential order. In accordance with the population synthesis, data from the Belgian national household travel survey were used to calibrate the model. Originally, BELDAM data are organized according to trips. Thus, a transformation of the dataset into activity chains was necessary before running the model. Moreover, simulations are focused on generating only activity chains related to the "work" cluster. Individuals whose longest activity is work belong, by definition, to this specific cluster. The results obtained thus far are very promising (Saadi et al. 2016a, 2016b). The agreement between predicted and observed activity chains is relatively high. According to the Kolmogorov-Smirnov statistical test, the two distributions reveal a p-value of 0.87 (Figure 4).

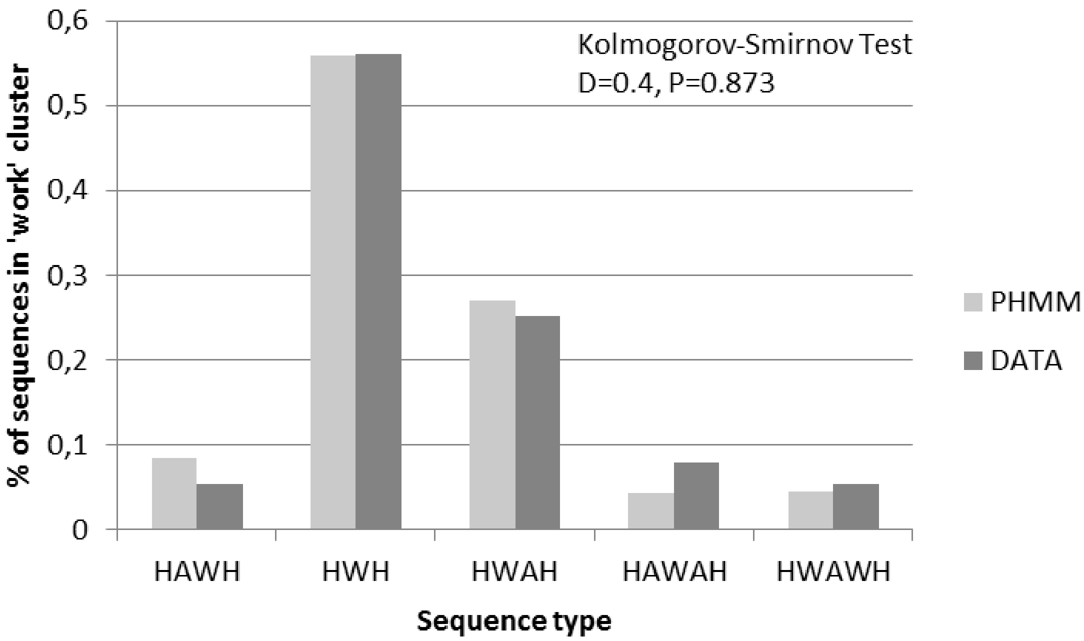

Figure 4. Comparison between the predicted activity sequences and BELDAM.

Finally, the generated activity-travel sequences are then assigned to the network using a dynamic traffic assignment (DTA) simulator. To this end, the DTA module developed within the context of MATSIM (Balmer, Axhausen, and Nagel 2006) was used. Details of the integration procedure can be found in Saadi, Teller, and Cools (2016).

2.2.1.2. Land-Use Model System. To understand ongoing and future urban dynamics, a comprehensive analysis of land-use changes is required. This understanding is also a key factor in evaluating the flood risk at different spatial scales. Recall from Figure 2 that the effects of spatial planning scenarios to mitigate the negative effects of river floods are calculated using the land-use model-system and that the outputs are then coupled with the hydrological models, as suggested by Poelmans, Van Rompaey, and Batelaan (2010). The most common methods for modeling land-use change are Cellular Automata (CA) (Aljoufie et al. 2013; Batty, Xie, and Sun 1999; García et al. 2011; Guan et al. 2011; Mitsova, Shuster, and Wang 2011) and Agent-Based (AB) methods (Augustijn-Beckers, Flacke and Retsios 2011; Bert et al. 2011; Hosseinali, Alesheikh, and Nourian 2013; Ralha et al. 2013). Other artificial intelligence approaches have also been used to forecast land-use change (Du et al. 2010).

Generally speaking, CAs are based on spatial inferences considering a series of territorial variables (distance to roads, distance to cities, slope, etc.), as well as neighborhood effects. ABs simulate the behavior of agents, such as households, companies, etc. For the simulations until 2030, a CA-based approach has been developed, whereas for the 2100 simulations, an integrated framework is developed combining the strengths of the CA- and AB-based approaches.

A CA model using Corine Land Cover (CLC) data has been developed. It focuses on urban cells (residential, industrial, commercial, etc.). The model considers built-up change probabilities based on three sets of transition rules: neighborhood effects, a suitability map and a stochastic component.

Based on explanatory variables, such as the distances to main roads and cities, a suitability map has been developed using a binomial logistic regression model. Its quality has been assessed (validated) using a Relative Operating Characteristic (ROC) procedure. The ROC value ranges from 0.5 for a model that assigns the probability randomly to 1 for a model that perfectly assigns the probability of change. The ROC of our suitability map is 0.742 (Mustafa et al. 2014). In comparison, ROC values for a number of suitability maps reported in other studies range from 0.62 to 0.74 (Pontius, Huffaker, and Denman 2004).

Regarding the development of the CA model, the following challenges have been identified. First, we were confronted with limitations inherent to the datasets used. Three datasets are utilized for land-use data: COSW, Corine Land Cover (CLC) and CADastral data (CAD). COSW is provided with a very short time span (2001, 2003 and 2005), which means it is not applicable for long-term forecast modeling. CLC covers a longer time span (1990, 2000 and 2006), but it still remains far too short for modeling the 2100 horizon. Moreover, the standards of CLC have changed over time, affecting the comparability of data. CAD data can be used for longer time frames as it provides the date of construction of each building, but only built-up land-use types can be derived from this dataset (Mustafa et al. 2015b). Secondly, with respect to the spatial resolution, it is important to analyze the model outcomes at different resolutions to determine whether the model is sufficiently detailed at a specific resolution. Our model has been validated for several resolutions up to 6,400 m $\times$ 6,400 m. The results show that the model begins to perform well for a resolution above approximately 800 m $\times$ 800 m, which is not yet sufficient for coupling with inundation models. Finally, land-use models are subject to uncertainties due to local unpredicted factors, such as real estate retention and administrative decisions. A stochastic perturbation component has been introduced in the CA model to handle these local uncertainties (Pontius, Huffaker, and Denman 2004). The model was calibrated using different magnitudes of randomness to determine whether the stochastic perturbation component is sufficient to handle these effects. The results show that our model accuracy increased as a result of the introduction of a stochastic perturbation component with a very small magnitude of randomness. Nonetheless, such a stochastic perturbation fails to address some spatial properties of observed land-use changes, especially the evolution of the size and the number of urbanized patches observed in the past.

The validation of different model runs has been evaluated by calculating the cell-to-cell agreement and by measuring the spatial properties. The cell-to-cell agreement of our model due to location is approximately 91.9% for all built-up cells and approximately 29\% for newly built-up cells, which lies well within the value ranges reported in the literature (Wang et al. 2013).

To ensure that the framework is sensitive to conditions that have never been observed in the past, the final model integrates AB and CA sub-models. Using this integration, the model will not only simulate the extrapolation of observed changes, it will also consider the preferences of households. In addition, the model couples deterministic process-based components with a stochastic component to better handle uncertainty due to global unpredicted factors, such as population growth and population movements. An overview of the integrated model is presented in Figure 5. The model includes the following three main components: a demand model, the calculation of the transition probabilities and an allocation model.

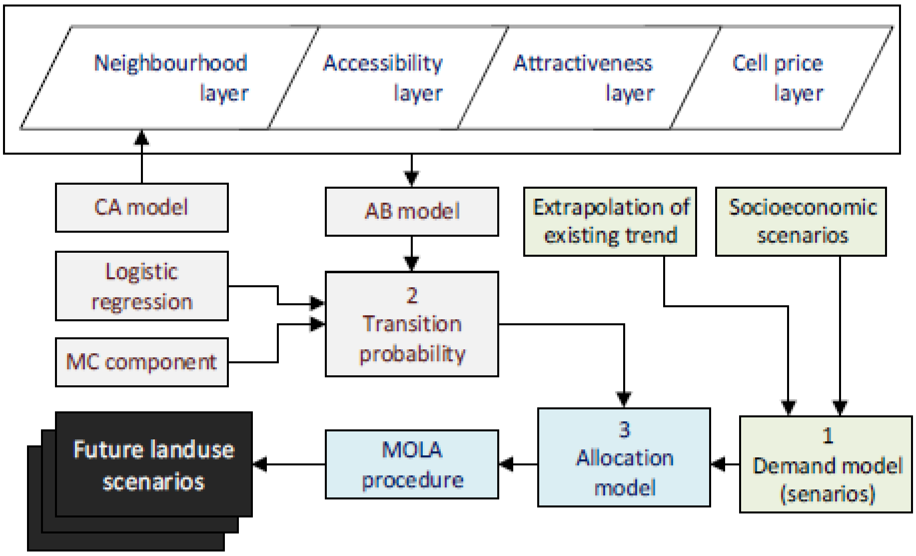

Figure 5. Integrated CA-AB land-use change modeling framework.

The demand model calculates the quantity of change of urban lands. Different scenarios of the quantity of change will be estimated by the following two methods: (*i*) a simple linear extrapolation of the past change trends and (*ii*) the use of socioeconomic factors to estimate future growth.

The transition probability of each undeveloped cell (non-urban) will be calculated using different components. The AB model calculates the transition probability using the following four layers (maps): neighborhood weights, accessibility, attractiveness and expected cell price. An agent represents a cell developer, and each undeveloped cell will be linked to an agent. Each agent will seek an appropriate cell to develop based on maximizing his profits. Each agent will develop one cell per time step (one year). Utility functions will be used to assign scores for each undeveloped cell based on the mentioned four layers. The neighborhood weights layer will be developed using the CA model. Other factors and parameters will be set using existing data, expert knowledge and data sensitivity analysis for various values of the parameters of each group. The AB model starts by selecting one agent randomly and then calculates a score for each undeveloped cell based on the agent category. The agent selects the cell with the best score. The model verifies whether the selected cell was already selected by another agent in a previous iteration. If this is the case, the model determines the winner (the richest one). A more elaborate description of the AB model is provided in Mustafa et al. (2015b).

Finally, the allocation model uses a Multi-Objective Land Allocation (MOLA) procedure to allocate the required quantity of growth. MOLA ranks cells according to their transition probability and selects cells with the highest relative ranking until it meets the requested quantity.

2.2.2. Meteorological Projections System

The assessment of the discharge statistics for the risk analysis requires continuous simulations with a physically based hydrological model using data time series of rainfall and temperature as input. To investigate future time horizons, the existing time series of meteorological observations (precipitation and temperature) need to be disturbed according to different climate change scenarios. The selection of an appropriate method to compute and apply the necessary disturbances is a twofold challenge, as the perturbed series must be representative of the future climate of Belgium and the overall consistency of the entire modeling procedure must be ensured (e.g., the time resolution).

Two methods of perturbation were compared in terms of suitability for long-term projections: (*i*) the CCI-HYDR tool from KU Leuven and (*ii*) the Advanced Delta Change method from the KNMI. A third approach was also considered, coupling a perturbation method and a stochastic weather generator. Although this method seems the most appropriate from a theoretical perspective, the use of a stochastic weather generator would introduce additional sources of uncertainty in the risk analysis and further increase the computational burden for the subsequent hydrological modeling. All three methods have been previously used in research dealing with hydrological impacts of climate change (Bruwier et al. 2015) and were validated in dedicated studies (Goderniaux et al. 2011; van Pelt et al. 2012; Ntegeka et al. 2014; Goderniaux et al., 2015).

The two retained approaches are based on a modified delta change method for estimating the perturbation factor from the comparison between meteorological variables during the control period of 1961-1990 and the results from various GCM and RCM at different future horizons. This perturbation factor is then used to perturb the observed rainfall and temperature time series. The resulting perturbed time series are 30 years long and stationary and they are representative of the climate at the designated target year or period.

More specifically, the CCI-HYDR tool proposes only three distinct scenarios (wet, mean, dry), which differ mainly in the results for rainfall (and not for temperature). Using this method enables the number of runs of the hydrological model to be reduced; however, uncertainties in the risk evaluation may remain, as in the end, only a limited number of estimates of future flood discharges are available. In contrast, the KNMI-ADC method includes 191 scenarios, which enables a broad range of possible climate changes to be explored. Nonetheless, using this complete set of scenarios in combination with a physically based hydrological model would simply not be computationally tractable. As a consequence, prior choices have to be made within the set of scenarios, which is, in essence, the principle followed by the CCI-HYDR approach.

Based on the conducted comparison, the CCI-HYDR method was considered as the most suitable, as it overcomes serious disadvantages of the other methods with respect to the choice of scenarios, time-resolution and applicability. Nonetheless, in its standard form, this method perturbs separately the time series of different gauges of the same catchment. This would lead to an artificial loss of the existing correlations between gauges located in the same area. Therefore, the CCI-HYDR tool has been adapted to perform perturbations of the time series at several gauges simultaneously, such that the correlations between these stations are preserved. This adapted version of the CCI-HYDR tool was deemed appropriate for perturbing rainfalls and temperatures in the present research.

Finally, the rain and temperature data can then be spatially distributed over the catchment, using an appropriate kriging procedure, to generate the required input data for the hydrogeological simulations.

2.2.3. Hydrological Model System

A physically based hydrological model is used to simulate water flows at the catchment level. It couples surface and groundwater flow modeling, as depicted in Figure 6 (Paulus et al. 2013). The surface runoff model was extensively described by Khuat Duy et al. (2010) and Dewals et al. (2012). The groundwater part of the model involves two layers, which correspond to the saturated and the unsaturated zones. In the former, the flow is computed by solving the three-dimensional (3D) Darcy equations, while the latter is modeled based on an original approach that couples one-dimensional (1D) and two-dimensional (2D) models to approximately solve the Richards equation.

Solving the complete 3D Richards equation for the unsaturated zone of real-world catchments is computationally costly (Wildemeersch et al., 2014). Moreover, the focus of the present research is mainly on overland flow, such that an approximate “quasi-3D” resolution of the unsaturated zone was deemed appropriate. It consists of replacing the 3D Richards equation by a set of 1D vertical models plus one 2D horizontal model (see “1Dv/2Dhz partially saturated groundwater flow” in Figure 6).

This dramatically reduces the computational cost while reasonably representing the vertical flow and the horizontal transfers in the unsaturated zone.

The models used for overland flow, the unsaturated zone and the saturated zone are coupled through so-called buffer cells (Figure 6), which accommodate the use of different time steps and different grid spacings in each model.

The main results of these simulations are time series of runoff reaching the rivers. Using the one-dimensional hydraulic model Wolf1D for flow routing (Khuat Duy et al. 2010, Dewals et al. 2012), river discharges are calculated at different locations in the watershed. These discharges are then used for flood-frequency analysis and serve in the end as input data for the 2D hydraulic model (section 2.2.4.).

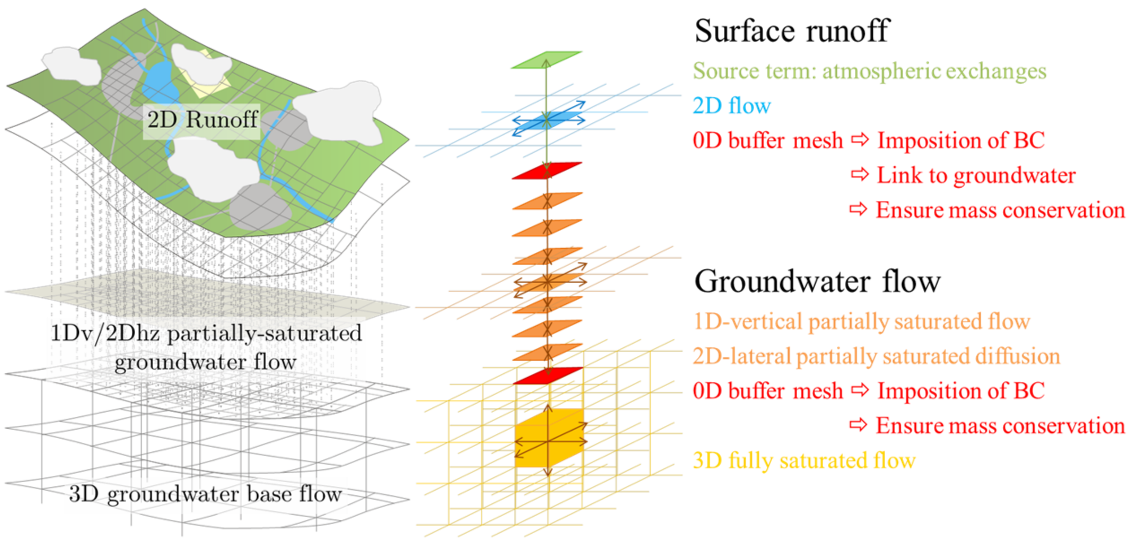

Figure 6. Coupling between the groundwater model and the surface hydrological model.

2.2.4. Hydraulic Model System

The hydraulic model aims to simulate the detailed flow characteristics at the level of the river and its floodplains. It uses the flood discharge and geometric data characterizing the main riverbed (bathymetry) and the floodplains (topography) as input data. It delivers detailed information on the inundation extent, the flow depth (Figure 7) and the flow velocity, as outputs, which in turn are used as inputs for exposure assessment and damage modeling (section 2.2.5.).

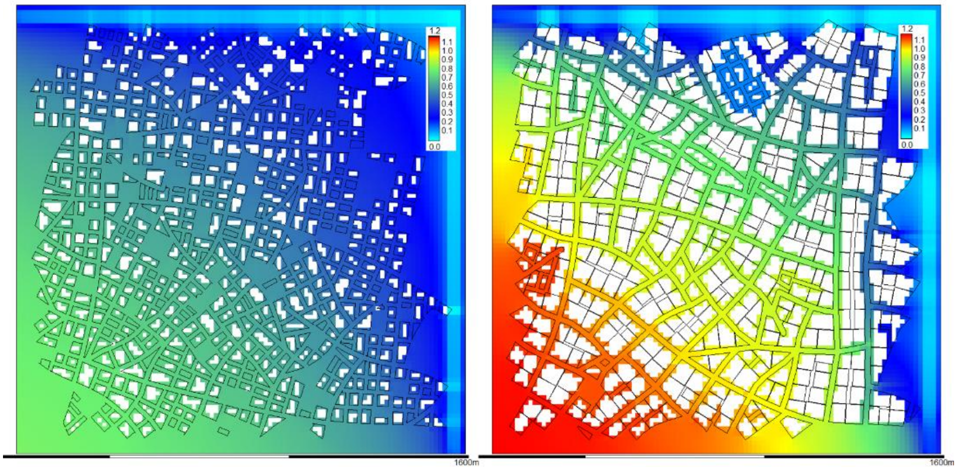

Figure 7: Distribution of water depths computed by the hydraulic model for the same flood event and two different scenarios of urban development.

High-resolution topographic data obtained from remote sensing techniques are increasingly available. The typical grid spacing of such data may be as fine as 1 to 5 m. However, performing detailed flood modeling at such a fine resolution is computationally demanding, particularly when multiple runs of the hydraulic model are necessary to assess the influence of uncertainties or various land-use and climate scenarios. Consequently, the present need is for high-performance computational models that nonetheless take full benefit of the available detailed topographic data, thus combining accuracy and high efficiency. One way to meet this challenge is through the development of subgrid models.

Subgrid models enable a decrease of the computational time while preserving information from the detailed topographic data to some degree. One such sub-grid modeling approach for simulation of inundation flow consists of solving the shallow-water equations with porosity. Shallow-water models with porosity are typically applied with a computational cell size of one to two orders of magnitude higher than the size of the available detailed topographic data. The topography is represented through porosity parameters reflecting the storage capacity inside a control volume and the conveyance across the borders of the control volumes.

Various shallow-water models with porosity exist. They differ mainly in how the porosity parameters are defined and evaluated. Some authors use porosity as a continuous mathematical field, in which storage porosity remains undistinguished from exchange (conveyance) porosity. Inversely, other authors use porosity as a discrete cell or border property, which enables storage porosity within a cell to be distinguished from exchange porosity at a border. Recently, some authors have used depth-dependent porosity to take into consideration the potential variation of the porosity values with the water depth. Based on quantitative analyses for theoretical and real-word urban areas, we have shown that models greatly benefit from being based on porosities defined as discrete cell or border properties.

The model is solved based on a finite volume scheme. A flux vectors splitting technique is used to compute the fluxes across the borders of each cell (Erpicum et al. 2010a, 2010b). An optimal discretization of the source term representing gravity is achieved, as detailed by Bruwier et al. (2016). The new discrete equations have been implemented in the existing Wolf 2D model, which has already been extensively applied for flood hazard and flood risk analyses (Ernst et al. 2010, Beckers et al. 2013, Bruwier et al. 2015, Detrembleur et al. 2015). The newly coded model has been verified and validated against 1D and 2D, steady and unsteady idealized test cases, as well as against experimental results (Figure 8).

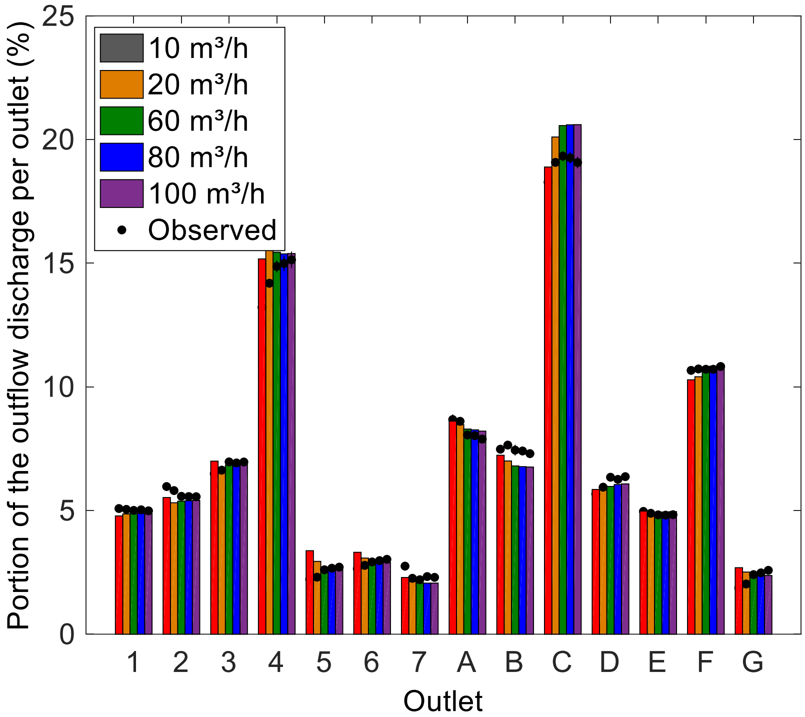

Figure 8: Satisfactory agreement between computed and observed distributions of the flow discharge between the different streets of an urban district. Reference data are from the scale model presented by Arrault et al. (2016).

2.2.5. Economic Impact Assessment Module

Flood risk is expected to increase in the future due to climate change and urbanization. While climate change affects flood hazard, urbanization influences flood exposure and vulnerability. Flood exposure for a given flood discharge and land-use scenario is evaluated here by overlaying the corresponding land-use map and the inundation maps obtained from hydraulic modeling. Next, flood damage estimation is performed in two steps. First, the relative damage is obtained by combining the flood exposure results with stage-damage curves developed in the framework of the FLEMO model (Kreibich et al. 2010). Second, for each land-use category or considered urban class, the relative damage is multiplied by the corresponding inundation extent and by a specific price, leading to the potential damage in absolute terms. This estimation is performed for both mobile and immobile assets.

The specific prices are assessed following Beckers et al. (2013), who derived specific prices from ATKIS data (a German database) and adapted them to the case study area. Here, the specific price for each urban class is computed as the product of an average density over all urban cells of a specific urban class and a price per m² of building. This latter price was calibrated such that the flood damage computed here in the baseline scenario corresponds to the baseline damage computed by Beckers et al. (2013).

The Land-Use Model System (Section 2.2.1.2) distinguishes between several urban density classes. The influence of the considered number of urban classes on the flood damage estimation was quantified. We found that using more than three different urban classes yields only marginal improvements in the calculations.

Figure 9 provides some preliminary results based on the following three urban expansion scenarios for 2030 derived from the coupled cellular automata (CA) and agent-based (AB) urban expansion model: (*i*) business-as-usual, (*ii*) limited expansion and (*iii*) extreme expansion scenarios. The main factor controlling these scenarios is the future demand for urban land. Each urban expansion scenario is developed by including or not including a ban on development in high and/or medium flood hazard zones. The resulting increases in flood damage are between 23 and 38% depending on the urban class (Figure 4). The highest increases in flood damage occur for the medium-density class, while the rise of flood damage for the high-density class is slightly higher than for the low-density class. Additionally, the increase in flooded area is higher for the low-density urban class, but nonetheless, flood damage increases more for the medium-density class where the flood induces higher damage. These results are of particular relevance for risk management as they enable the identification of areas wherein alternate urbanization policies could be implemented to mitigate future flood risk.

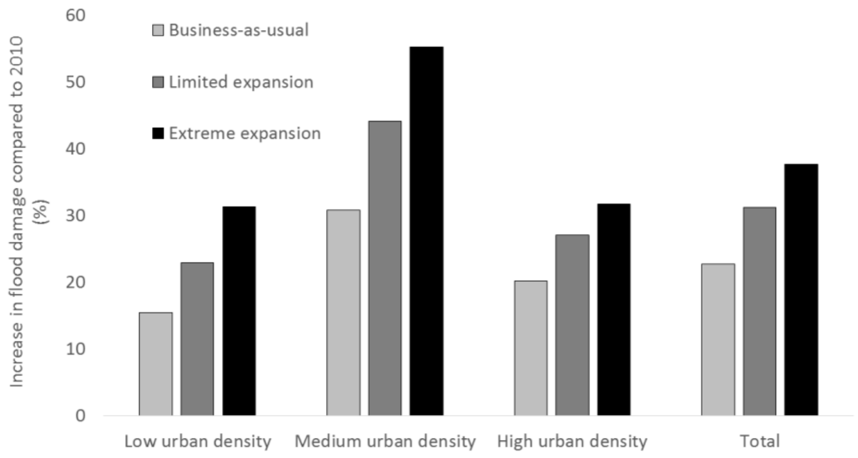

Figure 9: Increase in flood damage due to future urbanization for the horizon 2030 compared to the baseline situation (2010).

Regarding the assessment of the indirect economic impact, an Input-Output (I-O) model is being developed. The advantage of using an I-O approach is that it can easily be associated with the standard freight model (Section 2.2.1). The freight model plays the role of intermediate between the physical damage of the transportation network and the commodity flows subjected to eventual impacts. The Input-Output model will be calibrated using the I-O tables stemming from the Federal Planning Bureau using the NACE code referencing system. Preliminary results reported in Saadi et al. (2016c) show the efficiency of the I-O model in capturing the higher-order economic impacts.

2.2.6. Policy Module

The policy module steers the different policy and urbanization scenarios in the modeling chain. With respect to future urbanization, the following three groups of scenarios are proposed: (*i*) business-as-usual scenarios, (*ii*) an urban intensification scenario and (*iii*) a sustainable scenario.

The business-as-usual scenarios extrapolate the existing urbanization trends. Based on linear extrapolations of the urban expansion and intensification (low, medium and high density) between 1990, 2000 and 2010, the following three scenarios will be generated: low, medium and high demand. These scenarios were derived by respectively extrapolating the trends between 2000 and 2010, 1990 and 2010, and 1990 and 2000.

The intensification scenario stops developing new urban lands and alternatively intensifies existing ones. This scenario increases the vulnerability of high-density urban areas to flooding when they are located in places at risk.

The sustainable scenario suggests stopping the development of new lands and intensifying existing ones, those more exposed to flood risks (lowlands), following the "Room-for-the-River" policy adopted in the Netherlands. The lowlands are meant to receive the peak discharge of the river in flooding cases to prevent flooding in other areas. The low- and medium-density lands outside lowlands are intensified until specific thresholds are met. The definition of these thresholds is based on average density values for settlements that are homogeneous. The remaining required urban areas will be expanded outside existing ones.

3. Further development of the LUTI model

With respect to further developments, a key challenge lies in ensuring the interoperability of the different modules of the integrated modeling framework. If we focus on the land-use transport interaction model, the development of the input-output models is especially essential, as it offers the required methodology to correctly represent the relationship between economic systems and transport systems (Bachmann, Kennedy, and Roorda 2014). To develop the model, the activity locations should be derived from the land-use modeling component. A disaggregation of the freight demand model would serve, in this case, as an excellent starting point for the input-output model.

The accessibility measures, which are used in the land-use change models to determine the transition probabilities, should ideally reflect the generalized cost structure of the transportation network. To this end, the integration of (dynamic) traffic assignment of passenger and freight traffic will better reflect the actual load profiles on the network and correspondingly provide more realistic accessibility measures.

A final enhancement of the LUTI model concerns the feedback toward the climatological forecasts and inclusion of the reverse direct effect. After all, meteorological conditions also affect activity-travel patterns (Creemers, Cools, and Wets 2015).

4. Conclusions

In this research paper, we have discussed the development trajectory of an integrated framework for assessing spatial planning scenarios that could alleviate the negative effects associated with future river floods. To this end, we have considered a complete risk chain, from climate impact, via hydrological and hydraulic modeling, to damage and risk estimation using land-use transport interaction models.

The presentation of the design of the framework and discussion of the developments of the different submodules has highlighted the added value and potential of using LUTI models in the context of the development of a methodology for risk assessment.

One of the most significant challenges of this research lies in the coupling of different modeling tools, spanning from socio-economic to physical/hydrological aspects. In addition to interoperability issues, this research will require addressing the chain of uncertainties inherent in such approaches, especially when one considers a 2100 horizon.

Future research will focus on the development of different scenarios combining climatological and land-use change scenarios to quantify the influence of micro-scale spatial patterns in future land-use on flood hazard, exposure and risk. The developed models and methodology will be validated and demonstrated on a real-world case study corresponding to a Belgian sub-basin (Ourthe river) of the international Meuse basin.

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