

Impact of seasonal changes in vegetation on the river model prediction accuracy and real-time flood control performance

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Abstract

The vegetation along a river reach varies throughout a year. Seasonal vegetation affects the hydrodynamic behaviour of the river system. Accordingly, flood studies should take this temporal variation into account. This also applies to real-time flood forecasting and control. This paper studies the impact of seasonal vegetation when considering real-time flood control performance, based on a model predictive control (MPC) scheme. The scheme makes use of a conceptual river model to limit the computational times, as well as a reduced genetic algorithm (RGA) for the optimization of the flood control gates. The impact of seasonal vegetation on the conceptual model accuracy was analysed and a flexible data assimilation approach developed, to adjust the model predictions to different vegetation scenarios. This method can successfully improve the efficiency of a control strategy, by strongly predicting and reducing the impact of seasonal vegetation changes on river conditions.

KEYWORDS

conceptual modelling, data assimilation, model predictive control, real-time flood control, seasonal vegetation

1 | INTRODUCTION

In many parts of the world, the number of river floods have steadily increased during the last decades (EM-DAT, n.d.; MEA, 2005; MIRA, 2013). The rising urbanisation (Hawley & Bledsoe, 2011; Huang, Cheng, Wen, & Lee, 2008; Poelmans, Van Rompaey, Ntegeka, & Willems, 2011) and the increasing trend of extreme rainfall events due to climate change (IPPC, 2014; Lehner, Döll, Alcamo, Henrichs, & Kaspar, 2006; Vansteenkiste et al., 2014; Willems et al., 2012) are two ongoing trends associated with this increase. Intelligent control of river systems by means of model predictive control (MPC)

strongly improves the management of these economically costly natural disasters in comparison to classic programmable logic controller (PLC) based control strategies (Barjas-Blanco et al., 2010; Breckpot, Agudelo, Meert, Willems, & De Moor, 2013; Chiang & Willems, 2015). MPC is a model-based approach that uses rainfall forecasts and predictions of river flow conditions to optimise the retention basin regulation, for example, the controllable gate levels, in real-time, based on a given objective. Several successful applications of improved reservoir operation by MPC can be found in the literature (Ficchi et al., 2016; Galelli, Goedbloed, Schwanenberg, & van Overloop, 2014; Schwanenberg, Xu, Ochterbeck, Allen, &

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Karimanzira, 2014; Tian, van Overloop, Negenborn, & van de Giesen, 2015). They use target water levels, flood volumes, flood durations or even flood damages, and constraints on gate movements as objectives.

Recently, Vermuyten, Meert, Wolfs, and Willems (2018a) presented a successful and fast alternative approach replacing classic MPC controllers by combining MPC with a reduced genetic algorithm (RGA). They consider the economic damage cost of flooding, a penalty to minimise the overtopping of the retention basin dikes and an additional control objective to keep the water levels in the retention basins as low as possible. Based on fast conceptual river models (Wolfs, Meert, & Willems, 2015), RGA-MPC reduces the damage cost between 2 and 31% for the Demer basin in Belgium in comparison to the current PLC based regulation under the assumption of perfect model predictions. Model-based optimization techniques such as MPC, however, strongly depend on the accuracy of the river model applied. Model mismatches and rainfall forecast errors can have an important impact on the flood forecast accuracy of these models and consequently on the flood control performance of MPC (Brandimarte & Di Baldassarre, 2012; Walker et al., 2003). Uncertainties related to the hydrodynamic river model components result in deviations between the predictions used in the MPC based optimization process and the actual river system observations. Vermuyten, Meert, Wolfs, and Willems (2018b) investigated these deviations and the resulting loss in flood control performance. The proposed flexible data assimilation approach compensates for on average 75% of this loss.

Besides model parameter and structure uncertainties, also changes in the river bed roughness result in deviations between model predictions and observations and thus in a loss of flood control performance. This river bed roughness has an important influence on the flow regime along the river network and differs strongly between winter and summer conditions. In general, the bed roughness depends on several factors (Kummu, 2002; Moeskops, 2007). One of these factors is the vegetation in the river bed, which has a strong seasonal variation. An increased vegetation growth results in a higher bed roughness and, accordingly, in higher water levels (De Doncker, 2010). The roughness also depends on the water depth (Wu, Shen, & Chou, 1999; Zhang, Li, & Shen, 2013). These effects were studied before and the seasonality of the river bed roughness coefficient calibrated to discharge and water level measurements by Keupers, Nguyen, and Willems (2015). That research also shows that even after such calibration large uncertainties remain.

This paper studies the influence of seasonal vegetation growth on the real-time flood control performance.

For this, first the impact of this seasonal vegetation on the model accuracy of the conceptual model is analysed. Next, a revised conceptual model is set up that can account for the temporally varying vegetation growth. This new conceptual model is then used to assess the impact of seasonal vegetation on the flood control performance. Based on the data assimilation methods presented in Vermuyten et al. (2018b), the loss in control performance due to this vegetation uncertainty is tested.

2 | STUDY AREA

This paper focuses on the basin of the Herk river, located in the north-east of Belgium. The Herk basin can be seen as a rain-fed system as the river flows are very sensitive to rainfall. The region has faced many floods of which the flood of September 1998 was the most severe one. This flood had an approximate return period of 100 years and caused a total loss of 16 million EUR (HIC, 2003) in Belgium. In response to the long history of floods, the authorities of Flanders have installed several hydraulic structures and flood retention basins to reduce the flood risk in this very flood prone region.

The Herk subbasin consists of the rivers Kleine Herk in the north and Grote Herk in the south (Figure 1). The inline retention basin has a storage capacity of 700,000 m³ and protects the city of Stevoort. The water flow is regulated by means of three hydraulic structures. A full hydrodynamic river model of this subbasin has been implemented by the Flemish Environment Agency (VMM), based on detailed cross-section data. This model was implemented in the InfoWorks RS software and includes the main floodplains, retention basin and hydraulic structures.

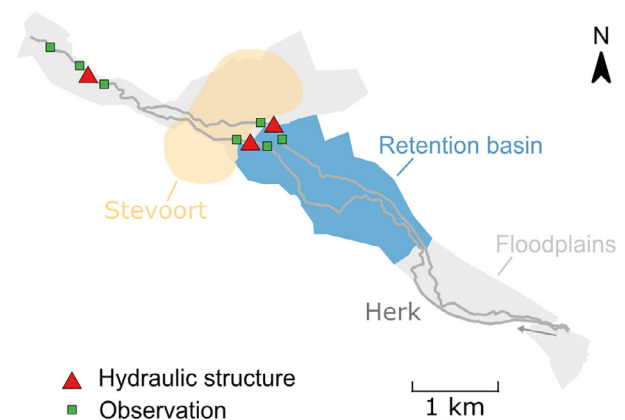


FIGURE 1 River network of the Herk study area, together with the retention basin, the hydraulic structures and the city of Stevoort

3 | MATERIALS AND METHODS

3.1 | Conceptual modelling

The full hydrodynamic river model available in the InfoWorks RS software for the study area is computationally too slow for optimization applications. Instead, fast conceptual models created semi-automatically by means of the Conceptual Model Developer (CMD) tool of Wolfs et al. (2015) are used. According to the storage cell concept, the network topology is simplified by dividing the entire network into distinct units. The resulting surrogate model or emulator is less detailed than the full hydrodynamic river model, but computationally much more efficient. Since the number of locations with water level and discharge observations available is too limited, direct calibration of the conceptual model to these data is not possible (Meirlaen, Huyghebaert, Sforzi, Benedetti, & Vanrolleghem, 2001; Vanrolleghem, Benedetti, & Meirlaen, 2005). Therefore, the conceptual model is calibrated based on the simulation results with the full hydrodynamic model. A brief description of the 10 calibration and validation events used in this study is given in Table 1, together with the maximum total rainfall-runoff peak discharge. The model was first calibrated to the largest recent historical events (E1–E6), where after the model was validated and fine-tuned based on more extreme events than the recent historical ones. Two types of more extreme events were generated: based on synthetic hydrographs (E7–E8), by applying a factor 1.3 to the largest historical event (E9) and by assuming that the largest historical event is followed by another event of the same magnitude (E10).

Several successful applications of conceptual models such as river flood modelling and mapping, integrated catchment modelling and recently real-time flood control can be found in the literature (De Vleeschauwer et al., 2014; Meert, Pereira, & Willems, 2016; Vermuyten et al., 2018a, 2018b; Wolfs, Tran Quoc, & Willems, 2016; Wolfs, Van Steenberghe, & Willems, 2012).

In a conceptual model, the river network is schematized by reservoirs interconnected by means of hydraulic structures. The volume in each reservoir is calculated based on a mass balance equation and the flows over the hydraulic structures. These volumes are transformed to water levels at one or more locations along the river reach represented by each reservoir by means of hypsometric curves. The flows over the hydraulic structures and the different control objectives are calculated based on these water levels. Rainfall-runoff discharges originating from measured or synthetic hydrographs or hydrological models serve as inputs to the conceptual river model. In this study, the probability distributed model PDM (Moore, 1985, 2007) is used as rainfall-runoff model, similar as in the original full hydrodynamic InfoWorks RS model.

3.2 | Seasonal vegetation

During the years, several roughness formulas have been defined and values for the coefficients assessed in order to represent the river bed roughness. This study makes use of the Manning's roughness coefficient, which is used in the InfoWorks RS models of the Demer basin to model the river bed roughness. The bed roughness does not only

TABLE 1 Overview of the 10 calibration and validation events with total rainfall-runoff peak discharges for the Herk study area

Event	Description	Total rainfall-runoff peak discharge (m ³ /s)	
E1	Sept 1998	Historical period of heavy rainfall.	46
E2	Aug 2003	Historical period of drought, followed by a small rainfall event.	25
E3	Dec 1999–Jan 2000	Historical period of heavy rainfall.	30
E4	Jan–Feb 1995	Historical period of heavy rainfall.	27
E5	Jan–Feb 2002	Historical period of heavy rainfall.	30
E6	Nov 2010	Historical period of heavy rainfall.	35
E7	Synthetic hydrograph VMM	Synthetic hydrograph starting with a very dry period, followed by a heavy rainfall event, developed by VMM.	42
E8	Synthetic hydrograph T1000	Synthetic hydrograph with a return period of 1,000 year, developed by VMM.	74
E9	Sept 1998 × 1.3	Artificial period of heavy rainfall, created by multiplying the historical period of Sept 1998 with a factor of 1.3.	93
E10	2 × Sept 1998	Artificial period of heavy rainfall, created by duplicating the historical event of Sept 1998 in time.	62

have a spatial variation, but also a temporal variation and is moreover dependent on the water depth. This study focuses on the temporal variation, which cannot be automatically considered in the InfoWorks RS modelling software. In order to consider different vegetation scenarios, different InfoWorks RS models with adjusted settings for the Manning coefficient have to be used.

In a conceptual model, the river bed roughness cannot be changed directly. In order to consider a different vegetation scenario, the Manning's roughness coefficients have to be changed in the InfoWorks RS model and the conceptual model needs to be recalibrated based on the simulation results with this adjusted model.

The conceptual models considered on the basis of the real-time flood control are calibrated based on the InfoWorks RS models with average vegetation growth settings. In this way, the conceptual models are supposed to be usable throughout the whole year. The effect of this approximation is investigated in the results section.

3.3 | Model predictive control and reduced genetic algorithm

The RGA-MPC approach developed by Vermuyten et al. (2018a) for real-time flood control applies model predictive control (MPC) to the fast conceptual river model in combination with a reduced genetic algorithm (RGA) for optimising the future gate positions. This optimization minimises the flood damage along the river network based on the conceptual model predictions of the future system states. This allows the controller to anticipate on future rainfall and flow conditions while taking the interactions between the different hydraulic structures into account. This proactive MPC controller outperforms the local reactive PLC based control strategy, as shown in Vermuyten et al. (2018a).

The RGA heuristic optimization method considers only a subset of the possible gate operation positions at future time moments as optimization variables, strongly reducing the number of possible solutions. Each RGA optimization starts with an update of the initial conditions of the prediction model in order to represent the actual system states. The algorithm then generates possible future control strategies, so-called gate level (GL) scenarios. These GL scenarios are generated randomly or the best control strategy so far is mutated. Each newly generated control strategy is applied to the conceptual river model and the results are compared with those of the best regulation so far. The best control strategy

with respect to the control objectives is selected and used during the next iteration until the stopping criteria are being met. This RGA converges faster towards a near-optimal solution than a standard genetic algorithm. More details about the RGA-MPC technique can be found in Vermuyten et al. (2018a).

3.4 | Data assimilation

Due to its receding horizon strategy, MPC has some "inherent robustness" towards uncertainties (De Nicolao, Magni, & Scattolini, 1996; Magni & Sepulchre, 1997; Mayne, Rawlings, Rao, & Sokaert, 2000). The impact of large uncertainties will, however, be unacceptable as this inherent robustness is limited. Therefore, an efficient real-time control system should not only consist of an efficient optimization algorithm, but also of efficient model updating and uncertainty propagation techniques (Sarma, Durlofsky, Aziz, & Chen, 2006). Data assimilation (DA) methods systematically eliminate the deviations between predictions and observations (Hutton, Kapelan, Vamvakeridou-Lyroudia, & Savic, 2014a, 2014b; Hutton, Vamvakeridou-Lyroudia, Kapelan, & Savic, 2011; Liu et al., 2012). They are also often applied in real-time flood forecasting systems.

State estimators update the initial states of the river model to match observations and improve the prediction accuracy of the river model. This improvement will, however, wash out with increasing lead time (Madsen & Skotner, 2005). Therefore, it is recommended to use these state estimators in combination with prediction error methods (Vermuyten et al., 2018b). Prediction error methods apply an error correction scheme to the forecast simulation based on an analysis of the past model residuals in order to improve the prediction accuracy. Figure 2 shows the flowchart of the reduced genetic algorithm with data assimilation.

This paper analyses the performance of several state estimators and predictions error methods with respect to seasonal vegetation uncertainty. Considered state estimators are: instant updating IU, total instant updating TIU (Vermuyten et al., 2018b), the well-known moving horizon estimator MHE (Haseltine & Rawlings, 2005; Liu et al., 2012; Rawlings & Bakshi, 2006) and the ensemble Kalman filter EnKF (Evensen, 1994). Considered prediction error methods are two prediction error models of Van Steenberg, Deschamps, Willems, Boeckx, and Mostaert (2013) PEM1 and PEM2 and the recently introduced flexible prediction error method Flex PEM by Vermuyten et al. (2018b). For a detailed description of these data assimilation methods, the reader is referred to Vermuyten et al. (2018b).

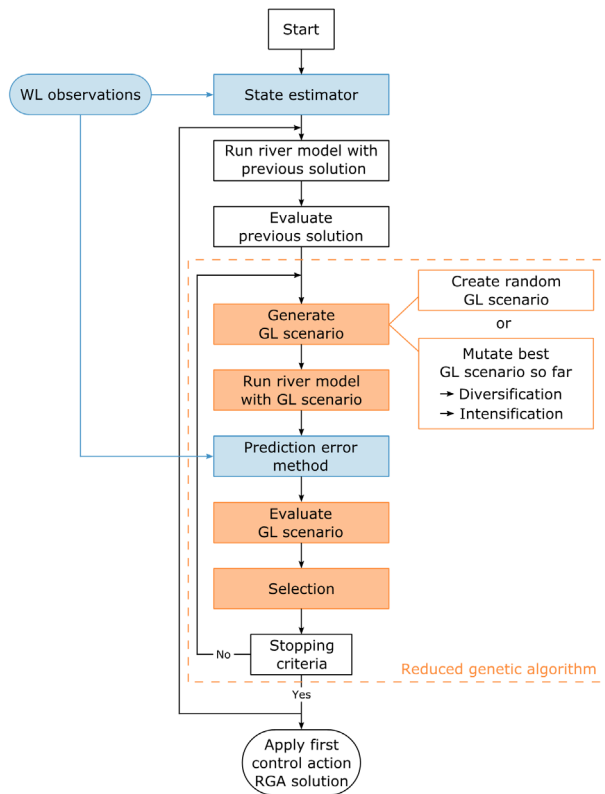


FIGURE 2 Flowchart of the reduced genetic algorithm with data assimilation (blue). (WL refers to water level; and GL to gate level)

3.5 | Real-time control performance

Vermuyten et al. (2018b) tested the above data assimilation methods with respect to hydrodynamic model uncertainty. This paper combines these methods with MPC in order to investigate their effect on the real-time control performance when considering vegetation uncertainty. Their performance is compared against two benchmarks: ideal MPC and no DA. Ideal MPC represents the best obtainable solution as the controller has perfect knowledge about the future system states. No DA introduces vegetation uncertainty in the control problem by considering a different vegetation scenario in the conceptual model used for the optimization than in the model representing the actual river system. No DA is used as a second benchmark as it represents an MPC regulation without feedback from observations. MPC DA also introduces vegetation uncertainty, but data assimilation methods are considered in order to reduce the performance loss due to this uncertainty. The following formula is used to evaluate the performance of the different data assimilation methods, based on the total damage costs of the MPC optimizations:

$$PI = \frac{(D_{no\ DA} - D_{MPC\ DA})}{(D_{no\ DA} - D_{ideal\ MPC})} * 100 \quad (1)$$

with PI the performance improvement [%] and D the total damage cost [€] (Vermuyten et al., 2018a). A good data assimilation method will have a performance improvement close to 100%, which means that the loss in control performance due to the vegetation uncertainty is almost completely compensated by the data assimilation method.

4 | RESULTS

4.1 | Prediction accuracy

In order to investigate the influence of seasonal vegetation, two vegetation scenarios are considered: average and summer vegetation growth. The average vegetation scenario was already modelled by the original InfoWorks RS model and the corresponding conceptual model. For the summer vegetation scenario, the Manning coefficients in the InfoWorks RS model are increased to model the increased vegetation growth and thus bed roughness. The conceptual model is recalibrated based on the simulation results of this modified InfoWorks RS model. Three events are considered: events E1, E7, and E8. During the recalibration process, the hydraulic structure parameters and hypsometric curves are adjusted, while the model structure is preserved.

The purpose of the model accuracy assessment presented in this section is twofold. In the first place, the loss in model accuracy towards seasonal vegetation is investigated. Second, it is tested if a quick recalibration of the conceptual model in which the model structure is preserved is capable of reducing this accuracy loss or whether a complete recalibration is required. For this, three different accuracy assessments are conducted. First, the model accuracy of the original conceptual model, with average vegetation growth, is assessed in comparison to the original InfoWorks RS model, also with average vegetation growth. Second, the accuracy of the original conceptual model is assessed in comparison to the modified InfoWorks RS model with summer vegetation growth. Finally, the accuracy of the recalibrated conceptual model, with summer vegetation growth, is assessed in comparison to the InfoWorks RS model with summer vegetation growth. Table 2 summarises the considered models for these three model accuracy assessments.

The model accuracy assessment consists of a comparison between the water levels in the conceptual model with those in the detailed InfoWorks RS model. Figure 3 presents the results of the three model accuracy

assessments when applying the PLC based regulation obtained in InfoWorks RS as a time series in the conceptual model. The left graph of Figure 3 shows the model error of the maximum water level at all modelled locations for the three considered calibration events, while the right graph analyses the model error in the full 5-min water level time series by means of the root-mean-square error (RMSE). A distinction is made between water level locations in the river reaches and in the floodplains.

The model accuracy of the conceptual model with average vegetation growth, evaluated after comparison with the InfoWorks RS model with average vegetation growth is discussed in Vermuyten et al. (2018b). It was concluded that the conceptual model is a good representation of the detailed InfoWorks RS model. Therefore, model accuracy assessment M0 is used as a reference, representing a good model accuracy.

Model accuracy assessment M1 compares the simulation results of the conceptual model representing average vegetation growth with those of the InfoWorks RS model with summer vegetation growth. It is clear from Figure 3 that the model accuracy strongly deteriorates in this case; the error of the maximum water level and the RMSE both strongly increase. In general, the conceptual model tends to underestimate the maximum water levels in the system, as can be seen from the left graph in Figure 3. It is concluded that the original conceptual model is not able to cover the impact of summer vegetation on the river system behaviour.

In order to improve the model accuracy for summer vegetation growth, the conceptual model is recalibrated based on the simulation results of the InfoWorks RS

model with summer vegetation growth. The conceptual model structure is persevered from the original conceptual model. Model accuracy assessment M2 compares the results of this recalibrated conceptual with those of the InfoWorks RS model with summer vegetation growth. It can be seen from Figure 3 that the acquired model accuracy is much better than in accuracy assessment M1 and slightly worse than in M0. When comparing accuracy assessment M2 with M0, a higher model accuracy is expected in M2 as the concerning conceptual model is specifically calibrated for the three considered events, while in M0 the conceptual model is calibrated for 10 events. On the other hand, however, the conceptual model structure in M2 is not optimised for the river system behaviour with summer vegetation growth, which is expected to result in a lower model accuracy for M2. In general, the obtained model accuracy in M2 and M0 is very similar. It is concluded that the recalibrated conceptual model is able to represent the river system behaviour with summer vegetation growth. Accordingly, a quick recalibration of the original conceptual model is sufficient to account for summer vegetation growth. The model structure does not need to be optimised, but can be retained from the original conceptual model.

4.2 | Real-time flood control performance

The previous section has shown that the original conceptual model is not able to adequately represent the river system behaviour during periods of summer vegetation growth. This section analyses the real-time flood control performance of MPC when the conceptual model with average vegetation growth is used in the optimization process during periods of summer vegetation in the actual river system. For this, closed-loop optimizations are performed in which the original conceptual model (average vegetation growth) is used as prediction model

TABLE 2 Overview of the considered models for the three model accuracy assessments with respect to seasonal vegetation

	Conceptual model	InfoWorks RS model
M0	Average vegetation	Average vegetation
M1	Average vegetation	Summer vegetation
M2	Summer vegetation	Summer vegetation

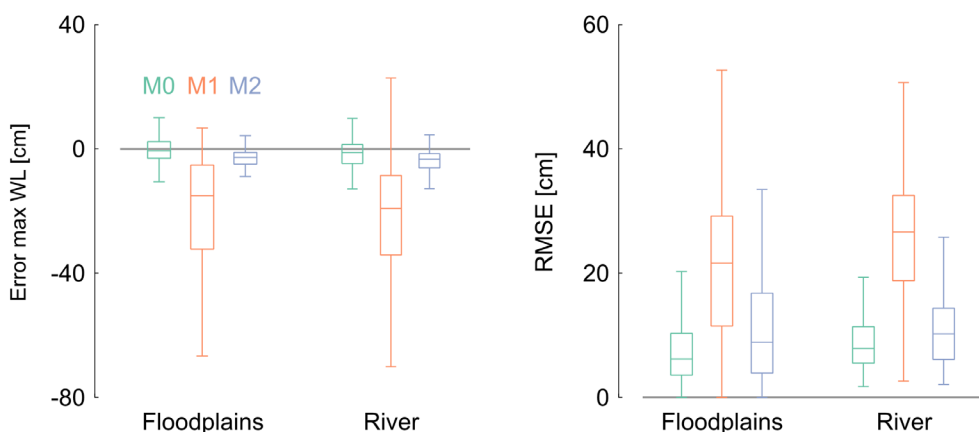


FIGURE 3 Conceptual model error assessments (M0, M1, and M2) considering the full hydrodynamic InfoWorks RS models as reference: Error in the maximum water levels (left graph) and root-mean-square error (RMSE) of the continuous 5-min water level series (right graph) in floodplains and river reaches after PLC regulation. Note: to make the graphs more legible, outliers were not plotted

while the recalibrated conceptual model (summer vegetation growth) represents the actual river system. Several data assimilation methods are considered in order to take the model uncertainty due to seasonal vegetation into account.

Figure 4 shows the performance improvement of the different data assimilation methods averaged over the eight damage relevant events for the Herk study area and the total damage cost reduction by each data assimilation method summed over the events. A performance improvement of 0% corresponds to MPC without data assimilation, while a performance improvement of 100% corresponds to ideal MPC. In ideal MPC, the conceptual model with summer vegetation growth is also used for the prediction model, which results in perfect system knowledge and represents the best attainable solution. Rainfall forecast uncertainty is not considered in this analysis.

It can be noticed that for both the MHE and the EnKF, the combinations with respectively PEM2 and PEM1 result in a slightly higher average performance improvement, but a lower total damage cost reduction. This indicates that the combinations with PEM2 and PEM1 perform in general better for less severe flood events with a low damage cost, while the data assimilation methods with only a state estimator perform better for severe flood events with a high damage cost. Furthermore, similar performance improvements are obtained with these data assimilation methods as with IU and TIU.

Most data assimilation methods have an average performance improvement of around 50%. Combining the MHE or EnKF with the flexible PEM, however, results in a strong increase in real-time flood control performance. The average performance improvement of these two methods is close to 80% and the total damage cost reduction is almost twice as high as those of the other data

assimilation methods. Also for each individual event, the combination of the MHE or EnKF with the flexible PEM strongly increases the performance improvement and shows the best real-time control performance. Based on these results, it is concluded that these two methods outperform the other data assimilation methods. This confirms the conclusions made in Vermuyten et al. (2018b) with respect to hydrodynamic model uncertainty. The reason for this improved real-time control performance is the more thorough analysis of the hindcast period by the flexible PEM and the selection of an appropriate prediction error model. Especially during periods of severe flooding, this approach shows clear benefits in comparison to the other considered data assimilation methods.

In general, all data assimilation methods with the EnKF result in a better real-time control performance than the corresponding ones with the MHE. Furthermore, the computational time of the EnKF is lower than that of the MHE. Therefore, the combination of the EnKF and the flexible PEM is selected as the most appropriate data assimilation method to take model uncertainty due to seasonal vegetation into account. Based on real-time observations, this approach compensates on average for 80% of the real-time control performance loss due to seasonal vegetation. In this way, the conceptual model representing average vegetation growth can be used throughout the whole year and there is no need to make use of a recalibrated model. Accordingly, there is no need to foresee a bank of models representing different vegetation scenarios and there is no need to switch between these different models as the data assimilation approach automatically adjusts for the current vegetation scenario. An additional advantage is that also the spatial variation of the vegetation is automatically corrected by the data assimilation method. The combination of different vegetation scenarios along the river network would

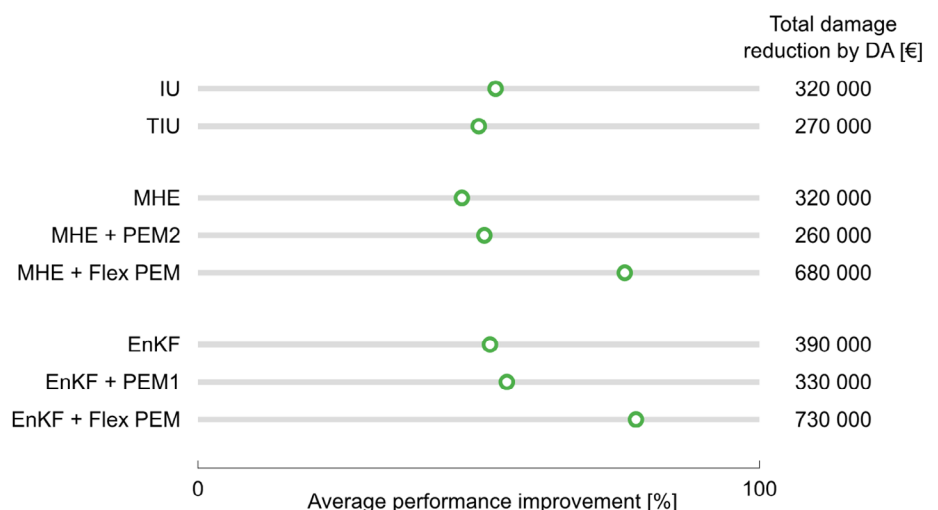


FIGURE 4 Average performance improvement for eight different data assimilation (DA) methods to account for seasonal vegetation, together with the summed total damage cost reduction by the data assimilation method, for the eight damage relevant events

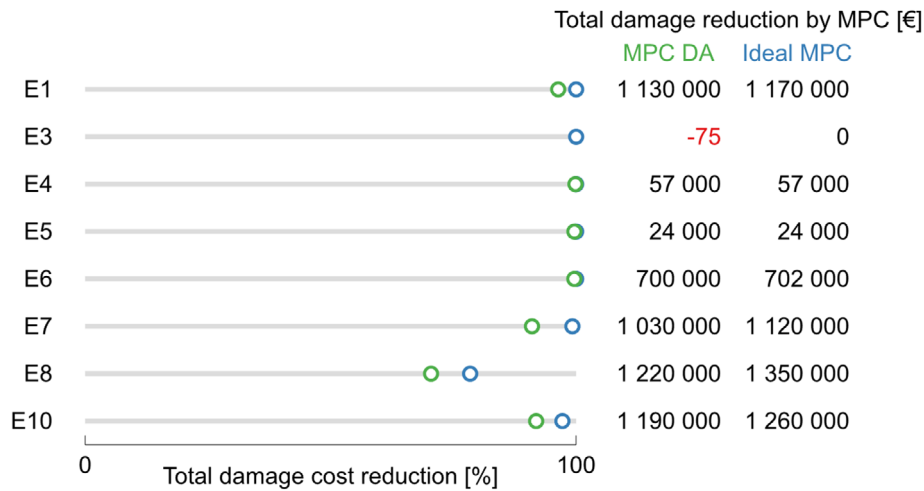


FIGURE 5 Relative and absolute total damage cost reduction by ideal MPC and MPC DA in comparison to the PLC based control strategy when considering seasonal vegetation, for the eight damage relevant events

require an immense bank of models, which is impractical. Different vegetation scenarios along the river network are, however, detected by the data assimilation method and an appropriate correction is applied at each location. Also the variation depending on the water depth is most likely to be automatically accounted for by the data assimilation method.

Figure 5 analyses the damage cost reduction by MPC in comparison to the current PLC based control strategy. Two MPC controllers are considered: ideal MPC, representing the best attainable solution by MPC, and MPC DA, in which the EnKF is applied in combination with the flexible PEM to account for model uncertainty due to seasonal vegetation. A damage cost reduction of 100% corresponds to a total damage cost of 0 EUR, while a damage cost reduction of 0% corresponds to the damage cost after applying the PLC based regulation.

For the less severe flood events (E3-E6), ideal MPC as well as MPC DA result in a damage cost reduction close to 100%. This means that no or only limited flooding occurs during these events when applying MPC. Only for event E3, MPC DA performs worse than the PLC based regulation, which has a damage cost close to 0 EUR. Due to the model uncertainty, however, MPC DA leads to a small damage cost of only 75 EUR, which is of course negligible. As the damage cost of the PLC based regulation is very low, this results in a large relative damage cost increase. Situations like these can be avoided by adapting the control objectives to provide some extra margin towards the occurrence of flood damage. Nevertheless, it can be concluded that for these four events MPC DA approaches the performance of ideal MPC as the impact of the seasonal vegetation is almost completely compensated for by the data assimilation method.

For the more severe flood events (E1, E7, E8, and E10), the introduction of seasonal vegetation results in a

larger loss in real-time control performance. The applied data assimilation approach, however, strongly reduces this loss, as shown in Figure 4. This results in high damage cost reductions by MPC DA in comparison to the PLC based regulation, as can be seen in Figure 5. Of course, these reductions are lower than in the case of ideal MPC, but the differences are limited thanks to the applied data assimilation method.

In general, MPC DA reduces the loss in real-time control performance due to seasonal vegetation by means of data assimilation and outperforms the current PLC based control strategy for all considered events.

5 | CONCLUSIONS

This study focused on the impact of model uncertainty due to seasonal vegetation growth, on the prediction accuracy and real-time flood control performance. During summer, an increase in vegetation results in a higher river bed roughness and consequently higher water levels. Seasonal vegetation can lead to inaccurate model prediction errors and lead to a deterioration of the conceptual model accuracy. In order to take the summer vegetation growth into account, a new conceptual model was calibrated based on the results of a detailed InfoWorks RS model with adjusted roughness coefficients. A quick recalibration of the existing conceptual model in which the original model structure was retained turned out to be sufficient to achieve a good level of model accuracy. The influence of seasonal vegetation on the real-time flood control performance can be limited by applying an appropriate data assimilation approach. The combination of the moving horizon estimator or the ensemble Kalman filter with the flexible prediction error method reduces on average 80% of the damage loss due to seasonal vegetation. Consequently, there is no need to

switch between different models for different vegetation scenarios as the conceptual model which represents average vegetation growth can be used throughout the whole year in combination with data assimilation. Moreover, data assimilation can automatically correct the spatial variability of the vegetation. Despite a small loss in real-time control performance due to seasonal vegetation, MPC still strongly outperforms the current PLC based control strategy thanks to data assimilation.

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DATA AVAILABILITY STATEMENT

Some or all data, models, or code generated or used during the study are available from the corresponding author by request.

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