Journal of
Flood Risk Management

Uncertainty of design water levels due to combined bed form and vegetation roughness in the Dutch River Waal

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DOI: 10.1111/jfr3.12014

Key words
Bed form roughness; classification error; flood plain vegetation; hydrodynamic modelling; river flooding; River Waal; uncertainty; vegetation roughness.

Abstract

Two-dimensional hydrodynamic models are frequently used for flood protection studies to compute inundation patterns and to estimate potential economic damage. However, the modelling of river processes involves numerous uncertainties. Knowledge of the type and magnitude of uncertainties is crucial for a meaningful interpretation of the model outcomes and its usefulness in decision making. The objective of this study was to quantify the uncertainty in the design water levels due to uncertain bed form and vegetation roughness for the Dutch River Waal. We quantified and combined these sources of uncertainty by means of a Monte Carlo simulation. The results showed that the 95% confidence interval of the design water levels is 0.49 m, 0.34 m and 0.12 m for bed form, vegetation classification and vegetation roughness parameterisation, respectively, and approximately 0.68 m for the combined roughness. These uncertainties are significant in view of Dutch river management practice.

Introduction

River flooding is an issue of international interest that costs many lives and causes large economic damage every year (Dilley *et al.*, 2005). Hydrodynamic models are commonly applied to estimate flood risk and aid strategies to improve flood protection. However, such model outcomes are inherently uncertain due to simplifications in the model set-up and uncertainty in input parameters, as is also evident from their inability to reproduce measured data at every location in time and space (Pappenberger *et al.*, 2006). A full understanding of the model and its uncertainties is important to make a meaningful interpretation of the model outcomes and to assure usefulness of model outcomes in decision making (Pappenberger *et al.*, 2006).

One of the main sources of uncertainties in hydrodynamic river models is the hydraulic roughness (Chang *et al.*, 1993; Hall *et al.*, 2005; Pappenberger *et al.*, 2006, 2008; Warmink *et al.*, 2011), which is an empirically based parameter that depends on material properties of the flow boundaries as well as on flow conditions and the modelling concept. As stated by Morvan *et al.* (2008), 'hydraulic roughness appears in fluid mechanics as a consideration at wall boundaries, to account for momentum and energy dissipation that is not explicitly accounted for in the simplified equations'. In other words, roughness is a parameterisation of the physical processes that are omitted (Huthoff, 2007; Morvan *et al.*, 2008). Roughness parameterisation for river flow models is a daunting task given the number of processes that are involved in flow energy dissipation of real river settings (e.g. Kouwen and Li, 1980; Julien *et al.*, 2002). Uncertainties in hydraulic roughness arise from the parameterisation structure, that is the equations used for roughness prediction, and from uncertainties in the data that are used for specifying the roughness parameterisations (Warmink *et al.*, 2010). Various roughness parameterisations are available for the main channel (e.g. Engelund, 1977; Van Rijn, 1984; Wright and Parker, 2004; Ministry of Transport, Public Works and Water Management, 2010) and for the flood plain areas (e.g. Van Velzen *et al.*, 2003; Baptist *et al.*, 2007; Huthoff *et al.*, 2007). These uncertainties in roughness parameterisations yield a significant uncertainty in predicted flood water levels, which according to Warmink *et al.* (2011) is only matched by uncertainty in river discharge and its impact on flood levels.

The hydraulic roughness in the main channel of many lowland rivers is dominated by the resistance caused by river bed forms, which may increase in height during flood conditions (Van Rijn, 1984; Julien *et al.*, 2002). The relation between roughness and the development of bed forms is not fully understood (e.g. Carling *et al.*, 2000; Paarlberg *et al.*, 2010), and leads to considerable uncertainties in their parameterisation (Warmink *et al*., 2012). Different available parameterisations for bed form roughness resulted in a large range of predicted roughness values (Warmink *et al*., 2012). Also, flood plain roughness, which in many lowland rivers is dominated by the presence of vegetation, is a significant source of uncertainty in predicted flood levels (e.g. Mason *et al*., 2003; Horritt, 2006; Straatsma and Huthoff, 2011). Vegetation roughness is often parameterised by a single roughness value (Horritt and Bates, 2002), and sometimes also linked to a remote sensing-based land cover map (Straatsma and Baptist, 2008). Augustijn *et al*. (2008) showed that different available vegetation roughness parameterisations diverge significantly if applied to large water depths typical for extreme discharge conditions. Horritt (2006) used a stochastic model to estimate the uncertainty for three simplified case studies: one for only channel flow, one for only flood plain flow, and one for compound flow with both channel and flood plain roughness parameters. In this study, it was found that if the considered cases became more complex (i.e. compound flow with spatial variation in topography), the model behaved increasingly non-linear. Horritt (2006) showed that the stochastic linear model proved to be able to quantify the uncertainty even in case of the non-linear nature of shallow water equations and their non-linear dependence on the roughness parameter. However, the author stated that if the uncertainty in all parameters is concerned, more research is required to determine whether spatial variability of roughness is significant relative to other uncertainty sources. On that subject, Straatsma and Huthoff (2011) quantified the uncertainty in 2D hydrodynamic models from uncertainties in roughness parameterisation based on aerial images. They showed that uncertainties related to spatial classification of vegetation had a large effect on uncertainties in predicted water levels.

Until now, the combined effect of uncertainties in spatial vegetation classification and bed form roughness parameterisation has not been quantified. Therefore, the objective of this study was to quantify the uncertainty in the design water levels due to uncertain bed form and vegetation roughness for the Dutch River Waal. We addressed the following sources of uncertainty: (1) the bed form roughness of the main channel, (2) the classification error of flood plain vegetation and (3) the choice of vegetation roughness parameterisation. To quantify the impact of these uncertainties on design flood water levels, we utilised a 2D hydrodynamic model of River Waal in the Netherlands.

Study area and model

Study area

River Waal is the largest distributary of River Rhine in the Netherlands (Figure 1). With an annual average discharge of 2250 m^3/s, River Rhine bifurcates into the Pannerdensch Kanaal and River Waal, 20 km after entering the Netherlands. River Waal has a length of 93 km, and roughly 2/3 of the total discharge in the Rhine is directed towards the Waal. The width of the main channel of River Waal between the groynes is 280 m on average (Yossef, 2005), and the cross-sectional width between the embankments varies between 0.5 km and 2.6 km (Straatsma and Huthoff, 2011). The total embanked area of River Waal in the Netherlands is about 184 km^2, including the main channel, the groyne fields and the flood plain areas. The flood plain area and groyne fields together make up 73% of the total embanked area. The land cover of the flood plains is dominated by meadows, but recent nature rehabilitation has led to increased areas with herbaceous vegetation, shrubs and forest (Straatsma and Huthoff, 2011). The Waal has an average water level gradient of 0.11 m/km (Middelkoop and van Haselen, 1999).

WAQUA model

In the Netherlands, the two-dimensional hydrodynamic river model, WAQUA, is the official standard for calculating design water levels for flood protection measures based on a design discharge wave (Rijkswaterstaat, 2007), and for determining the hydrodynamic effects of landscaping measures. The design discharge corresponds to a return period of 1250 years and a magnitude of 16 000 m^3/s at the Dutch–German border (Rijkswaterstaat, 2007). The WAQUA model consists of the discretised two-dimensional shallow water equations using a finite difference method to simulate the water flow, empirical equations to approximate energy losses and a schematisation of the river (Rijkswaterstaat, 2007) for a certain period with corresponding input parameters (e.g. stage-discharge relations, river bed roughness, upstream discharge). We used the 2007 version of the WAQUA model for River Waal for a steady case, which was based on a staggered curvilinear grid with 148 334 grid cells with a cell size of approximately 40 × 40 m. The model simulates water depths from 867 km to 960 km, along the river (Figure 1). The digital elevation model of River Waal was based on multibeam echo-sounding data for the main channel, and laser altimetry and photogrammetry data for the flood plains.

A constant discharge of 10 667 m^3/s was set as the upstream boundary condition, which is two third of the design discharge at station Lobith, as approximately two third of the design discharge flows into River Waal. The exact discharge fraction into the Waal is uncertain and depends on many factors (Rijkswaterstaat, 2007), but this uncertainty was not taken into account in this study. The downstream boundary condition near Werkendam was set to a constant water level of 4.8 m above Dutch ordnance datum (NAP), following Rijkswaterstaat (2007). A single simulation takes about 2.5 h on a 2.6 GHz computer with 4 GB of memory.

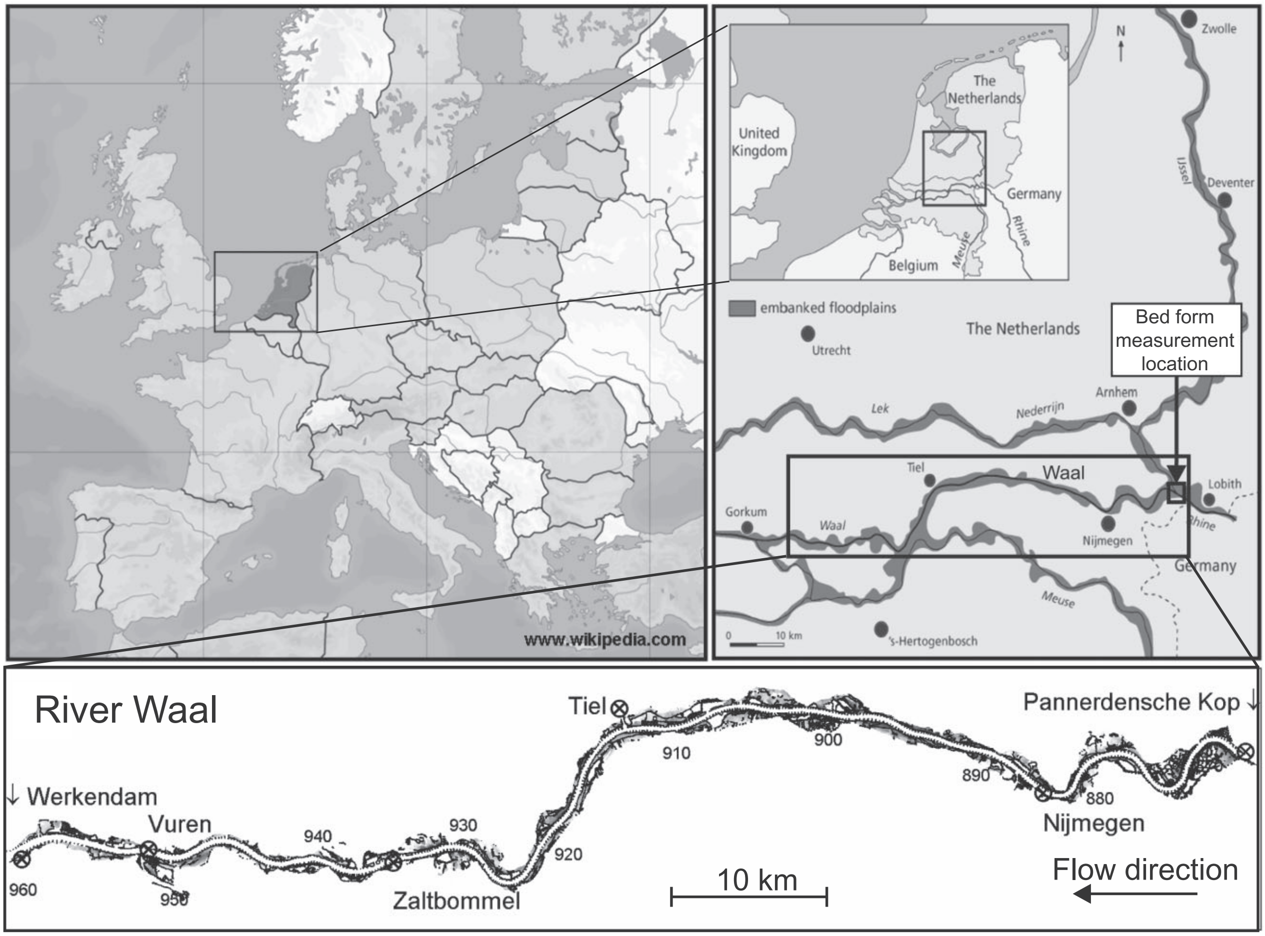

Figure 1 Study area. (top) Location of River Waal distributary in the Netherlands. (bottom) WAQUA model domain of River Waal; the numbers refer to the river kilometres, and the names refer to the water level measurement stations.

Hydraulic roughness

In the WAQUA model, the roughness of the main channel is expressed as an equivalent grain roughness [Nikuradse, k_N (m)] to represent the combined effect of grain roughness and roughness due to bed forms (ripples and subaqueous dunes). The roughness of the main channel is computed using a parameterisation of roughness based on the Van Rijn (1984) roughness model:

$$k_N = \alpha h^{0.7}\left(1 - e^{-\beta h^{-0.3}}\right)$$

where k_N is the roughness expressed as a Nikuradse roughness length (m), h is water depth (m), and α and β are calibration coefficients. Nikuradse roughness is related to the internationally more common Manning's n as $k_N = (n/0.04)^6$ (Van Rijn, 2011). In the WAQUA model, the Nikuradse roughness for a particular cell is converted to a Chézy value using White-Colebrook.

In current practice, the model is calibrated by adapting the roughness for each section between the six measurement stations (see Figure 1). Calibration was carried out such that the model adequately reproduces maximum water levels of the highest recorded discharge wave, which occurred in 1995 and which had a magnitude of 75% of the design discharge (Rijkswaterstaat, 2007). After calibration, the model results differ by ± 7 cm (Van den Brink *et al.*, 2006; Warmink *et al.*, 2007).

The roughness of the flood plains was derived from ecotope maps, scale 1:10 000 (Jansen and Backx, 1998), which were transformed into vegetation roughness types, following the method proposed by Van Velzen *et al.* (2003). In the model implementation, vegetation types were linked to average vegetation structural parameters, such as vegetation height and density, and a drag coefficient. The structural parameters were used as input in the vegetation roughness parameterisation, as proposed by Klopstra *et al.* (1997), which relates vegetation types to equivalent roughness (see also Appendix A and Van Velzen *et al.*, 2003). WAQUA computes a spatially varying and stage-dependent roughness value at run time for the flood plain area.

Methods

Uncertainty in hydraulic roughness consists of many different sources. For a structured and reliable uncertainty analysis, it is required to identify the individual sources of uncertainties before quantification is possible (Warmink *et al.*, 2010). In this study, we combined uncertainty derived from three sources: (1) bed form roughness of the main channel, (2) vegetation roughness due to classification errors of flood plain land cover and (3) vegetation roughness due to the choice of the roughness parameterisations. The method for deriving uncertainty from bed form roughness of the main channel and vegetation classification was performed in previous research by Warmink *et al.* (2012), and Straatsma and Huthoff (2011), respectively. In this research, the method for the third source is introduced, and the three sources are combined to capture their cumulative effect. The first two subsections describe uncertainty of bed form and vegetation classification. The third subsection presents a detailed description of the quantification of the vegetation roughness parameterisation uncertainty.

Uncertainty of bed form roughness parameterisation

The quantification of the uncertainty due to bed forms was carried out by Warmink *et al.* (2012). They selected five roughness parameterisations that predict the bed form roughness, based on measurements of bed form and flow characteristics: Van Rijn (1984), Vanoni and Hwang (1967), Engelund (1977), Haque and Mahmood (1983), and Wright and Parker (2004). The measurements from Wilbers and Ten Brinke (2003), and Julien *et al.* (2002), were used as input for the roughness parameterisations, which consisted of bed forms and flow measurements during three large discharge waves in River Rhine. The five roughness parameterisations were applied to predict the roughness for the measured flow conditions in River Waal. Subsequently, the generalised extreme value distribution (Coles, 2001) was used to extrapolate the predicted roughness values for each parameterisation to a return period of 1250 years. Figure 2 shows the resulting distribution of the roughness at the design return period, where the different colours refer to the individual roughness parameterisations. The combined 95% confidence interval of the Nikuradse roughness length (k_N) for the main channel of River Waal under design conditions ranged from 0.32 m to 1.03 m, with a positively skewed distribution, where skewness is the third moment of a distribution and is a measure of the asymmetry of the data around the sample mean.

Vegetation classification error

Straatsma and Huthoff (2011) quantified the uncertainties in flood plain vegetation due to the classification error, the

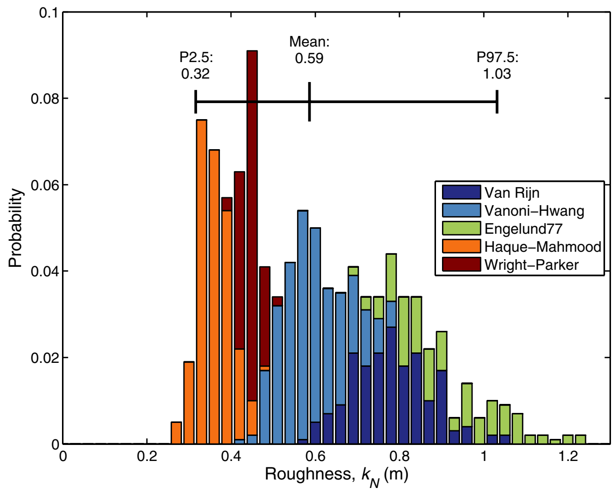

Figure 2 Uncertainty in the bed form roughness under design conditions. These data were quantified by Warmink *et al.* (2012). The different colours represent the five bed form roughness parameterisations. Furthermore, the mean and 95% confidence interval of the combined distribution are shown.

mapping scale (i.e. the spatial resolution) and the vegetation characteristics. They showed that the respective 68% confidence intervals in the design water levels for these flood plain uncertainty sources are 0.32 m, 0.05 m and 0.01 m along River Waal. Thus, the classification error of the flood plain vegetation was identified as the main source of uncertainty in flood plain roughness at a mapping scale of 1:10 000. Quantification of the classification error of the vegetation types along the Rhine branches was based on the work by Knotters *et al.* (2008), who referred this type of error as 'map purities'. The authors noted that overall the classification accuracy was rather low; only 69% of the polygons were correctly classified when aggregated to eight broad land cover classes.

To generate equally probable roughness maps of the flood plains, we followed the method presented in Straatsma and Huthoff (2011), which will not be iterated here. Straatsma and Huthoff (2011) used 15 samples for their Monte Carlo simulation to limit computational time. Due to the smaller model domain, we drew 500 samples for our Monte Carlo simulation and generated 500 realisations of the flood plain roughness. Each realisation has the same probability and can be seen as a different outcome of the same manual procedure of creating the ecotope map (Straatsma and Huthoff, 2011).

Uncertainty of vegetation roughness parameterisation

Selection of vegetation roughness parameterisations

Several parameterisations have been proposed to describe vegetation roughness of flood plains in terms of vegetation structure parameters (e.g. Petryk and Bosmajian, 1975; Kouwen and Li, 1980; Klopstra *et al.*, 1997; Baptist *et al.*, 2007; Huthoff *et al.*, 2007). Among these, a clear distinction is made between parameterisations for non-submerged and submerged vegetation. For non-submerged vegetation, there is a high degree of consensus about the equation used for roughness prediction (Baptist *et al.*, 2004). If the vegetation becomes submerged, the energy losses above the canopy of the vegetation become important. This process is poorly understood (Nepf and Vivoni, 2000), and subsequently different roughness parameterisations exist to account for these energy losses. For example, several relationships have been developed that link the effective roughness to the product of velocity (V) and the hydraulic radius (R), and some measure for the presence of vegetation (e.g. vegetation height; Fisher and Dawson, 2003). However, these so-called *VR* methods have little theoretical justification (Kouwen and Li, 1980; Smith *et al.*, 1990; Bakry *et al.*, 1992), and are therefore unreliable if applied outside of calibration conditions. Also, vegetation roughness parameterisations have been proposed that account for flexibility of vegetation (e.g. Kouwen and Li, 1980; Mason *et al.*, 2003; Järvelä, 2004). These parameterisations require a species-specific vegetation index, which is difficult to determine in the field because of the heterogeneity of natural vegetation (Straatsma and Baptist, 2008). Therefore, these parameterisations have limited practical applicability until values of the species-specific vegetation index are available for typical species of natural vegetation (Järvelä, 2004). Process-based roughness parameterisations have been proposed in which vegetation is treated as a collection of rigid cylinders. This approach assumes that the deflection of vegetation is negligible, which is the case for most Dutch flood plains. Streamlining of leaves does not present a large problem either as flood season lasts from November to March.

In this study, we considered four vegetation roughness parameterisations based on the rigid cylinder approach that relate vegetation height and density to roughness, as proposed by Klopstra *et al.* (1997), Van Velzen *et al.* (2003), and Huthoff *et al.* (2007), and the parameterisation derived from genetic programming from Baptist *et al.* (2007) (see Appendix A). From now on, these parameterisations are referred to as Van Velzen, Huthoff and Baptist. It is important to note that these parameterisations reduce to the Petryk and Bosmajian (1975) equation for flow conditions with non-submerged vegetation.

Performance of vegetation roughness parameterisations for flume and field conditions

The performance of the selected four rigid cylinder-based roughness parameterisations was tested against, by comparing with the flume data series of Meijer (1998a, b). These data resulted from flow studies with rigid cylinders and natural reed. The flume was 100-m long, 3-m wide, and vegetation was placed over a length of 22 m. The water depths ranged between 1 m and 2.5 m, vegetation height between 0.45 m and 1.65 m, and vegetation densities (A_r), which is the product of the number of stems per square meter and the average diameter of the stems, D, ranged between 0.5 m^{-1} and 2 m^{-1}. The performance of the roughness parameterisations was expressed by the Nash–Sutcliffe coefficient (NS: Nash and Sutcliffe, 1970), which represents the predictive power of a model. Possible values for NS vary between 1, indicating a perfect match between observed and predicted values, via 0, indicating that the model predictions are as accurate as the average of the observed roughness values, to minus infinity, which indicates that the average value is a better predictor than the parameterisation.

Subsequently, the parameterisations were applied to field conditions during design discharge with water depths up to 10 m. This will show deviations at conditions that exceed the capacities of flume studies. Augustijn *et al.* (2008) showed that the roughness of vegetation for water depths that are much larger than the vegetation height becomes increasingly uncertain. Therefore, to account for this large uncertainty in vegetation roughness at well-submerged conditions, we assumed that these four roughness parameterisations are equally valid to predict the roughness of flood plain vegetation for River Waal.

Implementation of vegetation roughness parameterisations in WAQUA-Waal

The WAQUA model only allows specification of constant roughness heights or utilisation of the Klopstra parameterisation to account for flood plain vegetation roughness. Therefore, the Van Velzen, Huthoff and Baptist parameterisations are approximated in the WAQUA model by using either best-fitting settings of the parameters that are used as input for the Klopstra parameterisation or a constant roughness height. To approximate the Van Velzen and Huthoff parameterisation, we adapted the vegetation drag (C_D) and vegetation height (k), which are used as input for the Klopstra equation for each vegetation type. These sets of C_D and k values were determined by minimising the mean squared error (MSE) between the parameterisations of Van Velzen and Huthoff on the one hand, and the adapted Klopstra parameterisation on the other hand. These adapted sets of input values are further referred to as the proxies for the Van Velzen, Huthoff and Baptist parameterisations. The MSE was computed for the water depths that occur under design conditions, namely 6.1 m on average with a 95% confidence interval of 3.3–9.7 m, which is approximately normally distributed. Therefore, we computed the MSE for water depths within this range. The Baptist parameterisation showed a

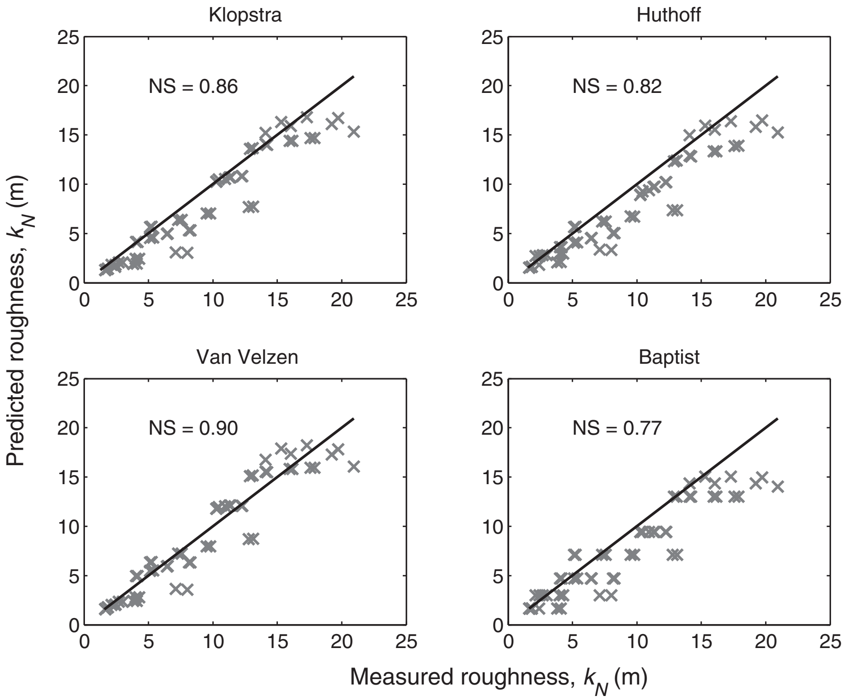

Figure 3 Performance of the four vegetation roughness parameterisations for the Meijer (1998a, b) data of submerged vegetation. The solid line represents the line of perfect agreement, and NS refers to the Nash–Sutcliffe coefficient.

constant roughness for submerged vegetation for different water depths. Therefore, we imposed a constant Nikuradse roughness height (k_N) in the WAQUA model to approximate the Baptist parameterisation.

Monte Carlo simulations

We determined the effects of the three sources of uncertainty in a Monte Carlo simulation using the WAQUA-Waal model. First, we carried out a reference run, in which all variables were set to their calibrated value, which were used for the computation of the design water levels by the Dutch Centre for Water Management (Rijkswaterstaat, 2007). Subsequently, five sets of Monte Carlo runs were carried out, with 500 samples each. Three of these sets corresponded to the individual roughness uncertainty sources: the bed form roughness, vegetation classification error and vegetation roughness parameterisation. For the bed form roughness, we randomly drew samples from the distribution shown in Figure 2, and for the classification error the 500 realisations were used, as described above in this paper. For the vegetation roughness parameterisation, four runs were carried out for each of the parameterisations, and afterwards 500 samples were drawn with equal probability to be able to compute the 95% confidence interval. The fourth set of 500 runs was carried out with both the bed form roughness and the vegetation classification error combined, and the fifth set of 500 runs was carried out incorporating all three sources of uncertainties. Because the three sources of uncertainty are independent, randomly drawing a roughness value from Figure 2, a realisation of the flood plain vegetation and a vegetation roughness parameterisation yielded a reliable estimate of the distribution of the water levels. At the end of the results section, we show that 500 samples proved to be sufficient for a reliable estimate of the 95% confidence interval of the water levels.

At the downstream boundary of the Waal model, uncertainties in water levels were suppressed because of the imposed fixed water level boundary condition. Through backwater effects, this downstream model boundary impacted water levels up to approximately 25 km further upstream (up to station Zaltbommel). Therefore, the uncertainties in this river reach were unreliable and were not further considered in the uncertainty analysis. Detailed results of the uncertainty analysis are, therefore, presented at a representative location at river kilometre 893 (close to the city of Ewijk), which is 67 km upstream from the downstream model boundary.

Results

Vegetation roughness parameterisations

Figure 3 shows that all four roughness parameterisations performed well for this dataset. The NS values show that the

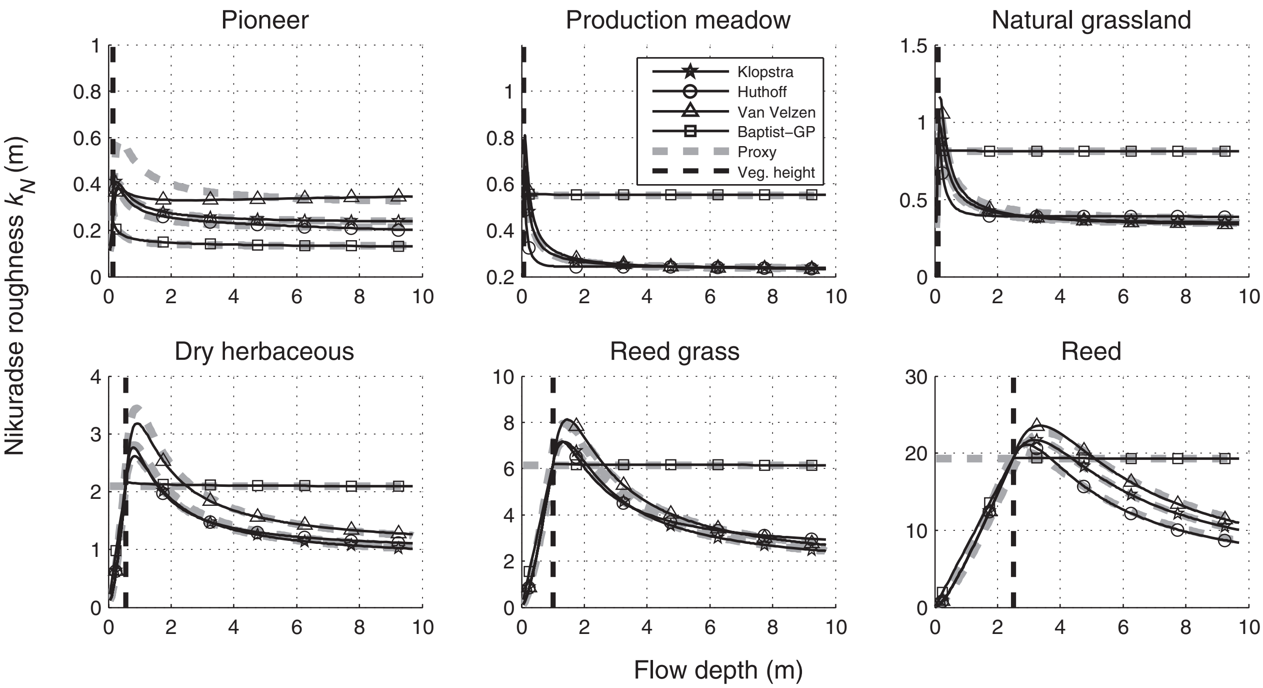

Figure 4 Predicted roughness for the vegetation roughness parameterisations for six submerged vegetation types. The solid lines with the symbols represent the four vegetation roughness parameterisations, the grey, dashed lines show the proxy (i.e. the fitted model) that was implemented in the WAQUA model. The vertical, dashed lines represent the vegetation height.

Van Velzen parameterisation performs slightly better than the other parameterisations. All parameterisations show a small underestimation of the roughness. It is noted that the data from Meijer (1998a, b) were part of the calibration dataset for the vegetation roughness parameterisations of Klopstra, Huthoff and Van Velzen.

Figure 4 shows the predicted roughness of the same four roughness parameterisations for varying water depths. This figure shows that the Klopstra, Van Velzen and Huthoff parameterisations have a similar trend, while the Baptist roughness parameterisation shows a quite different trend. For each parameterisation, the Nikuradse roughness increases with increasing water depth, up to the point where the vegetation becomes submerged. At that point, the Klopstra, Van Velzen and Huthoff parameterisations show an initial increase of the roughness up to approximately two times the vegetation height, and then a decrease of the roughness with increasing water depth. In contrast, Baptist's parameterisation shows an almost constant roughness height with changing water depth in case of submerged vegetation.

Table 1 shows the sets of parameters (i.e. the proxies) that were used to approximate the Van Velzen, Huthoff and Baptist vegetation roughness parameterisations, and Figure 4 shows the behaviour of the roughness parameterisations for the six submerged vegetation types. For example, for the pioneer vegetation type, the Huthoff parameterisation predicted a slightly smaller roughness than the original Klopstra parameterisation, which was approximated by a decrease in the k and C_D values, from 0.15 m and 1.8 m for the Klopstra parameterisation to 0.135 m and 1.45 m for the proxy of the Huthoff parameterisation. For the Van Velzen parameterisation, the roughness of the proxy overestimated the original Van Velzen parameterisation for low water depths, but slightly underestimated the roughness for high water depths. On average, the error that was made in the proxies had little influence on the computed uncertainties.

Reference run

Figure 5(a) shows the spatially distributed water depths for the reference run. The water depth in the main channel was about 13.5 m, while the water depth in the flood plains varied from 20 m for some deep lakes to 6 m for the vegetated areas. The roughness in the main channel had a standard deviation of 0.2 m, with an average of 0.59 m, while the roughness of the flood plains was spatially variable. The average flood plain roughness for the 500 realisations is shown in Figure 5(b) at the location where the results are reported (river kilometre 893). This figure shows that the roughness of the flood plains was generally much larger than the roughness of the main channel. Furthermore, comparison of Figure 5(b) and (c) illustrates that generally high roughness values correlated with regions with relatively high bed elevations (i.e. low water depths in Figure 5).

Table 1 Parameters for the Klopstra vegetation roughness model and adapted parameters as proxy for the Huthoff, Van Velzen and Baptist models

			Klopstra				Error range proxy		
							Huthoff	Van Velzen	Baptist
	r_code	Cov	k_N	A	k	C_D			
Roughness class		(%)	(m)	(m^{-1})	(m)	(-)			
Main channel (Type 0)								Variable	
Main channel roughness	102	31.0	var.					k_N: 0.28–1.24	
Type 1								Deterministic	
Groyne field/sand bar	111	1.4	0.15						
Stone protection	113	0.0	0.3						
Build-up area/paved	114	2.7	0.6						
Agricultural area	121	3.6	0.2						
Type 2									
Pioneer vegetation	1250	0.4	0.1	0.15	0.15	1.8	k:0.135 C_D:1.45	k:0.195 C_D:2.65	k:0.06 C_D:2.5
Production meadow	1201	13.2	0.1	45	0.06	1.8	k:0.063 C_D:2.3	k:0.061 C_D:2.35	k_N:0.55
Natural grass/hayland	1202	15.5	0.1	12	0.1	1.8	k:0.11 C_D:1.6	k:0.1 C_D:1.15	k_N:0.81
Type 3									
Dry herbaceous vegetation	1212	4.2	0.1	0.23	0.56	1.8	k:0.56 C_D:2.1	k:0.62 C_D:2.45	k_N:2.1
Reed grass	1804	0.6	0.1	0.4	1	1.8	k:1.00 C_D:2.6	k:1.10 C_D:1.6	k_N:6.15
Reed	1807	1.0	0.1	0.37	2.5	1.8	k:2.25 C_D:2.3	k:2.75: C_D:1.3	k_N:19.3
Type 4								Deterministic	
Softwood shrubs	1231	3.0	0.4	0.13	6	1.5			
Willow plantation	1232	0.1	0.4	0.041	3	1.5			
Thorny shrubs	1233	0.5	0.4	0.17	5	1.5			
Softwood product. forest	1242	1.4	0.3	0.01	10	1.5			
Hardwood forest	1244	0.1	0.4	0.023	10	1.5			
Softwood forest	1245	2.4	0.6	0.028	10	1.5			
Total		81.2							

The default vegetation structure parameters A_r, k and C_D are taken from Van Velzen *et al.* (2003).

Uncertainty due to bed form roughness

Based on the 500 sampled roughness values of the main channel shown in Figure 2, the variation in the water level was computed using the WAQUA-Waal model. Figure 6(a) shows the variation in water levels from the 500 simulations. The 95% confidence interval was relatively uniform along the main channel centreline upstream of river kilometre 935. This is because, for each simulation, the main channel roughness was set to a uniform value for the whole river. Slightly smaller ranges in water levels correlated positively with regions that have relatively wide flood plains. The regions between river kilometre 920 and 900 have slightly wider flood plains than the regions between 940 and 920, and 900 and 880 (see lower frame in Figure 1), which show a 5-cm smaller confidence interval.

Figure 6(b) shows the histogram of the water levels at river kilometre 893. At this location, the 95% confidence interval of predicted water levels ranges from 14.07 m to 14.56 m above mean sea level (NAP) with a mean of 14.29 m, which is an interval of 49 cm. The histogram of the input samples (Figure 2) shows a positively skewed distribution. The skewness of the roughness samples was 0.68, while the skewness of the resulting water levels was 0.15 (see Table 2). This shows that high roughness values for the main channel do not necessarily result in extreme water levels but are partly compensated by a higher discharge through the flood plain regions.

Uncertainty due to vegetation classification errors

The effect of the classification error of the flood plain vegetation on the water level is shown in Figure 6(c) and (d). The width of the 95% confidence interval was not uniform along the river. The 95% confidence interval at river kilometre 893 ranged from 13.93 m to 14.27 m, with a mean of 14.03 m. This 34-cm interval was slightly smaller than the effect due to bed form roughness. The histogram in Figure 6(d) shows a strongly positively skewed distribution with a skewness of 1.6. Outliers were observed along the river between river kilometre 890 and 935. These outliers were caused by randomly sampled combinations of vegetation types, which resulted locally in a strong increase of the flood plain roughness. Especially at locations with a small width of the flood plains, such as river kilometre 893 (bridge at Ewijk)

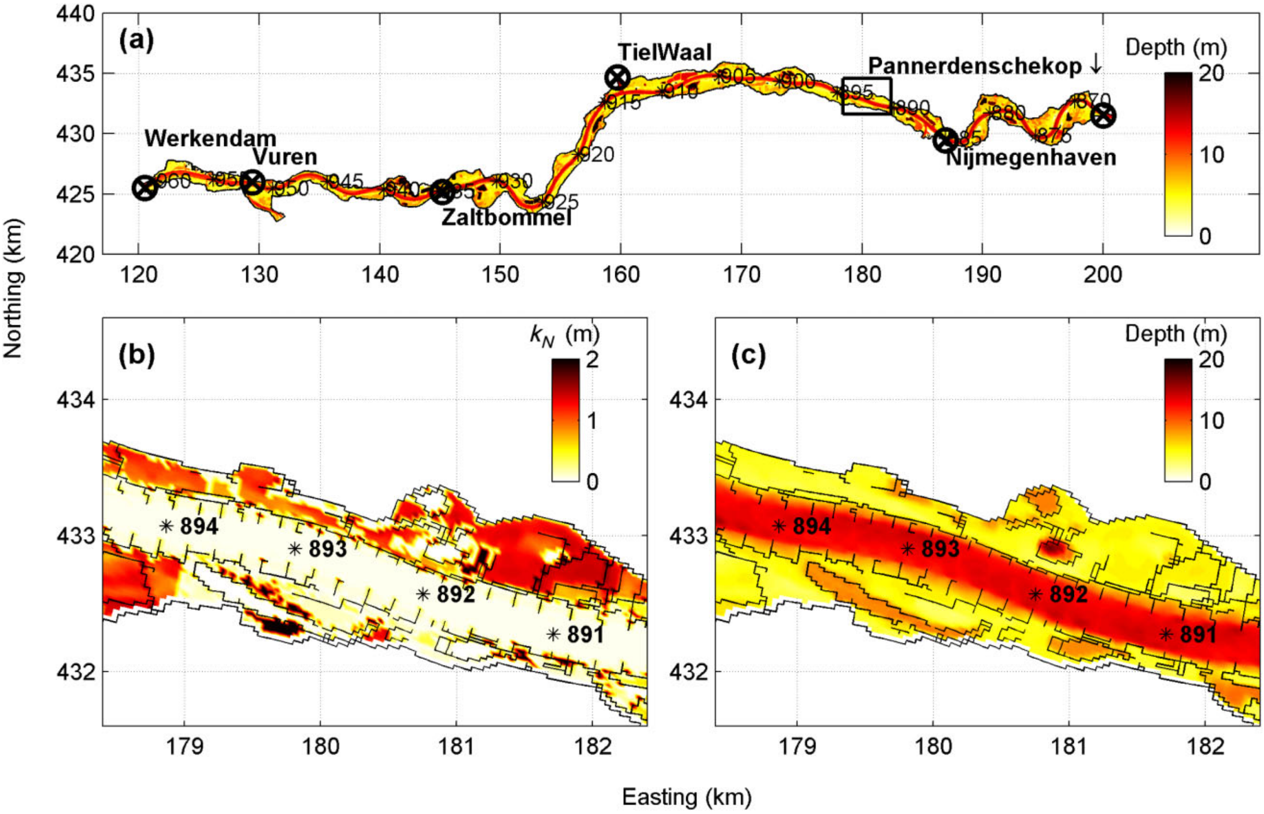

Figure 5 (a) Results of the reference run showing the water depth. (b) Input for the Monte Carlo simulation showing the average roughness of the 500 realisations (i.e. combined bed form and classification error). The main channel had an average roughness of 0.59, while the average of the flood plains was spatially variable. (c) Results of the Monte Carlo simulation showing the average water depths for the 500 simulations. Water depths in the main channel were around 13.5 m, while water depths in the flood plain areas were on average 6 m.

and river kilometre 909 (Willem-Alexander bridge), the water levels are very sensitive to increased roughness of the flood plains. Combinations of vegetation types that led to extremely smooth flood plains were also present in the input samples but proved to have less influence on the water levels. Consequently, the uncertainty due to classification error led to a rise in the average predicted water level (Table 2) compared with the reference run.

We assumed that the individual polygons had no spatial correlation and that the classification error was random without bias. As a result, the classification errors may partly have cancelled each other, if at a certain location a polygon was assigned a higher roughness, while in the same realisation at nearby locations polygons might be assigned a low roughness. Omitting the spatial correlation and bias might, therefore, result in an underestimation of the uncertainty in the design water levels.

Uncertainty due to the vegetation roughness parameterisation

The application of the four vegetation roughness parameterisations resulted in a small variation in the design water levels (Figure 6(e) and f). For each of the 500 samples, we randomly selected one of the four roughness parameterisations (with equal probability for each parameterisation). This yielded a 95% confidence interval of 12 cm, which is small compared with the uncertainty due to main channel roughness and vegetation classification. The proxies for the roughness parameterisations of Klopstra, Huthoff and Van Velzen resulted in a variation in the water levels of 0.003 m, which is negligible. This was already shown in Figure 4, where little variation is shown between the predicted roughness values from these parameterisations. Only the Baptist parameterisation, which is similar to adopting a constant roughness height for submerged vegetation, resulted in an increase of the water levels of 12 cm.

Combined uncertainty in design water levels

Figure 6(g) shows the variation in design water levels due to the combined effect of uncertainty in main channel roughness and classification error. In this set of simulations, only the Klopstra vegetation roughness parameterisation was used. This figure shows a combination of the relatively uniform 95% confidence interval for uncertain bed form

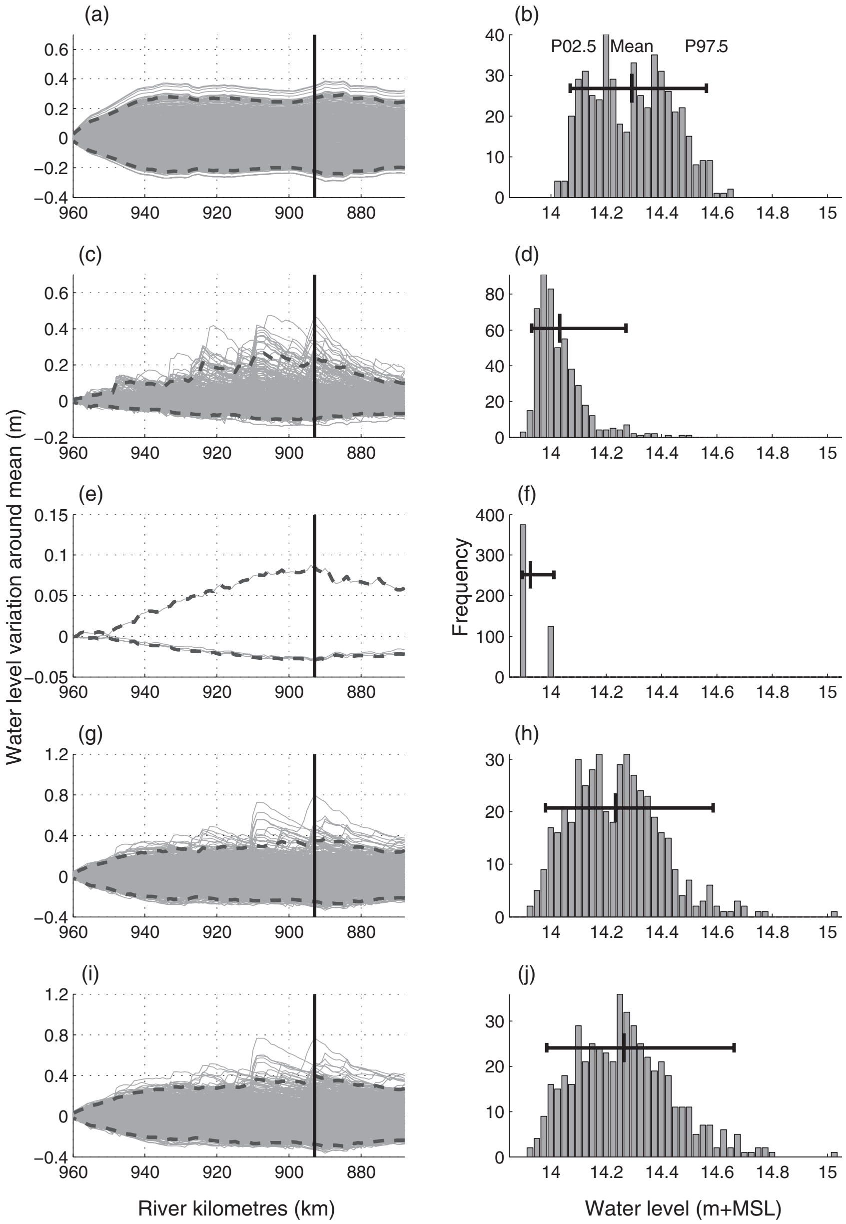

Figure 6 Variation in the design water levels. Due to (a,b) uncertain bed form roughness, (c,d) classification error of vegetation type, (e,f) uncertain vegetation roughness parameterisations, (g,h) uncertain bed form roughness and classification error, (i,j) results for all sources combined. Left column figures show the variation of the water levels around the average along the main channel centreline; the right column figures show the histograms of the water levels at river kilometre 893.

Table 2 Water level results from the five Monte Carlo simulations and the reference run

Simulation	P 2.5	Mean	P 97.5	95% CI	Std	Skewness
Reference run		13.95				
Bed form roughness	14.07	14.29	14.56	0.49	0.14	0.15
Classification error	13.93	14.03	14.27	0.34	0.087	1.87
Vegetation roughness model	13.90	13.93	14.01	0.12	0.057	1.15
Bed form + classification	13.98	14.23	14.59	0.61	0.16	0.71
All variable	13.99	14.26	14.66	0.68	0.18	0.60

The values of the 2.5 and 97.5 percentiles, mean water level at main channel centreline, 95% confidence interval, standard deviation, and skewness are given.

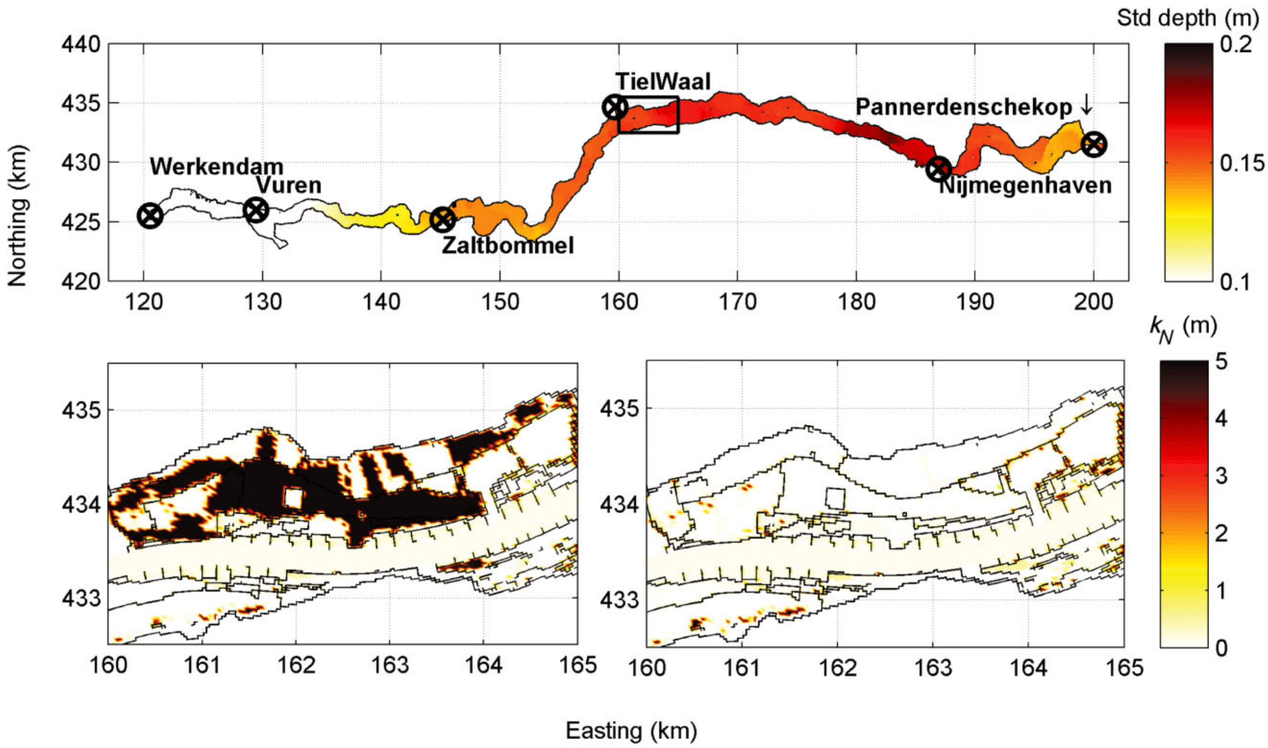

Figure 7 (Top) Standard deviation of the water levels due to the three sources of uncertainty combined. The lower panels show the Nikuradse roughness, k_N of two individual realisations that caused (left frame) the highest water level and (right frame) the lowest water level.

roughness and the irregular 95% confidence interval due to classification error. Figure 6(h) shows the 95% confidence interval at river kilometre 893, which ranges from 13.98 m to 14.59 m, with a mean of 14.23 m. The shape of the histogram shows a broad peak, which is caused by the variation in main channel roughness, and some positive outliers, which are caused by the classification error. This resulted in an increase of the 95% confidence interval from 49 cm and 34 cm for the respective individual bed form and vegetation classification errors to 61 cm for both uncertainty sources combined.

Figure 7(a) shows that the standard deviation of the computed water levels varied between 0.15 m and 0.2 m for the combined effect of all three sources of uncertainty. Generally, the standard deviation was relatively uniform along the river because backwater effects smoothen the effects of local roughness variations. Figure 7 (lower panels) shows two roughness realisations that caused the highest and lowest water level. A comparison revealed that in this particular flood plain section, a large area that was classified as meadows in the realisation shown in the right panel was replaced by softwood forest in the realisations shown in the left panel. This change in vegetation type caused a significant rise in the hydraulic roughness and resulted in an increase in the water levels.

Figure 6(i) and (j) show the simulated water levels for all three sources of uncertainty combined. Figure 6(j) and Table 2 show that the 95% confidence interval ranges from 13.99 m to 14.66 m at river kilometre 893, which is a range of 68 cm, with a skewness of 0.60. This shows that the uncertainty due to the vegetation roughness parameterisations increased the uncertainty from 61 cm to 68 cm. Therefore, we can conclude that the uncertainty due to the vegetation roughness parameterisation is less important than the uncertainty due to the main channel roughness and the vegetation classification error. To reduce the uncertainties in the design water levels, the effort should be focused on improving the bed form roughness parameterisation and on the classification accuracy of the land cover map, which is used as input for flood plain roughness parameterisation.

Accuracy of Monte Carlo simulation

The width of the confidence intervals in Figure 6(i) is relatively uniform (upstream of river kilometre 930), in longitudinal direction, which shows that the reported uncertainty statistics are not very sensitive to the location along the river, and the histogram in Figure 6(j) is therefore representative for the river reach. Only the confidence interval of the classification error shows variation in longitudinal direction.

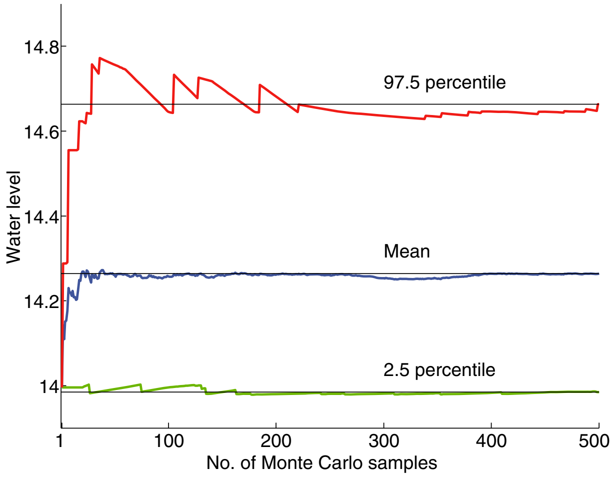

Figure 8 Stability analysis of the Monte Carlo Simulation for the three combined sources of uncertainty showing the values of the mean, lower and upper percentiles of the water levels (m above MSL) as function of the number of simulations.

This is caused by the outliers that are located in the centre part of the study area.

The number of simulations that was used for the Monte Carlo simulation influenced the accuracy of the results (Figure 8). For the set of simulations with the three combined sources of uncertainty, Figure 8 shows the convergence of the mean, the 2.5 percentile and the 97.5 percentile as a function of increasing number of simulations. The mean and 2.5 percentile converged to a constant value, while the 97.5 percentile still shows some noise. These variations of the mean and 2.5 percentile were small compared with the width of the confidence interval of 0.68 m (Table 2). More runs would have resulted in an increased accuracy of the 97.5 percentile, and therefore in the width of the confidence interval. However, as a single run takes 2.5 h of computer time, more runs cost too much time. Given the sensitivity of the results for the assumptions in the quantification of the sources (Warmink *et al.*, 2012), an increase in the number of samples will not significantly increase the accuracy of the results.

Discussion

In this paper, we applied Monte Carlo simulations to explicitly quantify flood water level uncertainty for a combination of uncertainty sources in hydrodynamic river model settings. We included the uncertainty due to bed forms, vegetation classification and the choice for the vegetation roughness parameterisation. In contrast, Pappenberger *et al.* (2006) studied the effect of uncertain boundary conditions and model structure on the uncertainty of inundation predictions for a 1D model on River Alzette. They concluded that the relative importance of any source of uncertainty depends largely on the topographical and hydraulic conditions in the reach. This observation is in agreement with our observation that the uncertainty due to main channel roughness depends on the width of the flood plain, which is locally variable. However, since River Waal is still relatively straight (sinuosity of 1.1; Julien *et al.*, 2002), with quite uniform flood plains, the effect of spatially variable roughness resulted in a relatively uniform uncertainty in the water levels along the river. This implies that for operational flood forecasting in case of a river with relatively constant width, the propagation of the uncertainties can be computed using a simple model based on cross-sections, which is a large advantage for management practice and significantly reduces the computational time. For other less uniform and less straight rivers, the uncertainty statistics will have a more local nature, and should therefore be treated as such.

In the current study, several debatable assumptions were made in the quantification of the vegetation parameterisation uncertainty, such as the selection of considered vegetation parameterisations and the utilisation of best-fitting proxies in the river flow simulations. However, the effect of this uncertainty source on flood water levels proved to be small compared with the uncertainties that are related to bed form parameterisation and flood plain vegetation classification. Including additional alternative vegetation roughness parameterisations, such as those proposed by Yang and Choi (2010) and Stone and Shen (2002), may increase the uncertainty of flood water levels, but even then the impact of uncertain vegetation roughness parameterisation is likely to remain a minor contributor to overall flood level uncertainty. In this respect, it is important to note that the parameterisation of Yang and Choi (2010) resembles the parameterisation of Huthoff. Furthermore, Augustijn *et al.* (2011) showed that the Stone and Shen (2002) parameterisation performed badly for flume data and showed some physically incorrect behaviour. Other vegetation roughness parameterisations should, thus, be favoured over Stone and Shen's (2002) proposed approach. As mentioned in the Selection of Vegetation Roughness Parameterisations section, the parameterisations accounting for flexibility of vegetation were not considered because the required input data are not available for River Waal. Furthermore, we omitted the uncertainty in the value of the C_D parameter, which might be significant according to some earlier studies (e.g. Nepf and Vivoni, 2000; Baptist, 2005), and may have important consequences for flow through non-submerged vegetation, such as forest-type vegetation. However, for vegetation types with large submergence ratios, the drag coefficient becomes less important because the portion of flow through the vegetation becomes relatively small and the flow over vegetation is more sensitive to the vegetation height. Follow-up studies should surely also take uncertainty in the drag coefficient into account.

In some previous Monte Carlo studies of roughness parameterisations (Romanowicz and Beven, 1998; Aronica *et al.*, 2002; Bates *et al.*, 2004), it was suggested that for the main channel, a uniform statistical distribution best describes the uncertainty in the bed roughness values. Horritt (2006), on the other hand, stated that a Gaussian description is quite suitable, for example as a result of a calibration process. In our study, we showed that it is possible to explicitly quantify the statistical distribution of uncertainty in the hydraulic roughness. The uncertainty distribution of the main channel roughness showed an approximately normal shape, and the distribution of the vegetation roughness more closely follows a log-normal type of distribution. Following the approach demonstrated here, there was no need to make *a priori* assumptions on the shape and magnitude of the distribution of the roughness values as these were explicitly quantified. Propagation of the uncertainty through the WAQUA-Waal model revealed that the shape of the uncertainty distribution changed, indicating non-linear effects and showing that the interactions between channel and flood plain roughness are important for the uncertainty in the design water levels.

Horritt (2006) stated that more research is required to determine whether uncertainty in the spatial variability of roughness is significant relative to other sources, such as the main channel roughness or the upstream boundary condition. Our study showed that uncertainty in spatially distributed vegetation has a smaller influence on the uncertainty in water levels than the main channel roughness. However, some sources of uncertainty that cause outliers (e.g. extremely dense vegetation in a region with high flow conveyance) are still important. Especially in combination with other uncertainties, such as the roughness of the main channel, this leads to an increased uncertainty in water levels. Therefore, in river management, the focus should be on the uncertainties around bottlenecks, as the uncertainties at these locations will probably have a large effect on the water levels. Furthermore, we found evidence that the effect of flood plain roughness uncertainty depends largely on the discharge conveyance through the flood plains compared with the discharge conveyance through the main channel. This ratio should, therefore, be determined to assess the relative contribution of the different sources of uncertainty. We recommend that in the application of models of compound river channels, the ratio between the main channel roughness and the flood plain roughness is subject to calibration instead of calibration on both the main channel and flood plain roughness separately.

The reference run in our study was calibrated on the highest recorded discharge peak of 1995, which is significantly lower than the design discharge level at which we evaluated the uncertainties in flood water levels. Applying this calibrated model to situations beyond the calibration event will surely introduce errors in predicted water levels, largely as a result of topographical inaccuracies in the model and unrealistic roughness definitions. As we accounted for the effect of uncertain roughness values in the current study, the principal remaining uncertainty source is related to topographical errors in the model, which we expect to have a small impact on flood water levels (Warmink *et al.*, 2011) given the high spatial resolution of the underlying digital elevation model. Also, strictly speaking, each of the 500 realisations in the Monte Carlo simulation should have been recalibrated at the 1995 peak discharge to assure that historic flood events are accurately reproduced by each model realisation. We did not carry out this recalibration step because of the practical difficulties associated with calibrating a 2D river reach model. Such a recalibration step would make the variation in water levels diminish at the calibration discharge, leading to a reduction in water level uncertainties at the design discharge level. The reported uncertainty range should, therefore, be considered as an estimate of the maximum uncertainty range. Further research is required on the possible reduction of the uncertainties due to calibration.

Conclusions

The objective of this study was to quantify the effects of combined uncertainty in channel and flood plain roughness on the design water level for an alluvial river using the 2D hydrodynamic model. We addressed the following uncertainty sources: (1) bed form roughness of the main channel, (2) classification error of flood plain vegetation and (3) choice of roughness parameterisation. We showed that combining the main contributions to the uncertainty in the design water levels resulted in a 95% confidence interval of approximately 68 cm, which is significant in view of Dutch river management practice. However, given that we did not account for calibration of the model, this estimate should be considered as a maximum value of the uncertainty range in the design water levels.

The uncertainty due to the classification error was spatially distributed and caused positive outliers in the design water levels due to clustering of rough vegetation types. These outliers increased the uncertainty, especially if they occurred in the same realisation with a high bed form roughness. Combining the uncertainty in the bed form roughness and vegetation roughness resulted in an increase of the 95% confidence interval in the design water levels compared with the individual sources, but less than the sum of the two individual sources. Including the uncertainty due to the choice of the vegetation roughness parameterisation resulted in only a small increase of the uncertainty in design water levels. This showed that in uncertainty analysis studies, it is not necessary to quantify all sources of uncertainty as only few sources are responsible for most of the uncertainty in the design water levels. For flood hazard assessment, taking into account the combined uncertainty of roughness from bed forms and flood plain vegetation is warranted given the high price of landscaping measured to mitigate peak flood levels.

Acknowledgements

The research reported in this paper was supported by the Technology Foundation STW, applied science division of NWO, and the technology program of the Ministry of Economic Affairs. We thank the Dutch Centre for Water Management for providing the WAQUA model to do the analysis. Furthermore, we thank Deltares for the use of their facilities. We thank Hanneke Van der Klis from Deltares for her constructive comment and assistance during the preparation of this paper. This research was also supported by the Flood Control 2015 program. For more information, please visit http://www.floodcontrol2015.com.

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Appendix

Appendix A: Equations of the used vegetation roughness parameterisations

Here, we give the equations for the Klopstra, Van Velzen, Huthoff and Baptist models.

Nikuradse equivalent roughness

We expressed roughness as an equivalent Nikuradse roughness, k_N. Therefore, the Chézy values (C_r) are converted to k_N values:

$$k_N = \frac{12h}{10^{C_r/18}} \tag{A1}$$

Equation for non-submerged vegetation

The equation for non-submerged vegetation is equal for all roughness parameterisations.

$$C_r = \sqrt{\frac{1}{C_b^{-2} + \frac{C_D mDh}{2g}}} \text{ for } h \le k \tag{A2}$$

where C_b is the roughness of the bed below the vegetation, m, D, C_D and k are vegetation characteristics, and h is the water depth. Here, m is the number of stems per square meter (m^{-2}), D is the average diameter of the stems (m), C_D is the drag coefficient, k is the vegetation height (m) and $g = 9.81$ (m/s^2) is the acceleration of gravity.

Klopstra *et al*. (1997)

The equation proposed by Klopstra *et al*. (1997) for submerged vegetation is as follows:

$$\begin{aligned} C_{r,K} = {} & \frac{2}{h^{\frac{3}{2}}\sqrt{2A}}\left(\sqrt{C_1 e^{k\sqrt{2A}} + u_{v0}^2} - \sqrt{C_1 + u_{v0}^2}\right) \\ & + \frac{u_{v0}}{h^{3/2}\sqrt{2A}} ln\left[\frac{\left(\sqrt{C_1 e^{k\sqrt{2A}} + u_{v0}^2} - u_{v0}\right)\left(\sqrt{C_1 + u_{v0}^2} + u_{v0}\right)}{\left(\sqrt{C_1 e^{k\sqrt{2A}} + u_{v0}^2} + u_{v0}\right)\left(\sqrt{C_1 + u_{v0}^2} - u_{v0}\right)}\right] \\ & + \frac{u_*}{h^{3/2}\kappa\sqrt{S_b}}\left[(h-(k-h_{s,K}))ln\left[\frac{h-(k-h_{s,K})}{z_{0,K}}\right] \right. \\ & \left. - h_{s,K} ln\left[\frac{h_{s,K}}{z_{0,K}}\right] - (h-k)\right] \end{aligned} \tag{A3}$$

where

$$A = \frac{C_D mD}{2\alpha_K} \tag{A4}$$

$$u_{v0} = \sqrt{\frac{2g}{C_D mD}} \tag{A5}$$

$$u_* = \sqrt{g(h-(k-h_{s,K}))S_b} \tag{A6}$$

$$h_{s,K} = g\frac{1+\sqrt{1+\frac{4E^2\kappa^2(h-k)}{g}}}{2E^2\kappa^2} \tag{A7}$$

$$z_{0,K} = h_{s,K} exp\left[\frac{-\kappa\sqrt{\frac{C_1}{S_b}e^{k\sqrt{2A}} + u_{v0}^2}}{\sqrt{g(h-(k-h_{s,K}))}}\right] \tag{A8}$$

$$E = \frac{\sqrt{2A}C_1 exp\left(k\sqrt{2A}\right)}{2\sqrt{C_1 exp\left(k\sqrt{2A}\right) + u_{v0}^2}} \tag{A9}$$

$$C_1 = \frac{2g(h-k)}{\alpha_K\sqrt{2A}\left[exp\left(k\sqrt{2A}\right) + exp\left(-k\sqrt{2A}\right)\right]} \tag{A10}$$

The hydraulic roughness can be computed if vegetation characteristics, m, D, C_D and k, the water depth, h, and a characteristic length scale according to Klopstra *et al*. (1997) α_K are known. Here, $\kappa = 0.4$ (-) is the Von Karman constant, A is a constant depending on the vegetation characteristics, S_b (-) is the bed slope, u_{v0} (m/s) is the characteristic constant flow velocity in non-submerged vegetation divided by the square root of the water level slope, $h_{s,K}$ (m) is the distance between the top of the vegetation and the virtual bed of the surface layer, $z_{0,K}$ (m) is the length scale for bed roughness of the surface layer according to Klopstra *et al*. (1997), and E and C_1 are assisting coefficients.

This characteristic length scale α_K was calibrated on data from flume studies by Tsujimoto and Kitamura (1990), Shimizu and Tsujimoto (1994), Starosolsky (1983), Tsujimoto *et al.* (1993), Nalluri and Judy (1989), and Kouwen *et al.* (1969), all referred to in Klopstra *et al.* (1997). This resulted in the following best-fit relation:

$$\alpha_K = 0.0793k \cdot \ln\frac{h}{k} - 0.00090 \text{ and } \alpha_K \geq 0.001 \tag{A11}$$

Van Velzen *et al.* (2003)

The equation proposed by Van Velzen *et al.* (2003) for submerged vegetation is equal to the Klopstra parameterisation. However, they used another characteristic length scale, α_V. They calibrated α using an extended dataset of flume experiments (Van Velzen *et al.*, 2003) compared with Klopstra *et al.* (1997) to yield the following:

$$\alpha_V = 0.0227k^{0.7} \tag{A12}$$

Huthoff (2007)

The equation proposed by Huthoff *et al.* (2007) for submerged vegetation is as follows:

$$C_{r,H} = \frac{U_T}{\sqrt{hS_e}} \tag{A13}$$

where

$$U_T = U_{r0}\left(\sqrt{\frac{k}{h}} + \frac{h-k}{h}\left(\frac{h-k}{s}\right)^{2/3}\right) \tag{A14}$$

$$U_{r0} = \sqrt{\frac{hi}{C_b^{-2} + C_D mDh/(2g)}} \tag{A15}$$

and

$$s = \sqrt{m} - D \tag{A16}$$

where U_T (m/s) is the depth-averaged flow velocity over the total flow depth, U_{r0} is the depth-averaged flow velocity in the vegetation layer in case of submerged vegetation and *s* is the separation length between neighbouring stems. Huthoff *et al.* (2007) noted that as U_{r0} is a depth-averaged value, the parameters *m*, *D* and C_D should be treated accordingly.

Baptist *et al.* (2007)

Based on the method of effective water depth, Baptist *et al.* (2007) developed an analytical formula for the representative roughness of vegetation. This approach includes the zero-plane displacement of the logarithmic velocity profile. This approach is similar to the method by Van Velzen *et al.* (2003), and is rather complex because it needs an estimate for the zero-plane displacement (Baptist *et al.*, 2007). The authors applied genetic programming to approximate the analytical formula, which resulted in a simple equation and showed a good approximation for the representative roughness, valid for a wide range of vegetation properties and flow conditions (Baptist *et al.*, 2007):

$$C_{r,B} = \sqrt{\frac{1}{C_b^{-2} + C_D mDk/(2g)}} + \frac{\sqrt{g}}{\kappa}\ln\frac{h}{k} \tag{A17}$$

where C_b is the roughness of the bed below the vegetation. Note that for non-submerged vegetation, the right-hand term approaches zero, and the equation is equal to the equation for non-submerged vegetation.