ROUGHNESS FACTOR IN OVERTOPPING ESTIMATION

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The roughness factor (γ_f) is a key variable to estimate wave overtopping discharge on mound breakwaters. In this study, the γ_f is re-calibrated using a dataset extracted from the CLASH database. Compared to previous roughness factors calibrated using less restrictive data, overtopping estimators with a few explanatory variables showed variations up to 15% in the 50% percentile of γ_f. On the contrary, the CLASH neural network overtopping predictor showed insignificant variations in the roughness factor, since it is less sensitive to the variability in the data used for calibration. The confidence interval width of the CLASH neural network was narrow compared to simple explicit overtopping estimators, given that it is less sensitive to the number of data used for calibration. The γ_f values used to estimate wave overtopping discharge should be carefully calibrated, especially when using simple empirical formulas.

Keywords: mound breakwater; overtopping; roughness factor; armor unit

INTRODUCTION

Overtopping on mound breakwaters is usually a key design factor affecting breakwater crest elevation, construction cost and environmental impact. Overtopping rates depend on a variety of structural and environmental characteristics. This study focuses attention on the roughness factor (γ_f) generally associated to the armor unit geometry, number of layers and placement type; the higher the roughness factor, the higher the overtopping rates.

During the last four decades, the roughness factor has been proposed as a parameter to consider the performance of different armoring systems, especially in regard to run-up and overtopping. After crest freeboard (R_c) and incident significant wave height (H_{m0}), the roughness factor (γ_f) is the third most common parameter used to estimate overtopping rates on mound breakwaters. Van der Meer and Janssen (1994) proposed Eq. [1] to estimate overtopping rates on dikes in non-breaking conditions:

$$Q_{VMJ} = \frac{q}{\sqrt{g \cdot H_{m0}^3}} = A \cdot \exp\left(- B \cdot \frac{R_c}{H_{m0}} \cdot \frac{1}{\gamma_f} \right) \qquad (1)$$

where A=0.2, B=2.6 and γ_f=roughness factor. Numerous formulas have been proposed to estimate overtopping rates on mound breakwaters; most of them include the use of γ_f to take into account the specific armoring system. For instance, one of the independent input variables in the CLASH overtopping neural network (CLASH-NN), downloaded from Deltares (2017), is the roughness factor taken from Molines and Medina (2015); a different γ_f list given by Coeveld et al. (2005) was originally used within the CLASH project. Fig. 1 shows the cross section and the 15 input variables considered for CLASH-NN.

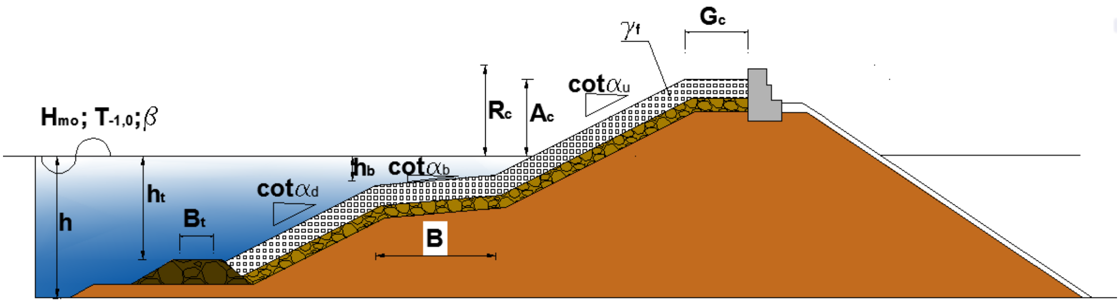

Figure 1. Breakwater cross section considered by CLASH-NN.

There are several lists of roughness factors given in the literature, but these do not always provide the same value for the same armoring system (see Table 1); for instance, the γ_f proposed for rock (2-layer) by Coeveld et al. (2005) and EurOtop (2007) were γ_f=0.50 and 0.40, respectively. Van der Meer and Bruce (2014) proposed new revised formulas for low and very low crest freeboards (R_c/H_{m0}<0.8)

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using the same roughness factors as those given in EurOtop (2007). Bruce et al. (2009) made changes in the γ_f proposed by Bruce et al. (2006) and calculated the confidence intervals.

As highlighted by Molines and Medina (2015), given a breakwater and a specific overtopping predictor (e.g. formula, neural network model, etc.), the roughness factor is the parameter which takes into consideration how overtopping is influenced by all structural variables not explicitly included in the predictor. For instance, armor thickness, armor unit geometry and placement, filter and core permeability, crest berm width and other structural characteristics are not included in Eq. [1]; however, they are implicitly considered by the roughness factor (γ_f) used in Eq. [1].

Smolka et al. (2009) proposed Eq. [2] to estimate overtopping rates for conventional cube and Cubipod armored breakwaters with high crown walls (R_c>A_c); recommended roughness factors were γ_f=0.50, 0.46 and 0.44 for double-layer cube and single- and double-layer Cubipod armoring, respectively.

$$Q_{SZM} = \frac{q}{\sqrt{g \cdot H_{m0}^3}} = A \cdot \exp\left(D \cdot Irp - C \cdot \frac{A_c}{R_c} - B \frac{R_c}{H_{m0}} \cdot \frac{1}{\gamma_f} \right) \quad (2)$$

where A=0.20, B=2.16, C=3.27, D=0.53 and γ_f =roughness factor.

Molines and Medina (2016) proposed Eq. [3] to emulate the CLASH-NN with an explicit relationship between input explanatory variables and overtopping rates. The authors used the methodology described previously by Molines and Medina (2015) to provide specific lists of calibrated γ_f to be used together with their corresponding overtopping estimator (see Table 1).

$$Q = \left(\frac{q}{\sqrt{g \cdot H_{m0}^3}} \right) = Q6 = \exp\left(\lambda_2 \cdot \lambda_3 . \lambda_4 \cdot \lambda_5 \cdot \lambda_6 \left[-1.6 - 2.6 \cdot \frac{R_c}{H_{m0}} \cdot \frac{1}{\gamma_f \gamma_\beta} \right] \right) \quad (3a)$$

$$\lambda_2 = 1.20 - 0.05 \cdot \left(Ir \sqrt{R_c / H_{m0}} \right) \quad (3b)$$

$$\lambda_3 = 1.0 + 2.0 \cdot \exp\left(-35 \cdot R_c / h \right) \quad (3c)$$

$$\lambda_4 = \max[0.95; 0.85 + 0.13 \cdot G_c / H_{m0}]; \quad (3d)$$

$$\lambda_5 = 0.85 + 0.15 \cdot A_c / R_c \quad (3e)$$

$$\lambda_6 = \begin{cases} \max[1.0; (1.2 - 0.5 \cdot R_c / h)] & if \quad Bt > 0 \\ 1.0 & if \quad Bt = 0 \end{cases} \quad (3f)$$

$$\gamma_\beta = \begin{cases} 1 - 0.0077 \, |\beta| & for\ long-crested\ waves \\ 1 - 0.0058 \, |\beta| & for\ short-crested\ waves \end{cases} \quad \text{valid for } \beta \leq 60^o \quad (3g)$$

where Ir = $T_{-1,0}/\cot\alpha[2\pi H_{m0}/g]^{1/2}$ and R_c, A_c, G_c, h and B_t are defined in figure 2.

Nevertheless, the roughness factor is still a convenient parameter to improve overtopping estimations with simple overtopping predictors, but it is clear that the optimum roughness factor which should be used in a given overtopping formula requires specific calibration with available experimental data. Using any list of roughness factors, independent of the overtopping predictor can lead to the increase in errors in overtopping prediction. This study focuses attention on estimating the appropriate roughness factor for a given overtopping predictor and experimental database. A change in the overtopping predictor or the experimental data used for calibration may significantly change the optimum roughness factor.

Table 1. Roughness factors given in the literature.

Type of armor 2L=double-layer 1L=single-layer	Coeveld et al. (2005)	Pearson et al. (2004) Bruce et al. (2006) EurOtop (2007)	Smolka et al. (2009)	Bruce et al. (2009)	Molines and Medina (2016)
Smooth	1.00	1.00	-	1.00	0.95
Rock (2L)	0.50	0.40	-	0.40	0.49
Cube (2L, random)	0.50	0.47	0.50	0.47	0.51
Cube (2L, flat)	-	0.47	-	0.47	0.52
Cube (1L, flat)	-	0.50	-	0.49	0.55
Antifer (2L)	0.50	0.47	-	0.50	0.52
Haro (2L)	0.47	0.47	-	0.47	0.51
Tetrapod (2L)	0.40	0.38	-	0.38	0.45
Accropode (1L)	0.49	0.46	-	0.46	0.48
Core-Loc (1L)	0.47	0.44	-	0.44	0.45
Xbloc (1L)	0.49	0.45	-	0.44	0.46
Dolos (2L)	0.43	0.43	-	0.43	0.42
Cubipod (2L)	-	-	0.44	-	0.47
Cubipod (1L)	-	-	0.46	-	0.48

EXPERIMENTAL DATA FROM CLASH DATABASE

This study focuses on conventional mound breakwaters with crown walls; the cross section is depicted in Fig. 2. This breakwater typology is common for large breakwaters using concrete armor units. Analyzing the CLASH database, 5,995 out of 10,532 tests corresponded to conventional mound breakwaters using the filter: $\cot\alpha_d=\cot\alpha_u=\cot\alpha$, $1.19\leq\cot\alpha\leq 4$, $R_c>0$, and $\tan\alpha_B=h_B=B=0$.

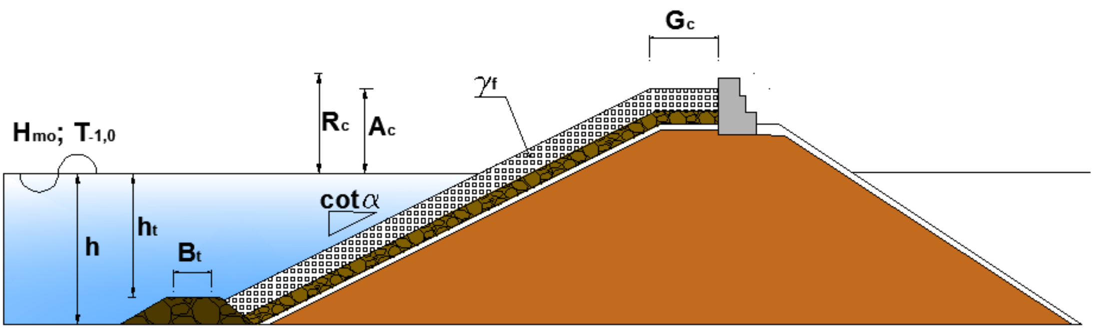

Figure 2. Cross section of a conventional mound breakwater with crown wall.

In order to estimate the appropriate roughness factor for different overtopping predictors, Molines and Medina (2015) suggested using the CLASH database with additional restrictions:

- Data with the best Complexity Factor (CF=1) → 4,809 tests
- Data with better Reliability Factors (RF=1 or 2) → 3,649 tests
- Tests in non-breaking conditions ($1.8\ H_{m0toe}<0.8h$ and $Ir_p= T_p/\cot\alpha[2\pi H_{m0}/g]^{0.5}>2$) → 2,444 tests
- Tests with references and no remarks → 2,193 tests
- Perpendicular incident wave attack, $\beta=0$ → 1,752 tests
- $Q\geq10^{-6}$ → 1,501 tests

- $0.38 \leq \gamma_f \leq 0.5$ and $\gamma_f = 1.00 \rightarrow$ 1,372 tests
- Data given by Stewart et al. (2002) were eliminated due to incoherence in the γ_f values→ 1,219 tests
- Moreover, 36 tests from the dataset 958 by Pearson et al. (2004) were eliminated because it was not possible to identify the type of armor unit.
- Only 1,183 out of 10,532 tests were considered valid for calibrating roughness factors.

CF and RF are the Complexity and Reliability Factors (see Van Gent et al., 2007). In this study, the same data filters described above were used but only with the most reliable tests (RF=1). After applying the filter RF=1, only 606 out of 10,532 tests were considered for calibrating roughness factors.

Table 2. Test data extracted from the CLASH database used in this study.

Armor type	No. data (Molines & Medina, 2015)	No. data (this study)	H_{m0} [m]	$T_{-1,0}$ [s]	R_c [m]	A_c [m]	G_c [m]	cot α	h_t [m]	h [m]	B_t [m]
Smooth	226	143	0.048-0.192	0.782-3.647	0.087-0.55	0.087-0.55	0.000	1.19-4.00	0.300-0.720	0.300-0.720	0.000
Rock (2L)	555	245	0.051-0.200	0.800-2.560	0.062-0.300	0.062-0.300	0.090-0.200	1.50-4.00	0.190-0.730	0.250-0.730	0.000-0.130
Cubes (2L, random)	171	85	0.041-0.136	0.747-1.791	0.070-0.160	0.070-0.160	0.089-0.130	1.50-2.00	0.425-0.722	0.455-0.722	0.000-0.130
Antifer (2L)	25	15	0.048-0.115	0.791-1.632	0.079-0.128	0.079-0.128	0.099	1.50	0.676-0.725	0.676-0.725	0.000
Tetrapod (2L)	86	10	0.079-0.113	0.952-1.630	0.083-0.135	0.083-0.135	0.105	1.50	0.674-0.731	0.674-0.731	0.000
Core-Loc (1L)	27	15	0.060-0.113	0.951-1.639	0.086-0.140	0.086-0.140	0.089	1.50	0.673-0.727	0.673-0.727	0.000

Using the specific dataset described above and the methodology given by Molines and Medina (2015), roughness factors were re-calibrated for Eq. [1], Eq. [2], Eq.[3] and the CLASH-NN. The roughness factors depend on the data used for calibration; the new filtering with RF=1 reduced the number of data compared to Molines and Medina (2015) in smooth, rock (2L), Cube (2L, random), Antifer (2L), Tetrapod (2L) and Core-Loc (1L) types of armor. Only the tests listed in Table 2 were used in this study to re-calibrate the roughness factors, as described in the following sections.

ROUGHNESS FACTOR RE-CALIBRATION

In this study Eq. [1], Eq. [2], Eq.[3] and the CLASH-NN are used with the data given by Table 2 to re-calibrate the roughness factors of different types of armor using the methodology described by Molines and Medina (2015). For a given armor type, 1000 bootstrap resamples of the initial dataset were created and the optimum γ_f, which minimized the error for each resample, was calculated. Fig. 3 illustrates the error depending on the γ_f for five different bootstrap resamples using Eq. [1] with Core-Loc armored breakwaters. It is clear that the optimum γ_f depends on the resample.

In this study, the relative Mean Squared Error (rMSE = MSE/Var) was used to evaluate the goodness of fit:

$$rMSE_e(o) = \frac{MSE_e(o)}{Var(o)} = \frac{\sum_{i=1}^{N} \left(\frac{1}{N}\right)\left(\log Qe_i - \log Qo_i\right)^2}{Var\left(\log Qo\right)} \tag{4}$$

where N= total number of data, i= data index, Qe and Qo are the estimated and target dimensionless mean overtopping discharges using estimator "e" and target data "o". 0%<rMSE<100% indicates the percentage of variance not explained by the estimator; the lower the rMSE, the better.

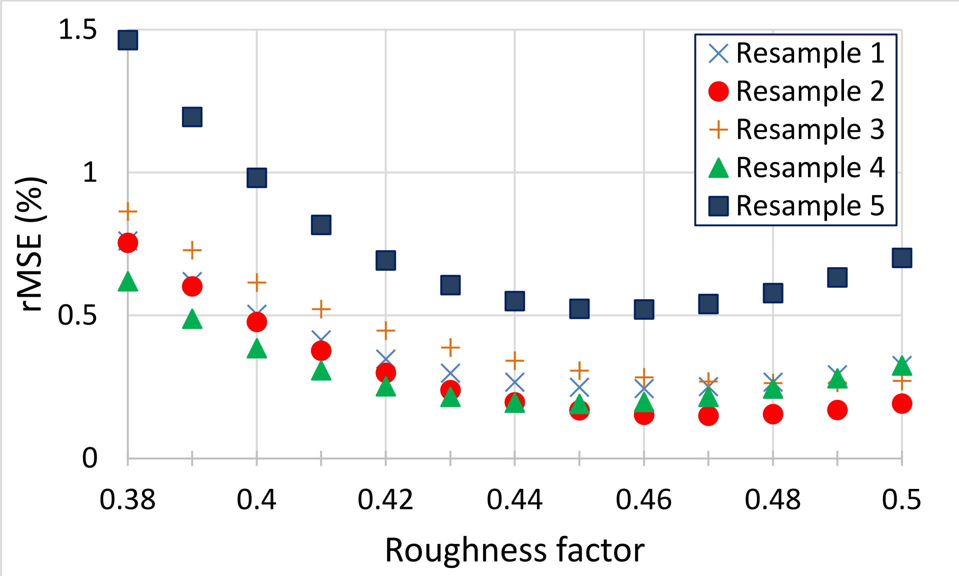

Figure 3. Roughness factor and rMSE for Core-loc (1L) using Eq. [1].

The 10%, 50% and 90% percentiles (γ_{f10}, γ_{f50}, γ_{f90}) of the 1000 optimum γ_f values were calculated. Fig. 4 illustrates the frequency distribution of optimum γ_f values using Eq. [1] with Core-Loc armored breakwaters. In this case, γ_{f10}=0.44, γ_{f50}=0.46 and γ_{f90}=0.48.

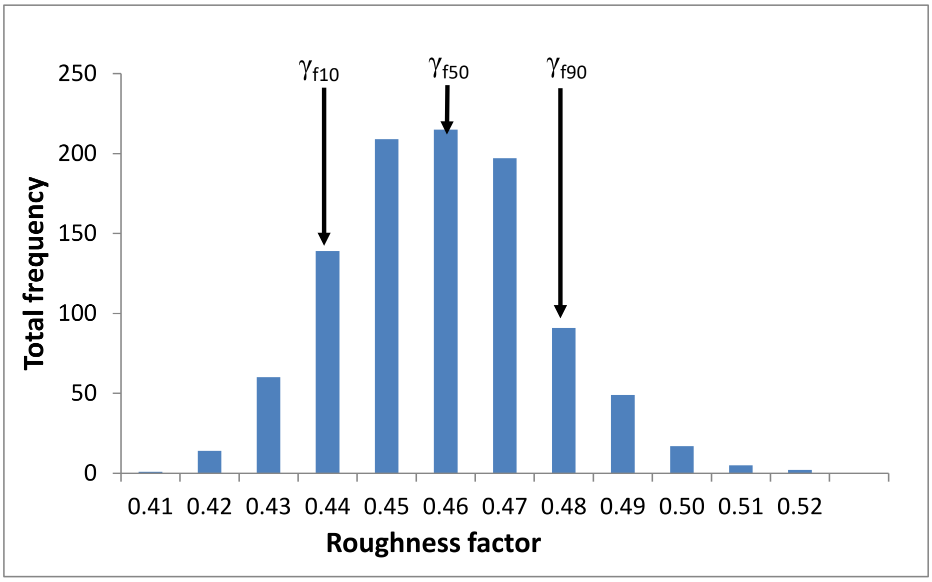

Figure 4. Roughness factor frequency histogram corresponding to Core-Loc (1L) using Eq. [1].

Table 3 compares the roughness factors given by Molines and Medina (2015 and 2016), γ_{fMM}, with the re-calibrated roughness factors obtained in this study, γ_{fs}. Table 3 shows significant variations in γ_{f50} values ($\gamma_{fs50} < \gamma_{f10MM}$ or $\gamma_{fs50} > \gamma_{f90MM}$) for overtopping estimators given by Eq. [1], Eq. [2] and Eq. [3]: up to 10% (three cases), 15% (one case) and 7% (two cases), respectively. On the contrary, the CLASH-NN shows insignificant variations in the roughness factor with $|\gamma_{f50MM}-\gamma_{fs50}| \leq 0.01$. CLASH-NN considers a large number of explanatory variables; therefore, the calibrated roughness factors are not as sensitive to the volume of the data used for calibration.

As shown in Table 3, the confidence interval of the re-calibrated roughness factors for Eq. [1], Eq. [2] and Eq. [3], calculated as γ_{f90}- γ_{f10}, were broader than those given by Molines and Medina (2015) for almost all types of armor unit, since those were based on 1,183 tests while the ones in this study were based on 606 tests only. By contrast, the confidence intervals of the re-calibrated roughness factors for the CLASH-NN showed insignificant differences compared to those given by Molines and Medina (2015); it is clear that the CLASH-NN are less sensitive to the number of data used to calibrate the γ_f.

Table 3: Roughness factors γ_{fMM} given by Molines and Medina (2015 and 2016) and γ_{fs} re-calibrated in this study.

Armor type	γ_f	Overtopping estimator							
		Q_{CLNN} (2007) CLASH-NN		Q_{VMJ} (1994) Eq. [1]		Q_{SZM} (2009) Eq. [2]		Q_{MM} (2016) Eq. [3]	
		γ_{fMM}	γ_{fs}	γ_{fMM}	γ_{fs}	γ_{fMM}	γ_{fs}	γ_{fMM}	γ_{fs}
Smooth	γ_{f10}	0.99	0.99	1.02	1.01	1.18	1.15	0.94	0.93
-	γ_{f50}	**1.00**	**1.00**	**1.03**	**1.04**	**1.21**	**1.18**	**0.95**	**0.94**
	γ_{f90}	1.00	1.00	1.05	1.06	1.24	1.22	0.96	0.96
Rock	γ_{f10}	0.48	0.49	0.45	0.40	0.43	0.43	0.48	0.48
(2L)	γ_{f50}	**0.49**	**0.49**	**0.45**	**0.41**	**0.44**	**0.44**	**0.49**	**0.49**
	γ_{f90}	0.50	0.50	0.46	0.41	0.44	0.44	0.49	0.49
Cube	γ_{f10}	0.52	0.52	0.44	0.41	0.43	0.44	0.50	0.49
(2L, random)	γ_{f50}	**0.53**	**0.53**	**0.45**	**0.42**	**0.44**	**0.44**	**0.51**	**0.50**
	γ_{f90}	0.53	0.53	0.46	0.43	0.45	0.45	0.51	0.50
Antifer	γ_{f10}	0.51	0.52	0.48	0.50	0.48	0.50	0.50	0.53
(2L)	γ_{f50}	**0.52**	**0.53**	**0.50**	**0.52**	**0.51**	**0.54**	**0.52**	**0.55**
	γ_{f90}	0.53	0.55	0.52	0.56	0.54	0.58	0.54	0.57
Tetrapod	γ_{f10}	0.41	0.40	0.42	0.39	0.38	0.44	0.44	0.40
(2L)	γ_{f50}	**0.42**	**0.41**	**0.43**	**0.41**	**0.39**	**0.46**	**0.45**	**0.42**
	γ_{f90}	0.43	0.42	0.43	0.43	0.40	0.49	0.46	0.43
Core-Loc (1L)	γ_{f10}	0.45	0.45	0.44	0.44	0.44	0.44	0.44	0.44
	γ_{f50}	**0.46**	**0.46**	**0.46**	**0.46**	**0.46**	**0.46**	**0.45**	**0.46**
	γ_{f90}	0.47	0.46	0.47	0.48	0.48	0.49	0.48	0.47

CONCLUSIONS

The roughness factor is dependent not only on the type of armor, number of layers and placement method, but also on the overtopping estimator and database used for calibration. In this study, the methodology to calibrate the γ_f given by Molines and Medina (2015) is applied to the CLASH database considering more restrictive data filters for the most reliable data only (606 instead of 1,183 tests). The γ_f is re-calibrated for smooth, rock (2Layer), Cube (2Layer, random), Antifer (2Layer), Tetrapod (2Layer) and Core-loc (1Layer) types of armor using Eq. [1], Eq. [2], Eq. [3] and the CLASH-NN.

For a given overtopping estimator and type of armor, the optimum γ_f is calculated for 1000 bootstrap resamples and the 10%, 50% and 90% percentiles of the optimum γ_f histogram are obtained (γ_{f10}, γ_{f50}, γ_{f90}). Considering the explicit overtopping predictors, Eqs. [1] to [3], significant variations in γ_{f50} are obtained in some cases. By contrast, when considering the CLASH-NN overtopping predictor, insignificant variations are observed. It is clear that CLASH-NN, which is a multi-parametric black-box overtopping predictor with a very large number of input parameters, is much less sensitive to the volume of data used to calibrate the roughness factor. Simple explicit overtopping estimators are more sensitive to the volume of data for calibration because they are highly dependent on the roughness factor to absorb the information not explicitly considered by a fewer explanatory input variables.
Considering Eqs. [1] to [3], the confidence interval width of the re-calibrated roughness factors in this study, γ_{fs90}-γ_{fs10}, is broader than that obtained by Molines and Medina (2015). Therefore, Eqs. [1] to

[3] are much more sensitive than the CLASH-NN to the number of data used to calibrate the optimum roughness factor γ_f, both in terms of the median value and confidence interval. The roughness factor, γ_f, should never be assumed as a constant value dependent on the type of armoring, but rather as a parameter which depends as well on the overtopping predictor and the experimental data used for calibration.

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