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Hydraulic

On the effect of the refinement of the roughness description in a 2D approach for a mountain river: a case study

Efecto del refinamiento de la descripción de la rugosidad en una aproximación 2D para un río de montaña: un caso de estudio

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Abstract

The prediction of water levels in rivers is important to prevent economical as well as human losses caused by flooding. Hydraulic models are commonly used to predict those water levels and take actions to mitigate flooding damage. In this research, a 2D approach to solve the depth average Reynolds Average Navier Stokes (RANS) equations, called Conveyance Estimation System (CES), is analyzed to explore its capabilities for prediction. This article presents an extension of the study performed in Knight et al. (2009). More specifically, in this study, a more detailed characterization of the roughness parameter and the number of roughness zones is explored producing additional scenarios. The performance of each scenario is evaluated by means of different fitting functions using rating curves for comparison. The research shows that the use of an adequate roughness description, such as a roughness factor calibrated for the whole cross section or a boulder roughness model calibrated for the channel bed plus roughness values from the CES roughness advisor for banks, leads to optimal model results in a mountain river.

Keywords: Conveyance Estimation System, Mountain Rivers, roughness coefficient

Resumen

La predicción de niveles de agua en ríos es importante para prevenir pérdidas económicas así como de vidas humanas causadas por inundaciones. Los modelos hidráulicos son comúnmente usados para predecir estos niveles de agua y tomar acciones para mitigar el daño debido a inundaciones. En la presente investigación, se analizó una aproximación 2D para resolver las ecuaciones promediadas en profundidad de Reynolds Average Navier Stokes (RANS), llamado Conveyance Estimation System (CES), para explorar sus capacidades predictivas. Este artículo presenta una ampliación del estudio realizado por Knight et al. (2009). De igual forma, en esta investigación se explora una caracterización más detallada del parámetro de rugosidad y del número de zonas de rugosidad produciendo diversos escenarios. Se evaluó el desempeño de cada escenario mediante diferentes funciones de ajuste usando curvas de descarga para comparación. La investigación muestra que el uso de una adecuada descripción de la rugosidad, como un factor de rugosidad calibrado para toda la sección transversal o un modelo de rugosidad para cantos rodados calibrado para el lecho junto con valores de rugosidad obtenidos en valores sugeridos por el CES para los bancos, produce resultados del modelo óptimos en un río de montaña.

Palabras clave: Sistema de estimación de capacidad de trasporte, Ríos de montaña, coeficientes de rugosidad.

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1 Introduction

Flooding is one of the most dangerous natural disasters producing human as well as economic losses (Douben, 2006; Camp et al., 2016). From the modeling point of view, the mitigation of flooding effects requires the computation of water levels. When 1-D hydrodynamic models are used, the Saint-Venant equations are solved (Papanicolaou et al., 2004). These equations contain one parameter for resistance, usually the Manning resistance parameter (n). However, this is sometimes not enough to have a useful tool for decision making. Motivated by this limitation, in this research, we focus on a 2-D approach called CES (Conveyance Estimation System) to estimate the water level at a specific cross-section of a mountain river.

There are different inputs for this 2D approach, such as the geometry of the river or the parameters that appear in different terms of the modelling equations. However, we focus on the roughness factor f. This roughness factor can be estimated in different ways (Marcus et al., 1992). In the methodology, empirical equations are considered. These equations require variables that are easily measurable, that consider at-a-site as well as between-site effects on resistance, and that are reliable (Jarrett, 1985; Bathurst, 2002; Ferguson, 2007). Usually, available formulas to estimate f may have errors of around 30% because they were developed through the average of variations in multiple sites (Bathurst, 2002).

Additionally, formulations derived "from local conditions to a single formulation" for mountain rivers are found under special conditions, in which skin friction is the only or main component of resistance (Bathurst, 2002; Romero et al., 2010). Hence, their application is limited to only certain type of reaches (straight, no vegetation, and no air intrusion). Moreover, the roughness factor comprises different elements depending on the model structure: 1D, 2D, or 3D. In 1D models, the parameter contains an incorrect representation of turbulence (Bhola et al., 2019), while in some 2D models the representation of roughness does not include turbulence (Morvan et al., 2008). In this research, the performance of three empirical equations is tested with data collected in a mountain river. Two of them are semilogarithmic expressions found by Knight et al. (2009) and Romero et al. (2010) and the remaining one is an exponential expression obtained in Bathurst (2002). These equations are comprehensively explained in the Materials and Methods section.

There are some characteristics of mountain rivers that influence the roughness factor, f. The water depth (d) is comparable to the bed material with a relative submergence d/D84 ranging between 4 to 10 (Bathurst, 2002). Consequently, the bed material contributes more to resistance than in flat rivers (Jarrett, 1984). The velocity distribution in mountain rivers has an S-shape instead of the semilogarithmic profile used in low gradient rivers (Bathurst, 1985) due to the presence of boulders, which have a mean diameter bigger than 256 mm, and less than 4000 mm (Bunte and Abt, 2001). There is low flow velocity below the boulder level and between boulders, as well as high velocities above the boulders. The velocity pattern is important since there is a relationship between velocity and resistance (Wohl, 2000). There are additional effects of boulders in resistance due to the impact of flowing water in its protruding surface as well as the formation of eddies behind it (Jarrett, 1984). In addition, Pagliara et al. (2008) demonstrate that the interaction of the water surface with the boulders increases as the boulder concentration increases.

The Conveyance Estimation System (CES) is a two-dimensional model solving the depth-averaged Reynolds Average Navier Stokes (RANS) equations across a cross section. These equations include a term to consider the boundary friction using a unitary roughness factor (nl), representative of a segment of the cross-section boundary. Furthermore, the factor nl is a resistance parameter obtained in a wide reach where the roughness elements are small relative to the water depth. Other resistance contributors such as transverse currents or secondary circulations are considered in different equation terms (Knight et al., 2009). CES was developed by different organizations in the UK such as the Environmental Agency, Northern Ireland Rivers Agency, Flooding Policy Team, and HR Wallingford/ JBA Project Team. Knight et al. (2009) performed several study cases around the world: in rivers located in the UK, Argentina, United States, and so on. In particular, there is an example of the application of CES in two cross-sections in mountainous rivers in Ecuador and New Zealand (Knight et al., 2009).

The main goal of this article is to explore the possibility of a better cross-sectional description of roughness in the application example given by Knight et al. (2009) for the Tomebamba river in Ecuador. In this study, the inclusion of additional roughness zones and additional empirical equations to predict the roughness parameter is tested. The roughness zones are varied according to the bed material. Some scenarios contain only one roughness zone and others contain three roughness zones: left bank, right bank, and channel bed. In banks, values from the roughness advisor in CES are used. This advisor has a database of roughness values from several references ((Fisher and Dawson, 2003) as cited in (Wallingford, 2013)). However, for channel bed, a constant calibrated value by Knight as well as empirical equations whose roughness values vary with water depth are used due to the presence of boulders, which affects resistance due to their interaction with water.

2 Materials and Methods

2.1 Site Description

The cross-section and the discharge curve data were taken from Knight et al. (2009). The cross section to be evaluated belongs to the Tomebamba river at Monay in Cuenca, Ecuador (Figure 1). The bed material is composed of boulders and gravel, giving a D_{90} =1.3 meters. The reach has a slope of 0.0176 and a width of 25 m. Information about the bed material sampling is available in Bunte and Abt (2001) and Wolman (1954).

2.2 Conveyance Estimation System (CES)

CES discretizes the width of a cross section at constant intervals. The intersection of the water level analyzed with the cross section is taken as the first and last element. In Figure 2a, those elements are y_1 and y_{100}. The number of elements taken by default is 100. Then, CES solves the depth-averaged RANS equations through the Finite Element Method (FEM), where the unitary flow (q) is obtained for each element ($y_1, y_2 \ldots, y_{100}$). The selection of q is due to its continuity properties (Knight et al., 2009). The boundary conditions at the extreme elements are unitary flows equal to zero. The unitary flow is then transformed into depth-averaged flow velocity (Ud in Figure 2b) for each element. However, the cross velocity distribution is not always available for model validation but a rating curve that relates flow with water depth. This data is obtained by CES since there is an integration of depth-averaged velocities to get an average flow for the whole section. All the previous process is repeated by CES for 25 depths automatically, so a rating curve is obtained.

The roughness input parameter in CES is through a coefficient called unitary roughness (nl), which has the same units as the Manning coefficient. This coefficient is representative of rivers in the UK, where there is high relative submergence and a 1-meter water depth. Thus, this parameter is related to boundary friction dissipation only. Depending on the variation of bed material, vegetation, or irregularities across the cross-section, it is possible to determine roughness zones where a certain unitary roughness value is assigned.

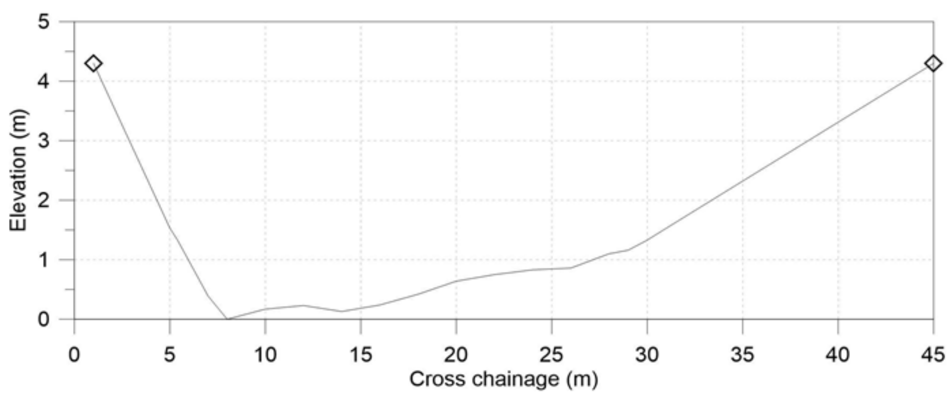

Figure 1. Cross section of Tomebamba river. Cross sectional data adapted from (Knight et al., 2009)

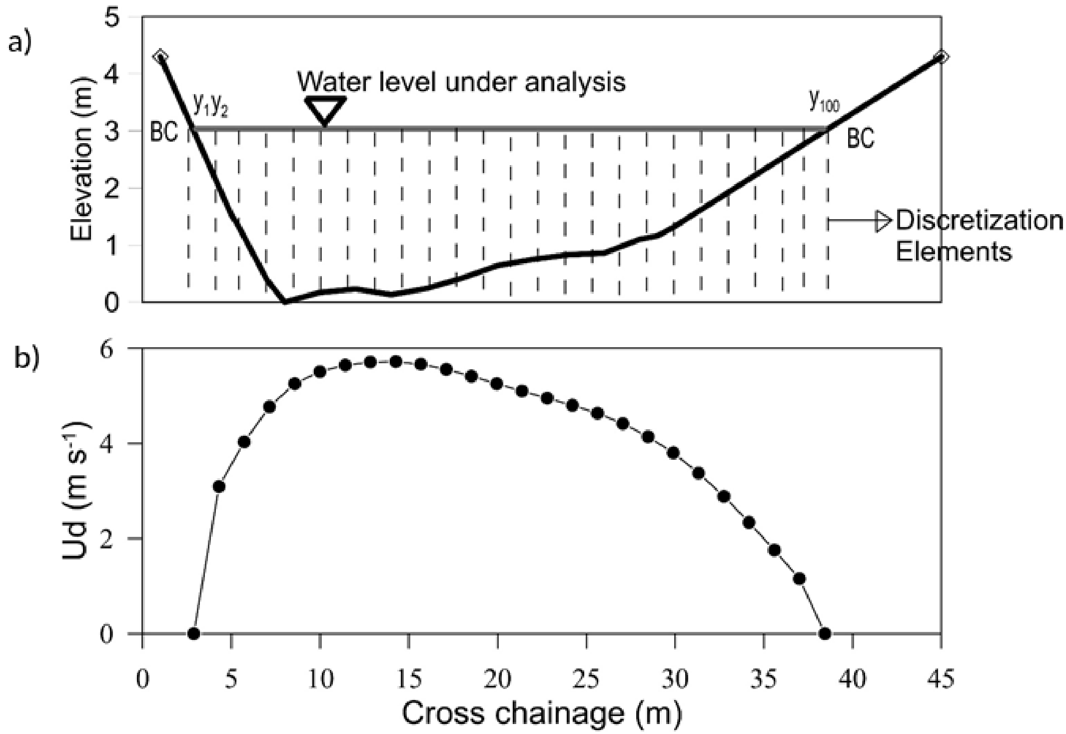

Figure 2. a) Cross section discretization. Cross section data adapted from (Wallingford, 2013) b) Example of cross sectional velocity distribution corresponding to cross section illustrated in a)

For example, in Figure 3 the red lines indicate the roughness zones limits. Left and right bank for example has a bed material of rock covered by vegetation, while channel bed has boulders without vegetation. CES software has a Roughness Advisor, which has typical values of unitary resistance for surface material, vegetation, and irregularities. Each term is described individually and combined with a root sum of squares.

2.3 Scenarios

In this work, we take as our point of departure the case study of the Tomebamba river presented in Knight et al. (2009). It consisted on applying CES to a mountain river whose channel bed is covered by boulders. Knight et al. (2009) analyzed three cases with a single roughness zone. First, they use the roughness advisor values. Second, they use a calibrated unitary roughness value. Finally, they consider a boulder model (see Equation 1). The validation data consisted of points of the rating curve. In our research, we expand those scenarios by adding two roughness zones and additional boulder models in order to explore the possibility to improve the model prediction by enhancing the cross-sectional roughness description. The boulder models are used to predict channel bed roughness values. On the other hand, the left bank and right bank roughness values were based on the Roughness Advisor in CES.

The boulder models used are based on exponential and semilogarithmic expressions considered as traditional approaches for resistance prediction (Zimmermann, 2010). The boulder model of Knight et al. (2009) is a calibrated model based on data from the Tomebamba and Cuenca rivers:

$$f_{mc} = 8 \cdot \left[5{,}75 \cdot log\left(\frac{12 \cdot d_{mc}}{3 \cdot D_{90}}\right)\right]^{-2} \qquad (1)$$

Where *dmc* is the maximum local cross section depth [m], D90 is the 90 percentile of the material size distribution [m]. Details of this model can be found in Abril and Knight (2004).

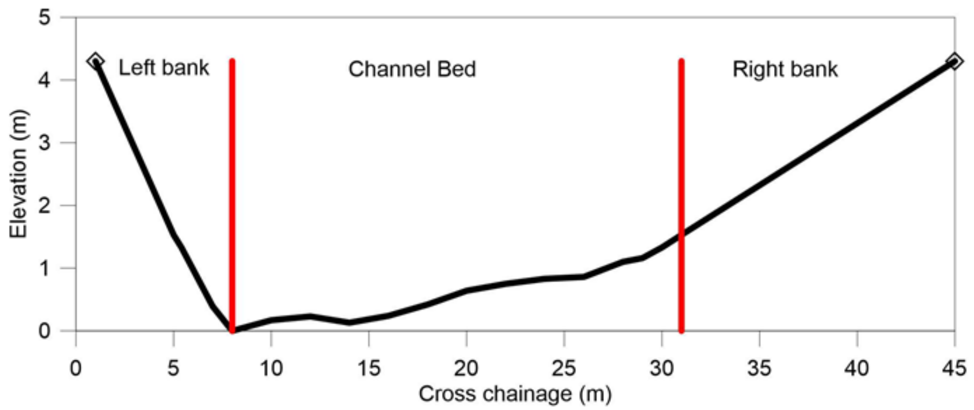

Figure 3. Division of roughness zones

The boulder model of Romero et al. (2010) (Equation 2), obtained through the regression of data from five mountain rivers in Bolivia, results in the following equation with S_O the bed slope:

$$f = 1{,}21 \cdot ln(S_O) + 6{,}259 \quad (2)$$

The boulder model of Bathurst (2002) was obtained with the analysis of twenty-seven data sets. In that article, the author focuses on the effects of at-a-site and between-site variations on resistance. Equation 3 is used for bed slopes higher than 0.8% and d is the mean water depth average [m].

$$\left(\frac{8}{f}\right)^{1/2} = 3{,}1 \cdot \left(\frac{d}{D_{84}}\right)^{0{,}93} \quad (3)$$

The reason behind the use of D84 is that it depicts a 3-D view of bed material. However, when there are morphologies such as step-pools or cascades this roughness height seems not to be appropriate (Lee and Ferguson, 2002; Maxwell and Papanicolaou, 2001; Aberle and Smart, 2003). However, there are other studies where D84 was successfully used for these morphologies (Comiti et al., 2007). If, in a scenario, one of the boulder models is used, the value of f will be calculated and transformed into a unitary roughness with Equation 4. Where g is the gravitational acceleration [m s^{-1}], nl unitary roughness [s m$^{-1/3}$], and d is water depth [m]. This equation is the rough-turbulent component of the Colebrook-White law.

$$f = \frac{8 \cdot g \cdot nl^2}{d^{\frac{1}{3}}} \quad (4)$$

The CES package calculates a rating curve (Flow-Water level) for each scenario described in Table 1. The results are compared against the measured rating curves points through different metrics. Each scenario is described in Table 1.

Table 1. Scenarios for the analysis of rating curves using the CES package.

Scenario	Description	Channel Bed	Banks
0	One roughness zone	Calibrated unitary roughness found in Knight et al. (2009)	
1	Two roughness zones	Calibrated unitary roughness found in Knight et al. (2009)	Height Varying grass +Fine Gravel
2	Two roughness zones	Calibrated unitary roughness found in Knight et al. (2009)	Height Varying grass +Cobbles
3	One roughness zone	Boulder model of Knight et al. (2009)	
4	Two roughness zones	Boulder model of Knight et al. (2009)	Height Varying grass+Fine gravel
5	Two roughness zones	Boulder model of Knight et al. (2009)	Height Varying grass+Cobbles
6	Two roughness zones	Boulder model of Bathurst (2002)	Height Varying grass+Cobbles
7	Two roughness zones	Boulder model of Romero et al. (2010)	Height Varying grass+Cobbles

2.4 Statistical Fitting Metrics

The quantification of the performance of each scenario was done through statistical indices. These statistical indices encompass in a single number the prediction quality of a model in comparison with validation data. Nevertheless, each metric shows a specific projection of the model accuracy relative to measured data (Chai and Draxler, 2014). In the following paragraphs, an explanation of the used metrics can be found.

RMSE (Root-mean-square error) is a widely used metric in meteorological and environmental studies such as air quality or climate research (Willmott and Matsuura, 2005; Nayak et al., 2013; Ritter and Muñoz-Carpena, 2013; Chai and Draxler, 2014). It is a qualitative methodology where larger errors of a model have more weight than smaller ones (Willmott and Matsuura, 2005; Chai and Draxler, 2014). Moreover, Ferguson (2007) states that this metric is useful to estimate the model performance of high values. It has the same units as the variable under analysis.

This metric is sensible towards outliers, so it is considered reasonable to remove observed values with several orders of magnitude larger than the other values in the sample (Chai and Draxler, 2014). The equation of RMSE is given by Equation 5. Where S mean simulated values, O is observed data, and N is the number of data. A perfect fit model will have a RMSE value of 0.

$$RMSE = \left(\frac{\sum_{i=1}^{n} S_i - O_i}{N} \right)^{0,5} \quad (5)$$

EF (Efficiency coefficient) is a statistical parameter that measures the capacity of estimation of the 1:1 line between observed and measured data (Nash and Sutcliffe, 1970). This metric is widely used to compute the goodness of fit of models due to its flexibility and reliability (McCuen and Cutter, 2006; Merz and Doppmann, 2006; Nayak et al., 2013). However, it is sensible towards bias, outliers (McCuen and Cutter, 2006; Ritter and Muñoz-Carpena, 2013) and overemphasizes large differences between observed and predicted values as RMSE does.

When Equation 6 is analyzed, the numerator represents the unexplained variation of the data by the model, while the denominator is the difference of the observed data with respect to the mean (McCuen and Cutter, 2006). Ritter and Muñoz-Carpena (2013) provides Table 2 with range of values for EF and its implications for the model performance. An EF of 1 means that the model and measured data fit perfectly; where $\bar{O}_i$ is the mean of the observations.

$$EF = 1 - \left(\frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O}_i)^2} \right) \quad (6)$$

Table 2. Model performance based on EF values.

Performance	EF
Very good	≥0.9
Good	0.8-0.9
Acceptable	0.65-0.8
Unsatisfactory	<0.65

Source: Ritter and Muñoz-Carpena (2013)

MAE (Mean Absolute Error) is the average of the errors (Equation 7). RMSE is bigger than MAE, so the magnitude of the difference indicates model goodness (Alvarado, 2001). This metric is widely used for model evaluations (Chai and Draxler, 2014). Willmott and Matsuura (2005) considers this metric a better indicator of the average error than RMSE. A model with a perfect fit has a MAE of 0.

$$MAE = \frac{\sum_{i=1}^{n} |S_i - O_i|}{N} \quad (7)$$

Relative error (RE) (Equation 8), this metric represents the relative error of the prediction taking as a base the measured data.

$$RE = \frac{S_i - O_i}{O_i} \cdot 100\% \quad (8)$$

3 Results

3.1 Rating Curve

Figure 4a depicts the rating curves when a calibrated unitary roughness is used. This figure shows that the inclusion of additional roughness zones for banks leads to a better approximation to measured data for flows higher than 20 m^3s^{-1}.

Figure 4b illustrates the sensibility of the model towards the selection of the boulder roughness model. For example, in models 6 and 7 new boulder roughness models plus additional roughness zones do not improve the rating curve prediction. Instead, it leads to lower values of water height. According to Figure 4b, the best scenario is number 3, which uses one roughness zone with the roughness boulder model of Knight et al. (2009).

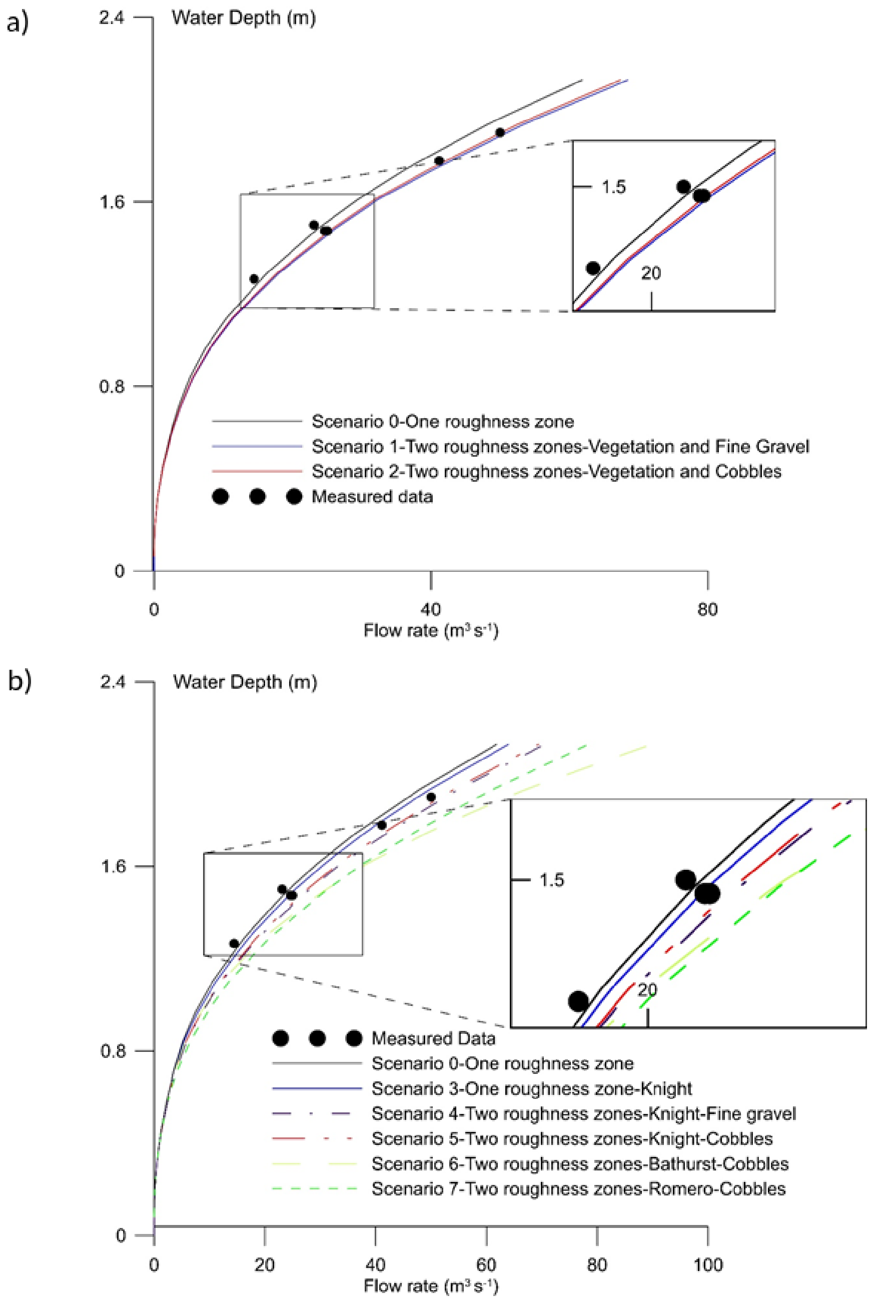

Figure 4. Rating curves for different scenario. a) Improvement of banks coverage description. b) Boulder model and improvement of bank coverage description.

3.2 Statistical Indices

Table 3 presents the results of statistical indices, and bold cells show the model with the closest match to the optimum value for each metric. RMSE shows that Scenario 3 (One roughness zone, Boulder roughness model of Knight et al. (2009)) is the best model. Moreover, the scenario with the smallest mean average error (MAE) was Scenario 2 (Two roughness zones, banks description: cobbles and varying height grass). The magnitude of the difference between these two indices shows that Scenario 3 is the best to predict the rating curve in the Tomebamba river. EF values confirm that Scenario 2 and Scenario 3 are the best, having a very good performance (see Table 2). Furthermore, Table 4 presents the relative error with respect to measured data for each flow and for each scenario. This table shows that for low flow values, Scenario 0 has less difference relative to the measured data. Also, at this flow magnitudes Table 4 depicts the highest relative error for all scenarios. However, for higher values of flow, Scenario 2 has the lowest relative difference for most data. This aspect is in accordance with the best MAE value seen in Table 3 for Scenario 2.

Table 3. Statistical Indices values for evaluated scenarios

	Scenario 0	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
RMSE	4.94	4.31	2.92	**2.38**	10.22	7.33	70.92	47.82
MAE	1.77	1.54	**1.1**	1.25	2.62	2.16	6.63	5.8
RMSE-MAE	3.16	2.77	1.81	**1.13**	7.6	5.17	64.3	42.03
EF	0.96	0.97	**0.98**	**0.98**	0.92	0.94	0.43	0.61

Table 4. Relative error related with flow magnitude

Q	Scenario 0	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
14.42	**7.12**	18.63	16.62	12.67	24.18	22.10	29.35	37.68
23.08	**5.47**	16.65	14.79	10.46	21.64	19.69	34.64	35.72
24.62	-5.67	4.57	2.86	**-1.28**	9.04	7.21	19.84	21.55
25.00	-7.12	2.96	**1.28**	-2.80	7.36	5.56	18.00	19.68
41.15	-6.67	3.83	**2.13**	-2.76	7.72	5.94	26.87	19.80
50.00	-8.38	1.62	**-0.02**	-4.74	5.18	3.52	27.46	17.06

4 Discussion

Two scenarios have shown to improve the CES predictability capacity. The best one according to the metrics, Scenario 3, uses a boulder model with a single roughness zone. This method had the best performance in Knight et al. (2009) as well. The model performance may be due to a better description of the resistance pattern in mountain rivers, where resistance values change with depth. In contrast, the original model had a fixed calibrated value of resistance for all the water depths. The model ranked as the second best is the one with three roughness zones: channel bed has a calibrated roughness parameter and banks a refinement of the bank description. This model is an improvement compared to the original scenario since there is a more realistic description of the resistance across the cross-section. This model has a better MAE than Scenario 3. MAE assigns the same weight across different error values, while RMSE assigns a higher weight to larger errors. The difference between both can be seen in Scenario 3.

Table 4 illustrates that the inclusion of a boulder model and/or roughness zones decrease the relative error as flow increases. At low flow, water and boulders interact generating jetting flows and waves behind particles which increase resistance to flow, increasing the roughness parameter (Jarrett, 1984; Bathurst, 2002). As flow increases, this effect is reduced, and the model seems to be more accurate to predict the points in the rating curve.

The boulder roughness of Bathurst (2002) and Romero et al. (2010) have the worst results according to the applied metrics. The data from which both models were derived made them, in principle, good candidates to represent boulder roughness in this river. Bathurst (2002) used an important amount of data from literature, and Romero et al. (2010) used data of rivers from the same Andean region than the Tomebamba river. Knight et al. (2009) boulder model was calibrated with data from this river and another from the same city, but the crucial aspect influencing its predictability may reside in its logarithmic relation to reflect the boulder roughness in comparison with the exponential relation obtained in Bathurst (2002). The model of Romero et al. (2010) may fail in the excessive simplicity of the relationship, since it does not have a term that represents the at-a-site resistance variation, such as relative submergence. Hence, the use of an inadequate boulder roughness description can imply important errors in the predictions. Furthermore, the results show that a calibrated roughness factor for the channel bed and the use of the roughness advisor for banks can potentially provide good modeling results when an appropriate boulder roughness boulder is not available.

5 Conclusions

In this research, an extension of the Tomebamba case study presented in Knight et al. (2009) is shown. We consider new scenarios where the boulder model and/or the roughness zones are varied. The predictability is quantified through different metrics to verify different aspects of the errors. The data used for validation was taken from a measured rating curve, which was compared with the output of the model.

The majority of the metrics depict that boulder roughness description of Knight et al. (2009) provides the best results to match the measured rating curve in this section of the Tomebamba river. Furthermore, the scenario where a calibrated roughness value and two additional roughness zones were added provides the best MAE value and the lowest relative error. Thus, CES is able to predict the rating curve in a mountain river, but it is limited to predict good results when the roughness description takes into account local conditions, as done by Knight et al. (2009). On the other hand, the use of a boulder roughness description obtained with a data set which did not include Tomebamba river ((Bathurst, 2002; Romero et al., 2010) in this study) underestimate the water levels having a potentially negative effect during flood prediction. Hence; the local knowledge of roughness values seems necessary to have appropriate modelling results, and the use of any empirical equation requires a previous test before using in a model.

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