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Discussions

Interactive comment on "A Process-Based Rating Curve to model suspended sediment concentration in Alpine environments" *by* Anna Costa et al.

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We thank Referee #1 for her/his helpful review. We have analysed the suggestions and we report in the following our response to the major comments.

1. Comment 2: Page 5, lines 17−18: A statistical test could be used to confirm this assumption (e.g., Grubb's test for outliers). Otherwise, selection of this threshold seems arbitrary. Alternatively, authors should additionally describe their decision.

We agree with Referee #1 that we should comment more extensively on the rationale behind the threshold selection, and we acknowledge that the term "outliers" (page 5,

line 17) is misleading. We removed SSC and NTU observations larger than the 90th percentile (corresponding to 2000 mg/l and 1000 NTU respectively) because we doubt the representativeness of such high measurements for the cross−section, due to the sampling procedure, which is punctual in space and in time, and due to possible measurement errors at high NTUs. For example, since SSC and NTU measurements are not taken exactly at the same point in space and in time, a short and highly concentrated suspended sediment pulse, due to the entrainment of fine sediment close to the measurement station, could be detected by one of the two sensors only. Nevertheless, following the suggestion of the Referee we applied the Grubbs' test to detect statistically significant outliers. We first log−transformed the SSC and NTU data to obtain a distribution as close as possible to a normal one, and second, we applied the test. At 5% significance level, the Grubbs' test does not identify outliers. We, thus, applied our methodology (computation of SSC−NTU relation, IIS algorithm and calibration/validation of the PBRC and the traditional RC) on the entire dataset, that is without excluding any high values. As shown in Fig. 1, the goodness−of−fit measures (coefficient of determination (R2), Nash–Sutcliffe efficiency (NSE), root mean squared error (RMSE), mean absolute relative error for values larger than the 90th percentile (MARE (SSC(t) > 90th)), and skewness of the residuals (λresiduals)) are very similar to the ones reported in the paper, meaning that excluding the data that we do not consider representative is not changing the results significantly. We will revise the manuscript to clarify the reason why we prefer to remove high values from the dataset and explain the test we have conducted to verify the effect.

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2. Comment 7: Page 11, section 4.2: I find this discussion very interesting. My question is: would SSC estimation results using just ERt−1 variable be much worse than using all three parameters? Additional calculations are needed in order to derive the IM and SM values. Thus, what is the trade−off between model complexity (adding additional variables) and estimation results? Authors could make a comparison or expand the

discussion about this.

We thank Referee #1 for this comment. We agree that it is indeed interesting to evaluate the performance of the PBRC taking as the predictor only erosive rainfall at 1 day lag, ER(t-1). However, to compute ER, defined as liquid precipitation over snow free areas, it is necessary to model snow cover and so snowmelt (SM). One option to evaluate the performance of the SSC estimation without modelling SM and IM, is to calibrate the PBRC with the single predictor liquid precipitation, R. We analysed this option as well. Results of the IIS algorithm confirm that the characteristic time lag for rainfall R in the upper Rhone basin is equal to 1 day. After calibration, the model, which we call here rainfall−RC takes the following form (Eq. 1): $SSC(t) = 0.787 \cdot R(t-1)^{0.978}$.

Although the performance of the rainfall−RC (Eq. 1) are lower than for the original PBRC, it performs satisfactorily especially in validation (Fig. 2), because the model can capture SSC peaks (Fig. 3b and Fig. 4). This result is not surprising because, as discussed in the manuscript, rainfall is responsible for large part (75%) of the variability in SSC(t). However, the new model, based on R(t-1) only, substantially underestimates medium and low values of SSC(t) (Fig. 3b and 2). This is particularly evident when looking at mean monthly values, especially in summer (June – August), when snow and icemelt largely contributes to runoff and suspended sediment load (Fig. 3a). In addition, the simulated SSC is equal to zero every time it does not rain, which is obviously an artefact of the model structure. So overall, such a model is not very satisfactory. We agree with Referee #1 that a discussion of the trade−off between model complexity and performance could be included in the revised manuscript. In Figure 5, we propose a sketch to qualitatively compare different approaches for predicting SSC (on the matrix columns) in terms of model complexity and model suitability for representing SSC features (on the matrix rows). We consider four modelling approaches to simulate mean daily SSC(t) at the outlet of an Alpine catchment, ordered in terms of model simplicity: the traditional RC, where the streamflow Q is the only predictor, the rainfall−RC with liquid precipitation R as the only predictor, the PBRC proposed in the paper, and

spatially distributed and physically based models of erosion and transport of sediment. To rank the model performance, we focus on 4 main features: the capability of capturing the seasonal pattern of SSC and the peaks of SSC, the sensitivity to climatic conditions and to the activation/deactivation of different sediment sources. Among the four models, the traditional RC and the rainfall−RC are the simplest because they are fully data−driven. They can both reproduce the time series of SSC(t), with better performances in calibration for the traditional RC and in validation for the rainfall−RC. As discussed in the manuscript, rainfall is mainly responsible for SSC peaks, due to its intense nature. Therefore, the rainfall−RC captures better the peaks of SSC than the traditional RC. However, the traditional RC captures the seasonal pattern of SSC better than the rainfall−RC, because the latter reproduces SSC only during rainy days, while RC reflects the seasonal pattern of streamflow. The traditional RC can be sensitive to changes in climatic conditions only if such changes directly influence discharge, which is not always the case (e.g., Costa et al., 2017), and it is insensitive to possible alterations of sediment sources being based solely on streamflow at the outlet of the basin. Conversely, rainfall−RC is clearly directly linked to changes in the precipitation regime, and so it can be partially sensitive to possible alterations of sediment sources. The PBRC is more complex than the RC and the rainfall−RC, because it requires to model snow accumulation, and snow and ice melting but it significantly improves predictions of SSC, both for peak values and seasonality. Moreover, PBRC is sensitive to climate induced changes in sediment dynamics and can partially (indirectly) account for alterations of sediment sources. Spatially distributed, physically based models have potentially higher modelling power than the PBRC and the RCs, and are in principle characterized by higher sensitivity both to changes in climatic conditions and alterations of sediment sources. On the other hand, they are characterized by much higher complexity both in representing the erosional and transport processes and in routing sediment fluxes to the outlet. They also require considerable effort to be calibrated and a significant amount of data to be used. In summary, we believe that the PBRC represents a good compromise between model performance and complexity (Fig. 5).

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3. Comment 9: Page 13, lines 1−3: Sediment connectivity could be estimated using the SedInConnect tool that was developed by Cavalli et al. (2013) (reference is also cited in the submitted paper) and is available at: https://github.com/HydrogeomorphologyTools or http://www.sedalp.eu/download/tools.shtml since DEM is available. Thus, you could confirm this hypothesis.

Thanks to the reviewer's comment, we realized that the sentence at page 12, lines 1−3 is misleading and we will remove it from the revised manuscript. The PBRC presented in the paper is indeed a lumped model where the spatial component is only partially accounted for by the time lags characteristic of the three hydroclimatic variables. We are currently working on a spatially distributed model based on the PBRC, in which we will account for sediment connectivity by applying the sediment connectivity index developed by Cavalli et al. (2013), as suggested by the Referee #1. Results of this on−going work will be presented in a separate manuscript.

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4. Comment 10: Page 14, Table 4: Besides these criteria you could also check the descriptive statistics of residuals because these can sometimes reveal additional information.

In the revised manuscript, we will add the skewness of the residuals (Figure 6). Results indicate that residuals of neither the PBRC nor the traditional RC are normally distributed. However, for the traditional RC residuals are more negatively skewed than for the PBRC.

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5. Comment 12: Page 18, line 17−19: Could this observation be confirmed with some statistical test or could maybe additional analysis proposed under comment Page 11,

section 4.2 be performed?

See reply to bullet point n. 2 (reviewer's comment n. 7).

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6. Comment 13: Pages 18−19, Conclusions: Some general conclusion could also be added about the complexity of tested methods.

See reply to bullet point n. 2 (reviewer's comment n. 7).

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-419, 2017.

	Calibration			
	PBRC (outliers removed)	**PBRC (entire dataset)**	RC (outliers removed)	**RC (entire dataset)**
R^2	0.65	**0.66**	0.61	**0.62**
NS	0.65	**0.66**	0.61	**0.62**
RMSE [dg l^{-1}]	2.77	**1.02**	2.93	**1.07**
MARE(> 90^{th}) [dg l^{-1}]	0.43	**0.42**	0.51	**0.50**
$\lambda_{residuals}$	−3.59	**−3.26**	−5.00	**−4.82**
	Validation			
	PBRC (outliers removed)	**PBRC (entire dataset)**	RC (outliers removed)	**RC (entire dataset)**
R^2	0.63	**0.63**	0.38	**0.39**
NS	0.63	**0.63**	0.38	**0.39**
RMSE [dg l^{-1}]	3.50	**1.29**	4.53	**1.66**
MARE(> 90^{th}) [dg $^{l-1}$]	0.38	**0.37**	0.53	**0.54**
$\lambda_{residuals}$	−2.14	**−2.15**	−3.68	**−3.58**

Fig. 1. Goodness of fit measures for the PBRC and the traditional RC in calibration and validation , on the entire dataset and after removing SSC and NTU observations larger than 2000 mg/l and 1000 NTU.

	Calibration			Validation		
	PBRC	**PBRC with only R_{t-1}**	RC	PBRC	**PBRC with only R_{t-1}**	RC
R^2	0.65	**0.47**	0.61	0.63	**0.60**	0.38
NS	0.65	**0.44**	0.61	0.63	**0.54**	0.38
RMSE [dg l^{-1}]	2.77	**3.50**	2.93	3.50	**3.90**	4.53
MARE(> 90^{th}) [dg l^{-1}]	0.43	**0.57**	0.51	0.38	**0.55**	0.53
$\lambda_{residuals}$	−3.59	**−3.16**	−5.00	−2.14	**−1.37**	−3.68

Fig. 2. Goodness of fit measures in calibration and validation for the PBRC, the traditional RC and the rainfall−RC with R(t-1) as only predictor.

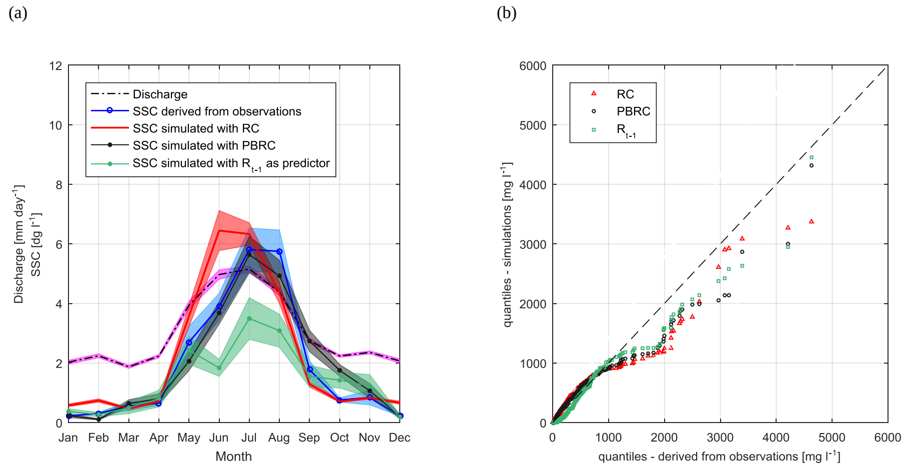

Fig. 3. (a) Mean monthly values of measured discharge and SSC derived from observations of NTU, and simulated with RC, PBRC and rainfall−RC. (b) Q−Q plot of mean daily SSC simulated with the three models.

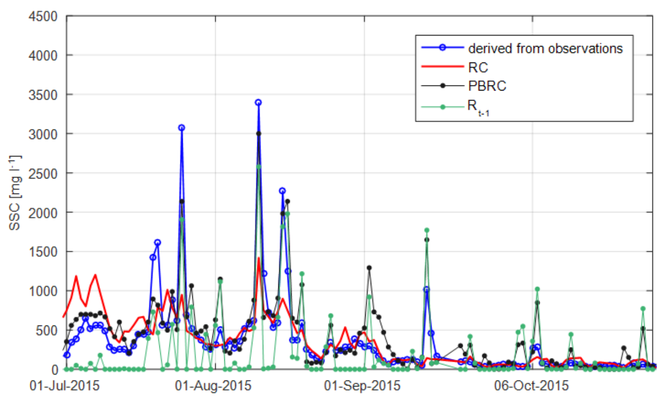

Fig. 4. Time series of mean daily SSC derived from observations of NTU and simulated with the traditional RC, the PBRC, and the rainfall−RC (01 July 2015 − 30 October 2015).

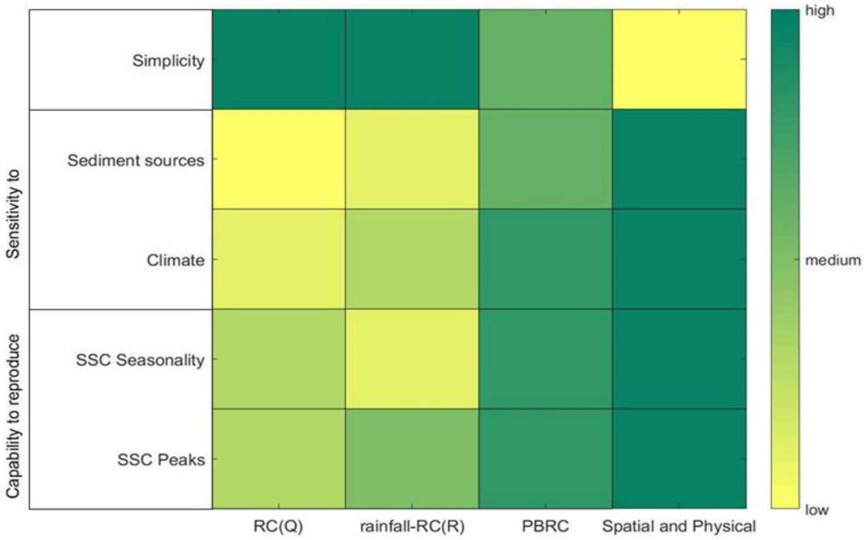

Fig. 5. Sketch representing the trade−off between model complexity and performance.

	Calibration		Validation	
	PBRC	RC	PBRC	RC
R^2	0.65	0.61	0.63	0.38
NS	0.65	0.61	0.63	0.38
RMSE [dg l^{-1}]	2.77	2.93	3.50	4.53
MARE(> 90^{th}) [dg l^{-1}]	0.43	0.51	0.38	0.53
$\lambda_{residuals}$	**−3.59**	**−5.00**	**−2.14**	**−3.68**

Fig. 6. Goodness of fit measures in calibration (left) and validation (right) for the PBRC and the traditional RC.