Dear Editor and Reviewers,

Thank you for your detailed comments and suggestions about our manuscript now entitled "*Even event-scale hydrological response characterization benefits from high density rain gauge observations*".
The paper has been revised accordingly. Please find hereafter the details of the changes in the form of an item-by-item response (in green) to your comments (in black). If our corrections are direct implementations of your remarks, the answer to the comment is simply 'Ok'. Please note that the line numbers indicated hereafter refer to the ones of the track-change revised manuscript attached below the answers. To avoid some confusion, letters will be used to refer to the figures from this author-reply document and the usual figure numbers will be used to refer to figures from the track-change version. To not unduly increase the length of this rebuttal, we refer at times to the public discussion.

We hope that our responses address all the raised concerns,

Best regards,

Anthony Michelon, Lionel Benoit, Harsh Beria, Natalie Ceperley, Bettina Schaefli

Responses to the comments of Reviewer #1:

1a - The title states "value of high density rain gauge observations for… hydrology". I'm struggling with this holistic formulation.

The title has been changed from "*On the value of high density rain gauge observations for small Alpine headwater catchment hydrology*" to "*Even event-scale hydrological response characterization benefits from high density rain gauge observations*".

1b - Indeed, the value is "only" (please don't get me wrong here) based on prediction of RC and deltaP/Q. While a realistic estimate of these characteristics is valuable, the uncertainties resulting from the final network with 3 rain gauges for these two criteria is not shown and should be added in a later version of the manuscript.

We initially proposed in the public discussion to add two figures showing i) the RC (Figure A) and ii) the lag time $\Delta_{P/Q}$ (Figure B) by comparing the values obtained from the best 1-station or 3-station raingauge network vs. the reference value calculated from the full raingauge network. These two scatter plots are shown below, but we finally found that these results were more visible as a polar plots. These two plots are gathered in the Figure 12 of the manuscript in "4.4.3 Optimum network evaluation", and they show the RC and lag time $\Delta_{P/Q}$ calculated from the best 1-station and 3-station network compared to the full raingauge network (L534-543).

As the stochastic method for generating rainfall fields cannot be used with a number of points as low as 1 or 3 stations, we performed the computations using the Thiessen polygons methods and consequently no error bars are associated to these plots. Nevertheless, the Figure C compares the two methods (stochastic vs Thiessen polygons) when the RC and the lag time $\Delta_{P/Q}$ are computed from the full raingauge network.

We observe for both the RC (Figure A) and $\Delta_{P/Q}$ (Figure B) a lower dispersion of values while increasing the density of the raingauge network. With a 3-station raingauge network the error on the RC (RMSE = 0.186) drops below the error obtained by comparing 2 different interpolation methods (RMSE = 0.256), giving a good confidence to the Thiessen polygons method used for this calculation. In the same way, for $\Delta_{P/Q}$ the error with a 3-station network (RMSE = 8.12) is lower than the error obtained with the model comparison (RMSE = 13.22).

On the Figure C, the dispersion of $\Delta_{P/Q}$ is originally low. Even with a 1-station network the lag can be reproduced correctly for most of the events but can also be completely wrong for one of them. Outliers are still observed with the 3-station raingauge network though, even if the error gets lower (RMSE reduced from 23.18 to 8.12).
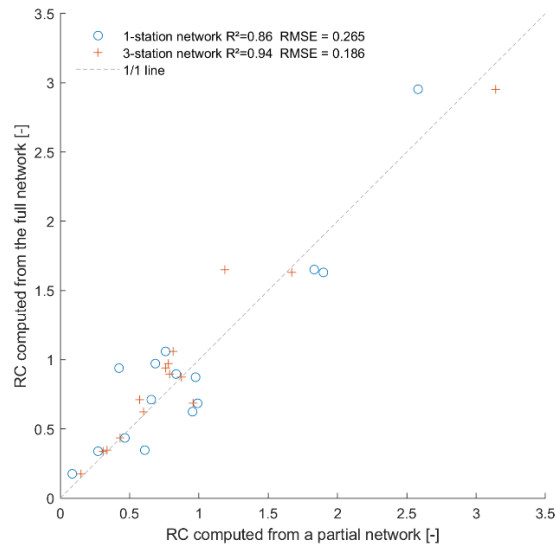
Figure A. Comparison of RC whether it is calculated from the full raingauge network or from a partial, considering the best 1-station and 3-station network. The dataset is based on the 15 rain events associated to a river reaction.
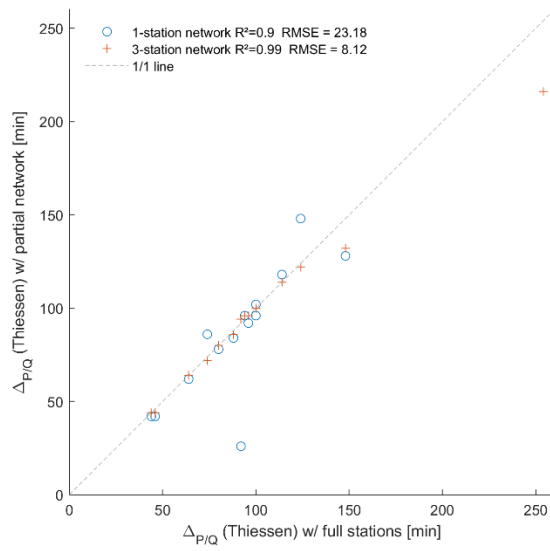

Figure B. Difference of lag time $\Delta_{P/Q}$ obtained from a partial network (1-station and 3-station network) and the full network.
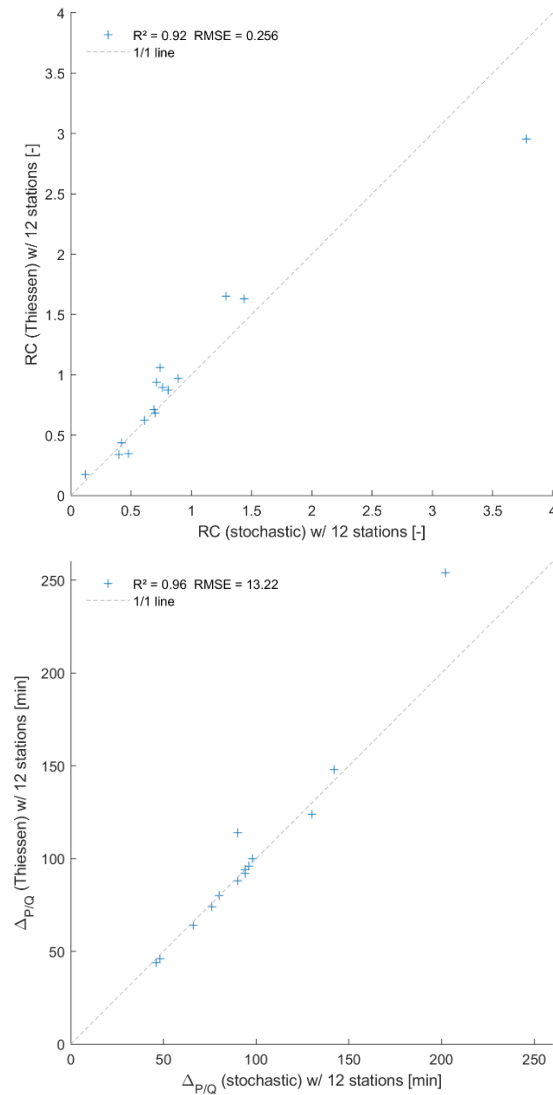
Figure C. Comparison of the RC (left) and lag time $\Delta_{P/Q}$ (right) calculated using the full raingauge network, but with a different rainfall field interpolation method (Thiessen polygons vs. stochastic).

1c - In general, I'm missing the runoff peak as important characteristic in the manuscript. Maybe the authors can involve it/comment on it why it was not considered.

This point has been clarified in the public discussion.
(https://editor.copernicus.org/index.php?_mdl=msover_md&_jrl=13&_lcm=oc108lcm109w&_acm=get_comm_sup_file&_ms=87052&c=189590&salt=1072061062177638648) and we added the figure showing the peak flows to the Supplementary Material (Figure S5).

1d - Also, although the analysis is designed mainly for discharge estimation, results should be also interpreted in terms of rainfall (e.g. resulting areal rainfall (extremes) for different rain gauge network densities, spatial rainfall characteristics…).

Accordingly to our answer in the public discussion, the impact of the raingauge density over i) the maximum rainfall intensities and ii) the number of misestimated events has been added in the new subsection "4.4.1 Raingauge density analysis" (L498-514) coming with the Figure 7 (new).

2 - Based on the comment before, the impact of the rain gauge network densities (and rain gauge locations) on the runoff is not analysed. In the additionally uploaded comment the main author states a rainfall-runoff modelling would go beyond the scope of the study. I do not agree with that and

recommend this modelling approach to analyse the impact on the resulting runoff itself instead on single runoff statistics. To attribute the spatial rainfall variability, a distributed rainfall-runoff model would be the best solution.

Accordingly to our answer in the public discussion, we added a modelling component to this paper; the model is discussed in the public discussion (https://editor.copernicus.org/index.php?_mdl=msover_md &_jrl=13&_lcm=oc108lcm109w&_acm=get_comm_sup_file&_ms=87052&c=189590&salt=1072061 06217776386148).
Corresponding modifications of the paper are i) at the end of the introduction (L92-94), ii) presenting the model used in the method part "3.6 Rainfall-runoff model" (L335-350), iii) in the results section in "4.4.3 Optimum network evaluation" (L544-555), iv) with the Figure 15 summarizing the results of the different simulations and v) in the Supplementary Material part 1 with the Figure S9 (map of subcatchments), Figure S10 (the results of all simulations per event) and Figure S11 (the results of simulations per event, cumulated over time).

3 - Also, I was wondering why is there not a consistent number of events analysed throughout the manuscript. I understand that there are always measuring issues and maybe some observations are questionable, but then please remove them at the beginning. There could be one number of rainfall events considered and one subset of them for discharge analysis, but at the current state results from different subsections cannot be compared with each other due to the different populations of considered events.

The different subsets used through this study are visually clarified by the table 2 (new) and introduced in the main text when discussing of the rainfall events subsets are brought up for the first time in "4.1.1 Areal rainfall and asymmetry" and in the same way with streamflow events in "4.2.1 Observed streamflow events". This table is also referred to several times later throughout the paper when using different subsets.

4 - L25-27 It should be mentioned here again that this issue is related to mountainous areas and is not a problem in general.

Ok (L30).

5 - Fig. 2 I don't see the additional worth of showing Fig. 2 and recommend to leave it out, especially since it is included in the supplement as Fig S2 as well.

The figure showing a picture of the hydrological station (previously Figure 2) has been removed from the paper. The Figure S2 in the Supplementary Material part 1 fulfills the aim of illustrating the measurement site.

6 - L90 "average elevation" Please change to mean or median, depending on how you determined the "average" value.

Ok. The misuse of "average" has been changed to "mean" when needed throughout the whole paper.

7 - L117-118 The construction of the rating curve is not interesting for the manuscript and can be left out, also the elements regarding its construction in the supplement.

The details about the rating curve have been moved from the main text to the caption of Figure S2 and Figure S3 in the Supplementary Material part 1.

8a - L154-155 The term interpolation is not suitable in my opinion due to the rainfall generation mechanisms behind. I suggest "areal rainfall is generated after Benoit et al. (2018a) by constraining actual observations at rain gauge locations". The authors should give a less brief explanation, since in the cited manuscript different versions are applied for rainfall generation (three versions due to different covariance models) and it remains unclear for the reader, which model is used for the current study.

The explanation of the rainfall generation has been revised and extended to make the gridding process clearer (L170-177). The reference to 'interpolation' is kept for the general gridding process only but has been removed from the description of the stochastic model. In practice, the stochastic model used in the present study corresponds to the model version C in Benoit et al. 2018a because it is the best suited version for high resolution data. This is now clearly specified in the revised manuscript. In addition, we provide an open-source MatLab implementation of the model to help interested readers better grasp each step of the gridding process.

8b - Why did the authors choose this rainfall generation instead of a regionalization approach as kriging (maybe with altitude as additional information), inverse distance weighting or Thiessen polygons. The latter is chosen later in the manuscript nevertheless due to computational efforts, so why not for the whole study? Was it the authors intention to add an uncertainty analysis.

Indeed, we choose the stochastic rainfall generation for the valuable estimation of the errors it provides. The Thiessen method also used throughout this paper fills the weak points of the stochastic approach, namely i) the computation time, which is very short using the Thiessen method and allows to explore within a reasonable amount of time all the possible combinations of raingauge networks for their optimization, and ii) to calculate rainfall fields even with a low number of raingauges. For this last point the stochastic method require at least 5 stations to capture correctly the spatial and temporal rainfall characteristics.

Concerning the altitude effect on rainfall, we do not observe any trend ($R^2 = 0.06$) between the cumulated rainfall per station and the altitude. This information has been added (L356-357) in "4.1. Areal rainfall and asymmetry". The Figure below is shown as illustration purpose for this document
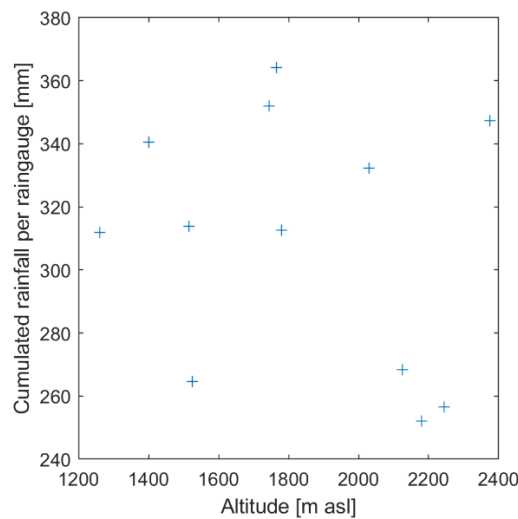

Figure D. Cumulated rainfall at each raingauge vs. altitude of each raingauge.

9 - L154-163 The authors should bring this argument in context with the catchment concentration time.

We clarify the justification about inter-event time chosen to separate 2 consecutive events, introducing the catchment's response time and the recent paper of Beven (2020) that extensively clarify this concept. This justification reads as: "Accordingly, we assume that this event gives a rough estimate of the catchment's response time (Beven, 2020) i.e. of the time required until the entire catchment contributes to the streamflow response, including the delay caused by runoff transfer to the stream network and from there to the outlet from the hydrologically most distant parts of the catchment. The 90 minutes were therefore selected to maximize the chances of observing a distinct streamflow response for two distinct consecutive rainfall events." (L183-186)

10 - L165-166 The location of the line chosen for the splitting of the catchment seems to be chosen arbitrary. Would a line constructed perpendicular to the main flow direction of the river (or even better, not a straight line but following the lines perpendicular to the isohypses to separate flows exactly) lead to more representative results, since the catchment is then split into a real upper and lower part? Or (thinking the other way around) does it not matter at all and the splitting line could be also drawn from South to North as long as both parts have the same area?

The possible geometries of the splitting line used to compute I_{ASYM} is now discussed in "5.1 Spatial heterogeneity of rainfall". This justification reads as: "It is noteworthy that this analysis could be affined by investigating different splitting geometries, e.g. by splitting the catchment into west and east parts, thereby separating the large slopes (west) from the steep slopes (east).This and similar spatial asymmetry metrics are case-specific as they rely on the particular geomorphology and topography of the catchment and are thus not directly applicable to other catchments. In particular I_{ASYM} cannot be used as a tool to compare different catchments." (L570-573)

Furthermore, we also justify the use of the current north/south splitting line when introducing it for the first time in "3.2.2 Spatial rainfall pattern metrics", discussing the Strahler stream order. This justification reads as "This heuristic splitting into two parts is interesting here due to i) the elongated catchment shape and furthermore ii) the clearly distinct stream network organisation in the upper (southern) part of the catchment with more branching than in the northern part (reflected in the Strahler stream order that does not further increase in the norther part, see Figure 1). Accordingly, we assume the rainfall events falling exclusively on one or the other part of the catchment lead to a distinct streamflow response, with a faster and stronger response for events falling on the northern part (closer to outlet, steeper hillslopes, less storage potential than for the southern part)." (L196-201)

11 - L211-215 I suggest to move this paragraph to the beginning of section 3.3.2

This comment refers to the statement on how baseflow is separated ("The beginning and the end of the streamflow response determine the initial and final baseflow, respectively; the streamflow volume above the line connecting these two points is considered here as fast runoff.") and we think that it is an integral part of event identification. However, we changed the subsection title "3.3.1 Event identification" to "3.3.1 Identification of streamflow events and fast runoff".

12 - L217-218 The authors declare volume and lag time as "the two key characteristics of streamflow reaction". I do not agree with that. The most important characteristic is peak flow, followed by volume and then lag time and flatting behaviour. Even if all characteristics are considered equal important, the authors should state why peak is not considered in the study. If there were attempts to include peaks which did not work, the authors should state so as "lessons learned" in the manuscript.

L234-239: we corrected the beginning of section 3.3.2. It now read as: "The key metrics to characterize the streamflow response are the peak flow, the fast streamflow volume, the lag time elapsed between rainfall and streamflow response, and the flatting behaviour. For technical reasons we discarded the peak flow (see section 3.3.1**Erreur ! Source du renvoi introuvable.**) and consequently the flatting behaviour. We use the fast streamflow volume through the runoff coefficient (RC), which is obtained by dividing the fast runoff volume by the total rainfall for the given event. The lag time […]" (L262-266).

And at the end of the section 3.3.1: "It is noteworthy that we do not use peak streamflow to characterize streamflow events, for two reasons: i) given the small size of the catchment and the complex temporal distribution of rain intensities, the streamflow response has rarely a single, well identifiable peak (all events are plotted in Figure S5 in Supplementary Material Part 1); ii) peak streamflow identification is further complicated by the noise in the stage recordings."

13 - L219-221 Is this criterion developed by the authors or should a reference be cited in this context? How was 1/3 chosen as threshold? This value should be catchment-dependent in my opinion, or not? Please clarify.

L241-244: we clarified how the 1/3 threshold on rainfall and streamflow reaction was selected. It now reads as: "Since the start of excess rainfall is not known, the concept of peak flow is difficult to apply to our observed events (Section 3.3.1) and given the varying shape of our hydrographs, we empirically tested different lag formulations; the lag between 1/3 of the rainfall event volume and 1/3 of the streamflow event volume gives the best results in the regression analysis, and is therefore retained. It is noted $\Delta_{P/Q}$ in the following." (L271-275).

14 - L222 Why is this criterion "1/3 of the rainfall amount" more robust than "start of the rainfall event", although both starting points are linear correlated?

The formulation was not well chosen and has been reformulated along with the sentence of the previous point (L271-275).

15 - L275 Same differences lead to higher asymmetry values for smaller values. To avoid a misinterpretation ("Interestingly…") Pnorth and Psouth could be normalized by the mean event rainfall amount. This would provide deeper insights, especially since larger differences between both parts cannot be seen in the current approach if they occur for events with high rainfall amounts.

We added the columns P_{NORTH}/P_{ALL} and P_{SOUTH}/P_{ALL} in the Table 3.

16 - L323-327. I cannot follow the argumentation here. Please explain in detail how you achieve this conclusion and consider at least one or two sentences for each argument.

The paragraph has been reformulated. It now reads as: "The correlation analysis (Table 4) reveals a strong correlation between rainfall amounts and Q_{FAST} (0.77, **Erreur ! Source du renvoi introuvable.**). This suggests that streamflow responses are triggered by saturation-excess, rather than by infiltration capacity-excess: If saturation is exceeded, every unit of rainfall leads to a corresponding unit increase of streamflow, which in turn leads to a strong linear correlation between rainfall amounts and fast streamflow volumes. Furthermore, saturation-excess also implies that a longer rainfall event leads to a higher streamflow response volume (once the saturation threshold is reached, all rainfall contributes to streamflow). This is confirmed by the high correlation (0.74) between the rainfall duration $P_{DURATION}$ and Q_{FAST}. If, on the contrary, the driving process was the exceedance of the soil infiltration capacity, then only rainfall intensities above the capacity threshold would trigger a corresponding streamflow increase; small rainfall amounts would trigger almost no response. In this case (infiltration-excess), there would be no linear correlation between rainfall amounts or rainfall duration and streamflow amounts, but a strong correlation between fast streamflow amounts and high or maximum precipitation intensity; positive correlations between Q_{FAST} and $P_{max\ ALL}$, $P_{max\ NORTH}$ or $P_{max\ SOUTH}$ are however all absent (values of -0.17, -0.16 and -0.08, Table 4). In addition, saturation-excess as a main driver of the fast streamflow response is further confirmed by the clear threshold effect for the generation of streamflow as a function of total event rainfall (**Erreur ! Source du renvoi introuvable.**); a streamflow response only occurs for total rainfall higher than 5 mm." (L429-443)

17 - L330 "to reach a higher "RC" Please rephrase, the manuscript is about observations, not modelling.

We rephrased "to reach a higher RC, we need a higher level of saturation [...]" by "we observe a higher RC when the level of saturation increases [...]" (L447).

18 - L341 composites: If there is a differentiation into wet and dry state, how do the authors achieve only one value for each criterion? Are two values estimated (for wet and dry) and then the arithmetic mean is mentioned? Please clarify!

First, we changed the name "composite network" to "pseudo-dynamic network" in the entire document. A column has been added to Table 3 to show which network (dry/wet) is used for each of the 15 rainfall events having a streamflow reaction, and the missing explanation of the network extent and pseudo-dynamic network calculation is now explained in "3.4.1 Pseudo-dynamic stream network extent". It reads as:

"In absence of exact observations of the stream network extent before the start of each streamflow event, we propose here to use a pseudo-dynamic stream network extent which assigns the dry or the wet network to each streamflow. The network state is chosen based on a measure of the initial catchment wetness conditions." (L284-285)

"This correlation analysis yields an optimum antecedent wetness indicator corresponding to the rainfall over the 3 days preceding the start of a rainfall event, noted W_{3days}. Using this indicator, the pseudo-dynamic network extent is obtained by assigning the dry network state to rainfall events that have W_{3days} < 20 mm and the wet network state to rainfall events that show $W_{3days} \geq 20$ mm. This threshold of 20 mm is selected by maximizing the correlation coefficient between D_{HILLS} and RC (see Section **Erreur ! Source du renvoi introuvable.**)." (L95-299).

19 - L351-355 It would be nice to have a table with all criteria, where it is stated which one was removed (and why) and which ones were kept. Maybe the information can be added to Table 5 or 6?!

We discuss in this section ("4.3 Identification of dominant hydrologic drivers via regression analysis") only the best models. Among all the models tested through this regression analysis (combining models having one or two explanatory variables), the selection is exclusively based on AICc ranking and R². The rejection of the models having a lower rank is therefore not detailed in the text or in the tables. We made the model selection method clearer in the text and it now reads as: "The tested models, based on one or two explanatory variables, are summarized in **Erreur ! Source du renvoi introuvable.** for RC and in **Erreur ! Source du renvoi introuvable.** for $\Delta_{P/Q}$. The analysis is based on 14 events (after removing the 24 July event, subset #4 of Table 2) and the best models are selected based on their AICc ranking and coefficient of determination (R²)." (L480-482)

20 - L354 Again, it feels as the number of considered events changes among all subsections.

This has been clarified (see also point 3 above).

21 - L380 What is the reason for IASYM preference in the Southern part? Due to the steeper areas? I would have estimated Northern part, since the hydrograph would have already been smoothed when originated in the South. Please try to find physical explanations to your results.

Thanks for pointing this out. Due to a legacy effect the sentence "And for a single station network, the metric I_{ASYM} prefers a station location in the southern part rather than in the northern part" is false and has been removed, as well as the plot of the best 1-station network for I_{ASYM} in the figure 12.

22 - General: Please double-check the abbreviation for "meter above sea level"; I have only seen "m a.s.l." and "m asl" so far, but not "m asl."

The abbreviations of meter above sea level have been corrected from "m asl." to "m asl" throughout the whole paper.

23 - L155 Benoit et al. 2018 <- a or b? I assume a.

Ok (it is "2018a" indeed).

24 - Eq 2, 3, 4 I'm a bit confused what rainfall characteristic is used as input for these equations. Is every raster cell with rainfall used (so I understood it from the text) or only the centre of the rainfall events (as mentioned in Table 1)?

The rainfall characteristics and space-time resolution used into the Equations 2, 3 and 4 have been clarified. The text now reads as "[…] where i and j are the coordinates of rainfall location within the grid, $P(i,j,t)$ is the rainfall amount previously calculated using the stochastic method (section 3.2.1) for each of the 10 x 10 meters grid cell at each 2-minute time step t, and $d_{HILLS}(i,j)$ is the distance of this grid cell to the nearest stream network grid cell (following the line of steepest descent in the 2 x 2 m DEM (swissALTI3D, 2012))." (L217-220)

25 - L163 "overlooked" -> ignored

Ok.

26 - Eq. 2, 3, 4 The term in the numerator should be put in brackets (Eq. 2: "P(..)dHills" -> "(P(..)dHills)")

The equations formulation (missing brackets) have been corrected for D_{HILLS}, D_{STREAM} and H_{HAND} (Equations 2, 3 and 4, respectively).

27 - L195 DHAND is not a distance as indicated by the D, and in the text the variable is introduced with HAND. I suggest to stick to HAND throughout the manuscript to avoid confusions with the other two "real" distances".

We now use the abbreviation H_{HAND} instead of D_{HAND} (and not $HAND$ like we initially proposed, to avoid variable names made from several letters) throughout the whole paper, figures and associated documents.

28 - L202 Section 3.5 includes no network extent description. Is it missing in the manuscript?

The missing explanation of the network extent is now explained in "3.4.1 Pseudo-dynamic stream network extent" (L278-299).

29 - L268 317.8 mm – Is it areal rainfall amount sum or sum over all stations?

We specified (L355) that the value of 317.8 mm is the areal rainfall amount.

30 - L268-269 please provide also the mean values, not only the highest and lowest values, so that the reader get a "feeling" for the rainfall events.

The mean values have been added (L356).

31 - L275 again, please don't use the term average, use mean or median to be more concise. Since Iasym can be positive and negative, the median of its absolute values would be worth to show instead of just the mean, since positive and negative values are levelling out each other.

Indeed, in this case using the median value of I_{ASYM} (0.025) is better than using the mean, it has been corrected (L363-364). Also, the misuses of "average" has been corrected when needed throughout the whole paper.

32 - Fig. 5 and 6 For a logical order the figures should show the rainfall events first, followed by the discharge plot.

The figures showing rainfall events records (Figure 3 and Figure 4 in the main text, and all the figures of the Supplementary Material part 2) have been rearranged to have rainfall data above streamflow data.

33 - L279 "One strongly asymmetric and high intensity event" -> "One strong asymmetric and very intense event"

Ok.

34 - L283 A volume can't be fast (check also for later occurrences…)

Ok.

35 - L288 In the sentence before authors mention that the number of events under consideration are reduced by "1", but here again 48 events are studied (also in the following subsections).

Indeed, it is confusing. The line it is referred to "This event and its streamflow reaction are excluded from further analysis" has been replaced by "This event and its streamflow reaction are excluded from further analysis involving the hydrological response" (L373-374).

36 - L289 The authors should state what wet and dry networks are. I found it later in the caption of Table 1 in S1, but it would lead to clarifications here. Also, the Table 1 in S1 should be shown in the manuscript, since the written part in Section 4.1.2 is more confusing than explaining for me.

The dry and wet networks are now introduced in "2 Study area". It now reads as: "The actual extent of the stream network is based on observations during Summer 2017 (dry and wet periods) and its exact path was calculated using the Swiss digital elevation model at a resolution of 2 m (swissALTI3D, 2012)." (L126-127)

It is detailed later on in "3.4.1 Pseudo-dynamic stream network extent" and it reads as "The extent of the stream network evolves as a function of the catchment wetness conditions. Its minimal and maximal extent (**Erreur ! Source du renvoi introuvable.**) are determined manually by identifying the uppermost points of the catchment where streamflow was observed in the field during summer baseflow (minimum extent, called *dry* state) and during summer high flow (maximum extent, called *wet* state)."

37a - Fig9 "events without reaction are not shown" belongs to part b), not a). Please correct the caption.

Ok.

37b - General: Maybe I missed it, but which temporal resolution was used to calculate the correlation (and other criteria)? 2min as this is the resolution of the rain gauge? Or are values aggregated up to e.g. 1h? This has a high impact on the values of the correlation coefficient.

The temporal resolution of times series used for correlation calculations is 2 minutes. The correlation between events is done at the event-scale. This is now clarified in the text.

38 - L339 "absence of correlation". Correlation cannot be absent. Better to speak of low correlation or provide absolute values.

Ok.

39 - L384-386 "is assessed", "is evaluated" – two verbs, please rephrase the sentence.

Ok. It now reads as "Considering the small dataset underlying this analysis (23 events), the robustness of the best networks is assessed for two selected metrics (for the P_{ALL} and I_{ASYM}) by re-computing the optimal network if between 1 and 3 events are removed from the dataset." (L329-331)

40 - L402 "what we previously thought"? What was the hypothesis of the authors before?

We reformulated the explanation about the outperformance of D_{STREAM} over D_{HILLS} for the prediction of RC and lag time. It now reads as: "We could expect that in that kind of steep environments, the residence time in hillslopes strongly dominates over residence times in the stream network (Nicotina et al., 2008); the fact that D_{STREAM} outperforms here D_{HILLS} for the prediction of RC and lag time may show that even in steep environments, with a priori fast instream processes and limited storage, the riparian area and related subsurface exchange processes could play a more prominent role. The fact that the travel distance in the stream network explains more of the RC variation than D_{HILLS} might be an indirect effect: the longer the travel distance in the stream network, the more likely are delays due to exchange with groundwater in the riparian area." (L578-584)

41 - L421 "three station network" It would be nice to provide the resulting density here as well as "(general) recommendation".

The results are now also presented in term of raingauge density in the figure 7 and in the text referring to (L505-506) and later in the text L536-537.

Responses to the comments of Reviewer #2:

1) I already reviewed the initial version of this paper, which aims at highlighting the values of high density rain gauges networks for hydrological purposes in a small catchment of mountainous areas. I still believe that the topic is interesting and relevant for the community. It furthermore has other potential applications in urban areas which are also small and quickly reactive catchments where rainfall variability has strong consequences.

A reference to urban hydrology (Cristiano et al., 2017) has been added into the introduction. It now reads as "While our analysis focuses here on a small natural headwater catchment, it is noteworthy that the developed rainfall monitoring and data analysis framework might also be of interest for urban hydrology, which deals with similar questions regarding how spatial rainfall patterns, runoff generation processes and flow network geometry lead to peak flows in urban drainage systems (for a review, see the work of Cristiano et al., 2017)." (L77-81)

2) The minor difficulties with regards to the presentation and understanding of the paper have been corrected. Results are now better presented with the new figures. However, the main point was not addressed, i.e. the fact that the authors aims at showing the importance of grasping the spatio-temporal variability of the rainfall process in the prediction of flows, but the chosen indicators are only event based averages.

First of all, we would like to point out that we accidentally used the formulation "runoff prediction" rather than "runoff coefficient prediction" in the abstract. We removed the misleading formulation "runoff prediction" from the abstract, that has also been adapted to the changes made to the paper. This having said, we did not mean to pretend that we study the predictability of streamflow but well the relation between rainfall field characteristics and runoff event characteristics, which has indeed a long tradition in hydrology as a basis for model development and comparative hydrology (Merz et al., 2006).

We believe that a focus on the scale of runoff response events is fully justified. We use for our event-based analysis descriptors of two fundamental properties of runoff events, which refer to the time until a response occurs and the magnitude of the response; we choose here the runoff coefficient and a lag time.

We agree that these average streamflow event properties hide other interesting aspects of the hydrological response namely referring to the shape of the response and including e.g. the occurrence of double-peak response. A further detailed analysis of such double-peaked events versus single peaked events is however not possible for this small data set (see Figure showing all streamflow events at the end of this document).

One additional descriptor of hydrograph shape could be what Tarasova et al. (2018) call the runoff event time scale, i.e. the ratio of runoff volume in mm and the runoff event peak flow in mm/day (see also Gaál et al., 2015). This descriptor could potentially shed light on the mixture of fast and slow runoff response processes. The identification of peak runoff is however extremely challenging for this case study because the moment of peak flow occurrence is often not well defined (see **Erreur ! Source du renvoi introuvable.** and our response to the point 8 of this document).

Another descriptor for this mixture could be the rising time of an event, quantifying the time to peak (normalized by the event duration). We refrained however from using descriptors requiring a precise quantification of event duration since the identification of an exact start and end time remains extremely challenging (Tarasova et al., 2018) and could largely affect the results in presence of a relatively small data set.

3) Furthermore, the main rainfall variability (which is at the core of the paper) indicator used is too simplistic since it is basically an asymmetry indicator on the total depth splitting the catchment in two. So I still think that indicators actually accounting for the spatiotemporal variability of the rainfall and hydrologic response should be implemented to actually address the stated topic of the paper. Implementing them requires major modifications of the paper. I guess that this would enable to highlight more precisely the importance of dense networks of rainfall measurement devices.

We agree that I_{ASYM} is a simple indicator to capture the key rainfall field properties for the hydrological response. In other studies and namely in urban hydrology such an indicator is typically based e.g. on the variogram or on the spatial moments of rainfall with continuously observed rainfall fields (radar images). We added this comment in "3.2.2 Spatial rainfall pattern metrics" and it reads as: "Spatial rainfall patterns are classically characterized with geostatistical tools, including variograms (Berne et al., 2004) or with spatial moments of rainfall (Smith et al., 2002;Zoccatelli et al., 2011;Mei et al., 2014), in particular in presence of observed rainfall fields, e.g. from radar images. Here we propose to use more hydrological-process oriented metrics that explicitly account for known features of the catchment and the stream network." (L190-194)

The asymmetry indicator is just one of the indicators used in the study, along with the geomorphological distances, which corresponds to the above first order spatial moments, albeit decomposed according to hillslope and stream network flow distances. As we answered in the public discussion, we tried the second order moment of distance metrics, but it does not show any noticeable correlation with a rainfall or streamflow metric. We added this result in the text: "It is noteworthy that these two metrics, D_{HILLS} and D_{STREAM} correspond to the aforementioned first order spatial rainfall moments, albeit decomposed according to hillslope and stream network distances, similar to what was proposed by Zoccatelli et al., 2015 in their analytical framework to quantify the smoothing of spatial rainfall organisation effects by channel residence time. It would be tempting to use also higher order rainfall moments; however, no significant correlation could be found the retained streamflow metrics." (L229-233)

Finally, we also added the section "4.1.3 Temporal evolution of rainfall metrics", please see our answer to the point 7 below.

4) l. 110 – 115: "The actual extent of the stream network is based on observations during dry and wet periods during Summer 2017 and its exact path was calculated using the Swiss digital elevation model at a resolution of 2 m (swissALTI3D, 2012)." I think that the intrinsic fractal nature of river networks should be mentioned and discussed. The concept of variable network used after also seems interesting.

We implemented at the end of "5.1 Spatial heterogeneity of rainfall" a comment about the fractality of the river network. It reads as: "However, future work on the role of water residence time in the stream network will necessarily require more detailed field data on the temporal evolution of the stream network. This will in addition open new perspectives to quantify how the stream network extension is imprinted in the streamflow response: in fact, as discussed by Rinaldo et al. (1995), the intrinsic fractal nature of the stream network is not transferred to the streamflow response and, accordingly, there is potential to infer the stream network extension from observed streamflow records, provided that we have high resolution rainfall data to disentangle the different effects." (L587-592)

5) l. 150-151: "Some additional artefacts were recorded, probably generated by strong winds creating resonance. These periods have been manually removed from the data". It should clarified how the data was selected for being removed and what portion was removed.

We clarified how raw rainfall data were selected and some parts removed. It now reads as: "Additional artefacts were recorded, probably generated by strong winds creating resonance. Some stations in fact recorded very strong and highly variable rainfall over several hours during periods with high wind velocity but during days without any observed rainfall in the combined MeteoSwiss radar-rain gauge

data (Sideris et al., 2014). Four periods (over 4 different days) have been manually removed from the data." (L164-167)

6) 1. 154-157: It is a great improvement to use this stochastic procedure. Nevertheless, I believe that more details on the interpolation procedure are needed. It should be clarified how the 20 samples are used (computing the error bars in 8-10)?

We added details about the stochastic procedure and error bar computation. It now reads as: "Before further analysis, the rainfall amounts measured by each station were interpolated to a 10 by 10 m grid at a 2 min time step using a high-resolution stochastic approach developed by Benoit et al. (2018a). In a nutshell, it generates an ensemble of stochastic space-time rain fields constrained by the actual observations at the rain gauge locations. The resulting ensemble (here composed of 20 realizations) can be used to analyze spatial rainfall uncertainty or to construct a single rainfall estimator. Following Benoit et al. (2018a), a non-separable and asymmetric covariance function was used to perform the simulations, which allows modelling rainfall advection and diffusion observed in the raw data. Areal rainfall time series are calculated for each of the 20 realization, and from these a single time series (mean and standard deviation) of the areal rainfall." (L170-177)

7) Eq. 1 on I_ASYM. As already mentioned, it seems a too simplistic indicator to grasp spatio-temporal variability of the rainfall process. An initial simple suggestion could for instance be to look for the temporal evolution of I_ASYM during an event. But other indicators are needed

We added figures showing the evolution of D_{STREAM}, D_{HILLS} and I_{ASYM} in the supplementary Material, and added in the text a qualitative discussion of the temporal evolution of the rainfall metrics in "4.1.3 Temporal evolution of rainfall metrics". It reads as:

"We computed the temporal evolution of the rainfall metrics to unravel potential temporal evolution patterns in I_{ASYM}, D_{HILLS} and D_{STREAM} and their relation to the streamflow response (full results are available in the Supplementary Material part 1). The temporal evolution of the two distance metrics is overall rather flat with no clear fluctuation patterns. There is only one event with a pronounced temporal trend for D_{HILLS} (Q event #1).

For I_{ASYM}, some events show interesting temporal patterns. For example, during the double peak runoff of **Erreur ! Source du renvoi introuvable.**, I_{ASYM} shows an almost constant negative value suggesting that the corresponding double peak rainfall event remained stationary on the northern part of the catchment over its entire duration and therefore caused the double peak streamflow response.

For the first two streamflow events, the I_{ASYM} metric switches from strongly positive to close to zero during the event, implying that the rainfall field moved towards the outlet during the event; in other words, the rainfall cloud follows the overall water movement through the catchment and thereby leads to a stream response concentration. This might explain why these two events are the only ones that show a pronounced single peak streamflow response. However, given the low number of observed events and the diversity of temporal patterns, these insights cannot be further used for a quantitative analysis." (L391-404)

8a) l. 212-215: the explanation on why not using streamflow variations (notably peak flow) is not very convincing.

This point has been clarified in the public discussion. (https://editor.copernicus.org/index.php?_mdl=msover_md&_jrl=13&_lcm=oc108lcm109w&_acm=get_comm_sup_file&_ms=87052&c=189590&salt=10720610621776386148) and we added the figure showing the peak flows to the Supplementary Material (Figure S5).

8b) If the purpose is to investigate the importance of spatiotemporal variability, I guess studying the temporal variability of the simulated streamflow is needed.

We decided to add a modelling component to this paper; the model is discussed in the public discussion (https://editor.copernicus.org/index.php?_mdl=msover_md&_jrl=13&_lcm=oc108lcm109w&_acm=get_comm_sup_file&_ms=87052&c=189590&salt=10720610621776386148).

Corresponding modifications of the paper are i) at the end of the introduction (L92-94), ii) presenting the model used in the method part "3.6 Rainfall-runoff model" (L335-350), iii) in the results section in "4.4.3 Optimum network evaluation" (L544-555), iv) with the Figure 15 summarizing the results of the different simulations and v) in the Supplementary Material part 1 with the Figure S9 (map of subcatchments), Figure S10 (the results of all simulations per event) and Figure S11 (the results of simulations per event, cumulated over time.

~~On the value of~~Even event-scale hydrological response characterization benefits from high density rain gauge observations

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Abstract.

Spatial rainfall patterns exert a key control on the catchment scale hydrologic response. Despite recent advances in radar-based rainfall sensing, rainfall observation remains a challenge particularly in mountain environments. This paper analyzes the importance of high-density rainfall observations for a 13.4 km^2 catchment located in the Swiss Alps where rainfall events were monitored during 3 summer months using a network of 12 low-cost, drop-counting rain gauges. We developed a data-based analysis framework to assess the importance of high-density rainfall observations to help predict ~~hydrologic processes.~~the hydrological response. The framework involves the definition of spatial rainfall distribution metrics based on hydrological and geomorphological considerations, and ~~the~~a regression analysis of how these metrics explain the hydrologic response in terms of runoff coefficient and lag time. The gained insights on dominant predictors are then used to investigate the optimal ~~raingauge~~rain gauge network density for predicting the ~~hydrological~~streamflow response metrics ~~in~~, including an extensive test of the ~~studied catchment.~~effect of down-sampled rain gauge networks and an event-based rainfall-runoff model to evaluate the resulting optimal rain gauge network configuration. The analysis unravels that besides rainfall amount and intensity, the rainfall distance from the outlet along the stream network is a key spatial rainfall metric. This result calls for more detailed observations of stream network expansions, as well as the parameterization of along stream processes in rainfall-runoff models. In addition, despite the small spatial scale of this case study, the results show that an accurate representation of the rainfall field (with at least three rain gauges) is of prime importance to capture the key characteristics of the hydrologic response in terms of generated runoff volumes and delay. ~~In the present case, at least three rain gauges were required for proper runoff prediction.~~The potential of the developed rainfall monitoring and analysis framework for rainfall-runoff analysis in small catchments remains to be fully unraveled in future studies, potentially including also urban catchments.

1 Introduction

Rainfall is known to be highly variable in space even at small scales, in particular in mountain areas (Henn et al., 2018;Tetzlaff and Uhlenbrook, 2005). Despite recent progress in the observation of spatial rainfall in mountainous areas with the help of

Commenté [AM1]: Precision added according to Reviewer #1 – Point 4

1

30 radar (Berne and Krajewski, 2013;Germann et al., 2006;Germann et al., 2015), it remains crucially difficult to observe and spatially interpolate (Foehn et al., 2018a;Sideris et al., 2014).

Understanding the interrelation between spatial rainfall patterns and the hydrologic response has been of concern for many decades, ranging from a theoretical viewpoint (Shah et al., 1996;Singh, 1997;Woods and Sivapalan, 1999), to a rainfall-runoff model perspective (Obled et al., 1994;Nikolopoulos et al., 2011), and extending to a hydrological process understanding

35 perspective (Guastini et al., 2019;Zillgens et al., 2007). Even earlier work in this field focused on the model-based investigation of optimal rain gauge density for reliable areal rainfall estimation (Bras and Rodriguez-Iturbe, 1976a) and runoff prediction (Bras and Rodriguez-Iturbe, 1976b;Tarboton et al., 1987). Chacon-Hurtado (2017) provides a recent review on rain gauge network optimisation.

A wide range of methods has been proposed to analyze the hydrologic response as a function of spatial rainfall patterns. We

40 can broadly distinguish between empirical methods that identify systematic response patterns by scrutinizing individual observed events (Blume et al., 2007) and model-based methods that try to identify systematic or theoretical relationships between rainfall and the hydrologic response. In this latter category, we first of all find stochastic methods that describe the stochastic aspects of the hydrologic response as a function of the rainfall field properties. These approaches range from simplified stochastic models (Tarboton et al., 1987) to full space-time representations of rainfall forcing and streamflow

45 generation (Mei et al., 2014;Pechlivanidis et al., 2017;Viglione et al., 2010;Woods and Sivapalan, 1999;Zoccatelli et al., 2015). These stochastic tools are developed to understand the relative importance of the two key components of the hydrologic response, i) the runoff generation processes at the hillslope scale and ii) the routing mechanisms in the channel network. Such an assessment of the relative role of unchanneled-state and channeled-state processes (Rinaldo et al., 1991;Rinaldo et al., 2006a) gives key insights into the relative role of runoff generation processes and of the geomorphology of a catchment. This

50 can also be achieved with virtual modelling experiments with hydrological models that explicitly account for geomorphological dispersion along the channel network. An example is the work of Nicótina et al. (2008) who assessed the importance of well representing spatial rainfall variability for medium size catchments (a few hundreds to thousands km²) where saturation-excess overland flow dominates (rather than Hortonian flow). They conclude that for rainfall events with a spatial correlation length larger than the hillslope size, an exact representation of the spatial rainfall variability is not required

55 to well represent the hydrologic response - provided that the mean areal rainfall is preserved at each time step. They explain this result by the fact that if the total catchment-scale residence time is controlled by the travel time within the hillslopes, large enough rainfall events sample all possible residence times, independent of the actual spatial rainfall configuration. Their findings were subsequently confirmed by the work of Volpi et al., (2012) amongst others, where a simplified modelling approach based on a geomorphological unit hydrograph was used. While the conclusions were similar, this study also added

60 that spatial variability does not matter "when the integral scale of the excess-rainfall field is much smaller or much larger than the basin drainage area".

Similar results were obtained in studies that assess the impact of undersampling or of coarse graining an observed rainfall field on the performance of streamflow simulations obtained with more or less complex process-based hydrologic models (Bardossy

2

and Das, 2008;Moulin et al., 2009;Lobligeois et al., 2014;Shah et al., 1996;St-Hilaire et al., 2003;Stisen and Sandholt, 2010;Xu et al., 2013). A key result of these model-based studies is that the hydrologic response depends more on the accurate estimate of the mean areal rainfall than on the actual exact form of the rainfall field, (Obled et al., 1994). However, such model-based studies face the challenge that conceptual hydrological models require recalibration when used with different input fields, which makes disentangling effects from rainfall versus parameters a cumbersome exercise (Bardossy and Das, 2008;Bell and Moore, 2000;Stisen and Sandholt, 2010).

The above hypothesis that the ~~area-average~~mean areal rainfall might play a more important role for the streamflow response than the actual spatial rainfall pattern is largely based on modelling experiments and remains to be tested in the field. In this paper, we therefore propose to investigate this hypothesis with a data-based ~~analysis of~~framework to analyze the importance of rain gauge density for the event-specific hydrologic response (Ross et al., 2019) of a small, high elevation Alpine headwater catchment (13.4 km^2) where the hydrologic processes have been intensely monitored since 2015. Studying such a small catchment has, in addition, the potential to shed new light on the often used assumption that for catchments smaller than a few tens of km^2, a single rain gauge is sufficient for reliable runoff prediction. While our analysis focuses here on a small natural headwater catchment, it is noteworthy that the developed rainfall monitoring and data analysis framework might also be of interest for urban hydrology, which deals with similar questions regarding how spatial rainfall patterns, runoff generation processes and flow network geometry lead to peak flows in urban drainage systems (for a review, see the work of Cristiano et al., 2017).

To assess the number of point observations required to properly capture the hydrologic response of our target catchment, we set up a dense rain gauge network made of commercially available and low cost devices, which increases the interest of this case study for future hydrologic studies in similar settings. These high-density rain gauge observations (approximately one rain gauge per km^2) are then used to answer two key questions:

i.   Which spatial characteristics of the rainfall field explain the timing and the amplitude of the hydrologic response?

ii. What is the required spatial design of the rain gauge network to capture these characteristics?

To answer these questions, we developed a methodological framework to analyze the rainfall events, the hydrological response, and ultimately the optimal rain gauge density. This framework can be summarized as follows: i) define appropriate metrics to describe the rainfall fields and the hydrological response, ii) understand the relationships between these metrics through correlation analysis, iii) identify the main drivers (i.e. the corresponding metrics) through regression analysis, and ~~finally~~iv) use the gained insights to optimize the rain gauge network based on selected metrics. We conclude the analysis with an event-scale modelling of all recorded runoff response events with a semi-distributed model to evaluate the identified rain gauge network configuration.

The remainder of the paper is structured as follows. First, Section 2 describes the target area of the study, namely the Vallon de Nant catchment located in the Western Swiss Alps. Next, Section 3 presents the observational methods and the analysis framework. The results are presented in Section 4 and discussed in Section 5, with a focus on the impact of rainfall heterogeneity on the streamflow response. Section 6 summarizes the main conclusions.

3

Commenté [AM2]: Added according to Reviewer #2 – Point 1

Commenté [AM3]: Added according to Reviewer #1 point 2 and Reviewer #2 point 8b

2 Study area

The area of interest is the Vallon de Nant, a 13.4 km² catchment located in the Western Swiss Alps (Figure 1). The elevation ranges from 1,200 m asl at the outlet of the Avançon de Nant river () to 3,051 m asl (Grand Muveran),) and has an averagea mean elevation of 1,975 m asl. The catchment benefits from a protected status (Natural Reserve of the Muveran) since 1969 and is of national importance for Switzerland in terms of biodiversity (Cherix and Vittoz, 2009). The Vallon de Nant has been intensively studied over the recent years, in disciplines ranging from hydrology (Beria et al., 2020a) and hydrogeology (Thornton et al., 2018), to geomorphology and pedology (Lane et al., 2016;Rowley et al., 2018), to biogeochemical cycling (Grand et al., 2016), and to stream ecology (Horgby et al., 2019).

The Vallon de Nant belongs to the reverse side of the Morcles nappe, a structural geological unit that determines the catchment's shape. The old Cretaceous and Tertiary layers are recognizable as a succession of thick, blocky lithologies overlooking and surrounding the valley. They lie on a substratum of flysch, i.e. softer rocks (schistose marls and sandstone benches), which explains the deepening and widening of the valley at its southern part (Badoux, 1991).

Figure 2 summarizes the dominant hydrological units of the Vallon de Nant. The western side is mainly characterized by grassy slopes, with deep soils and a relatively high water storage capacity as revealed by gauging along the stream during the late summer and autumn yearly streamflow recession period (Horgby, 2019). The northern part of these western slopes shows a less dense drainage network than the rest of the catchment (Figure 1), explained by steeper slopes, a large hydraulic conductivity or locally deeper soils.

The eastern side of the catchment is characterized by steep and rocky slopes that react quickly to rain events due to shallow soils that drain quickly. At the foot of the rock walls, large alluvial cones and screes extend down to the river. The bottom of the valley is mainly composed of fine alluvial deposits with a large water storage capacity. In the southern part of the valley, the Glacier des Martinets (area less than 1 km^2) is now confined to a small area shaded by the Dents de Morcles. The water flow paths of rainfall inputs over this southern (and higher elevation) part of the catchment, composed of moraines and permafrost, remain unclear and have not been investigated so far.

The Avançon de Nant river shows a typical snow dominated streamflow regime marked by a high flow period during spring and early summer when the snowpack accumulated during the winter melts (Supplementary Material Figure S1). The river length within the study area reaches 6 km in early summer, while during autumn and winter low flow, the river may start to flow as low as 1480 m asl (close to the gauge No. 5 on the Figure 1), reducing the instream flow distance to the outlet to 2.95 km. The actual extent of the stream network is based on observations during Summer 2017 (dry and wet periods during Summer 2017) and its exact path was calculated using the Swiss digital elevation model at a resolution of 2 m (swissALTI3D, 2012). The streamflow at the outlet is monitored via river height measurements using a sonar above the middle point of a trapezoidal shaped weir (). It averages water height every 1 minute continuously since September 2015. The height is thenan optical height sensor and is converted into streamflow using a rating curve (Supplementary Material Figure S3) based on 55 salt streamflow measurements (Ceperley et al., 2018).

Commenté [AM4]: Modified according to Reviewer #1 – Point 36

4

~~We fit a power-relationship using the nonlinear least squares fitting algorithm of MatLab's "fit" function with the trust region algorithm and least absolute residual method to obtain a 95% confidence interval.~~ The annual ~~average~~mean streamflow in 2018 is between 0.60 and 0.72 m³.s⁻¹ (between 3.89 and 4.61 mm.day⁻¹); ~~average~~mean annual water temperature is 5.0°C, ranging from a frozen river during some days in winter to ~~an average~~a mean temperature of 8.5°C during summer (from July 1st to

135 August 31st, 2017). The maximum streamflow measured at the gauging station was between 10.4 and 12.4 m³.s⁻¹ (between 67.2 and 80.0 mm.day⁻¹) during an intense rainfall event (August 6th, 2018).

Meteorological variables are monitored at three locations (Michelon et al., 2017) along a north/south transect (at 1253 m asl, 1530 m asl and 2136 m asl) since September 2016. ~~The average~~ From these stations, the mean air temperature at ~~the~~ mean elevation of 1,975 m asl is estimated ~~from these stations equals~~to 3.1 °C in 2017.

140 We do not use any further data from the Swiss meteorological network since there are no ground measurement stations nearby, and the Vallon de Nant catchment is largely in the shadow of the Swiss weather radar network (Foehn et al., 2018b), which might see here at best rainfalls above 2800 m asl (Marco Gabella personal communication, February 27th 2019).

3 Instruments and methods

3.1 Instruments

145 A network of 12 Pluvimate drop-counting rain gauges (www.driptych.com) was distributed across the Vallon de Nant catchment from July 1st to September 23rd 2018 to monitor rainfall (Figure 1). A similar deployment during the cold season would not be possible due to snowfall at all elevations throughout the winter. The sites were selected to represent the distribution of slope orientations and elevation, but also to meet constraints of accessibility and disturbance risk (livestock, hikers). The distance between measurement locations within the network ranges from 350 m to 1,550 m (630 m on average),

150 and the greatest distance from any point in the basin to a rain gauge is 1,670 m.

The gauges are low-cost (around 600 USD each), consisting of a tube (11 cm of diameter, 40 cm of length) mounted to an aluminum funnel (Figure 2). The collected rainwater is concentrated to a nozzle that creates a drop of water of calibrated size (0.125 mL), which then falls on the impact-sensitive surface of the sensor, 30 cm below. The datalogger counts and records the number of drops over a time set up to 2 minutes. In the field, the devices are set up vertically, attached to a wooden stick.

155 The funnel aperture is between 0.8 and 1.2 m above the ground.

The Pluvimates were set-up to count drops over an interval of 2 minutes, with an accuracy of 0.3 mm/h. Benoit et al. (2018a) experimentally evaluated the device uncertainty to 5 % for rainfall intensities under 20 mm/h. Given that some of the rainfall intensities measured in the present study exceed this value (intensities up to 140 mm/h were recorded), we extended the calibration to intensities up to 150 mm/h, and few saturation effects were noticed (Appendix A).

160 To prevent clogging, steel sponges were disposed in the funnel of each Pluvimate. This appeared to have caused i) a dampening effect on low rainfall intensities as it delayed slightly the beginning of very small events (lower than 1 mm/h) and ii) created drops remaining after the end of an event. The data are not corrected for these effects.

5

Some Additional artefacts were recorded, probably generated by strong winds creating resonance. TheseSome stations in fact recorded very strong and highly variable rainfall over several hours during periods with high wind velocity but during days without any observed rainfall in the combined MeteoSwiss radar-rain gauge data (Sideris et al., 2014). Four periods (over 4 different days) have been manually removed from the data.

<comment>Commenté [AM5]: Clarified according to Reviewer #2 – Point 5</comment>

3.2 Rainfall events event characterisation

3.2.1 Event identification

Before further analysis, the rainfall amounts measured by each station were interpolated to a 10 by 10 m grid at a 2 min time step using a high-resolution stochastic interpolation procedureapproach developed by Benoit et al. (20182018a). In a nutshell, it aims at generatinggenerates an ensemble of stochastic space-time rain fields constrained by the actual observations at raingaugethe rain gauge locations (over. The resulting ensemble (here composed of 20 realizations), and) can be used to use this ensemble analyze spatial rainfall uncertainty or to interpolate sparse rain observationsconstruct a single rainfall estimator. Following Benoit et al. (2018a), a non-separable and asymmetric covariance function was used to perform the simulations, which allows modelling rainfall advection and diffusion observed in the raw data. Areal rainfall time series are calculated for each of the 20 realization, and from these a single time series (mean and standard deviation) of the areal rainfall.

Commenté [AM6]: Changed according to Reviewer #1 – point 23</comment>

<comment>Commenté [AM7]: Modified according to Reviewer #2 – Point 6 and Reviewer #1 – 8a</comment>

Using the interpolatedareal rainfall fields, time series, the rainfall events wereare identified as rainy periods with rainfall higher than 1 mm separated by at least 90 minutes without rain.with rainfall smaller than 1 mm. This inter-event duration was selected based onof 90 minutes corresponds to the observed delay between the rainfall onset and the streamflow response for the large event recorded on August 23rd (detailed in the part 2 of supplementary material);for details see Supplementary Material), which occurred during an otherwise dry period. The streamflow reactionresponse to the first half-hour of this rainfall event was caused only by rainfall in the southern half of the catchment (stations 8 to 12). Ninety minutes was), corresponding thereby to the most distant event (from the outlet). Accordingly, we assume that this event gives a rough estimate of the catchment's response time (Beven, 2020) i.e. of the time required until the entire catchment contributes to the streamflow response, including the delay caused by runoff transfer to the stream network and from there to the outlet from the hydrologically most distant parts of the catchment. The 90 minutes were therefore selected to maximize the chances of observing a distinct streamflow reactionresponse for two distinct consecutive rainfall events. In addition, events with a total amount of rainfall under 1 mm are overlooked in the following.

<comment>Commenté [AM8]: Catchment time definition added according to Reviewer #1, point 9.</comment>

3.2.2 Spatial rainfall pattern metrics

To investigate the relationship between dominant spatial rainfall patterns and streamflow responseSpatial rainfall patterns are classically characterized with geostatistical tools, including variograms (Berne et al., 2004) or with spatial moments of rainfall (Smith et al., 2002;Zoccatelli et al., 2011;Mei et al., 2014), in particular in presence of observed rainfall fields, e.g. from radar

images. Here we propose to use more hydrological-process oriented metrics that explicitly account for known features of the catchment and the stream network.

195 To build a first such metric, the catchment is split into two parts of equal area by a west-east line (Figure 1), delimiting an area close to the outlet in the northern part, and an area farther away in the southern part. This heuristic splitting into two parts is interesting here due to i) the elongated catchment shape and furthermore ii) the clearly distinct stream network organisation in the upper (southern) part of the catchment with more branching than in the northern part (reflected in the Strahler stream order that does not further increase in the norther part, see Figure 1). Accordingly, we assume the rainfall events falling exclusively

200 on one or the other part of the catchment lead to a distinct streamflow response, with a faster and stronger response for events falling on the northern part (closer to outlet, steeper hillslopes, less storage potential than for the southern part).

The interpolated amounts of rainfall received by the southern and northern parts of the catchment, P_{NORTH} and P_{SOUTH}, are compared and normalized by the total amount of rainfall to create an index of spatial rainfall asymmetry I_{ASYM}:

$$I_{ASYM} = \frac{P_{SOUTH} - P_{NORTH}}{(P_{SOUTH} + P_{NORTH})},$$ (1)

205 If rainfall is equally distributed between the northern and the southern parts, then $I_{ASYM} = 0$. The extreme values -1 and 1 express rainfall concentration exclusively in the northern or the southern part of the catchment, respectively. We consider a rainfall event as asymmetric when at least 2 times more rain ~~is~~has precipitated over one part of the catchment than over the other, i.e. when I_{ASYM} is below -0.33 or above +0.33.

To further analyze the relationships between the spatial distribution of rainfall and the streamflow response, we characterize

210 the geomorphological distance of incoming rainfall from the outlet, assuming that this distance should reflect to some degree the timing and the shape of the streamflow ~~reaction~~response of the catchment: following the terminology of Rinaldo et al. (2006b), transport at the basin scale can be analyzed in terms of travel in the unchannelled state (i.e. in the hillslopes) and travel in the channelled state (i.e. in the stream network).

Accordingly, we estimate for each rainfall event the weighted ~~average~~mean unchannelled distance to the stream network as:

215 $$D_{HILLS} = \frac{1}{t} \sum_t \frac{\sum_i \left[\sum_j (P(i,j,t) d_{HILLS}(i,j)) \right]}{\sum_i \sum_j P(i,j,t)},$$ (2)

where ~~t is the time step,~~ i and j are the coordinates of rainfall location within the grid, $P(i,j,t)$ is the rainfall amount previously calculated using the stochastic method (section 3.2.1) for each of the 10 x 10 meters grid cell at each 2-minute time step t, and $d_{HILLS}(i,j)$ is the distance of this grid cell to the nearest stream network grid cell (following the line of steepest descent in the

220 2 x 2 m DEM (swissALTI3D, 2012)).

Similarly, we compute the weighted ~~average~~mean channelled distance between a point of introduction into the stream network and the outlet as:

$$D_{STREAM} = \frac{1}{t} \sum_t \frac{\sum_i \left[\sum_j (P(i,j,t) d_{STREAM}(i,j)) \right]}{\sum_i \sum_j P(i,j,t)},$$ (3)

7

225 where $d_{STREAM}(i,j)$ is the distance along the stream network from the point of introduction to the outlet. For each cell of the stream network, this distance is calculated once based on the 2 x 2 m DEM.

~~The D_{HILLS} metric gives an estimate of the average distance that incoming rainfall has to travel on the hillslopes before reaching the stream network, and D_{STREAM} the average distance for the water particle entering the stream network to reach the outlet.~~ It is noteworthy that these two metrics, D_{HILLS} and D_{STREAM} correspond to the aforementioned first order spatial rainfall
230 moments, albeit decomposed according to hillslope and stream network distances, similar to what was proposed by Zoccatelli et al., 2015 in their analytical framework to quantify the smoothing of spatial rainfall organisation effects by channel residence time. It would be tempting to use also higher order rainfall moments; however, no significant correlation could be found to ~~retained~~ the streamflow metrics.

In addition to the above two metrics related to the theory of geomorphological dispersion (Rinaldo et al., 2006b), we use the
235 height above the nearest drainage (~~HAND~~H_{HAND}) terrain metric (Renno et al., 2008;Gharari et al., 2011;Nobre et al., 2011) to account for the topography. Based on the 2 x 2 m DEM, the normalized terrain heights ~~d_{HAND}~~h_{HAND} are calculated by comparing the elevation of each grid cell to the elevation of the nearest stream network cell in which the water is routed. The ~~average HAND~~mean H_{HAND} value for a rainfall event is given by:

$$\cancel{D_{HAND}}H_{HAND} = \frac{1}{t}\sum_t \frac{\sum_t\sum_j(P(i,j,t)d_{HAND}(i,j))}{\sum_t\sum_j P(i,j,t)}\sum_t \frac{\sum_i\left(\sum_j(P(i,j,t)h_{HAND}(i,j))\right)}{\sum_i\sum_j P(i,j,t)}.$$

240   (4)

~~Since the extent of the stream network is dynamic, its minimal and maximal extent () are determined manually by identifying the uppermost points of the catchment where streamflow has been observed in the field during summer baseflow (minimum extent) and during high flow (maximum extent).~~ The 3 distance metrics are computed with respect to both the dry and wet river network ~~extents~~extent; the network extent to be used per rainfall event is then determined during the rainfall-streamflow
245 response analysis (Section 3.4.1).

3.3   Streamflow response

~~3.3.1   Event identification~~

3.3.1   Identification of streamflow events and fast runoff

The beginning and the end of each streamflow event are identified manually using a data visualization tool (developed in
250 MathWorks MatLab 2017a, see Figure 3 and Figure 4). This choice of a visual expertise was made based on the observation that automatic identification of streamflow events would require almost a case-by-case filtering and parametrization, and thus would not be generalizable. This is partly related to a potentially high signal-to-noise ratio for river stage recordings during sediment transport events, a phenomenon potentially very important after a strong streamflow variation. The result of this visual identification for each streamflow event is displayed in ~~the~~ part 2 of Supplementary Material.

255 The beginning and the end of the streamflow response determine the initial and final baseflow, respectively; the streamflow volume above the line connecting these two points is considered here as fast runoff. It is noteworthy that we do not use peak streamflow to characterize streamflow events, for two reasons: i) given the small size of the catchment and the complex temporal distribution of rain intensities, the streamflow response has rarely a single, well identifiable peak; (all events are plotted in Figure S5 in Supplementary Material Part 1); ii) peak streamflow identification is further complicated by the noise

260 in the stage recordings.

3.3.2 Streamflow metrics

The key metrics to characterize the hydrologicstreamflow response in terms of are the peak flow, the fast streamflow volume, the lag time elapsed between rainfall and streamflow response, and the flatting behaviour. For technical reasons we discarded the peak flow (see section 3.3.1timing.) and consequently the flatting behaviour. We use the runoff coefficient and the lag

265 time, the two key characteristics of streamflow reaction.fast streamflow volume through the runoff coefficient (RC)), which is obtained by dividing the fast runoff volume by the total rainfall for the given event. A metric for the elapsed The lag time between the rainfall event and the streamflow reaction is obtainedusually defined as the lag between the moment when one third of the rainfall event has fallen and when one third of the corresponding streamflow volume has passed the gauge and is called $\Delta_{P/Q}$. Given the visual assessment of the start of the streamflow event, this measure is deemed more robust

270 than the elapsed time between the start of the event, and is indicative for the time when a significant part of excess rainfall (the part of rainfall that causes the streamflow response) and the peak flow (McCuen, 2009). Since the start of excess rainfall is not known, the concept of peak flow is difficult to apply to our observed events (Section 3.3.1) and given the varying shape of our hydrographs, we empirically tested different lag formulations; the lag between 1/3 of the rainfall event volume and 1/3 of the streamflow volume has reached the outletevent volume gives the best results in the regression analysis, and is therefore

275 retained. It is noted $\Delta_{P/Q}$ in the following.

3.4 Rainfall-streamflow response characterization

3.4.1 We analyze Pseudo-dynamic stream network extent

The extent of the relationships between the spatial distribution of rainfallstream network evolves as a function of the catchment wetness conditions. Its minimal and maximal extent (Figure 1) are determined manually by identifying the hydrological

280 response based on a correlation analysisuppermost points of the above metrics, followed by a regression analysis to identify the key variables that explain the runoff coefficient and catchment where streamflow lag time. This analysis requires a was observed in the field during summer baseflow (minimum extent, called *dry* state) and during summer high flow (maximum extent, called *wet* state).

In absence of exact observations of the stream network extent before the start of each streamflow event, we propose here to

285 use a pseudo-dynamic stream network extent which assigns the dry or the wet to each streamflow. The network state is chosen

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based on a measure ~~for~~of the initial catchment wetness conditions, which ~~are~~is known to be the major variable explaining the dynamics of the hydrological response to different rainfall events (Penna et al., 2011;Rodriguez-Blanco et al., 2012), in particular through the creation of runoff thresholds (Zehe et al., 2005;Tromp-van Meerveld and McDonnell, 2006). Many studies use the baseflow before the start of a streamflow event as an indicator for the antecedent ~~moisture state~~wetness

290 conditions of the catchment. For snow-influenced catchments with a highly seasonal streamflow regime, this indicator might not reflect the actual ~~saturation~~wetness conditions. Hence, we rather quantify initial wetness conditions in terms of antecedent rainfall, i.e. using the cumulative rainfall (in mm) that occurred during a period from 1 to 5 days before ~~an~~a given rainfall event. ~~All used~~The actual time span is selected based on a correlation analysis between antecedent rainfall over 1 to 5 days and the retained streamflow metrics (Section 4.2.1~~are summarized in Table 1.~~ and following).

295 This correlation analysis yields an optimum antecedent wetness indicator corresponding to the rainfall over the 3 days preceding the start of a rainfall event, noted W_{3days}. Using this indicator, the pseudo-dynamic network extent is obtained by assigning the dry network state to rainfall events that have $W_{3days} < 20$ mm and the wet network state to rainfall events that show $W_{3days} \geq 20$ mm. This threshold of 20 mm is selected by maximizing the correlation coefficient between D_{HILLS} and RC (see Section 0).

> **Commenté [AM22]:** Added according to Reviewer #1 – point 18

300 **3.4.2   Regression analysis**

We analyze the relationships between the spatial distribution of rainfall and the hydrological response based on a correlation analysis between the spatial rainfall pattern metrics (Section 3.2.2) and the streamflow metrics (Section 3.3.2) at the event scale, followed by a regression analysis to identify the key variables that best explain the runoff coefficient, RC, and the streamflow lag time, $\Delta_{P/Q}$. All used metrics are summarized in Table 1.

> **Commenté [AM23]:** Point 37b. Precise in the answer that it is at event scale only. There is no intra-event correlation.

305 After the initial screening via correlation analysis, we use a pure quadratic regression to further investigate which combination of rainfall pattern ~~characteristics~~metrics and initial wetness ~~conditions are~~condition yields the best ~~predictors of the runoff coefficient~~prediction of RC and ~~the lag time~~$\Delta_{P/Q}$. Pure quadratic regression (i.e. without multiplication of explanatory variables) is chosen because the small number of observed streamflow events prevents using more complex models. Model selection is performed using the Akaike Information Criterion (AIC)(Akaike, 1974), noted here as I_{AIC}:

310 $$I_{AIC} = n \ln\left(\frac{S_{RSS}}{n}\right) + 2k + C \, , \tag{5}$$

where n is the number of events, k the number of coefficients, S_{RSS} the residual sum of squares and C a constant that can be ignored when comparing different models based on the same data set. As we manage small sample sizes (Burnham et al., 2011), we compute and use a corrected version of the AIC (AICc, noted here I_{AICc}):

$$I_{AICc} = I_{AIC} + \frac{2k(k+1)}{n-k-1} \tag{6}$$

315 For both AIC and AICc, the best model is the one having the lowest score.

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3.5 ~~Measurement~~Rain gauge network configuration analysis

Assuming that the actual rainfall measurement network is sufficient to capture the full spatial distribution of rainfall in the studied catchment, we assess the ability of partial networks to reproduce the identified best explanatory variables. The aim is twofold: i) identifying the best configuration for a future permanent observation network and ii) evaluate the added value of additional rain gauges in a partial network with respect to the identified key metrics (Section 4.4 and 0).

The quality of a partial network configuration is evaluated comparing the value (e.g. total rainfall) by event obtained with the partial network to the reference value obtained with the full network setup. We evaluate all the possible combinations of partial networks composed of less than 12 stations, i.e. 4094 possibilities. Each configuration is evaluated based on the root mean square error (RMSE):

$$\text{RSME} \coloneqq \sqrt{\sum_{\forall t} \frac{\left(X_k(t) - X_{ref}(t)\right)^2}{N}}, \tag{7}$$

where X_k is the selected rainfall metric (e.g. rainfall amount) at time step t corresponding to the k-th network configuration, X_{ref} the respective value obtained reference network set-up, and N the number of time steps. The rainfall amounts measured by each station were interpolated to a 10 by 10 m grid at a 2 min time step using the Thiessen polygons method. The interpolation method developed by Benoit et al. (see section 3.2) cannot be used in this context because i) it requires at least 5 measuring points to perform adequately and ii) the computation time would be excessive to explore the 4094 combinations of stations for each event.

The best network for each number of stations is the one with the lowest RMSE. A sensitivity analysis is completed by removing from 1 to 3 rainfall events to the 23 events dataset, yielding 2047 datasets evaluated for each partial network configuration. The most frequent network configuration validates the robustness of the result.

3.6 Rainfall-runoff model

To further validate the obtained optimal rain gauge network configuration, we set up a a semi-distributed, event-based rainfall-runoff model. This model first simulates the mobilization of water at the sub-catchment scale (25 sub-catchments) using a Soil Conservation Service Curve Number (SCS-CN) approach (SCS, 1972). Next, the streamflow response is obtained by convolving the resulting hillslope responses with a travel path distribution derived from the stream network geometry (Schaefli et al., 2014). The subcatchments and the stream network geometry are identified using *TopoToolbox* (https://topotoolbox.wordpress.com), in which travel paths correspond to the distance between the bottom part of each sub-catchment and the catchment outlet. In this model we focus on the fast response (i.e. runoff) of the catchment, and baseflow (defined here as the average discharge during the 30 min preceding event start) is subtracted from the actual discharge prior to runoff modeling. For calibration, the model is run using the mean of the 20 stochastic rainfall realizations as reference input; it is then calibrated against observed runoff (i.e. discharge - baseflow) through likelihood maximization assuming that the model residuals are normally distributed (e.g. Schaefli et al., 2007). After calibration the event-based runoff model is applied to the different network configurations to test how rain gauge network geometry influences the simulated runoff response. As

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the stochastic rainfall interpolation cannot be performed with a number of observation points as low as 3 stations (or less), we use the Thiessen polygons method to interpolate the rainfall fields from the 1 to 3-station rain gauge network obtained during optimal network analysis. .

Commenté [AM24]: Added according to Reviewer #1 point 2 and Reviewer #2 point 8b

4 Results

4.1 Rainfall events

4.1.1 ~~Amounts~~Areal rainfall and asymmetry

The available 3-month measurements window between July 1st and September 23th 2018 captured 48 rain events (detailed in the part 2 of the Supplementary Material) for a total areal rainfall amount of 317.8 mm. The areal rainfall amount per event ranges from 1 mm to 43.5 mm, (mean of 6.6 mm), and event duration ranges from 32 minutes to 10.5 hours. (mean of 2.8 hours); these records do not show any evidence of altitude effect on the rainfall amount ($R^2 = 0.06$). Despite the sequential deployment of the 12 rain gauges and other technical issues (see section 3.1), the rainfall events were all measured by at least 7 stations; 36 out of 48 events were recorded by at least 10 stations and 23 events were recorded by 12 stations. The different subsets used in this study are detailed in Table 2. Details for all recorded rainfall events and the corresponding streamflow are shown in summary plots, as illustrated in Figure 3 and Figure 4 (all events are presented in the Supplementary Material). Most events show a relatively homogeneous spatial distribution of rainfall events (see an example in Figure 4), with only few events showing a strong asymmetry (Figure 5): the correlation between P_{NORTH} and P_{SOUTH} equals 0.91, with ~~an average~~a median I_{ASYM} of -0.~~01~~025. Interestingly, strong spatial asymmetry mainly affects events with low rainfall amounts, with 7 out of 8 asymmetric events (when $|I_{ASYM}| > 0.33$) receiving below 5 mm (Figure 5). For the events that actually triggered a streamflow ~~reaction~~response, the correlation between P_{NORTH} and P_{SOUTH} is thus significantly ~~lower~~higher (r=0.69, Table 4).

One ~~strongly~~strong asymmetric and ~~high intensity~~very intense event occurred on July 24th at 6:32 PM (Figure 3). The rainfall map shows a heterogeneous distribution of rainfall, centered close to the outlet in the northern part of the catchment, over 6 out of the 12 stations. One of the rain gauges recorded up to 35.3 mm of rainfall, whereas 1.8 km upstream, half of the stations (on the southern and western parts of the catchment) did not record any rainfall. The interpolated amount of rainfall over the basin was 8.0 ± 1.3 mm, and a fast runoff volume between 28.3 and 32.5 mm was measured, resulting in a runoff coefficient between 3.0 and 4.8 that remains difficult to explain. One possible explanation is that important rainfall amounts fell on the north-eastern part of the catchment, over steep slopes that are difficult to access and were therefore not gauged. This event and its streamflow ~~reaction~~response are excluded from further analysis involving the hydrological response (see also Section 4.2 and the summary of analysed events in Table 2).

Commenté [AM25]: Changed according to Reviewer #1 – Point 29

Commenté [AM26]: Mean values added according to Reviewer #1 – Point 30

Commenté [AM27]: Altitude effect added according to Reviewer #1 – Point 8b

Commenté [AM28]: Subsets details added according to Reviewer #1, point 3

Commenté [AM29]: Changed according to Reviewer #1 – Point 31

Commenté [AM30]: Changed according to Reviewer #1 – point 33

Commenté [AM31]: Modified according to Reviewer #1 – Point 34

Commenté [AM32]: Modified according to reviewer #1 – Point 35

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4.1.2 ~~Geomorphological and topographical~~Stream network distance metrics

For the 48 recorded rainfall events, ~~all~~the three distance metrics D_{HILLS}, D_{STREAM} and H_{HAND} show ~~a~~ significantly different ~~distribution of the distances~~median values if they are computed with respect to the wet network than with respect to the dry network; we can reject for each metric the hypothesis that ~~the distributions~~they have the same median value for the wet state and the dry state with a Wilcoxon rank sum test at level 0.05 (see distributions in Figures ~~S4~~S6 and ~~S5). The three~~S7 of the Supplementary Material part 1). However, each of the distance metrics ~~show~~shows a strong correlation between its values for the wet and for the dry network state (from 0.94 for D_{HAND} H_{HAND} to 1.00 for D_{STREAM}, Figure 7). The between-metric correlation ~~between the distance metrics~~for all 48 rainfall events (Table S2 in Supplementary Material part 1) ranges for the wet state range from 0.~~70~~78 (D_{HILLS} - D_{STREAM}) to 0.95 (D_{HILLS} - $D_{HAND}$$H_{HAND}$) and for the dry state from 0.~~75~~70 (D_{STREAM} - $D_{HAND}$$H_{HAND}$) to 0.95 ($D_{HILLS}$ - D_{HAND}). ~~For the~~H_{HAND}). Considering only the rainfall events with streamflow ~~reaction~~response, these correlations are slightly lower (Table 3), but with a clear correlation between D_{HILLS} and $D_{HAND}$$H_{HAND}$ for both the wet and the dry state; accordingly, we do not further use the $D_{HAND}$$H_{HAND}$ metric in this analysis. None of the distance metrics shows a strong correlation (>0.6) with the rainfall spatial distribution metrics, i.e. P_{SOUTH}, P_{NORTH} or I_{ASYM}. They also do not show any correlation higher than 0.6 with the hydrologic response metrics (Table 4). This confirms our hypothesis that the network state needs to be included in a dynamic way (see Section 0).

4.1.3 Temporal evolution of rainfall metrics

We computed the temporal evolution of the rainfall metrics to unravel potential temporal evolution patterns in I_{ASYM}, D_{HILLS} and D_{STREAM} and their relation to the streamflow response (full results are available in the Supplementary Material part 1). The temporal evolution of the two distance metrics is overall rather flat with no clear fluctuation patterns. There is only one event with a pronounced temporal trend for D_{HILLS} (Q event #1).

For I_{ASYM}, some events show interesting temporal patterns. For example, during the double peak runoff of Figure 3, I_{ASYM} shows an almost constant negative value suggesting that the corresponding double peak rainfall event remained stationary on the northern part of the catchment over its entire duration and therefore caused the double peak streamflow response.

For the first two streamflow events, the I_{ASYM} metric switches from strongly positive to close to zero during the event, implying that the rainfall field moved towards the outlet during the event; in other words, the rainfall cloud follows the overall water movement through the catchment and thereby leads to a stream response concentration. This might explain why these two events are the only ones that show a pronounced single peak streamflow response. However, given the low number of observed events and the diversity of temporal patterns, these insights cannot be further used for a quantitative analysis.

Commenté [AM33]: Added according to Reviewer #2 – Point 7

4.2 Hydrologic response

4.2.1 Observed streamflow events

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For 13 days (6 of the 48 rainfall events (13 days in total), the water stage sensor was disturbed by the proximity of a rock (see picture of the Figure S2 in the part 1 of the Supplementary Material), resulting in missing streamflow data. For the remaining 42 rainfall events, a streamflow response was observed for 15 of them (see Table 2(and Table 3).

The fast streamflow volume during these events, $Q_{FAST,}$ shows a strong correlation with total rainfall and with P_{SOUTH} (Figure

410 8a); however, the event on 24 July with only 8.0 mm of rain and 30.4 mm of fast streamflow falls far away from this relationship, which further motivated the exclusion of this event from the analysis.

The 14 remaining events are distributed over the entire observation period, covering a wide range of streamflow conditions, which is reflected in the initial streamflow before each event, ranging from 7.9 mm in early July to 2.6 mm by mid-September (Table 3), with an almost linear decrease between the dates (correlation between initial streamflow and day of the year of -

415 0.90, see also Figure S3 in the Supplementary Material S1).

The correlation of this initial flow before events with Q_{FAST} or with the runoff coefficient RC is extremely low (correlation of -0.02 and -0.05).), which confirms our hypothesis that antecedent streamflow is not a good proxy for antecedent moisture.

The highest correlation between RC and antecedent precipitation occurs for a time span of 3 days preceding the streamflow event (0.67); this metric, called $W_{3\ days}$, is thus retained as a proxy for antecedent moisture for further analysis. The role of

420 initial wetness conditions can also be discussed more qualitatively by comparing a pair of rainfall events with very similar spatial patterns and amounts (Figure 4). For the first event (24 August), the measured rainfall ranges from 6.2 mm to 11.8 mm, corresponding to 8.5 mm of rainfall over the catchment in 2 h 38 min. For the second event (29 August), the rainfall ranged between 5.4 mm and 11.4 mm, corresponding to 8.4 mm over the catchment during 1 h 14 min. Despite the similar total amount of rainfall and event duration (during the first event 76 % of the total rain happened for a duration similar to the second

425 event), the first event shows a fast runoff volume of 7.4 mm, whereas for the second event the streamflow response is almost invisible. This difference can be explained by the initial wetness conditions, with 29.5 mm of rainfall during the 3 days preceding the first event, compared to 12.4 mm for the second event.

4.2.2 Streamflow generation processes, RC and lag

The The correlation analysis (Table 4) reveals a strong correlation between rainfall amounts and Q_{FAST} (0.77, Table 4)). This

430 suggests that streamflow reactionsresponses are triggered by saturation-excess, rather than by infiltration capacity-excess. This is confirmed by i) the absence: If saturation is exceeded, every unit of correlation between maximum rainfall intensity over 10 minutes and the RC (), ii) the leads to a corresponding unit increase of streamflow, which in turn leads to a strong linear correlation between rainfall duration and Q_{FAST} (0.73) and iii)amounts and fast streamflow volumes. Furthermore, saturation-excess also implies that a longer rainfall event leads to a higher streamflow response volume (once the saturation threshold is

435 reached, all rainfall contributes to streamflow). This is confirmed by the high correlation (0.74) between the rainfall duration

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Commenté [AM34]: Subsets details added according to Reviewer #1, point 3

P_{DURATION} and Q_{FAST}. If, on the contrary, the driving process was the exceedance of the soil infiltration capacity, then only rainfall intensities above the capacity threshold would trigger a corresponding streamflow increase; small rainfall amounts would trigger almost no response. In this case (infiltration-excess), there would be no linear correlation between rainfall amounts or rainfall duration and streamflow amounts, but a strong correlation between fast streamflow amounts and high or maximum precipitation intensity; positive correlations between Q_{FAST} and $P_{\text{max ALL}}$, $P_{\text{max NORTH}}$ or $P_{\text{max SOUTH}}$ are however all absent (values of -0.17, -0.16 and -0.08, Table 4). In addition, saturation-excess as a main driver of the fast streamflow response is further confirmed by the clear threshold effect for the generation of streamflow as a function of total event rainfall (Figure 8); a streamflow ~~reaction~~response only occurs for total rainfall higher than 5 mm~~.~~

This threshold effect supports the formulation of the lag time ~~(after~~$\Delta_{\text{P/Q}}$ as the time ~~when~~between one third of the rainfall event volume ~~has occurred)~~and one third of the streamflow event volume, since a lag time between the starts of the events would here be misleading. Accordingly, the streamflow events show a relatively strong correlation (0.71, Table 4~~)~~) between the RC and the lag $\Delta_{\text{P/Q}}$: ~~to reach~~we observe a higher RC~~, we need~~ when the level of saturation increases; reaching such a higher level of saturation~~,~~ requires more time, which results in a longer lag before a significant amount of streamflow reaches the outlet. We furthermore find a positive correlation between I_{ASYM} and the lag $\Delta_{\text{P/Q}}$ (0.59, Table 4), which supports our initial assumption that negative I_{ASYM} values (corresponding to rainfall concentrated on the northern part, close to the outlet) correspond to low lag times. However, the assumed negative correlation between RC and I_{ASYM} (higher RC values for rainfall events with negative I_{ASYM} values) is not confirmed by the observed data (the correlation is 0.44, Table 4), thereby not confirming our hypothesis that rainfall on the northern catchment part (showing less water storage potential) leads to more fast streamflow.

However, there is also a ~~non-negligible~~strong negative correlation between $\Delta_{\text{P/Q}}$ and the maximum rainfall intensity over 10 minutes, ~~especially with~~ which is stronger for $P_{\text{max NORTH}}$ ~~(r =~~(-0.71, Table 4~~).~~) than for $P_{\text{max SOUTH}}$.(-0.58). This probably reflects the fact that in the northern part of the catchment, there is a lack of soil storage capacity due to the large rock walls on the right stream side, which is not compensated by the available soil storage on the left stream side, with ensuing Hortonian (infiltration-excess) streamflow generation processes becoming more ~~dominant~~important in the northern part than in the southern part of the catchment. This significant difference in streamflow generation processes is also visible in the drainage density, which is ~~much~~higher on the right stream side in the northern part than on the left stream side (Figure 1).

4.2.3   Dynamic stream network state

~~Given the absence of correlation between~~As discussed in 4.1.2, the rainfall distance metrics ~~and~~if computed with respect to the dry or the ~~hydrologic response~~wet stream network state show very low correlations with the streamflow metrics. Accordingly, we attribute either the dry or the wet network state to each streamflow event as a function of the antecedent wetness $W_{\text{3 days}}$, which is used as a measure for the stream network expansion. In the following, we call these new distance metrics "pseudo-dynamic" since only two different states are observed. Setting a $W_{\text{3 days}}$ threshold to 20 mm to discriminate between the dry and the wet state yields correlations between D_{HILLS} – ~~composite~~pseudo-dynamic and RC of -0.70, and between

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D_{HILLS} composite pseudo-dynamic and $\Delta_{P/Q}$ of -0.66 (Table 5). D_{STREAM} composite pseudo-dynamic shows correlations of 0.53 and 0.60 with the RC and with the $\Delta_{P/Q}$ in this case, and we retain both composite pseudo-dynamic distances for further analysis. A sensitivity test showed that setting a $W_{3\,days}$ threshold of between 12 mm and 20 mm to discriminate between the dry and the wet state yields very similar results, and accordingly, we retain a threshold of 20 mm for W_{3days} $W_{3\,days}$ to compose the combined pseudo-dynamic network state. It should however be kept in mind that this composite these pseudo-dynamic distance metrics represent simply a heuristic solution to overcome the absence of detailed stream network state observations before each event. The resulting composite distance metrics do not show correlations >0.6 with the other rainfall metrics; accordingly, all rainfall metrics are retained for further analysis in addition to the composite distance metrics.

4.3   Identification of dominant hydrologic drivers via regression analysis

The above correlation analysis results in a range of potential explanatory variables for RC and $\Delta_{P/Q}$ referring to the rainfall amounts, maximum intensity and asymmetry, the composite pseudo-dynamic rainfall distance metrics and initial wetness conditions ($W_{3\,days}$). However, according to the correlation analysis, we retain the maximum rainfall intensities as explanatory variables only for $\Delta_{P/Q}$. The tested models, based on one or two explanatory variables, are summarized in Table 6 Table 5 for RC and in Table 7 Table 6 for $\Delta_{P/Q}$. The analysis is based on 14 events (after removing the 24 July event). , subset #4 of Table 2) and the best models are selected based on their AICc ranking and coefficient of determination (R^2).

In terms of AICc, The best ranked model (in terms of AICc) for RC is a single predictor model using $D_{STREAMS}$ (composite pseudo-dynamic) as explanatory variable, which yields better results than using antecedent moisture $W_{3\,days}$ as a single predictor; it should be kept in mind here that the composite pseudo-dynamic distance metrics also embed information on antecedent moisture conditions (since $W_{3\,days}$ decides on the moisture state). However, the coefficient of determination (R^2) becomes considerably higher (0.75) using P_{ALL} and D_{STREAM} (composite pseudo-dynamic) as explanatory variables. Slightly less good results are obtained with D_{HILLS} (composite pseudo-dynamic) as a single predictor or in combination with P_{SOUTH}. The fact that D_{STREAM} (composite pseudo-dynamic) plays a prominent role to explain the RC might be surprising; a possible explanation lies in the fact that the length of instream flow paths is also a metric for runoff storage and exchange within the riparian area, especially in the southern part of the catchment.

For $\Delta_{P/Q}$, the best model (in terms of AICc) has the two explanatory variables $P_{max\,SOUTH}$ and I_{ASYM} with a R^2 of 0.83 and is considerably better in terms of R^2 than any single predictor model. The best model including a distance metric is $P_{max,All}$ in combination with D_{STREAM} (R^2 0.78), which underlines the prominent role of D_{STREAM} (composite pseudo-dynamic) to explain the hydrologic response in this catchment.

Commenté [AM37]: Modified according to Reviewer #1 – Point 19

16

4.4 Measurement network analysis

4.4.1 Raingauge density analysis

During the observation period, 23 out of 48 events (subset #2, Table 2) were captured by the full network of 12 stations, measuring a total amount of rainfall of 120.7 mm. We tested what a partial rain gauge network (all possible combinations of networks composed with less than 12 stations) would record compared to the full rain gauge network of 12 stations taken as a reference, using the Thiessen polygons method to interpolate the rainfall fields (since, as discussed earlier, the stochastic method cannot be applied to a small station number).

Figure 6a shows, in term of rain gauge density, the number of events having the total amount of rainfall P_{ALL} overestimated or underestimated by a factor 2. We globally observe a misestimation inversely proportional to the rain gauge density, with up to 3 events overestimated by a factor 2 and 8 events underestimated by a factor 2 with the lowest rain gauge density of 0.07 rain gauge per km² (1 rain gauge). It is necessary to reach 0.82 rain gauges per km² (11 rain gauges) to no longer have events misestimated by a factor 2. In presence of few rain gauges, Figure 6a also shows a strong tendency to underestimate rather than overestimate rainfall amounts. This can be explained by the fact that for a heterogeneous rainfall event, it is more likely to miss a localized important part of the rainfall field rather than to capture it.

Figure 6b presents in the same way the maximum error encountered on the maximum rainfall intensity over 10 minutes P_{MAX}(10 min). We notice the expected inversely proportional trend, reducing the error if the rain gauge density increases. The figure also shows that in general a low rain gauge density tends to overestimate more than underestimate the P_{MAX}(10 min). This bias originates from the large footprint associated to each station in presence of a low rain gauge density, increasing the disparities between the observation points while interpolating the rainfall fields.

> **Commenté [AM38]:** Added according to Reviewer #1, point 1d

4.4.2 Optimum network identification

Based on the hydrologic driver analysis, we retain P_{ALL}, $P_{max,ALL}$, I_{ASYM} and D_{STREAM} (~~composite~~pseudo-dynamic) as key metrics for the optimal rain gauge network analysis. Figure 10 shows the best network configurations for 1 to 5 stations and the corresponding RMSE for the select reference metric for the network optimisation (one metric per line).

For a 1-station network, P_{ALL} is best captured when the station is located in the middle of the catchment, while a 2-station network improves substantially the RMSE by arranging the measuring points between the northern and southern parts. Additional stations still improve the RMSE, although to a lesser extent. With a 4-station and 5-station network, the stations tend to align along a north-south transect. For I_{ASYM} and $P_{max,ALL}$, we see very similar evolution of the spatial patterns as for P_{ALL} for increasing network sizes; for $P_{max,ALL}$, the RMSE continues however to considerably decrease with the number of stations, which is to be expected for this measure that is more sensitive to spatial-temporal variations of rainfall amount. ~~And for a single station network, the metric I_{ASYM} prefers an station location in the southern part rather than in the northern part.~~

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For D_{STREAM} as a network optimisation metric, the optimal network configuration first selects stations at the extreme ends of the stream network before organizing along a transect as for the other metrics, with one lateral station on the left stream side included in the 5-station network as for $P_{\text{max,ALL}}$ (the same) and for I_{ASYM} (a different one).

Considering the small dataset underlying this analysis (23 events), the robustness of the best networks is assessed for two selected metrics (for the P_{ALL} and I_{ASYM}) ~~is evaluated~~ by re-computing the optimal network if between 1 and 3 events are removed from the ~~error computation.~~dataset. Figure 11 shows how frequent a given configuration is identified as being the optimal solution for networks composed of 1 to 3 stations and clearly confirms the optimal solutions found previously.

4.4.3   Optimum network evaluation

To evaluate this optimum network analysis, we compare in a first step the RC and lag time $\Delta_{\text{P/Q}}$ obtained from the full stochastic rainfall field (median field) to the RC and $\Delta_{\text{P/Q}}$ values obtained from the best 1-station and 3-station networks and from the worst 3-station network (Figure 12). The corresponding rain gauge densities are 0.07 rain gauge per km² for a 1-station network, 0.15 rain gauge per km² for a 3-station network and 0.90 rain gauge per km² for the full network. For both the RC and $\Delta_{\text{P/Q}}$, the dispersion of the values obtained with the reduced rain gauge network decreases from the best 1-station network to the best 3-station network but remains sensibly the same for the worst 3-station network, underlining thereby that a 3 rain gauge can give could results conditional on a good location selection.

It is noteworthy that for the lag, even a 1-station network can reproduce this metric correctly for most of the events but can also be completely off (Figure 12b). With the best 3-station rain gauge network, the RMSE with respect to the full stochastic rainfall field reduces from 23.18 to 8.12 compared to the best 1-station network.

In a second evaluation step of the identified optimum rain gauge network, we simulated the event-based streamflow response for the best 1-station network and the best and the worst 3-station network, to compare the result to the simulation with the original rainfall field and thereby obtain a validation on the entire streamflow dynamics rather than on RC or lag only (all simulations are available in Supplementary Material part 1). It is important to point out here that the semi-distributed hydrological model cannot reproduce all observed events equally well as shown by low correlation coefficients between observed and simulated streamflow inFigure 13. Even with the stochastic generation of rainfall fields, fast streamflow tends to be underestimated with the model; improving the simulation quality for all events would require an in-depth analysis of different subsurface flow mechanisms related also to snow melt and shallow-groundwater recharge, work that is ongoing in this catchment (Beria, 2020b).

Despite of this, we clearly see that the best 1-station network and the worst 3-station network considerably underperform with respect to the full network and that the best 3-station network yields a simulation performance close to the original rainfall field, confirming the results obtained for the summary streamflow response metrics RC and lag.

Commenté [AM39]: Rephrased according to the remark of Reviewer #1 – Point 39

Commenté [AM40]: Added according to Reviewer #1, point 1b

Commenté [AM41]: Added according to Reviewer #1 point 2 and Reviewer #2 point 8b

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5 Discussion

5.1 Spatial heterogeneity of rainfall

One of the key identified metrics to characterize the spatial distribution of rainfall, in relation to RC and lag prediction is I_{ASYM} splits. It splits the catchment into two parts, and averages aggregates rainfall observations into two values. Among the records showing a strong rainfall asymmetry, 7 out of the 8 events are too small to cause a detectable streamflow reaction response (Figure 5), but one does create a reaction streamflow response although it only rains over half of the 12 rain gauge stations. Despite of this absence of a strong asymmetry in the 14 rainfall events that cause a streamflow response, the regression analysis based on 14 out of 48 rainfall events suggests that for rainfall events that create a streamflow reaction, the spatial distribution might play an important role for the explanation of the lag time. The importance of this asymmetry predictor can be related to the fact that it captures the key feature of the spatial catchment organisation in terms of distance to the outlet, drainage density and subsurface storage potential.

The second dominant metric of spatial rainfall distribution to predict the RC and the lag is D_{STREAM} (pseudo-dynamic). This suggests that for this catchment, the rainfall distance to the outlet is the overall the dominant predictor for the analyzed streamflow response metrics.

It is noteworthy that this analysis could be affined by investigating different splitting geometries, e.g. by splitting the catchment into west and east parts, thereby separating the large slopes (west) from the steep slopes (east). This and similar spatial asymmetry metrics are case-specific as they rely on the particular geomorphology and topography of the catchment and are thus not directly applicable to other catchments. In particular I_{ASYM} cannot be used as a tool to compare different catchments. The rainfall distance metrics to the stream network (D_{HILLS}) and along the stream network (D_{STREAM}) were designed here to overcome the limitations of the simple asymmetry measure. The prominent role of D_{STREAM} - composite pseudo-dynamic to explain the lag time and RC underlines the importance of characterizing the spatial heterogeneity in terms of geomorphological distances to the actual stream network, which requires more detailed network expansion analyses in future studies.

We could expect that in that kind of steep environments, the residence time in hillslopes strongly dominates over residence times in the stream network (Nicotina et al., 2008); the fact that D_{STREAM} outperforms here D_{HILLS} for the prediction of RC and lag time is an interesting result: it underlines may show that even in steep environments, with a priori fast instream processes and limited storage, the riparian area and related subsurface exchange processes could play a more prominent role than what we previously thought. The fact that the travel distance in the stream network explains more of the RC variation than D_{HILLS} might be an indirect effect: the longer the travel distance in the stream network, the more likely are delays due to exchange with groundwater in the riparian area. This implies that along-stream processes might need a better representation in rainfall-runoff models, even for small and steep catchments; to date, these processes are often ignored in rainfall-runoff hydrological models at this scale, or are represented with a simple constant velocity transport term (e.g. Schaefli et al., 2014).

However, future work on the role of water residence time in the stream network will necessarily require more detailed field data on the temporal evolution of the stream network. This will in addition open new perspectives to quantify how the stream

Commenté [AM42]: Discussion about the splitting line added according to Reviewer #1, point 10.

Commenté [AM43]: Modified according to Reviewer #1 – Point 40

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network extension is imprinted in the streamflow response: in fact, as discussed by Rinaldo et al. (1995), the intrinsic fractal nature of the stream network is not transferred to the streamflow response and, accordingly, there is potential to infer the stream network extension from observed streamflow records, provided that we have high resolution rainfall data to disentangle the different effects.

> **Commenté [AM44]:** Added according to Reviewer #2 – Point 4

5.2   Rain gauge network density

The selected metrics showed the importance and potential of a high density rain gauge network to capture rain events, and to investigate the dynamics of the hydrologic response. The rain gauge network analysis can then be used as a preliminary investigation to implement a permanent network, composed of fewer stations. The reliability of the study is directly dependent on the number of observed rainfall events, i.e. on deployment duration of the rain gauge network. Despite the small size of the catchment, there could potentially be storms that are not or only partially seen by the rain gauge network.

This possibility of missing localized events is highlighted by the event of July 24th (Section 4.1.1), which was considerably underestimated despite of the high density of the deployed network (1 station for 0.9 km² on average, maximal distance of 1,670 m from a point to a rain gauge). The best partial networks composed of 1, 2 or 3 stations (Section 4.4) give for this extremely localized event a total amount of rainfall respectively 12.0 mm, 9.4 mm and 9.2 mm, not far from the 10.6 mm measured with the full network, but these partial networks were trained on the dataset containing the particular event.

With only one station, there is a high risk of totally missing an event, whereas a 2-station network design measuring at least the northern and the southern part of the catchment would i) capture most of the events and ii) give a first estimation of the rainfall spatial distribution.

Overall, the network optimisation analysis with different metrics clearly suggests that to optimally reproduce the hydrologic response in terms of RC and $\Delta_{P/Q}$, we would need to implement at least a three station network in this catchment, organized along a north-south transect, with one of the stations being located in the remote southern part. The north-south organization can be explained by i) the shape of the catchment that also extends longitudinally or ii) a general tendency for rainfall events to move longitudinally, emphasizing the importance, for this case study, to capture spatial configuration of rainfalls over a north-south transect rather than over a west-east transect and iii) the general increasing trend of elevation along this transect.

6   Conclusion

Our analysis of the role of rainfall patterns for the streamflow response is one of the first data-based studies carried out at such a small scale in an Alpine environment. The detailed analysis of 48 events from one summer suggests that spatial rainfall patterns might play a key role to explain the hydrologic response in small Alpine catchments. The novelties of the study include the use of a low-cost rain gauge network to capture rainfall patterns, and the design of a ~~new~~data-based framework to analyze the rainfall-runoff response. The main conclusions from our analysis are:

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- A high density rain gauge observation network is a major asset to identify critical areas that are influenced by local rainfall forcing, and give an estimation of the rainfall amount errors made by a partial network.
- A detailed analysis of the hydrological response as a function of rainfall patterns and geomorphology requires a rain gauge network specifically designed for this purpose in conjunction with detailed observations of the stream network expansion before events.
- Such a network should take into account the spatial distribution of distances to and along the stream network.
- As shown here, even for small catchments the rainfall distance to the outlet along the stream network might play a key role to explain the hydrologic response. Accordingly, future hydrological modelling studies in small Alpine catchments should investigate the representation of instream transport and storage processes.

The analysis framework developed here is readily transferable to other settings, including natural or even urban catchments. Given the low cost of the deployed rainfall sensor network, the approach has potential for future detailed studies in to-date sparsely gauged catchments.

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Appendix A: Drop-counting rain gauge calibration and data correction

Technical characteristics of the Pluvimate drop-counting rain gauges (see Section 3.1) are detailed in the work of Benoit et al. (2018a); for this study we extended the experimental tests to intensities up to 150 mm/h. It appears that for intensities up to 20 mm/h (99.88 % of the measured 2-min intensities during the 2018 observation period, see Figure A1) the linear relationship between drop count and rain intensity gives a good estimate (uncertainty below 5 %); beyond 20 mm/h the linear relationship underestimates the rainfall intensities, to reach 10 % of error at 60 mm/h and 15 % at 150 mm/h (Figure A1). For this study, rainfall intensities over 20 mm/h are corrected using a polynomial law based on the experimental measures.
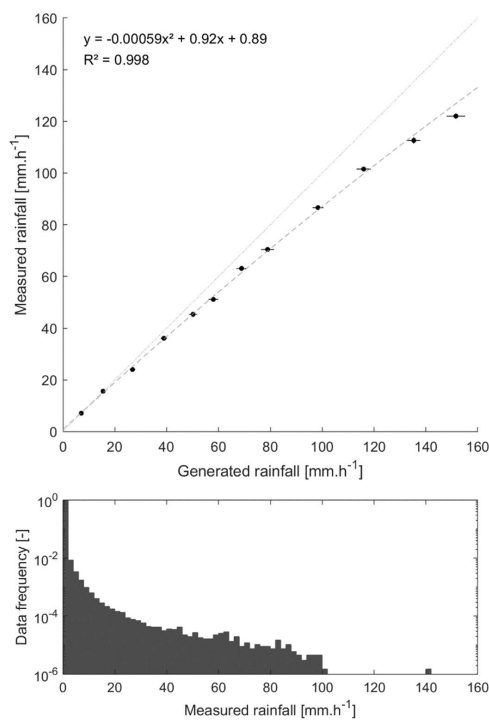
Figure A1. Calibration curve (on top) of the Pluvimate rain gauges based on experimental measures with controlled rainfall input, and (at the bottom) the data frequency measured in situ.

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The Vallon de Nant in Switzerland

	100 m contour lines
	Contracted river network
	Expanded river network
	N/S equal area line
■	Outlet
■	Raingauges

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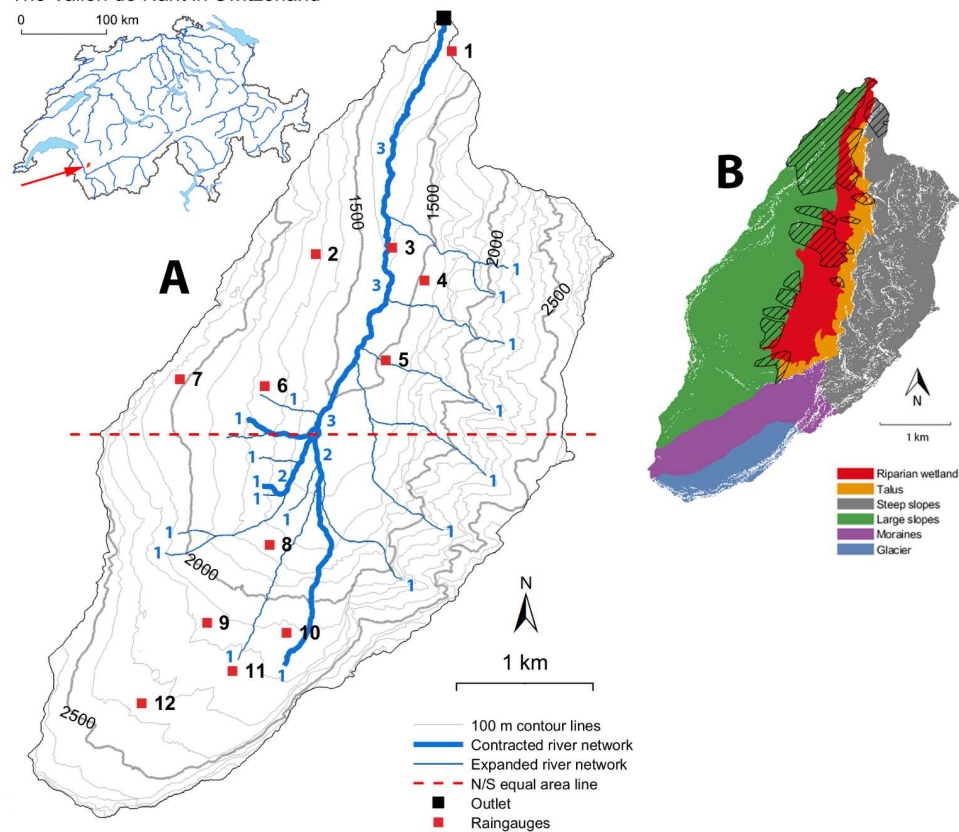
Figure 1. Map of the Vallon de Nant and location of the 12 rain gauges. The streamflow is measured on the main river at the outlet (46.25301 N / 7.10954 E in WGS84 coordinates). The red dashed line splits the catchment area into two parts of equal area. The small numbers next to the streams indicate the Strahler stream order (Strahler, 1957).

Figure . River stage measure at the outlet. The streamflow is here measured between 0.96 and 1.13 $m^3.s^{-1}$.

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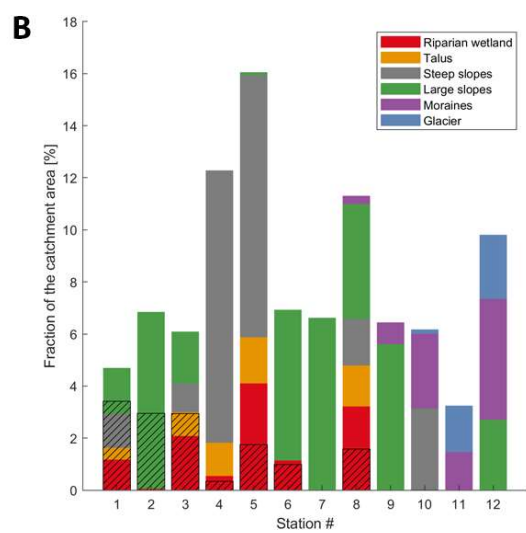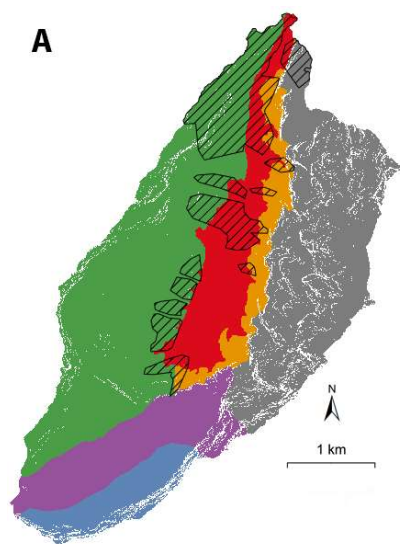
Figure 2. Drop-counting rain gauge used for rainfall measures. The Pluvimate is set-up vertically between 0.8 and 1.2 meters above the ground level (a). A tip at the end of the funnel (b) creates a calibrated drop of water that falls on the sensor, (c) which counts and records the number of drops during a given amount of time.
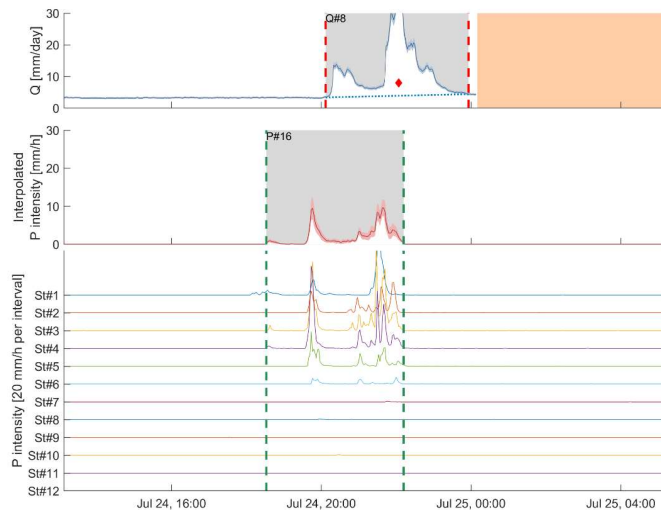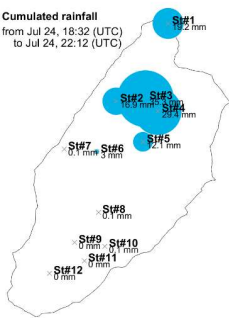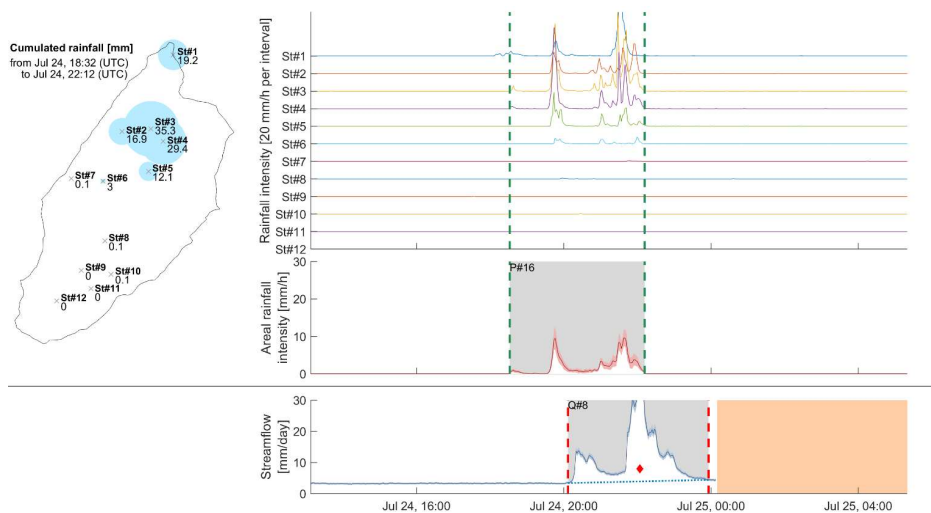
845 Figure 3. Summary of the recorded rainfall and streamflow for the rainfall event of July 24th 2018 at 6:32 PM (UTC).

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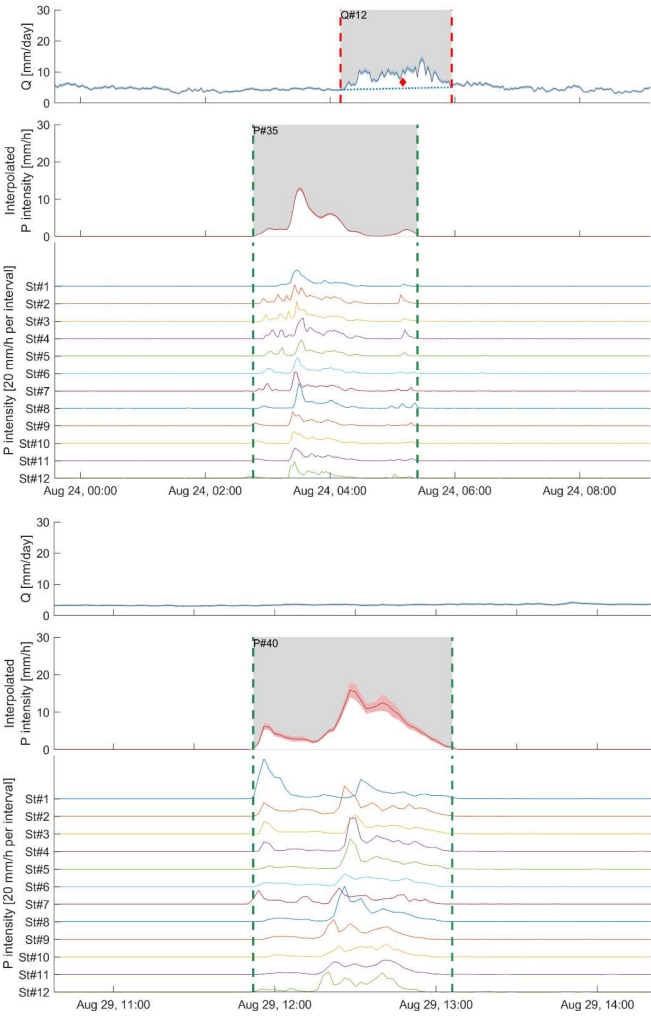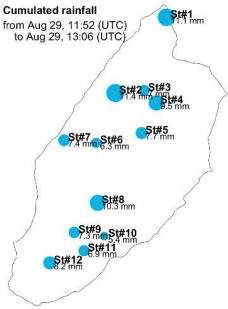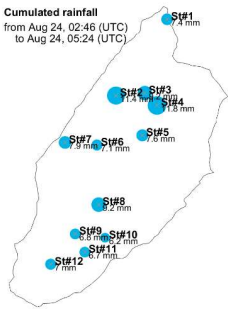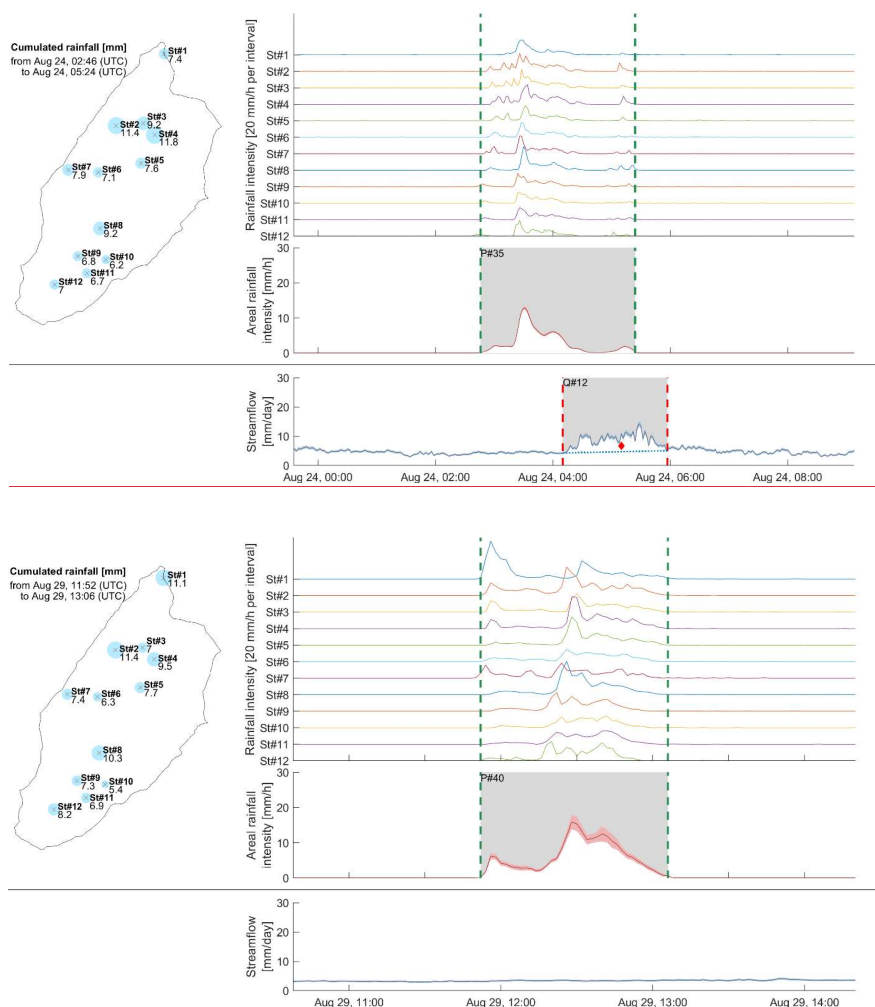
Figure 4. Summary of the recorded rainfall and streamflow for the rainfall events of August 24th 2018 at 2:46 AM (top) and August 29th 2018 at 11:52 AM (bottom).

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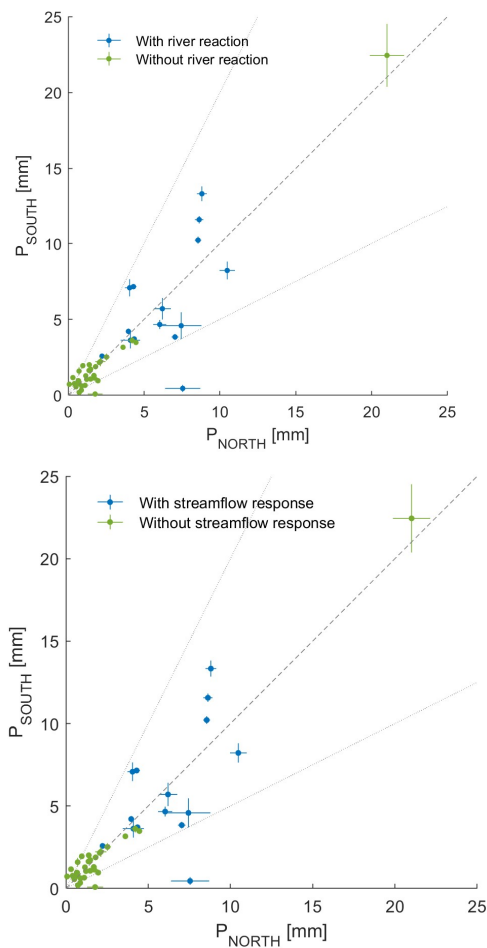
Figure 5. Scatterplot of the rainfall amounts over the northern and the southern parts of the catchment for all 48 rainfall events. The dotted lines show the 1/2 and 2/1 lines which correspond to twice more rainfall in one part of the catchment than in the other or to $|I_{ASYM}| > 0.33$. The highest event is an outlier (event of 6-Aug with 43.5 mm of rainfall in total)): is flagged without ~~river reaction as~~streamflow response because the river stage measure was disturbed during this period.

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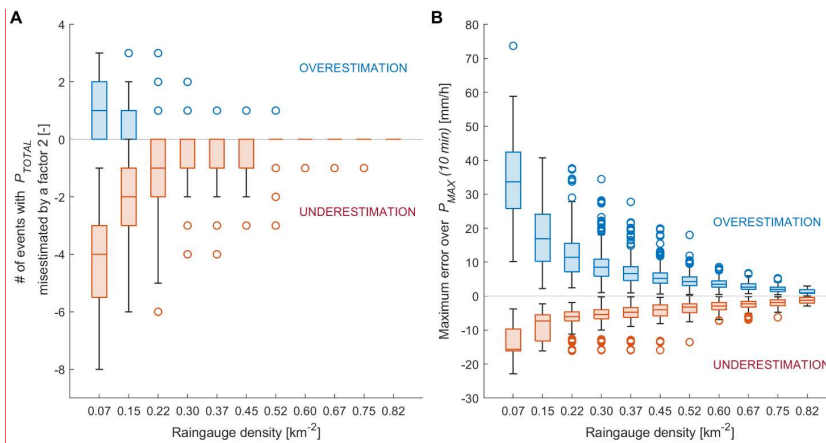
Figure 6. A) Number of rainfall events for which the total amount of rainfall is overestimated or underestimated by a factor 2, according to the rain gauge density, going from 0.07 to 0.82 rain gauges per km² (respectively 1 to 11 rain gauges within the catchment). B) Error on the maximum rainfall over 10 minutes $P_{MAX}(10\ min)$ according to the raingauge density. For each rain gauge density, all possible combinations of rain gauge networks are tested. The reference value is estimated from the full 12-rain gauge network. The bottom and top of each boxes are the 25th and 75th percentiles of the sample, the middle line the sample median. The whiskers go up to 1.5 times the interquartile range; values beyond the whiskers (outliers) are marked with circles.

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Commenté [AM45]: Added according to Reviewer #1, point 1d
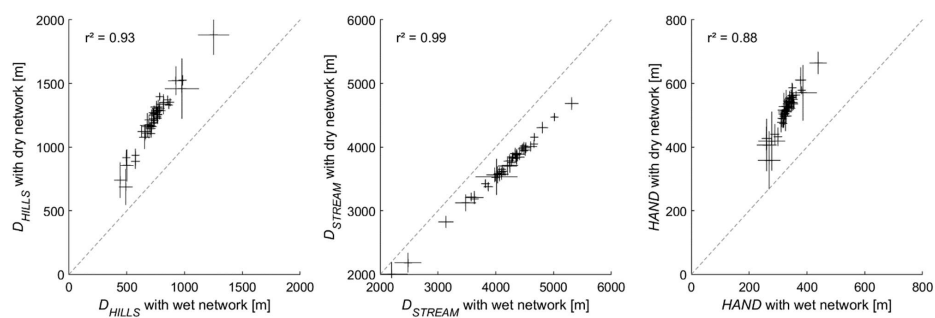
875 Figure 7. Scatterplots of the distance metrics for the dry network state versus the wet state, for all 48 rainfall events. The bars indicate the standard deviation obtained from the 20 rainfall field realisations. r^2 indicates the linear correlation.

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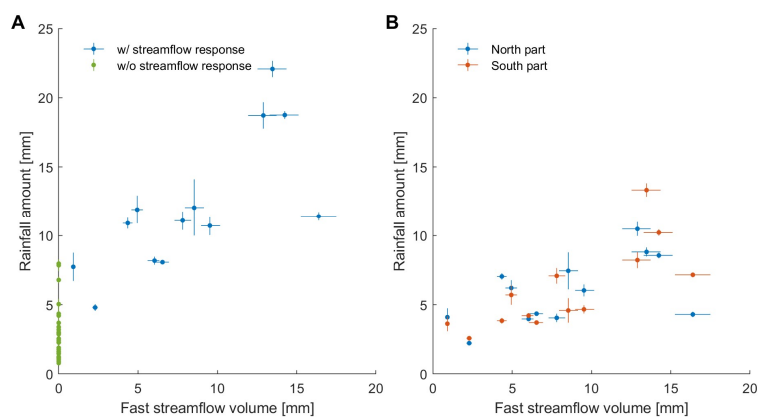
Figure 8.–. Scatterplots of A) total rainfall amounts againstversus fast streamflow, separating (highlighting the threshold for streamflow response) and B) of rainfall amounts in the northern and the southern parts of the catchmentpart against fast streamflow (for separation line, see Figure 1); events without reaction are not shown. The events 24 July (P_ALL=8.0 mm, Q_FAST = 30.4 mm and of 6 Aug (P_ALL=43.5 mm, Q not recorded) are out of the axis. B) total rainfall amounts against fast streamflow, highlighting the threshold for streamflow reaction.). The bars show the standard deviation of estimated rainfall (Section 3.2) and of streamflow (Section 2). The events of 24 July (P_{ALL}=8.0 mm, Q_{FAST} = 30.4 mm) and of 6 Aug (P_{ALL}=43.5 mm, Q not recorded) are out of the axes in A and in B

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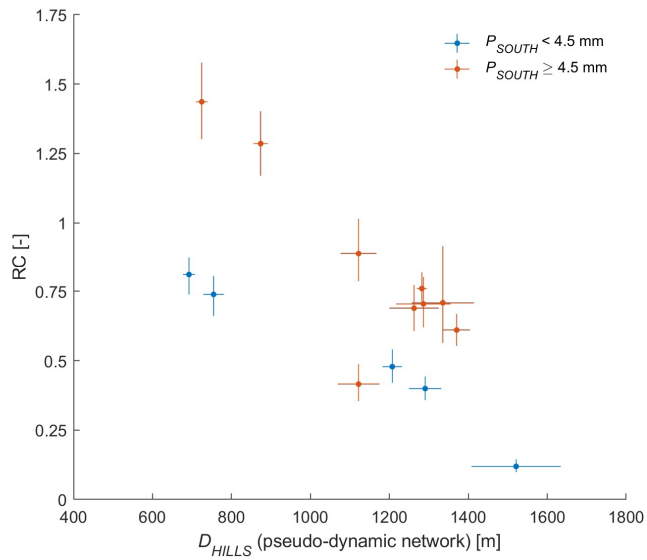
Figure 9. Runoff coefficient against D_{HILLS}, highlighting events with high rainfall amounts in the southern part, i.e. events with P_{SOUTH}>4.5 mm~,; the 24 July event with 3.02 <RC<4.85 and D_{HILLS}=740±140 m has been discarded (see Section 4.1.1).

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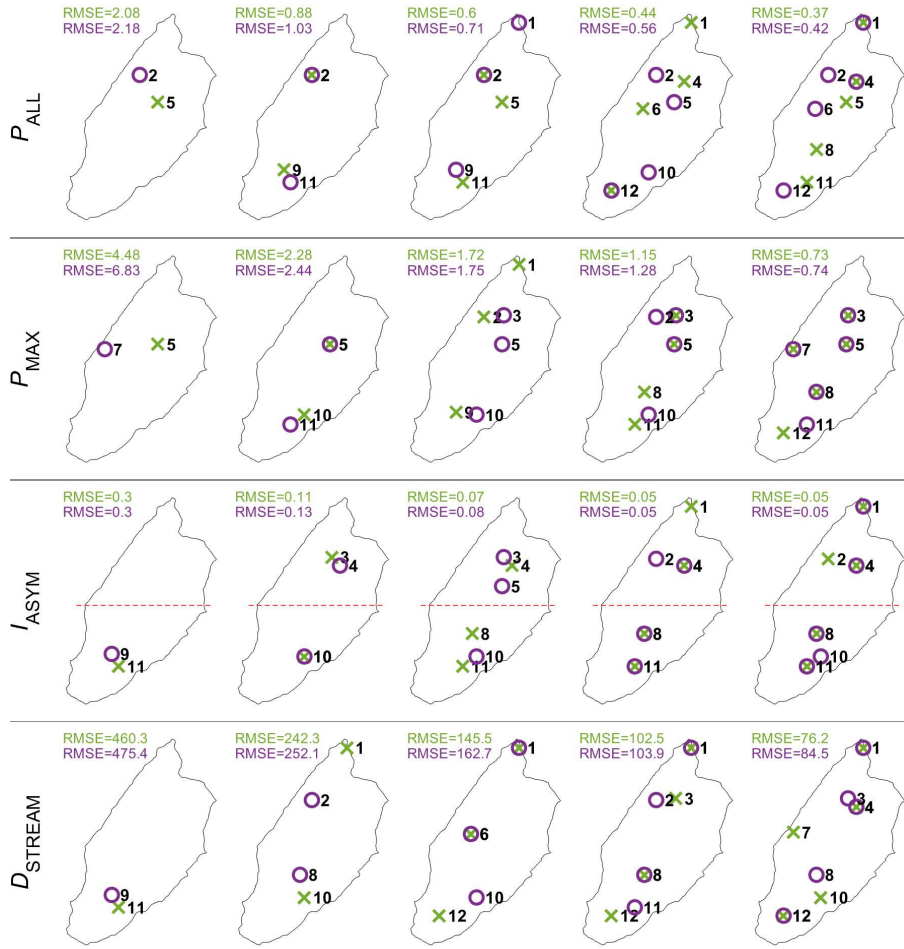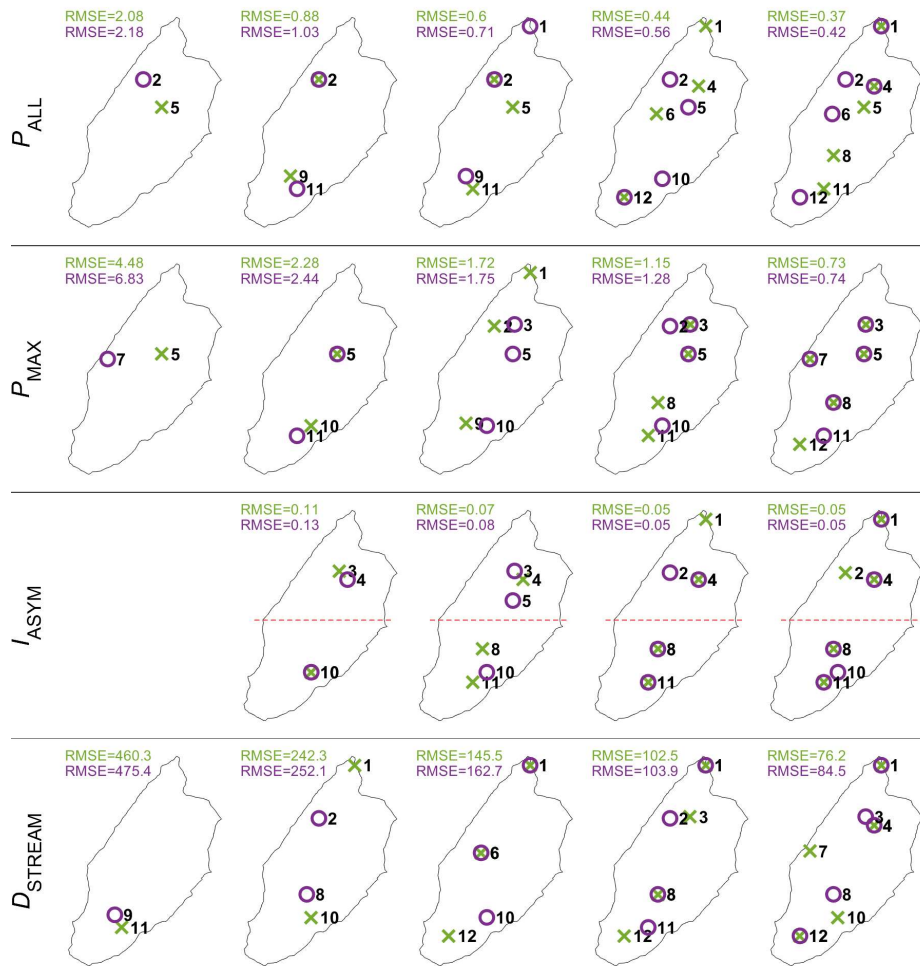
Figure 10. First. Best (green) and second best (purple) best networks and associated RMSE values for 1 to 5 stations resulting from the minimization of the RMSE over 23 events for the P_{ALL}, P_{MAX}, I_{ASYM} and D_{STREAM}. The red dashed line splits the catchments into two parts of equal area.
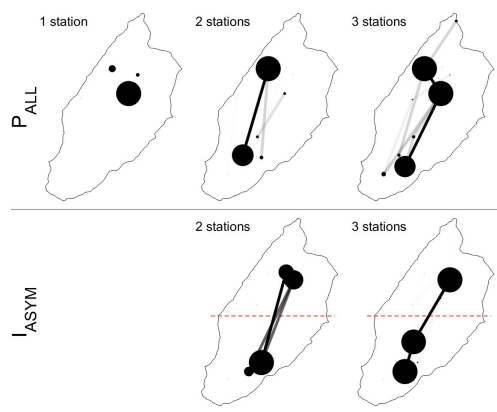
Figure 11. Sensitivity test over the best network from 1 to 3 ~~station~~stations, evaluated by removing from 1 to 3 events over the 23 events (2047 combinations) for the P_{ALL} and I_{ASYM}. The result is presented graphically: larger dots and wider links represent configurations that are found more frequently than others over the different ~~altered~~ simulations. The red dashed line splits the catchments into two parts of equal area.

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RC (partial/full network) [-]

$\Delta_{P/Q}$ (partial/full network) [-]

Legend:
- Best 3-station
- Best 1-station
- Worst 3-stations

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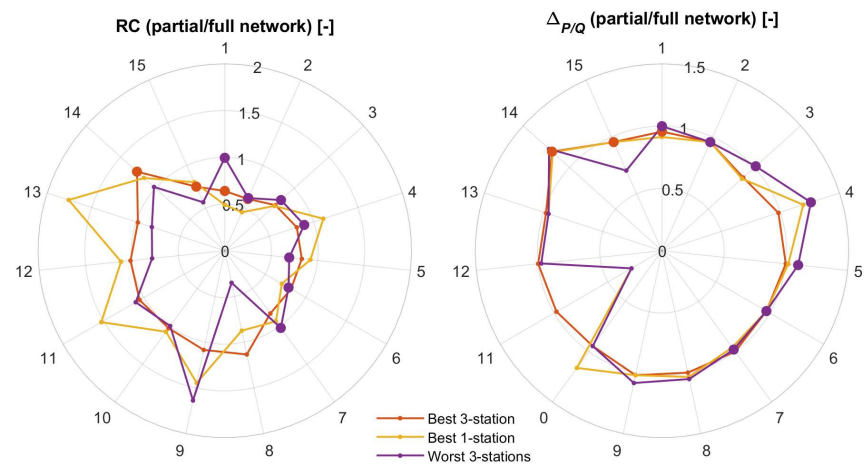
Figure 12. Comparison of streamflow response metrics ratios between a partial network (best 3-station, best 1-station and worst 3-station networks) and the full rain gauge network, using the RC (left) and lag time $\Delta_{P/Q}$ (right). The dataset is subset#4 of Table 2. Larger dots highlight events where events where only 2 of 3 stations were operational (see Section 4.1.1).

Commenté [AM46]: Added according to Reviewer #1, point 1d

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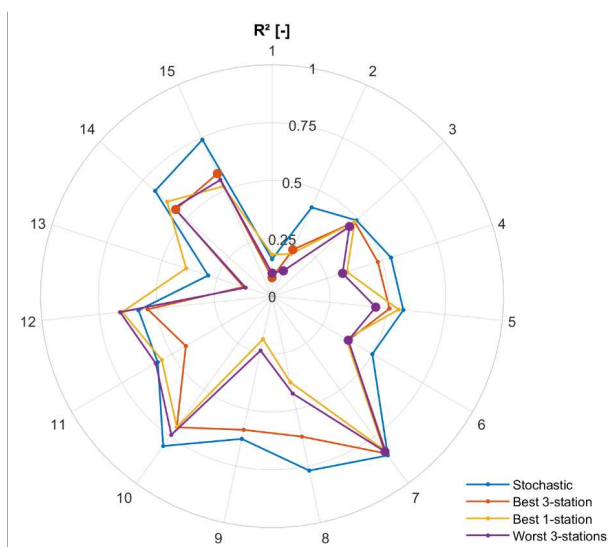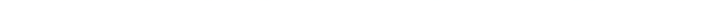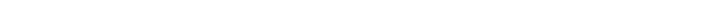
Figure 13. Analysis of 15 rainfall-runoff model events (subset #3, Table 2) with the correlation coefficient between simulated and observed streamflow for different rainfall fields inputs: the stochastic generation of rainfall fields based on all available rain gauge stations, the best 3-stations and the best 1-station network, and the worst 3-stations network. Larger dots highlight events where events where only 2 of 3 stations were operational (see Section 4.1.1).

Commenté [AM47]: Added according to Reviewer #1 – Point 2 and Reviewer #2 – Point 8b

915   Table 1. List of used ~~in this study~~metrics, with corresponding parameter name or abbreviation ~~used in the text~~.

Description	Notation, Unit
Rainfall interpolated over entire catchment	P_{ALL}, mm
Rainfall interpolated over north half of catchment	P_{NORTH}, mm
Rainfall interpolated over south half of catchment	P_{SOUTH}, mm
Rainfall event duration	$P_{DURATION}$, min
~~River reaction event duration~~Maximum rainfall intensity over the event, i = {ALL, NORTH, SOUTH}	~~$Q_{DURATION}$, min~~$P_{max\ i}$, mm
Index of spatial asymmetry of rainfall	I_{ASYM}, -
~~Mean~~ Distance of rainfall spatial center of mass to stream network (along hillslopes)	D_{HILLS}, m
~~Mean~~ Distance of rainfall spatial center of mass to outlet along the stream network	D_{STREAM}, m
Mean height above the nearest drainage	~~D_{HAND}~~H_{HAND}, m
Cumulated amount of rainfall for the last X days	$W_{X\ days}$, mm
Streamflow at the start of the streamflow event	Q_{INIT}, mm
Fast streamflow amount	Q_{FAST}, mm
Streamflow response event duration	$Q_{DURATION}$, min
Rainfall runoff coefficient	RC, -
Lag time between the first third of cumulated rainfall and the first third of cumulated ~~river quickflow~~fast streamflow	$\Delta_{P/Q}$, min

Table 2. Summary of the different subsets of rainfall events used within this study. The streamflow response outlier event discarded in subset #4 corresponds to July 24th 2018.

Table 3. List of recorded precipitation events with streamflow ~~reaction (in 2018~~response (event series #3 of Table 2). Full details are available in the Supplementary Material.

Date	$P_{DURATION}$ [min]	$Q_{DURATION}$ [min]	$\Delta_{P/Q}$ [min]	P_{ALL} [mm]	P_{NORTH} [mm]	P_{SOUTH} [mm]	P_{NORTH}/P_{ALL} [-]	P_{SOUTH}/P_{ALL} [-]	I_{ASYM} [-]	$W_{3\,days}$ [mm]	Stream network	Q_{INIT} [mm]	Q_{FAST} [mm]	RC [-]	D_{HILLS} [m]	D_{STREAM} [m]	HAND H_{HAND} [m]
2-Jul	42	44	24	7.7	4.1	3.6	0.53	0.47	-0.06	3.2	dry	7.9	0.9	0.12	1521	4008	611
3-Jul	40	135	23	12.1	7.4	4.6	0.62	0.38	-0.24	12.7	dry	7.5	8.5	0.71	1336	3842	550
5-Jul	224	309	71	8.2	4.0	4.2	0.49	0.51	0.03	29.8	wet	6.0	6.0	0.74	755	4374	350
6-Jul	478	587	65	20.2	8.6	11.6	0.43	0.57	0.15	40.3	wet	5.8	25.9	1.29	874	4450	355
14-Jul	358	302	49	18.7	10.5	8.2	0.56	0.44	-0.12	0.0	dry	4.5	12.9	0.69	1263	3574	554
15-Jul	136	281	33	10.7	6.0	4.7	0.56	0.44	-0.13	18.9	dry	5.5	9.5	0.89	1122	3377	528
20-Jul	288	228	49	18.8	8.6	10.2	0.46	0.54	0.09	3.4	dry	4.8	14.2	0.76	1282	3823	541
24-Jul	220	229	45	8.0	7.5	0.5	0.94	0.06	0.02	12.2	dry	3.1	30.4	3.78	740	2184	419
14-Aug	204	152	47	11.1	4	7.1	0.37	0.64	0.27	10.2	dry	4.0	7.8	0.70	1286	4305	540
17-Aug	152	109	38	11.9	6.2	5.7	0.52	0.48	-0.04	17.5	dry	3.2	4.9	0.42	1122	3780	490
23-Aug	388	237	47	22.1	8.8	13.3	0.40	0.60	0.20	5.4	dry	2.4	13.5	0.61	1371	3756	563
24-Aug	158	107	40	8.1	4.4	3.7	0.54	0.46	-0.08	29.5	wet	4.1	6.5	0.81	692	4114	320
29-Aug	72	116	48	4.8	2.2	2.6	0.46	0.54	0.07	12.4	dry	3.0	2.3	0.48	1207	3526	524
01-sept	628	341	101	11.4	4.3	7.2	0.38	0.63	0.25	20.4	wet	3.4	16.4	1.44	725	4487	331
13-sept	370	59	45	10.9	7.0	3.8	0.65	0.35	-0.29	0.0	dry	2.6	4.4	0.40	1291	3594	556

Cellules insérées

Commenté [AM50]: Added according to Reviewer #1 – point 18

Commenté [AM49]: Columns added according to Reviewer #1, point 15

Table 4. Correlations between rainfall ~~amounts, asymmetry~~ metrics and hydrologic response metrics for ~~the 14 events with streamflow reaction (after discarding the 24 July event)~~. <u>series #4 of Table 2.</u> Absolute values equal or ~~over~~<u>higher than</u> 0.60 are in bold.

	P_{ALL} [mm]	P_{NORTH} [mm]	P_{SOUTH} [mm]	$P_{max\ ALL}$ [mm.h^{-1}]	$P_{max\ NORTH}$ [mm.h^{-1}]	$P_{max\ SOUTH}$ [mm.h^{-1}]	I_{ASYM} [-]	$W_{3\ days}$ [mm]	Q_{INIT} [mm]	Q_{FAST} [mm]	$P_{DURATION}$ [min]	$Q_{DURATION}$ [min]	$\Delta_{P/Q}$ [min]
P_{ALL} [mm]	-												
P_{NORTH} [mm]	**0.89**	-											
P_{SOUTH} [mm]	**0.94**	**0.69**	-										
$P_{max\ ALL}$ [mm.h^{-1}]	0.01	0.19	-0.12	-									
$P_{max\ NORTH}$ [mm.h^{-1}]	0.09	0.33	-0.11	**0.96**	-								
$P_{max\ SOUTH}$ [mm.h^{-1}]	0.19	0.19	0.16	**0.87**	**0.78**	-							
I_{ASYM} [-]	0.25	-0.20	0.55	-0.42	-0.56	-0.06	-						
$W_{3\ days}$ [mm]	-0.19	-0.30	-0.09	-0.22	-0.27	-0.23	0.18	-					
Q_{INIT} [mm]	-0.13	0.00	-0.21	0.52	0.54	0.27	-0.28	0.26	-				
Q_{FAST} [mm]	**0.77**	0.58	**0.80**	-0.17	-0.16	-0.08	0.43	0.33	-0.01	-			
$P_{DURATION}$ [min]	0.56	0.38	**0.62**	-0.59	-0.52	-0.48	0.44	0.14	-0.43	**0.74**	-		
$Q_{DURATION}$ [min]	0.56	0.39	**0.61**	-0.27	-0.27	-0.17	0.42	0.52	0.11	**0.89**	0.64	-	
$\Delta_{P/Q}$ [min]	0.13	-0.11	0.29	**-0.71**	**-0.71**	-0.58	0.59	0.41	-0.33	0.52	**0.81**	**0.60**	-
RC [-]	0.31	0.13	0.40	-0.25	-0.29	-0.22	0.44	**0.65**	-0.05	**0.81**	0.67	**0.80**	**0.72**

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Table 5. Correlations between distance metrics for ~~the 14~~rainfall events with streamflow ~~reaction (after discarding the 24 July event).~~response (series #4 of Table 2). Absolute values equal or ~~over~~higher than 0.60 are in bold. ~~For correlations covering~~Correlations for all rainfall events~~, see the part 1 of~~ are available in the Supplementary Material.

		D_{HILLS}	D_{HILLS}	D_{STREAM}	D_{STREAM}	$D_{HAND}H_{HAND}$	$D_{HAND}H_{HAND}$	D_{HILLS}	D_{STREAM}	$D_{HAND}H_{HAND}$
	River network	*Wet*	*Dry*	*Wet*	*Dry*	*Wet*	*Dry*	*~~Composite~~Pseudo-dynamic*	*~~Composite~~Pseudo-dynamic*	*~~Composite~~Pseudo-dynamic*
D_{HILLS}	*Wet*	-								
D_{HILLS}	*Dry*	**0.96**	-							
D_{STREAM}	*Wet*	0.59	**0.61**	-						
D_{STREAM}	*Dry*	0.54	0.53	**0.99**	-					
$D_{HAND}H_{HAND}$	*Wet*	**0.91**	**0.93**	0.51	0.44	-				
$D_{HAND}H_{HAND}$	*Dry*	**0.75**	**0.89**	0.40	0.28	**0.90**	-			
D_{HILLS}	*~~Composite~~Pseudo-dynamic*	0.42	0.45	0.08	0.04	0.51	0.49	-		
D_{STREAM}	*~~Composite~~Pseudo-dynamic*	0.32	0.31	**0.75**	**0.77**	0.18	0.09	-0.57	-	
$D_{HAND}H_{HAND}$	*~~Composite~~Pseudo-dynamic*	0.26	0.30	-0.05	-0.10	0.40	0.42	**0.98**	**-0.68**	-
RC		-0.20	-0.21	0.10	0.13	-0.28	-0.28	**-0.70**	0.53	**-0.70**
$\Delta_{P/Q}$		-0.10	-0.05	0.21	0.21	-0.13	-0.06	**-0.66**	0.60	**-0.68**

Table 6. List of the tested predictors for the RC with a pure quadratic regression, and ~~their~~ the corresponding statistics: root mean square error (RMSE), coefficient of determination (R^2), variance of residuals (var. residuals), p-value, corrected Akaike criterion (AICc) and AICc ranking. The acceptable p-values (≤ 0.05) and first 3 ranks are highlighted. The analysis is over the 14 events ~~(without the outlier event of 24-Jul).~~ series #4 of Table 2.

Predictor 1	Predictor 2	RMSE	R^2	var. residuals	p-value	AICc	rank AICc
P_{ALL}	-	0.34	0.14	0.10	0.44	-24.96	17
P_{NORTH}	-	0.36	0.02	0.11	0.88	-23.20	18
P_{SOUTH}	-	0.31	0.28	0.08	0.17	-27.44	12
I_{ASYM}	-	0.33	0.22	0.09	0.25	-26.37	16
$W_{3\,days}$	-	0.27	0.48	0.06	**0.03**	-31.90	7
D_{HILLS} (~~composite~~pseudo-dynamic)	-	0.26	0.52	0.06	**0.02**	-33.00	**3**
D_{STREAM} (~~composite~~pseudo-dynamic)	-	0.23	0.61	0.04	**0.01**	-36.13	**1**
P_{ALL}	I_{ASYM}	0.33	0.35	0.07	0.36	-19.88	19
P_{NORTH}	I_{ASYM}	0.34	0.29	0.08	0.50	-18.53	21
P_{SOUTH}	I_{ASYM}	0.33	0.35	0.07	0.37	-19.84	20
$W_{3\,days}$	I_{ASYM}	0.25	0.62	0.04	**0.05**	-27.38	13
D_{HILLS} (~~composite~~pseudo-dynamic)	I_{ASYM}	0.23	0.68	0.04	**0.03**	-29.55	9
D_{STREAM} (~~composite~~pseudo-dynamic)	I_{ASYM}	0.25	0.62	0.04	**0.05**	-27.30	14
P_{ALL}	D_{HILLS} (~~composite~~pseudo-dynamic)	0.22	0.70	0.03	**0.02**	-30.65	8
P_{NORTH}	D_{HILLS} (~~composite~~pseudo-dynamic)	0.26	0.60	0.05	0.06	-26.76	15
P_{SOUTH}	D_{HILLS} (~~composite~~pseudo-dynamic)	0.21	0.74	0.03	**0.01**	-32.80	4
$W_{3\,days}$	D_{HILLS} (~~composite~~pseudo-dynamic)	0.24	0.65	0.04	**0.04**	-28.34	11
P_{ALL}	D_{STREAM} (~~composite~~pseudo-dynamic)	0.20	0.75	0.03	**0.01**	-33.18	**2**
P_{NORTH}	D_{STREAM} (~~composite~~pseudo-dynamic)	0.21	0.74	0.03	**0.01**	-32.55	5
P_{SOUTH}	D_{STREAM} (~~composite~~pseudo-dynamic)	0.21	0.74	0.03	**0.01**	-32.46	6
$W_{3\,days}$	D_{STREAM} (~~composite~~pseudo-dynamic)	0.24	0.67	0.04	**0.03**	-29.10	10

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Table 7 As Table 6 but for the lag $\Delta_{P/Q}$.

corresponding statistics: root mean square error (RMSE), coefficient of determination (R²), variance of residuals
940 (var. residuals), p-value, corrected Akaike criterion (AICc) and AICc ranking. The acceptable p-values (≤0.05) and
first 3 ranks are highlighted. The analysis is over 14 events (without the outlier event of 24-Jul).

Predictor 1	Predictor 2	RMSE	R²	var. residuals	p-value	AICc	rank AICc
$P_{max\ ALL}$	-	13.07	0.64	144.52	**0.00**	76.99	**3**
$P_{max\ NORTH}$	-	12.70	0.66	136.56	**0.00**	76.20	**2**
$P_{max\ SOUTH}$	-	16.52	0.43	231.05	**0.05**	83.56	11
I_{ASYM}	-	17.25	0.37	251.75	0.08	84.76	13
$W_{3\ days}$	-	19.83	0.17	332.65	0.35	88.66	19
D_{HILLS} (~~composite~~pseudo-dynamic)	-	16.28	0.44	224.27	**0.04**	83.14	10
D_{STREAM} (~~composite~~pseudo-dynamic)	-	13.39	0.62	151.71	**0.00**	77.67	4
$P_{max\ ALL}$	I_{ASYM}	11.10	0.79	85.35	**0.00**	78.72	5
$P_{max\ NORTH}$	I_{ASYM}	12.89	0.71	115.01	**0.02**	82.89	8
$P_{max\ SOUTH}$	I_{ASYM}	10.06	0.83	70.06	**0.00**	75.95	**1**
$W_{3\ days}$	I_{ASYM}	15.86	0.57	174.17	0.08	88.70	20
D_{HILLS} (~~composite~~pseudo-dynamic)	I_{ASYM}	12.97	0.71	116.52	**0.02**	83.07	9
D_{STREAM} (~~composite~~pseudo-dynamic)	I_{ASYM}	13.83	0.67	132.39	**0.03**	84.86	15
$P_{max\ ALL}$	D_{HILLS} (~~composite~~pseudo-dynamic)	14.18	0.65	139.25	**0.03**	85.57	17
$P_{max\ NORTH}$	D_{HILLS} (~~composite~~pseudo-dynamic)	13.95	0.67	134.65	**0.03**	85.10	16
$P_{max\ SOUTH}$	D_{HILLS} (~~composite~~pseudo-dynamic)	16.57	0.53	190.15	0.12	89.93	21
$W_{3\ days}$	D_{HILLS} (~~composite~~pseudo-dynamic)	15.65	0.58	169.50	0.07	88.32	18
$P_{max\ ALL}$	D_{STREAM} (~~composite~~pseudo-dynamic)	11.40	0.78	89.99	**0.01**	79.46	6
$P_{max\ NORTH}$	D_{STREAM} (~~composite~~pseudo-dynamic)	11.55	0.77	92.36	**0.01**	79.82	7
$P_{max\ SOUTH}$	D_{STREAM} (~~composite~~pseudo-dynamic)	13.37	0.69	123.70	**0.02**	83.91	12
$W_{3\ days}$	D_{STREAM} (~~composite~~pseudo-dynamic)	13.82	0.67	132.18	**0.03**	84.84	14