Response to Reviewers

The first part of the document reports the responses to the two anonymous referees, indicating also the relevant changes in the manuscript (the lines in the replies refer to the marked document copied in the following). The second part is a marked-up version of the revised manuscript (main changes and new parts are in blue font).

Response to Reviewer 1

General comments:
This paper compared several kinds of regionalization strategies with two kinds of rainfall-runoff models. Generally speaking, this paper is well written and provides convincing evidence to support the conclusion. The title, abstract, introduction and discussion should be substantially revised. Here are some detailed comments.

Specific Comments:
1. The title is inconsistent with the numerical experiments of this paper. In this paper, 5 kinds of regionalization approaches (KR, NN-1, MS-1, NN-OA, MS-OA) were comprehensively compared with test data from Austria. The effects of nested catchments and gauging station density were also evaluated. Two rainfall-runoff models (TUW and GR6J) were used in the evaluation and similar results can be obtained from different models, indicating the conclusion of this work can potentially be extended to various models. However, the key words 'Importance of the information content' has not been intensively discussed in the discussion part (please search 'information'). The concept 'information content' has not been well defined in this paper, and it seems not very necessary to have it defined. This paper is more likely to be a 'inter-comparison' paper instead of a 'concept promoting' paper. Consequently, I suggest the authors to revise the title in order to sharply and concisely show what have been done in this paper in a few words.
Reply: We thank the referee for suggesting more clarity in highlighting what the paper presents: the main focus and novelty of the work is the analysis of the role of the available data set, that is which and how many gauged catchments are available (to be used as donors) for the regionalisation (this is what we mean with information content of the data set: we will explain it better). And in order to do so, we compare different regionalisation approaches, to understand which approaches are more or less impacted by a change in the donors' data set (and, as you wrote, we applied two well-known rainfall-runoff models, for generalisation purposes). We agree with the referee that the term "information content" may confuse the reader, since it could be also associated to the Shannon's definition in the 'information theory' discipline, for the hydrological literature in this period.
In order to further clarify our main focus, we have:
   i)   modified the introduction (lines 56-57 and 92-96) and the conclusions (lines 637-640 and 680)
   ii)   replaced the term "information content" with "informative content" in both title and manuscript, which keeps the meaning we want to give but it avoids referring to other research subjects.

2. The abstract is too long! Please briefly introduce your work in a single paragraph. A wordy 'abstract' is not friendly to your potential readers. It is uncomfortable to locate useful information from a 'one-page, 5 paragraphs abstract'.
Reply: As suggested, we have substantially cut and revised the abstract, in order to have a more useful and agile summary (and also here focussing more on our main objective).

3. line 43-53: In order to clarify the relationships between different regionalization approaches, please add a 'mind map' about: regression-based, distance-based, output-averaging, parameter-averaging.
Reply: We have tried to clarify it, reorganising the sentence in bullet points (so that is more 'graphical') in order to make the difference between the approaches easier to understand (lines 35-47).

4. line 67: the best the best?
Reply: We have corrected this typo.

5. line 155: routing routine?

Reply: Yes, it is the programming routine used for computing the flow response and routing. It is the same terminology used in the TUW model manual but we agree that it is an alliteration and it does not "sound" well, and we have replaced "routine" with "module" (lines 151-152).

6. Discussion and conclusion part.

In this paper the hydrographs of simulated and observed streamflow were not presented. Although this is not necessary, a hydrograph may possibly intuitively show a lot of detailed mismatching patterns which are helpful for model diagnose. I suggest to add hydrographs from a typical catchment to compare not only the KGE and NSE criterions but also the details of systematic errors of different regionalization approaches. KGE and NSE criterions are good objective functions for optimization, but hydrographs can tell more useful information about the physical processes.

Consequently, the discussion part of this paper is mainly about explaining the results, but lack of physical reasons. This paper has too much statistics but not enough hydrological mechanics on explaining the performance of different regionalization approaches. A comparison of regionalized parameters is strongly suggested to be added in the discussion part in order to provide fundamental physical reasoning of regionalization. For an example, please compare the parameter values from KR, NN and MS methods in a typical catchment, and discuss the influence of parameter values to corresponding hydrographs.

Reply: We understand your concern about the robustness of the regionalisation processes and their effect on the simulated hydrographs.

The analysis that you propose of comparing the regionalised parameters would be very interesting (and to our knowledge it would be novel) when using a regression-based method, where the parameters are estimated as a regression function of catchment characteristics and such function might allow to discuss the influence of regionalisation on the corresponding hydrographs: in such case we might expect to identify patterns of how the regionalised parameters vary across the study area, having a direct relationship with the attributes, which may contribute to systematic errors in the simulations.

But such comparison is not possible in our work because the regionalisation methods that we tested all belong to the "distance-based" class of approaches, which identify the model simulation at the target section based on the repetition of the simulation with one or multiple sets of parameters found for donor catchments (spatially closer in NN or most similar in MS) or based on the spatial correlation of the parameters (KR) and there is not a univocal influence of the regionalisation (or of the exclusion of nested donors or of the reduction of the density) on the parameters and therefore on the hydrographs.

We fully agree that reporting only goodness-of-fit indexes do not fully diagnose the capability of the model to accurately reproduce observations, but we did not show any hydrograph in the manuscript because we think that focusing on a single catchment could be misleading: the effect of the regionalisation, and the effect of the exclusion of nested catchments or of the density reduction on the approaches (that is our main focus) is strictly related to the single watershed and its donors, it varies based on the approaches and the specific topological relationships and characteristics of the catchment location.

As an example, we report below the analysis on the effect of the exclusion of nested donor basins when regionalising model parameters for one of the catchments in the Austrian dataset, and in particular we chose one target where excluding a nested donor resulted in a very strong deterioration for one of the methods, so that it is well visible on the hydrographs.

For the sake of brevity, the results regarding the only TUW model and the NN-1, MS-1 and KR regionalisation methods are reported. Moreover, just Criterion 2 is used for nested exclusion.

Figure R1.1 shows the position of the example target catchment T (yellow) and the selected donor basins according to the NN-1 and MS-1 method: basin A is the basin selected as donor for both methods NN-1 and MS-1 and it is nested to T. If we imagine to remove the availability of nested catchments, A would be no longer available and the methods would select respectively basin B (closest for NN-1) and C (most similar for MS-1). Of course, this representation is not feasible for the kriging method KR since it regionalises each model

parameter independently, based on the parameters of all donors, and it is not based on the selection of one or more specific donors.
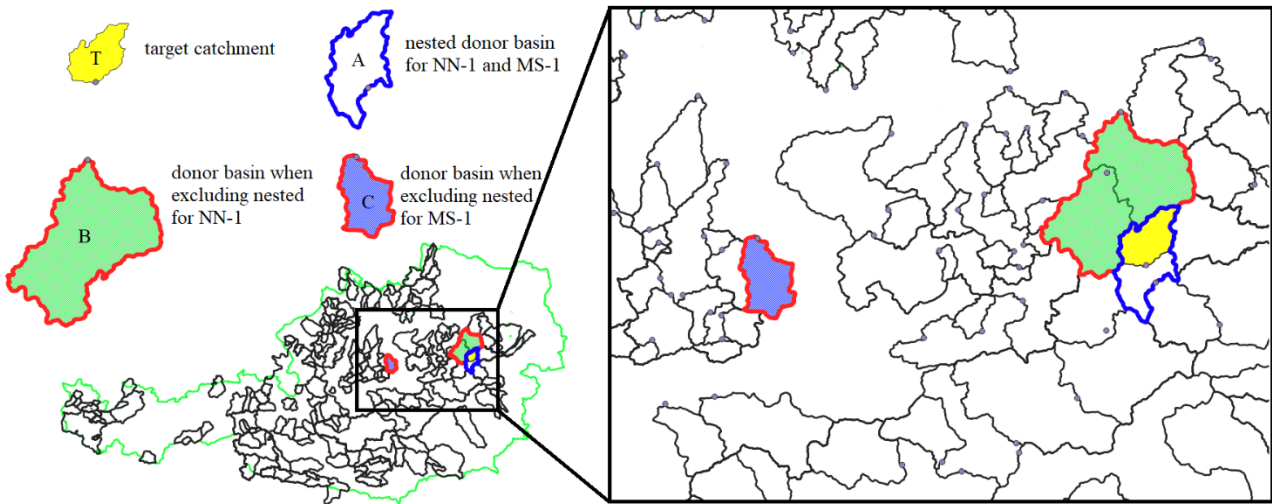

Figure R1.1. Location of the donor catchments for an example target basin *T*: nested basin *A* is the selected donor catchment for both methods NN-1 and MS-1, while if nested are not considered (following Criterion 2) basin *B* and *C* are selected as donor respectively from NN-1 and MS-1 approaches.

Figure R.1.2 reports observed and simulated hydrographs in year 1997 for the three approaches when including or excluding (Criterion 2) the nested donors and Table R.1.1 reports the parameter sets "at site" and regionalised. It can be noticed that, for this specific catchment, the method that deteriorates more when excluding the nested donor is MS-1 (panel c) whose simulated hydrograph (red line) differs substantially from observation (grey points) and from the regionalised simulation obtained when using the nested donor (blue line) as well, while for NN-1 and KR simulations are just slightly affected by the exclusion of A from the potential donors. The reason behind the strong degradation of MS-1 performances can be found looking at the change in the parameter set when excluding the nested donor *A*: the at-site parameter sets of the target and of its nested donor *A* are quite similar, while the parameters of donor *B* differ substantially; the smaller value of FC and k_1, along with a lower threshold L_{UZ}, lead to small storage capacity and thus to much more higher flow peak (red line in Figure R.1.2, panel c) in disagreement with observation. This does not happen, in this example, for the remaining two approaches where the regionalised parameter sets are still quite similar to the "at site" calibrated one, even when *A* is excluded.

Table R1.1. Parameter sets for example target catchment *T*.

|	At Site	NN-1 Regionalized (no exclusion)	NN-1 Regionalized (Criterion 2)	MS-1 Regionalized (no exclusion)	MS-1 Regionalized (Criterion 2)	KR Regionalized (no exclusion)	KR Regionalized (Criterion 2)
SCF	0.9	0.9	0.9	0.9	1.2	0.9	0.9
DDF	1.9	2.4	3.1	2.4	3.4	2.5	2.5
LP	0.2	0.0	1.0	0.0	1.0	0.4	0.7
FC	285.1	114.4	150.7	114.4	33.5	177.7	137.1
β	1.0	20.0	20.0	20.0	1.3	15.7	13.2
k_0	0.3	0.3	0.4	0.3	1.9	0.4	0.4
k_1	16.1	6.3	8.0	6.3	2.3	9.0	12.5
k_2	86.8	51.0	73.6	51.0	30.0	88.8	84.9
L_{UZ}	42.8	65.0	87.1	65.0	18.8	71.4	76.3
C_{PERC}	1.2	4.7	5.8	4.7	1.9	4.6	4.7
C_{ROUTE}	49.7	19.3	43.5	19.3	16.0	32.6	43.9
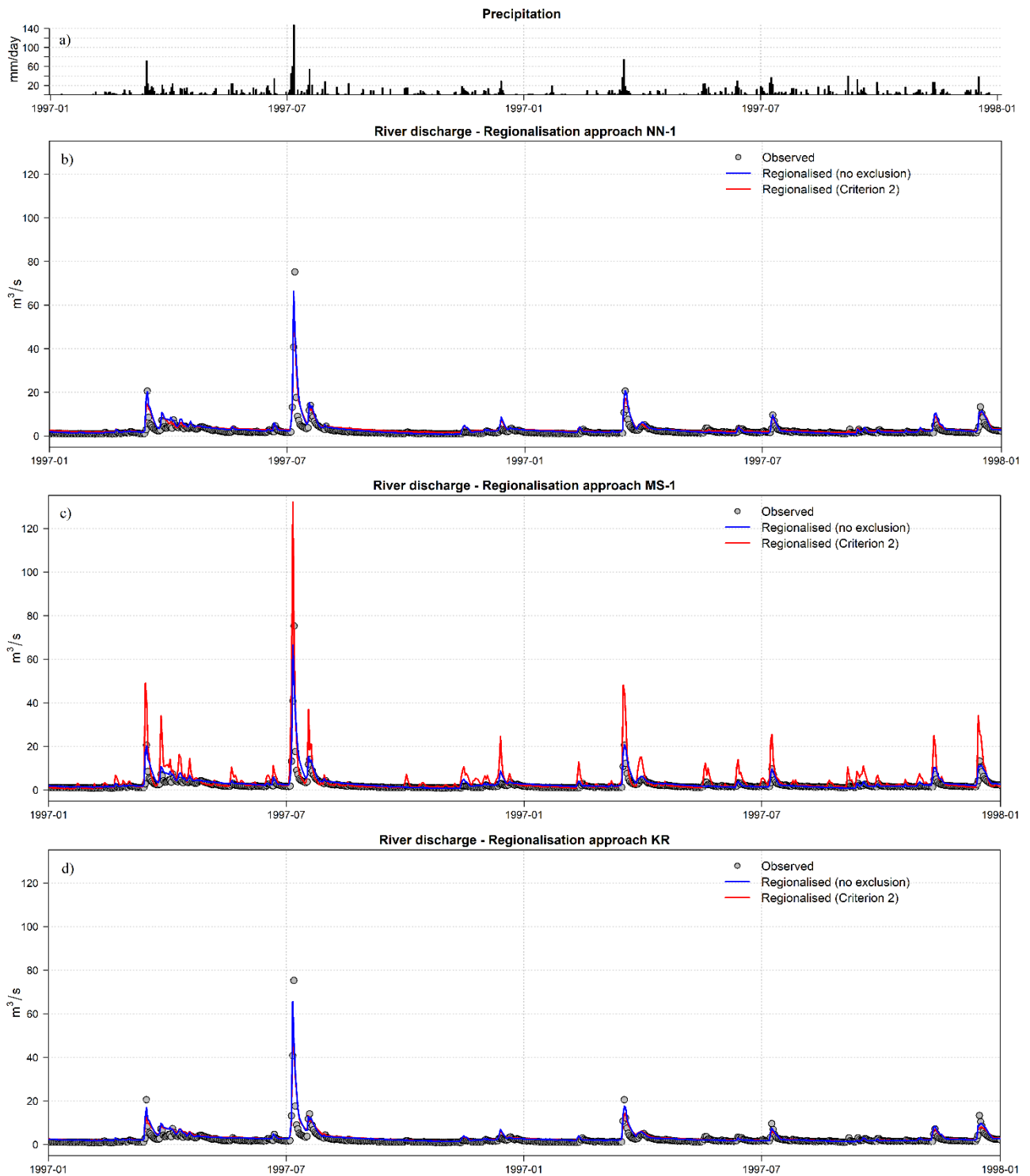
Figure R1.2. Observed and simulated hydrographs in year 1997 for the example target catchment *T*: panel a) average catchment precipitation, panel b c and d) observed streamflow (grey points) and simulated streamflow (respectively for approaches NN-1, MS-1 and KR) when nested catchments are available (blue line) or not (red line).

The selected target catchment represents an unlucky case in which one of the method (MS-1) is deeply affected by the exclusion of the available nested donor, since the "most similar" among the not-nested donors, *C*, is evidently not so hydrologically similar to the target and its parameters do not allow a good simulation of the rainfall-runoff transformation in *T*. Anyway, we decided to display it to highlight the differences between the simulated hydrographs, otherwise not visible in less 'unlucky' cases.

A different catchment would include different multiple donors and different changes in the parameters and, consequently, in the hydrographs: the effect of the regionalisation and of the presence of nested donors is strictly related to the characteristic and the location of the single target catchment analysed.

(And it should also be noted that this example shows the behaviour for the single donor methods, but if we analysed the output averaging methods, we would need to take into account other 3 (for NN-OA) plus 3 (for MS-OA) sets of parameters (and other 3+3 when excluding the nested donors), thus making this kind of representation even longer).

For these reasons, we would prefer not to include specific examples in the manuscript.

Response to Reviewer 2

General comments:
The authors present a very good work on assessing the reliance of model regionalization approaches on the gauged data content. The methodology is clear and easy to follow. Their results indicate that transferring the entire parameter set, thus keeping the correlation among model parameters, outperforms the parameter-averaging kriging method. The output-averaging methods using more than one donor basins is more robust than the one-donor method. The most similar method based on geomorphological and climatic descriptors tends to show higher transferability in sparsely gauged areas than the nearest neighbor method. The findings provide important reference for the community when conducting hydrological modeling in sparsely or ungauged basins.

A) My major concern is that the structure of the manuscript is a bit scattered. The abstract and results sections are lengthy, from my taste. The authors could consider potential rephrase or reorganization. In addition, some Paragraphs in the results section should move to the methodology section.
Reply: As suggested, we have substantially cut and revised the abstract and moved some paragraphs (moved to lines 349-358, 363-379) from the results to the methodology section (see also reply to minor comments).

B) My second concern is that the applied two hydrological models have different calibrated/regionalized parameter spaces. In particular, the TUW model implies 11 parameters for calibration, while the GR6J model has less 8 parameters for calibration/regionalization. Some discussions on the effects of the size of parameter space on the results are needed.
Reply: The issue of the complexity/parsimony of the models is a very important topic: in our case, we assume that the complexity of the two models is similar, since the number of parameters is not so different (8 vs 11 parameters).
Previous studies in the literature applied parameter regionalisation to different conceptual rainfall-runoff models with different number of parameters: Chiew et al. (2010) and Petheram et al. (2012) implemented various models with parameter number varying between 6 and 14 without reporting a clear dependence of model performances on the dimension of parameter space; Viney et al. (2009) used models with 6 to 13 parameters and reported an increasing calibration performance for larger parameter space, but results did not show such a clear behaviour in regionalisation, where results were more dependent on the approach.
For what concern our study, in both results (old lines 382-383, 443-444, 538-540) and discussion (old lines 649-651, 665-666, 697-699) sessions we argued that GR6J model performances "at site" are slightly better than TUW despite the lower number of model parameters, while in general, for regionalisation, the TUW parameters seems to be easier to transfer from gauged to ungauged catchments (and this is even more accentuated when excluding nested donor catchments).
We think that this effect is probably not so much related to the number of parameters, but rather due the higher conceptualisation level of the GR6J model, that may lead to have some parameters that are very case-dependent, and are therefore related to physical basin characteristic (and thus to catchment similarity): for example, the groundwater module of GR6J includes an exchange function (not complying with the volume balance) based on two parameters X2 and X5 which are very sensitive to the specific local conditions and therefore likely difficult to transfer.
In conclusions of the revised version (lines 664-668) we have added, as suggested, that the results may depend on the different model structure and on the different transferability of model parameters (depending also on their meaning and their relation with the available catchment attributes). This aspect would deserve more attention and investigation but it would need a separate ad-hoc analysis, since the comparison of the structures and of the physical meaning of the parameters of the two models is not the specific objective of our work.

C) Third, the studied 209 catchments vary across a large range of area from 13 to 6000 km². But, the models didn't use distributed parameter values. That is, the spatial variability of parameters in large basins wasn't considered. The author should also add discussions on the performance of the regionalization approaches in catchments with distinct basin areas (small, moderate and large basin).

Reply: This is indeed a very interesting question, that we had not explicitly analysed yet. In general, evidence from the literature tends to show that regionalisation performance as well as "at site" performances (see, e.g. Merz et al., 2009; 2011; and Nester et al., 2011) improve for increasing catchment size. For instance, in the review of Parajka et al. (2013) the authors gather and compare the outcomes of different studies predicting runoff hydrographs through rainfall runoff model regionalisation, finding a clear pattern of an increase of model accuracy with catchment scale. As they say, this is generally due to two reasons. The first is a trend for an increasing number of raingauges within a catchment as the catchment size increases, which increase accuracy of rainfall input to models. The second may be related to the aggregation effect of runoff: as the catchment size increases, some of the hydrological variability is averaged out due to an interplay of space–time scale processes, which will improve hydrological simulation.

We have checked, as suggested by the referee, if the performance of the regionalisation methods is influenced by basin size: as suggested, we have divided the study sample in three equally numerous groups:

- Small (area <= 99 km², 70 catchments)
- Medium (99 km² < area <=285 km², 69 catchments)
- Large (area > 285 km², 70 catchments)

and we have checked for any change in regionalisation performance. Similarly to Figure 7 in the manuscript, Figure R.2.1 below shows KGE regionalisation performances for the three groups and the two models.

It may be seen that there are no strong differences between the three groups but, as expected, worse regionalisation accuracies occur in general for smaller catchments.

More interestingly, the ranking of the performances obtained by the different methods does not significantly change for different catchment size.

In the revised manuscript (lines 452-456) we have addressed the issue and specified that despite the different extension of the catchments in the dataset, even if worse performances tend to occur in general for smaller catchments, consistently with previous evidence from the literature (see, e.g. Parajka et al 2013), the efficiencies of the regionalisation methods (and their ranking) do not show a clear relation with the size of the watershed. And we have also specified (line 110) that in our study region catchment size ranges mainly between 13 and 1000 km² (90% of the basins) and just 3 watersheds extend over more than 3000 km² (we thank the referee for having highlighted the usefulness of such clarifications). We do not think that adding a new, large figure in the revised manuscript is needed (as highlighted by the referee we have already too many figures), but of this may be done if needed.
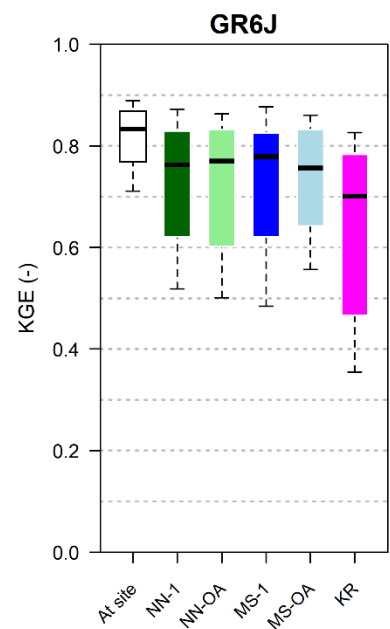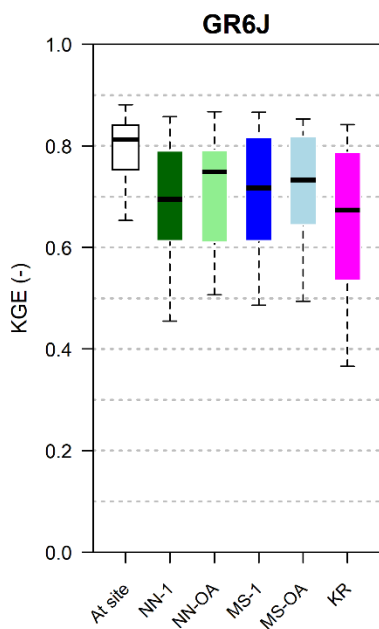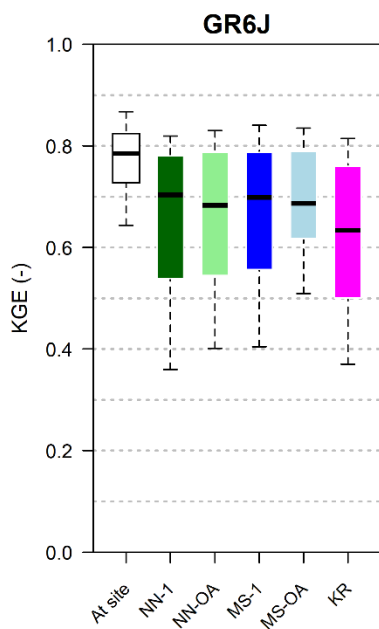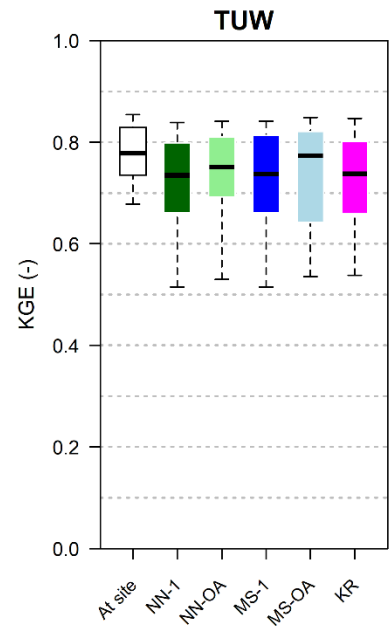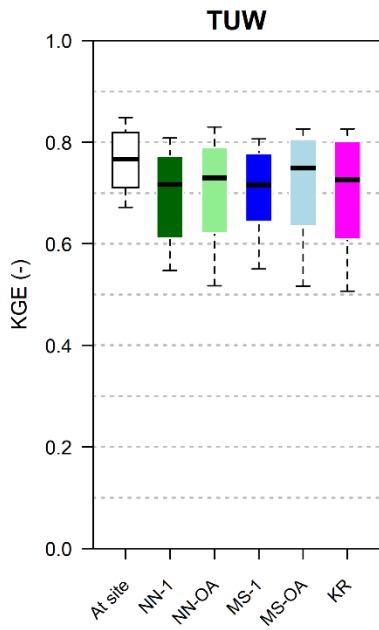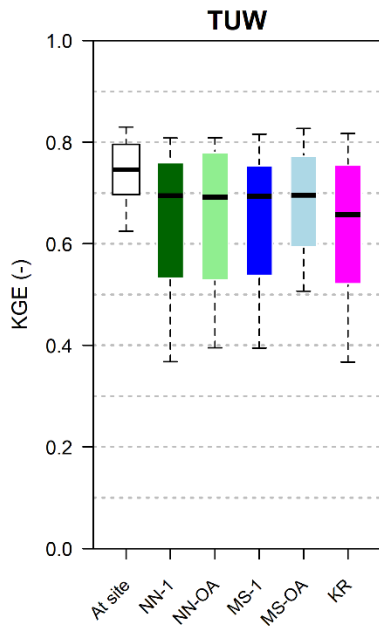
Figure R2.1.

D) Finally, the authors should also specify how they sampled catchment subsets from the total 209 catchments when investigating the effects of station density. Did they sample manually or using automatic scripts? The thing here is how to guarantee that the sampled catchments are evenly distributed across the country. The sampled catchments concentrating in a small region could result in a same station density with the evenly distributed catchments.

Reply: Thank you for expressing your concern about this issue: we agree that it deserves additional clarification and further analysis.

We performed a simple automatic non-supervised sampling (now specified at line 353).

The chance that a cluster of catchments results to be sampled in a small region can not be excluded, even if it is unlikely. For this reason, the samplings are repeated 100 times for each value of station density, thus considering several groups of basins with the same density in the study region.

For addressing the point suggested by the referee, we have verified the distribution of our samples across the country, and we have added such new analysis to the revised version at lines 561-581.

In order to verify if the catchment samples are sufficiently evenly distributed across the country, let's consider a group of catchments and let's measure the distance of each catchment from its closest potential donor as shown the following figure:
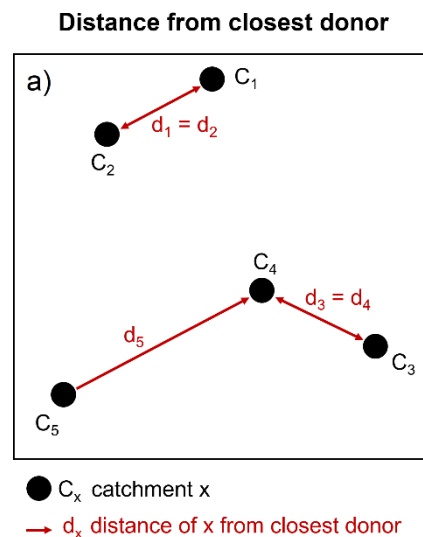

Figure R2.2. Example of distance from closest donor.

The average of the distances (d_1, d_2, d_3, d_4, d_5) of each catchment from the closest catchment (i.e. a potential donor) in a sample can be considered as a measure of the sample spatial distribution: the higher the distance the less dense the sample. As above said, for each density, 100 different samples are generated, so that for each density, we have 100 different values for such averages.

The figure below shows the average "distance within sample" of the closest available donor catchment across the 100 generated sub-sets for the different values of station density (each boxplot refers to the 100 values of average distance calculated for each sub-set). The average distance from the closest donor in the original, full density dataset (grey point in the figure) is around 8.5 km. As expected, the median target/donor distance (middle black solid line in each box) increases with decreasing density: it is true that also the variability of the distance, as shown by box size and whiskers, gradually increases with the reduction of station density, but such increase is overall modest: even for the lowest density, it is limited to +/- 18% of the median for the 80% of the samples. The fact that, on average, the distance between a target catchment and the closest gauged catchment consistently increases for decreasing density proves that the samples with lower density do not tend to cluster/concentrate the catchments in a small region, but there is an even distribution over the country.

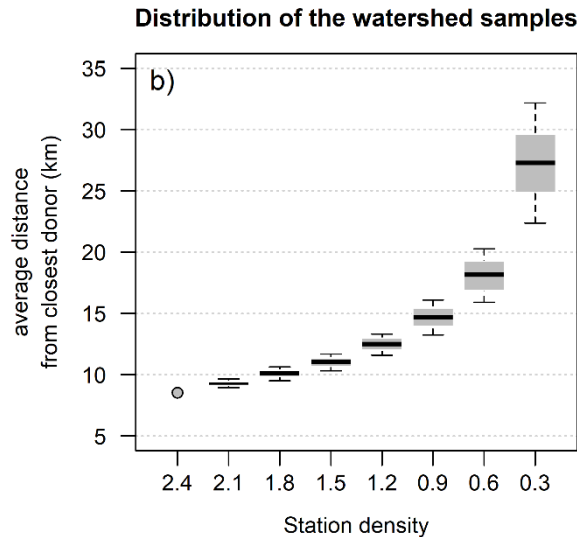**Distribution of the watershed samples**

Figure R.2.3. Boxplots of the average distance within sample from the closest available potential donor catchment across the 100 generated sub-sets, for different values of station density (gauges/1000km^2). Whiskers extend to 10th and 90th percentiles. The grey point indicates the average distance from the closest donor in the original dataset."

We are extremely grateful to the Referee for having suggested this interesting analysis, that we have added in the manuscript (section 4.4), since it is indeed a very important point.

Specific Comments:
1. Please, keep "HBV" and "TUW" consistent. Otherwise, the readers would find three hydrological models in this study. Actually, there are only two models.
Reply: Thank you for the correction. We have changed "HBV" to "TUW" when referring to the model used in this study.

2. Lines 8-10, consider to move to introduction section.
Reply: We think that it may be useful for introducing the topic to readers that may not be acquainted with the regionalisation of rainfall-runoff models, and we would prefer keeping this sentence in the abstract.

3. Lines 21-22, may consider to remove.
Reply: We agree, it has been removed in the revised abstract.

4. Lines 33-34, you already specified "how" above. Consider to remove.
Reply: We agree and have modified the abstract avoiding the repletion.

5. Line 67, "the best the best".
Reply: We corrected this typo.

6. Line 96, what do you mean by "continuous simulating daily models"?
Reply: We mean they are not event-based models. We have changed it to "continuous-simulation daily rainfall-runoff models" as used more frequently in hydrology (e.g., by Crooks and Naden 2007).

7. Line 116, "the more".
Reply: We have changed "to the more than" to "to more than".

8. Line 259, how to calculate "stream network density", please specify this

Reply: This attribute was computed in previous studies over the same data set (Section 2, l. 133-135), but we tried to explain it better in the revised manuscript (lines 130-131).

9. Lines 305-322, consider to move that to introduction. Here, you could add description on your method to choose the number of donor catchments.
Reply: We would prefer to keep this section here since it is specific for the choice of the number of donors, which is not the main issue of the manuscript. We are afraid it could divert the readers' attention from the main research focus if moved to introduction.

10. Line 289, by running.
Reply: We corrected it, thank you.

11. Lines 366-373, move to methodology section.
Reply: We agree: we moved it to a new methodology sub-section (lines 363-379).

12. Line 392, "as anticipated" → "as introduced".
Reply: We corrected it, thank you.

13. Line 402, "so relevant" → "so obvious".
Reply: We have rephrased the sentence.

14. Lines 425-426, 460-471, move to methodology.
Reply: The first lines have been moved to the new methodology section (along with old lines 366-373). We have also moved Figure 7 to section 3.3, but for what concerns lines 460-471, we consider the resulting sets of the nested catchments and the definition of the percentage threshold as part of the results, since they depend on the case study. Thus, we would prefer to keep them in section 4.3.1.

15. Line 507, KGE and NSE.
Reply: We have corrected it, thank you.

16. Lines 528-533, consider to rephrase that. Hard to follow.
Reply: We have simplified and divided the sentences, thank you.

17. Lines 538-540, could you add some discussions on that?
Reply: We believe it is related to the different structure and number/sensitivity of model parameters. As said above, it is of course a matter of strong interest and it would deserve more attention but we prefer to not include further discussion here since it is not the focus of the study. However, we will address again the issue in this section as well.

18. Lines 570-577, consider to move to methodology.
Reply: As prompted also by comment D, we agree that we need to better clarify the sampling procedure already in the methodology section and we have moved the description in Section 3.4.

19. Lines 685-687, please rephrase that, cannot follow.
Reply: The sentence has been removed to simplify the paragraph.

20. Please, consider to reduce the number of figures. Try to aggregate Figures 1 and 2. One of the options is try to present the performance of the two hydrological models in one figure instead of showing separately, such as figures 10-11, 12-13, 14-15. Or you may consider to provide the figures in a supplementary file.
Reply: As suggested, we have put together figures 1 and 2, as well as figures 10-11, 12-13 and 14-15. We would prefer to keep them in the main text, since they are needed to interpret the discussion and conclusions.

References used in this response to the reviewer

Chiew, F. H. S.: Lumped Conceptual Rainfall-Runoff Models and Simple Water Balance Methods: Overview and Applications in Ungauged and Data Limited Regions, Geogr. Compass, 4/3, 206–225, doi:10.1111/j.1749-8198.2009.00318.x, 2010.

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Parajka, J., Viglione, A., Rogger, M., Salinas, J. L., Sivapalan, M., and Blöschl, G.: Comparative assessment of predictions in ungauged basins – Part 1: Runoff-hydrograph studies, Hydrol. Earth Syst. Sci., 17, 1783–1795, https://doi.org/10.5194/hess-17-1783-2013, 2013.

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Importance of the informative content in the study area when regionalising rainfall-runoff model parameters: the role of nested catchments and gauging station density

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Abstract.

The setup of a rainfall-runoff model in a river section where no streamflow measurements are available for its calibration is one of the key research activity for the Prediction in Ungauged Basins (PUB): in order to do so it is possible to estimate the model parameters based on the hydrometric information available in the region. The informative content of the data set (i.e. which and how many gauged river stations are available) plays an essential role in the assessment of the best regionalisation method: this study analyses how the performances of model regionalisation approaches are influenced by the "information richness" of the available regional data set, that is by the availability of potential donors, and in particular by the gauging density and by the presence of nested donor catchments, that are expected to be hydrologically very similar to the target section.

The research is carried out over a densely gauged dataset covering the Austrian country, applying two rainfall-runoff models and different regionalisation approaches.

The regionalisation techniques are first implemented using all the gauged basins in the dataset as potential donors, and then re-applied decreasing the informative content of the data set. The first analysis consists in excluding the basins that are nested with the target one and the status of "nestedness" is identified taking into account either the position of the closing section along the river or the percentage of shared drainage area. Secondly, the impact of reducing station density on regionalisation performance is analysed.

The results show that the predictive accuracy of parameter regionalisation techniques strongly depends on the informative content of the dataset of available donor catchments. The "output-averaging" approaches, exploiting the information of more than one donor basin but preserving the correlation structure of the parameter set, and using, as similarity measure, a set of catchment descriptors, rather than the geographical distance, seem to be preferable for regionalisation purposes in both data-poor and data-rich regions.

1 Introduction

In the hydrological practice, it is often needed to gain information on ungauged river sections and one of the most informative way to do so is implementing a rainfall-runoff model, when, as it is often the case, the meteorological input variables are retrievable in reference to its drainage area. Since in such cases the model parameters may not be obtained through a calibration procedure, it is necessary to regionalise them, exploiting the information of the hydrometric measurements collected in hydrologically similar catchments in the study area.

1

35 Regionalisation approaches for model parameterisation can be classified into two wide categories (He et al., 2011),
36 "regression-based" and "distance-based" methods:

37 1) Regression-based methods, which try to define relationships between each model parameter and geomorpho-climatic
38   catchment attributes (see e.g., Seibert 1999) and apply these relationships to estimate model parameters at ungauged
39   sites.
40 2) Distance-based methods, which, instead, identify a set of similar donor watersheds and transfer their calibrated
41   parameters to the ungauged ("target") catchment. This type of approaches includes:

42   2-i) "output-averaging" methods which transfer the entire set of model parameters from donor catchments, thus
43   maintaining correlation among parameters (which run the model multiple times and average the simulations),

44   2-ii) "parameter-averaging" methods which derive each target parameter independently, as a function (generally a
45   weighted average) of the calibrated donors' ones. To this class (distance-based group of the parameter-averaging
46   type) belong also the kriging methods, where the parameters are regionalised based on their spatial correlation and
47   independently from each other (Merz and Blöschl, 2004; Parajka et al., 2005).

48 In the last two decades, hydrologic scientists from all around the word have focused on the determination of the more
49 accurate regionalisation techniques for different case studies and rainfall-runoff models (see e.g., the reviews of Merz et
50 al. 2006, He et al. 2011, Peel & Blöschl 2011, Parajka et al. 2013, Hrachowitz et al. 2013, Razavi and Coulibaly 2013).
51 Synthesis of existing studies presented in Parajka et al. (2013) has shown that different groups of regionalisation
52 approaches have similar efficiency, but the performance is related to data availability, i.e. to the number of catchments
53 used for analysis.
54
55 A very important aspect for choosing the most adequate regionalisation technique, and that is worthy of further analyses,
56 is the informative content of the study region, that is which and how many gauged stations are available for inferring the
57 hydrological behaviour at the target, ungauged section. In particular, in very densely gauged areas, spatial proximity is
58 expected to be a good similarity measure, as demonstrated by the studies by Merz and Blöschl (2004) and Parajka et al.
59 (2005), who tested different regionalisation approaches on a dense dataset of more than 300 watersheds across Austria,
60 and by Oudin et al. (2008), on a set of 913 French catchments without snow impact, finding that the techniques based on
61 spatial proximity alone provided excellent performances. But different outcomes may result when the gauged stations are
62 less dense and less interconnected (that is with less availability of stations along the same river), as shown for instance,
63 by Samuel et al. (2011): they regionalised the parameters of HBV model for a much more sparsely gauged dataset (135
64 watersheds on the wide area of Ontario, in Canada) and found that the best approach for such study area was an inverse-
65 distance parameter-averaging for a pre-selected set of physically similar catchments.
66
67 The availability in the data set of gauged river stations representative of hydrological conditions similar to the ungauged
68 ones plays an essential role in the assessment of the best regionalisation method. This availability can be, in some way,
69 estimated with the station density (i.e. number of stations per km^2) and with the topological relationship between
70 catchments. In particular, the presence of several nested catchments (i.e. gauged river sections on the same river) in the
71 study region can strongly influence the performance of certain techniques: if for an ungauged basin model parameter sets
72 are available for down/upstream gauged river sections, donor and target watersheds share indeed part of their drainage
73 area, and thus they may be also hydrologically very similar. This may actually lead to very good regionalisation

Commentato [MN4]: Modified based on comment 3 of Reviewer 1

Commentato [MN5]: Added based on comment 1 of Reviewer 1

performances for a given approach, but such accuracy may not represent what would be obtained in different conditions. Therefore, regionalisation performances obtained for datasets with high degree of "nestedness" may be not transferrable to study regions poor of nested basins.

So far, very few studies have been presented in the literature regarding the impact of the presence of nested catchments on the performances of parameter regionalisation techniques. Merz and Blöschl (2004), Parajka et al. (2005) and Oudin et al. (2008) tested the effect of the removal of nested catchments from the available donor catchments, but only for one or two regionalisation techniques, without analysing in detail the differences between different types of approaches. Additionally, the contribute of the immediate downstream and/or upstream gauged stations has never been compared to that of the remaining nested catchments, that may share significant portions of drainage area with the ungauged one.

Also the influence of the density of the gauging stations on the parameterisation of rainfall-runoff models has been little explored, with two notable exceptions: Oudin et al. (2008) applied the spatial proximity and physical similarity output-averaging techniques for decreasing values of station density in France and Lebecherel et al. (2016) tested the robustness of the spatial proximity output-averaging approach to an increasing sparse hydrometric network on the same study region. In Austria, the effect of station density has been investigated by Parajka et al. (2015), but in reference to the interpolation of streamflow time-series and not to the parameterisation of rainfall-runoff models.

The purpose of the present paper is to analyse the role of the informative content of the available regional data set, that is which and how many gauged catchments are available to be used as donors for the regionalisation in a target, ungauged section. This will be done comparing first the impact of the presence of nested donors and then the effect of the reduction of station density on the performances of different parameter regionalisation techniques for a dataset of 209 catchments across Austria.

The tested regionalisation approaches include a set of consolidated techniques, applied to two different continuous-simulation daily rainfall-runoff models, for generalisation purposes: the first is the TUW model (semi-distributed version of HBV, used by Parajka et al. 2005), and the second model, never used so far for regionalisation in the Austrian region, is the GR6J model implemented with the Cemaneige snow routine (Coron et al., 2017b).

We believe that the present analysis may provide further insights for assessing the performances and selecting the parameter regionalisation approaches most suitable to a specific study region, keeping into account the impact of data availability, and in particular of gauging density and of the presence of nested catchments.

The paper is organised as follows: Section 2 introduces the case study and data. Section 3 first describes the rainfall-runoff models and the tested regionalisation schemes, then the methodology for assessing the impact of nested catchments and of station density is presented, while the results are presented in Section 4. Finally, Section 5 reports the discussion and the conclusions.

2 Study region and data

The case study is composed by 209 catchments (see Figure 1, panel a) covering a large portion of Austria. Their size varies considerably, mainly under 1000 km^2 (90% of the basins) and just 3 watersheds extend over more than 3000 km^2. The topography of the country varies significantly from the flat and hilly area in the north-east to the Alps in the centre and in the south-west, particularly steep in the extreme west. The annual precipitation ranges from about 600 mm in the

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Commentato [MN6]: This paragraph was extended based on comment 1 of Reviewer 1

Commentato [MN7]: Modified based on specific comment 6 of Reviewer 2

Commentato [MN8]: Modified based on comment C of Reviewer 2

east, where the evaporation plays an important role in the water balance, to more than 2000 mm in the west, mainly due to orographic lifting of north-westerly airflows at the rim of the Alps (Viglione et al., 2013). Land use is mainly agricultural in the lowlands and forest in the medium elevation ranges. Alpine vegetation and rocks prevail in the highest catchment (Parajka et al., 2005). The aridity index assumes values from 0.2 to 1, meaning that the watersheds are mainly wet or weakly arid (annual evapotranspiration is never higher than precipitation).

Data have been provided by the Institute of Hydraulic Engineering and Water Resources Management (Vienna University of Technology), which previously screened the runoff data for errors and removed all stations with significant anthropogenic effects. Hydro-meteorological data include daily streamflow and daily inputs to the rainfall-runoff models for the 33 years period 1976-2008: daily average precipitation, temperature and potential evapotranspiration defined for 200 meters elevation zones for all the study catchments. The potential evapotranspiration is estimated by a modified Blaney-Criddle method (Parajka et al., 2005) using interpolated daily air temperature and grid maps of potential sunshine duration (Mészároš et al., 2002).

In order to implement some of the parameter regionalisation approaches, we make use of several geo-morphoclimatic catchment attributes, reported and briefly described in Table 1. Topographic attributes such as mean catchment elevation and mean slope are derived from 1 x 1 km digital elevation model while climatic features such as mean annual precipitation, and aridity index are derived from climatic input time series. Figure 1 (panels b, c and d) shows the spatial pattern of mean annual precipitation, snow depth and aridity index across the study area. Mean annual solar irradiance is computed trough GRASS GIS software (http://grass.osgeo.org). Stream network density was calculated from the digital river network map at the 1:50000 scale for each catchment (Merz and Blöschl, 2004). FARL (flood attenuation by reservoir and lakes), boundaries of porous aquifers, areal portions of regional soil types and main geological formation were the same used and described in detail in Parajka et al. (2005). Finally, Land use coverage is derived from CORINE Land Cover maps updated to year 2012 (https://land.copernicus.eu/pan-european/corine-land-cover/clc-2012). For land cover classes, as well as for geology and soil type classes, the catchments are associated to more than one single attribute: each basin is described by the portions of the total catchment area corresponding to each class (and for this reason, Table 1 does not report the min/median/max values of such descriptors).

Commentato [MN9]: Added based on specific comment 8 of Reviewer 2

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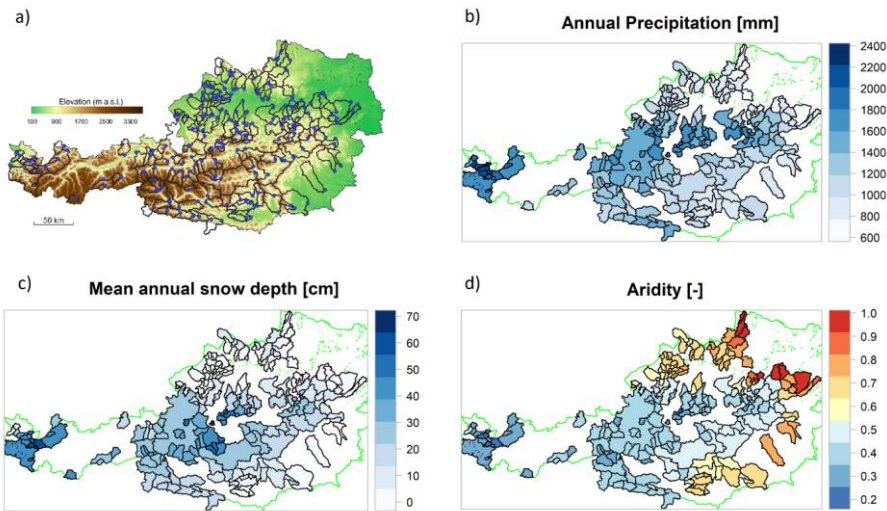
Figure 1. Panel a) Study area, blue points refer to stream gauges and black lines to catchment boundaries. Panels b), c) and d) Spatial pattern of some climatic catchment attributes across the study area.

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Table 1. Available catchment attributes.

Code	Unit	Min	Median	Max	Description
Elev	m a.s.l.	287	915	2964	Mean elevation
Area	km^2	14	168	6214	Drainage area
Slope	m/m	0.9	12.4	28.5	Mean slope
meanP	mm	675	1230	2310	Mean annual total precipitation
maxP	mm	35	49	84	Mean annual maximum daily precipitation
meanPET	mm	281	608	715	Mean annual total evapotranspiration
SnowF	-	0.06	0.17	0.60	Fraction of precipitation fallen as snow (i.e. precipitation fallen in days below 0°)
SnowD	mm	1	14	68	Mean annual snow depth
Aridity	-	0.21	0.46	0.96	Aridity index (meanPET/meanP)
Irrad	kWh/(m²*day)	1750	1899	2274	Mean annual solar irradiance
RiverD	m/km^{-2}	0	830	1256	Stream network density
FARL	-	0.56	1	1	Flood attenuation index by reservoir and lakes
Corine	%	-	-	-	Portions of land use coverage
Geology	%	-	-	-	Portions of geological formations
Soils	%	-	-	-	Portions of regional soil types
Forest	-	0	0.47	0.93	Fraction of catchment covered in forest
AcqPort	-	0	0.01	0.83	Fraction of catchment with porous aquifers

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Commentato [MN10]: Old Figures 1 and 2 were merged

3 Materials and methods

3.1 Rainfall-runoff models structure and calibration

Two models for simulating daily streamflow were applied in this study. This choice is made in order to analyse the effect of nested catchments and station density on the performance of parameter regionalisation methods for different model structures.

3.1.1 TUW model

The first is the TUW model, a semi-distributed version of the HBV model (Bergström 1976, Lindström et al., 1997) developed by Parajka and Viglione (2019). It consists in a snow module, a soil moisture module and a flow response and routing module. The model processes the elevation zones as autonomous entities that contribute separately to the total outlet flow. The inputs are daily air temperature, precipitation and potential evapotranspiration over the different elevation zones, on which the model is run in the version schematised in Figure 2. Finally, the different outputs from the elevation zones are averaged taking into account the sub-catchment areas.

The snow routine is based on a simple degree-day concept and it is ruled by five parameters: two threshold temperature parameters distinguishing rain and snow, Tr and Ts, a melting temperature Tm, a snow correction factor SCF and the degree-day factor DDF. The soil moisture routine represents soil moisture state changes and runoff generation and involves three parameters: the maximum soil moisture storage FC, a parameter representing the soil moisture state above which evapotranspiration is at its potential rate, LP, and a parameter β ruling the non-linear function of runoff generation. Finally, an upper and a lower soil reservoirs and a triangular transfer function compose the runoff response and routing routine, involving seven additional parameters. The sum of excess rainfall and snowmelt enters the upper zone reservoir and leaves this reservoir through three paths: i) outflow from the reservoir based on a fast storage coefficient k_1; ii) percolation to the lower zone with a constant percolation rate C_{PERC}, iii) if a threshold of the upper storage state L_{UZ} is exceeded, through an additional outlet based on a very fast storage coefficient k_0. Water leaves the lower zone based on a slow storage coefficient k_2. The outflows from both reservoirs are then routed by a triangular transfer function representing runoff routing in the streams, where the base of transfer function, B_Q, is estimated with the scaling of the outflow by the C_{ROUTE} and B_{MAX} parameters. More details about the model structure and application in R can be found in Parajka et al. (2007) and Ceola et al (2015), respectively.

The model is run for all the study catchments with the semi-distributed model structure obtained dividing them into 200-meters elevation zones: model daily inputs (precipitation, temperature and potential evapotranspiration) and model states are defined over such zones, while model parameters are assumed to be the same for the entire catchment.

Following the work by Parajka et al. (2005) on the same study area, 4 out of the 15 total parameters are pre-set and 11 are calibrated: threshold temperatures Tr and Ts are fixed respectively to 2 and 0 °C, Tm to 0 °C and the maximum base of the transfer function at low flows B_{MAX} to 10 days. Table 2 briefly reports and describes the calibrated parameters, defining also their lower and upper bounds.

Commentato [MN11]: Changed based on comment 5 of Reviewer 1

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183   **Table 2. TUW model parameters and their ranges.**

Parameter	Units	Range	Description
SCF	-	0.9 - 1.5	Snow correction factor
DDF	mm/(°C*day)	0 - 5	Degree day factor
LP	-	0 - 1	Parameter related to the limit of evaporation
FC	mm	0 - 600	Field capacity, i.e., max soil moisture storage
β	-	0 - 20	Non linear parameter for runoff production
k_0	days	0 - 2	Storage coefficient for very fast response
k_1	days	2 - 30	Storage coefficient for fast response
k_2	days	30 - 250	Storage coefficient for slow response
L_{UZ}	mm	0 - 100	Threshold storage state, very fast response starts if exceeded
C_{PERC}	mm/day	0 - 8	Constant percolation rate
C_{ROUTE}	days^2/mm	0 - 50	Scaling parameter

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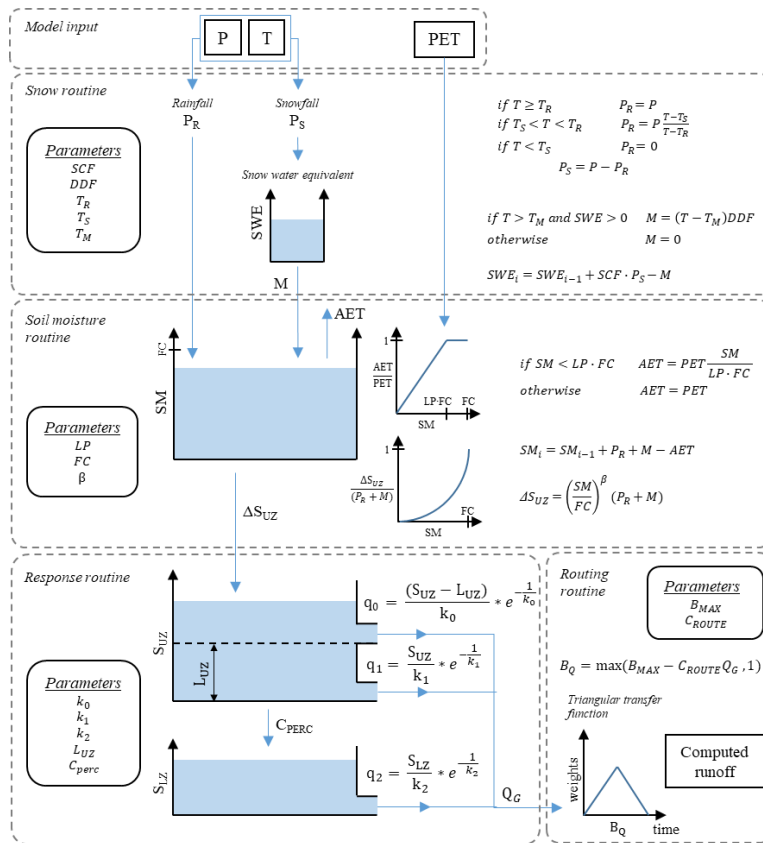
186   **Figure 2. TUW model scheme – Lumped version.**

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3.1.2 CemaNeige-GR6J model

The second model is the French CemaNeige-GR6J (Coron et al., 2017b). It is the combination of the CemaNeige snow accounting routine (Valéry et al., 2014) with the GR6J model (Pushpalatha et al., 2011), a daily lumped continuous rainfall-runoff model, developed at INRAE (Antony, France), by the Équipe Hydrologie des Bassins versants. The software is freely available in the *airGR* R-package (Coron et al., 2017a).

The inputs of the model are spatially-averaged catchment daily air temperature, precipitation and potential evapotranspiration. Catchment hypsometric curve is also required.

The CemaNeige snow accounting routine is based on a degree-day concept, where the thermal inertia of the snowpack is also taken into account. It involves two parameters, a snowmelt factor, θ_{G1}, and a cold-content factor, θ_{G2}. Although the module requires daily lumped inputs, for better simulating snow accumulation and melting it allows to divide the catchment into more elevation zones of equal area, through the use of the hypsometric curve. Inputs for each elevation zone are extracted through interpolation of the mean catchment values using precipitation and temperature gradients (Valéry et al, 2010), and not from "clipping" of the actual spatial fields like for the TUW elevation zones. The module functions are applied with a lumped set of calibrated parameters; but internal states are allowed to vary over each elevation layer according to the different extrapolated inputs. On each elevation layer, two outputs are computed: rain and snowmelt, which are summed in order to find the total water quantity feeding the hydrological model. At every time step, the total liquid output of CemaNeige at catchment scale is the average of every elevation zone outputs. Here we decide to maintain, as default, the number of elevation layers equal to five. For a detailed description of CemaNeige routines, the readers may refer to Valéry et al. (2014).
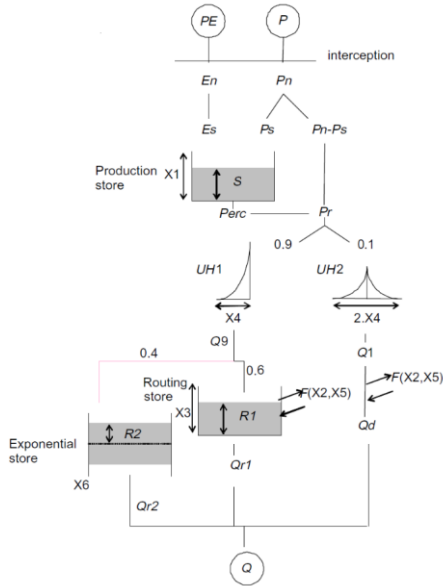
The total liquid output of CemaNeige module and potential evapotranspiration are the inputs of the GR6J rainfall-runoff model. In the model, the water balance is controlled by a soil moisture accounting reservoir and a conceptual groundwater exchange function, while the routing part of the structure consists in two flow components routed by two unit hydrographs, a non-linear store and an exponential-store, with a total of six parameters. The structure of the model is represented in Figure 3 and a detailed description of the model routines is given in Pushpalatha et al. (2011).

The CemaNeige-GR6J model is fed with mean catchment daily precipitation, air temperature and potential evapotranspiration. All the 8 parameters of the combined model (2 for CemaNeige, 6 for GR6J) are calibrated. Lower and upper bounds of the parameters space are kept as default: all the parameters are allowed to vary between the normalised interval [-9.99 9.99] and then specific parameter transformations are applied before the model is run. Table 3 reports brief parameters description and transformed boundaries. For the sake of simplicity, we will refer to this model just with the acronym GR6J, even if it will always include the CemaNeige snow module.

Table 3. Cemaneige-GR6J model parameters and their transformed real ranges.

Parameter	Units	Range	Description
θ_{G1}	mm/(°C*day)	0 - 109	Snowmelt (degree-day) factor
θ_{G2}	-	0 - 1	Cold content factor
X1	mm	0 - 21807	Non-linear production storage capacity
X2	mm/day	-1903 - 1903	Groundwater exchange coefficient
X3	mm	0 - 21807	Non-linear routing store capacity
X4	days	0 - 22	Time parameter for unit hydrographs routing
X5	-	0 - 1	Threshold parameter for water exchange with groundwater
X6	mm	0 - 21807	Exponential routing store capacity

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Commentato [ET12]: Amended as suggested by the Guillaume Thirel (INRAE group) who read the HESSD paper

Figure 3. GR6J model scheme.

3.1.3 Model calibration

The sets of parameters for both rainfall-runoff models are estimated for all the study catchments with an automatic model calibration procedure, using the Dynamically Dimensioned Search (DDS algorithm, Tolson et al. 2007).

The objective function to be maximised is the Kling-Gupta Efficiency (Gupta et al., 2009) between observed and simulated streamflow, defined as:

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \qquad Eq.\ 1$$

where r is the Pearson product moment correlation coefficient, α is ratio between the standard deviations of the simulated and observed values and β is ratio between the means of the simulated and observed values.

The 33 years of observation (1976-2008) are split into two sub-periods: the first one, from 1 November 1976 to 31 October 1992, is used for model calibration, and the second one, from 1 November 1991 to 31 October 2008, for model validation. Warm-up periods of one year are used in all cases. Calibration and validation performances for both models are reported in Section 4.1.

3.2 Regionalisation approaches

In order to assess the impact of the presence of nested catchments and station density on the performance of the parameter regionalisation methods, a set of consolidated approaches for the study area are implemented. Three types of techniques are tested, all belonging to the distance-based group, since recent studies have demonstrated how they are generally to be

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preferred to regression-based techniques (see e.g. Kokkonen et al. 2003, Merz and Blöschl 2004, Oudin et al. 2008, Reichl et al. 2009, Bao et al. 2012, Steinschneider et al. 2015, Yang et al. 2018, Cislaghi et al. 2019).

3.2.1 Ordinary Kriging (KR)

The first is a parameter-averaging technique, based on an Ordinary Kriging approach (termed in the following KR), where each model parameter is regionalised independently from each other, based on their spatial correlation. Catchment position is defined by the coordinates of the catchment centroid and the Ordinary Kriging is based on an exponential variogram with a nugget of 10% of the observed variance, a sill equal to the variance, and a range of 60 km both for TUW and Cemaneige-GR6J model parameters.

3.2.2 Nearest Neighbour (1 donor, NN-1)

The second approach is a Nearest Neighbour method (NN-1), where the complete set of model parameters is transposed from the geographically nearest donor catchment.

3.2.3 Most Similar (1 donor, MS-1)

In the third technique, termed "Most Similar" approach (MS-1), a single donor catchment is again identified, for transposing the entire parameter set but, instead of choosing the catchment that is geographically the closest, the "hydrologically most similar" donor is identified, based on a set of geo-morphological and climatic descriptors. Five descriptors are used for assessing such similarity: mean catchment elevation, long-term mean annual precipitation, stream network density, land cover classes, geology classes. Such set of descriptors was selected by preliminary tests: since it is not the focus of the work, the analysis for the assessment of the best catchment descriptors is reported in Appendix A. The donor catchment is identified as the catchment with the smallest dissimilarity index ϕ (e.g. Burn and Boorman, 1993):

$$\phi = \sum_{j=1}^{5} \frac{d_j(D,U)}{\max(d_j)} \qquad \text{Eq. 2}$$

which represents the sum of the differences d_j of the 5 descriptors of the donor catchment D and of the ungauged catchment U of interest, normalised by their maximum. For the attributes described by a single value (mean catchment elevation, long-term mean annual precipitation and stream network density), d_j is expressed by the absolute difference between the descriptors X_j^D and X_j^U of the donor and target catchments respectively (Eq. 3). For land cover and geology, whose attributes X_j are the vectors containing the portions of the total catchment area $X_{j,c}$ corresponding to each class c, the difference d_j is calculated as the Euclidean distance between such vectors (Eq. 4).

$$d_j(D,U) = \left| X_j^D - X_j^U \right| \qquad \text{Eq. 3}$$

$$d_j(D,U) = \sqrt{\sum_c (X_{j,c}^D - X_{j,c}^U)^2} \qquad \text{Eq. 4}$$

10

3.2.4 Output-averaging version of NN and MS techniques (NN-OA and MS-OA)

Nearest Neighbour (NN) and Most Similar (MS) approaches allow to maintain correlation among model parameters, and overcomes the well-known limitation of the regression approach due to interaction between them. In the regression-based methods in fact, as well as in the parameter-averaging approaches (e.g, KR technique), parameters are regionalised independently from each other, possibly affecting simulation performances. On the other hand, one single donor catchment (as in NN-1 and MS-1 approaches) is often not fully representative of the hydrological behavior of the target watershed. Recent studies have been demonstrating how averaging the outputs of the simulations (rather than model parameters) obtained with different donor parameter sets may be preferred (see e.g., Oudin et al. 2008, Viviroli et al. 2009). For this reason, NN and MS techniques are also tested identifying more than one donor (here termed NN-OA and MS-OA respectively), with an output-averaging approach (introduced by McIntyre et al., 2005): n donor basins (the geographically closest ones for the Nearest Neighbour method, or those with the smallest dissimilarity indexes for the Most Similar method) are identified. The regionalised streamflow for the ungauged catchment is calculated from all the simulations $Q(d, P_i)$, obtained by running the model (fed by the meteorological input of the target catchment) with each one of the n parameter sets (P_i, with i in [1 ; n]) corresponding to each of the donor catchments. Streamflow for day d, $Q(d)$, is computed as the weighted average of the simulated outputs:

$$Q(d) = \sum_{i=1}^{n} w_i \, Q(d, P_i) \qquad\qquad Eq. 5$$

where w_i is the weight associated to each donor catchment i, computed as function of a measure of dissimilarity between the donor and the target catchments. In the NN-OA case, the dissimilarity is defined by the spatial distance D_i between the centroids of donor i and target catchments (Eq. 6), while in the MS-OA method it corresponds to the dissimilarity index ϕ_i (see Eq. 2) and the corresponding weights are computed accordingly to Eqs. 6 and 7, respectively.

$$w_i = \frac{\frac{1}{D_i}}{\sum_{i=1}^{n} \frac{1}{D_i}} \qquad\qquad Eq. 6$$

$$w_i = \frac{\frac{1}{\phi_i}}{\sum_{i=1}^{n} \frac{1}{\phi_i}} \qquad\qquad Eq. 7$$

3.2.5 Choice of the number of donor catchments for NN-OA and MS-OA

The choice of the number of donor catchments for output-averaging represents a central issue in the methodology. Previous studies showed that the optimal number of donors is strongly related to the rainfall-runoff model and, of course, to the case study. McIntyre et al. (2005) were amongst the first to apply an ensemble (output-averaging) approach and to explore the use of different numbers of donors on the performance of the Probability Distribution Model (PDM, Moore, 1985) for a set of more than 100 UK catchments. They tested the impact of an increasing number of donors, either selecting the first n catchments with the smallest dissimilarity measure, or including all the donors with a value of dissimilarity below a defined threshold (in the latter case, the number of donors may thus vary depending on the target-donors attributes). They found that a fixed number of ten donors resulted in the best regionalisation performances. Oudin et al. (2008) applied an output-averaging regionalisation for the TOPMO and GR4J models to a large French dataset of

311   almost 1000 basins, but with no weights in flow averaging, since they used an arithmetic average (thus not taking into

312   account magnitude of donor dissimilarities). They found that the two models performed optimally with a different number

313   of donor catchments (seven and four respectively) and the efficiency of the regionalised model decreased almost linearly

314   when increasing the number of donors above such values. In fact, the higher is the number of donor basins included in

315   the regionalisation process, the more dissimilar will be the donors with respect to the target watershed, possibly leading

316   to a deterioration of the results. The use of weights in flow averaging may indeed help to smooth this effect, giving less

317   and less importance to the donors as their similarity decreases.

318   In the present work, the effect on regionalisation performances due to the number of donor basins is explored in detail,

319   applying NN-OA and MS-OA for increasing number n of donor catchments, as discussed in Section 4.2.

320

321   **3.3 Impact of nested catchments: which catchments should be considered (to be) nested?**

322   As already introduced, the main purpose of the present analysis is to quantify the impact of the presence of several nested

323   catchments on the regionalisation techniques. In particular, since nested catchments may have a strong hydrological

324   similarity with the ungauged one, they are expected to play an essential role in the determination of method performances.

325   Once the performances have been evaluated using all the study catchments as potential donors, the regionalisation

326   procedures are repeated for each target basin (assumed to be ungauged) by excluding, from the donors set, the watersheds

327   which are considered to be nested in relation to the target section.

328   In general, two or more catchments are nested between each other if their closure sections are located on the same river,

329   i.e. they share part of their drainage area. Since it may happen that several gauged stations are located on the same river,

330   we propose to follow two different criteria in order to identify the nested basins:

331   -   *Criterion 1*: the gauged sections that are immediately downstream and upstream of the target section (Figure 4,

332   panel a)).

333   -   *Criterion 2*: all the catchments sharing a given percentage of drainage area with the ungauged one (Figure 4,

334   panel b)).

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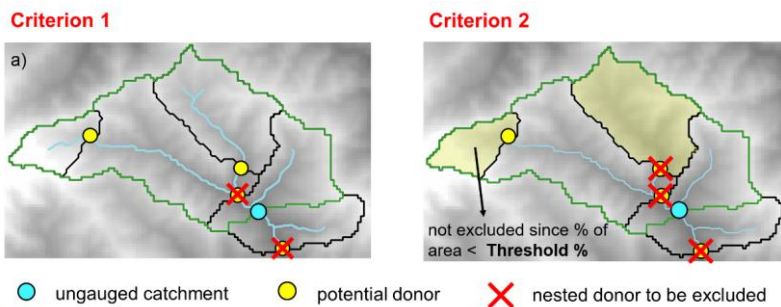
336

337   **Figure 4. Criteria for excluding nested catchments when regionalising model parameters.**

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| 340 | Another way to evaluate the performances of regionalisation methods taking into account the richness in hydrometric
| 341 | information of the study area is to analyse the spatial density of the potential donors.
| 342 | It is expected that the effect of the presence of several nested watersheds in a dataset is related to the effect due to station
| 343 | density. Because of that, further purpose of the study is to analyse the impact of station density on regionalisation
| 344 | accuracy. Parajka et al. (2015) tested the impact of the station density not for rainfall-runoff modelling but for the direct
| 345 | weighted interpolation of daily runoff time-series with the topological-kriging (or Top-kriging) approach (see Skøien et
| 346 | al., 2006), founding that direct interpolation is superior to hydrological model regionalisation if station density exceeds 2
| 347 | stations per 1000 km^2. Here, the same approach for analysing the density is applied to all the parameters regionalisation
| 348 | techniques.
| 349 | The full station density in the dataset is about 2.4 gauges per 1000 km^2, estimated dividing the total number of stations
| 350 | by the area of Austrian territory, which is approximately 84000 km^2. All the applied regionalisation approaches are tested
| 351 | for decreasing station density in the catchments dataset. Seven different values from 0.3 to 2.1 gauges per 1000 km^2 are
| 352 | tested, which correspond to a total number of stations across Austria from 25 to 175. For each value of station density,
| 353 | the corresponding number of gauged stations is randomly sampled (simple automatic non-supervised sampling) from the

| 354 | original set of 209 catchments and the regionalisation approaches are applied on this subsample (catchments input dataset)
| 355 | in leave-one-out cross validation: in turn, each of the catchment in the subsample is considered to be ungauged and the
| 356 | remaining basins are used as potential donors. This operation is repeated 100 times in order to consider different samples
| 357 | of watersheds with the same density across the study area. Figure 5 shows an example of three samples for two different
| 358 | station densities, corresponding to 25 and 100 stations in the input dataset.
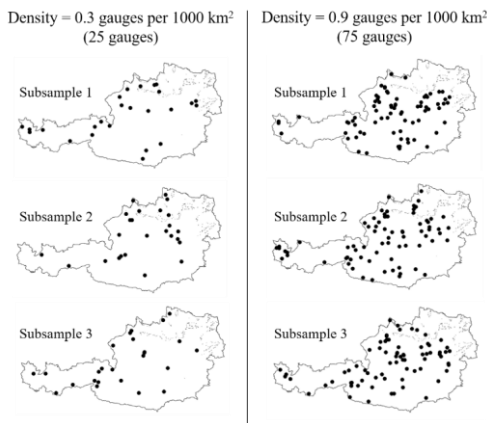
Figure 5. Example of three samples for two different station densities.

| 363 | **3.5 Evaluation of model performances**

| 364 | As anticipated, the rainfall-runoff models are calibrated against Kling-Gupta Efficiency (Eq. 1). In addition to KGE,
| 365 | model performances are evaluated through Nash-Sutcliffe Efficiency (Eq. 8) as well. While KGE considers different types

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of model errors (the error in the mean, the variability and the dynamics of runoff), NSE is a standardised version of the mean square error.

$$NSE = 1 - \frac{\sum(Q_{sim} - Q_{obs})^2}{\sum(Q_{obs} - \overline{Q_{obs}})^2} \qquad \text{Eq. 8}$$

where Q_{sim} is the simulated runoff, Q_{obs} is the observed runoff and $\overline{Q_{obs}}$ is the average observed runoff.

The regionalisation approaches are tested through leave-one-out cross-validation for all the described analyses. The parameter sets of the donor catchments are obtained through a calibration procedure over the years 1977-1992, whereas for assessing the performances of the regionalisation methods, only the results obtained over the validation period (1992-2008) are reported. Spatiotemporal transfer of model parameters is therefore the most exacting task (as confirmed by the study of Patil et al. 2015), since we are using parameters obtained over different catchments (in regionalisation) and over a different observation period. On the other hand, this is exactly what would happen in a real-world forecasting application or for assessing the impact of a climate change scenario, where you have to identify the parametrisation of a model to be used for independent hydro-climatic conditions and in any possible river section in the region.

4 Results and discussion

4.1 Model performances "at-site"

Table 4 shows the model performances obtained calibrating the models "at-site", that is over the streamflow measured in each catchment during the calibration period (1977-1992) and validated over the years 1992-2008 (no regionalisation procedure is involved).

Both rainfall-runoff models behave well for the study area: in calibration, the median Kling-Gupta efficiencies are 0.85 for TUW and 0.88 for GR6J model, while in validation they deteriorate to 0.76 and 0.81 respectively. In the calibration period, KGE is always above 0.66 and 0.76, respectively for TUW and GRJ6, whereas in validation, the KGE is over 0.72 for both models for 75% of the basins (even if it drops below 0.3 for one and two basins, respectively for GR6J and TUW).

Looking at Nash-Sutcliffe efficiency the difference between the two models is even more marked than for the KGE: GR6J model tends to perform better than TUW, despite the lower number of parameters.

Table 4. At-site performances: values of the 25% (1st quar.), 50% (med.) and 75% (3rd quart.) quantiles for Kling-Gupta (KGE) and Nash-Sutcliffe (NSE) efficiencies.

		KGE [-]			NSE [-]		
		1st quart.	med.	3rd quart.	1st quart.	med.	3rd quart.
TUW	Calibration 1977 - 1992	0.82	0.85	0.90	0.65	0.72	0.80
TUW	Validation 1992 - 2008	0.72	0.76	0.82	0.59	0.66	0.72
GR6J	Calibration 1977 - 1992	0.86	0.88	0.91	0.72	0.77	0.81
GR6J	Validation 1992 - 2008	0.75	0.81	0.84	0.67	0.74	0.79

14

4.2 Regionalisation performances using all catchments as potential donors

4.2.1 Choice of the donors for the *output-averaging* regionalisation methods

Before comparing performances of regionalisation methods, it is necessary to choose the optimal settings for the output-averaging versions of Nearest Neighbour (NN-OA) and Most Similar (MS-OA) techniques.

As introduced in the methodology Section 3.2.5, we first investigate the effect of using different numbers of donors: in particular, values between 1 and 50 are tested for both regionalisation techniques.

Regionalisation methods are repeated through leave-one-out cross-validation for each number of donors n and the median Kling-Gupta efficiency obtained for each value of n over all the 209 catchments is computed. Tests are performed for calibration and validation periods, but results are reported only for the validation period.

Figure 6 shows the median Kling-Gupta efficiency when the changing number of donors for TUW (upper panel) and GR6J (lower panel). Looking at the figures, we may see that in all the four cases, the index always deteriorates when more than 10 donors are chosen. On the other hand, there is not a unique optimal number of donors for the two models nor for the two regionalisation techniques. The optimal number of donors identified according to the median of the KGE varies between 3 and 7 depending both on the rainfall-runoff model (TUW or GRJ6) and on the regionalisation approach (NN-OA or MS-OA). Since the KGE differences between 3 and 7 donors are small (around 0.02), we decided to use 3 donors for both regionalisation methods and both models, which is also the most parsimonious option. In addition, the choice of a low number of donors is convenient also in view of the analysis to be done on decreasing density, where a large number of donors would imply the use of catchments that are less and less similar to the target one.

It may be noted that the results by Oudin et al. (2008) highlighted a clearer pattern of model performances when increasing the number of donors, with a stronger decrease in efficiency when using high numbers of donors. This may be explained by the fact that they were using a simple not-weighted average of outputs. Here instead, the influence of the additional donors is gradually poorer, due to the weights implemented in the output-averaging procedure (Eq. 5): when adding further donors to the approaches, the corresponding weights in the average are gradually lower according to the increasing distance (for NN-OA) or dissimilarity index (for MS-OA) from the target. Thus, the impact of the less similar catchments is smoothed, compared to what may be achieved using a not-weighted output average.

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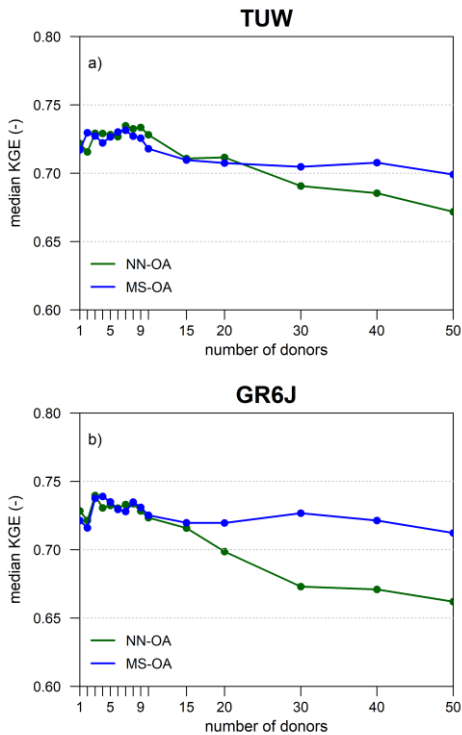
Figure 6. Impact of the number of donors on output-averaging Nearest Neighbour (NN-OA) and Most Similar (MS-OA) regionalisation methods for TUW (panel a)) and GR6J (panel b)) model.

4.2.2 Performances of the regionalisation methods

This section shows the performances of the regionalisation methods without excluding any candidate donor: the above descripted regionalisation methods are tested over all the 209 study catchments through leave-one-out cross validation, for both models. Here all the basins in the dataset are used as potential donors: in turn, each basin is considered to be ungauged and all the remaining (208) catchments are available in the donors set for testing the regionalisation approaches. Figure 7 reports Kling-Gupta and Nash-Sutcliffe efficiency boxplots for the two models when regionalising following each of the techniques.

For TUW (Figure 7, upper panels), all regionalisation methods provided good simulations: with respect to the performances (always on the validation period) obtained when the models have been calibrated on the target section (at-site simulations, white boxes): the loss in efficiency indexes is, overall, limited. The Nash-Sutcliff efficiencies of KR, MS-1 and NN-1 methods are consistent with the findings of Parajka et al. (2005), who computed only the NS: their results are very similar to the present ones, even if they worked on a greater number of Austrian catchments and calibrating the model against a different objective function.

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439   For the GR6J model (Figure 7, lower panels), the efficiencies of the Nearest Neighbour (NN-1 and NN-OA) and Most

440   Similar (MS-1 and MS-OA) regionalisations are closer to those of the TUW in respect to what happened when the models

441   are calibrated at-site. In fact, the GR6J model in regionalisation mode deteriorates more than TUW in respect to the

442   parametrisation obtained considering the target as gauged.

443   In addition, we notice that, for GR6J model, the Ordinary Kriging has performances always poorer than all the other

444   regionalisation methods.

445

446   For both rainfall-runoff models MS-OA tends to provide the best results and in general the two methods based on output

447   average (NN-OA and MS-OA), that exploit the information from more than one donor, outperform NN-1 and MS-1, in

448   particular in terms of Nash-Sutcliffe efficiency. This confirms the usefulness of regionalising on the basis of more than

449   one donor, as indicated by previous studies (e.g. McIntyre et al. 2005, Oudin et al. 2008, Viviroli et al. 2009, Zelelew and

450   Alfredsen 2014).

451

452   In order to verify if there is an influence of the catchments' area on the results, due to the lumped structure of the model,

453   an additional analysis (not shown here for sake of brevity), showed that despite the different drainage area of the

454   catchments in the dataset, regionalisation accuracies do not show a clear relation with the size of the watershed, even if

455   worst performances occur in general for smaller catchments. This is consistent with previous evidence from the literature

456   (see, e.g. Parajka et al 2013).
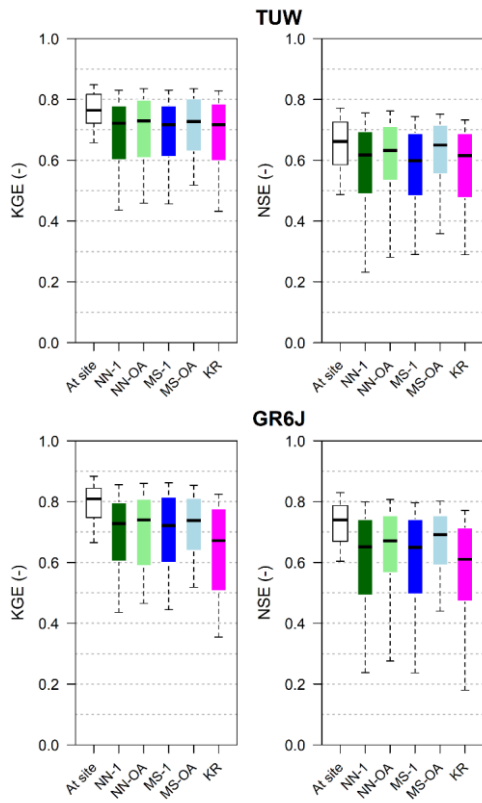
Figure 7. Original performances of the regionalisation methods for TUW model (upper panels) and for GR6J model (lower panels) for the 209 Austrian catchments in the validation period 1992-2008. Boxes extend to 25% and 75% quantiles while whiskers refer to 10% and 90% quantiles.

4.3 Impact of nested donors: performance losses in regionalisation

4.3.1 Catchments identified as nested by the two criteria

As introduced in Section 3.3, two different Criteria are implemented for identifying which donor catchments are considered to be nested in relation to a target catchment: *Criterion 1* (Figure 4, panel a)) assumes that the only nested donors are the first downstream and the first upstream gauged sections. Following this approach, 81% of the catchments in the dataset have at least one downstream or upstream nested donor (red dots in Figure 8, panel a)).

Instead, *Criterion 2* (Figure 4, panel b)) excludes all the potential donors sharing a given percentage of drainage area with the target catchment. It requires the definition of a percentage threshold value of shared drainage area. A preliminary sensitivity analysis (not reported here) was performed, investigating the effect of different values between 5% and 20% for such percentage. Results show that differences in terms of regionalisation performance are not significant and the threshold was fixed to 10%. The choice of the threshold influences the number of catchments which can be included in the study: in fact, the higher is the threshold, the lower is the number of basins classified as nested following *Criterion 2*.

18

474 Using 10% as a threshold allows to include most of the watersheds in the analysis: 65% (137 catchments) of the basins

475 have at least one nested donor catchment sharing at least the 10% of its area (red dots in Figure 8, panel b)).

476 All the watersheds having potential nested donors according to the second criterion have nested gauged catchments also

477 according to the first criterion, but not vice versa: the impact of nested catchments on regionalisation performances is

478 therefore evaluated only for those 137 catchments which are considered to have nested gauged catchments following both

479 criteria.

480 It is important to highlight that the remaining 35% of the basins are still used as potential donor catchments, but the

481 regionalisation approaches are not repeated using such basins as targets (since they have no nested donors, their

482 performance would not change and they would distort the results).

483 Among the 137 catchments considered for the analysis of the nestedness, 43% result to have only downstream nested

484 donor(s), 28% only upstream nested donor(s), and 29% at least one upstream and one downstream nested donors.

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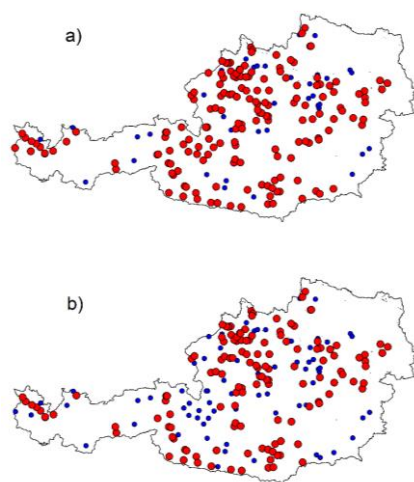
Figure 8. Panel a) Red dots (170) refer to catchments with at least one upstream or downstream nested gauged catchment (Criterion 1). Panel b) Red dots (137) refer to catchments with at least one nested gauged catchment sharing more than 10% of drainage area (Criterion 2).

490

4.3.2 Performance losses in regionalisation when excluding nested donors

492 The regionalisation methods are applied again in leave-one-out cross validation, this time excluding from the available

493 donors the catchments which are nested in relation to the target (ungauged) basin. This is done for both nestedness criteria

494 (down/upstream or overlapping of drainage area) and the analysis applies exclusively to the 137 catchments classified as

495 nested according to both criteria (red dots in Figure 9, panel b)). The figures of this section (Figures 9 and 10) therefore

496 refer to such subset.

497

Figure 9 compares the different performances (Kling-Gupta and Nash-Sutcliffe efficiencies in the upper and lower panels respectively) obtained in regionalisation (always over the validation period), when nested catchments are available or not as candidate donor basins for both TUW model (Figure 9, upper panels) and GR6J (Figure 9, lower panels). Each group of boxplots refers to a different regionalisation method: within such groups, the first box indicates the performance when no basins are excluded from the donor set, while the second and the third boxes report the performances due to the exclusion of the nested donors following Criterion 1 or 2 respectively.

The performance deterioration is highlighted by bar plots in Figure 10, showing the mean loss in Kling-Gupta and Nash-Sutcliffe efficiencies when excluding nested donors following the two criteria.

Finally, Table 5 reports the interquartile variability of Kling-Gupta and Nash-Sutcliffe efficiencies for both models and all the regionalisation approaches when nested donors are excluded or not.

The method that is less affected is the Ordinary Kriging, especially for the TUW model, due to the fact that such method is not based on the identification of one or more "sibling" donors which may have been excluded if nested. On the other hand, it should also be highlighted that such method is the regionalisation approach that performs worst, when nested basins are available.

As expected, for both TUW and GR6J, NN-1 is always the most heavily affected method (dark green bars in bottom panels of Figure 10): this is due to the fact that the nearest donor is a nested one in more than 80% of the catchments, for both criteria and its exclusion seriously compromise the performance.

Excluding the nested catchments has also a strong impact on MS-1 (dark blue bars in bottom panels of Figure 10), even if to a lesser extent than for NN-1, since for more than 60% of the catchments the most similar donor is a nested one according to both criteria.

The degradation of performance moving from Criterion 1 (upstream/downstream) to Criterion 2 (overlapping drainage area) highlighted in Figure 9 demonstrates that using as donors not only the immediate downstream or upstream gauged river sections, but also all the catchments partially sharing their drainage area with the target one, has a strong positive influence on the regionalisation performance.

Furthermore, the use of output-averaging for both Nearest Neighbour and Most Similar approaches (NN-OA and MS-OA), in addition to outperform the NN-1 and MS-1 when using all (nested and non-nested) donors (see also Section 4.3), can also clearly improve the robustness of the methods to the exclusion of the nested donors. In fact, the bottom panels of Figure 10 show that the loss in the efficiencies of NN-OA and MS-OA are always smaller than those corresponding to the single donor approaches (NN-1 and MS-1), for both rainfall-runoff models and for both regionalisation methods. This confirms that the use of output-averaging (or more in general the use of more than one donor basin) is preferable for regionalisation purposes also for regions that do not have so many nested catchments as the Austria study area.

Finally, the values reported in Table 5 (as well as Figure 10) show how, especially for NSE, the losses resulting when excluding nested donors from the regionalisation are higher for the GR6J model than for the TUW: the GR6J seems to be

20

539 slightly more affected by the presence of nested basins, except for MS-1 and MS-OA whose performances remain more
540 similar to those of TUW. As already anticipated, it may be due to the different structure and parameter transferability of
541 the models, which would indeed deserve a dedicated study.

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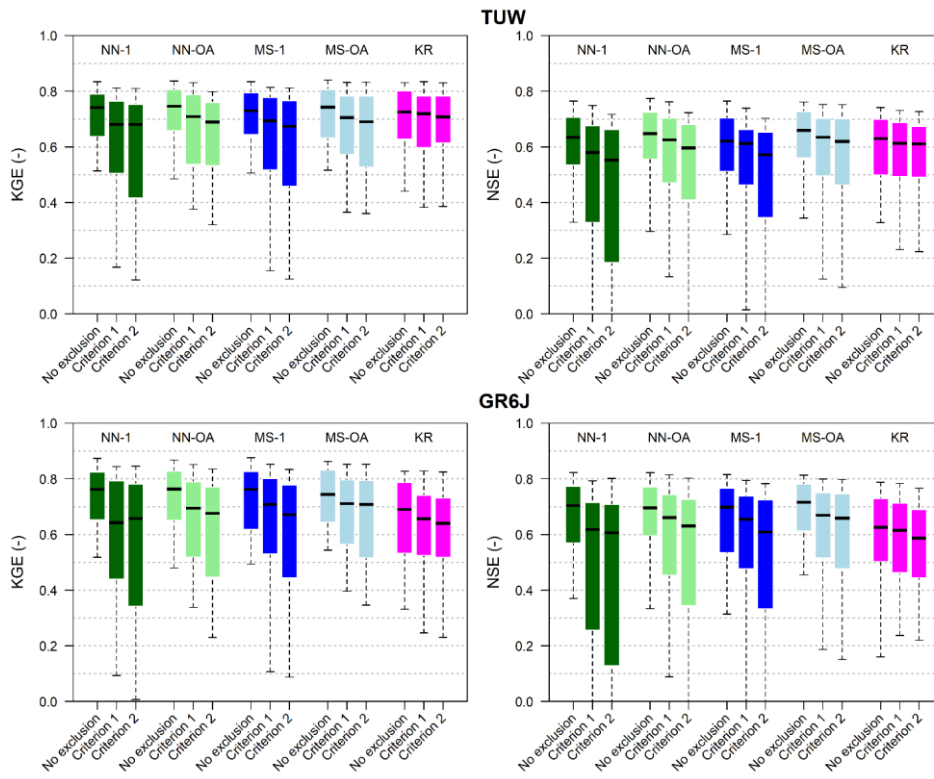
543

544 **Figure 9. Effect of the exclusion of nested catchments for the subset of 137 watersheds classified as nested: Kling-Gupta (left**
545 **panels) and Nash-Sutcliffe (right panels) efficiencies when regionalising the TUW (upper panels) and GR6J (lower panels)**
546 **models. "No exclusion": all the donors are available. "Criterion 1" or "Criterion 2": nested catchments are excluded from**
547 **donor set. Box colours refer to the different methods: green is Nearest Neighbour (1 donor is dark green and 3 is light green),**
548 **blue is Most Similar (1 donor is dark blue and 3 is light blue) and magenta is Ordinary Kriging. Boxes extend to 25% and 75%**
549 **quantiles while whiskers refer to 10% and 90% quantiles.**
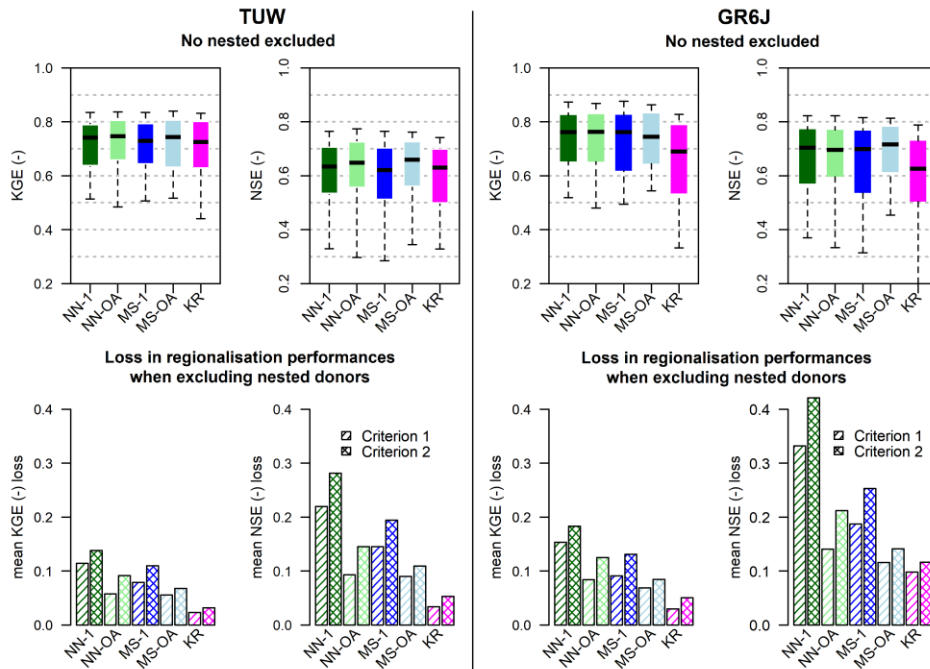
Figure 10. Kling-Gupta and Nash-Sutcliffe efficiencies and mean losses in the same methods resulting when excluding the nested donors with Criterion 1 and 2 (bottom panels) for TUW and GR6J models.

Table 5. Inter-quartile values of Kling-Gupta and Nash-Sutcliffe efficiencies when regionalising TUW and GR6J models excluding or not excluding nested donor catchments.

		Inter-quartile KGE [-]				
		NN-1	**NN-OA**	**MS-1**	**MS-OA**	**KR**
TUW	No nested excluded	0.64/0.79	0.66/0.81	0.64/0.79	0.63/0.81	0.63/0.80
	Criterion 1	0.50/0.76	0.54/0.79	0.52/0.78	0.57/0.78	0.60/0.78
	Criterion 2	0.42/0.75	0.53/0.76	0.46/0.77	0.53/0.78	0.61/0.78
GR6J	No nested excluded	0.65/0.82	0.65/0.83	0.62/0.83	0.64/0.83	0.53/0.79
	Criterion 1	0.44/0.79	0.52/0.79	0.53/0.80	0.56/0.80	0.52/0.74
	Criterion 2	0.34/0.78	0.45/0.77	0.44/0.78	0.52/0.79	0.52/0.73
		Inter-quartile NSE [-]				
		NN-1	**NN-OA**	**MS-1**	**MS-OA**	**KR**
TUW	No nested excluded	0.53/0.71	0.56/0.73	0.51/0.70	0.56/0.73	0.50/0.70
	Criterion 1	0.33/0.68	0.47/0.70	0.46/0.66	0.50/0.70	0.49/0.69
	Criterion 2	0.18/0.66	0.41/0.68	0.35/0.65	0.46/0.70	0.49/0.67
GR6J	No nested excluded	0.57/0.77	0.60/0.77	0.54/0.77	0.61/0.78	0.50/0.73
	Criterion 1	0.26/0.71	0.45/0.74	0.48/0.74	0.52/0.75	0.46/0.71
	Criterion 2	0.13/0.71	0.34/0.73	0.33/0.72	0.48/0.75	0.45/0.69

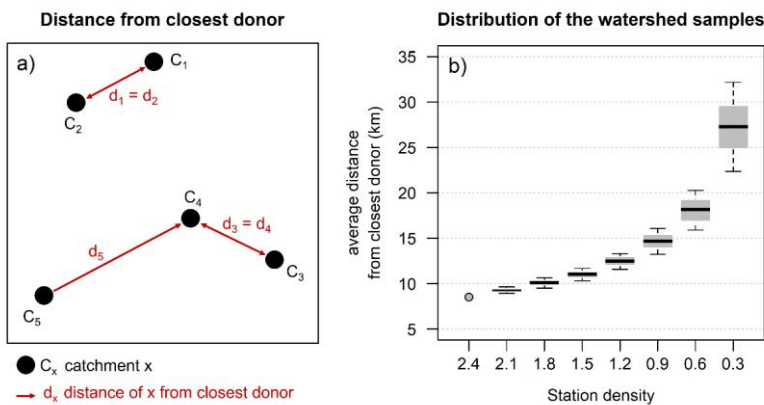## 4.4 Impact of station density: performance losses in regionalisation

The last results concern the analysis on the impact of station density on regionalisation performances. As introduced in Section 3.4, for each of the seven assigned density values, the described procedure provides 100 different sets of regionalised target catchments. For a given density, each one of these 100 subsamples is formed by the same number of target catchments, resulting therefore in the same number of efficiencies to be analysed.

First, it is important to verify that catchment samples are evenly distributed across the country: to do so we consider the distance of each catchment from its closer potential donor as shown in panel a) of Figure 11. The average of the distances (d_1, d_2, d_3, d_4, d_5) of each catchment from the closest catchment (i.e. a potential donor) in a sample can be considered as a measure of the sample spatial distribution: the higher the distance the less dense the sample. As above said, for each density, 100 different samples are generated, so that for each density, we have 100 different values for such averages. Panel b) of Figure 11 shows the average "distance within sample" of the closest available donor catchment across the 100 generated sub-sets for the different values of station density (each boxplot refers to the 100 values of average distance calculated for each sub-set). The average distance from the closest donor in the original, full density dataset (grey point in the figure) is around 8.5 km. As expected, the median target/donor distance (middle black solid line in each box) increases with decreasing density: it is true that also the variability of the distance, as shown by box size and whiskers, gradually increases with the reduction of station density, but such increase is overall modest: even for the lowest density, it is limited to +/- 18% of the median for the 80% of the samples. The fact that, on average, the distance between a target catchment and the closest gauged catchment consistently increases for decreasing density proves that the samples with lower density do not tend to cluster/concentrate the catchments in a small region, but there is an even distribution over the country.

Figure 11. Panel a) Example of distance from closest donor. Panel b) Boxplots of the average distance within sample from the closest available potential donor catchment across the 100 generated sub-sets, for different values of station density (gauges/1000km^2). Whiskers extend to 10th and 90th percentiles. The grey point indicates the average distance from the closest donor in the original dataset.

In order to analyse the results, the median regionalisation performances of each subsample are computed and presented here: thus, for each gauging density, the results consist in 100 values of median performances.

For sake of brevity, only the median Kling-Gupta efficiencies over the validation periods are reported. They are shown in Figure 12 for both TUW and GR6J models: each plot contains the boxplots of the median Kling-Gupta efficiencies for each station density (i.e. number of gauges per 1000 km^2), that is, each boxplot presents the 100 values of median Kling-Gupta efficiencies obtained applying the regionalisation approaches to the 100 subsamples generated with an assigned density. The colored point and the dotted line in the plots indicate the "original" (and maximum) median regionalisation efficiency of the approaches, that is the one obtained when using all available donors (i.e. full station density, corresponding to 2.4 gauges/1000 km^2).

The NN-1 method (Figure 12, panels a) and f)) is the most affected by the decreasing density. In fact, when the density declines, there is a higher probability that the less dense subsamples do not include the catchment that is the nearest one to each target river section. And, as we have seen in the analyses on the nested donors, in the large majority of the cases, the nearest catchment is a nested one, whereas the second best may be substantially different from the target basin.

Also the output-averaging version of the Nearest Neighbour methods (Figure 12, panels b) and g)) strongly deteriorates for less dense networks. In general, Nearest Neighbour methods are highly sensitive to gauging density: geographical distance results to be a good similarity measure only for densely gauged study areas (like Austria), since they firmly rely on the presence of gauged catchments in the immediate surroundings that are also hydrologically very similar. If the density decreases, the closest donor may be relatively far from the target, and it may therefore have little in common with it.

As far as the MS-1 (Figure 12, panels c) and h)) is concerned, its performances degrades more gracefully (with the exception of the GR6J model for the minimum density) than the NN-1 or the NN-OA. Also in this case (like for the NN-1), when the density decreases it becomes less probable that the most hydrologically similar catchment (identified by MS-1 in full density) is still part of the subsample; but it is also true there is more than one catchment in the original data set that is similar enough to the target in terms of catchment attributes.

This holds also for the output–averaging MS (Figure 12, panels d) and i)), which is even less affected by a reduction in donors' density and is the best-performing approach for any density (for both rainfall-runoff models).

We may note that, also in this analysis, analogously to what resulted for the exclusion of nested catchments, for both approaches (NN and MS), the implementation of output-averaging allows to reduce the degradation in the performances in comparison to the corresponding 1-donor version.

The impact of station density is similar to that of excluding nested catchments also for the Ordinary Kriging approach (Figure 12, panels e) and j)), which deteriorates less than the other methods for decreasing values of station density. For the TUW model, the Kriging regionalisation, starting from an already high KGE in full density, results in performances that are inferior only to those of MS-OA when the density goes below 0.9. For the GR6J model, even if the deterioration is limited, since KR was poorly performing for the full density regionalisation (Figure 7), the median KGE is always worse than those of all the other regionalisation approaches, for all the station densities.

Overall, all methods (excluding the poorly performing NN-1 and KR for the GR6J) result in relatively good performances provided that the station density is at least 0.9 gauges per 1000 km^2. On the other hand, leaving aside the Kriging method, the median KGE drops very steeply when the density passes from 0.6 to 0.3 gauges per 1000 km^2.

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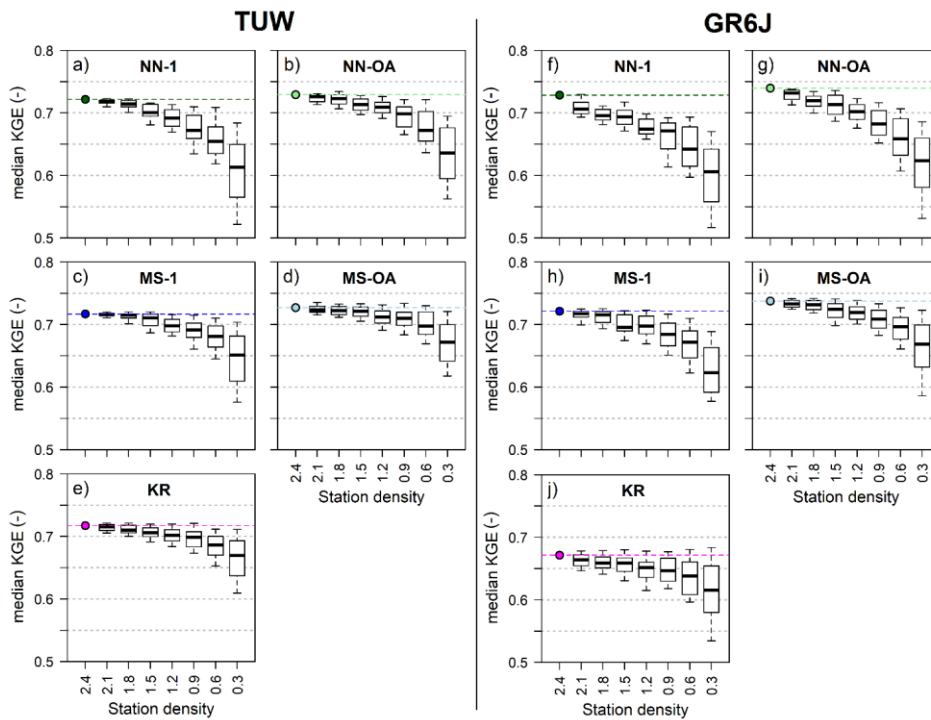
Figure 12. Median Kling-Gupta efficiency of the 100 sampled datasets for varying station density (number of gauges per 1000 km²) for the TUW and GR6J models using NN-1 (panels a) and f)), NN-OA (panels b) and g)), MS-1 (panels c) and h)), MS-OA (panels d) and i)) and KR (panels e) and j)) regionalisation methods. The colored point and dotted line in the plots indicate the original median regionalisation efficiency of the approaches when using all available donors (i.e. full station density, corresponding to 2.4 gauges/1000 km²).

5 Conclusions

An assessment of the impact of the presence of nested catchments and of station density on the performance of parameter regionalisation techniques in a large Austrian dataset has been performed. The main motivation for this work lies in the lack of systematic studies in the literature about the effect of data-richness and informative content when evaluating the accuracy of various methods for transferring rainfall-runoff model parameters to ungauged catchments. In fact, studies conducted on different study sets often do not lead to the same ranking of the tested approaches and the obtained results are not extendable to different study regions. This is indeed due also to the diverse topological relationships between catchments (nestedness) in the datasets and to the diverse density of the streamgauges.

The purpose of the work is to give support to the choice of the most appropriate parameter regionalisation approaches, taking into account the available hydrometric information in the region, showing and quantifying if and how the informative content of the available gauged sections, here expressed by the presence of several nested catchments in a dataset or by the gauging density of the study region, can distort the predictive power of a certain technique.

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Commentato [MN22]: Old Figures 14 and 15 were merged

Commentato [MN23]: Based on comment 1 of Reviewer 1, some sentences were added/modified in order to further clarify the main focus of the manuscript.

Commentato [MN24]: The sentence was modified based on comment 1 of Reviewer 1

The research has been conducted for a very densely gauged dataset covering a large portion of the Austrian country. Two rainfall-runoff models for simulating daily streamflow have been calibrated for the 209 study watersheds: a semi-distributed version of the HBV model (TUW model), and the lumped GR6J model coupled with the Cemaneige snow routine.

Both models perform very well when applied in at-site mode, that is when parameterised in the traditional (not regionalised) way, and for each target section the historical gauged streamflow data are used for fitting the parameter set. The calibration and validation performances are very good for both rainfall-runoff models, with better values of the chosen goodness-of-fit indexes for the GR6J model, which demonstrates to perform very well also in this Alpine dataset.

In order to assess the capability of the models when used on ungauged basins, the streamgauge data for every section was, in turn, considered not to be available, and five regionalisation approaches were implemented for using the rainfall-runoff models in such "ungauged" sections over the validation period. This is indeed an exacting task because we are attempting to use the model over an ungauged catchment and for an observation period different from the one used for parameterising the gauged donor catchments. The first regionalisation approach is an Ordinary Kriging approach (KR), which separately interpolates each of the model parameter based on their spatial correlation in the study area. Two approaches selecting one single donor catchment and transposing its parameter set to the target basin are also tested: in the first (NN-1) the geographically nearest catchment is selected, while in the second approach (MS-1) the single donor that "lends" all its parameters to the target one is the most similar one in terms of a set of physiographic and climatic attributes. The latter two approaches are implemented also in the output-averaging (OA) version, where the entire parameter set of more than one donor is used for the simulation on the target section and the model outputs are then averaged accordingly to the distance/dissimilarity between donors and target.

In regionalisation mode, the performances of the GR6J model deteriorates more than those of the TUW model, in comparison with the "gauged", at-site parameterisation. Reasons for this behavior may lie in the different model structure and in the different transferability of model parameters (depending also on their meaning and their relation with the available catchment attributes). Such issue would deserve further attention and investigation but it would need a separate ad-hoc analysis, since the comparison of the structures and of the physical meaning of the parameters of the two models is not the specific objective of our work. For both rainfall-runoff models, the use of the output-averaging approach outperform the use of a single donor (NN-OA and MS-OA performed better than NN-1 and MS-1), confirming the outcomes of other studies on the importance of exploiting the information available from more than only one donor (see e.g., McIntyre et al. 2005, Oudin et al. 2008, Viviroli et al. 2009, Zelelew and Alfredsen 2014). The output-averaging methods also outperform the parameter-averaging Kriging method (especially for the GR6J model), showing that it is preferable transferring the entire parameter set of each donor, thus maintaining the correlation between the parameter values. The results of the MS-OA are close but tend to be better than those of the NN-OA, indicating that hydrological similarity is more important than geographical closeness for choosing the donors.

We expect that spatial proximity alone may be even less representative of hydrological similarity in a drier climate: in fact Patil et al. (2012) and Li and Zhang (2017) shown that in dry runoff-dominated regions, nearby catchments tend to exhibit less hydrological similarity than in more humid regions.

The impact of the richness of the data set (i.e. the informative content of the region) was then analysed, in order to assess the deterioration of the regionalisation approaches for decreasing availability and "worth" of the available donors, starting from the influence of using nested basins as donors.

Commentato [MN25]: Added based on comment B of Reviewer 2

Commentato [MN26]: The sentence was modified based on comment 1 of Reviewer 1

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684 Two criteria have been proposed for identifying a basin that is nested with the target one: the first one, already used in
685 the few analysis of nestedness in the literature, classifies as nested the first upstream and the first downstream gauges on
686 the river network. The second, novel criterion, identifies as nested all the catchments that share more than a given
687 percentage (here chosen as 10%) of the drainage area with the target one. It results that the first Criterion identifies a
688 larger number of nested catchments with at least one potential donor. In fact, the first criterion considers as nested also a
689 number of catchments that share less than 10% of area with the target one: this means that, in some cases, the first
690 downstream or upstream gauge may be not representative of the same drainage area and their catchments may be governed
691 by very different hydrological processes.

692

693 All the regionalisation approaches have been repeated by excluding from the donor set the catchments assumed to be
694 nested in relation to each target basin, according to each one of the two criteria.
695 For both rainfall-runoff models and for all the regionalisation approaches, when using the second criterion (that excludes
696 all the basins that share a significant portion of the same watershed), the regionalisation procedure deteriorates more than
697 when excluding the first up/downstream river sections, whose catchment may, in some cases, not have much in common
698 with the target one.
699 Looking at the two rainfall-models, when excluding the nested catchments, the regionalisation performances tend to
700 deteriorates more for the GR6J than for the TUW: this seems to indicate that the TUW model may be more robust for
701 regionalisation purposes, even when nested donors are not available.
702 Comparing the different regionalisation approaches, the parameter-averaging Kriging is the method that is less impacted
703 by the exclusion of the nested donors, since it does not depend only on the choice of one or few "sibling" donors, that are
704 very often the nested ones, but it takes into account a number of donors in a given radius. This is consistent to the outcomes
705 of Merz and Blöschl (2004) and Parajka et al. (2005) who observed almost no deterioration of regionalisation
706 performances when excluding the first down and upstream nested donors using the same Ordinary Kriging approach.
707 When using, instead, a method transferring the entire parameter set from one or more donor catchments, the deterioration
708 is more sizeable. The method that experiences the worst deterioration is the NN-1, since in 80% of the cases, the nearest
709 basin is a nested one, and it is thus excluded from the potential donors; second worst is the MS-1, that, when free to
710 choose any single potential donor in the entire region, would choose a nested one in 60% of the cases. The output-
711 averaging methods degrade less severely, showing that exploiting the information resulting from more than one donor
712 increases the robustness of the approach also in regions that do not have so many nested catchments as the Austrian one
713 (where the importance of nested donors in regionalising model parameters is highlighted also by Merz and Blöschl, 2004).

714

715 Finally, an assessment of the impact of station density on the regionalisation has been also implemented. The Nearest
716 Neighbour approaches (both NN-1 and NN-OA) are the methods that suffer more from the decrease in gauging density,
717 whereas the Most Similar methods (MS-1 and MS-OA), which use as similarity measure a set of catchment descriptors,
718 are more capable to adapt to less dense datasets: in fact the Most Similar methods are able to find other adequate donors,
719 that may be anywhere in the region, whereas the Nearest Neighbour techniques, in a more "sparse" monitoring network
720 risk to identify a "not so near" donor that may be very different from the target one. The impact of decreasing station
721 density on the performance of the output-averaging approach based on spatial proximity (NN-OA) is in line to what
722 observed by Lebecherel et al. (2016). The performances of both the output-averaging methods, in agreement with the

> **Commentato [MN27]:** Rephrased as requested by Reviewer 2 (specific comment 19)

723 results obtained for similar methods by Oudin et al. (2008), strongly deteriorate when the station density drops below 0.6

724 gauges per 1000 km^2.

725

726 The study confirms how the predictive accuracy of parameter regionalisation techniques strongly depends on the

727 informative content of the dataset of available donor catchments, quantifying the contribution of nested catchments and

728 station density for different approaches and rainfall-runoff models. The outcomes obtained in reference to the Austrian

729 data set indicate that the reliability and robustness of the regionalisation of rainfall-runoff model parameters can be

730 improved by making use of output-averaging approaches, that use more than one donor basin but preserving the

731 correlation structure of the parameter set. Such approaches result to be preferable for regionalisation purposes in both

732 data-poor and data-rich regions, as demonstrated by the analyses on the degradation of the performances resulting from

733 either removing the nested donor catchments or decreasing the gauging station density.

734

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865

**Appendix A: Choice of best catchment descriptors**

867 The implementation of the Most Similar approach requires the choice of the geo-morphologic and climatic attributes to

868 be used for selecting the donor catchment(s), i.e. to calculate the dissimilarity indices of equation 2.

869 This similarity study is part of a preliminary analysis carried out through a regionalisation experiment using the whole

870 period of available daily data (from 1976 to 2008, again with 1 year of warm-up) for calibrating the rainfall-runoff models.

871 In order to individuate the best catchment descriptors (all reported in Table 1 with a brief description), the Most Similar

872 approach with one single donor catchment (MS-1) is applied sequentially to the entire dataset in leave-one-out cross-

873 validation, using at each step an increasing number of attributes when defining the dissimilarity index ϕ. At each step,

874 the method is tested multiple times, adding one by one each of the attributes and the one which gives the best

875 regionalisation performances is selected. For greater clarity, Figure A1 (panel a) refers to TUW and panel b) to GR6J)

876 shows the boxplots of the consecutive best combinations of descriptors: at the first step, only one attribute is used, the

877 Most Similar approach is tested for all the available catchment features, and the similarity in the land cover classes

878 (Corine) gave the best efficiency. At the second step, the operation is repeated using land cover and each of the remaining

879 attributes one at a time, finding the geology classes to be the best attribute to add, and so on. The analysis stops when the

880 performances are decreasing or stop improving.

881 As can be inferred from Figure A1, both rainfall-runoff models reach good regionalisation performances when using up

882 to 5 attributes. Since the first best 5 attributes are the same for both models and from the sixth step the performances are

883 not substantially improved, we decide to choose those five descriptors to characterize catchment similarity: land use

884 classes, geological classes, mean annual precipitation, stream network density and mean elevation.

885

886
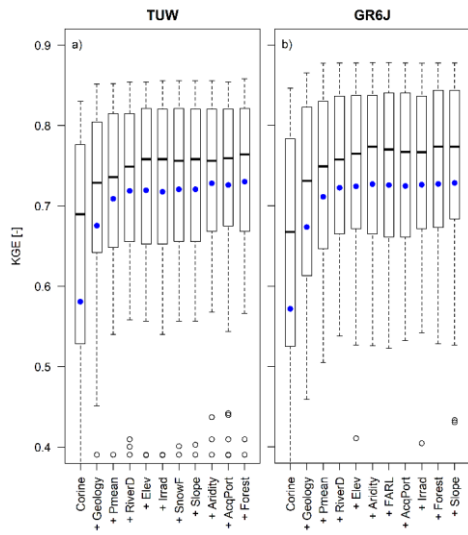
Figure A1. Kling-Gupta efficiencies for TUW (panel a)) and GR6J (panel b)) models for the consecutive steps of the similarity analysis. Boxes refer to 25% and 75% quantiles, whiskers refer to 10% and 90% quantiles and the blue points to the average.