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Research papers

Can continuous simulation be used as an alternative for flood regionalisation? A large sample example from Chile

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ABSTRACT

Flood frequency analysis lies at the core of hydrology and water engineering as one of the most required estimates for water planning and design of hydraulic structures. For ungauged basins, where no information is available, various flood regionalisation techniques have varying degrees of complexity and resulting performance, depending on the study's goal, the region analysed, and the information available. This study evaluates the use of hydrological models for flood regionalisation in Chile, using 1) A large sample dataset of 101 catchments; 2) the continuous simulation approach with the GR4J model; 3) the leave-one-out strategy for performance testing; and, 4) two regionalisation methods: Nearest Neighbour (NN) and Physical Similarity (PS), together with several alternative objective functions for calibration purposes and regionalisation strategy (in all cases adopting a single criterion, single variable and determinist approach for the parameter's selection). Our results showed that performance (both in calibration–validation and regionalisation) is highly variable (in terms of reproducing the runoff hydrograph and flood statistics), depending on the catchment's aridity (e.g., around 66–82% of catchments with NSE above 0 in humid regions but it severely drops to 12–44% of catchments with NSE above 0 when evaluating arid catchments). We also found that flood-specific calibration strategies produce better results for floods but poorer performance in runoff hydrograph reproduction. Finally, we highlight that our regionalisation results were in close agreement with those from one of the currently recommended methods by Chilean engineering for flood regionalisation. This is particularly promising, considering that the continuous simulation approach gives access to the complete time series and not only flood statistics. We end this manuscript by discussing several sources of uncertainty, hoping that these can be accounted for in future studies.

1. Introduction

1.1. Motivation

Floods historically had a special place in the development of hydrology, mainly because their statistical (frequency) analysis plays an essential role in designing civil engineering structures (Singh and Strupczewski 2002; Rogger et al., 2012a; Zhu et al., 2018; Mishra et al. 2022). It can be argued that both hydrology and water engineering have developed (coevolved) with hydrological extremes when dealing with changing flood risk over time for human societies (Di Baldassarre et al. 2017), a topic particularly relevant when dealing with the threat of changes in flooding dynamics, which has become an essential topic of discussion in recent times (Blöschl et al. 2015; Berghuijs et al. 2017; Sharma, Wasko, and Lettenmaier 2018; Blöschl et al. 2019). However, while much can be said regarding the complexity of floods, either because of a) their numerous types and classifications (Merz and Blöschl 2003; Tarasova et al. 2019); b) their variability in terms of spatial and temporal scales (Merz et al. 2012; Hall et al. 2014; Berghuijs et al. 2019); and, c) their economic and environmental importance (Vorogushyn et al. 2018; Talbot et al. 2018), their estimation has been traditionally viewed as a statistical problem (Merz and Blöschl 2003; Dawdy, Griffis, and Gupta 2012; Miniussi, Marani, and Villarini 2020). In this regard, it is a well-known issue that floods do not always follow the traditional assumptions of statistical analysis (i.e., independent and identically distributed - IID, see Fischer, Schumann, and Schulte 2016; Zaghloul et al. 2020; Klemeš 2000; Brunner et al. 2021, for a historical perspective) and, therefore, the classic flood frequency analysis (FFA) is limited from the beginning. Worthy mentioning is that FFA assumes available data, becoming an obvious problem when dealing with ungauged

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basins.

1.2. Literature review

The problem of predictions in ungauged basins (PUB) has been covered repeatedly in the hydrology community and was the focus of huge developments during the 2000 s and early 2010 s (see Sivapalan 2003; Hrachowitz et al. 2013; Blöschl et al. 2013). In terms of regionalisation methods (i.e., how to estimate the hydrology of ungauged basins), there are many and quite varied methods available, but generally can be classified into two main groups depending on whether the method depends on a hydrological model or is independent of them by using, for instance, hydrological signatures or runoff time series directly (Razavi and Coulibaly 2013; Blöschl et al. 2013). Other classifications can be found in the literature; for instance, Viglione et al. (2013)) classified them according to process based vs statistical methods. Notwithstanding the above, both classifications overlap pretty well.

According to Razavi and Coulibaly (2013)), most of these regionalisation methods share standard procedures, which are briefly mentioned as follows: 1) Identification of catchment attributes (meteorological or physiographic characteristics); 2) Hydrological variables of interest (mainly runoff and its derivatives); 3) A model performance evaluation technique, typically the leave-one-out cross-validation method; 4) The regionalisation method per se; and, finally 5) An uncertainty analysis (typically ignored in most studies. See the following references where uncertainty analysis was included: Blazkova and Beven 2002; Wagener and Wheater 2006; Cibin et al. 2014; Arsenault and Brissette 2014; Sellami et al. 2014). Remarkable, and in contrast to these commonalities across studies, we also find a vast diversity of approaches when analysing the regionalisation methods per se, even among groups of model-dependent or model-independent methods.

There are regression-type methods for the model-dependent types, which look to find relationships between catchment characteristics and model parameters to interpolate the latter for the ungauged catchment. Some methods transfer entire sets of model parameters based on hydrological similarity among catchments (He, Bárdossy, and Zehe 2011), which is typically assumed that can be approximated by minimising geographical distance (also known as spatial proximity, or nearest neighbours, NN) or minimising physical, meteorological or hydrological differences (also known as physical similarity, PS), among others. There is, therefore, extensive literature on the application and comparison of these different approaches. Among them, Oudin et al. (2008) tested regression, NN and PS with two different hydrological models (TOPMO and GR4J) on a large sample of catchments (913) in France. Razavi and Coulibaly (2016) applied an ensemble multi-modelling approach with four models (two hydrological models and two data-driven models) for estimating the daily hydrograph in 90 catchments treated as ungauged in Canada. Arsenault et al. (2019) tested three lumped hydrological models and six regionalisation approaches (among them, combinations of the NN, PS and regression approaches) for 30 catchments in Mexico. Neri, Parajka, and Toth (2020) studied the effects of station density in a large sample of catchments (209) in Austria, employing both NN and PS methods while also employing two different hydrological models (TUW and GR6J); and, most recently, Qi et al. (2022) tested several approaches for regionalisation (NN, PS, hybrids of the two, regression; averaging parameters and outputs, simple mean or weighted mean) for a large sample of global catchments (2,277) and with four hydrological models (GR4J, SIMHYD, HAJ, and HMETS). Among the methods that do not require a hydrological model (but instead look for relationships between discharge and other variables), we also have several methods available such as the class of purely statistical methods, which include several regression types (Ouali, Chebana, and Ouarda 2016), index-flood methods (Hailegeorgis and Alfredsen 2017; Dalrymple 1960; Hosking and Wallis 1997), kriging (Archfield et al. 2013), process-based and event-based methods such as the rational formula (Grimaldi and Petroselli 2015) and the different variants of the unit hydrograph (Brunner et al. 2018).

Razavi and Coulibaly (2013) pointed out that there is no universal method for regionalisation, so finding such significant variability in methods, models, studies, and results available in the literature is not surprising (both for model-dependent and model-independent methods). However, in terms of their applications, and based on the reviews by Parajka et al. (2013) and Salinas et al. (2013), there is a clear preference for the employment of methods based on hydrological models for the estimation of ordinary properties of runoff (e.g., flow-duration curves, hydrological signatures, and the entire runoff hydrograph), also known as continuous streamflow regionalisation. Methods based on regression, geostatistics, and others (e.g., index-flood methods) are preferred for the regionalisation of extreme events. In fact, Salinas et al. (2013), covering the estimation of extreme events, did not find studies exploiting model-dependent methods for flood regionalisation. Remarkably, most of the studies used global/regional regression, the index-flood method, and geostatistics. Because all methods have advantages-disadvantages, in principle, the decision to use one method above others should be made once a direct comparison between methods' results has been established. Unfortunately, the review of Salinas et al. (2013) shows us that model-dependent methods for flood regionalisation have hardly been tested in the scientific literature, with very few exceptions (Blazkova and Beven 2002; Viviroli et al. 2009; Grimaldi et al. 2021; Moretti and Montanari 2008).

Model-based methods have some interesting properties compared to the other approaches. They can explicitly account for changes in the catchment (such as soil type and climate); they allow the calculations of the whole hydrograph and not just specific elements of it; and, coupling the continuous simulation approach with weather generators, they can produce long time series, increasing the reliability of the extreme frequency analysis (Blazkov and Beven 1997; Lamb et al. 2016; Winter et al. 2019). These reasons and some recent developments in using the continuous simulation approach for FFA motivate the use of these models for flood regionalisation purposes. However, as far as we know, explicitly studying flood regionalisation with the continuous simulation approach has been covered in very few studies (e.g., Calver, Lamb, and Morris 1999; Blazkova and Beven 2002; Lamb and Kay 2004; Moretti and Montanari 2008; Viviroli et al. 2009; Grimaldi, Petroselli, and Serinaldi 2012; Biondi and Luca, 2015; Grimaldi et al. 2013, 2021).

This paper aims to apply the continuous simulation approach for flood regionalisation in continental Chile. As mentioned before, the literature on this topic is surprisingly small compared with the extensive literature on regionalisation, floods, and FFA per se (see Guo et al. 2021) for a review on regionalisation; Boughton and Droop (2003) for a review on continuous simulation methods; Mishra et al. (2022) for a general review on floods; Nerantzaki and Papalexiou (2022) for a review on flood statistics; and, Smithers (2012) and Dawdy, Griffis, and Gupta (2012) for a review on the specific topic of flood regionalisation). Regarding PUB studies in Chile, we can mention at least two important contributions: i) the National Water Balance, recently updated (DGA 2017; 2018; 2019), where the Variable Infiltration Capacity (VIC, Liang et al. 1994)) hydrological model was employed to regionalise runoff time series at several Chilean catchments, and ii) the work of Baez-Villanueva et al. 2021), where they evaluated the performance of four different gridded precipitation products in reproducing the daily hydrograph over 100 Chilean catchments (treated as ungauged) with the TUW hydrological model. Unfortunately, none of these studies covered the specific topic of estimating FFA in ungauged catchments, which is the interest of this study. Last but not least, since the Chilean territory encompasses a huge spatial-climatic variability, including several different types of climates (3 first-order, 6 s-order, and 9 third-order types of climate following the Koppen-Geiger climate classification (Sarricolea, Herrera-Ossandon, and Meseguer-Ruiz 2017), and strong elevation gradients (from north to south and from east to west (Fernández and Gironás 2021), we anticipate a substantial variability in the results, considering the well-known effect of aridity and elevation in regionalisation results (Parajka et al. 2013; Salinas et al. 2013; Blöschl et al. 2013).

1.3. Manuscript's goals

The following research questions are addressed:

- What is the role of calibration criteria, regionalisation method, and other methodological decisions in regionalisation performance?
- How well does the continuous simulation approach reproduce flood quantiles?
- How do the results compare with currently employed methods for flood regionalisation in Chile?

This paper is structured in the following format: Section 2 describes the selected catchments for analysis, their properties, data availability (e.g., inputs and evaluation period), the hydrological model selected, and the calibration strategies employed (i.e., the objective functions to be optimized and the regionalisation strategies considered). Section 3 shows the results of the calibration/validation for the different calibration strategies and presents the results of regionalisation, both for daily runoff reproduction and flood statistics. Finally, Section 4 discusses our findings, including a summary of manuscript limitations and potential ways to improve the analysis.

2. Methodology

2.1. Study area

The study area consists of 101 Chilean catchments (Fig. 1) belonging to the CAMELScl database (Alvarez-Garreton et al. 2018). Their main attributes are presented in Table 1. These catchments have huge variability; for instance: their areas range between 80 and 18.550 km^2 (with a median of 690 km^2); the mean annual precipitation ranges between 70 and 3200 mm/yr (with a median of 900 mm/yr); elevations ranging between 140 and 4780 m a.s.l. (with a median of 1230 m a.s.l.); and the aridity index ranges between 0.3 and 14.5 (with a median of 1). This high aridity is an essential feature of the northern and central regions of Chile, and significant difficulties in reproducing the full hydrograph for all these catchments can be anticipated when employing only one

Table 1
Summary of Catchment's Attributes. Sample size = 101.

	Unit	Min	Median	Max
Elevation	m.a.s.l.	137	1230	4777
Area	km^2	81	688	18,550
Mean Annual Precipitation	mm	68	906	3194
Mean Slope	%	5.2	18	29.8
Aridity	–	0.29	0.99	14.49
Snow Cover	%	0	0	5
Glaciar Cover	%	0	0	9
Forest Fraction	%	0	15	83
Crop Fraction	%	0	1	53

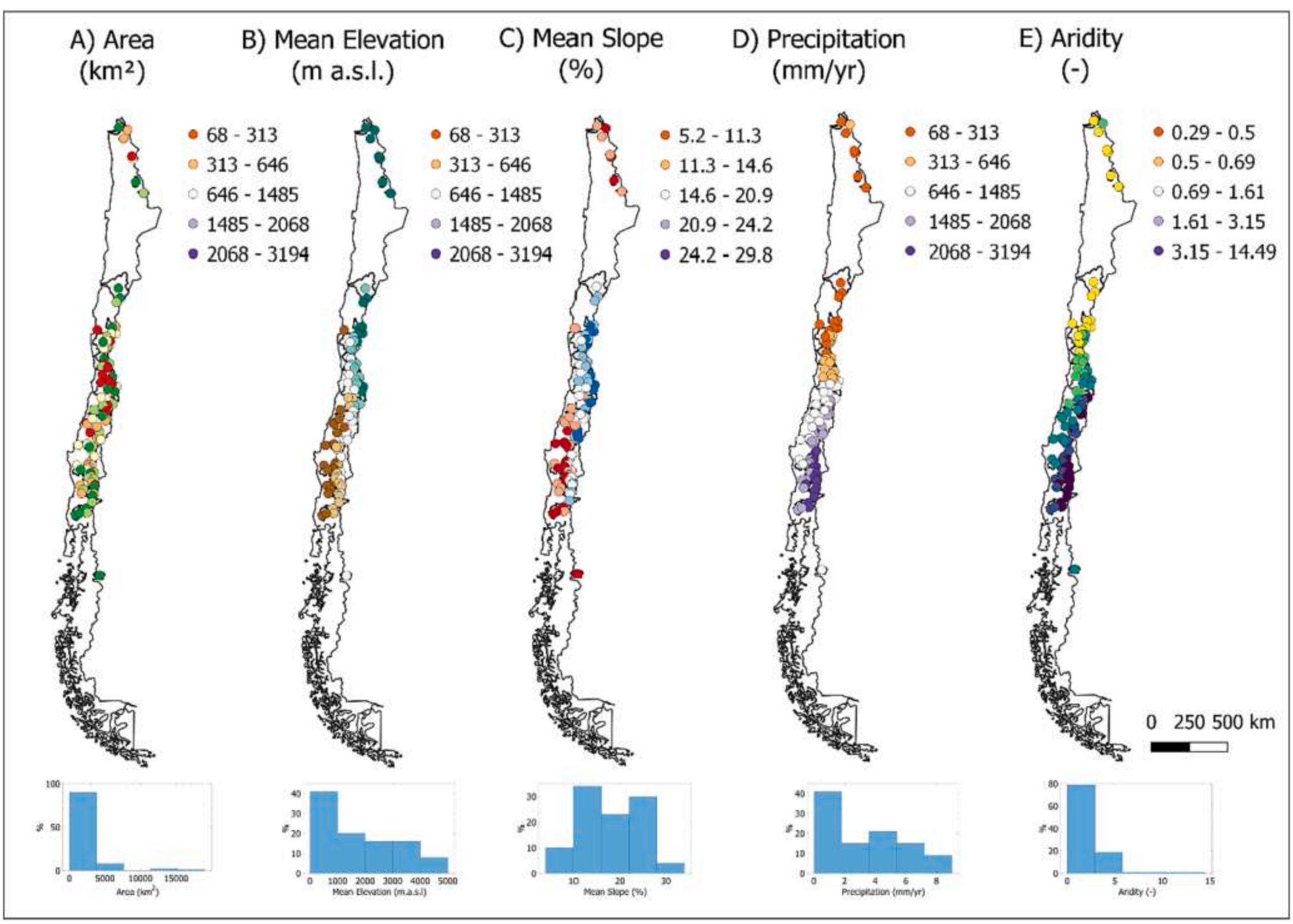

Fig. 1. Mean annual hydro-meteorological variables and catchment properties. The histograms indicate the number of catchments (out of 101) in each bin. The points represent the locations of catchment outlets.

hydrological model, especially considering the well-known difficulties of any hydrological model in reproducing runoff in arid regions (Liu et al. 2021). The latter, in part, is attributed to the non-linearities of the hydrology of arid regions (Blöschl et al. 2013) and its high spatial–temporal variability (Wheater, Sorooshian, and Sharma 2007). Additionally, in the case of the Andes mountains, we have many glaciers, some of which are strongly affected by climate change (Fernández and Gironás 2021), which introduces non-stationarity issues into the modelling of these catchments.

In terms of seasonality, winter rainfall (austral winter, JJA) is the predominant precipitation pattern over continental Chile (Sarricolea, Herrera-Ossandon, and Meseguer-Ruiz 2017), with a few exceptions in the extreme north (the Chilean altiplano) due to the South American monsoon (Garreaud 2009) where precipitation events occur during austral summer. In terms of spatial climatic patterns, typically, temperatures decrease while precipitation increases when moving from the north to the south (Sarricolea, Herrera-Ossandon, and Meseguer-Ruiz 2017). In terms of interannual variability, it is a well-known fact that Chile – together with Peru and other South American countries – are strongly affected by El Niño–Southern Oscillation (ENSO) (Cai et al. 2020), which typically materialises in above-normal precipitation during warm ENSO phases in central Chile and during cold ENSO phases in northern Chile (Fernández and Gironás 2021). Other modes of interannual variability are also known to play a role in the region (Cai et al. 2020; Fernández and Gironás 2021).

2.2. Inputs and model selection

To develop FFA, the catchments were selected based on a tradeoff between increasing data length (increasing the reliability of the FFA) and catchments availability (to increase the sample size). As a result, the evaluation period considers a data length of around 33 years (1987–2020, consecutive and the same period for all catchments). Note that the hydrological year is considered from 1 April to 31 March. However, due to missing data, the degree of information's completeness is between 69 and 100%, with a median of 90% for the period considered. The data extracted from the CAMELScl database (data acquired on 11 November 2021) corresponded to daily catchment-averaged: a) Precipitation; b) Potential Evapotranspiration; and, c) Temperature (mean, minimum and maximum), together with daily specific discharge (discharge divided by the catchment area) and catchment properties (area, aridity, mean slope, outlets' location, among others) (Alvarez-Garreton et al. 2018). Additionally, the hypsometric curves and centroids for each catchment were obtained from the SRTM DEM product, modified by Reuter, Nelson, and Jarvis 2007) with a 90 m resolution (data acquired on 19 April 2021).

All the modelling and calculations were done with the open software R, which is widely employed in hydrology (Slater et al. 2019). In particular, we employed the GR4J model (Perrin, Michel, and Andréassian 2003), which belongs to the GR model family coded in the airGR package (Coron et al. 2017). The GR4J is a conceptual-lumped model for estimating daily discharge based on: i) Net (effective) precipitation estimation, ii) Runoff production, and iii) Runoff transportation with unit hydrographs. GR4J accounts for four parameters with two additional parameters related to the CemaNeige snow module (Valéry, Andréassian, and Perrin 2014), which is based on the degree-day method (Rango and Martinec 1995; Kuusisto 1980). The GR4J-CemaNeige model considers six parameters and balances parsimony, complexity, and good performance (Perrin, Michel, and Andréassian 2003). The latter was the primary reason for its selection, together with its good performance in an ample variety of climates (Oudin et al. 2010).

2.3. Calibration-Validation strategy

Calibration was performed using the 1987–1997 period (11 years) and validation with the 1998–2020 period (22 years). Regarding the calibration process, we initially considered three optimisation criteria: i) the Nash–Sutcliffe efficiency (NSE), ii) the Kling-Gupta efficiency (KGE), introduced by Gupta et al. (2009), and iii) its variant introduced by Kling, Fuchs, and Paulin (2012) (KGE2012), which are the default options for the calibration method coded in the airGR package, designated here as "calibration Michel", and based on Michel's calibration strategy described in Perrin (2002). This calibration method combines a global search (1st step) using a predefined list of parameters set and a local search (2nd step) based on the steepest descent local search to optimise the selected objective function.

However, because we wanted to explore more options than the ones available by default in the package, we developed a set of several alternative objective functions, focusing on the correct reproduction of high flows, flood dynamics, and/or flood statistics. In total, we employed the following ten objective functions presented in Table 2 (See Appendix, section A.1, for the formulation of each objective function and a more in-depth explanation):

The reasoning behind this choice of calibration criteria goes as follows: While the KGE, NSE, and KGE2012 are the default options of the "calibration Michel", they naturally give more weight to the high flows due to the squared error in their formulations, and particularly the KGE and NSE have been found to produce a good performance for the reproduction of high flows (Mizukami et al. 2019). Following this rationale, it is expected that when more weight is given to the bias between simulated and observed standard deviation and Pearson term of the KGE/KGE2012 (as it is done with the KGE/KGE2012 variants) and the observation value of the NSE (as it is done here with the NSEw), we could potentially achieve even better performance at reproducing high flows and subsequently, flood statistics. Finally, the APFB and RMSNE are explicit flood statistics reproduction criteria. However, as mentioned before, the RMSNE was done by averaging with the corresponding inverse of their return periods as weights, in contrast to averaging them with equal weights as its typical formulation. The reason behind this methodological choice can be found in the role of the most significant errors (typically associated with the largest floods) in the value of this indicator. Because preliminary calculations showed us that this error was mostly controlled by the largest flood ($T = 100$ in this case), we employed this weighted average to reduce the influence of this error and include the lesser magnitude floods in the calibration process and evaluation of results.

2.4. Regionalisation strategies

Two common approaches were used to establish similarity among catchments: PS and NN. Notice that while NN is a straightforward computation – by calculating the Euclidean distance between catchment centroids – it is not straightforward to determine the best catchment attributes for PS. Here, we initially employed the following attributes: Area; Aridity; Elevation; Mean Annual Precipitation; Mean Slope; Fraction Cover of Snow, Glacier, Forest, Crop, Grass and Barren areas. Posteriorly, their Euclidean distance with respect to the catchment under analysis was normalised with the corresponding maximum attribute and uniformly averaged (Neri, Parajka, and Toth 2020). Regarding the number of donors, we employed the 1 to 10 most similar catchments (in terms of PS and NN) because it has been found in the literature that the optimum number of donors ranges between 2 and 10 or 5–10 (Oudin et al. 2008; Viviroli et al. 2009; Brunner et al. 2018). Notice that the nomenclature adopted for the number of used donors is REG-Dζ, where ζ ranges between 1 and 10. For instance, REG-D4 means regionalisation with 4 donors (see, e.g., Fig. 4).

Regionalisation results were computed (taking into consideration the output time series generated by the model using the parameters of the donors) as follows:

- Average of output time series (nomenclature: MEAN. See, e.g., Fig. 4);

Table 2
Ten objective functions used in calibration.

Objective function	Equation	Observations
NSE	$NSE = 1 - \frac{\sum_{i=1}^{N}(S_i - O_i)^2}{\sum_{i=1}^{N}(O_i - \overline{O})^2}$	Nash-Sutcliffe efficiency S_i: Simulated streamflow at the i position (time); O_i: Observed streamflow at the i position (time); $\overline{O}$: Mean of the observed streamflow.
NSEw	$NSEw = 1 - \frac{\sum_{i=1}^{N}O_i(S_i - O_i)^2}{\sum_{i=1}^{N}O_i(O_i - \overline{O})^2}$	Modified version of the NSE (Vormoor et al. 2015) S_i: Simulated streamflow at the i position (time); O_i: Observed streamflow at the i position (time); $\overline{O}$: Mean of the observed streamflow.
KGE	$KGE = 1 - \sqrt{s_1(r-1)^2 + s_2(\alpha-1)^2 + s_3(\beta-1)^2}$	Kling-Gupta efficiency r: Pearson correlation coefficient. α: Ratio between the standard deviations of the simulated and observed streamflow; β: Ratio between the means of the simulated and observed streamflow; s_i: Scaling factors for each term i.
KGE2012	$KGE2012 = 1 - \sqrt{f_1(r-1)^2 + f_2(\gamma-1)^2 + f_3(\beta-1)^2}$	A modified version of KGE r: Pearson correlation coefficient. γ: Ratio between the coefficients of variations of the simulated and observed streamflow; β: Ratio between the means of the simulated and observed streamflow; f_i: Scaling factors for each term i
KGEpearson	$KGEpearson = 1 - \sqrt{s_1(r-1)^2 + s_2(\alpha-1)^2 + s_3(\beta-1)^2}$	A modified version of the KGE where more weight (specifically five times more) was given to the Pearson correlation coefficient $s_1 = 5/7 s_2 = 1/7 s_3 = 1/7$
KGE2012pearson	$KGE2012pearson = 1 - \sqrt{f_1(r-1)^2 + f_2(\gamma-1)^2 + f_3(\beta-1)^2}$	A modified version of the KGE2012 where more weight (specifically five times more) was given to the Pearson correlation coefficient $f_1 = 5/7 f_2 = 1/7 f_3 = 1/7$
KGEalpha	$KGEalpha = 1 - \sqrt{s_1(r-1)^2 + s_2(\alpha-1)^2 + s_3(\beta-1)^2}$	A modified version of the KGE where more weight was given to the bias $s_1 = 1/7 s_2 = 5/7 s_3 = 1/7$
KGE2012alpha	$KGE2012alpha = 1 - \sqrt{f_1(r-1)^2 + f_2(\gamma-1)^2 + f_3(\beta-1)^2}$	A modified version of the KGE2012 where more weight was given to the bias $f_1 = 1/7 f_2 = 5/7 f_3 = 1/7$
APFB	$APFB = \sqrt{\left(\frac{\mu_{peak\_S}}{\mu_{peak\_O}} - 1\right)^2}$	Annual peak flow bias (Mizukami et al. 2019) μ_{peak_S}: Mean of the simulated annual flow series; μ_{peak_O}: Mean of the observed annual flow series.
RMSNE	$RMSNE = \sqrt{\sum_{i=1}^{n}\frac{1}{T_i}\left(\frac{S_{peak\_Ti} - O_{peak\_Ti}}{O_{peak\_Ti}}\right)^2}$	Root mean square normalized error. ANE corresponds to the case where i = 100 years S_{peak_Ti}: Simulated flood with i return period; O_{peak_Ti}: Observed flood with i return period; T_i: Return period. Here we considered i = 2, 5, 10, 20, 25, 50, 75 and 100 years.

- Median of output time series (nomenclature: MEDIAN. See, e.g., Fig. 4);
- Weighted mean with the calibration error (nomenclature: W.ERROR. See, e.g., Fig. 4);
- Weighted mean with the distance to the donors (nomenclature: W. DIST. See, e.g., Fig. 4).

Results were analysed for both reproduction of the daily runoff hydrograph and flood regionalisation by using the same error indicators calculated for the calibration phase and by also adding the percentage bias (PBias), the Pearson correlation coefficient (R^2) and the absolute normalised error for the T = 100 yr flood (ANE, (Salinas et al. 2013)), which is a particular case of the RMSNE but only considering the T = 100 yr flood (See Table 2). Notice that ANE, RMSNE, and APFB require the identification of flood events, which in this case was done with the annual maxima of each hydrological year (also known as the annual maximum series, AMS or block maxima in the literature). In particular, ANE and RMSNE require the extrapolation of floods statistics (for the T = 50; T = 75 and T = 100 yr flood), which in this case was done by adjusting the sample of annual maxima to a GEV distribution, whose parameters were calculated employing the L-Moments method (Hosking and Wallis 1997) and using the "extRemes" R package (Gilleland and Katz 2016). The same procedure was used to obtain the remaining flood quantiles of all other time series evaluated in this study.

Finally, results from the FFA under regionalisation were compared with one of the methods recommended by the Chilean engineering manual, in this case, the DGA-AC method (DGA 1995). The DGA-AC method is essentially an index-flood method, with the regional growth curve calibrated with catchments located within homogeneous regions and with the T = 10 yr flood as the index flood (which is regionalised using the corresponding precipitation with T = 10 yr, catchment area, and locally calibrated coefficients for three regions: North, Centre, and South). Other methods are available in the Chilean literature, including the rational formula and others based on synthetic unit hydrographs. However, because all of them required the computation of the concentration time, here we preferred the DGA-AC method due to its simplicity and deterministic nature (worth mentioning is that the concentration time has several additional subjective and wildly variable elements; see, e.g., (Grimaldi, Petroselli, and Serinaldi 2012; A. Efstratiadis et al. 2014).

3. Calibration-Validation and regionalisation results

3.1. Calibration-Validation results

Results of the calibration–validation phase are shown in Fig. 2, Fig. 3, Table A.1a, and Table A.1b (Appendix). Here we present the boxplots of the achieved A) KGE, B) NSE, C) PBias, and D) R^2 as measures of error in the reproduction of the daily runoff hydrograph when employing each type of the ten calibration criteria described before. Results are also separated by aridity (>1 or < 1), with approximately half of the catchments belonging to each of these groups (50 and 51, respectively).

Based on Fig. 2 and Fig. 3, there is a substantial difference in performance among all error measures (NSE, KGE, PBias, and R^2), both in terms of median and variability, with the best and less variable results achieved in low aridity catchments and with the worst and most variable results occurring in high aridity catchments. In particular, it can be seen that all calibration criteria result in NSE and KGE around and above 0.5 for low aridity catchments and 67%-98% (65%-96%) of catchments with NSE above 0 for calibration (validation). In contrast, their performance for high aridity catchments results in most median NSE and KGE around 0 and 32%-96% (19%-55%) catchments with NSE above 0 during calibration (validation). Most calibration criteria produce error measures that are more variable in validation than calibration. This situation is particularly notorious when looking at the resulting PBias in high aridity catchments. However, there are some situations where the variability is maintained and only the median performance changes (typically decreases). There are a few exceptions where the opposite is true. Most of the calibration criteria that produced the worst and most variable results were calibration criteria specialised for high flow reproduction (i.e., APFB, NSEw, and RMSNE). In particular, it was interesting to note that the KGE/KGE2012 variants typically achieved a worse performance than their original criteria, excepting the reproduction of the R^2, which is expected considering that both variants included in this study give more weight to this indicator, either directly in their formulations (Pearson factor) or indirectly through the standard deviation (alpha factor).

3.2. Regionalisation results

3.2.1. Selection of regionalisation conditions

When evaluating regionalisation, we need to consider the uncertainty due to the large amount of data resulting from each different modelling decision. In this case, we considered ten calibration criteria (objective functions), two regionalisation techniques (NN and PS), ten different combinations of donors (REG-D1 to REG-D10), and four different ways to estimate the donor ensemble's output (MEAN, MEDIAN, W.ERROR, and W.DIST). This led us to 800 different time series for each of the 101 catchments evaluated in this study. Additionally, as shown in the previous section, we have several available objective functions (both for daily hydrograph and flood statistics reproduction) to evaluate, which for pragmatic reasons, prevents us from evaluating case by case the impact of these modelling decisions. For this purpose, we reduced the problem's dimensionality by focusing on the following targets: i) central trend, and ii) spread of performance in reproducing flood statistics.

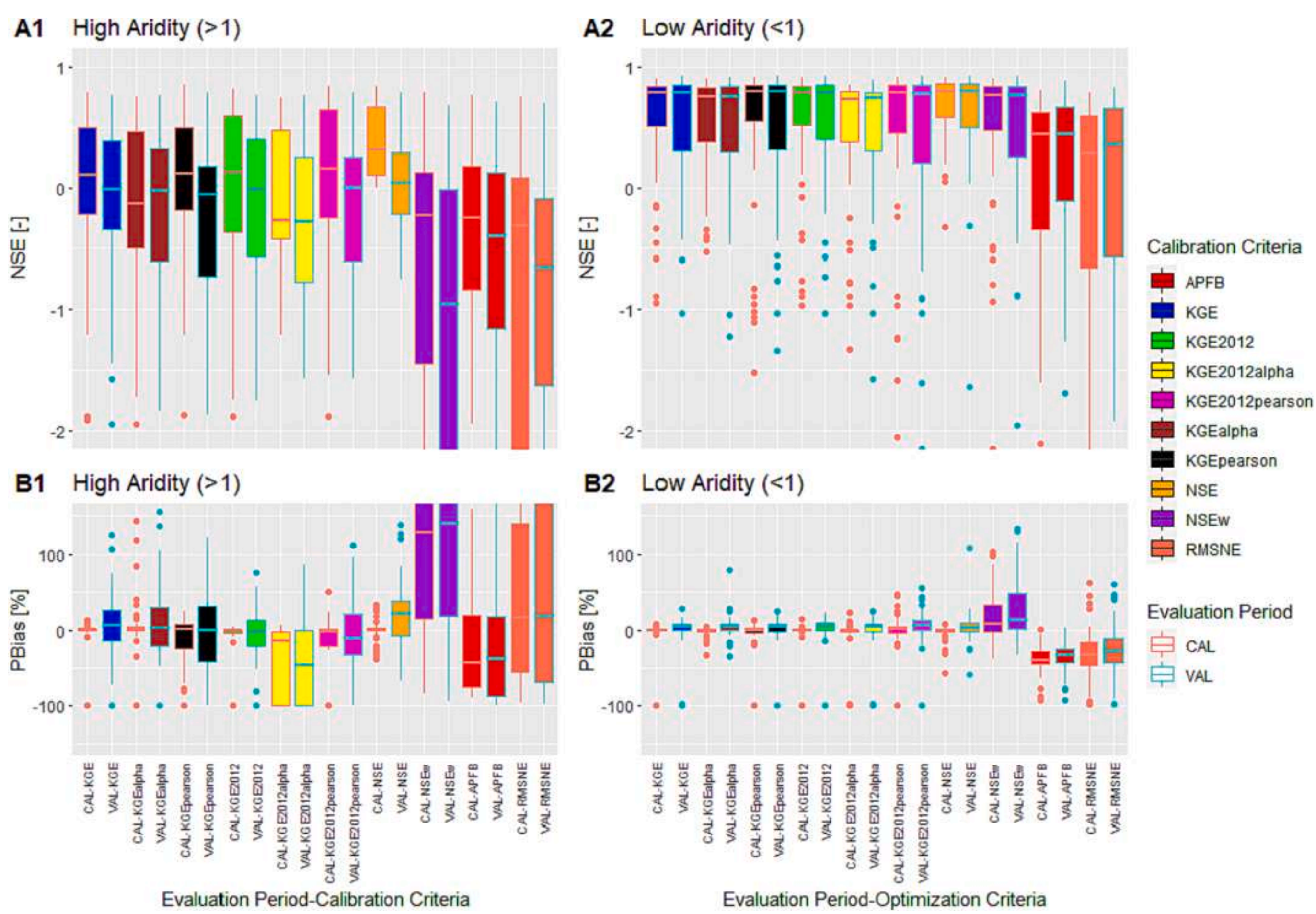

Fig. 2. Resulting A) NSE and B) PBias objective functions for Calibration (CAL) - Validation (VAL) of 1) High aridity (>1) and 2) Low aridity (<1) catchments. Note: This figure was truncated due to high variability in results.

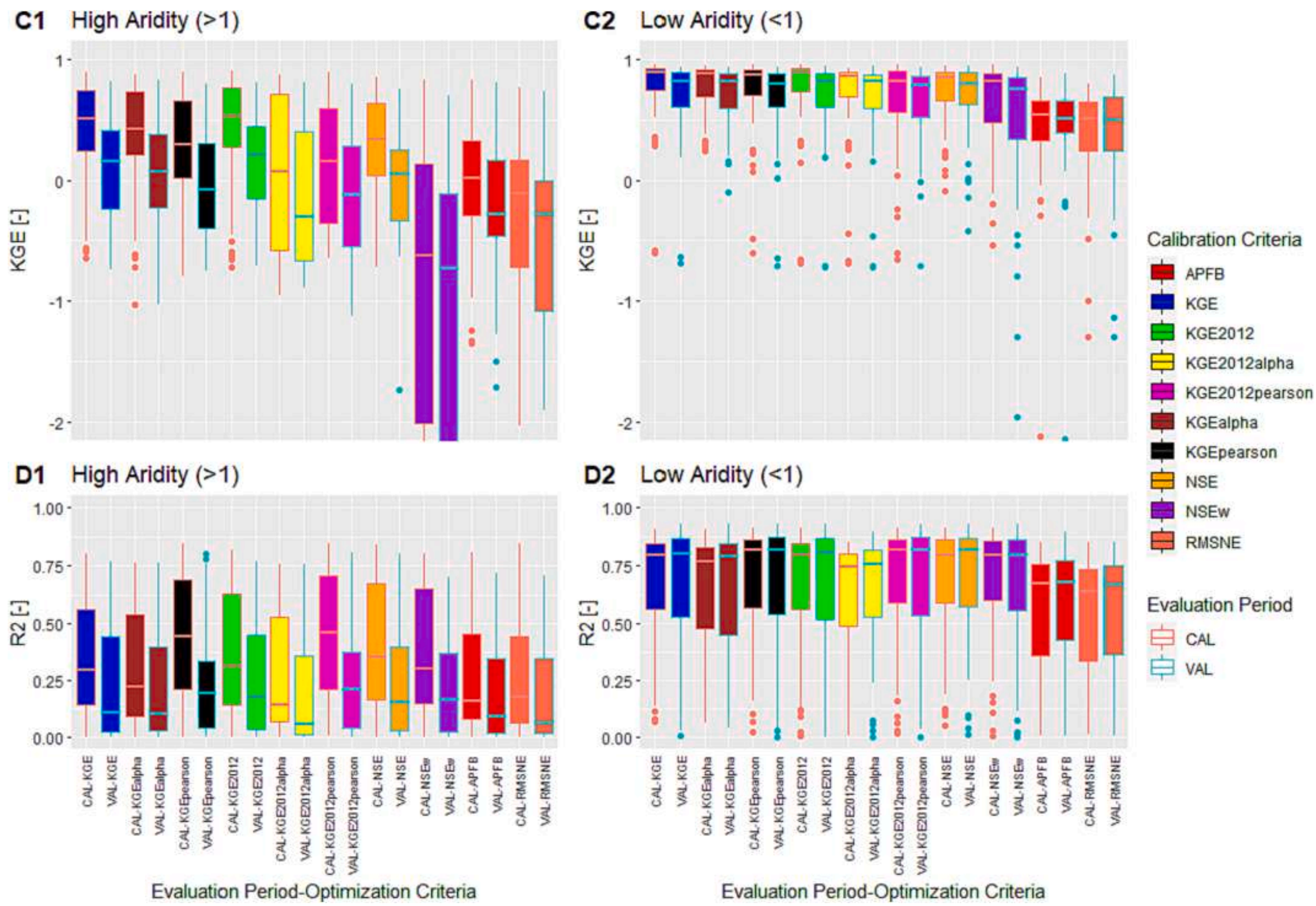

Fig. 3. Resulting C) KGE and D) R2 objective functions for Calibration (CAL) – Validation (VAL) of 1) High aridity (>1) and 2) Low aridity (<1) catchments. Note: This figure was truncated due to high variability in results.

With these in mind, we summarised the results of these different 800x101 time series in Fig. 4 and Fig. 5, where we present the median ANE and the Interquartile range (IQR) obtained by all high- and low-aridity catchments, and for all different: i) ways of averaging the outputs of each donor; ii) calibration criteria; iii) the number of donors; and, iv) regionalisation method. Considering that using short streamflow time series to compute floods with high return periods is surrounded by high uncertainty, the calibration and validation periods (CAL-VAL) were combined to increase the extrapolation reliability. So, in contrast to the results presented in the previous sections, where each series simulated either the calibration (1987–1997) or the validation (1998–2020) period, here, all results consider the full simulation of the available period (1987–2020). Notice that we included the DGA-AC method, which corresponds to one of Chile's recommended methods for flood regionalisation.

Fig. 4 and Fig. 5 show that there is a clear difference in the performance between the CAL-VAL simulated series, particularly the ones calibrated with the APFB and RMSNE flood-specific error indicators (which achieve the lowest errors), and the regionalised series, with the DGA-AC at the frontier between the two. However, even if this situation occurs for both types of aridity and different modelling decisions, we can see significant differences in the level of performance achieved between the different types of aridity (notice the different axis limits between the figures), and the way of averaging the series. For example, MEAN-High Aridity REG-D10 achieves similar performance to the DGA-AC (Fig. 4a). However, this situation does not occur in the other figures. In fact, there is no similar level of performance when employing the median (Fig. 4b), while W.DIST-High Aridity REG-D10 KGEalpha and the W.ERROR-High Aridity REG-D7-8 KGEalpha achieve similar performance to the DGA-AC (Fig. 4c and 4d). On the other hand, when looking at the low aridity catchments, the closest to the DGA-AC is the MEAN-Low Aridity REG-D9-10 RMSNE (Fig. 5a), while the MEDIAN-Low Aridity REG-D9-10 APFB (Fig. 5b), and the W.ERROR-Low Aridity REG-D5-6 RMSNE (Fig. 5d). Notice that we did not include a legend for the regionalisation method per se (NN or PS). In principle, each combination of calibration criteria and the number of donors (colour and shape) appears two times in each graph in Fig. 4 and Fig. 5. However, intercomparisons between them showed us that the NN typically outperforms the PS, with the settings selected in this study (selection of attributes and their normalization).

Additional analyses consider the NN regionalisation method with MEAN REG-D6 and their calibration error for the weighted average. This combination produces one of the best performances in low and high aridity catchments (Fig. 5d and Table A.2a from Appendix, and Fig. 4d and Table A.2b from Appendix, respectively) in terms of reduced ANE, but also produces a good performance in terms of other flood criteria such as the RMSNE and APFB. However, it must be mentioned that this selection does not account for the high uncertainty of the regionalisation process but is merely made for demonstration purposes.

3.2.2. *Regionalised runoff hydrograph*

In order to assess the performance of the regionalisation strategies in the reproduction of the daily hydrograph, we present the boxplots (Fig. 6 and Fig. 7) of the achieved a) KGE, b) NSE, c) PBias, and d) R^2, when employing each type of the ten objective functions described before, separated by aridity (>1 or < 1), similar to what was done for section

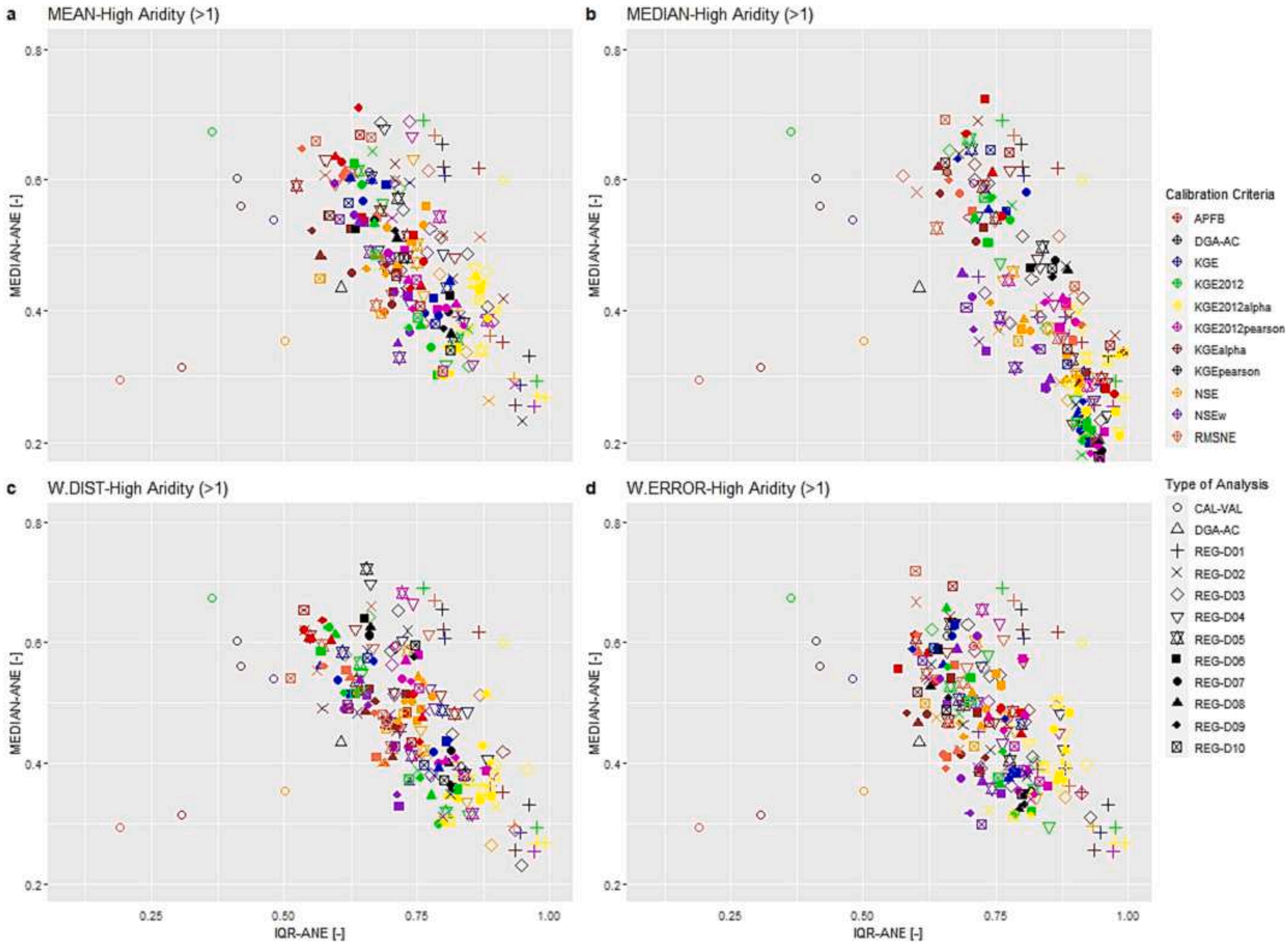

Fig. 4. Median and IQR of the ANE of high aridity (>1) catchments employing: Combined calibration and validation (CAL-VAL), Chilean recommended method for flood regionalisation (DGA-AC), and regionalisation with multiple calibration criteria (different colours), averaging method (a, b, c and d), and the number of donors (different shapes). Note: Legend for the regionalisation method per se (NN or PS) is not included explicitly.

3.2.1, but only comparing the performance during validation and regionalisation, for the period 1998–2020. Notice that here we are only showing the results of the NN regionalisation with MEAN REG-D6 because these regionalisation conditions achieved one of the best performances when reproducing flood statistics (particularly when employing donors whose parameters were calibrated with the RMSNE as shown in section 3.2.1). If other regionalisation conditions are chosen (based on the optimisation of other objective functions or other hydrological signatures), results would likely differ from those presented here.

Based on Fig. 6 and Fig. 7, regionalisation typically achieves a lower performance than validation, mainly in terms of median and IQR, with very few exceptions. This is a consistent result in the literature (Blöschl et al. 2013), although, as mentioned before, this does not occur in all cases (see R^2 and PBias for the model calibrated with the RMSNE for both types of aridity). Regarding regionalisation performance, around 12%-44% of the catchments achieve an NSE above 0 for high aridity, while 66%-82% of the catchments achieve an NSE above 0 for low aridity catchments. In terms of median change of performance (%) for arid (humid) catchments for each calibration criteria from validation to regionalisation (each with their corresponding calibration criteria), the median change is −17% (-8%) for the NSE; −47% (–22%) for the KGE; 38% (91%) for the Pbias; and, 4% (-1%) for the R^2. However, it is interesting to note that when evaluating low aridity catchments, both the NSE and KGE are above 0 and $1-\sqrt{2}$ (approx. −0.41), which implies that, despite this reduction of performance due to the regionalisation procedure, the model can still successfully lead to better performance than employing the mean observation as a predictor (Knoben, Freer, and Woods 2019).

3.2.3. Regionalised flood statistics

Although we already analysed the performance of the regionalisation to reproduce flood statistics in section 3.2.1, we only covered the median and IQR behaviour for the resulting ANE. The latter leaves the question of how the performance is for all catchments. To analyze this behaviour, Fig. 8 present the boxplots of the achieved RMSNE and ANE when employing each type of the ten objective functions for calibration–validation, regionalisation, and the DGA-AC method for high and low aridity catchments.

Based on Fig. 8, all models whose donors were regionalised with flood calibration criteria (NSEw, APFB, RMSNE, and KGE/KGE2012 variants) typically achieved the best median performance in reproducing flood objective functions (RMSNE and ANE) for both types of aridity. The RMSNE and KGEpearson achieved the best results for low and high aridity catchments, respectively. This is not a surprise because it is known in the literature that the best results of a specific signature are achieved when focusing the calibration on reproducing this specific signature (Haberlandt and Radtke 2014; Mizukami et al. 2019; Viviroli et al. 2009; Pool et al. 2017).

Worthy of notice is that similar to what was observed in the previous section for daily runoff hydrograph performance, the best and less

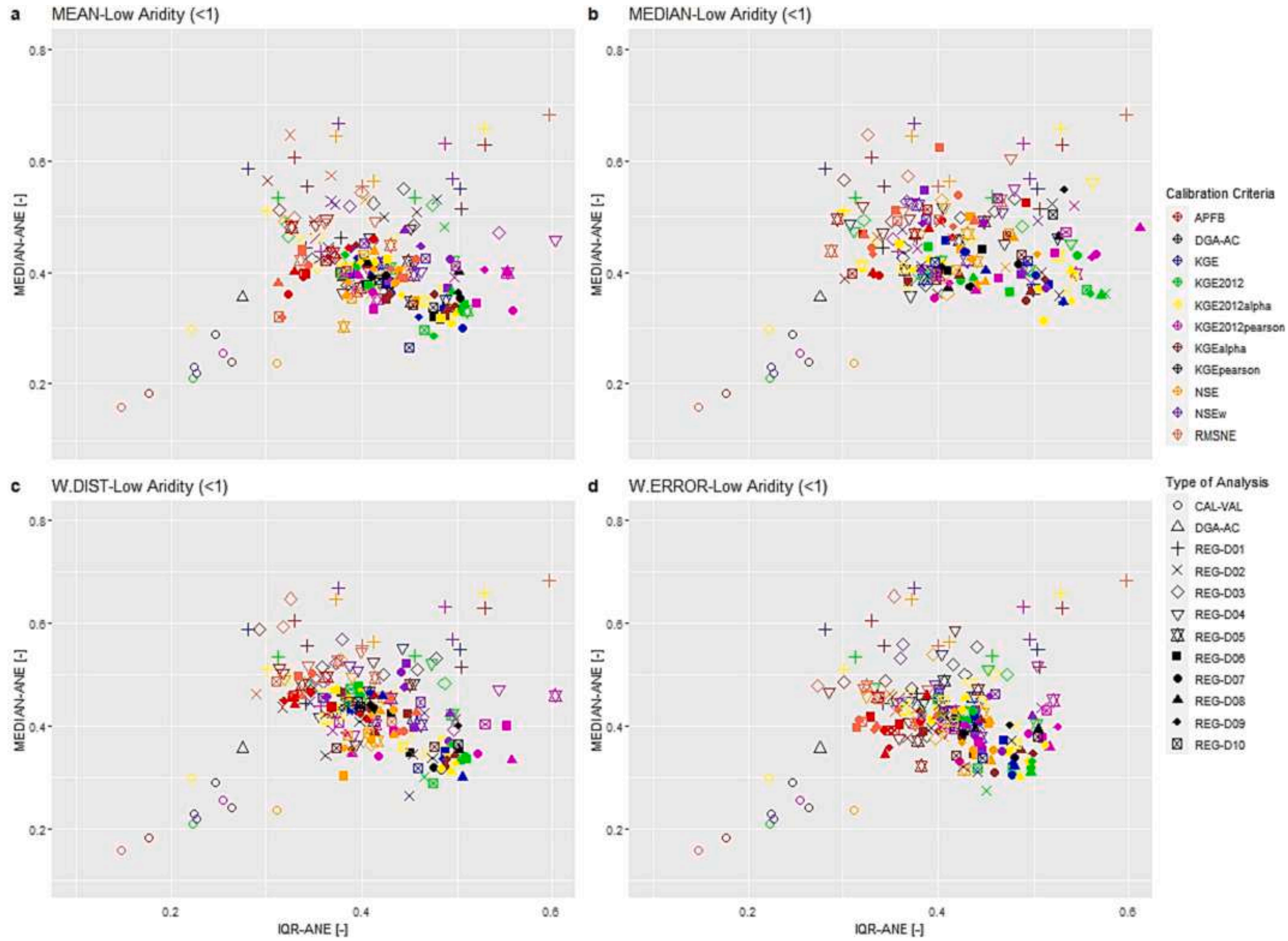

Fig. 5. Median and IQR of the ANE of low aridity (<1) catchments employing: Combined calibration and validation (CAL-VAL), Chilean recommended method for flood regionalisation (DGA-AC) and regionalisation with multiple calibration criteria (different colours), averaging method (a, b, c and d) and the number of donors (different shapes). Note: Legend for the regionalisation method per se (NN or PS) is not included explicitly.

variable performances are achieved for the low-aridity catchments. In contrast, the worst and most variable performances are achieved for the high-aridity catchments, suggesting other controlling dynamics that cannot be predicted with different calibration indicators. In fact, a quick review of the high aridity catchments with the consistently worst resulting flood error indicators showed us that they typically presented one (or many) of the following characteristics: 1) Pure Nivo-Glacial regime; 2) Regime change between calibration and validation period; 3) Only 1 or 2 flood events during the whole evaluation period; and, 4) Monsoon period (although this represents only a tiny sample of catchments). Unfortunately, because a deeper evaluation of these sources of error within the hydrological modelling of these highly arid catchments is beyond the scope of this study, further comments are avoided.

4. Discussion

4.1. The role of aridity

The aridity index was expected to have a significant role in model performance for calibration–validation and regionalisation. Indeed, our results showed significant differences between the two types of catchments in terms of median and IQR for all modelling conditions. In fact, our findings were immediately presented in terms of aridity (see Fig. 2 to Fig. 8). The latter was motivated by internal calculations showing that the aridity index consistently achieved high correlation (both Pearson and Spearman) with most of the objective functions employed (see Fig. A.1a and Fig. A.1b from Appendix). This result is consistent with the literature. For instance, Parajka et al. (2013), who developed a literature review of hydrograph prediction in ungauged basins, found better results for humid regions and larger catchments than for arid and smaller ones. Similar conclusions were found by Salinas et al. (2013), who reviewed flood and low-flow prediction studies. However, we also found a considerable uncertainty associated with the regionalisation procedure (see 3.2.1), which was not quantified here for brevity but needs to be considered to assess the robustness of regionalisation conclusions.

4.2. Calibration criteria

Regarding the use of different calibration criteria, we found that calibration on specific signatures increases performance on the regionalisation of that specific signature, which is a result already found in the literature (Viviroli et al. 2009), particularly during calibration–validation settings. Regarding the magnitude of our results, for almost all high-aridity catchments (and all tested modelling conditions), the NSE performance (for both calibration–validation and regionalisation) was below 0. The latter means that the mean value is a better predictor than the simulated one. However, it is interesting to note that while almost all arid catchments got an NSE below the mentioned threshold for runoff hydrograph reproduction, still a significant number of catchments (around half of the sample) achieved a similar and even

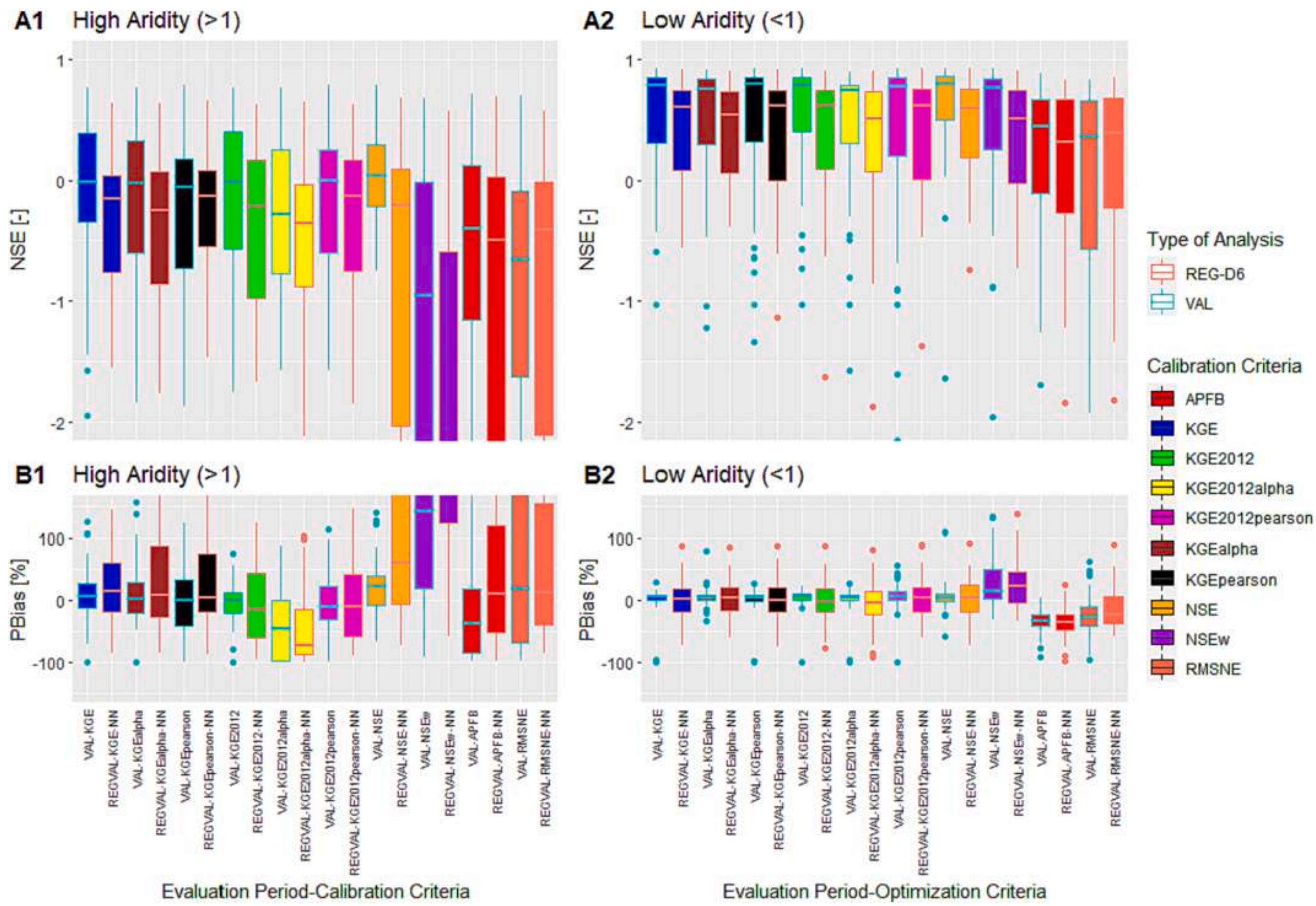

Fig. 6. Resulting A) NSE and B) PBias objective functions for Validation (VAL) - Regionalisation (REG) of 1) High aridity (>1) and 2) Low aridity (<1) catchments. Note: This figure was truncated due to high variability in results.

better flood regionalisation performance than the DGA-AC method (see Fig. 4 and Fig. 8, A1 and B1). This is quite a contradictory result because it implies that despite its low performance in reproducing the runoff hydrograph, the model is still helpful for flood regionalisation. However, this is not a fair comparison because the DGA-AC method is not recommended for these types of catchments (DGA 1995), particularly because this method was developed for floods generated by liquid precipitation, while we found several high-aridity catchments with nivo-glacial regimes. Additionally, the GR4J model has low performance in reproducing the hydrology of this kind of catchments, leaving us in a situation where even if the model predictions are helpful, it is likely to get these correct answers for the wrong reasons (Kirchner 2006). In any case, we found a different situation when looking at the performance of low-aridity catchments: almost all catchments achieved an NSE above 0. Similarly, the median ANE achieved for flood regionalisation of low-aridity catchments is similar to the DGA-AC value, although, as mentioned before, this performance varies depending on the calibration criteria and other regionalisation conditions. Overall, our regionalisation results for humid catchments can be considered acceptable (compared with those reported in the literature) and promising in re-evaluating and updating flood regionalisation techniques for Chilean engineers (Fernández and Gironás 2021), particularly in the context of the level of performance achieved (similar to the achieved by the established method) with only 11 years of data for single criteria calibration and with a deterministic-lumped model, working at daily resolution.

Regarding the calibration criteria, the best results for flood regionalisation were achieved for the donors whose model was calibrated with the RMSNE (and to a minor degree using the APFB), above other objective functions such as the NSEw and the KGE/KGE2012 variants. The latter is somehow expected, considering that this indicator explicitly incorporates flood statistics errors in its formulation. This supports the findings of Haberlandt and Radtke (2014), who also obtained better reproduction of the flood frequency distribution when explicitly including this item in the calibration of the model as part of the objective function. The findings of Mizukami et al. (2019) are also aligned with our results (they also tested the APFB, the NSE and the KGE for a large sample of catchments in the USA using two distributed hydrological models and found the best performance in reproducing floods when employing the APFB). On this matter, it was interesting also to note that while the KGE/KGE2012 variants employed here typically achieved a lower performance than their original counterparts in calibration/validation settings, they also achieved some of the best-worst performances for regionalisation, mainly on high aridity catchments. However, results may be misread because performance on these catchments was poor overall. On a similar note, while KGE, KGE2012, and their variants are very similar in their formulations, the levels of performance achieved were notably different, indicating that for modelling purposes (particularly for regionalisation), they can be considered as totally different calibration criteria. A similar comment can be made regarding the NSE and NSEw, which not only achieved contrasting results (best-worst respectively for specific objective functions and vice versa), but contrary to our expectations, did not achieve a better performance reproducing flood statistics than the other tested calibration criteria (neither in calibration–validation nor in regionalisation).

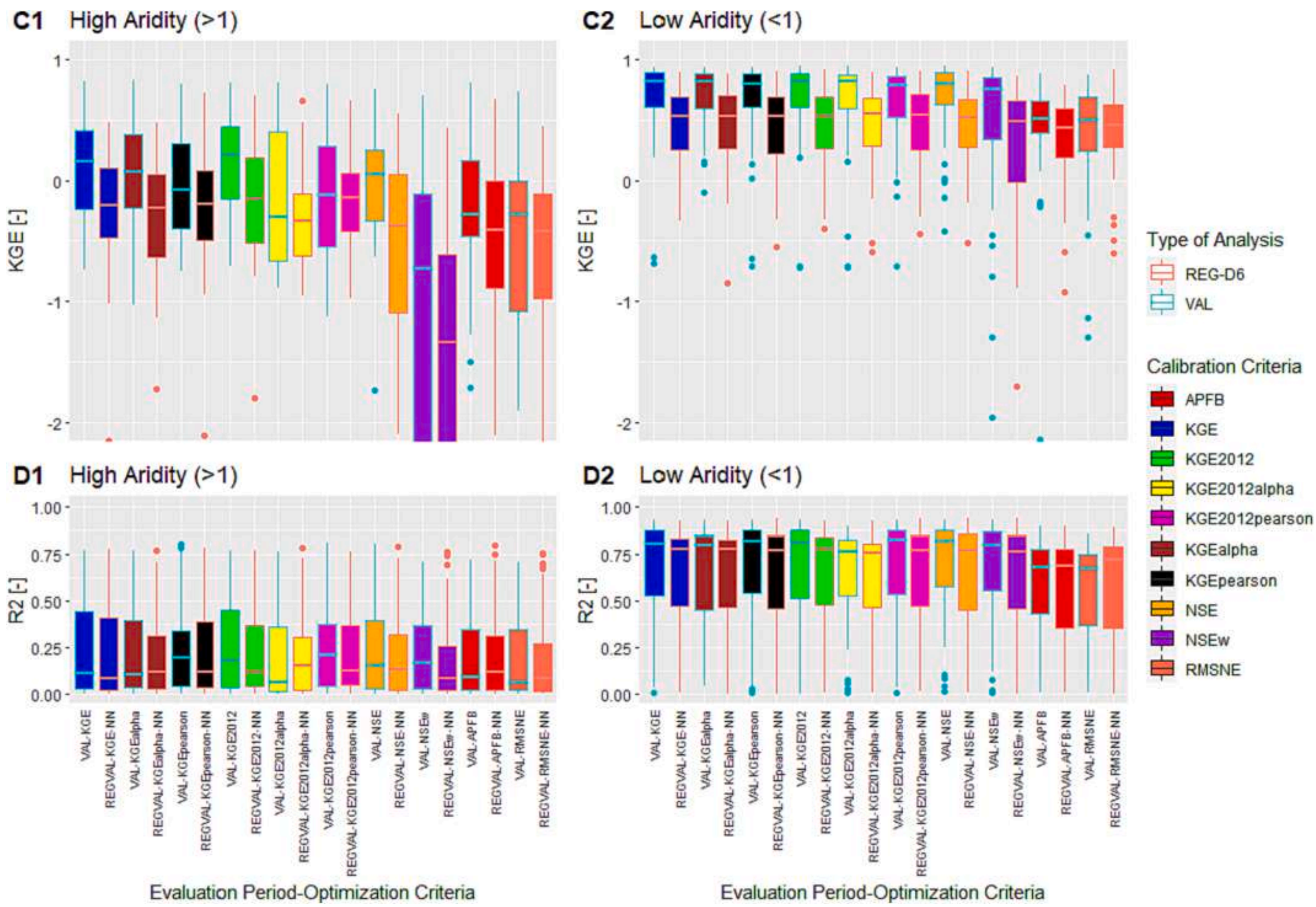

Fig. 7. Resulting C) KGE and D) R2 objective functions for Validation (VAL) - Regionalisation (REG) of 1) High aridity (>1) and 2) Low aridity (<1) catchments. Note: This figure was truncated due to high variability in results.

4.3. Regionalisation methods

Our results support the fact that regionalisation based on NN tends to beat those based on PS, which is also a consistent finding in the literature (Oudin et al. 2008; Neri, Parajka, and Toth 2020); but contrasting the results found by Baez-Villanueva et al. 2021) also for Chile (although this may be attributed to different methodologies between studies). Based on Oudin et al. 2008; Neri, Parajka, and Toth 2020; Lebecherel, Andréassian, and Perrin 2016), the performance of these regionalisation methods (particularly NN) strongly depends on gauge density, being higher for spatial proximity but similar when this density decreases to<0.6 per 1,000 km^2. In this case, the NN regionalisation method consistently outperformed PS in daily hydrograph reproduction and flood statistics. The mean station density corresponding to the entire area of the study corresponded to 1.3 per 1,000 km^2, which is above the threshold where these two methods start to converge. We highlight that this station density greatly varies across regions (employing regional borders, ranging from 0.7 per 1,000 km^2 to 6.2 per 1,000 km^2, i.e. still above the threshold where NN outperforms PS). However, internal calculations found that PS results are susceptible to the chosen similarity criteria, although none consistently beat the NN for all the combinations tested in this study.

5. Limitations

Although highly relevant, the following elements were considered beyond the scope of this study: i) Comparison with additional flood regionalisation methods such as the ones described in the literature review section (e.g., index-flood, geostatistics, among others), and ii) Uncertainty assessment.

5.1. Additional flood regionalisation methods

Regarding comparisons with other flood regionalisation methods, we already mentioned a clear preference for employing continuous simulation for daily hydrograph and statistical methods for flood regionalisation. Because of this division, the number of publications where there is a direct comparison between continuous simulation and other methods is relatively small. As far as we know, this comparison was made by Lamb and Kay 2004; Moretti and Montanari 2008; Viviroli et al. 2009; S. Grimaldi, Petroselli, and Serinaldi 2012; Grimaldi et al. 2013; Biondi and Luca, 2015; Grimaldi et al. 2021). Similar to this study, their comparisons were also made with relatively simple event-based methods (rational formula) and flood transposition. Some of these methods may be considered the selected design approach in several countries; it is essential to acknowledge that more complex methods are already available in the literature for flood regionalisation (Salinas et al. 2013). Then, there is a solid motivation to produce more comparisons between these different techniques to assess the benefits/weaknesses of the continuous simulation approach versus the alternatives. However, we believe that the utility of process-based methods such as the continuous simulation approach can be found not only in pragmatic terms (potentially better results than its alternatives) but also in terms of increased knowledge of hydrological processes. For example, Rogger et al., 2012a) found usefulness in introducing the derived flood frequency analysis, in terms of complementary information for design

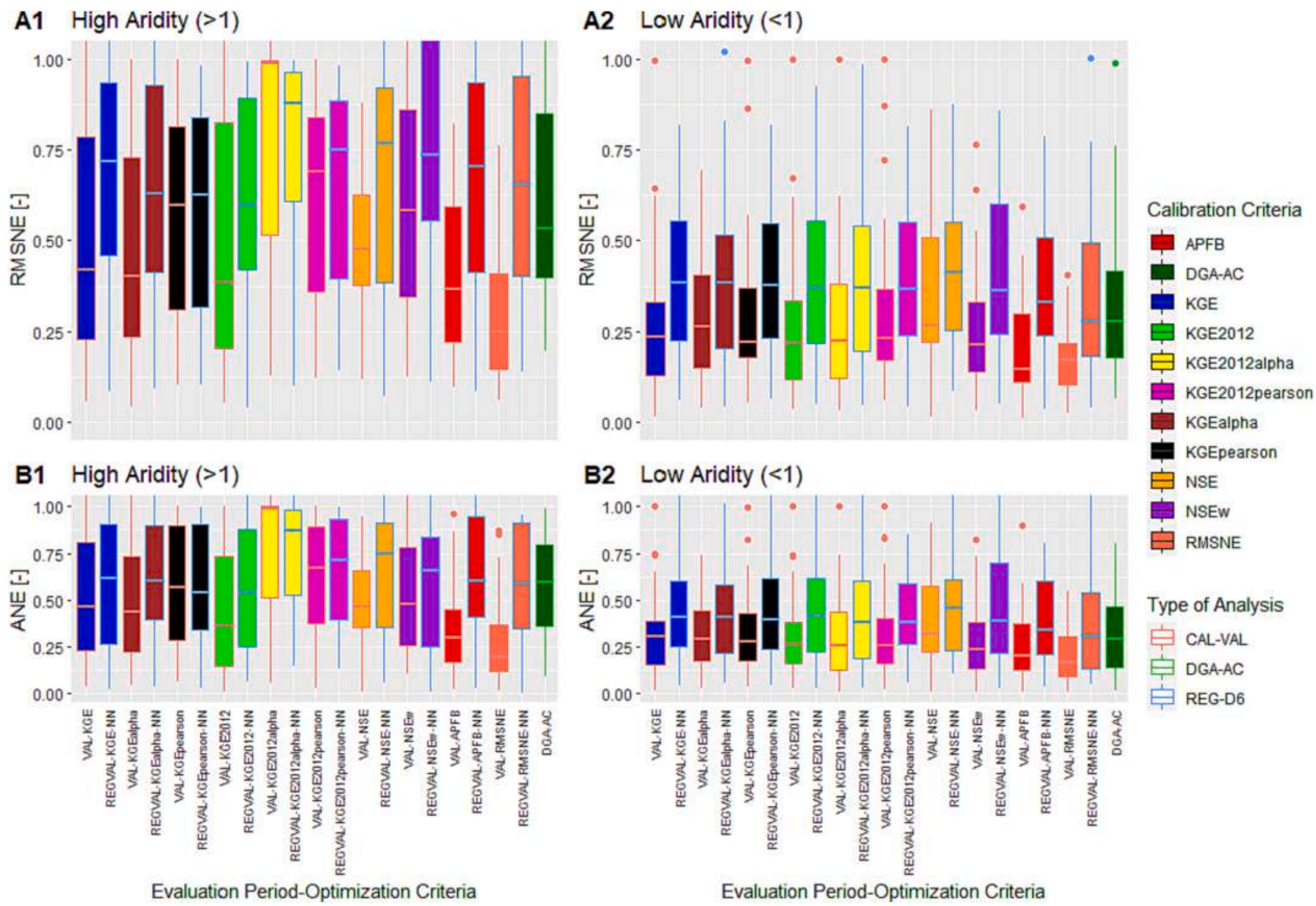

Fig. 8. Resulting A) RMSNE and B) ANE objective functions for Validation (VAL) - Regionalisation (REG) - Chilean recommended method for flood regionalisation (DGA-AC) of 1) High aridity (>1) and 2) Low aridity (<1) catchments. Note: This figure was truncated due to high variability in results.

purposes and gaining deeper insight into the flood-generating processes. Additionally, in the same study and previous work by Rogger et al., 2012b), they found discontinuities in the flood distribution for high return periods (around T = 30 yr), which they attributed to threshold behaviour when soil moisture storage was exceeded. The event-based methodology was not able to reproduce this finding that was only detected by the continuous simulation approach (adding Monte Carlo analysis with synthetic data). The latter showed the utility of the continuous simulation method for improved flood frequency assessment, which can also be extrapolated for flood regionalisation applications.

5.2. Uncertainty assessment

Regarding uncertainty assessment, we could employ the “cascades of uncertainty” framework (Smith et al. 2018), typically used in the context of climate change impacts (Clark et al. 2016), in order to identify the sources of uncertainty in these types of study. These are typically associated with uncertainties in the data inputs, model parameters (calibration process), and model structure (Beven and Binley 2014; Mai, Craig, and Tolson 2020; Moges et al., 2020). Additionally, we also need to include uncertainty regarding the regionalisation process and the FFA procedure regarding the statistical extrapolation approach, the distribution choice, and the parameter estimation method. Regarding these sources of uncertainty, notice that individual assessments of uncertainty within the model structure, model parameters or data inputs are not the same as uncertainty assessments of the model outputs (Montanari 2007). And while the former can be combined to form the latter within the context of chaining uncertainty with a Monte Carlo approach (McMillan, Westerberg, and Krueger 2018), by assuming the uncertainty model (statistics) of the input and the system (such as the GLUE framework, Beven and Binley 2014), or with Bayesian analysis, (Schoups and Vrugt 2010; Sadegh and Vrugt 2014), the latter can also be analysed independently with a post-process approach, by using the statistics of the model error (Sikorska, Montanari, and Koutsoyiannis 2015; Koutsoyiannis and Montanari 2022). Such distinction is relevant because while from a purely theoretical perspective, there is not enough research to say which approach is better, we can infer that, from a pragmatic perspective, the post-process approaches have limited utility when evaluated in regionalisation studies (Montanari 2007), given the inherent lack of streamflow data for their use (unless we could find ways to regionalise these post-process uncertainty assessments themselves).

Here, we will limit ourselves to exclusively discussing the FFA uncertainty for brevity. For further discussions on the other elements of the cascade of uncertainty, the reader is referred to (Müller-Thomy and Sikorska-Senoner 2019; Clark et al. 2021) for data input uncertainty and error indicator uncertainty, respectively; (Clark et al. 2015) for modelling frameworks, which address model structure uncertainty; (Efstratiadis and Koutsoyiannis 2010) for multicriteria/multivariable calibration modelling, which addresses parameter uncertainty; and, (Montanari and Koutsoyiannis 2012; Sikorska-Senoner, Schaefli, and Seibert 2020) for stochastic and ensemble modelling respectively, which address the problem of uncertainty quantification.

Regarding uncertainty within the FFA, this manuscript only applied the AMS method, mainly for reasons of simplicity over the alternatives, such as the Partial Duration Series (PDS, also known as peak over threshold (POT) in the literature) due to additional methodological uncertainties associated with the estimation of the latter (Madsen, Pearson, and Rosbjerg 1997), although the PDS allows the use of more than one flood per year. Alternatively, we could also have mixed distributions, which account for different flood-generating mechanisms either: a) indirectly by separating events depending on seasonality (seasonal maxima), such as the seasonal mixture model (Fischer 2018); b) directly by employing some flood typology or classification method to separate heterogeneous flood events into homogeneous groups (Barth, Villarini, and White 2019; Fischer and Schumann 2021; Yan et al. 2019). Alternatively, we could employ entirely different approaches to FFA, such as the Metastatistical Extreme value distributions (Miniussi, Marani, and Villarini 2020); or the Complete Time-series Analysis (Volpi et al. 2019), whose methodologies include the use of all ordinary peaks instead of just selecting the events resulting from applying the AMS or PDS framework. Unfortunately, a comparison or a deeper analysis of these sources of uncertainty could not be made in this study, but we highlight the advantage of using the continuous simulation approach in all the potential scenarios recently mentioned because of its capabilities for giving the full runoff hydrograph, allowing to extract of a more significant number of flood peaks (in case PDS or meta statistical distributions are used) and because it gives enough information to account for flood generation mechanism (in case of a flood typology scheme is required). Additionally, notice that only one parameter estimation method (L-moments method) and only one flood distribution (GEV) were used, and no sensitivity analysis of their choice was performed due to the increasing complexity of the analysis (despite the literature showing that these choices are relevant, depending on the parent distribution, fitted distribution, its parameters, the method for calculation of the parameters, the target return period and the sample size. See Madsen et al., 1997 and references therein).

6. Conclusions

Continuous simulation was tested to assess its ability for flood estimation in ungauged locations. The approach involves the use of mathematical models to simulate the hydrological response of the catchment over time, allowing for the prediction of flood events as well as flood risk management and mitigation. Continental Chile was taken into consideration as case study because of its varied climates (from north to south) and elevation gradients (from west to east). In total, 101 catchments were analysed. The GR4J hydrological model coupled with the CemaNeige snow module was used for this purpose. Ten different objective functions were adopted for calibration purposes and two regionalisation methods were considered (nearest neighbour: NN; and, physical similarity: PS). 80,800 (800 time series $\times$ 101 catchments) time series of simulated streamflow were generated for regionalisation analyses. Results reinforced that reproduction of flood characteristics depends on the objective function. Our findings also showed that NN typically outperforms PS with the settings selected in this study (selection of attributes and their normalisation), and our regionalisation results were in close agreement with those from one of the currently recommended methods by Chilean engineering for flood regionalisation (DGA-AC) which is an index-flood method.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The code used in this study as well as the findings are available in Pablo Acuña, & Alonso Pizarro. (2022). Data, codes, and analyses for “Can continuous simulation be used as an alternative for flood regionalisation? A large sample example from Chile”. Zenodo. https://doi.org/10.5281/zenodo.6774560

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2023.130118.

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