On the selection of precipitation products for the regionalisation of hydrological model parameters

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Abstract.

Over the past <u>yearsdecades</u>, novel parameter regionalisation techniques have been developed to predict streamflow in datascarce regions. In this paper, we examined how the choice of gridded daily precipitation (P) products affects individual eatchment calibration and verification, as well as the relative performance of three well-known <u>parameter</u> regionalisation

- 5 techniques (spatial proximity, feature similarity, and parameter regression) over 100 near-natural catchments with diverse hydrological regimes across Chile. We configured set up and calibrated a conceptual semi-distributed HBV-like hydrological model (TUWmodel) for each catchment, using four *P* products (ERA5, CR2MET, RF-MEP, ERA5, and MSWEPv2-8, RF-MEPv2, and CR2MET), and two objective functions. The three regionalisation techniques were applied and evaluated for each combination of *P* product and objective function, using -8). We assessed the ability of these regionalisation techniques
- 10 to transfer the parameters of a rainfall-runoff model, implementing a leave-one-out cross-validation procedure for each P product. Despite differences in the spatio-temporal distribution of P-quantities, all P, all products provided good performance during calibration (median KGE's > 0.77), two independent verification periods (median KGE's > 0.70 and 0.61, for near normal and dry conditions, respectively), and regionalisation results (with (median KGE's for the best method ranging from 0.56 to 0.63). Our results suggest that We show how model calibration is able to compensate, to some extent, differ-
- 15 ences between forcing datasets, and that the spatial resolution of P products does not substantially affect the regionalisation performanceforcings by adjusting model parameters, and thus the water balance components. Overall, feature similarity provided the best results, followed elosely by spatial proximity, while parameter regression performed the worst, thus resulted in the worst performance, reinforcing the importance of transferring complete model parameter sets to ungauged catchments. Our results suggest that: *i*) merging *P* products and ground-based measurements does not necessarily translate into an im-
- 20 proved hydrological modelling hydrologic model performance; *ii*) the spatial resolution of *P* products does not substantially affect the regionalisation performance; *iii*) a *P* product that provides the best individual model performance during calibration and verification does not necessarily provide yield the best performance in terms of parameter regionalisation; and *iii*) the

hydrological regime affects *iv*) the model parameters and the performance of regionalisation methods , with rain-dominated eatchments with a snow component performing the best over Chile are affected by the hydrological regime, with the best results

25 for spatial proximity and feature similarity - obtained for rain-dominated catchments with a minor snowmelt component.

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1 Introduction

Daily streamflow (Q) data are crucial for a wide range of scientific and operational water resources applications, such as climate change impact assessment (e.g., Kling et al., 2012; Rojas et al., 2013; Mendoza et al., 2016; Galleguillos et al., 2021), Q and

- 30 flood forecasting (e.g., Clark and Hay, 2004; Addor et al., 2011; Coughlan de Perez et al., 2016; Sharma et al., 2018), and catchment classification (e.g., Wagener et al., 2007; Sawicz et al., 2011; Kuentz et al., 2017; Jehn et al., 2020), among others. *Q* is typically estimated through the implementation of hydrological models, which rely on parameters to represent hypotheses about the dominant processes in a catchment (Beven, 2006). In most cases, these parameters cannot be measured at the scales relevant for model applications (Beven, 1989; Uhlenbrook et al., 1999; Beven, 2000; Wagener et al., 2001), and are therefore estimated
- 35 through model calibration. To this end, optimisation techniques are used to provide reliable estimates of model parameters, requiring the comparison of observed *Q* against simulated *Q* data (Duan et al., 1992; Yapo et al., 1998; Vrugt et al., 2003, 2009; Pokhrel et al., 2012; Shafii and Tolson, 2015; Pool et al., 2017). Because the vast majority of streams worldwide are remain ungauged (Young, 2006; Beck et al., 2016), the scientific initiative Prediction in Ungauged Basins (PUB; see review by Hrachowitz et al., 2013) has fostered the development of novel regionalisation techniques
- 40 to predict Q in ungauged basins, a task that is far from complete (Yang et al., 2019; Dallery et al., 2020). The spatial transfer of hydrological model parameters from monitored to ungauged catchments, a process known as regionalisation (Oudin et al., 2008), therefore remains an active research topic (see review by Guo et al., 2021).

In the hydrological modelling literature, there are three main regionalisation approaches (Oudin et al., 2008; Parajka et al., 2013): *i*) spatial proximity; *ii*) feature similarity; and *iii*) parameter regression. Spatial proximity assumes that climatic and

- 45 physiographic characteristics are relatively homogeneous within a region and, therefore, neighbouring catchments exhibit similar hydrological behaviour (Vandewiele and Elias, 1995; Oudin et al., 2008). Although this method requires a dense network of gauging stations to perform well, it may lead to inadequate representations of rainfall-runoff behaviour over areas with heterogeneous climate and geomorphological characteristics (Beck et al., 2016). Feature similarity techniques transfer calibrated model parameter sets from donor to ungauged catchments based on geomorphological and climatic similarities (McIntyre et al.,
- 50 2005; Beck et al., 2016; Carrillo et al., 2011). Finally, parameter regression methods develop statistical relationships between calibrated model parameters and catchment characteristics, which are subsequently used to estimate parameter values for ungauged catchments (Fernandez et al., 2000; Carrillo et al., 2011). Recently, Samaniego et al. (2010) and Beck et al. (2020a) applied multiscale parameter regionalisation techniques that link model parameters to predictors related to geomorphological

and climatological characteristics by optimising coefficients in transfer equations which helps to account for problems re-

lated with to equifinality. The performances of these three regionalisation techniques vary due to many factors, including the 55 selected sample of catchments, the presence of nested catchments, hydroclimatic conditions, physiographic catchment properties, model configuration (including meteorological forcings, model structure, and simulation setup), and evaluation criteria (Parajka et al., 2013; Guo et al., 2021; Neri et al., 2020)(Parajka et al., 2013; Neri et al., 2020; Guo et al., 2021).

Most regionalisation studies have been conducted over regions with a dense network of meteorological stations (see Table 1), including Europe (e.g., McIntvre et al., 2005; Parajka et al., 2005; Oudin et al., 2008; Singh et al., 2012; Zelelew and 60

- Alfredsen, 2014; Garambois et al., 2015; Rakovec et al., 2016; Neri et al., 2020), the conterminous United States (Athira et al., 2016; Saadi et al., 2019), India (Swain and Patra, 2017), and China (Bao et al., 2012). However, in developing countries, P has traditionally been estimated through interpolation within sparse rain gauge networks, which is subject to large uncertainties (Villarini and Krajewski, 2008; Hofstra et al., 2010; Woldemeskel et al., 2013; Adhikary et al., 2015; Xavier et al., 2016)(Hofstra et al., 2010)
- , hindering an accurate spatio-temporal representation of P patterns. Over the last decades, the emergence of near-global and 65 high-resolution gridded P products has introduced new possibilities for hydrological modelling in data-scarce regions (Maggioni and Massari, 2018; Sun et al., 2018), despite these products still being affected by systematic, random, and detection errors (Ren and Li, 2007; Sevruk et al., 2009; Zambrano-Bigiarini et al., 2017; Baez-Villanueva et al., 2018), which are more pronounced over mountainous regions (Maggioni and Massari, 2018; Beck et al., 2019). Although hydrological model calibra-
- 70 tion can partly compensate for errors in the representation of P (Elsner et al., 2014; Maggioni and Massari, 2018), this may lead to unrealistic model behaviour (Nikolopoulos et al., 2013; Xue et al., 2013; Ciabatta et al., 2016), thus affecting the quality of parameter regionalisation results.

To date, few regionalisation studies have used gridded P products at the daily time scale. Beck et al. (2016) used the Climate Prediction Center unified gauge-based P product (CPC) to provide spatially distributed HBV parameters at the global scale.

- They selected CPC because it yielded better performance than ERA-Interim during calibration. Rakovec et al. (2016) used the 75 European daily high-resolution gridded dataset (E-OBSv8.0) to force a mesoscale hydrological model over 400 catchments in Europe, providing regionalised model parameters through a multivariate parameter estimation technique. More recently, Beck et al. (2020a) combined MSWEPv2.2 with a novel multiscale parameter regionalisation approach to provide global gridded parameter estimates using daily Q observations from 4,229 catchments. Although these studies have successfully used gridded 80 P products for parameter regionalisation, they only selected one product, and thus the effects that the choice of a P dataset can

have on regionalisation results remains unknown. This study aims to answer the following questions:

i) to what extent does the choice of gridded P forcing used in calibration affect the relative performance of regionalisation techniques?

ii) how does this relative performance vary across catchments with different hydrological regimes?

Table 1. Summ regionalisation	lary of sel((MPR). TI	ected regionalisatior. his study has been ac	t studies the studies studies the studies studies the studies stu Studies studies	at used spatial proximity (SP), feature similarity (FS), parameter regression (PR), or multiscale parameter mpleteness.
Study	Region	Catchments (donor / evaluation)	Approach	Relevant conclusion
McIntyre et al. (2005)	United Kingdom	127 / Leave-one-out cross-validation	SP and FS	The transfer of complete model parameter sets increased the performance of regionalisation. The use of the 10 best model parameter sets provided a more robust representation of flood peaks and generated a better ensemble of the overall flow regime, although flow peaks were underestimated. A
)			comparison against the PR approach showed that FS produced better results.
Parajka et al. (2005)	Austria	320 / Jack-knife Leave-one-out cross-	SP, FS, and PR	All methods performed better than the average of the model parameters of all catchments. Two methods performed the best: FS and any SP kriging approach, where the model parameters were regionalised independently based on their spatial correlation. Local regression methods outperformed the
		validation		global regression method, highlighting the importance of accounting for regional differences during PR.
Oudin et al. (2008)	France	913 / Jack knife	SP, FS and pp	SP performed the best, followed closely by FS. The reduced performance of FS was attributed to the lack of soil-related properties used as inputs. To
		validation	AL A	construct the ensemble output using mutuple calcinnents, averaging the Q time series performed benefit than averaging the model parameters. They concluded that the dense network of calcinnents favoured the SP method.
Samaniego et al.	Germany	1 / 10 stations within	MPR	The MPR method showed improved results compared to the standard PR when the global parameters were calibrated at a coarser modelling scale and
(2010)		the study area		then transferred to a finer one.
Bao et al. (2012)	China	55 / Leave-one-out	FS and PR	FS outperformed PR over both humid and arid regions. Moving from humid to arid regions, the degree to which the FS approach outperformed PR
Zelelew and Al-	Southern	cross-vandation 11 / Jack-knife	SP and FS	increased. The ensemble of the 10 most similar catchments outperformed the other approaches (the performance increased when 2–6 catchments were used).
fredsen (2014)	Norway	Leave-one-out cross-		They recommended identifying the parameters that influence the model response in order to minimise the model parametric dimensionality.
	1		00 F 00	
Garambois et al.	Southern	I6 / Jack-knile Leave-one-out cross-	SP and FS	FS outperformed SP. They reported only a small decrease of performance from calibration/ventication to regionalisation (~ 10%) when evaluated during flach flood avoids 1 [cing on assembla of 2.4 donor catchments vielded the best the review alisation performance. Using well-modelled catchments does
(0107)	1.1alloc	validation		nan nove events. Come an ensemble of 2-4 event electricents pretectine ossi un regionansation periormance. Come wer-movered calcriments occa not always produce good performances during regionalisation and parameter sets from low performing calchments can produce higher performances
				when transferred to ungauged settings.
Athira et al. (2016)	Contermino	us 8 / Leave-one-out	PR	The parameter values using multi-linear regression models were different to those obtained through model calibration, indicating the deficiency of
	NSA	cross-validation		regionalising the parameters directly as a function of catchment attributes. For the one catchment where SP was also tested, PR performed better.
Beck et al. (2016)	Global	674 / 1,113; indepen-	FS	The derived global maps of HBV parameter sets conform well with large-scale climate patterns, demonstrating demonstrating the effect of climate on interferences and the set of adverses to configure of and a more (seen to demonstration) supported to the set of
		uent evaluation		ratinati-turoit patterns. For 75% or carcinitens, ute averaging or mover ourputs (nom 10 donor carcinitens) outperformer the use or spatiarly uniform parameters. P underestimation appeared to be the dominant cause of low calibration scores, particularly for tropical and arid catchments.
Rakovec et al.	Europe	36 / 400, cross-	MPR	The model performed well in simulating daily Q over a wide range of physiographic and climatic conditions, with the median of KGEvalues-median
(2016)		validation		KGE's greater than 0.55. This performance reduced in heavily regulated catchments. Further evaluation against complementary datasets showed the
				best agreement for ET, followed by TWS, and the lowest for SM.
Swain and Patra	India	32 / Leave-one-out	SP, FS, and	SP (both kriging and IDW) outperformed PR and FS. The methods were evaluated against a global mean approach, which produced worse results than
(2017)		cross-validation	PR	all tested regionalisation methods.
Neri et al. (2020)-	Global	4,229 / Ten-told cross-	MPR	They incorporated within-catchment variability in climate and landscape, and yielded an improvement in 88% of the catchments (median KGE'
Austria 209 /		Validation		improved from 0.19 to 0.46). They found a weak positive correlation between regionalisation performance and catchment humidity. Considerable immenements were obtained for orighments located both near and for from these used for excitninging
Leave-one-out				пирточеннень were обащее гот саксиптены тосавее вош пеат али гат итоти циже иже пот ориппзацоп-д у запицатоп региотпансе was всем и пиппи телетот на чотот ја од состото
eross validation SP				regions and worst in and regions.
and FS Compared				
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the regionalisation				
performance using				
the TUWmodel				
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GR6J model. With				

85 2 Study area and selection of catchments

Our study domain is continental Chile (Figure 1), which is bounded to the west by the Pacific Ocean, to the north by Peru, and to the east by Bolivia and Argentina. The territory spans 4300 km of latitudinal extension $(17.5^{\circ}S-56.0^{\circ}S)$ and on average 180 km of longitudinal extension $(76.0^{\circ}W-66.0^{\circ}W)$, with elevation (Jarvis et al., 2008) ranging from 0 to 6892 m a.s.l. in the Andean Andes Mountains. Figure 1 shows the elevation, land cover (Zhao et al., 2016), hydrological regime (classified through visual

- 90 screening of the mean monthly Q), and the Köppen-Geiger climate classification (Beck et al., 2018), and hydrological regimes for the five major macroclimatic zones presented in Zambrano-Bigiarini et al. (2017). A large variety of climates are present across the country, with the macroclimatic zones transitioning from the (hyper)arid and semi-arid climates in the northFar North (17.50–26.00°S) and Near North (26.00–32.18°S), through temperate climates in central Chile Central Chile (32.18–36.40°S), to more humid and polar climates in the southSouth (36.40–43.70°S) and Far South (43.70–56.00°S). P increases with altitude
- and latitude (in the southern direction) ranging from almost zero in the Atacama Desert to \sim 6000 mm yr⁻¹ in the surroundings of Puerto Cardenas (\sim 43.2°S). Similar to the *P* patterns, both the mean annual *Q* and rainfall-runoff ratio tend to increase from north to south (Alvarez-Garreton et al., 2018; Vásquez et al., 2021).

The El Niño-Southern Oscillation (ENSO) has a large impact on winter *P*, with negative anomalies during La Niña and positive anomalies during El Niño events (Verbist et al., 2010; Robertson et al., 2014). Although neutral ENSO conditions have pre-

- 100 vailed since 2011 (except for a strong El Niño event during 2015), an uninterrupted sequence of dry years with increased temperatures has been observed from 2010–2018, with annual P deficits of about 25–45% across Chile. This long-term deficit in P volume, also known as the Chilean megadrought (Garreaud et al., 2017; Boisier et al., 2016) (Boisier et al., 2016; Garreaud et al., 2017), has reduced snow cover, river flows, reservoir storage, and groundwater levels across Chile (Garreaud et al., 2017, 2020).
- Hydroclimatic indices and characteristics for 516 catchments in continental Chile were acquired from the Catchment Attributes and MEteorology for Large-sample Studies dataset in Chile (CAMELS-CL; Alvarez-Garreton et al., 2018). The dataset includes location, topography, geology, soil types, land cover, hydrological signatures, and human intervention degree, among others. *Q* data were obtained from the Center for Climate and Resilience Research (CR2; http://www.cr2.cl/datos-de-caudales/, last accessed October 2020) for 1930–2018 because *Q* data from CAMELS-CL ended in 2016 at the time of conducting this study. We selected the near-natural catchments from the CAMELS-CL database that fulfilled the following criteria:
- 110 1. Less than 25% of missing values in the daily Q time series for 1990–2018 (may be non-consecutive).
 - 2. Absence of large dams (big_dam = 0).
 - 3. Less than 10% of the Q allocated to consumptive uses (interv_degree < 0.1).
 - 4. Not dominated by glaciers (lc_glacier < 5%).
 - 5. Less than 5% of the area defined as urban (imp_frac < 5%).
- 115 6. Absence of substantial irrigation abstractions (crop_frac < 20%).



Figure 1. Study area: *a*) elevation (SRTMv4.1; Jarvis et al., 2008); *b*) land cover classification (Zhao et al., 2016); *c*) Köppen-Geiger climate classification (Beck et al., 2018); and *d*) hydrological regimes of the selected catchments over the five major macroclimatic zones according to Zambrano-Bigiarini et al. (2017).

- 7. Less than 20% of the area covered by forest plantations (fp_frac < 20%).
- 8. No signs of artificial regulation in the hydrograph (10 excluded in total).

The drainage area of the selected catchments (100) ranges from 35 to $11,137 \text{ km}^2$, with a median value of 645 km². The selected catchments contain 42 nested catchments (i.e., catchments that are contained in a larger catchment). Through

120 visual screening, these selected catchments were classified by hydrological regimes as We adjusted the classification of these catchments according to hydrological regime, building on the classifications presented in several national and regional technical reports (e.g., DGA, 1998, 1999, 2004a, b, c, 2006, 2016a, b, 2018), by visually analysing the contribution of solid and liquid *P* to the mean monthly *Q* values. These regimes were classified as: *i*) snow-dominated, *ii*) nivo-pluvial, i.e., snow-dominated with a lower rain component, *iii*) pluvio-nival, i.e., rain-dominated with a lower snow component, and *iv*) rain-dominated, as

125 shown in Figure 1d. Figure A1 shows conceptual hydrographs for each of these regimes and is presented in Appendix A.

3 Methods

3.1 Meteorological forcings

3.1.1 Precipitation products

Four P products were used to investigate how the choice of P forcing affects the performance of regionalisation techniques.

The *P* products are presented in Table 2, and were selected because previous studies have reported good agreement with when evaluated against *in situ* measurements over continental Chile (Zambrano-Bigiarini et al., 2017; Boisier et al., 2018; Baez-Villanueva et al., 2018, 2020). We included the coarse-resolution ERA5 product because *i*) Chile is dominated by large-scale, frontal systems (Zhang and Wang, 2021) and therefore, coarse-resolution products may perform well over small catchments; *ii*) reanalysis products tend perform well at high latitudes (Beck et al., 2017a); *iii*) we consider that its inclusion represents
a realistic situation that may exist in many practical applications (i.e., where a catchment size is small relative to *P* product resolution).

Table 2. Gridded P products used in this study.

P product	Period	Spatial and temporal resolution	References
CR2MET	1979–2018	0.05° ; daily	Boisier et al. (2018)
RF-MEP	1990–2018 - <u>1983–2018</u>	0.05° ; daily	Baez-Villanueva et al. (2020)
ERA5	1950-present	$\sim 0.28^{\circ}$; hourly	Hersbach et al. (2020)
MSWEPv2.8	1979-present	0.10° ; 3-hourly	Beck et al. (2017b, 2019)

The Center for Climate and Resilience Research Meteorological dataset version 2.0 (CR2MET; Boisier et al., 2018) provides daily gridded P estimates over continental Chile at a 5 km spatial resolution for <u>1979–20191979–2018</u>. These estimates are produced by combining rain gauge observations with reanalysis data from ERA5(Boisier et al., 2018)., while CR2MET version

140 1.0 of this product was produced using ERA-Interim data (Boisier et al., 2018). As CR2MET was developed specifically for Chile and uses all the Chilean rain gauges (874 across Chile; see Figure S1 in the supplement), it is considered as the 'reference' *P* product of Chile.

The random forest merging technique procedure (RF-MEP; Baez-Villanueva et al., 2020) combines gridded P products, ground-based measurements, and other spatial covariates to generate P estimates. We applied this methodology to generate

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a spatially distributed, daily *P* product for continental Chile, using daily records from 331–334 rain gauges (obtained from CR2; http://www.cr2.cl/datos-de-precipitacion/), gridded *P* data from the ERA5 reanalysis (Hersbach et al., 2020) aggregated to the Chilean time, and elevation (SRTMv4.1; Jarvis et al., 2008) as covariates. This RF-MEP version 2 product (hereafter, RF-MEP) was generated for 1990–2018 with a spatial resolution of 0.05° using the RFmerge R package (Zambrano-Bigiarini et al., 2020).

- ERA5 (Hersbach et al., 2020) is a reanalysis product that provides hourly P estimates (as well as other variables) from 1950-present at a spatial resolution of around 30 km (~0.28°). There are important improvements in its P estimates compared to its predecessor ERA-Interim, such as improved i) representation of mixed-phase clouds, iii) prognostics variables for rain and snow; iii) parametrisation of microphysics, and iv) representation of tropical variability (Hersbach et al., 2020). Although ERA5 also assimilates NCEP Stage IV P estimates over the conterminous USA, which combine NEXRAD data
- 155 with in-situ measurements, it does not incorporate information from any ground-based P stations over Chile. Hourly ERA5 estimates were aggregated into daily P values taking into account the reporting times of the Chilean rain gauges (08:00–07:59 local time, which represents 11:00–10:59 UTC). Although this product has a relatively low spatial resolution compared to the remaining products, we included it because *i*) Chile is dominated by large-scale, frontal systems (Zhang and Wang, 2021) and therefore, coarse-resolution products may perform well even over small catchments; *ii*) reanalysis products tend to perform
- 160 well at high latitudes (Beck et al., 2017a); and *iii*) we consider that its inclusion represents a realistic situation that may exist in many practical applications (i.e., where a catchment size is small relative to *P* product resolution).

The Multi-Source Weighted-Ensemble Precipitation (MSWEPv2.8; Beck et al., 2017b, 2019) is a 3-hourly P product with a spatial resolution of 0.10°, which takes advantage of the complementary strengths of satellite, reanalysis and ground-based data. MSWEPv2.8 applies daily and monthly corrections to its estimates using data from around 77,000 rain gauge stations globally and accounts (628 of these are over Chile, see Figure S1) accounting for their local reporting times (Beck et al., 2019)

. The 3-hourly MSWEPv2.8 estimates were also aggregated into daily *P* to account for the difference in the reporting times. Figure **??** shows the 2a shows the spatial distribution of mean annual *P* patterns for all products over 1990–2018, while Figure 2b shows boxplots of the mean monthly *P* averaged over catchments located within each macroclimatic zone. All *P* products show relatively similar patterns of spatial variation variability across continental Chile; however, there are some

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- 170 marked differences in the substantial differences in their total P amounts. In general, P increases from the (hyper-arid) northern Chile to the south, as well as Far North to the South, and decreases again in the Far South. P also increases from the west coast into towards the Andes Mountains. Over the arid region (17–30°S), ERA5 provides higher P amounts over all five macroclimatic zones, while RF-MEP generally yields the lowest annual P values. Over the Far North, all products show a marked rainy season during December–March due to summer convective P, which differs from the marked seasonality
- 175 evident over the Near North, Central Chile, and South regions. Over the Far North, ERA5 presents a the highest mean annual *P* of 420 mm(157 mm), which is four times the value of almost twice the amount provided by the second-highest product MSWEPv2.8 (83 mm), followed by CR2MET (10663 mm), while RF-MEP has the lowest mean annual *P* (40 mm). Although ERA5 presents the highest mean annual *P* values over the Near North, Central Chile, and South regions (208 mm, 902 mm, and 2172 mm, respectively), when considering only our case study catchments (Figure 2b), CR2MET has the highest mean
- 180 monthly values over the Central Chile and South regions during April–June. Over this region, RF-MEP and MSWEPv2.8 present have similar mean annual P values (61 and 66 mm over Central Chile (670 mm for both products) and the South (1670 mm and 1735 mm, respectively). For central Chile (30–40°S), CR2MET has the regions, although RF-MEP consistently shows the largest monthly P amounts of the two products over the corresponding catchments. ERA5 provides the highest mean annual P (889values over the Far South (3,018 mm), followed by ERA5 CR2MET (1888 mm), MSWEPv2.8 (1714 mm), and

185 RF-MEP (646 and 599 mm815 mm). Finally, each product shows low seasonality over the Far South. Here, ERA5 presents higher monthly *P* values throughout the year, with the largest difference from the other products between January–March and September–December.

To gain a deeper understanding of the differences between the four P products, we examined the spatial distribution of median annual values of four Climdex Indices (Karl et al., 1999) for 1990–2018 (Figure 3). First, to account for days without

- 190 rain (P < 1 mm), we used the consecutive dry days index (CDD; Figure 3a), which retrieves the maximum dry spell length. It is evident that CR2MET yields longer dry spells, mainly across the Far North and Near North regions, while ERA5 has shorter dry spells over these regions, especially over the Andes Mountains. CR2MET, respectively), while RF-MEP, and MSWEPv2.8 has the lowest mean value (446 mm). Finally, for latitudes lower than 40°S, have similar spatial patterns over the Central Chile and South regions, while ERA5 has less consecutive dry days over the Andes Mountains. Similarly, ERA5 provides shorter
- 195 dry spells over the Far South, while CR2MET has the highest mean annual P (1,397 mm), followed by ERA5 (1,313 mm), and RF-MEP present similar patterns. These results are consistent with the consecutive wet days index (CWD; Figure 3b), which assesses the frequency and intermittency of P. ERA5 provides the highest CWD values over the driest regions (Far North and Near North), with medians ranging from 0 to 25 days, followed by MSWEPv2.8 (1,034 mm) and 0 to 15 days). ERA5 also shows higher CWD values over high-elevation areas in Central Chile, while the remaining products show similar
- 200 spatial patterns to each other. The four products show agreement in the CWD over the South region, with values ranging from 5 to 25 days. Finally, RF-MEP (727 mm)shows the lowest consecutive days with P in the Far South, followed by CR2MET and MSWEPv2.8, while ERA5 shows substantially higher CWD values at latitudes greater than 47°S.

To characterise high P intensities, we used the Rx5day (Figure 3c) and R95pTOT (Figure 3d) indices, which represent the maximum P accumulated over five consecutive days, and the total P above the 95th percentile of the daily P for wet days,

205 respectively. Figure 3c shows that ERA5 and CR2MET generally yield the highest Rx5day values, followed by MSWEPv2.8 and RF-MEP. A similar spatial variability is obtained with R95pTOT (Figure 3d), indicating that there is a greater contribution of *P* from extreme events in ERA5 over high-elevation areas. These spatial patterns are replicated to some extent by CR2MET, which provides R95pTOT values up to 1200 mm over the Andes Mountains in Central Chile.

3.1.2 Air temperature and potential evaporation

210 Maximum and minimum daily air temperature (T) at a spatial resolution of 0.05° were taken from CR2MET. T is estimated using multivariate regression from the Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) and ERA5 estimates as covariates (Alvarez-Garreton et al., 2018; Boisier et al., 2018). The Hargreaves-Samani equation (Hargreaves and Samani, 1985) was used to obtain daily potential evaporation (*PE*) from CR2MET maximum and minimum daily T at the same spatial resolution (0.05°).

215 3.2 Hydrological model

The TUWmodel (Viglione and Parajka, 2020) is a conceptual hydrological model that follows the structure of the Hydrologiska Byråns Vattenbalansavdelning (HBV) model (Bergström, 1976; Bergström, 1995; Lindström, 1997). The model simulates the



Figure 2. Mean Comparison of P products over 1990–2018 (full time period): a) mean annual P for each product over 1990–2018, resampled to a 0.05° spatial resolution using the nearest neighbour method. The dark red horizontal lines represent the limits of each major macroclimatic zone; and b) mean monthly P averaged over each catchment located within each macroclimatic zone (see Figure 1d).

catchment-scale water balance at daily time steps, including processes related to snow accumulation and melting, change of moisture in the soil profile, and surface flow in the drainage network. The TUWmodel was validated over 320 catchments in

- Austria (Parajka et al., 2007) and has subsequently been used in numerous studies (e.g., Ceola et al., 2015; Parajka et al., 2016; Sleziak et al. (e.g., Parajka et al., 2016; Zessner et al., 2017; Melsen et al., 2018; Sleziak et al., 2020). We selected a HBV-like conceptual model because it has shown good results in *i*) many regionalisation studies (e.g., Parajka et al., 2005; Jin et al., 2009; Singh et al., 2012; Wa (e.g., Parajka et al., 2005; Singh et al., 2012; Beck et al., 2016; Neri et al., 2020); and *ii*) catchments with diverse hydroclimatic and geomorphological characteristics (Merz and Blöschl, 2004; Driessen et al., 2010; Samuel et al., 2011; Vetter et al., 2015; Ding et al., 2018; Huang et al., 2010)
- 225 (Vetter et al., 2015; Ding et al., 2016; Unduche et al., 2018; Huang et al., 2019).

The TUWmodel requires as inputs daily time series of P, T, and PE. The parameters used by the TUWmodel to represent the hydrological processes are listed in Table 3, including the ranges selected for model calibration, that which were adopted from previous studies (Parajka et al., 2007; Ceola et al., 2015), which that calibrated the TUWmodel over a large number of mountainous catchments with snow influence. We ran the TUWmodel with a semi-distributed configuration for the period 1000, 2018 based on metagralagies and Q data qualibrility. For each established the number of EZ and based by the results of the period

230 1990–2018 based on meteorological and Q data availability. For each catchment, the number of EZ equal-area elevation bands was defined as $EZ = (H_{max} - H_{min})/200$, where H represents elevation. In cases where EZ > 10, EZ was set to 10 to reduce the computational demand of the simulations. Furthermore, in catchments with H_{min} below 900 m a.s.l., the upper bound (H_{max}) of the first EZ band was set to 900 m , under the assumption that there is no snow influence below this elevation for the particular case of continental Chile.



Figure 3. Median annual values of four Climdex indices over 1990-2018 (full-period): a) number of consecutive dry days (CDD); b) number of consecutive wet days (CWD); c) maximum P over five consecutive days (RX5day); and d) annual P that is above the 95th percentile of P accumulated for events that are above the 95th percentile of the daily P for wet days (R95pTOT). The dark red horizontal lines represent the limits of each macroclimatic zone.

235 **3.3** Individual Independent catchment calibration and verification

The simulation period used for this study was 1990–2018, using . For calibration purposes, we used the first ten years as a conservative warm-up period to initialise the model stores, as in Beck et al. (2020a). The calibration period (2000–2014)

Table 3. Summary of the TUW model parameters considered for calibration, following the conceptualisation presented in Széles et al. (2020).

\mathbf{N}°	Parameter ID	Description	Units	Process	Range
1	SCF	Snow correction factor	_	Snow	0.9 – 1.5
2	DDF	Degree-day factor	mm $^{\circ}$ C day $^{-1}$	Snow	0.0 - 5.0
3	Twb	Wet bulb temperature	°C	Snow	-3.0 - 3.0
4	Tm	Threshold temperature above which melt starts	°C	Snow	-2.0 - 2.0
5	LPrat	Parameter related to the limit for potential evaporation	_	Evaporation	0.0 - 1.0
6	FC	Field capacity	mm	Infiltration	0.0 - 600
7	BETA-Beta	Non-linear parameter for runoff production	_	Infiltration	0.0 - 20
8	cperc	Constant percolation rate	${ m mm}~{ m day}^{-1}$	Infiltration	0.0 - 8.0
9	k0	Storage coefficient for very fast response	day	Runoff	0.0 - 2.0
10	k1	Storage coefficient for fast response	day	Runoff	2.0 - 30
11	k2	Storage coefficient for slow response	day	Runoff	30 - 250
12	lsuz	Threshold storage state	mm	Runoff	1.0 - 100
13	bmax	Maximum base at low flows	day	Runoff	0.0 - 30
14	croute	Free scaling parameter	$day^2 mm^{-1}$	Runoff	0.0 - 50

includes near normal conditions and the beginning of the Chilean megadrought. The first evaluation period (hereafter, Verification 1, 1990–1999) represents near-normal/wet hydroclimatic conditions, while the second evaluation period (hereafter, Verification 2, 2015–2018) spans the second half of the Chilean megadrought, and was used to test the ability of the hydrolog-

ical simulations to represent dry conditions.

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To examine how the goodness-of-fit function used for calibration affected the regionalisation results, we considered two different objective functions to calibrate the TUWmodel. The first function was To initialise model stores for the Verification 1 period, we used an 8-year warm up period due to P product availability. We replicated Figures 2 and 3 for these three periods to analyse the differences between the selected P products (see the supplement, Figures S2-S7).

We used the modified Kling-Gupta efficiency (KGE', Eq. 1; Kling et al., 2012) to calibrate the TUW model, which typically provides better hydrograph simulations than other squared-error indices (Gupta et al., 2009; Kling et al., 2012; Mizukami et al., 2019) and has been used in numerous studies (e.g., Garcia et al., 2017; Beck et al., 2019; Baez-Villanueva et al., 2020; Neri et al., 2020; Széles et al., 2020). The KGE' has three components: the Pearson correlation coefficient (*r*; Eq. 2); the bias ratio

250 (β ; Eq. 3); and the variability ratio (γ ; Eq. 4). μ is the mean Q, CV is the coefficient of variation, σ represents the standard deviation of Q, and the subscripts s and o represent simulated and observed Q, respectively. The KGE' and its components have

their optimum value at one, and its optimisation seeks to reproduce the temporal dynamics (measured by r), while preserving the volume and variability of Q, measured by β and γ , respectively (Kling et al., 2012).

KGE' =
$$1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2}$$
 (1)

255
$$r = \frac{\sum_{i=1}^{n} (O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^{n} (S_i - \bar{S})^2}}$$
(2)

$$\beta = \frac{\mu_s}{\mu_o} \tag{3}$$

$$\gamma = \frac{CV_s}{CV_o} = \frac{\sigma_s/\mu_s}{\sigma_o/\mu_o} \tag{4}$$

Based on previous research (Shafii and Tolson, 2015; Vis et al., 2015; Beck et al., 2016), we also implemented a new aggregated objective function (AOF) that combines Q signatures (AOF_{sig}) and classical goodness-of-fit indices (AOF_{gof}):-

$$260 \quad AOF = \frac{AOF_{gof} + AOF_{sig}}{2}$$

For the AOF_{gof} (Eq. ??) To calibrate the model parameters, we used the average of the KGE' recommended by Garcia et al. (2017), which is computed for both the Q and its inverse (KGE'(Q) and KGE'(1/Q), respectively). The use of this function should lead to improved estimates of mean annual runoff, seasonality, and low flow indices. To avoid problems with zero Q values while computing KGE'(1/Q) (Santos et al., 2018), we added a small constant to all Q values, defined as one-hundredth of the mean daily Q (Pushpalatha et al., 2012; Garcia et al., 2017).

$$AOF_{gof} = \frac{KGE'(Q) + KGE'(1/Q)}{2}$$

Similar to Yilmaz et al. (2008) and Beck et al. (2016), we selected four Q signatures to calculate AOF_{sig} (Eq. ??): the difference between the observed and simulated baseflow indices (*eBFI*), which may be thought of as the proportion of river runoff deriving from stored sources; and the percent bias in the slope of the lower, medium, and higher segments of

270 the flow duration curve (*pbiasFDC_{Low}*, *pbiasFDC_{Med}*, *pbiasFDC_{High}*, respectively). Equations **??a** d present the four aforementioned components of AOF_{sig}, where BFI represents the base flow index; *sim* hydroPSO global optimisation algorithm (Zambrano-Bigiarini and Rojas, 2013), which implements a state-of-the art version of the Particle Swarm Optimisation technique (PSO; Eberhart and Kennedy, 1995; Kennedy and Eberhart, 1995). We used the standard PSO 2011 algorithm (Clerc, 2011a, b)

275 <u>swarm (npart = 80), the maximum number of iterations (maxit = 100), and *obs* represent the simulated and observed Q values, respectively; and Q_{99} the relative convergence tolerance (reltol = 1E - 10), Q_{70} , Q_{20} , Q_{10} , Q_1 represent streamflows with 99, 70, 20, 10 and 1% probability of exceedance, respectively.</u>

$$AOF_{sig} = 1 - (eBFI + pbiasFDC_{Low} + pbiasFDC_{Med} + pbiasFDC_{High})$$

 $eBFI = |BFI_{sim} - BFI_{obs}|$

280 $pbiasFDC_{Low} = 100 \cdot \left| \frac{log(Q_{70,s}) - log(Q_{99,s})}{log(Q_{70,o}) - log(Q_{99,o})} - 1 \right|$

$$pbiasFDC_{Med} = 100 \cdot \left| \frac{log(Q_{20,s}) - log(Q_{70,s})}{log(Q_{20,o}) - log(Q_{70,o})} - 1 \right|$$

$$pbiasFDC_{High} = 100 \cdot \left| \frac{Q_{1,s} - Q_{10,s}}{Q_{1,o} - Q_{10,o}} - 1 \right|$$

To calibrate the model parameters, we used the hydroPSO global optimisation algorithm (Zambrano-Bigiarini and Rojas, 2013)
 , which implements a state-of-the art version of the Particle Swarm Optimisation technique (PSO; Eberhart and Kennedy, 1995; Kennedy and While the default values were used for all other parameters. Over the last decade, hydroPSO has been successfully used to calibrate numerous hydrological and environmental models (e.g., Brauer et al., 2014a, b; Silal et al., 2015; Bisselink et al., 2016;

Kundu et al., 2017; Kearney and Maino, 2018; Abdelaziz et al., 2019; Ollivier et al., 2020; Hann et al., 2021). The default hydroPSO settings were used for all calibrations (Zambrano-Bigiarini and Rojas, 2013)For more details on the use of the hydroPSO package to calibrate the TUWmodel, readers are referred to Zambrano-Bigiarini and Baez-Villanueva (2020).

290 3.4 Regionalisation techniques

After obtaining catchment-specific model parameters through individual catchment-calibration using the KGE' and AOF separately independent catchment calibration (Section 3.3), we compared three parameter regionalisation techniques: i) spatial proximity, iii) feature similarity, iii and iii) parameter regression. We assessed performance through a leave-one-out cross-validation exercise, which consists of leaving out each one of the 100 catchments, transferring model parameters, conducting O simulations and computing performance and computing metrics.

295 Q simulations and computing performance evaluation metrics.

3.4.1 Spatial proximity

The spatial proximity method assumes that climatic and physical characteristics are relatively homogeneous over a region (Oudin et al., 2008). We quantified the spatial proximity between the target pseudo-ungauged and the remaining catchments using the Euclidean distance between catchment centroids, computed with geographic coordinates (i.e., latitude and longitude):

300
$$\operatorname{ED}_{ij} = \sqrt{\sum_{k=1}^{n} (x_{k,i} - x_{k,j})^2}$$
 (5)

For each pseudo-ungauged catchment, the donor was chosen according to the minimum Euclidean distance, and the full parameter set obtained during the individual-independent calibration of the donor catchment was transferred to the pseudo-ungauged catchment.

3.4.2 Feature similarity

- 305 In the feature similarity method, we transferred the calibrated parameter sets from 10 donor catchments to the pseudo-ungauged catchment based on similarity between climatic and geomorphological features, quantified using the catchment characteristics presented in Table 4. To exclude redundant information, we first performed correlation analyses between catchment descriptors using the Pearson and Spearman rank correlation coefficients (to account for linear and monotonic correlation, respectively), and discarded three descriptors with high correlations (mean elevation, mean annual *PE*, and SDII; see Appendix B). Also, we
- 310 discarded snow cover because it was found to be unreliable, leaving nine catchment features for this method. To assign equal weight to each catchment characteristic, they were normalised into the range [0, 1] using Eq. 6:

$$Z_f = \frac{x_f - x_{min}}{x_{max} - x_{min}} \tag{6}$$

where x_f is the value of the characteristic for catchment f, while x_{max} and x_{min} are the maximum and minimum values of the characteristic x over all catchments. After normalising all catchment characteristics, we calculated the dissimilarity as follows:

315
$$S_{i,j} = \sum_{m=1}^{n} |Z_{i,m} - Z_{j,m}|$$
 (7)

where $S_{i,j}$ is the dissimilarity index between catchments *i* and *j*; $Z_{i,m}$ and $Z_{j,m}$ are the normalised values of the *m* catchment characteristic for catchments *i* and *j*, respectively; and *n* is the total number of characteristics.

For each pseudo-ungauged catchment *i*, the 10 catchments *j* with the lowest dissimilarity indices $(S_{i,j})$ were selected as donors (MeIntyre et al., 2005; Oudin et al., 2008; Zhang and Chiew, 2009; Zhang et al., 2015; Beck et al., 2016)(Oudin et al., 2008; Zhang and Chiew, 2009; Zhang et al., 2015; Beck et al., 2016)

320 . The full parameter sets obtained during the individual-independent calibrations of each donor catchment were used to run TUWmodel in the pseudo-ungauged catchment, thus producing an ensemble of 10 Q simulations, as in previous studies (McIn-

Table 4. Selected climatic and physiographic characteristics to quantify feature similarity between catchments. All variables related to P were computed using the corresponding P product used as an input to the TUWmodel for 1990–2018.

Variable	Data source	Importance
Aean elevation	CAMELS-CL	Composite indicator that influences a range of processes such as long-term
		P and T , and hence soil moisture availability. In some environments, it is
		also related to aridity and snow processes.
Aedian elevation	SRTMv4.1	Same as mean elevation but provides a more robust representation of eleva-
		tion over mountainous catchments. \sim
Catchment area	CAMELS-CL	Related to the degree of aggregation of catchment processes related to scale
		effects. Additionally, it is an indicator of total catchment storage capacity. $\!$
Slope	CAMELS-CL	Related to the response of the catchment, routing, and infiltration processes.
Forest cover	CAMELS-CL	Forested catchments are associated with a trade-off between high water con-
		sumption rates and enhanced soil.
bnow cover	CAMELS-CL	Related to the influence of snow processes within the catchment.
Iean annual precipitation	P product	Related to the generation of runoff and P related to orographic gradients
		(e.g., coastal areas). \sim
Aean annual air temperature	CR2MET	Indicator of snow processes in cold environments. It is also related to aridity,
		and consequently to the evaporative demand. $\!\!\!\!\!\!\!\!\!\!\!$
from annual notantial avan	Computed	A manufacture of the struggeborie system demand (separability of the separal tem
mean annual potential evap-	from CR2MET	A measure of the atmospheric water demand (especially at the annual tem-
ration	CD2MET and	poral scale).
Aridity index	R product	Represents the competition between energy and water availability.
aily temperature range	CP2MET	Monthly mean difference between daily maximum and minimum T . De
Jany temperature range	CK2WIE1	leted to variations in the diversal cuele and evaporative demands.
timple presinitation inten	<i>P</i> product	Paletion of annual P to the number of wet days $(P > 1 \text{ mm})$. Sorved as a
ity index	1 product	Relation of annual T to the number of wet days ($T > T$ min). Serves as a
Any much	<i>P</i> product	Poloted to extreme P events
recipitation		
	Variable Iean elevation Iedian elevation atchment area lope brest cover now cover lean annual precipitation Iean annual air temperature lean annual potential evap- ration ridity index aily temperature range imple precipitation inten- ty index taximum consecutive 5-day recipitation	VariableData sourceIcan elevationCAMELS-CLIcan elevationSRTMv4.1Icathment areaCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCAMELS-CLIopeCamerationIcan annual precipitationCR2METIcan annual potential evap- rationComputed from CR2METIndity indexCR2METInple precipitation inten- ty indexP productImple precipitation inten- ty indexP productImple precipitation inten- ty indexP productIcanium consecutive 5-dayP product

tyre et al., 2005; Zelelew and Alfredsen, 2014; Beck et al., 2016). The 10 Q time series were then averaged to produce a single Q time series.

Finally, to quantify the overall uncertainty in model simulations when different objective functions are used for regionalisation, we adapted the P- and R-factor concepts described in Abbaspour et al. (2007); Schuol et al. (2008); Abbaspour et al. (2009) to be calculated using only 10 *Q* simulations. We defined the uncertainty band as the area between the maximum and minimum *Q*

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values for all time steps, obtained from the ensemble of the 10 simulations. Two indices were used to quantify the uncertainty of model simulations with respect to observations: i) P_{reg} , which is defined as the percentage of Q observations bracketed by the uncertainty band; and ii) R_{reg} , which represents the average width of the uncertainty band divided by the standard

330 deviation of the observations. Ideally, we would capture all observations within the uncertainty band (i.e., $P_{reg} = 1$), with no uncertainty (i.e., $R_{reg} = 0$); however, a more realistic good result would be to achieve $P_{reg} \sim 1$ with the same spread as the observations (i.e., $R_{reg} \sim 1$).

3.4.3 Parameter regression

The parameter regression technique aims to detect statistical relationships between parameter values and catchment character-

- 335 istics, and uses these relationships to estimate model parameters for ungauged catchments (Parajka et al., 2005; Oudin et al., 2008; Swain and Patra, 2017). To account for non-linear relationships between model parameters and catchment characteristics, we implemented the random forest machine learning algorithm (RF; Breiman, 2001; Prasad et al., 2006; Biau and Scornet, 2016) provided in the RandomForest R package (Liaw and Wiener, 2002). RF uses an ensemble of decision trees between predictand and predictor values (also known as covariates) for regression and supervised classification, and has the capability to
- deal with high-dimensional feature spaces and small sample sizes (Biau and Scornet, 2016). Previous studies have shown that RF can deal with several covariates as well as non-informative predictors, because it does not lead to overfitting or biased estimates (Díaz-Uriarte and Alvarez de Andrés, 2006; Biau and Scornet, 2016; Hengl et al., 2018), which is why it has been used for numerous hydrological applications (Saadi et al., 2019; Beek et al., 2020b; Baez-Villanueva et al., 2020; Zhang et al., 2021)(Saadi et al., 2019; For a more detailed description of RF, we refer the reader to Prasad et al. (2006), Biau and Scornet (2016), and Addor et al.
 (2018).

For this study, we developed one RF model for each TUWmodel parameter, using the set of all thirteen independent catchment characteristics listed in Table 4 as covariates. Our experimental setup used an ensemble of $\frac{2,000}{2000}$ regression trees, a minimum of five terminal nodes for each model, and p/3 variables randomly sampled as candidates at each split, where prepresents the number of predictors. The trained RF models were then used to predict parameter values in the pseudo-ungauged catchments, using its climatic and physiographic descriptors as covariates.

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We performed all analyses using the R Project of Statistical Computing (R Core Team, 2020). In addition to the R packages described in the methodology, we used the hydroGOF (Zambrano-Bigiarini, 2020a), hydroTSM (Zambrano-Bigiarini, 2020b), fifstat (Koffler et al., 2016), raster (Hijmans, 2020), rastervis (Perpiñán and Hijmans, 2020), rgdal (Bivand et al., 2020), and rgeos (Bivand and Rundel, 2020) packages.

355 3.5 Influence of nested catchments

To evaluate the influence of nested catchments on the performance of the three regionalisation methods, we repeated the three regionalisation methods for each target catchment, with catchments considered to be nested (in relation to the pseudo-ungauged catchment) excluded from the set of potential donor catchments. Following Neri et al. (2020), we used a cutoff point of 10% of

drainage area, meaning that only catchments that cover more than 10% of the area of the parent catchment are were considered

360 to be nested.

3.6 Influence of donor catchments for feature similarity

To evaluate the influence of the number of donors used in feature similarity, we repeated the process followed in Section 3.4.2 to assess the performance of this regionalisation method when 1, 2, 4, 6, 8, and 10 donor catchments are selected. This analysis evaluates the impact of averaging varying numbers of simulations compared to the results that are based on only the most similar catchment

365 <u>similar catchment.</u>

We performed all analyses using the R Project of Statistical Computing (R Core Team, 2020). In addition to the R packages described in the methodology, we used the hydroGOF (Zambrano-Bigiarini, 2020a), hydroTSM (Zambrano-Bigiarini, 2020b), lfstat (Koffler et al., 2016), raster (Hijmans, 2020), rasterVis (Perpiñán and Hijmans, 2020), rgdal (Bivand et al., 2020), and rgeos (Bivand and Rundel, 2020) packages.

370 4 Results

4.1 Performance of *P* products

4.1.1 Calibration and verification

Figure 4 shows the performance of the TUWmodel during calibration (2000–2014) and the two verification periods (1990–1999 and 2015–2018), prior to any regionalisation procedure. These results were obtained using the KGE' (Figure 4a) and the

- 375 AOF (Figure 4b) for the calibration process. When the KGE' was used as the objective function, CR2MET provided the best performance for all evaluated periods, with median KGE's of 0.84, 0.76, and 0.66, for calibration, Verification 1 (1990–1999, near-normal/wet) and Verification 2 (2015–2018, dry), respectively, followed closely by RF-MEP. However, when the AOF was used as the objective function to drive calibration, ERA5 (median KGE' of 0.72) outperformed CR2MET (0.71) during Verification 1. Surprisingly, MSWEPv2.8 provided the poorest performance for calibration and Verification 1, while ERA5 and
- 380 **RF-MEP** performed the worst during Verification 2, when using the KGE' and AOF, respectively. 1. For all *P* products, the lowest performances were obtained during the (dry) Verification 2 period, emphasising the challenges of estimating *Q* over dry environments in dry conditions, as discussed by Maggioni et al. (2013) and Beck et al. (2016). Despite the substantial variations between *P* products (see Section 3.1.1), TUWmodel performed well for all *P* products in the calibration, Verification 1 and Verification 2 periods, with median KGE' (AOF) values greater than 0.77, 0.71, and 0.62(0.78, 0.70, and 0.61), respectively.
- 385 The calibrated model parameters were lay well within the selected parameter ranges in the large majority of the cases (see Figure S4 and S5 Figure S8 of the supplementmaterial).). In other words, the selected parameter ranges were wide enough so that calibrated parameter values were not concentrated at their lower or upper limits.

Figure 5 shows the performance of the TUWmodel during calibration, Verification 1 and Verification 2 per hydrological regime (see Figure 1d). The TUWmodel performed better over the pluvio-nival catchments, with median KGE' values above



Figure 4. Performance of TUWmodel during the calibration (2000–2014), Verification 1 (1990–1999) and Verification 2 (2015–2018), prior to any regionalisation, using $\frac{a}{b}$ the modified Kling-Gupta efficiency (KGE'). The solid line represents the median value, the edges of the boxes represent the first and $\frac{b}{b}$ third quartiles, and the aggregate objective function (AOF) whiskers extend to the most extreme data point which is no more than 1.5 times the interquartile range from the box. The blue line indicates the optimal value for the KGE'.

- 390 0.77, 0.76, and 0.69 for calibration, Verification 1 and Verification 2, respectively. During the calibration period, there was no clear second best regime. For instance, the snow-dominated catchments presented slightly higher median KGE' values but a more pronounced dispersion, while the pluvio-nival and rain-dominated catchments presented lower dispersion but reduced median values. The snow-dominated catchments presented a more pronounced decrease from calibration (median KGE' > 0.85) to both verification periods (> 0.55 and 0.23 for Verification 1 and Verification 2, respectively). During both verification
- 395 periods, the rain-dominated catchments presented the highest dispersion increases in both verification periods compared to calibration.

Over the snow-dominated catchments, ERA5 performed the worst as it presented the highest dispersion and the lowest median KGE' values during Verification 1 (0.55) and Verification 2 (0.25), despite having the highest median KGE' during calibration (0.87). RF-MEP performed the best during Verification 1 (0.68), while MSWEPv2.8 performed the best during the

- 400 dry Verification 2 period (median KGE' of 0.60). CR2MET performed the best over the nivo-pluvial catchments with median KGE' values above 0.64, while RF-MEP performed relatively worse for both verification periods with median KGE' values above 0.48 and a larger dispersion than the other products, despite having a similar median KGE' (0.62) in Verification 1 to ERA5 and MSWEPv2.8 (0.61, and 0.60, respectively). Over the pluvio-nival catchments, all products showed a relatively good performance, with CR2MET being the best *P* product in calibration and Verification 1 (median KGE's of 0.87 and 0.84,
- 405 respectively), while ERA5 performed the best during Verification 2 (median KGE' of 0.78). RF-MEP performed the best over the rain-dominated catchments in calibration and Verification 1 with median KGE' values of 0.84 and 0.77, respectively, while ERA5 performed the worst (median KGE' values of 0.69 and 0.70). Finally, CR2MET performed the best in Verification 2 (median KGE' of 0.72), followed by MSWEPv2.8 (median KGE' of 0.69).



Figure 5. Performance of TUWmodel during calibration (2000–2014), Verification 1 (1990–1999) and Verification 2 (2015–2018), prior to any regionalisation over catchments with different hydrological regimes: *a*) snow-dominated; *b*) nivo-pluvial; *c*) pluvio-nival; and *d*) rain-dominated.

4.1.2 Performance during regionalisation

- 410 Figure 6 summarises the leave-one-out cross-validation results for the three tested regionalisation methods(spatial proximity, feature similarity, parameter regression), obtained when TUWmodel was forced with obtained from the application of three regionalisation methods, for each P productover the entire simulation period (1990–2018). The results are displayed for the calibration (2000–2014; panel a), Verification 1 (1990–1999; panel b), and Verification 2 (2015–2018; panel c) periods. Overall, the median performance of all P products was the highest-best for feature similarity(KGE' and AOF ~ 0.60), with median
- 415 KGE' values between 0.44–0.62 for all periods, followed by spatial proximity (KGE' and AOF ~ 0.550.39–0.55) and parameter regression (KGE' ~ 0.35, AOF ~ 0.25-0.12–0.51). In addition to exhibiting a considerably lower overall performance, parameter regression also resulted in returned a larger spread in performance. KGE's for all periods.

Focusing on only the two best-performing regionalisation methods and bearing in mind that KGE'and AOF have different theoretical grounds, the results presented on Figure 6 show that the overall performance. The overall performances obtained

- 420 for feature similarity and spatial proximity are quite relatively close for different *P* products , and for both objective functions. For exampleover each period (Figure 6). For feature similarity, all *P* products generate acceptable KGE' results (median KGE' > 0.56) for feature similarity, with the 0.54) during the calibration and Verification 1 periods, while the median KGE' values during the dry Verification 2 period lowered to a median KGE' of > 0.44. The best model performance obtained by CR2METv2 (KGE' = 0.63), for feature similarity was obtained by CR2MET, with median KGE' values of 0.62 for calibration
- 425 and Verification 1, and 0.53 for Verification 2, followed closely by RF-MEP (0.62). When using the AOF for feature similarity, the best model performance was again obtained by CR2METv2 (median AOF of 0.64), but this time followed closely by for calibration (0.59), ERA5 for Verification 1 (0.59), and MSWEPv2.8 (0.62). MSWEPv2.8 slightly outperformed ERA5 (median KGE'=0.61) in feature similarity, which is consistent with the results obtained for spatial proximity. for Verification 2 (0.52). In the case of spatial proximityusing the KGE', CR2MET performed the best, with a median KGE' of 0.57, followed
- 430 MSWEPv2.8 yielded the best performance in the calibration period (0.55), followed closely by RF-MEP (0.56, but with a higher dispersion), and CR2MET (0.53). For Verification 1, RF-MEP provided the best performance (0.54), while MSWEPv2.8 showed a slightly better KGE' performance than ERA5 produced the best results over Verification 2 (0.54-0.48). For spatial proximity, ERA5 performed the worst over the three evaluated periods. Finally, parameter regression yielded the lowest results, with CR2MET and 0.51, respectively). In the case of the AOF, MSWEPv2.8 showed a better AOF performance than RF-MEP
- 435 (0.55 and 0.53, respectivelyERA5 showing the highest median KGE' values (> 0.42 for calibration and Verification 1, and > 0.22 for Verification 2).

For each regionalisation technique, Figure 7 summarises the spatial distribution of the performance of the four each P products and both objective functions used in regionalisation product for the calibration, Verification 1, and Verification 2 periods. The spatial patterns obtained for all regionalisation methods were similar, independent of the P product or objective

- 440 function the evaluated period, except for parameter regression using the AOF, which yielded worse poor results over highelevation catchments and under dry conditions (Verification 2). These results suggest that the choice of objective function used to drive calibration does not greatly impact the spatial performance of regionalisation methods that transfer complete sets of model parameters (feature similarity and spatial proximity) indicate that spatial proximity and feature similarity present very similar spatial performance patterns, with feature similarity yielding higher KGE' values over the three evaluated periods.
- All *P* products performed better in central (30-40°S) and southern Chile (40-56.5°S) the Central Chile and South regions than in the arid north (17-30°S)Far North, Near North and Far South regions. The low performance of regionalisation in the arid north is very likely due to the convective nature of storms occurring in the highlands of the Chilean Altiplano (elevations above 4,000 m4000 m a.s.l.), and the low density of *Q* stations over this area. Despite this general low performance, RF-MEP was the best performing *P* product over northern Chile (17-30°S) the Far North region for both spatial proximity (median
- 450 KGE' of 0.370.28) and feature similarity (median KGE' of 0.51), for the 10 most northern catchments (see Figure 1)0.46) in the calibration period, suggesting that merging P products and ground-based observations helps to improve, to some extent, the performance of hydrological modelling across arid regions. Conversely, all products outperformed RF-MEP over the far



Figure 6. Leave-out-out Leave-one-out cross-validation results for the three regionalisation methods according to applied with different P product used to force TUW model products during 1990-2018, using the: a) the KGE', and calibration (2000–2014); b) the AOFVerification 1 (1990–1999); and c) Verification 2 (2015–2018) periods.

southFar South. Figure 7 also highlights that spatial proximity provides the best performance over the far southFar South, with median KGE' (AOF) values over the 10 most southern catchments of 0.47 (0.59), 0.45 (0.49), 0.25 (values higher than 0.46, 0.27, 0.30, and 0.35), and 0.30 (0.35) for MSWEPv2.8, for CR2MET, RF-MEP, and ERA5, and MSWEPv2.8, respectively.

455 0.27, 0.30, and 0.35), and 0.30 (0.35) for MSWEPv2.8, for CR2MET, RF-MEP, and ERA5, and MSWEPv2.8, respectively. The systematic lower performance of feature similarity compared to spatial proximity over the south Far South (except for the case of ERA5) could be attributed to: *i*) the lack of catchment characteristics that represent the hydrological behaviour of this complex area -

The panels located below each map in Figure 7 show the empirical cumulative distribution functions (ECDFs) of the performance of each regionalisation technique. These ECDFs compare the relative performance of each regionalisation method against those obtained from the individual calibration and verification of each catchment (used as benchmarks). As expected, all regionalisation methods presented a lower performance than the individual calibration and verification, with this reduction more pronounced for parameter regression. For feature similarity, all *P* products yielded a performance similar to that obtained for individual basin verification during dominated by polar and temperate climates; and *ii*) the dry Verification 2 period. low

465 amount of potential donor catchments (eleven for latitudes $> 49^{\circ}$ S), combined with their varied hydrological regimes. For the most southern catchments, the highest *P* intensities occur during March–May, while the lowest *P* occurs between June–August, which differs to catchments throughout the rest of the country (Alvarez-Garreton et al., 2018, their Figure 9). This may affect the hydrological simulations when model parameters from catchments located $< 49^{\circ}$ S are transferred to these far southern catchments.

470 4.2 Evaluation of regionalisation techniques

4.2.1 Overall performance

For each P product, Figure 8 compares the performances of the three regionalisation techniques using the AOF with those obtained in the individual independent calibration and verification periods. The individual independent calibration of each catchment represents the highest model performance that can be obtained for a specific combination of hydrological model,

- 475 objective function and catchment (i.e., an absolute benchmark), whereas the two verification periods were used to evaluate the performance of the regionalisation techniques over independent time periods (i.e., as verification benchmarks). For There are marked differences in performance according to the *P* product used to force the TUWmodel, regardless of the regionalisation method and the evaluated period. For example, ERA5 has more dispersion in the KGE' values compared to other products for the cases of feature similarity and spatial proximity; while for parameter regression, it tends to perform the best. For
- 480 all P products and evaluation periods, feature similarity performed the best, followed by spatial proximity and parameter regression, which is consistent with results from multiple studies (e.g., Parajka et al., 2005; Oudin et al., 2008; Bao et al., 2012; Garambois et al., 2015; Neri et al., 2020). Median AOFs obtained for feature similarity were the highest, followed elosely by spatial proximity, regardless of the selected P product, but with a larger spread. Parameter regression had both the lowest median AOFs KGE's as well as the largest spread. Comparing the two verification periods, results obtained during the
- 485 (near-normal/wet) Verification 1 period were close to those obtained during calibration, while those obtained during the (dry) Verification 2 were substantially lower, especially for spatial proximity and parameter regression. Results obtained for the evaluation of regionalisation methods using the KGE' are presented in Figure S1 of the supplement material, and are similar to those for the AOF

These results are in agreement with the lower panels located below each map in Figure 7, which show the empirical cumulative distribution functions (ECDFs) of the performance of each regionalisation technique during the complete period of analysis (1990–2018). These ECDFs compare the relative performance of each regionalisation method against those obtained from the independent calibration and verification of each catchment (used as benchmarks). As expected, all regionalisation methods presented a lower performance than the independent calibration and verification, with this reduction more pronounced for parameter regression.

495 4.2.2 Impact of hydrological regimes

We also analysed the impact of the hydrological regime (see Figure 1d) on the performance of the three regionalisation methods. Figure 9 and ?? show Figure 9 shows the performance of the regionalisation techniques according to hydrological regime for all *P* products and the KGE' and AOF objective functions, respectively. Figure 9 shows that when using the KGE', feature during the calibration period (and Figures S9 and S10 of the supplement

- 500 show the same for the two verification periods). Feature similarity provided the best median performance for all hydrological regimes and *P* products except for snow-dominated catchments, where spatial proximity performed the best for CR2MET and ERA5. Similarly, Figure ?? shows that feature similarity performed better over all hydrological regimes, except for the case of snow-dominated catchments with CR2MET as the *P* product. MSWEPv2.8 for calibration and Verification 2. These results demonstrate that there was no single *P* product that outperformed the others for all regionalisation techniques and hydrological
- 505 regimes. In other words, the best performing *P* product depends on the hydrological regime , and chosen regionalisation method , and objective function used to drive the hydrological model calibration for our case study. For feature similarity in snow-dominated catchments, RF-MEP performed the best using both the KGE' and AOF; while for for calibration and Verification 1, while CR2MET performed the best during Verification 2. For nivo-pluvial catchments, CR2MET provided the best performance with the KGE', and all of during calibration and Verification 1, while MSWEPv2.8 , ERA5 and CR2MET
- 510 performed similarly well with the AOF. performed the best during Verification 2. CR2MET and ERA5 performed the best in pluvio-nival catchments for the case of feature similarity when using the KGE', and CR2MET and RF-MEP with the AOF. Finally, across rainfall-dominated catchments, MSWEPv2.8 performed best, while all products performed similarly for spatial proximityand. Finally, ERA5 for feature similarity using the KGE'; and CR2MET for both regionalisation methods when the AOF was used.
- 515 Results obtained with the AOF were similar to those obtained with the KGE'. Although the two objective functions used are not directly comparable, results for the snow-dominated and the pluvio-nival catchments using the AOF for parameter regression were markedly lower than those obtained using the KGE', suggesting that the choice of the objective function has a greater influence in the performance of parameter regression resultsperformed the best for feature similarity in all periods across the rain-dominated catchments.
- 520 Performance of regionalisation methods using the AOF objective function according to the hydrological regimes: a) snow-dominated,
 b) nivo-pluvial, c) pluvio-nival, and d) rain-dominated. N denotes the number of catchments per hydrological regime.

4.3 Impact of nested catchmentsin regionalisation performance

Finally, we We evaluated the influence of the nested catchments in on the regionalisation results. Figure 10 shows the performance of the three regionalisation methods for the subset of 56 nested catchments that share a common area with at least one
other catchments catchment (i.e., the 42 nested catchments as well as all corresponding parent catchments). Here, we compare the regionalisation performance using all potential donors (dark colours) with the performance when excluding nested catchments as potential donors (light colours). The order of performance of the regionalisation methods and *P* products did not vary when the nested catchments were excluded, as feature similarity and CR2MET remained the best performing method and product, respectively. As expected, the regionalisation technique with the largest reduction in performance when excluding nested

530 catchments was spatial proximity, followed closely by feature similarity. All *P* products showed a slight performance reduction and increased dispersion for spatial proximity, except for MSWEPv2.8, which showed a slight increase in the KGE' median value. Feature similarity showed a slight reduction in performance when the nested catchments were excluded; however, the median values remained almost the same. The change in performance of parameter regression did not change substantially when evaluated with and without nested eatchments was negligible after the exclusion of nested catchments because, in the particular case of Chile, excluding only a few catchments had a negligible effect on the non-linear relationships between model

535 particular case of Chile, excluding only a few catchments had a negligible effect on the non-linear relationships between n parameters and the selected climatic and physiographic characteristics (see Table 4).

4.4 Impact of the number of donors in feature similarity

Figure 11 shows the performance of feature similarity during the calibration and both verification periods when varying the number of donors used to transfer model parameters to ungauged catchments (see Section 3.6). In general, the highest median
performance is obtained when using 4 or more donor catchments. However, the application of a t-test demonstrated that the improvement in the KGE' values obtained when increasing to more than one donor was not statistically significant. The results show that the performance varies according to the *P* product and selected period of analysis. For the calibration period, feature similarity produced similar median values to those obtained with spatial proximity when one donor was used, while the performance improved as more donors were included. For both verification periods, feature similarity (median KGE' values)

545 from 0.44 to 0.64) outperformed spatial proximity (median KGE' values ranging 0.39 to 0.54). For all three periods, feature similarity provided better performance considering the distribution of the KGE' values.



Figure 7. Spatial performance of the leave-one-out cross-validation results for the three regionalisation methods according to P product used to force TUWmodel. Results are presented for the: a) calibration (1990-20182000-2014)using a); b) Verification the KGE'-1 (1990-1999); and b)c) the AOF Verification 2 (2015-2018) periods. The panels beneath each the map plot plots refer to the ECDFs of the corresponding regionalisation technique for the entire period of analysis (1990-2018) and P product (black) against the performances during the independent calibration (bluegreen), Verification 1 (purpleblue), and Verification 2 (red) periods.



Figure 8. Performance of the regionalisation methods <u>using during the AOF objective function for</u>: a) calibration (2000–2014); b) Verification 1 (1990–1999), and c) Verification 2 (2015–2018) periods.



Figure 9. Performance of regionalisation methods using the KGE' objective function for calibration (2000–2014) according to the hydrological regimes: *a*) snow-dominated, *b*) nivo-pluvial, *c*) pluvio-nival, and *d*) rain-dominated. *N* denotes the number of catchments per hydrological regime.



Figure 10. Comparison of regionalisation performance using all catchments as potential donors (dark colours) against the performance when nested catchments that share a common area with the pseudo-ungauged catchment are excluded as potential donors (light colours). Results are for *a*) the KGE', and *b*) the AOF.



Figure 11. Influence of the number of donors used for feature similarity for calibration (2000-2014); Verification 1 (1990-1999); and Verification 2 (2015-2018). The results from spatial proximity are included on the right of each panel for comparison purposes. The dark yellow box denotes the upper and lower bounds of the median performance (of the four *P* products) obtained with spatial proximity, while the lighter yellow box represents the upper an lower bounds of the interquartile range for spatial proximity.

5 Discussion

5.1 Performance of *P* products

During the individual independent catchment calibration (2000-2014) and two verification periods (1990-1999 and 2015-

- 550 2018), good performances were obtained with all *P* products (see Figure 4). When decomposing the results of the KGE' objective function into its three components (see Appendix C), *r* exhibited the lowest performance, while β and γ values were generally closer to their optimal values, particularly for calibration and Verification 1. The results obtained with ERA5, which is a reanalysis-only reanalysis product, were as good or even better than those obtained with the gauge-corrected products CR2MET, RF-MEP, and MSWEPv2.8 (e.g., see AOF results for Verification 1 results for the pluyio-nival catchments in Fig-
- 555 ure 45). This is in agreement with Tarek et al. (2020), who concluded that ERA5 should be considered a high-potential dataset for hydrological modelling in data-scarce regions. The good performance of ERA5 suggests that, for the particular case of Chile, merging P products with ground-based measurements does not necessarily translate into improved hydrological model performance, which may be attributed to the: *i*) lack of P rain gauges in the Andes mountain range. Mountains; *ii*) ability of the rainfall-runoff model to compensate for the P forcing (visible in the performances of the β and γ components; Appendix C);
- 560 and *iii*) fact that P products still have errors in the detection of P events that could impact the representation of the modelled Q dynamics (as suggested by the relative lower performance of the r component of the KGE').
 - Furthermore, the similar performances obtained with uncorrected (ERA5) and gauge-corrected (CR2MET, RF-MEP, and MSWEPv2.8) P products, both in wet and dry periods, highlight that there was no single P dataset outperforming the others in all periodsand for both objective functions. These results demonstrate that the calibration of hydrological model pa-
- 565 rameters smooths out, to some extent, the spatial differences among spatio-temporal differences between P products (see Figure ??Figures 2, 3, 6 and 9), which is in agreement with previous studies that have demonstrated that model recalibration calibration with each P product improves the performance of Q simulations (e.g., Artan et al., 2007; Stisen and Sandholt, 2010; Bitew et al., 2012; Thiemig et al., 2013). The systematic higher performance of CR2MET and RF-MEP for decomposition of the KGE' into its components also demonstrated the ability of the TUWmodel to compensate for the total volume of P, as the
- 570 β component was close to the optimum value, particularly for calibration and Verification 1 compared to MSWEPv2.8 (see Figure 4)(see Appendix C), which can be attributed to the improved detection of P events of the merged products (regarding RF-MEP, see Baez-Villanueva et al., 2020). However, This can also be observed for MSWEPv2.8 performed similar to these merged products, as it produced the best performance over snow-dominated catchments under dry conditions (Verification 2).

Regarding the suitability of P products for parameter regionalisation, RF-MEP provided slightly better results in northern

- 575 Chile (17-30°S) the Far North for the calibration period using both spatial proximity and feature similarity, suggesting that P products that are merged with ground-based information over arid climates can improve regionalisation performance. The low performance obtained lower performance obtained in regionalisation with ERA5 in the north Far North compared to the other P products (median values < 0.18 for feature similarity in all periods) can be attributed to the absence its high P values, which are likely due to the lack of ground-based meteorological stations in its development. The use of ground observations as
- 580 they *P* stations over Chile in the development of the product. The incorporation of ground-based stations has the potential to:

i) help to compensate compensate for overestimations caused by the evaporation of hydrometeors before they reach the ground (Maggioni and Massari, 2018); and *ii*) improve event-based detection skills (Baez-Villanueva et al., 2020; Zhang et al., 2021). The latter is evident in CR2MET and MSWEPv2.8, which are both based on ERA5 but included several rain gauges in the Far North, and have a higher performance than ERA5 (see Figures 2, 3, and S1).

- Despite the low performance of all P products in the north Far North and Near North (median KGE' and AOF values 585 <0.50,58, see Figure 7), the TUW model appears to be flexible enough to compensate, to some extent, for differences between P products. A similar conclusion was obtained by Elsner et al. (2014), who examined differences between four meteorological forcing datasets and their implications in hydrological model calibration in western USA using the Variable Infiltration Capacity model (VIC; Liang et al., 1994). Our results are also in agreement with Bisselink et al. (2016), who concluded that
- 590

LISFLOOD model in four catchments in southern Africa.

An unexpected result from this study is that the spatial resolution of the P products did not play a major role in model performance during calibration, verification and regionalisation; although CR2MET and RF-MEP have a higher spatial resolution $(0.05^\circ; \sim 25 \text{ km}^2)$ than MSWEPv2.8 ($\sim 0.10^\circ; \sim 100 \text{ km}^2$) and ERA5 ($\sim 0.28^\circ; \sim 625 \text{ km}^2$), all four products performed well

parameter sets obtained during calibration partially compensated the bias of seven P products used to force the fully-distributed

- during the individual independent calibration of the hydrological model and the two verification periods. The performance of 595 ERA5 over the 25 smallest catchments during regionalisation (area $< 353.1 \text{ km}^2$) was similar to that obtained with products with a higher spatial resolution (Figure S3 S11 of the supplement material). This can be attributed to the fact that Chile is dominated by large-scale frontal systems (Zhang and Wang, 2021), and therefore, coarse-resolution products may perform well over small catchments. These results Our results also align with the findings of Maggioni et al. (2013), who concluded that the loss of spatial information associated with coarser resolution (e.g., ERA5) can be compensated through model calibration.
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5.2 Evaluation How does the calibration of regionalisation techniques TUW model compensate for differences in P?

Feature similarity provided the best performance when the TUWmodel was forced with all The calibration of TUWmodel was able to compensate, to some extent, for differences in annual and intra-annual P products (Figure 8) amounts, intermittency, and extremes (see Figures 2 and 3) among the four products. Using the example of the nivo-pluvial catchments, Figure 12 illustrates

- how TUWmodel parameters compensate for differences between the P forcings used in calibration, while Figure 13 shows 605 the corresponding variations in the mean monthly water balance components. Similar figures for snow-dominated, reinforcing the idea that this conceptual hydrological model has a flexible enough structure to correct inter-forcing differences without losing predictive capability in space, as observed in the obtained P_{reg} values (only applied to pluyio-nival, and rain-dominated catchments can be found in the supplement (Figures S12–S17).
- 610 In general, the best performing regionalisation technique, i. e. calibrated parameters behave as expected for each hydrological regime. A notable exception is ERA5, which shows low values for the snow correction factor (SCF) in nivo-pluvial and snow-dominated catchments (Figures 12 and S12). These catchments are primarily located in the arid Near North region (see Figure 2 and Figure S15), where the estimated winter P is substantially lower for CR2MET, feature similarity). Spatial RF-MEP, and MSWEPv2.8, and a high SCF corrects this apparent underestimation. The lower P amounts presented in these

615 products may reflect the incorporation of information from rain gauges located in drier, low-lying areas to correct their *P* estimates (see Figure S1).

ERA5 presented relatively low SCF values over nivo-pluvial catchments compared to the other P products (Figure 13), which is expected because it exhibits the highest P values. Conversely, because RF-MEP has the lowest mean monthly P over the nivo-pluvial catchments, the model adjusts the evaporation, snow water equivalent, and soil moisture components

- 620 (Figure 13), thus increasing the simulated Q (to match the observed Q). Substantial differences were obtained for LPrat and field capacity (FC), which directly affect evaporation and soil moisture. For example, over the nivo-pluvial catchments, the LPrat and FC values for RF-MEP are similar to those of ERA5, despite RF-MEP having substantially lower P amounts, which in turn is reflected in the reduced soil moisture and evaporation amounts. The differences between LPrat and FC according to P product are even more pronounced for snow-dominated catchments (Figure S12).
- Finally, higher values of the nonlinear parameter for runoff production Beta reduce the amount of water that leaves the catchment as runoff (Széles et al., 2020, their Eq. 7). For all hydrological regimes except pluvio-nival, the median Beta parameter is substantially higher for ERA5 than for the other P products. The larger Beta values obtained with ERA5 are expected to attenuate the runoff generation from extreme P events (see Figure 3c–d). Interestingly, the Beta parameter is zero in some pluvio-nival catchments, which means that all liquid P and snowmelt was used to generate runoff (Figure S16). This behaviour
- 630 was more pronounced with RF-MEP and MSWEPv2.8, which exhibited the lowest *P* amounts and longer dry spells (Figure 3a) over these catchments. In general, the storage components obtained from each *P* product (computed as the sum of the two deepest reservoirs of the model (see Széles et al., 2020, their Figure 3)) are similar for all four *P* products.

5.3 Evaluation of regionalisation techniques

- The compensation due to the flexibility of the TUWmodel observed during the independent calibration and verification (see Section 5.2) also influences the regionalisation performance. Feature similarity provided the best performance when the TUWmodel was forced with all *P* products (Figure 8), while spatial proximity provided similar performance to feature similarity over southern-central Chile the Central Chile and South regions, where there is a high density of *Q* stations. These results are in agreement with Parajka et al. (2005), Oudin et al. (2008) and Neri et al. (2020), who demonstrated that spatial proximity performs well over densely gauged regions.
- The inclusion of donor catchments with low model performance introduces a diversity that has the potential to benefit *Q* prediction in ungauged catchments, as discussed by Oudin et al. (2008). We decided to incorporate these catchments in the regionalisation process because of the diversity of climates and physiographic characteristics across continental Chile (see Figure 1), with the potential downside that this may lead to errors in the transferred model parameters. Additionally, the similarity between the performance of spatial proximity and feature similarity can be partially attributed to the fact that six
- 645 of the nine selected catchment characteristics are directly or indirectly related to climate, which in Chile is highly related to catchment spatial proximity the geographical locations of the catchments. Parameter regression was the regionalisation method that provided the worst results (Figures 6 and 8); however, Figure 7 shows that this method generated good results over



Figure 12. Model parameters obtained through calibration in nivo-pluvial catchments. The vertical blue lines indicate the upper and lower limits of the parameter ranges.

southern-central Chile (except for high-elevation areas)low-elevated areas of the Central Chile and South regions, where there are many potential donor catchments . The equifinality of model parameters may also impact located nearby.

- 650 The compensation for *P* differences obtained through model calibration also affected the relative performance of the regionalisation techniques producing unrealistic parameter sets, particularly for the case of parameter regression. Unlike regionalisation techniques, producing unrealistic parameter sets in some donor catchments. In particular, such compensation may have impacted the spatial transferability of model parameters with the parameter regression method, the main reason for this is that, unlike techniques that transfer the entire parameter sets, the regression process denatures the already uncertain
- 655 model parameters by applying independent regression procedures using climate and physiographic characteristics (Arsenault and Brissette, 2014). This challenge can be overcome by simultaneously optimising both the model parameters and the regression equations (e.g., Samaniego et al., 2010; Rakovec et al., 2016; Beck et al., 2020a), but such an exercise is <u>out_outside</u> of the scope of this study.

Figures 9 and ?? show the performances of the three regionalisation techniques according to hydrological regimes (see 660 Figure 1). For both spatial proximity and feature similarity, the best and worst results were obtained for pluvio-nival catchments and rain-dominated catchments, respectively, regardless of the objective function. The relative performance of snow-dominated catchments and nivo-pluvial catchments was related to the selection of the objective function. A better performance was achieved over snow-dominated catchments when the KGE' was used as the objective function, while the opposite was observed for the AOF.



Figure 13. Mean monthly water balance components over nivo-pluvial catchments, obtained by forcing the TUW model with different *P* products for the: *a*) calibration (2000–2014); *b*) Verification 1 (1990–1999); and *c*) Verification 2 (2015–2018) periods. Mean monthly *P* was added for comparison purposes.

- We calculated P_{reg} and R_{reg} to evaluate the ensemble spread in simulated Q resulting from the implementation of each of the 10 donor catchment parameter sets for feature similarity using both objective functions, as described in Section 3.4.2. Figure ?? shows the catchments according to whether P_{reg} was higher (indicating better performance) using the KGE' (green) or the AOF (orange), while catchments with P_{reg} differences of less than 0.05 were excluded (plotted as empty circles). The use of the AOF resulted in higher P_{reg} values over northern Chile, implying that a larger fraction of daily Q observations
- 670 lie within the uncertainty bands, with median values for the P products ranging from 0.69 (MSWEPv2.8)to 0.74 (RF-MEP). Figure 9 shows the performances of the three regionalisation techniques according to hydrological regimes (see Figure 1d) for the calibration period. Comparing Figures 5 and 9, it is evident that the snow-dominated catchments performed substantially worse than in the independent performance during the same period (Figure 5). On the other hand, the KGE' resulted in higher P_{reg} values over the humid south-central Chile, with median values ranging from 0.69 (MSWEPv2.8) to 0.76 (CR2MET and
- 675 ERA5). These results are in agreement with (Beck et al., 2016), who reported that the inclusion of hydrological signatures in the objective function reduced regionalisation performance over more humid (tropical) catchments. The comparison of the two objective functions with the R_{reg} index (Figure S2 in the supplement material) shows that the uncertainty band was narrower in the northern region when using KGE', with median values ranging from 2.20 (ERA5) to 1.16 (RF-MEP). Conversely, the use of the AOF over south-central and southern Chile provided better results, with median values ranging from 0.89 (ERA5)
- 680 to 0.81 (RF-MEP), suggesting that there is a trade off between P_{reg} and R_{reg} . Interestingly, all P products, regardless of their differences, provided very similar spatial patterns of P_{reg} and R_{reg} , with the exception of R_{reg} for RF-MEP, where the use of the AOF consistently resulted in better P_{reg} and R_{reg} values.

Comparison of whether P_{reg} is greater for KGE' and AOF according to catchment. Catchments with similar results (difference < 0.05) are plotted as empty circles.

- Figure ?? displays pluvio-nival catchments performed systematically better in the independent calibration and verification as well as in regionalisation. This could be attributed to: i) the ability of the model to reproduce Q time series for two catchments where good performance was obtained with feature similarity as the regionalisation technique, over a snow-dominated (in the north, Figure ??a) and a rain-dominated (in the south, Figure ??b) catchment, using CR2MET as the P forcing. In the snow-dominated catchment, the AOF resulted in a higher P_{reg} , while in the rain-dominated catchment , the KGE' led to a
- 690 higher P_{reg} value. In the snow-dominated catchment, the AOF was better at reproducing the recession curves of small events at the expense of returning a wider uncertainty band (i. e., higher R_{reg}). In the rain-dominated catchment, both objective functions produced good representations of the recession curves, and again the KGE' showed a slightly wider uncertainty band (i.e., higher R_{reg}) than AOF. in this regime; and *ii*) the increased likelihood of transferring model parameters from a catchment with the same hydrological regime, as they are grouped closed together and form 40% of the total number of catchments.
- 695 Visualisation of three hydrological years (2000–2005) of two well performing catchments: a) Rio Claro en Rivadavia (snow-dominated); and b) Rio Negro en Chahuilco (rain-dominated). The left panel shows the location of these catchments, the middle panel plots its hydrographs, and the right panel shows the flow duration curves for the KGE' and AOF calculated over 2000–2014, emphasising the low flows.

5.4 Impact of nested catchments

- Nested catchments play an important role in the performance of regionalisation methods because nested catchments as they are more likely to have a strong climatological and physiological similarity to each other. As observed in Figure 10, the regionalisation method that was most impacted by the exclusion of nested catchments was spatial proximity, followed by feature similarity. These results are in agreement with previous studies where the exclusion of nested catchments reduced the performance of regionalisation techniques (Merz and Blöschl, 2004; Oudin et al., 2008; Neri et al., 2020). Feature similarity
- 705 only presented a slight decrease when the nested catchments were neglected, which can be attributed to the low degree of nestedness (i.e., the number of catchments that are nested in a larger one). As expected, parameter regression was affected the least by the the exclusion of nested catchments , as their removal had had a negligible effect on parameter regression, as the removal of relatively few catchments had a negligible impact on the non-linear relationships between the climatic and physiographic characteristics and the model parameters that were determined using all potential donor catchments. The
- 710 reduction of regionalisation performance when the nested catchments were removed was lower compared to the results than the reduction reported in a case study over Austria (Neri et al., 2020, ; their Figure 9a)(Neri et al., 2020, their Figure 9a), which could be attributed to: *i*) the degree of nestednessof the selected catchments, as the unique geography of Chile limits, to some extent, the number of nested catchments within any larger catchment (only 10 of the 100 selected catchments contained more than 3-three nested catchments); and *ii*) the percentage of total catchments that are nested (42% in this study, compared to 65%)
- 715 in the Austrian case study).

5.5 Impact of number of donor catchments

Increasing the number of donor catchments in feature similarity improved the regionalisation performance. This is in agreement with several studies that have demonstrated that using an ensemble of multiple donor catchments improves regionalisation results (McIntyre et al., 2005; Zelelew and Alfredsen, 2014; Garambois et al., 2015; Beck et al., 2016; Neri et al., 2020). Figure 11
shows that there is a slight increase in performance when 4 donors or more are used, independent of the *P* product and evaluated period. These results are similar to those of Neri et al. (2020), who determined that three donors were optimal for the TUWmodel over Austrian catchments. Feature similarity still outperformed spatial proximity when only one catchment was used to transfer the model parameters to the ungauged catchments, which is in agreement with multiple studies that have shown the ability of this method to produce good regionalisation results (Parajka et al., 2005; Oudin et al., 2008; Bao et al., 2012; Garambois et al.

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6 Conclusion

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Streamflow prediction Accurate streamflow predictions in ungauged catchments is an essential task are critical for water resources management, and their generation is challenged by uncertainties arising from P products provide a challenge for the accurate prediction of daily Q. In this paper, we assessed the relative performance of three common regionalisation techniques

- 730 (spatial proximity, feature similarity, and parameter regression) over 100 near-natural catchments located in the topographically and climatologically diverse Chilean territory. Four P products (CR2MET, RF-MEP, ERA5, and MSWEPv2.8) were used to force the semi-distributed TUWmodel model at the daily temporal scale, and two objective functions (KGE' and AOF) were used for calibration time scale, using the KGE' as the calibration objective function and metric to assess: i) the impact of selecting different P forcings on the relative performance of regionalisation techniques; and ii) possible connections between
- regionalisation performance and hydrological regimes. Our key findings are as follows:
 - 1. For the selected *P* products, the one with that provided the best (worst) performance during independent calibration and verification did not necessarily provide yielded the best (worst) results during regionalisation.
 - 2. From the selected The *P* products, the use of those that are corrected with daily gauge observations did not necessarily translate into improved yielded the best hydrological model performance. However, we expect that *P* products with lower performances compared to than the ones used in this study might benefit from such a correction.
 - 3. The spatial resolution of the P products did not noticeably affect model performance during both the calibration and verification periods.
 - 4. The TUWmodel was able to compensate, to some extent, the differences between *P* products through model calibration by adjusting the model parameters and, therefore, adjusting the water balance components (e.g., snow water equivalent, evaporation, and soil moisture).
 - 5. Feature similarity was the best performing regionalisation technique, regardless of the choice of gridded *P* product or the calibration criteria we explored (KGE' or AOF)hydrological regime.
 - 6. Spatial proximity was the second best performing regionalisation method . This can be explained by the fact that because, in our study area, spatial proximity is a good proxy of climatic similarity for most neighbouring catchments.
- 750 7. Parameter regression provided the worst regionalisation performance, reinforcing the importance of transferring complete parameter sets to ungauged catchments.
 - 8. The performance of regionalisation techniques can depend on the hydrological regime. We obtained the best results in pluvio-nival catchments with spatial proximity and feature similarity, while the same techniques provided the worst performance in rain-dominated catchments.
- 9. When using feature similarity, smaller uncertainty bands were obtained using the ensemble of parameter sets obtained with AOF calibrations across the arid north, while the KGE' provided a more reliable ensemble in more humid central-southern

Chile The exclusion of (relatively few) nested catchments had a minimal impact on the non-linear relationships between the climatic and physiographic characteristics (i.e., predictors) and model parameters (i.e., predictands), having a negligible effect on parameter regression results.

760 10. The performance of feature similarity increased when four or more catchments were used as donors; however, the differences in performance were not statistically significant when compared to the results of using only one donor.

The results presented in this study here are valid only for Chile and might not necessarily be valid for other regions. Despite this near-natural catchments across continental Chile. Nevertheless, they provide guidance for ongoing and future studies involving the application of gridded *P* products for regionalisation of regionalising hydrological model parameters in ungauged

- 765 basins. The feature similarity procedure described here could be used to refine the parameter transfer approach that has been preliminary adopted in regionalisation approach adopted for national scale hydrological characterisations for in Chile (e.g., Bambach et al., 2018; Lagos et al., 2019). Additionally, further analyses could cover address: *i*) the effects that objective functions may have on the simulation of streamflow-derived hydrological signatures (e.g., Pool et al., 2017); *ii*) other states and fluxes derived from remote sensing data (e.g., Dembélé et al., 2020); *iii*) the influence of parameter equifinality (mainly
- for parameter regression), which can be accounted for by simultaneously optimising the model parameters and the regression equations, as described in Beck et al. (2020a); iv) the use of additional model structures, implemented through flexible modelling platforms (e.g., Clark et al., 2008; Knoben et al., 2019); and v) assessments of the sensitivity of regionalisation results with respect to modified climate scenarios.



Figure A1. Conceptual illustration of the hydrological regimes used to classify the 100 near-natural catchments used in this study.

775 Appendix B: Selection of catchment characteristics for feature similarity

To avoid including redundant information when quantifying catchment similarity, we examined the correlations between the catchment characteristics described in Table 4. Figure B1 shows correlation matrices between catchment characteristics using the Pearson correlation (a) and the Spearman rank (b) correlation coefficients. We only present correlations obtained with CR2MET, since very similar results were obtained with the remaining *P* products. Because the mean and median elevation are highly correlated (values of 1.0 and 0.99 for the Pearson and Spearman correlation coefficients, respectively), we decided to keep the median elevation under the assumption that it is more representative of topographic conditions, given the pronounced

elevation gradients in continental Chile. Similarly, mean annual PE was excluded because of high correlations between this variable and its high correlation with mean annual T (0.87 and 0.86 for the Pearson and Spearman correlation coefficients, respectively):-, notwithstanding that T was used to calculate PE. SDII was also excluded due to its high correlation to the
rx5day (0.97 for both coefficients). Finally, we excluded the snow cover from CAMELS-CL, as we found it to be unreliable over the snow-dominated catchments selected in our analysis.



Figure B1. Correlation matrices of the catchment characteristics described in Table 4 using CR2MET as the *P* product for: *a*) the Pearson correlation, to evaluate linear correlation; and *b*) the Spearman correlation to evaluate the monotonic correlation.

Appendix C: Performance of the components of the KGE'

Pearson correlation (r)	<u>CR2MET</u>	RF-MEP	ERA5	MSWEPv2.8
Calibration (cal.)	0.78-0.90	0.77-0.88	0.71-0.86	0.77-0.88
Verification 1 (Ver. 1)	0.74-0.88	0.72-0.87	0.67-0.87	0.69-0.86
Verification 2 (Ver. 2)	0.68-0.86	0.59-0.85	0.59-0.86	0.67-0.85
Spatial proximity (cal.)	0.70-0.87	0.68-0.84	0.57-0.82	0.66-0.84
Spatial proximity (Ver. 1)	0.66-0.86	0.63-0.84	0.61-0.84	0.62-0.84
Spatial proximity (Ver. 2)	0.61-0.83	0.51-0.82	0.56-0.83	0.59-0.82
Feature similarity (cal.)	0.74-0.89	0.71-0.88	0.69-0.85	0.72-0.88
Feature similarity (Ver. 1)	0.69-0.88	0.70-0.88	0.67-0.88	0.69-0.86
Feature similarity (Ver. 2)	0.64-0.87	0.59-0.85	0.64-0.87	0.65-0.84
Parameter regression (cal.)	0.54-0.80	0.54-0.69	0.60-0.82	0.42-0.63
Parameter regression (Ver. 1)	0.58-0.80	0.50-0.68	0.64-0.86	0.43-0.62
Parameter regression (Ver. 2)	0.50-0.79	0.43-0.65	0.59-0.84	0.37-0.57

Table C1. Quantiles 0.25 and 0.75 of the correlation coefficient (r) of the KGE' over the selected catchments.

Correlation matrices of the catchment characteristics described in Table 4 using CR2METv2 as the P product for a) the Pearson correlation, to evaluate linear correlation, and b) the Spearman correlation to evaluate the monotonic correlation.

$\underbrace{\text{Bias ratio } (\beta)}_{\text{Bias ratio } (\beta)}$	CR2MET	RF-MEP	ERA5	MSWEPv2.8
Calibration (cal.)	0.95-0.99	0.93-1.01	0.97-1.02	0.90-1.02
Verification 1 (Ver. 1)	0.89-1.03	0.84-1.02	0.90-1.12	0.77-1.04
Verification 2 (Ver. 2)	0.96-1.19	0.86-1.11	1.00-1.25	0.74-1.06
Spatial proximity (cal.)	0.73-1.09	0.70-1.15	0.74-1.22	0.70-1.13
Spatial proximity (Ver. 1)	0.72-1.12	0.70-1.12	0.72-1.22	0.69-1.08
Spatial proximity (Ver. 2)	0.73-1.30	0.73-1.23	0.77-1.46	0.68-1.14
Feature similarity (cal.)	0.81-1.19	0.78-1.29	0.81-1.35	0.68-1.3
Feature similarity (Ver. 1)	0.80-1.17	0.74-1.24	0.80-1.36	0.69-1.29
Feature similarity (Ver. 2)	0.86-1.40	0.77-1.40	0.86-1.57	0.69-1.27
Parameter regression (cal.)	0.99-2.04	0.89-1.72	0.76-1.78	0.82-3.07
Parameter regression (Ver. 1)	0.99-1.73	0.87-1.65	0.76-1.62	0.83-2.64
Parameter regression (Ver. 2)	1.10-2.05	0.90-1.83	0.88-1.94	0.83-2.54

Table C2. Quantiles 0.25 and 0.75 of the bias ratio (β) of the KGE' over the selected catchment.

Table C3. Quantiles 0.25 and 0.75 of the variability ratio (γ) of the KGE' over the selected catchments.

<u>Variability ratio (γ)</u>	CR2MET	RF-MEP	ERA5	MSWEPv2.8
Calibration (cal.)	0.97-1.00	0.95-1.00	0.95-1.01	0.96-1.01
Verification 1 (Ver. 1)	0.93-1.07	0.92-1.06	0.93-1.07	0.93-1.11
Verification 2 (Ver. 2)	0.92-1.13	0.91-1.17	0.91-1.12	0.79-1.05
Spatial proximity (cal.)	0.84-1.20	0.84-1.23	0.88-1.24	0.88-1.22
Spatial proximity (Ver. 1)	0.89-1.24	0.84-1.30	0.85-1.32	0.86-1.27
Spatial proximity (Ver. 2)	0.88-1.34	0.85-1.37	0.85-1.38	0.75-1.19
Feature similarity (cal.)	0.74-1.06	0.75-1.06	0.75-1.10	0.78-1.07
Feature similarity (Ver. 1)	0.79-1.04	0.76-1.06	0.77-1.07	0.81-1.03
Feature similarity (Ver. 2)	0.79-1.13	0.75-1.12	0.79-1.15	0.66-0.97
Parameter regression (cal.)	0.80-1.18	1.02-1.50	0.84-1.23	1.26-1.89
Parameter regression (Ver. 1)	0.82-1.20	1.02-1.35	0.87-1.25	1.27-1.69
Parameter regression (Ver. 2)	0.86-1.38	1.15-1.83	0.86-1.46	1.22-1.82

Competing interests. No competing interests

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