Title

A methodology to downscale water demand data with application to the Andean region (Ecuador, Peru, Bolivia, Chile)

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Abstract

Mountainous regions are a hotspot for water scarcity and anthropogenic pressure on water resources. Substantial uncertainty surrounds projections of future climate and water availability. Furthermore, quantitative and distributed data on water demand are generally scarce, dispersed, and highly heterogeneous. This forms a major bottleneck to study water resources issues and develop strategies to improve water resources management. Here we present a methodology to produce and evaluate high resolution gridded maps of anthropogenic surface water demand with application to the Andean region. These data are disaggregated in the major types of water demand: domestic users, irrigated area and hydropower. This dataset has been built by homogenizing, integrating and interpolating data obtained from various national institutions in charge of water resources management as well as relevant global datasets. The maps can be used to research anthropogenic impacts water resources, and to guide regional decision making in regions such as the Andes.

Keywords

population, water demand, land use, irrigation, hydropower, mountain regions

1. Introduction

1.1. Overview

Water resources management and governance are increasingly affected by systemic changes in water availability and socio-economic development (Wada et al., 2016). This renders quantifying spatiotemporal patterns of water demand a critical but often challenging task (Nazemi and Wheater, 2015). Existing datasets are usually scarce, dispersed, heterogeneous and difficult to access. As the population of developing countries is expected to increase by an additional two billion over the next forty years, significant supply-demand deficits are expected with estimated investments in water infrastructure of over 6.7 trillion USD needed worldwide (Hunt and Watkiss, 2011; OECD, 2015). Inadequate spatial mapping of anthropogenic surface water demand results in a lack of proper water accounting. For instance, partly as a response to this data scarcity, many prominent hydrological models do not fully incorporate the impact of anthropogenic activities on natural processes, leading to major errors in hydrological outputs (Gleick et al., 2013). Some models do characterise anthropogenic surface water demand but at very coarse spatial resolutions (Döll and Siebert, 2002; Van Beek et al., 2011; Bierkens, 2015) . Furthermore, water footprint studies are often limited to national or international scales, which is incompatible with areas of strong local gradients in water availability and demand, as is particularly the case in mountain environments (Mekonnen and Hoekstra, 2011).

These assumptions are particularly problematic in areas with large topographical variability and spatial constraints on water sourcing such as mountains (Buytaert et al., 2009; Viviroli et al., 2011, 2020). In fact, water resources in mountainous regions are under substantial stress both due to climate change as well as increased anthropogenic impacts (Correa et al., 2020). This could have substantial effects on the estimated 1.9 billion people that live in or downstream of mountainous areas by increasing potential damages due to floods or droughts (Immerzeel et al., 2020). Limited spatial understanding of water demand is a key hindrance to conducting comprehensive water-related risk assessments (Drenkhan et al., 2015, 2019). This can also have negative consequences on adequately allocating surface water abstraction rights, leading to an increase in water-related conflicts (Nazemi and Wheater, 2015).

Therefore, the objective of this study is to develop a method that is able to disaggregate spatially lumped data of anthropogenic surface water demand using the best available data for various sectors. We use the following definition of 'surface water demand': human water needs that are addressed by means of a direct anthropogenic disruption to natural surface runoff processes within a river network –for example, in the form of water withdrawal from a river– or artificially altering the flow regime –for example, via a dam–. We consider here demand in terms of end-purpose, i.e. number of users (inhabitants), irrigated area (hectares), and generated hydropower (MW). We do not consider industrial water requirements because of the lack of relevant data and the very specific requirements of different types of industries. We also do not quantify actual *volumetric* water abstraction, deviation, or storage, because such estimates depend on a number of additional variables (e.g. per capita water requirement; crop water requirements) that are methodologically well understood but require further local information.

1.2. Case study

The aforementioned challenges are manifest in the Andes, where climate and the ensuing water availability are extremely variable and affected by various drivers (Garreaud, 2009). For example, the eastern slopes of the tropical Andes display high precipitation frequencies and magnitudes due to moist air influx from the Amazon rain forest (Buytaert and De Bièvre, 2012), whereas the Pacific coast of Peru and northern Chile are one of the most arid regions of the world (Clarke, 2006). Overall, precipitation ranges from above 8000 mm yr^{-1} on the Pacific coast of Colombia to approximately 200 mm yr^{-1} over the Bolivian Altiplano (Garreaud et al., 2003; Garreaud, 2009), to less than 5 mm yr^{-1} in the Atacama Desert of northern Chile and southern Peru. Many major population centres are located in highly seasonal and vulnerable environments prone to water scarcity, such as the 12 million inhabitants of the capital of Peru, Lima. Furthermore, the region is witnessing rapid demographic growth, with an average annual growth rate of 1.5% until 2050 under a medium scenario across all four countries considered (United Nations Population Division, 2019).

The method developed here aims to produce spatially disaggregated maps of observed or estimated domestic demand and irrigation demand as well as hydropower production at 3 arcseconds (approximately 90 m at the equator) resolution (Figure 1). The geographical extent covers Ecuador, Peru, Bolivia, and Chile down to the 45S latitude, and therefore excludes Patagonia, Chile.

Comprehensive, homogenized datasets of anthropogenic surface water demand are highly valuable to provide researchers and decision makers, as an input in analyses such as assess and forecast water availability in the context of population growth and climate change. The data can also be used for research on the impacts of human pressure on water resources, potential impacts of environmental changes on human development, adaptation, or resilience, and to guide regional decision making on water resources in regions such as the Andes.

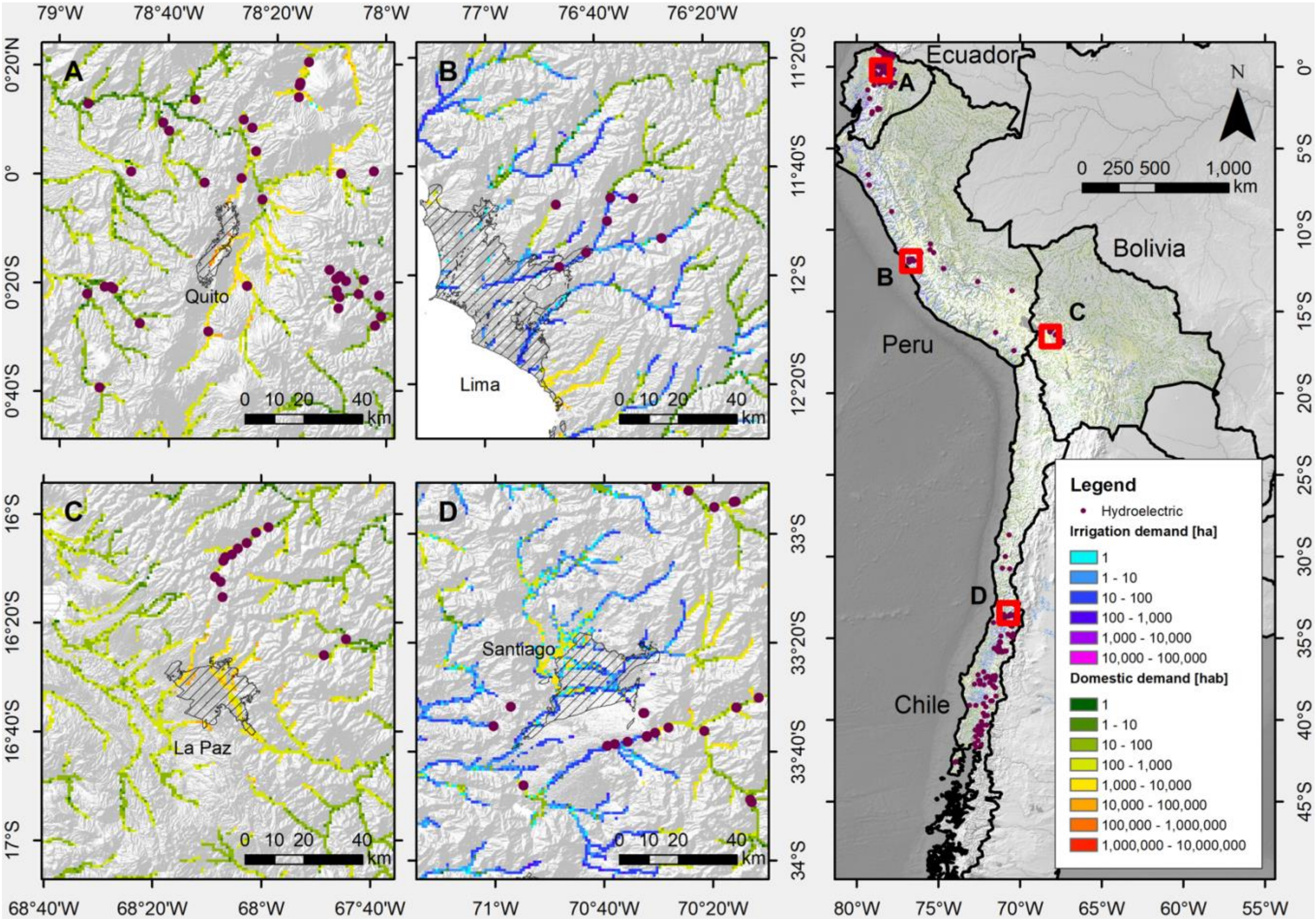

Fig. 1 | Surface water demand maps of the four capital city areas of the study region. The colored pixels represent river points coded with the number of people and the irrigated area that depend on this pixel for their water supply. In the cases of Quito, Ecuador (a) and La Paz, Bolivia (c), domestic water demand is visualised on top of irrigation demand. In the cases of Lima, Peru (b) and Santiago, Chile (d), irrigation demand is visualised on top of domestic water demand.

2. Methods

In order to derive the datasets mentioned previously, we first compiled existing national databases as well as other globally available datasets on surface water demand across all three sectors. We then develop an algorithm to homogenise, combine, infill, and disaggregate these datasets. Finally, we validated our results by comparing them to actual data for two major Ecuadorian rivers, which are the only systems in our study region for which high-resolution data are available.

2.1. National databases

The countries in the study region display varying degrees of data availability, accessibility and spatiotemporal completeness. We describe here the available data that were obtained as well as how they were incorporated in the dataset for each country (Table 1).

Country	Domestic users [number of inhabitants]		Irrigated area [hectares]		Hydropower production [MW]	
	Raw data	Use	Raw data	Use	Raw data	Use
Ecuador	Abstraction point coordinates accounting for only 62% of population as of 2016 (SENAGUA)	Abstractions on the Guayas and Esmeraldas rivers used for validation only	Abstraction point coordinates accounting for only 79% of irrigated area according to	Abstractions on the Guayas and Esmeraldas rivers used for validation only	Major hydropower plant coordinates and peak power production statistics as of 2016 (SENAGUA)	Used in main dataset

			FAO as of 2016 (SENAGUA)			
Peru	Abstraction point coordinates for all major cities with population served statistics as of 2017 (ANA)	Used in main dataset	No spatially disaggregated data available	N.A.	Major hydropower plant coordinates and peak power production statistics as of 2017 (ANA)	Used in main dataset
Bolivia	Abstraction point coordinates for La Paz with population served statistics as of 2014	Used in main dataset	No spatially disaggregated data available	N.A.	2010 National Dam Inventory including major hydropower plant coordinates and peak power production statistics	Used in main dataset
Chile	Abstraction point coordinates for entire country as of 2017 with no information on population served (Universidad de Concepción)	Not used	Abstraction point coordinates for entire country as of 2017 with no information on irrigated area (Universidad de Concepción)	Not used	Major hydropower plant coordinates and peak power production statistics as of 2017 (Universidad de Concepción)	Used in main dataset

Table 1. Summary of surface water demand data availability and use in dataset elaboration in the countries of interest: domestic users served by abstraction point [number of inhabitants], irrigated area served by abstraction point [hectares] and hydropower plant locations with associated peak electricity production [MW].

In Ecuador, the National Water Secretariat (SENAGUA) is the highest official authority responsible for maintaining an updated registry of all authorized surface water and groundwater abstraction allocations as well as granting new requests. It contains limited information on the coordinates of given abstraction points accounting for all major sectors, irrigation, domestic and hydropower.

In Peru, hydropower locations and peak power production data were obtained from the Peruvian Ministry of Energy and Mines. The National Water Authority (ANA) provided data for domestic demand numbers of major cities and irrigated areas.

Bolivian water demand data are scarce, with only a 2010 national dam inventory available for hydropower. Domestic demand data for the city of La Paz were provided by the state-run water company (EPSAS).

Chile has the most comprehensive water demand characterisation within our study region, with monthly allocations per officially registered surface abstraction point available for all major sectors as of 2015. However, irrigated area and population served per abstraction point are not available.

2.2. Disaggregation and combination procedure

We discuss here the process of combining or using available data on anthropogenic surface water demand with our estimates.

In the case of hydropower, it is typically possible to obtain data the relevant authorities or other publicly available datasets.

Direct spatially disaggregated data on domestic and irrigation water demand is often inaccessible, unavailable or incomplete. In those cases, we estimated anthropogenic surface water demand with an algorithm that estimates the most likely water abstraction point for a certain subset of population or irrigated area. Here we use 2015 population maps from the WorldPOP project

(Sorichetta et al., 2015) at 3 arcseconds resolution in addition to agricultural land use and land cover (LULC) maps from the MapSPAM initiative (International Food Policy Research Institute, 2019) at 10 km spatial resolution. We combined these data with high-resolution topographical data from the USGS Hydrosheds maps at 3 arcseconds resolution (Lehner, B., Verdin, K., Jarvis, 2008), to identify the most likely abstraction point as follows:

1. Identification of the river network

We derived the river network from digital elevation data from USGS Hydrosheds at 3 arcseconds resolution using a D8 hillslope flow algorithm

2. Separation of surface water and groundwater abstraction

We obtained data on the domestic and irrigation water demand from surface water (SW) and groundwater (GW) sources at the finest possible level in each country. We then compile statistics on the percentage of surface and groundwater use.

3. Identification of the location of surface water abstractions

For surface water abstractions, we assume that water is sourced from the nearest river or water body that satisfies the following criteria:

(a) the size of the associated catchment is above a predetermined threshold a.

(b) the abstraction point is not below a threshold elevation difference d.

In our application, we used a catchment area a threshold of 40 km^2, and an elevation threshold of 50 m, which represents the typical elevation difference that can be bridged with small pumping infrastructure. These values are based on our field observations and experience in the Andes but can be adjusted for specific purposes if needed.

4. Correction for groundwater use

In order to correct for groundwater use, we multiply both our obtained population served and irrigated area maps by the percentage of surface water use in the relevant administrative unit following the approach of Gleeson et al. (2012) (Appendix A).

2.3. Application to the Andes

2.3.1. Domestic demand

We used population maps from the 2015 WorldPOP project (Sorichetta et al., 2015) at 3 arcseconds resolution, which provide an estimated number of inhabitants per pixel.

In Ecuador, we implemented the water allocation algorithm described previously using the 2015 WorldPOP dataset in addition to available data for the city of Quito alone. We used available data from two major rivers in the validation process. Provincial-level statistics on groundwater use are available from the SENAGUA database.

In Peru, as domestic water demand data for major cities were available, those were masked out and the remaining rural areas were assigned withdrawal points using the water allocation algorithm and the 2015 WorldPOP dataset. National-level statistics on groundwater use are available from the International Groundwater Resource Assessment Centre (IGRAC).

For Bolivia, no domestic water demand data were available except for the city of La Paz. Therefore, we implemented the water allocation algorithm described above in all four countries using the 2015 WorldPOP dataset. National-level statistics on groundwater use are available from the International Groundwater Resource Assessment Centre (IGRAC).

Our data for Chile include coordinates of actual abstraction points but do not provide information on the number of people served by these abstractions. Therefore, we simply ran the algorithm for the entire country using the WorldPOP dataset as well. Provincial-level statistics on groundwater use are available from the Chilean Public Works Ministry.

2.3.2. Irrigation

We obtained irrigated area maps by crop type from the MapSPAM initiative (International Food Policy Research Institute, 2019) regridded at 3 arcseconds using nearest neighbor resampling. We combine all individual crop maps to obtain a total irrigated area per pixel of analysis.

In Ecuador, we implemented the water allocation algorithm described previously using the MapSPAM dataset with available data used in the validation process. Provincial-level statistics on groundwater use are available from the SENAGUA database.

In Peru and Bolivia, we implemented our water allocation algorithm using data from the MapSPAM initiative. National-level statistics on groundwater use for both countries are available from the International Groundwater Resource Assessment Centre (IGRAC).

The data for Chile contain irrigation abstraction coordinates, but no information about the area that they serve. Therefore, we also ran the algorithm over the entire country using the MapSPAM dataset. Provincial-level statistics on groundwater use are also available from the Chilean Public Works Ministry.

2.3.3. Hydropower

Hydropower generation locations as well as peak electricity production statistics are available in all four countries as of 2010.

Figure 2 summarises the steps used to develop and validate the final data outputs.

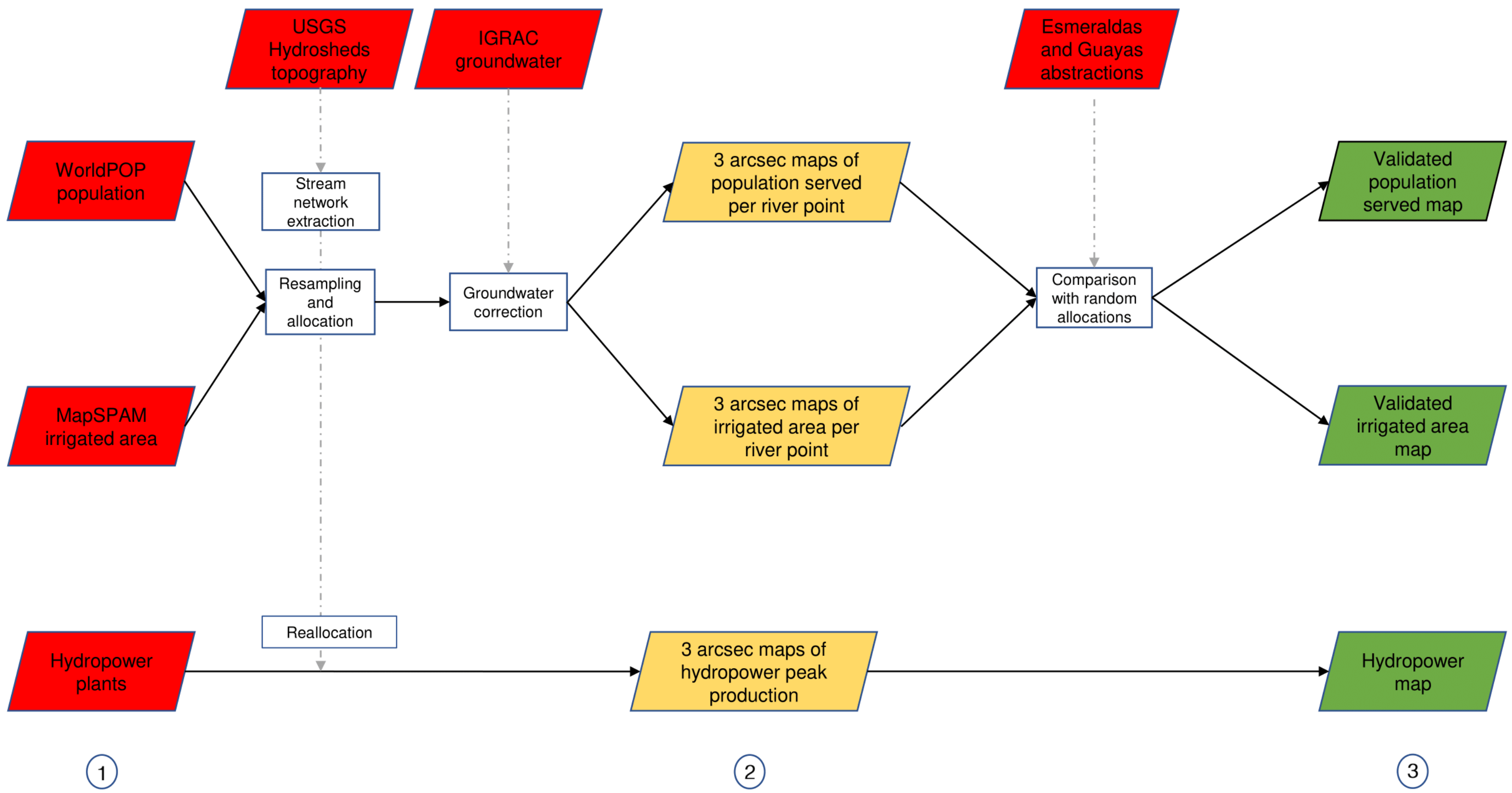

Fig. 2 | Computational steps involved in the development and validation of water demand maps of domestic users, irrigated agricultural area, and hydropower. Red: input data; orange: intermediate products; green: final products; parallelograms: datasets; squares: processes.

2.4. Validation

It is not possible to completely quantify potential errors in the input data because most datasets come without the necessary metadata to analyse those errors. Instead, we examined the performance of our algorithm by selecting two major Ecuadorian river catchments for which data are available and of sufficiently high quality from SENAGUA (Figure 3): the Guayas river, which serves the city of Guayaquil, the largest in Ecuador; and the Esmeraldas river, which passes through the capital Quito (where it is known locally as the Guayllabamba river).

We first examined normalised cumulative plots of simulated and observed abstractions over the normalised distance along each river transect x to assess the performance of our algorithm. To do so, we used a discrepancy factor A_d, defined as the extent to which both simulated A_{sim} and observed A_{obs} cumulative water demand profiles diverge, i.e. the value of the integral area between the two curves defined in Eq. 1 below. A value of zero indicates total a perfect alignment whereas a value of one indicates maximum divergence.

$$A_d = \int_0^1 abs(A_{sim} - A_{obs})\, dx \tag{1}$$

We then compared our results with 10,000 random allocations of the MapSPAM and WorldPOP irrigated area and population served pixels respectively to river cells without accounting for topography or distance, also. We then computed the discrepancy factor between both the cumulative curves generated by the algorithm and the average cumulative river profile of all random allocations in both river cases.

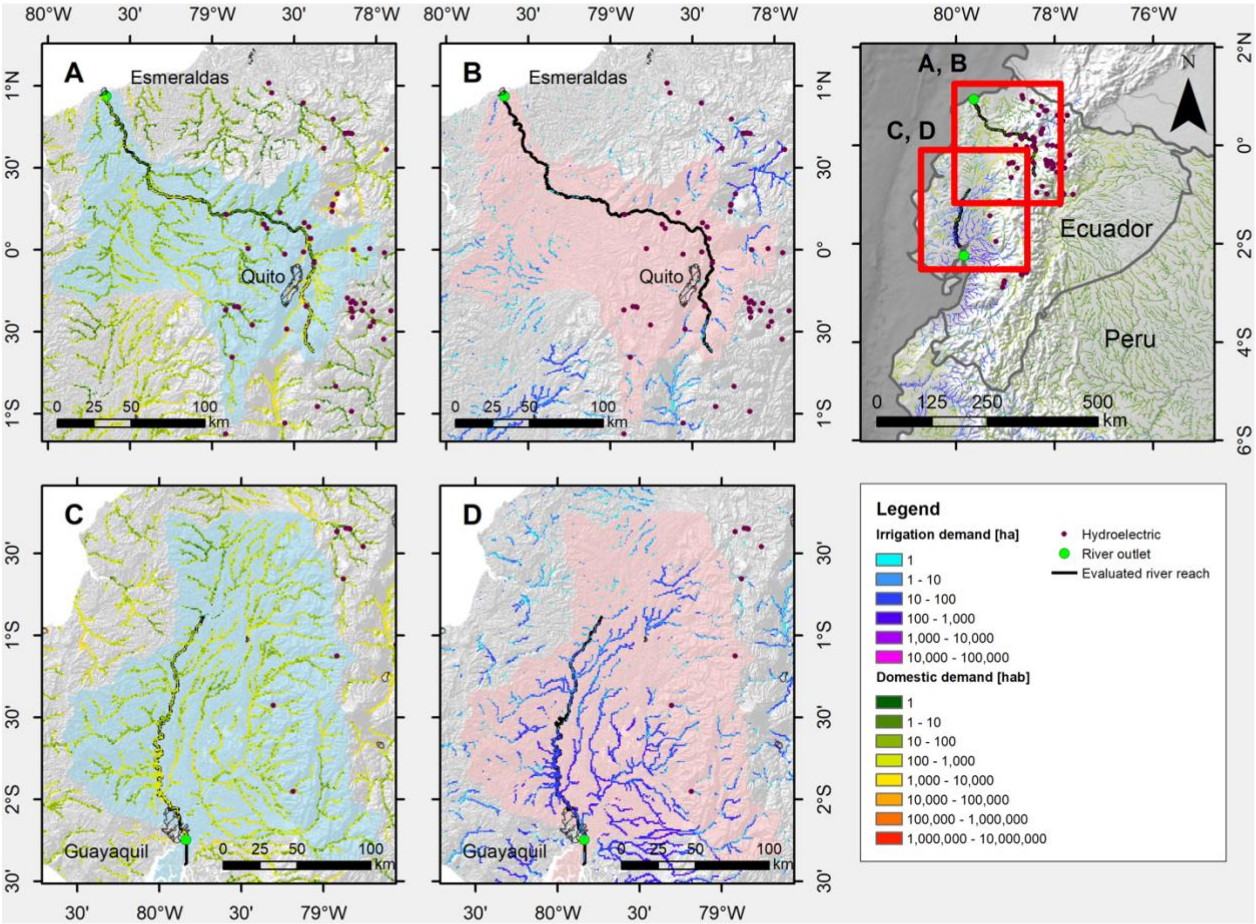

Fig. 3 | Map of Ecuadorian catchments used for data validation. Top: Esmeraldas river catchment; bottom: Guayas river catchment**.** (a) and (c) show domestic demand in the catchments whilst (b) and (d) highlight irrigation demand.

3. Results and discussion

The data and method presented here produce maps of domestic water demand, irrigated area and hydropower production from surface water resources. Table 2 summarizes the main results.

Country	Number of inhabitants allocated by algorithm	Percentage of total population	GW share of domestic use	Total population allocated after GW correction	Irrigated area allocated by algorithm (ha)	Percentage of total irrigated area	GW share of irrigation use	Total irrigated area allocated after GW correction (ha)	Total hydropower production (MW)
Ecuador	10551912	68%	31%	9105474	596628	95%	14%	475705	3293
Peru	26742361	87%	25%	20237483	949345	87%	60%	357473	8184
Bolivia	9235179	86%	60%	3613803	90911	73%	10%	84270	324.88
Chile	17558561	100%	52%	8494332	365871	90%	39%	259449	5857.22

Table 2. Summary of results across all four countries. MapSPAM and WorldPOP total irrigated area and population are respectively used as reference points. Total population and total irrigated area statistics were obtained from FAO (2016). Groundwater (GW) use is obtained from the IGRAC database (Gleeson et al., 2012) (see Appendix A).

We make the following observations. First, the proportion of the population that the algorithm is unable to allocate ranges between 32% in Ecuador to 0% in Chile. These are populations that live in headwater catchments above the highest river pixels in the river map. These highest pixels are determined by the catchment size threshold of 40 km^2 and represents a trade-off with the density of the river network that the D8 algorithm generates. We chose this threshold based on field observations that rural communities tend to source water from nearby small streams instead of larger rivers because the former tend to have better water quality. However, unallocated populations will need to be allocated manually as these are often small upland communities that draw water from various small rivers and suffer recurring water scarcity.

To evaluate the accuracy of the allocation of domestic and irrigation demand allocation, we compare our results to a baseline that consists of a random allocation (Figure 4). This visually demonstrates the improvement in performance of our algorithm.

A similar trend can be observed in the normalised cumulative plots of simulated and observed abstractions along our selected river profiles (Figure 5). The results display a good agreement between our results and observed data but substantial divergence between our results and the random allocation, with A_d decreasing an order of magnitude between the random allocation and the allocation algorithm (e.g., 0.37 to 0.04 for domestic users in Esmeraldas, Table 3). This provides evidence for the ability of the algorithm to identify the (approximate) location of water use.

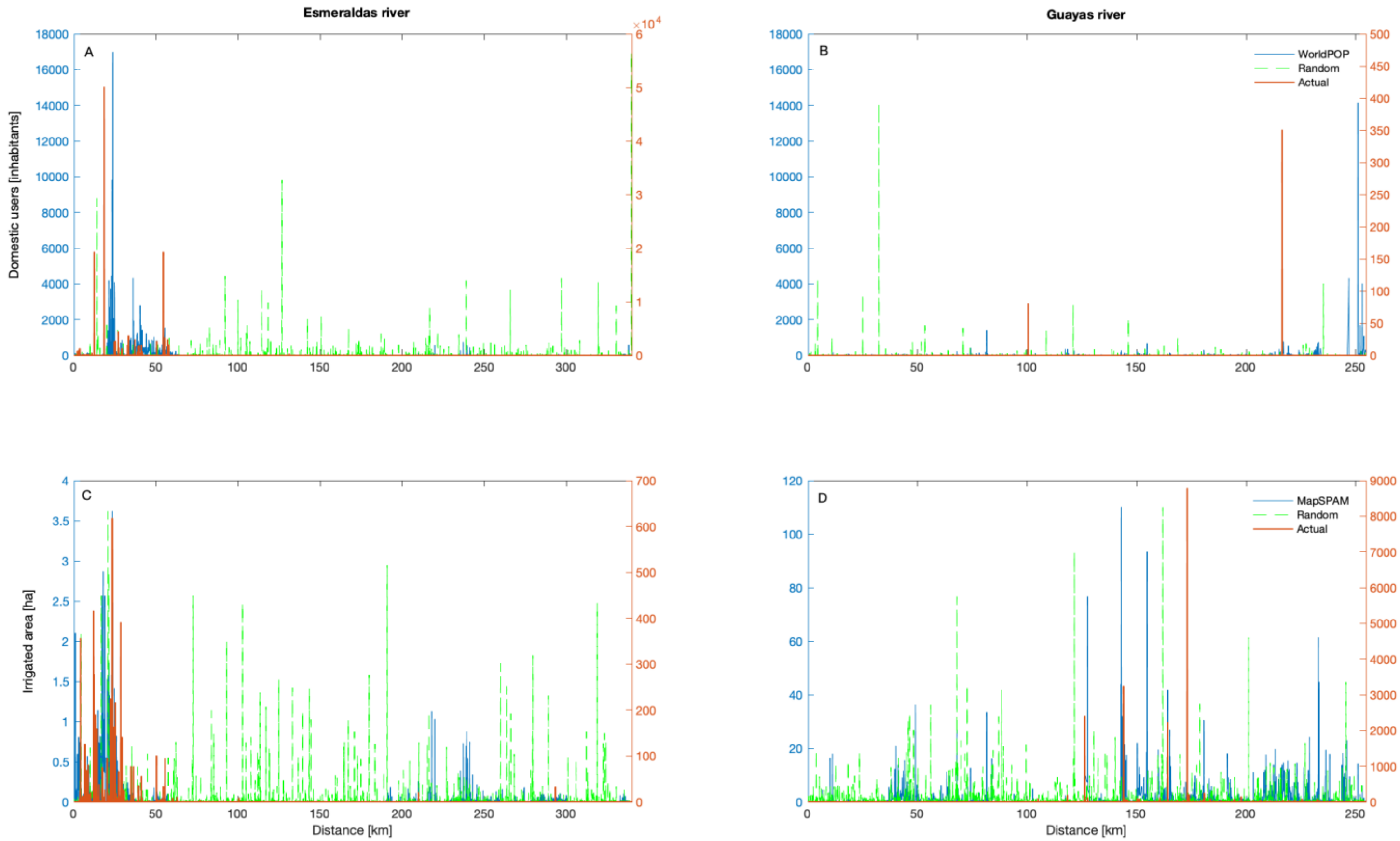

Fig. 4 | Longitudinal profiles of domestic water demand and irrigation demand for the Esmeraldas river: (a) and (c) respectively; Guayas river: (b) and (d) respectively. Blue: data estimated using the procedure presented here; green: random allocation of domestic water demand and irrigation demand from WorldPOP and MapSPAM datasets respectively; orange: independent data obtained from the Government of Ecuador (SENAGUA).

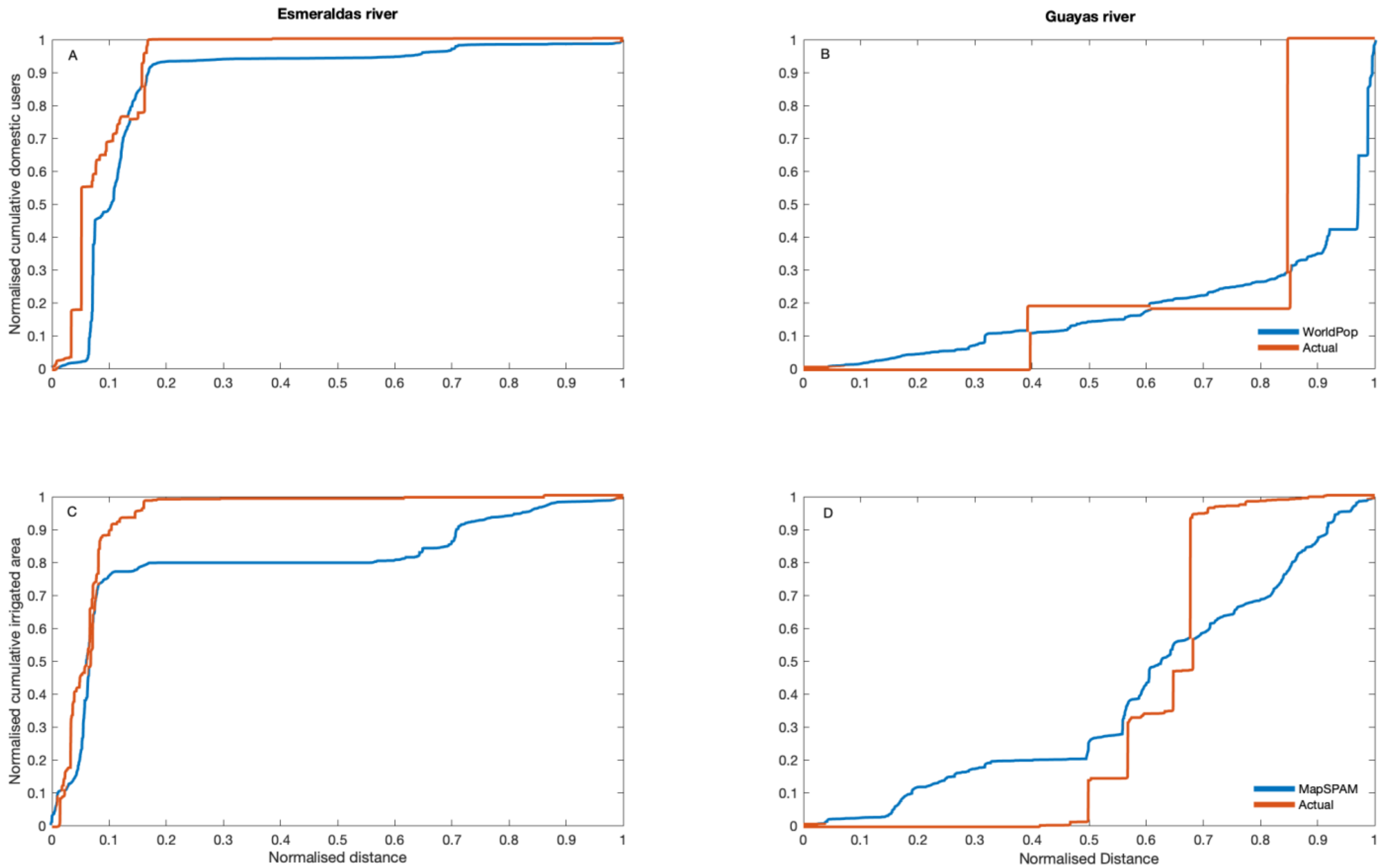

Fig. 5 | Normalised cumulative profiles of domestic water demand and irrigation demand for the Esmeraldas river: (a) and (c) respectively; Guayas river: (b) and (d) respectively. Blue: data estimated using the procedure here; orange: independent data obtained from the Government of Ecuador (SENAGUA). The difference between observed and simulated data curves (S) is highlighted in grey. A smaller S indicates a better agreement between the datasets.

River	Domestic users		Irrigated area	
	Observed	Random	Observed	Random
Esmeraldas	0.0470	0.3710	0.1226	0.4339
Guayas	0.0162	0.2096	0.0384	0.3918

Table 3. Computation of discrepancy factor A_d between normalised cumulative estimates from our algorithm and (a) available observations and (b) the average of 10,000 random allocations.

The algorithm does not account for the existence of advanced infrastructure such as pumping and inter-basin transfers nor is it able to represent return flows. This leads to an underestimation of demand in certain locations. For example, several major irrigation projects on the Pacific Coast of Peru rely on bulk water transfers from the Andean highlands. It would be straightforward to implement this in the procedure, conditional on the availability of abstraction and supply points. Additionally, the effect of this problem on our domestic demand estimates is limited as we use direct data from major cities in the region, where major water supply infrastructure is mainly used and water use is generally well documented (McDonald et al., 2014).

The algorithm is also prone to overestimating the number of abstraction points because it allocates each population pixel individually, while in practice larger clusters of users (e.g. a village) will be served by infrastructure drawing water from a single location. This results in an overestimation of the smoothness of the cumulative abstraction profile compared to the actual curve. The actual data shows major spikes as a result of the existence of large water major abstraction points. This again relates to the abovementioned lack of integration of large infrastructure in the methodology as a result of sparsity of available information.

Lastly, our method to correct for groundwater use is necessarily spatially coarse, because groundwater abstraction data are only available at the national level for Peru and Bolivia, limiting the accuracy of the correction. For example, in Peru, surface water sources account for 40% of total irrigation requirements. However, there is considerable variability within the country with several major irrigation projects along the Pacific Coast relying on complex infrastructure schemes involving groundwater abstractions whereas certain upland small-scale farmers might rely entirely on surface water. Nevertheless, the approach we have taken in such circumstances is consistent with previous attempts to quantify water use (e.g. Gleeson et al., 2012).

Such information is highly valuable in the context of water resources management and regional assessment of water stress. Especially in mountain regions, water stress can show strong spatiotemporal patterns (Buytaert et al., 2017), which are difficult to identify using population and irrigated area maps. Additionally, the methodology allows setting specific surface water abstraction rules depending on local management context, including for instance environmental flows, and allocation priorities during a hydrological drought. We should note that our analysis only focuses on quantifying water demand, irrespective of water availability. As such, we do not account for water scarcity or environmental flow requirements, which are beyond the scope of this study. In addition, our results are able to better capture rural water demand which is especially poorly documented. This can prove particularly useful in studies on rural to urban water reallocation (Garrick et al., 2019).

It is feasible to calculate actual volumetric surface water use (e.g. in m^3) from our spatially disaggregated surface water demand maps. This will depend on locally specific technical characteristics as well as particular management and policy constraints. The most straightforward approach to estimating volumetric domestic water use would be to multiply our domestic demand maps by per capita water consumption statistics at the relevant spatial scale. Irrigation water use can be estimated in a similar way by combining our maps with specific crop distribution and water demand information.

Future work should focus on developing actual water abstraction datasets for the countries under consideration, which will necessarily involve the cooperation of the various agencies responsible for maintaining such datasets. There is progress in this regard, as evidenced by the public availability of the national databases that we have used in this analysis. However, there considerable data scarcity still remains, which must be addressed to promote integrated water resources management at both the regional and national levels. Focus should be directed initially at regions with substantial demand. Moreover, instead of measuring individual abstraction points, decision-makers can set up measurement stations upstream and downstream of a river reach with known significant anthropogenic pressures to get an initial estimate of water use. Such efforts are crucial to assess actual water stress in a region undergoing major demographic changes with population growth rates up to 2050 projected between 37.7% and 62.4% in Ecuador and Bolivia respectively (United Nations Population Division, 2008). Such data could then be coupled with regional and global hydrological models to determine anthropogenic impacts on water availability. Furthermore, more work needs to be done on understanding water use amongst upper Andean communities who might rely on various water sources across a hydrological year or use unconventional methods such as rainwater collection or fog harvesting.

4. Conclusions

This dataset is intended to help both decision-makers and scientists in achieving a better spatial understanding of the impact of surface water demand on water security. Whilst we do not estimate actual volumetric water use, our datasets and methodology complement past studies which do estimate such requirements but fail to allocate them adequately in space, mainly due to their coarse spatial resolution. Therefore, possible specific applications include combining our maps with relevant hydrological data to obtain actual water use, developing risk and vulnerability analyses considering the cumulative irrigated area located downstream of a given mining project for example.

We do not consider the data, particularly in Peru and Bolivia, to be suitable for localised applications due to the uncertainties involved in the allocation algorithm. Specifically, as the algorithm assigns a given demand pixel to the nearest river point, it assumes all demand sources use gravity as the main water transport mechanism or use a maximum pumping elevation of 50m. Engineering solutions such as transport from upstream areas are therefore unaccounted for. Various steps limit the uncertainty generated from such structural issues such as correcting the obtained datasets for groundwater abstraction. Finally, as hydrological extremes increase in frequency and intensity, adequately mapping the full extent of risk will be key towards ensuring better societal preparedness.

Data availability

The data are intended to assist in developing more thorough and accurate assessment of water resources availability in the Andean region. The surface water demand data also enable more rigorous decision-making across all management and governance scales. Any raw data obtained from the respective country national databases used in this analysis can be obtained from the corresponding author on reasonable request. The datasets are publicly available at http://dx.doi.org/10.6084/m9.figshare.9168041 (Zogheib, et al., 2019).

The scripts used in the analysis are in the form of freely available GRASS GIS scripts located in the Figshare repository. Calculations were done using GRASS GIS (version 7.0) and Python (version 3.6.5), both of which are available as open source software.

Code availability

The allocation algorithm is available at: https://www.github.com/ICHydro/r.waterdemand

Competing interests

The authors declare no competing financial interests.

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References

Van Beek, L. P. H., Wada, Y. and Bierkens, M. F. P.: Global monthly water stress: 1. Water balance and water availability, Water Resour. Res., 47(7), doi:10.1029/2010WR009791, 2011.

Bierkens, M. F. P.: Global hydrology 2015: State, trends, and directions, Water Resour. Res., 51(7), 4923–4947, doi:10.1002/2015WR017173, 2015.

Buytaert, W. and De Bièvre, B.: Water for cities: The impact of climate change and demographic growth in the tropical Andes, Water Resour. Res., 48(8), 1–13, doi:10.1029/2011WR011755, 2012.

Buytaert, W., Célleri, R. and Timbe, L.: Predicting climate change impacts on water resources in the tropical Andes: Effects of GCM uncertainty, Geophys. Res. Lett., 36(7), n/a-n/a, doi:10.1029/2008GL037048, 2009.

Buytaert, W., Moulds, S., Acosta, L., De Bièvre, B., Olmos, C., Villacis, M., Tovar, C. and Verbist, K. M. J.: Glacial melt content of water use in the tropical Andes, Environ. Res. Lett., 12(11), 114014, doi:10.1088/1748-9326/aa926c, 2017.

Clarke, J. D. A.: Antiquity of aridity in the Chilean Atacama Desert, Geomorphology, 73(1–2), 101–114, doi:10.1016/J.GEOMORPH.2005.06.008, 2006.

Correa, A., Ochoa-Tocachi, B. F., Birkel, C., Ochoa-Sánchez, A., Zogheib, C., Tovar, C. and Buytaert, W.: A concerted research effort to advance the hydrological understanding of tropical páramos, Hydrol. Process., doi:10.1002/hyp.13904, 2020.

Döll, P. and Siebert, S.: Global modeling of irrigation water requirements, Water Resour. Res., 38(4), 8-1-8–10, doi:10.1029/2001wr000355, 2002.

Drenkhan, F., Carey, M., Huggel, C., Seidel, J. and Oré, M. T.: The changing water cycle: climatic and socioeconomic drivers of water-related changes in the Andes of Peru, Wiley Interdiscip. Rev. Water, 2(6), 715–733, doi:10.1002/wat2.1105, 2015.

Drenkhan, F., Huggel, C., Guardamino, L. and Haeberli, W.: Managing risks and future options from new lakes in the deglaciating Andes of Peru: The example of the Vilcanota-Urubamba basin, Sci. Total Environ., 665, 465–483, doi:10.1016/j.scitotenv.2019.02.070, 2019.

FAO: AQUASTAT Main Database, Food Agric. Organ. United Nations [online] Available from: http://www.fao.org/nr/water/aquastat/water_use_agr/index2.stm (Accessed 30 May 2018), 2016.

Garreaud, R., Vuille, M. and Clement, A. C.: The climate of the Altiplano: Observed current conditions and mechanisms of past changes, Palaeogeogr. Palaeoclimatol. Palaeoecol., 194(1–3), 5–22, doi:10.1016/S0031-0182(03)00269-4, 2003.

Garreaud, R. D.: The Andes climate and weather, Adv. Geosci, 22, 3–11 [online] Available from: www.adv-geosci.net/22/3/2009/ (Accessed 10 April 2018), 2009.

Garrick, D., De Stefano, L., Yu, W., Jorgensen, I., O'Donnell, E., Turley, L., Aguilar-Barajas, I., Dai, X., de Souza Leão, R., Punjabi, B., Schreiner, B., Svensson, J. and Wight, C.: Rural water for thirsty cities: a systematic review of water reallocation from rural to urban regions, Environ. Res. Lett., 14(4), 043003, doi:10.1088/1748-9326/ab0db7, 2019.

Gleeson, T., Wada, Y., Bierkens, M. F. P. and Van Beek, L. P. H.: Water balance of global aquifers revealed by groundwater footprint, Nature, 488(7410), 197–200, doi:10.1038/nature11295, 2012.

Gleick, P. H., Cooley, H., Famiglietti, J. S., Lettenmaier, D. P., Oki, T., Vörösmarty, C. J. and Wood, E. F.: Improving Understanding of the Global Hydrologic Cycle, in Climate Science for Serving Society, pp. 151–184, Springer Netherlands, Dordrecht., 2013.

Hunt, A. and Watkiss, P.: Climate change impacts and adaptation in cities: A review of the literature, Clim. Change, 104(1), 13–49, doi:10.1007/s10584-010-9975-6, 2011.

Immerzeel, W. W., Lutz, A. F., Andrade, M., Bahl, A., Biemans, H., Bolch, T., Hyde, S., Brumby, S., Davies, B. J., Elmore, A. C., Emmer, A., Feng, M., Fernández, A., Haritashya, U., Kargel, J. S., Koppes, M., Kraaijenbrink, P. D. A., Kulkarni, A. V., Mayewski, P. A., Nepal, S., Pacheco, P., Painter, T. H., Pellicciotti, F., Rajaram, H., Rupper, S., Sinisalo, A., Shrestha, A. B., Viviroli, D., Wada, Y., Xiao, C., Yao, T. and Baillie, J. E. M.: Importance and vulnerability of the world's water towers, Nature, 577, 364–369, doi:10.1038/s41586-019-1822-y, 2020.

International Food Policy Research Institute: Global Spatially-Disaggregated Crop Production Statistics Data for 2000 Version 3.0.7, Harvard Dataverse, V1, doi:https://doi.org/10.7910/DVN/A50I2T, 2019.

Lehner, B., Verdin, K., Jarvis, A.: New global hydrography derived from spaceborne elevation data, Eos, Trans. Am. Geophys. Union, 89(10), 93–94, 2008.

McDonald, R. I., Weber, K., Padowski, J., Flörke, M., Schneider, C., Green, P. A., Gleeson, T., Eckman, S., Lehner, B. and Balk, D.: Water on an urban planet: Urbanization and the reach of urban water infrastructure, Glob. Environ. Chang., 27, 96–105, 2014.

Mekonnen, M. M. and Hoekstra, A. Y.: National water footprint accounts: The green, blue and grey water footprint of production and consumption, Delft, the Netherlands. [online] Available from: http://waterfootprint.org/media/downloads/Report50-NationalWaterFootprints-Vol1.pdf (Accessed 25 June 2018), 2011.

Nazemi, A. and Wheater, H. S.: On inclusion of water resource management in Earth system models -Part 1: Problem definition and representation of water demand, Hydrol. Earth Syst. Sci., 19(1), 33–61, doi:10.5194/hess-19-33-2015, 2015.

OECD: The Governance of Water Regulators., Organisation for Economic Co-operation and Development, Paris., 2015.

Qin, Y., Mueller, N. D., Siebert, S., Jackson, R. B., AghaKouchak, A., Zimmerman, J. B., Tong, D., Hong, C. and Davis, S. J.: Flexibility and intensity of global water use, Nat. Sustain., doi:10.1038/s41893-019-0294-2, 2019.

Sorichetta, A., Hornby, G. M., Stevens, F. R., Gaughan, A. E., Linard, C. and Tatem, A. J.: High-resolution gridded population datasets for Latin America and the Caribbean in 2010, 2015, and 2020, Sci. Data, 2, 150045, doi:10.1038/sdata.2015.45, 2015.

United Nations Population Division: World population prospects. The 2008 revision population database, technical report, New York. [online] Available from: http://www.un.org/esa/population/publications/WPP2004/wpp2004.htm, 2008.

United Nations Population Division: World Population Prospects 2019: Data Booklet (ST/ESA/SER.A/424)., New York., 2019.

Viviroli, D., Archer, D. R., Buytaert, W., Fowler, H. J., Greenwood, G. B., Hamlet, A. F., Huang, Y., Koboltschnig, G., Litaor, M. I., López-Moreno, J. I., Lorentz, S., Schädler, B., Schreier, H., Schwaiger, K., Vuille, M. and Woods, R.: Climate change and mountain water resources: Overview and recommendations for research, management and policy, Hydrol. Earth Syst. Sci., 15(2), 471–504, doi:10.5194/hess-15-471-2011, 2011.

Viviroli, D., Kummu, M., Meybeck, M. and Wada, Y.: Increasing dependence of lowland population on mountain water resources, EartArXiv, doi:10.31223/osf.io/fr5uj, 2019.

Viviroli, D., Kummu, M., Meybeck, M., Kallio, M. and Wada, Y.: Increasing dependence of lowland populations on mountain water resources, Nat. Sustain., 1–12, doi:10.1038/s41893-020-0559-9, 2020.

Wada, Y., Flörke, M., Hanasaki, N., Eisner, S., Fischer, G., Tramberend, S., Satoh, Y., van Vliet, M. T. H., Yillia, P., Ringler, C., Burek, P. and Wiberg, D.: Modeling global water use for the 21st century: the Water Futures and Solutions (WFaS) initiative and its approaches, Geosci. Model Dev., 9(1), 175–222, doi:10.5194/gmd-9-175-2016, 2016.

Zogheib, C., Ochoa-Tocachi, B. F., Moulds, S., Ossa-Moreno, J., Villacis, M., Verano, C., Buytaert, W. High-resolution maps of the main types of anthropogenic surface water demand for 4 Andean countries. Figshare, http://dx.doi.org/10.6084/m9.figshare.9168041 (2019).

Appendices

Appendix A

	Domestic		Irrigation	
Province	**SW**	**GW**	**SW**	**GW**
Azuay	22%	78%	88%	12%
Bolivar	97%	3%	87%	13%
Canar	97%	3%	93%	7%
Carchi	78%	22%	94%	6%
Chimborazo	56%	44%	74%	26%
Cotopaxi	44%	56%	81%	19%
El Oro	81%	19%	98%	2%
Esmeraldas	98%	2%	98%	2%
Guayas	96%	4%	87%	13%
Imbabura	67%	33%	91%	9%
Loja	31%	69%	94%	6%
Los Rios	91%	9%	69%	31%
Manabi	36%	64%	98%	2%
Morona	17%	83%	0%	0%
Napo	98%	2%	100%	0%
Orellana	90%	10%	17%	83%
Pastaza	99%	1%	94%	6%
Pichincha	51%	49%	80%	20%
Santa Elena	1%	99%	92%	8%
Santo Domingo de los Tsachilas	83%	17%	94%	6%
Sucumbios	67%	33%	59%	41%
Tungurahua	76%	24%	90%	10%
Zamora-Chinchipe	99%	1%	99%	1%
AVERAGE	**69%**	**31%**	**82%**	**14%**

Table A1. Ecuador domestic and irrigation water demand percentage from surface water (SW) and groundwater (GW) sources per province, based on publicly available data from the Ecuadorian National Water Secretariat (SENAGUA).

	SW	GW
Irrigation	40%	60%
Domestic	75%	25%

Table A2. Peru domestic and irrigation water demand percentage from surface water (SW) and groundwater (GW) sources at country level, based on publicly available data from the international Groundwater Resources Assessment Centre (IGRAC).

	SW	GW
Irrigation	90%	10%
Domestic	40%	60%

Table A3. Bolivia domestic and irrigation water demand percentage from surface water (SW) and groundwater (GW) sources at country level, based on publicly available data from the international Groundwater Resources Assessment Centre (IGRAC).

	Domestic		**Irrigation**	
Province	**SW %**	**GW %**	**SW %**	**GW %**
Antofagasta	0%	0%	0%	0%
Arauco	99%	1%	98%	2%
Arica	60%	40%	58%	42%
Aysen	100%	0%	100%	0%
Bio-Bio	27%	73%	99%	1%
Buble	0%	0%	0%	0%
Cachapoal	29%	71%	28%	72%
Capitan Prat	100%	0%	100%	0%
Cardenal Caro	92%	8%	91%	9%
Cauquenes	27%	73%	97%	3%
Cautin	81%	19%	98%	2%
Chacabuco	3%	97%	4%	96%
Chacaral	0%	0%	0%	0%
Chañaral	16%	84%	0%	100%
Chiloe	94%	6%	98%	2%
Choapa	82%	18%	95%	5%
Colchagua	3%	97%	71%	29%
Concepcion	22%	78%	99%	1%
Copiapo	0%	100%	23%	77%

Cordillera	100%	0%	98%	2%
Coyhaique	100%	0%	100%	0%
Curico	9%	91%	91%	9%
Del Tamarugal	0%	0%	0%	100%
El Loa	99%	1%	100%	0%
Elqui	14%	86%	58%	42%
General Carrera	100%	0%	0%	0%
Huasco	0%	100%	1%	99%
Iquique	2%	98%	78%	22%
Limari	0%	100%	39%	61%
Linares	5%	95%	96%	4%
Llanquihue	78%	22%	98%	2%
Los Andes	100%	0%	21%	79%
Magallanes	99%	1%	96%	4%
Maipo	0%	100%	3%	97%
Malleco	85%	15%	100%	0%
Marga Marga	0%	0%	17%	83%
Melipilla	7%	93%	76%	24%
Ñuble	60%	40%	97%	3%
Osorno	81%	19%	94%	6%
Palena	98%	2%	100%	0%
Parinacota	100%	0%	100%	0%
Petorca	1%	99%	12%	88%
Quillota	0%	100%	1%	99%
Ranco	85%	15%	87%	13%
San Antonio	99%	1%	62%	38%
San Felipe	96%	4%	13%	87%
Santiago	25%	75%	75%	25%
Talagante	0%	100%	14%	86%
Talca	14%	86%	88%	12%
Tierra Del Fuego	99%	1%	92%	8%
Tocopilla	0%	0%	0%	100%
Ultima Esperanza	100%	0%	99%	1%
Valdivia	99%	1%	97%	3%
Valparaiso	29%	71%	8%	92%
AVERAGE	**48%**	**52%**	**61%**	**39%**

Table A4. Chile domestic and irrigation water demand percentage from surface water (SW) and groundwater (GW) sources per province, based on publicly available data from the Chilean Public Works Ministry.