J. Mt. Sci. (2026) 23(2): 489-504 e-mail: jms@imde.ac.cn http://jms.imde.ac.cn
https://doi.org/10.1007/s11629-025-0031-4

Original Article

Modelling water use in Nepal's highlands: a multidisciplinary and probabilistic framework

Megan KLAAR[1*] https://orcid.org/0000-0001-8920-4226; e-mail: m.j.klaar@leeds.ac.uk
Duncan QUINCEY[1] https://orcid.org/0000-0002-7602-7926; e-mail: d.j.quincey@leeds.ac.uk
C. Scott WATSON[1] https://orcid.org/0000-0002-6942-2469; e-mail: c.s.watson@leeds.ac.uk
Lee E. BROWN[1] https://orcid.org/0000-0002-2420-0088; e-mail: l.brown@leeds.ac.uk
Bishnu PARIYAR[2] https://orcid.org/0000-0001-8395-4413; e-mail: bishnu.pariyar@leicester.ac.uk
Arjan GOSAL[1] https://orcid.org/0000-0001-6782-0706; e-mail: a.gosal@leeds.ac.uk
Jon LOVETT[1] https://orcid.org/0000-0002-5839-3770; e-mail: j.lovett@leeds.ac.uk

* *Corresponding author*

1 School of Geography, water@leeds, University of Leeds, Leeds, LS2 9JT, UK
2 School of Criminology, University of Leicester, Leicester, LE1 7RH, UK

Citation: Klaar M, Quincey D, Watson CS, et al. (2026) Modelling water use in Nepal's highlands: a multidisciplinary and probabilistic framework. Journal of Mountain Science 23(2). https://doi.org/10.1007/s11629-025-0031-4

Abstract: Mountain communities in Nepal are increasingly exposed to climate-induced shifts in water availability, driven by glacial retreat, altered precipitation/snowmelt regimes, and declining groundwater sources. This study presents an integrated framework combining hydrological source analysis with socio-demographic survey data to evaluate seasonal water contributions and community-level water use patterns in the Upper Marsyangdi catchment, Manang District, Nepal. Isotopic ($\delta^{18}O$) and geochemical (silica) tracers were used in a Bayesian mixing model to quantify the seasonal contributions of glacial melt, snow, rain, and groundwater to river flow. Findings indicate that groundwater dominates pre-monsoon flow (60%- 70%) while post-monsoon discharge reflects more balanced inputs from all sources. In parallel, 120 household surveys were analysed using Latent Class Analysis to characterise water use across domestic, agricultural, energy, and tourism sectors. Results reveal spatial and demographic gradients in water source dependency, including gender and occupation as important predictors of water use. Respondents reported perceived increases in spring flow, alongside reductions in the availability of snow for household and tourism use and deteriorating river water quality and quantity, particularly affecting hydropower operations. Adaptation strategies include increased reliance on water storage infrastructure and source switching. The study highlights the value of applying probabilistic methods to hydrological and socio-cultural data to identify vulnerable populations and inform targeted, context-sensitive adaptation strategies. The proposed framework is transferable to other high-altitude regions, offering a robust approach for assessing climate resilience through the synthesis of scientific and local knowledge systems.

Keywords: Water source attribution; High mountain hydrology; MixSIAR Bayesian mixing model; Annapurna; Himalaya

Received: 04-Aug-2025
Revised: 31-Oct-2025
Accepted: 18-Dec-2025

1 Introduction

Receding glaciers, rising snowlines and increasingly unpredictable precipitation events are some of the clearest symptoms of climate change affecting mountain regions of the world. The impacts of climate change are projected to become more intense, and more extreme at high elevations, irrespective of carbon emissions now or in the future (Rounce et al. 2024; Duncan et al. 2013; Pepin et al. 2015; Pepin et al. 2022). Changes to the cryosphere will have cascading effects on biodiversity, ecosystem functioning and power generation, as well as initiating global feedbacks as a consequence of modified land surface and atmospheric interactions (Xu et al. 2009). Perhaps most significant is the impact these changes will have on water availability, since a reliable and predictable water supply supports the predominantly tourism and agriculture-based economies of mountain communities and is essential for their daily sanitation and cooking needs (Sharma et al. 2021). In this context, access to water in the mountain regions underpins a number of Sustainable Development Goals (United Nations 2015).

Some locations and communities are predicted to be more vulnerable than others to changes in the demand and supply of water resources; for example, the Indus and the Amu Darya in South Asia are densely populated and heavily irrigated as well as being characterised by transboundary tensions (Immerzeel et al. 2020), which add a political component to the management and use of natural resources. The same can be said for most major catchments in Asia where large populations, rising economic growth rates and loose governance structures are common. In remote mountain regions, demand for water tends to be high, with large numbers of people directly dependent on natural water supplies to irrigate food crops, and to provide hydroelectric energy and potable water for sanitation (Quincey et al. 2018; Immerzeel et al. 2020). This is also where natural resources are changing, and diminishing, the fastest. This study focuses on Nepal, where resource-based livelihoods dominate in remote regions (McDowell et al. 2020), the impacts of climate change are already playing out for many (Konchar et al. 2015), and the balance between different water sources is likely to shift in coming decades (Manandhar et al. 2012).

In the mountainous regions of Nepal, river discharge during summer months comprises melt from permanent and seasonal snow and ice reserves as well as elevated rainfall and groundwater flows during the monsoon. During the winter period, groundwater is a critical component of river discharge (Laskar et al. 2018). In recent decades there have been consistent increases in average temperature twinned with changing precipitation patterns including increased rainfall in the monsoon season but decreasing precipitation at all other times (Panthi et al. 2015; Sharma et al. 2021), resulting in decreased water availability to some areas which are already considered to be an arctic desert (Alford and Armstrong 2010; Paudel et al. 2011). Communities often rely on groundwater sources (springs and wells) for their freshwater supply (Tambe et al. 2012; Chapagain et al. 2019; Adhikhari et al. 2021), but these have been reported to be declining (Poudel and Duex 2017; Chapagain et al. 2019; Gurung et al. 2019; Adhikari et al. 2021), or vanishing (Chauhan et al. 2023). At the same time many regions are approaching, or have already passed, peak water (Huss and Hock 2015), and water scarcity at certain times of the year is now a reality (Merz et al. 2003b).

The aim of this study is to demonstrate how a multidisciplinary approach can yield insights into which sources of water are most important for maintaining river flows and providing resources for varying uses, and thus identify pinch points where water security may be compromised. Our approach couples Bayesian water source contribution mixing model techniques with clustering methods applied to householder surveys to assess water use attitudes and behaviours. The use of probability-based water source partitioning models and latent class analysis of household responses within our framework provides a greater account of model uncertainty, incorporation of prior knowledge and the ability to incorporate hierarchical data, resulting in more robust and transparent results (Clark 2005). This new framework has broad application within the current climatic context as well as providing insight into future stresses as the balance between different source contributions evolves. We test the approach in the high mountain Annapurna region of Nepal where changes in temperature, precipitation, snow cover and glacier extent impact directly on village communities that have strong connections to the land, and who depend directly on meltwater resources for irrigation (Konchar et al. 2015). We illustrate how these methods provide important information relating to seasonal water source availability that could be used to build community knowledge and progress adaptation to these changes.

2 Study Area and Methods

2.1 Study area

We focussed on the Manang District (28.67°N, 84.03°E) of north-central Nepal. The district covers an area of 2,246 km², ranging from 4,200 to 3,000 masl (Aase and Vetaas 2007), and is home to a total population of 5,658 (2021 census, Government of Nepal), one of the most sparsely populated regions of Nepal. Manang receives some of the lowest rainfall of any district of Nepal (an average of 1,530 mm per year vs 3,345 mm in monsoon-influenced Pokhara) due to a dampened monsoonal influence linked to its position to the north of the Himalayas (Aase and Vetaas 2007; Parajuli et al. 2015), resulting in a cold and arid climate with extreme winter and mild summer temperatures (Chapagain 2016). The area encompasses the headwaters of the Marsyangdi (also referred to as the Marshyangdi) River (catchment area = 4,787 km²), which originates from the northern slope of the Annapurna mountain range. Two rivers drain the highest elevations (Fig. 1), and further downstream, the Marsyangdi River flows eastwards into the Trishuli River and, ultimately, the Ganges. The river hosts three operating hydropower projects totalling 189 MW (Chiluwal et al. 2021), representing an important economic resource for Nepal (Mudbhari et al. 2022).

The geology of the Marsyangdi River transitions from the west of the catchment to the east, with the headwaters of the river originating in Tethyan Himalaya Sequence (THS), moving to the Greater Himalayan Sequence (GHS) west of Chame village at the South Tibetan Detachment System fault (Ghezzi et al. 2019). Modelled river flow in the upper Marsyangdi (Fig. 2; ICIMOD 2023) illustrates a monsoonal influence from June-September, with highest rainfall and river discharges starting from April at the start of the monsoon season (Bajracharya et al. 2011), and reduced river flow between October and December.

A number of small communities are located along a 30 km length, from the head of the Marsyangdi River to Chame. Households rely on a mix of subsistence farming, pastoralism and tourism for their livelihoods, with an increasing trend of out-migration to the major cities in Nepal and diversification of agropastoral practices, including cash-crop production (Konchar et al. 2015). Wheat, barley and buckwheat are grown in the summer months in the valley bottom and on south facing slopes, overseen by village governance with input from the local Lama (Aase and Vetaas 2007).

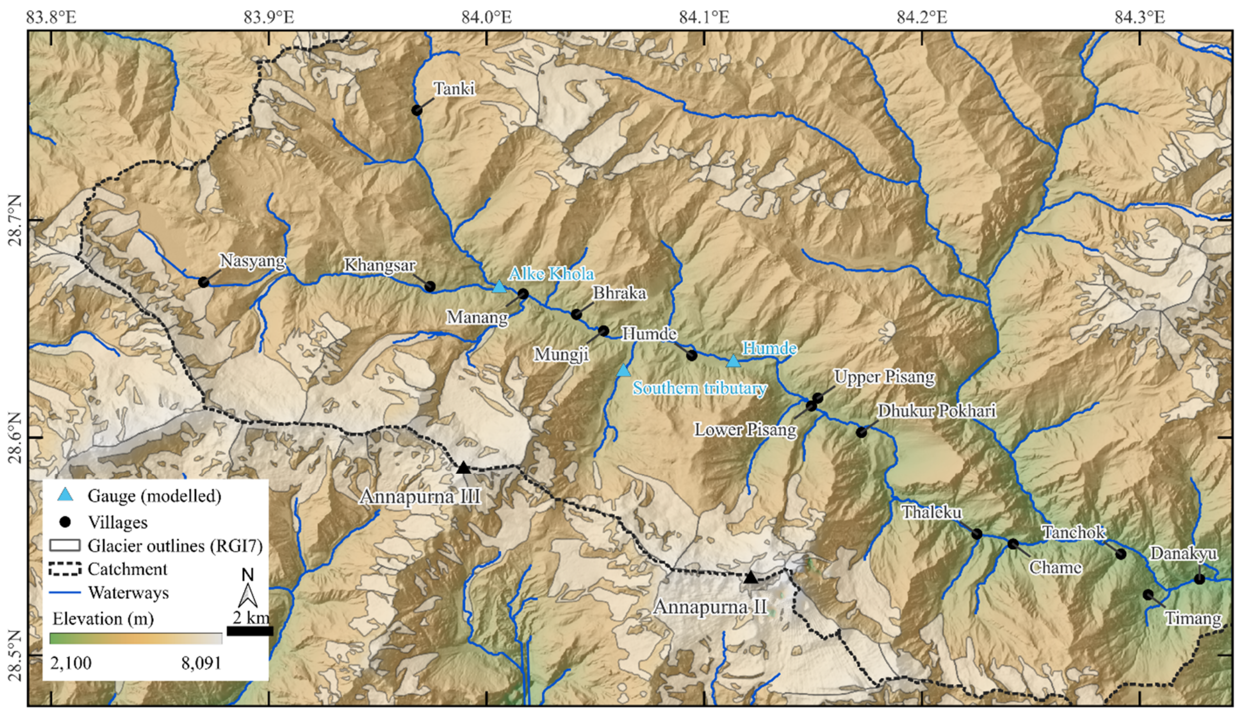

Fig. 1 Manang- Marsyangdi valley study area (Nepal) with household village survey and river gauge locations indicated.

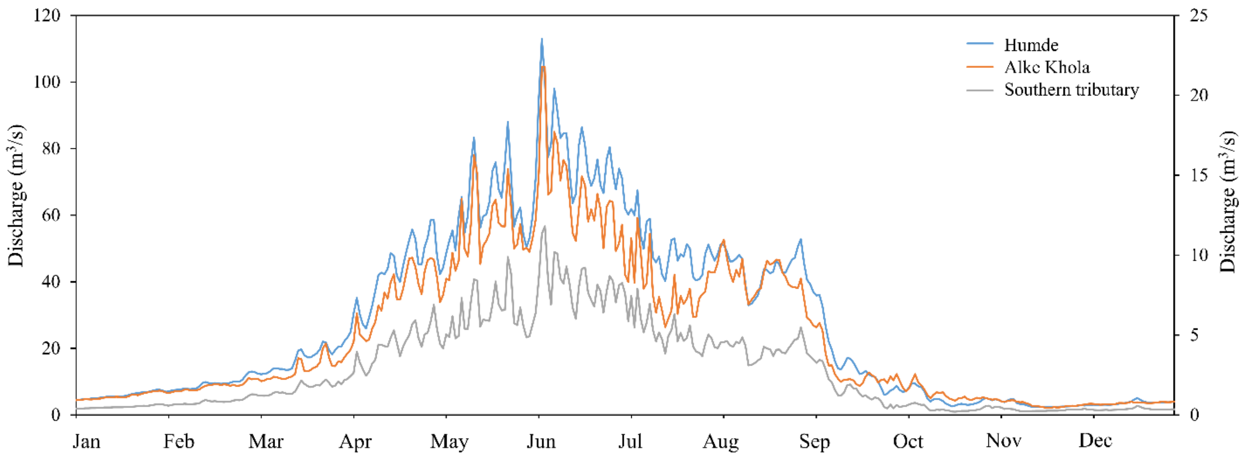

Fig. 2 Average daily modelled river flow 2007-2017 in the Upper Marsyangdi River at Humde (blue, primary *y* axis, River ID 5018175), Alke Khola at Khangsar (orange, secondary *y* axis, River ID 5017637) and southern tributary, entering the Marsyangdi above Humde (grey, secondary axis, River ID 5017818). Data from ICIMOD, 2023.

Following the construction of a road along the Marsyangdi valley, tourism is popular, with an increasing number of hotels and lodges supporting trekkers along the Annapurna circuit (Aase et al. 2010).

2.2 Water source analysis

Sampling of four key water source contributors to flow within the Marsyangdi River was undertaken pre- (April) and post- (November) summer monsoon season in 2017. Glacial (both glacial ice and recent meltwater), rain, snowpack and groundwater (sampled from hillside groundwater springs and deeper drinking water wells within settlements) were collected. River water samples were collected along the length of the main river and from several large tributaries upstream of Chame to enable source member contribution analysis, as outlined in Fig. 3, and Appendix 1.

Samples were filtered immediately (snow and ice samples allowed to melt at ambient temperature first) using nylon 0.45 µm filter paper into HDPE bottles and stored on ice prior to isotopic and geochemical analysis. Isotopic ($\delta^{18}O$ and $\delta^2H/\delta D$) analyses were conducted at the Natural Environment Research Council National Environmental Isotope Facility (Nottingham, UK). Oxygen isotope ($\delta^{18}O$) measurements were made using the CO_2 equilibration method with an Isoprime 100 mass spectrometer plus Aquaprep device. Deuterium isotope (δD) measurements were made using an online Cr reduction method with a EuroPyrOH-3110 system coupled to a Micromass Isoprime mass spectrometer. Isotope measurements used internal standards calibrated against the international standards VSMOW2 and VSLAP2. Errors are typically ± 0.05‰ for $\delta^{18}O$ and ±1.0‰ for δD. Geochemical analysis was conducted at the University of Leeds (School of Geography laboratory) to quantify Na^+, Mg^{2+}, Ca^{2+}, Si, K^+, Cl^-, NO_3^- and SO_4^{2-} using a Thermo Scientific (Waltham, MA, USA) iCAP 7600 ICP-OES analyser calibrated with Cranberry -05 lake water sample.

A three end-member mixing model was constructed utilising $\delta^{18}O$ and silica (Si) as final end-members. The approach of using $\delta^{18}O$ and a second conservative tracer together is common in water source attribution models due to the strong correlation between $\delta^{18}O$ and δD (Mondal et al. 2023), which prevents adequate discrimination between end-members and source attributions. Silica has been utilised in similar glacierised High Mountain Asia hydrological tracer studies to distinguish between reacted (subsurface flow pathways) and unreacted (surface flow pathways) due to the underlying geology and residence time (Wilson et al. 2016). The differences in tracer signatures between surface water sources and those from groundwater are substantial, and well-known, in the study area (Evans et al. 2004; Ghezzi et al. 2019). Rain and snow were treated as separate end-members, rather than grouped as 'precipitation' due to the documented seasonal differences in both sources in central Himalaya (Andermann et al. 2012; Laskar et al. 2018). This seasonal pattern further warranted the use of separate (April and November) mixing models for source attribution.

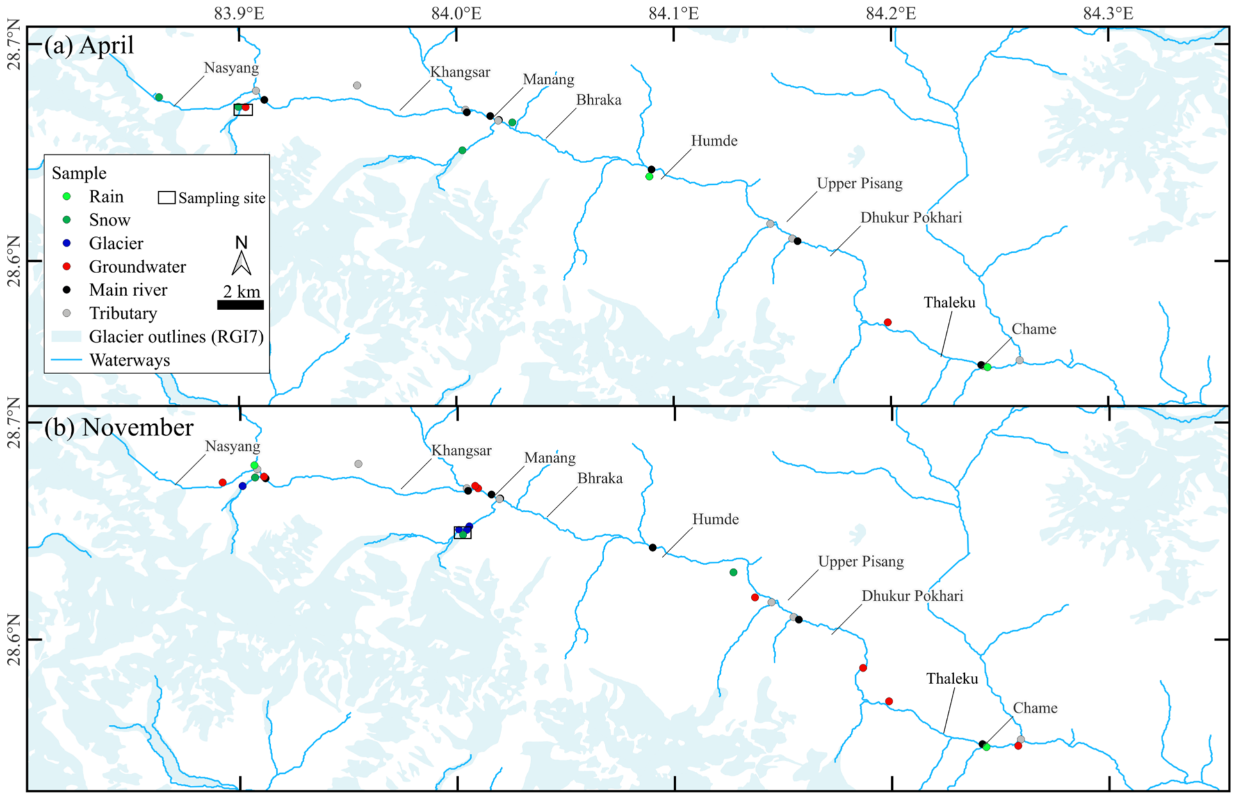

Fig. 3 Locations of surface water (river and tributary) and isotope samples collected in (a) April 2017 and (b) November 2017.

The R package (R Core Team 2022) MixSIAR (version 3.1.12; Stock and Semmens 2016a) was used to run a Bayesian mixing model that incorporated seasonal source variability, more than three sources (Stock and Semmens 2016b; Fang et al. 2022) and a robust assessment of the likelihood of source proportions using a Markov Chain Monte Carlo (MCMC) algorithm, which is best suited for small sample sizes like ours (He 2020). Separate models were run for each season, with site set as a random effect and residual error as a measure of model uncertainty (Stock and Semmens 2016b). Average and standard deviation tracer data were used as source data and a zero value for discrimination data, using an uninformative prior (1,1,1). Both models used 'long' model run settings (chain length = 300,000; burn = 200,000; thin = 100; chains = 3 and alpha prior = 1). Model convergence was assessed using Gelmen-Rubin and Gewke diagnostic tests (Stock and Semmens 2016b) and in all cases variables were below 1.05, which indicates model convergence. The summary statistics for the 2.5%, 50% and 97.5% credible intervals of the posterior distributions were examined alongside the posterior density plots to assess model uncertainty and parameter stability. Consistency between the numerical summaries (posterior means/medians and credible intervals) and the visual posterior distributions indicated that parameter estimates were well constrained and not unduly influenced by model uncertainty or poor mixing.

2.3 Household surveys

A total of 293 face-to-face surveys were conducted in April 2017, collecting responses from a wide geographical and topic range (Appendix 2). Given the abrupt change in geology, and the presence of a large tributary immediately downstream of Chame (Fig. 1), a sub-section of survey responses from respondents identifying as living in or up valley of Chame (catchment area = 710 km^2) was used within the household survey analysis. Data cleaning and processing to distil the responses to those within the geographical area of interest reduced the number of survey responses to 120, encompassing 11 villages from the Upper Marsyangdi valley; Bhraka, Chame, Dhukur Pokhari, Humde, Khangsar, Manang, Mungji, Nasyang, Pisang, Thalekhu, and Tanki (Fig. 1). Metrics describing catchment area, along-stream distance and the elevation of each village were derived remotely, using the ALOS World 3D - 30m (AW3D30) digital elevation model (Tadono et al. 2014).

The survey was designed in two parts. The first captured socio-demographic information which included ethnicity, occupation, gender and age. The second part focused on current water usage for household, irrigation, power generation, and tourism. Participants were asked for each category (if relevant) about their dependency on glacial, spring (issuing from the ground), river, lake and groundwater (well and aquifer) sources using a six-point scale (most used, more used, moderately used, less used, least used and not used). Questions relating to the respondent's perceived changes in water source quality and quantity over the last 20 years (increasing, decreasing, stable, don't use/ not applicable) and changes in the seasonality of water sources and coping practices relating to these changes were also collected to help provide more detailed information on water usage.

2.4 Latent Class Analysis of household survey data

To disentangle any differences in the local population water usage behaviour, Latent Class Analysis (LCA), a probabilistic statistical method for exploring and identifying underlying latent classes within groups, was used. LCA has previously been successfully applied to investigate a range of socio-environmental issues, including characterising the awareness and attitudes of people who visit, and therefore impact, protected areas (Rhead et al. 2018; Gosal et al. 2021). In the current study, household survey responses were used to categorise local community members of the case study area into different water usage groups (with household, irrigation, energy generation, and water for tourism, individually modelled) using LCA, to understand water usage behaviour.

As water usage behaviour differed for each use type (e.g. not all individuals used water for tourism), responses for each type of water use resulted in a different total number of respondents in each grouping (Appendix 3). Responses were recoded into a polytomous variable, based on whether participants were dependent on a water source (most used, more used), somewhat dependent (moderately used, least used, less used), or not (not used) as outlined in Appendix 4. The 'poLCA' package was used in R to run the models (Linzer et al. 2011; R Core Team 2022), with multiple LCA models run for each water usage type, with the lowest Bayesian Information Criterion (BIC) value being used to determine the optimal number of groups. The LCA posterior probabilities were then used to classify survey respondents into a class for each water use model. Results from each village were presented as percentage of all users from each identified latent class to determine spatial patterns of water usage and to identify those villages at higher risk of changing water sources. Where a single response to the specified water usage section was recorded from a village, this was excluded from the visual representation of the results.

2.5 Water use probability

Using the latent classification groupings identified in the household and irrigation water use categories, we further investigated the factors influencing water source usage among respondents using binary (spring water used or not) logistic regression modelling. Predictor variables obtained from the interviews including gender, village of residence, occupation (limited to agriculture, business and service industries), age group (20-29; 30-39; 40-49; 40-59; 60+) and ethnicity (Brahmin, Dalit and Janajati) were used first singly and then in combination as an additive model to determine which factors best predict the use of spring sources to act as a baseline for comparison between water use classes. A binary approach was used when assessing both household (where two water use categories were identified) and irrigation (where three water use categories were identified) due to the low number of respondents classified in one of the irrigation water use classes which prevented the use of multinomial regression modelling. Both water use categories identified a water use group which relied on spring sources, and hence this was used as the baseline water use class for comparison.

Model fitting was conducted in R using the *glm* function with binomial family and logit link function binary logistic regression. Akaike Information Criterion (AIC) and residual difference were used to compare between models and select the models and predictor variables which best explained water class membership. Model fit was further assessed by comparing the fitted model to the null (intercept-only) model using a Chi-squared likelihood ratio test, with a p-value <0.05 used to determine statistical significance.

Predicted probabilities of respondents' water class membership using the two best performing models (as identified by the lowest AIC values) were calculated to assist with the interpretation of the logistic regression results. Predicted log-odds were transformed using the inverse logit function to produce predicted probabilities and 95% confidence intervals. For categorical predictors, one category was set as the baseline group against which the others were compared. The reported coefficients represent the change in the log-odds of the outcome relative to the baseline. Odds ratios greater than 1 indicate increased odds relative to the baseline, while values less than 1 indicate decreased odds. Only water usages which had more than one identified LCA grouping were analysed in this way. These tests allowed an estimation of the probability that a respondent in a particular group (e.g. village, gender, occupation group) used a particular water source identified using the LCA, while accounting for the relative likelihood of the alternatives.

All statistical analyses and visualizations were conducted using R (R v.4.3.2), including use of the dplyr and tidyr packages.

3 Results

3.1 Water source analysis

Both seasonal end-member analyses showed good discrimination between water sources, with all of the samples sitting within the isospace geometry (Fig. 4), indicating agreement with mixing model assumptions (Stock and Semmens 2018). Groundwater sources were more numerous and variable in silica concentration post-monsoon, validating the use of a two-season mixing model which was able to constrain the river sample composition (Fig 4a). Source contribution to the main river and tributary flows also showed a seasonal difference, with April (pre-monsoon) river flow being dominated by groundwater inputs (60%-70%; Fig. 5a, 5c) and limited glacial (20%-30%) and precipitation (snow and rain <10% respectively) contributions. In November, the main river and tributary source contributions were much more

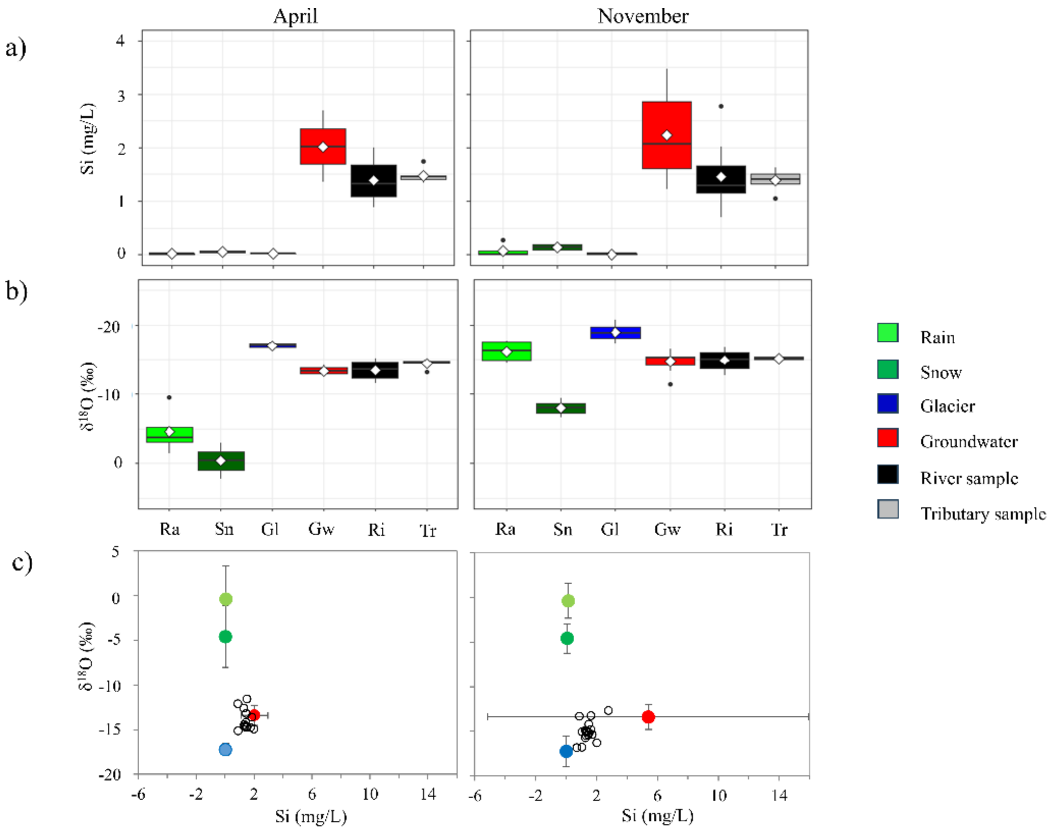

Fig. 4 Summary of a) silica and b) oxygen isotope concentrations in source and river samples in April and November, with median (black line), mean (white diamond), 25th and 75th percentiles (bottom and top of box respectively) and variation (whiskers) and c) isotope mixing space including +/- 1 standard deviation.

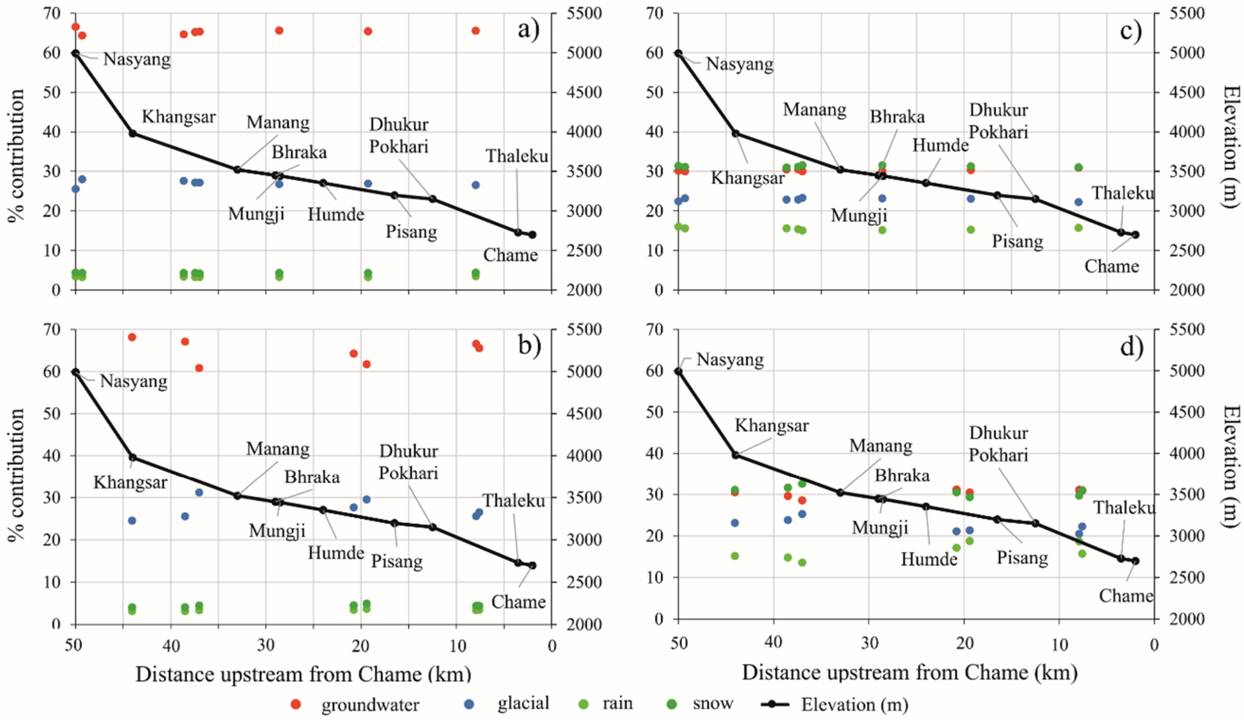

Fig. 5 End-member source contribution to river flow with increasing distance upstream of Chame for a) main river, April 2017; b) main river, November 2017; c) input tributaries, April 2017; d) input tributaries, November 2017. Note the reversed x-axis.

equitable, with sources ranging from ~15% (rain) to 32% (snow), and groundwater sources contributing approximately 30% of water composition. Glacial contribution remained relatively constant between sampling periods, generally ranging from 20-30%. There was little difference in source composition between the tributaries and main river or distance along the river.

3.2 Household survey and LCA grouping

The location of respondents was skewed towards the larger villages and settlements in the valley, including Chame, Humde and Pisang, with fewer respondents from smaller villages including Thaleku and Khangsar (Fig. 6). Due to the low representation of these villages, they were excluded from the logistic regression models, which used village as a predictor.

Household water usage had the highest number of responses (96%), with an optimal grouping (lowest BIC) of two groups (Appendix 5). The classes predominantly differentiated between respondents who utilise a range of water sources, excluding springs (Class 1- Fig. 7a) and those who predominantly rely on spring rather than other water sources (Class 2- Fig. 7b). Class 1 groups were mainly situated in the middle

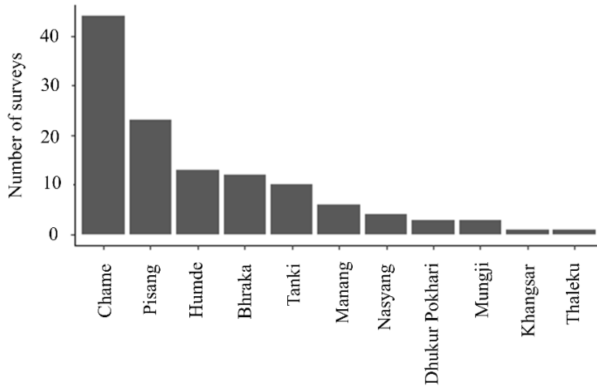

Fig. 6 Histogram of the location of survey respondents used within the Latent Class Analysis (LCA) (n = 120).

section of the river length (Fig. 7c), including the villages of Humde, Bhraka and Manang. Tanki, located on a northern headwater tributary, revealed a dominance (90% of respondents) who were classified as using water sources other than springs (Class 1). Respondents from villages at higher elevations also had a higher probability of not using spring sources (with the exception of Nasyang), relying more heavily on snow as a water source for household use. Free text responses identified individual rivers (kholas) that provided household water sources, in addition to the practice of gathering snow and storing it in vessels

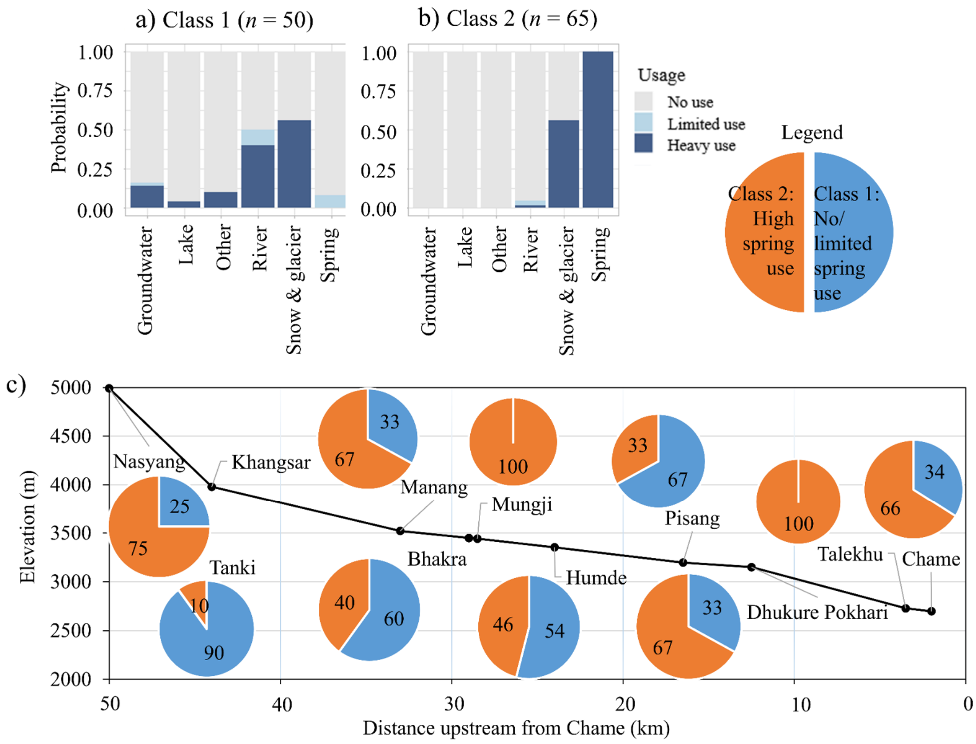

Fig. 7 Household water usage sources results. a) probability of water source usage for Class 1; b) probability of water source usage for Class 2; c) percentage of village within each LCA grouping.

inside the house by Class 1 households. Of those who responded to questions regarding coping strategies for changing water quality and quantity (Question 2.5-Appendix 2; n = 58), the most common response was that users have begun switching to other water sources (17% of respondents identified this directly) with river water the most common alternative supply (22% of respondents). Alternative strategies for storing water for use in the household included tank storage (17% of respondents) and using vessels (19%) or storing water in the house for use (5%). Interestingly, 115/164 (70% of those surveyed who indicated they used springs for household use; Appendix 6) reported that the amount of water available via springs had increased over the last 20 years, while 47/164 (29%) indicated that these sources had remained stable. Conversely, 81% (48/59) of respondents who indicated that they use snow for household use indicated a decrease in availability. The quality of river water used for household use was reported to be declining by 56% of those surveyed.

Irrigation water usage groups displayed three distinct groupings, with the first class (Class 1) being characterised as predominantly utilising 'other' water sources for irrigation (Fig. 8a). Free text within the responses clarify that in these instances, tanks were filled using various sources, predominantly rivers, rainwater and springs and artificial canals or pipes used to transport the water to crops. A small number of respondents (Class 2) were identified as those who rely on snow for irrigation, with limited use of additional sources. Members of this class were largely located towards the head of the catchment (Fig. 8d), including Tanki which is located on the northern headwater tributary, at a high elevation. This is in contrast with Class 3, whose members predominantly used river and spring sources for irrigation water. This class was dominant in most of the villages surveyed.

Results for the source of water for energy generation and tourism models showed that there was only one latent class present amongst water users in each water usage type (as lowest BIC was for a single grouping; Appendix 5) indicating a common water usage behaviour for energy generation, and tourism. The river was the only source of energy generation (via hydropower) and water for tourist use was largely sourced from snow and more limited spring sources (Fig. 9). The majority of respondents who indicated use of snow for tourism (73%) highlighted a decrease in the availability of this source, as well as a shortening of the snow season.

Where river water was used for energy generation a number of respondents highlighted the declining

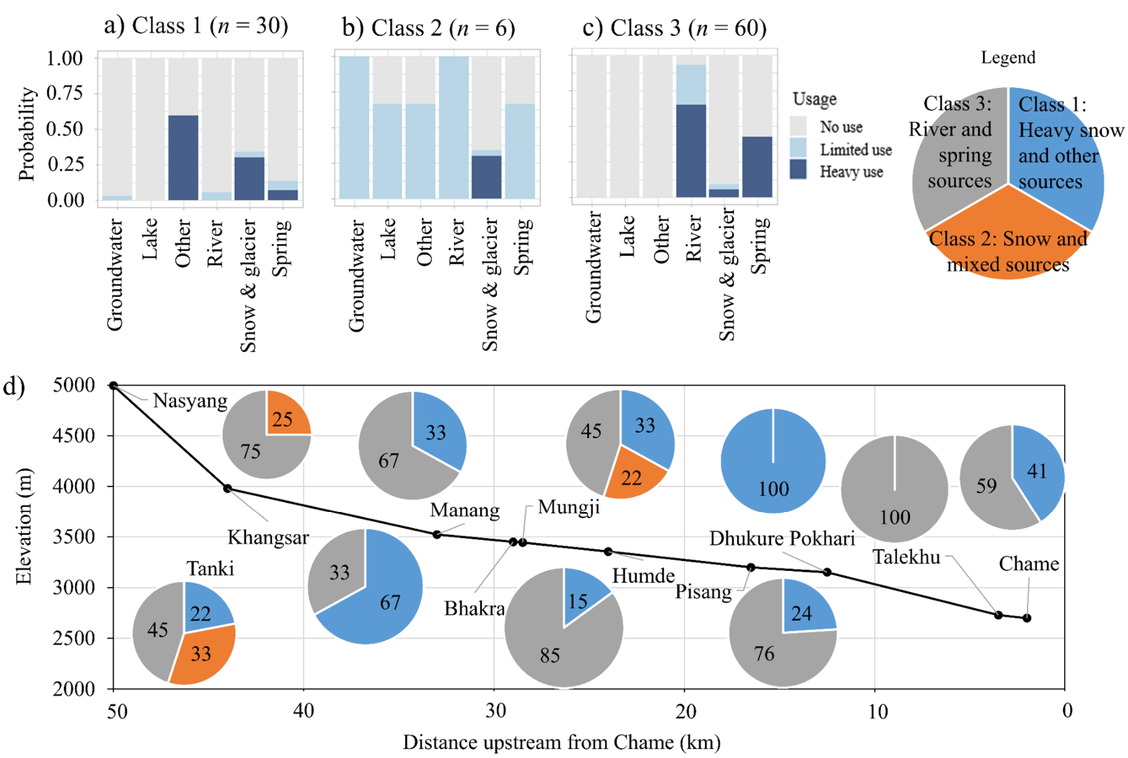

Fig. 8 Irrigation water usage sources results. a) probability of water source usage for Class 1; b) probability of water source usage for Class 2; c) probability of water source usage for Class 3; d) percentage of village within each LCA grouping.

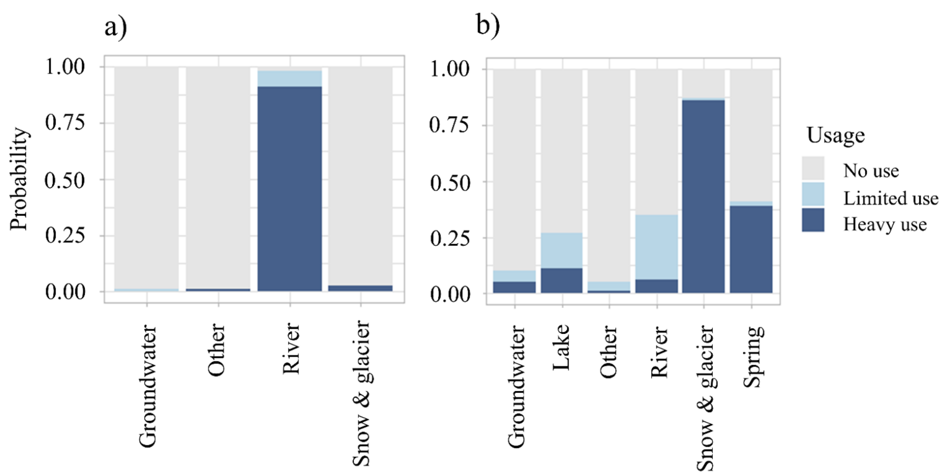

Fig. 9 Energy generation and tourism water usage groupings. a) probability of water source usage for energy generation; b) probability of water source usage for tourism.

quantity (28%) and quality (34%) of these resources and the reliance on alternative sources, such as kerosene lamps or candles, for electricity as a backup.

3.3 Water use probability

Further analysis of the likelihood of respondents using spring water sources in both household and irrigation revealed that village location, with Chame as the reference village due to its most downstream location, was a significant predictor in the top performing models (Appendix 7). The combination of village location, occupation (with agriculture as the baseline) and gender (female as the baseline) best predicted the likelihood that a household's primary water source was spring dominated (AIC 112.34 and

130.81, respectively, Appendix 7). Further analysis of significant predictors in household water use showed that both Tanki, and households whose primary occupation is business ownership, were less likely to use spring water than respondents residing in Chame and whose main occupation involves agriculture (Table 1). Males were twice as likely than females to use spring water; apart from in the village of Tanki. These results are likely to be driven by the dominance of snow as the main water source (section 3.2) and male respondents who identified as working in agriculture in this village.

Village and occupation were the best predictors for the use of spring sources for irrigation use, with the additive village and occupation model having the lowest AIC of all the models (99.81; Appendix 7). Neither of these models, however, had significant χ^2 results (Table 1), likely due to the lower number of respondents within each grouping which reduces the power of the model, increasing the chance of Type II errors (failing to reject the null when it is false). Odds ratios suggest that respondents in the village of Tanki were nearly twice as likely to use spring water for irrigation purposes than Chame.

4 Discussion

4.1 Changing water availability and sources

Water source attribution modelling revealed a notably high contribution of groundwater within the main river pre-monsoon, and source contribution changed minimally with decreasing elevation and distance downstream in the headwater study area. The contribution of groundwater sources to the rivers, springs and wells at these locations is of note, as previous research has theorised that groundwater contribution to riverflow would be limited in headwater high mountain areas due to steep slopes and shallow soils which prevent groundwater storage (Chapagain et al. 2019; Adhikari et al. 2021). Previously, glacial and snowmelt sources were generally considered to dominate streamflow in upland mountain areas (Rees and Collins 2006), with increasing groundwater contribution with increasing basin area and distance downstream as relative glacier coverage decreases (Brown et al. 2006). However, more recent research (Andermann et al. 2012; Somers and McKenzie 2020; Kuang et al. 2024) has indicated

Table 1 Summary of the Chi-squared likelihood ratio tests for the two top models predicting spring water source use in both household and irrigation uses. SE= standard error; CI= confidence interval. Significant p values (<0.05) are indicated in bold, and reference categorical groups are denoted in parentheses in the model equations.

Household water use	Predictor	β (SE)	Odds Ratio (95% CI)	P value
Model:	Intercept	1.372 (0.510)	3.94 (1.54- 11.66)	**0.007**
HH dominant spring water use ~	Bhakra	-0.389 (0.873)	0.69 (0.12- 4.11)	0.656
occupation (agric) + village (Chame)	Humde	-0.939 (0.706)	0.39 (0.09- 1.54)	0.184
$\chi^2(6) = 16.919$,	Pisang	0.156 (0.623)	1.17 (0.35- 4.15)	0.802
$p < 0.01$	Tanki	-3.174 (1.164)	0.04 (0- 0.29)	**0.006**
	Business	-1.142 (0.578)	0.32 (0.10- 0.97)	**0.048**
	Service	-1.24 (0.651)	0.29 (0.08- 1.01)	0.056
Model:	Intercept	0.379 (0.366)	1.46 (0.72- 3.05)	0.300
HH dominant spring water use ~	Bhakra	-1.350 (0.757)	0.26 (0.05- 1.11)	0.074
village (Chame) + gender (female)	Humde	-0.912 (0.655)	0.40 (0.11- 1.45)	0.164
$\chi^2(5) = 16.02$,	Pisang	-0.063 (0.573)	0.94 (0.31- 2.98)	0.912
$p < 0.01$	Tanki	-3.100 (1.124)	0.05 (0- 0.27)	**0.006**
	Male	0.694 (0.464)	2.00 (0.82- 5.11)	0.135
Irrigation water use	Predictor	β (SE)	Odds Ratio (95% CI)	P value
Model:	Intercept	-0.38 (0.39)	0.69 (0.31- 1.47)	0.339
IR dominant spring and river ~	Bhakra	0.598 (0.777)	1.82 (0.34- 8.87)	0.442
village (Chame)	Humde	-1.33 (0.863)	0.26 (0.04- 1.24)	0.123
$\chi^2(4) = 7.28$,	Pisang	-0.789 (0.645	0.46 (0.12- 1.56)	0.221
$p = 0.122$	Tanki	0.598 (0.777)	1.82 (0.040- 8.87)	0.442
Model:	Intercept	-0.248 (0.467)	0.78 (0.30- 1.95)	0.596
IR dominant spring and river water	Bhakra	-0.114 (0.873)	0.89 (0.15- 4.97)	0.896
use ~ occupation (agric) + village	Humde	-1.48 (0.897)	0.23 (0.03- 1.14)	0.099
(Chame)	Pisang	-0.851 (0.66)	0.43 (0.11- 1.51)	0.198
$\chi^2(6) = 7.032$,	Tanki	0.363 (0.886)	1.44 (0.25- 8.94)	0.682
$p = 0.318$	Business	0.409 (0.62)	1.51 (0.44- 5.17)	0.51
	Service	-0.327 (0.703)	0.72 (0.17- 2.76)	0.642

that groundwater can contribute substantially to riverflow, particularly during low flow periods. For example, it has been estimated that water flow through the fractured geology of the Himalayas supplies six times the annual contribution of glacier and snowmelt sources to adjacent water bodies (Ghimirie et al. 2019). While increased climate-induced glacier and permafrost thawing is expected to increase groundwater contribution to rivers in glacierised regions (Kuang et al. 2024), participants in this study suggested that these groundwater sources are declining, findings supported by several previous studies (Poudel and Duex 2017; Chapagain et al. 2019; Gurung et al. 2019; Adhikari et al. 2021; Chauhan et al. 2023). Together, these findings highlight the need to better understand the hydrology of groundwater aquifers in high mountain environments (Somers and McKenzie 2020).

The high groundwater contribution pre-monsoon (April) coincides with increasing river discharge and rainfall experienced during this time in the upper Marsyangdi (Fig. 2), which is the opposite of that documented in other basins which are more influenced by the monsoon. Research in the three main catchments draining the Himalayas (Sapta Koshi, Narayani and Karnali) using daily precipitation and river flow data has shown that precipitation is stored within groundwater units in the catchment and not directly transferred to streams in the pre-monsoon and monsoon seasons. These storages subsequently become depleted during the post-monsoon, when groundwater was found to dominate riverflow, with snow and glacial sources only contributing approximately 10% of annual river flow (Andermann et al. 2012). The observed post-monsoon proportional reduction in groundwater in our study, together with modelled decreases in post-monsoon river flow, suggests a lack of groundwater storage and/or rapid residence time in the study area. These results suggest that the studied headwater river system is 'leaky' (Fan 2019), potentially due to the relatively small catchment size, the dominance of the THS geology (characterised by various limestone and shale deposits; Ghezzi et al. 2019) and drier climate, which are hypothesised to drive increased groundwater import and export (Fan 2019). This limited groundwater storage potential presents a risk to local populations who rely on water availability in the summer for agriculture, tourism and household usage.

Projected climate change scenarios (under RCPs 4.5 and 8.5, using three regional climate models to 2040s and 2070s) in the wider Marsyangdi river basin suggest that maximum and minimum air temperatures will increase in future (Mudbhari et al. 2022). Rainfall is predicted to increase outside of the monsoon season (+10% to 2040s) but modelled river flow estimates show a decrease in average annual discharge (-6.3%-19% by 2031-2050), with monthly values outside of the monsoon season particularly affected. Further climate change modelling, using statistical downscaling at a finer geographic resolution, confirms these trends at higher elevation locations, including Chame (Khadka and Pathak 2016). Modelling of temperature and precipitation suggests an increase in extreme summer monsoon precipitation intensity, but an overall decrease in annual rainfall at the highest elevations (3400 masl), leading to longer and hotter summers, and shorter and warmer winters. These projected changes will greatly impact communities at higher elevations (Shrestha et al. 2022), including Tanki and Nasyang, who reported a reliance on snow for household and irrigation use. It is therefore critical that vulnerable communities begin now to build resilience to decreased water availability.

4.2 Community adaptation to changing water sources and availability

Results from the community interviews and LCA analysis identified differences in water use behaviour between local (village) communities. Communities located at lower elevations (e.g. Chame, Talekhu, Pisang) typically relied on spring and river sources for household use. Odds-ratio analysis highlighted the village of Tanki, located at a high elevation on a northern tributary of the Marsyangdi to be more likely to use spring sources for irrigation. Free-text responses within the household survey highlighted the concerns of residents in securing new water sources and the general observed trend in decreasing snowfall and snowpack. A number or respondents also reported their increased use of tanks and vessels to collect water during increased rain and snowfall. These were reported to be used both in individual homes (water kept indoors for use) as well as community-based collection tanks and associated pipework to distribute water resources.

Increased harvesting of rain and snow at both the household (using smaller tanks, vessels and containers) and village level (via construction of community ponds) have been highlighted by the Asian Disaster Preparedness Centre (Sharma et al. 2023) as an essential strategy for meeting the Nepalese government's National Water Plan, water resources and climate change policies which recognise extreme seasonal variation in water availability. Various 'water harvesting' technologies which promote surface water storage and groundwater recharge are increasingly being utilised in a number of communities throughout Nepal. For example, farmers in central Nepal have implemented measures such as the construction of water tanks, deeper wells and piping of spring sources to maintain water security (Poudel and Duex 2017). Research in the middle-mountains of the Hindu Kush has identified several solutions available to rural communities in adapting to water scarcity due to climate change (Merz et al. 2003a), including the creation and maintenance of ponds along ridges and slopes for livestock watering which can also recharge local shallow springs, as well as rooftop water collection into tanks. In western Nepal, declining precipitation and water availability during key agricultural growing periods have prompted apple farmers to build structures to collect and retain winter snow for later drip irrigation of apple crops, resulting in nearly 2.5 times more net income than traditional rain-fed agricultural practices due to increased crop productivity and quality (Bhattarai et al. 2022).

While these examples of successful community adaptation illustrate the resilience of individuals and communities in adapting to rapid climate change it is important to consider the need for place-based rather than generic adaptation measures as socio-ecological, political and cultural contexts of rural upland populations play an important role in the type and success of adaptation measures (McDowell et al. 2014). For example, previous research by Aase (2007; 2010) has documented the response of farmers in Manang to changing climate conditions. The use of irrigation channels fed by river and glacial sources were documented in the study area (Aase and Vetaas 2007; Konchar et al. 2015), reflecting the LCA grouping of 'Class 1' irrigation water users who reported using pipes and collection tanks to divert water to crops and agricultural land. Due to local customs and beliefs, farmers in Manang were found to take a less risk-spreading approach to farming, limiting the timing of sowing, harvesting and crop species. The use of communal farming timing and practices in the Manang region were identified as a potential drivers of local water shortage during spring and summer periods (Aase and Vetaas 2007).

Additional research within the Manang region has also documented a shift in agricultural practices away from the use of traditional grain field crops which included buckwheat and barley, to the production of fruit, leafy vegetables and wheat in agroforestry schemes (Konchar et al. 2015). This change in agricultural practices was found to be driven by increasing summer temperatures which allow new species to grow at higher elevation and increasing tourism which drives the demand for new foods. Interviews with villagers note concerns regarding increased irregularity in precipitation and decreased snowfall which also indicate ongoing increases in water resource demand as the community continues to adapt to changing climate.

4.3 A multi-disciplinary framework to support adaptation

Further research in high mountain areas, including those outside of monsoonal influence and where societal and religious networks determine community adaptation, is urgently required. Remote mountain communities are frequently geographically and politically excluded from centrally developed policies and adaptation initiatives, as well as being those least able to implement new practices or technologies (McDowell et al. 2014). Consequently, migration away from villages and rural areas to large urban conurbations has increased (Adhikhari et al. 2021). Those who remain are particularly vulnerable to climate change due to their dependence on natural resources for subsistence livelihoods (Xu et al. 2009; Aryal et al. 2014), in addition to traditional transhumance practices that rely on predictable and reliant water resources (Aryal et al. 2014). Our regression model results indicate that gender was a significant predictor in the use of spring sources, with males more likely to use spring sources than females, further demonstrating important differences in vulnerability to changing water availability. Supporting adaptation in these regions requires an understanding of current and future environmental changes in tandem with identifying specific villages and water use practices, underlying local-scale politics and social arrangements, which determine a community's response to such changes (Poudel and Duex 2017).

This research highlights the utility of combining diverse qualitative and quantitative research methods to identify populations, communities and individuals at risk from changing water sources due to climate change. The multi-disciplinary approach has identified the spatio-temporal diversity of water resource availability and community adaptation within the upper Manang district of Nepal. Use of probability rather than frequentist statistics which rely on fixed parameters and often assume homogeneity across populations allow for the incorporation of uncertainty and variability in both data and interpretation. This is particularly valuable in remote mountain contexts, where data may be sparse, heterogeneous or influenced by complex socio-cultural factors. The integration of prior knowledge, including local water use practices or environmental conditions within Bayesian models such as MixSIAR improve inference in data limited settings (Clark 2005), while latent class models allow for the identification of hidden subgroups within communities, revealing patterns of vulnerability or adaptation that may not be apparent through conventional methods.

Further use of this multidisciplinary framework may offer a comprehensive and context-sensitive approach to climate adaptation in other high mountain regions by integrating scientific, social, and local knowledge systems. This approach is able to incorporate varying local water resource dynamics while also capturing local adaptation strategies including socio-cultural and political factors, ensuring that adaptation measures are tailored to specific community needs. Ensuring that adaptation measures remain genuinely place-based, by identifying effective local practices, village-specific customs and traditions, and the socio-demographic conditions that underpin the most vulnerable communities, will enable more precise, inclusive and context-specific responses to the growing threat of water scarcity under climate change.

5 Conclusions

This study demonstrates the value of a multidisciplinary approach to understanding water resource vulnerability in high mountain regions. By integrating isotopic analysis, household surveys, and regression modelling, we identified significant spatial and social variations in water use, with gender and location emerging as key factors in spring source reliance. Importantly, probabilistic statistical models including Bayesian and latent class approaches enhance this framework by capturing uncertainty and revealing hidden patterns in community behaviour. These tools can help support more targeted, context-sensitive adaptation strategies, especially in regions where socio-demographic factors shape responses to climate change. Expanding this framework to other mountain areas can help ensure that adaptation efforts are inclusive, locally grounded, and responsive to the growing threat of water scarcity.

Acknowledgements

The authors would like to thank Himalayan Research Expeditions for logistical support, in particular Mahesh Magar for guiding and assisting with data collection. This research was funded by the Natural Environment Research Council's Global Challenges Research Fund (NE/P016146/1). Isotopic analysis was conducted by the Natural Environment Research Council's National Environmental Isotope Facility, grant number IP-1721-0517. The research was approved by the ESSL, Environment and LUBS (AREA) Faculty Research Ethics Committee, University of Leeds (Reference AREA 16-155).

Author Contributions

M. KLAAR: Investigation, visualisation, data collection, formal analysis, writing- original draft, writing- review and editing. D. QUINCEY: Funding, data collection, writing- original draft, writing- review and editing. C. WATSON: data collection, formal analysis, visualisation, writing- review and editing. L. BROWN: Funding, data collection, writing- review and editing. B. PARIYAR: data collection, writing- review and editing. A. GOSAL: formal analysis, writing-review. J. LOVETT: Funding.

Ethics Declaration

Availability of Data/Materials: Data is available upon request to the corresponding author

Conflict of Interest: The authors have no relevant financial or non-financial interests to disclose.

Open Access

Electronic Supplementary Material

Supplementary materials (Appendixes 1-7) are available in the online version of this article at https://doi.org/10.1007/s11629-025-0031-4.

References

Aase TH, Vetaas OR (2007) Risk management by communal decision in trans-Himalayan farming: Manang valley in central Nepal. Hum Ecol 35(4):453-460. https://doi.org/10.1007/s10745-006-9057-6

Aase TH, Chaudhary RP, Vetaas, OR (2010). Farming flexibility and food security under climatic uncertainty: Manang, Nepal Himalaya. Area 42(2):228-238. https://doi.org/10.1111/j.1475-4762.2009.00911.x

Adhikari S, Gurung A, Chauhan R, et al. (2021) Status of springs in mountain watershed of western Nepal. Water Policy 23(1):142-156. https://doi.org/10.2166/wp.2020.187

Alford D, Armstrong R (2010) The role of glaciers in stream flow from the Nepal Himalaya. The Cryosphere Discuss 4:469-494. https://doi.org/10.5194/tcd-4-469-2010

Andermann C, Longuevergne L, Bonnet S, et al. (2012) Impact of transient groundwater storage on the discharge of Himalayan rivers. Nat Geosci 5:127-132. https://doi.org/10.1038/ngeo1356

Bajracharya TR, Acharya S, Ale BB (2011) Changing climatic parameters and its possible impacts in hydropower generation in Nepal (A case study on Gandaki river basin). J Inst Eng 8:160-173. https://doi.org/10.3126/jie.v8i1-2.5108

Bhattarai S, Chian, JL, Upadhyaya S (2022) Effectiveness of snow harvesting and water productivity practices in combatting climate change-induced drought in a Himalayan district of Nepal. Irrig Drain 72(4):554-568. https://doi.org/10.1002/ird.2774

Brown LE, Hannah DM, Milner AM, et al. (2006) Water source dynamics in a glacierized alpine river basin (Taillon-Gabietous, French Pyrenees). Water Resour Res 42:W08404. https://doi.org/10.1029/2005WR004268

Chapagain PS (2016) Land and livelihood changes in Upper Manang valley of Nepal Himalayas. The Third Pole 14:33-41.

Chapagain PS, Ghimire M, Shrestha S (2019) Status of natural springs in the Melamchi region of the Nepal Himalayas in the context of climate change. Environ Dev Sustain 21:263-280. https://doi.org/10.1007/s10668-017-0036-4

Chauhan R, Shrestha A, Oh SE, et al. (2023) The degradation of spring water sources in Nepal: some policy gaps. Water Policy 25(2):338-358. https://doi.org/10.2166/wp.2023.159

Chiluwal N, Basnyat DB, Kafle MR, et al. (2021) Climate change impact on hydropower projects in Marsyangdi basin Nepal: a comparative study using GCM-led top-down and bottom-up approaches. Int Res J Eng Technol 8(5):129-149.

Clark JS (2004) Why environmental scientists are becoming Bayesians. Ecol Lett 8(1):2-14. https://doi.org/10.1111/j.1461-0248.2004.00702.x

Dhungana N, Silwal N, Upadhay S, et al. (2020) Rural coping and adaptation strategies for climate change by Himalayan communities in Nepal. J Mt Sci 17(6):1462-1474. https://doi.org/10.1007/s11629-019-5616-3

Duncan JMA (2013) Spatio-temporal trends in precipitation and their implications for water resources management in climate-sensitive Nepal. Appl Geogr 43:138-146. https://doi.org/10.1016/j.apgeog.2013.06.011

Fan Y (2019) Are catchments leaky? WIREs Water 6(6):e1386. https://doi.org/10.1002/wat2.1386

Fang J, Yi P, Stockinger M, et al. (2022) Investigation of factors controlling the runoff generation mechanism using isotope tracing in large-scale nested basins. J Hydrol 615:128728. https://doi.org/10.1016/j.jhydrol.2022.128728

Gain AK, Wada Y (2014) Assessment o future water scarcity at different spatial and temporal scales of the Brahmaputra river basin. Water Resour Manage 28:999-1012. https://doi.org/10.1007/s11269-014-0530-5

Gosal AS, McMahon JA, Bowgen KM, et al. (2021) Identifying and mapping groups of protected area visitors by environmental awareness. Land 10(6):560. https://doi.org/10.3390/land10060560

Ghezzi L, Iaccarino S, Carosi R, et al. (2019) Water quality and solute sources in the Marsyangdi River system of Higher Himalayan range (West-Central Nepal). Sci Total Environ 677:580-589. https://doi.org/10.1016/j.scitotenv.2019.04.363

Ghimire M, Chapagain PS, Shrestha S (2019) Mapping of groundwater spring potential zone using geospatial techniques in the Central Nepal Himalayas: A case example of Melamchi-Larke area. J Earth Syst Sci 128:26. https://doi.org/10.1007/s12040-018-1048-7

Gurung A, Adhikari S, Chauhan R, et al. (2019) Water crises in a water-rich country: case studies from rural watersheds of Nepal's mid-hills. Water Policy 21:826-847. https://doi.org/10.2166/wp.2019.245

He Z, Unger-Shayesteh K, Vorogushyn S, et al. (2020). Comparing Bayesian and traditional end-member mixing approaches for hydrograph separation in a glacierized basin. Hydrol Earth Syst Sci 24:3289-3309. https://doi.org/10.5194/hess-24-3289-2020

ICIMOD (2023) Streamflow prediction tool-Nepal. Available from: https://servir.icimod.org/science-applications/streamflow-prediction-tool-nepal/. Accessed 28 July 2023.

Immerzeel WW, Lutz AF, Andrade M, et al. (2020) Importance and vulnerability of the world's water towers. Nature 577:364-369. https://doi.org/10.1038/s41586-019-1822-y

Khadka D, Pathak D (2016) Climate change projection for the Marsyandgi river basin, Nepal using statistical downscaling of GCM and its implications in geodisasters. Geoenviron Disasters 3:15. https://doi.org/10.1186/s40677-016-0046-0

Khadka G, Pathak D (2021) Groundwater potential as an indicator of water poverty index in drought-prone mid-hill region of Nepal Himalaya. Groundwater Sustain Dev 12:100502. https://doi.org/10.1016/j.gsd.2020.100502

Konchar KM, Staver B, Chapagain A, et al. (2015) Adapting in the shadow of Annapurna: A climate tipping point. J Ethnobiol 35(3):449-471. https://doi.org/10.2993/etbi-35-03-449-471.1

Kuang X, Liu J, Scanlon BR, et al. (2024) The changing nature of groundwater in the global water cycle. Science 383(6673):962-968.

https://doi.org/10.1126/science.adj1984
Laskar, AH, Bhattacharya SK, Rao DK, et al. (2018) Seasonal variation in stable isotope compositions of water from a Himalayan river: Estimation of glacier melt contribution. Hydrol Processes 32(24):3866-3880. https://doi.org/10.1002/hyp.13295
Linzer D, Lewis JB (2011) poLCA: An R Package for Polytomous Variable Latent Class Analysis. J Stat Softw 42(10):1-29. https://doi.org/10.18637/jss.v042.i10
McDowell G, Ford JD, Lehne B, et al. (2013) Climate-related hydrological change and human vulnerability in remote mountain regions: A case study from Khumbu, Nepal. Reg Environ Change 13(2):299-310. https://doi.org/10.1007/s10113-012-0333-1
McDowel G, Stephenson E, Ford J (2014) Adaptation to climate change in glaciated mountain regions. Clim Change 126(1-2):77-91. https://doi.org/10.1007/s10584-014-1215-z
Mandandhar S, Prasad Pandey V, Ishidaira H, et al. (2012) Perturbation study of climate change impacts in a snow-fed river basin. Hydrol Processes 27(24):3461-3474. https://doi.org/10.1002/hyp.9433
Merz J, Nakarmi G, Weingartner R (2003a). Potential solutions to water scarcity in the rural watersheds of Nepal's middle mountains. Mt Res Dev 23(1):14-18. https://doi.org/10.1659/0276-4741(2003)023[0014:PSTWSI]2.0.CO;2
Merz J, Nakarmi G, Shrestha SK, et al. (2003b). Water: A scarce resource in rural watersheds of Nepal's middle mountains. Mt Res Dev 23(1):41-49. https://doi.org/10.1659/0276-4741(2003)023[0041:WASRIR]2.0.CO;2
Mondal SK, Bharti R, Kumar S (2023) Spatio-temporal variations in oxygen and deuterium isotope of different water sources in Sikkim Himalayas: An understanding towards regional scale basin hydrology. J Hydrol 621:129613. https://doi.org/10.1016/j.jhydrol.2023.129613
Mudbhari D, Lal Kansal M, Kalura P (2022) Impact of climate change on water availability in Marsyangdi river basin, Nepal. Q J Meteorolog Soc 148(747):1407-1423. https://doi.org/10.1002/qj.4261
Nepal Hydropower Portal (2023) https://hydro.naxa.com.np/Accessed 22 August, 2023.
Palazzi E, Filippi L, von Hardenberg J (2017) Insights into elevation-dependent warming in the Tibetan Plateau-Himalayas from CMIP5 model simulations. Clim Dyn 48(11-12):3991-4008. https://doi.org/10.1007/s00382-016-3316-z
Panthi J, Khatiwada KR, Shrestha ML, et al. (2019) Water poverty in the context of climate change: A case study from Karnali river basin in Nepal Himalaya. Int J River Basin Manage 17(2):243-250. https://doi.org/10.1080/15715124.2018.1531421
Panthi J, Dahal P, Shrestha ML, et al. (2015) Spatial and temporal variability of rainfall in the Gandaki river basin of Nepal Himalaya. Climate 3(1):210-226. https://doi.org/10.3390/cli3010210
Parajuli A, Devkota LP, Adhikari TR, et al. (2015) Impact of climate change on river discharge and rainfall pattern: A case study from Marshyangdi river basin, Nepal. J Hydrol Meteorol 9(1):60-73. https://doi.org/10.3126/jhm.v9i1.15582
Pariyar B, Lovett JC, Snell C (2018) Inequality of access in irrigation systems of the mid-hills of Nepal. Area Dev Policy 3(1):60-78. https://doi.org/10.1080/23792949.2017.1399784
Paudel PK, Bhattarai BP, Kindlmann P (2012) An overview of the biodiversity in Nepal. In: Kindlmann P (ed.), Himalayan Biodiversity in the Changing World Springer, Dordrecht. pp 1-40. https://doi.org/10.1007/978-94-007-1802-9_1
Pokharel S (2001) Hydropower for energy in Nepal. Mt Res Dev 21(1):4-9. https://doi.org/10.1659/0276-4741(2001)021[0004:HFEIN]2.0.CO;2
Poudel DD, Deux TW (2017) Vanishing springs in Nepalese mountains: Assessment of water sources, farmers' perceptions and climate change adaptation. Mt Res Dev 37(1):35-46. https://doi.org/10.1659/MRD-JOURNAL-D-16-00039.1
Quincey DJ, Klaar M, Haines D, et al. (2018) The changing water cycle: The need for an integrated assessment of the resilience to changes in water supply in High-Mountain Asia. WIREs Water 5(2):e1258. https://doi.org/10.1002/wat2.1258
R Core Team (2022) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.
Rees HG, Collins DN (2006) Regional differences in response of flow in glacier-fed Himalayan rivers to climatic warming. Hydrol Process 20(10):2157-2169. https://doi.org/10.1002/hyp.6209
Rhead R, Elliot M, Upham P (2018) Using latent class analysis to produce a typology of environmental concern in the UK. Soc Sci Res 74:210-222. https://doi.org/10.1016/j.ssresearch.2018.06.001
Rijal S, Gentle P, Khanal U,, et al. (2022) A systematic review of Nepalese farmers' climate change adaptation strategies. Clim Policy 22(2):132-146. https://doi.org/10.1080/14693062.2021.1977600
Roxburgh N, Stringer LC, Evans A, et al. (2021) Impacts of multiple stressors on mountain communities: Insights from an agent-based model of a Nepalese village. Global Environ Change 66:102203. https://doi.org/10.1016/j.gloenvcha.2020.102203
Sharma L, Gupta N, Basnayake S (2023) Water Harvesting: A Needs Assessment in Nepal. Climate Adaptation and Resilience (CARE) for South Asia. Asian Disaster Preparedness Centre, Bangkok.
Sharma S, Baidya M, Poudel P, et al. (2021) Drinking water status in Nepal: An overview in the context of climate change. J Water Sanit Hyg Dev 11(5):859-872. https://doi.org/10.2166/washdev.2021.045
Shrestha S, Chapagain PS, Ghimire M (2019) Gender perspective on water use and management in the context of climate change: A case study of Melamchi watershed area, Nepal. SAGE Open, 9(3):1-9. https://doi.org/10.1177/2158244018823078
Shrestha S, Poudel DD, Duex TW, et al. (2022) Changing climatic conditions affect snow cover in Annapurna region of Nepal. Strategic Plann Energy Environ 41(3):215-240. https://doi.org/10.13052/spee1048-5236.4125
Somers LD, McKenzie JM (2020) A review of groundwater in high mountain environments. WIREs Water 7(3):e1475. https://doi.org/10.1002/wat2.1475
Stock BC, Semmens BX (2016a) MixSIAR GUI User Manual. Version 3.1. https://github.com/brianstock/MixSIAR.
Stock BC, Semmens BX (2016b) Unifying error structures in commonly used biotracer mixing models. Ecology 97(10):2562-2569. https://doi.org/10.1002/ecy.1517
Tambe S, Kharel G, Arrawatia ML, et al. (2012) Reviving dying springs: Climate change adaptation experiments from the Sikkim Himalaya. Mt Res Dev 32(1):62-72. https://doi.org/10.1659/MRD-JOURNAL-D-11-00079.1
Tadono T, Ishida H, Oda F, et al. (2014) Precise Global DEM Generation by ALOS PRISM. ISPRS Ann. Photogramm, Remote Sense Spatial Inf Sci II-4:71-76. https://doi.org/10.5194/isprsannals-II-4-71-2014
Vishwakarma BD, Ramsankaran RAAJ, Azam MF, et al. (2022) Challenges in understanding the variability of the cryosphere in the Himalaya and its impact on regional water resources. Front Water 4:909246. https://doi.org/10.3389/frwa.2022.909246
Wilson A, Williams M, Kayastha RB, et al. (2016) Use of a hydrologic mixing model to examine the roles of meltwater, precipitation and groundwater in the Langtang River basin, Nepal. Ann Glaciol 57(71):155-167. https://doi.org/10.3189/2016AoG71A067
Xu J, Grumbine RE, Shrestha A, et al. (2009) The melting Himalayas: Cascading effects of climate change on water, biodiversity and livelihoods. Conserv Biol 23(3):520-530. https://doi.org/10.1111/j.1523-1739.2009.01237.x