Climate change and local anthropogenic activities have altered river flow regimes across Canterbury, New Zealand

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Abstract

River flow regimes influence ecologic, cultural, social, aesthetic, and economic values. Detecting changes in river flows and attributing their causes is important but challenging due to the combined influence of climate and relevant local activities, and the lack of data on water abstraction, drainage modification or land use management. This study assessed the degree to which trends in river flows could be attributed to changes in climate versus local anthropogenic activities across Canterbury, Aotearoa New Zealand. Trends were assessed for a period that started immediately after a change in regulatory regime in 1991 and ended in 2020, that coincided with increases in water abstraction and changes in water management practices. Trends in observed summer conditions indicated that rainfall was stable, temperature increased, and flows decreased for many sites during the assessed period. Models representing flow as a function of rainfall and temperature were trained and tested using cross-validation for an earlier baseline period. Predictions for the 1991–2020 period made with the models were used to account for the effect of change in climate. The difference between predicted and observed flows were attributed to changes in local activities. Decreases in summer flows were partially associated with changes in climate, but changes in summer flows in several catchments were also associated with local activities. The findings indicate changes to both climate and local activities have combined to alter flow regimes, suggesting that hydrological impacts of local activities should be considered alongside climate change when making river flow management decisions.

Introduction

River flow regimes in natural catchments are determined by climate (Stahl et al., 2010) and various catchment characteristics such as slope, soil, vegetation, and geology (Thompson et al., 2011). Potential for future climate change to impact hydrological conditions has prompted investigations of the consequences of climate variability on soil moisture (e.g. Grillakis, 2019), groundwater levels (e.g. Havril et al., 2018), and river flows (e.g. Givati et al., 2019). Prediction of hydrological changes under different climate conditions whilst assuming fixed catchment characteristics can be informative (e.g. Rogers et al., 2021). However, human actions can also alter hydrological conditions directly by manipulating river flows (e.g. water abstraction, damming, river diversion), or indirectly by altering physical catchment characteristics (e.g. deforestation, afforestation, drainage modification). Human actions with potential to alter hydrological conditions directly are referred to here as local activities but have also been referred to as human activities (Chen et al., 2019), anthropogenic activities (Margariti et al., 2019), or anthropogenic pressures (Best, 2019). Local activities that alter hydrological conditions occur in most of the world's catchments due to changes in landcover or because water is being used for farming, domestic use, industry, or hydro-electric power production (Best, 2019). Flows in modified catchments can therefore no longer be considered as being solely controlled by earth system processes as demonstrated by recent drought events that have been linked to climate warming (e.g. Williams et al., 2020) and local activities (e.g. Margariti et al., 2019). The dual influences of climate and local activities on river flow regimes are

important because these factors combine to confound analysis of observed patterns and introduce uncertainty when predicting future hydrological conditions (AghaKouchak et al., 2021).

Although local activities are often associated with economic and social benefits, river flows also play a role in supporting ecosystems and humans (Arthington et al., 2018). River flow is important because it is a master variable influencing channel geomorphology, sediment, habitat size, physical habitat templates, disturbance regime, food resources and water quality (Sofi et al., 2020). Hydrological alterations can have detrimental consequences for biophysical systems and humans (Anderson et al., 2019) through influences on aesthetic and cultural values (Tipa, 2009). It is widely recognised that flow regime changes should be managed within the constraints of maintaining healthy river systems (Poff et al., 2010). In this context, environmental flows are defined as the quantity, timing, and quality of water flows required to sustain freshwater and estuarine ecosystems, and the human livelihoods and well-being that depend on these ecosystems (Brisbane Declaration, 2007).

Environmental flow setting philosophies have evoked the natural flow paradigm to support environmental flows that maintain several aspects of natural flow regimes (Poff et al., 1997). Other approaches have promoted greater recognition of climate change impacts, and a need to maximize natural capital as well as support economic growth, recreation and cultural values (Acreman et al., 2014). There has also been a call to employ ecological theory and field observations to target ecologically important parts of the flow regime, and also account for non-stationary climate and the influence of additional environmental stressors such as temperature and sediment (Poff, 2018). Thus, adaptive management principles may be applied to evaluate and improve river flow management effectiveness (Stoffels et al., 2018). Increased emphasis on monitoring for adaptive management purposes has necessitated detection and attribution of river flow changes, but this is a challenging task.

Attributing river flow alterations to local activities is complicated because climate conditions and local activities are both influential, and because there is often a lack of data describing their spatial and temporal variability. For example, rates of anthropogenic water consumption are often not well quantified due to poor measurement coverage and quality (e.g. Office of the Auditor General, 2018), despite legislative requirements (e.g. Ministry for the Environment and Statistics New Zealand, 2020), technological advancements in data collection and management (e.g. Stewart et al., 2010), and the possibility of utilizing remotely sensed data (Anderson et al., 2012).

In many countries, national-scale regulations require and guide sustainable use of environmental resources. However, regulations do not immediately influence river flows because of lags between enactment, local planning decisions, and ongoing local activities. Some local activities can have an immediate effect on river flows, for example, building a dam can abruptly influence flow regimes and aquatic ecosystems (e.g. Lessard et al., 2013). Other local activities can have more gradual influences, for example, the effect of groundwater abstraction on rivers flows can be delayed due to temporal lags in groundwater systems (Malakar et al., 2021). Landcover change can have an important influence on river flows through changes in evaporation and surface runoff (Mark and Dickinson, 2008), but these may

occur rapidly due to forest harvesting, or gradually due to spread of invasive species or ecological succession (Guzha et al., 2018).

The aim of this study was to assess the presence, direction and likely causes of trends in river flow regimes across a region since a change in regulatory regime in 1991. The specific objectives were to evaluate: trends in river flows; trends in climate; and whether trends in river flows are attributable to changes in climate versus changes in local activities. A transparent and replicable approach was required in a situation with limited data describing local activities.

Methods

Study region

The study region was Canterbury, Aotearoa New Zealand (Figure 1). Canterbury is bounded by the Southern Alps to the west, with the Canterbury Plains extending eastwards towards the Pacific Ocean. Native vegetation is largely restricted to mountains and foothills in the west, with lowlands towards the east being dominated by agricultural landcover.

Contrasting river flow regimes exist across the region, with flows draining mountainous areas being more variable with higher flow per unit catchment area (Snelder and Booker, 2013). Flow regimes are predominantly driven by rainfall and evapotranspiration, however, snowfall-snowmelt is influential in mountainous catchments (Porhemmat et al., 2021). Seasonal evaporation patterns produce seasonal low flows, but high rainfall and flow events occur at any time of year.

Enactment of the Resource Management Act (RMA) in 1991 was the most recent significant change amongst regulations relating to land and water management activities with potential to influence flow regimes enacted since 1840 (Figure 2a). Development of local activities with potential to influence flow regimes has been ongoing since the earliest regulations (Figure 2b). For example, dams have been built of and irrigated area has expanded since 1900 (Birendra et al., 2018). Between 2007 and 2012 irrigated area is estimated to have increased by 60,000 ha within the region (Statistics New Zealand, 2012). These activities have coincided with a period of upward trending air temperatures (Figure 2d).

The RMA requires that taking, using, damming, or diverting of water is allowed by a local regulation, allowed for by a resource consent (a license), or to be specifically exempted. A database describing current and historic consents to take water obtained from the regional authority shows a steady rise in consents for consumptive water use since the early 1990’s (Figure 2c). After exclusion of hydro-electric uses, 87% of water currently consented for consumptive purposes was for irrigation with a further 6% for animal drinking water. Previous analysis has shown that water is abstracted from rivers and aquifers across the region (Booker, 2018). Some water is diverted between catchments (e.g. Rankin and Orchard, 2019) and some consents stipulate restriction or cessation of abstraction during low flow periods (Canterbury Regional Council, 2018). Local regulations allow water to be used for some specified activities (e.g. domestic use) without a consent.

National regulations introduced in 2010 stipulate that measurements of consumptive water use consented for more than 0.005 m^3 s^{-1} must be reported to the regional authority. However, accurate water use data is lacking, furthermore, data supplied to regional authorities have been irregular and of poor quality in some cases (Ministry for the Environment and Statistics New Zealand, 2020).

Alterations to landcover, including loss of indigenous vegetation, have occurred in the region, but there are gaps in the data describing the timing and spatial extent of these changes (Dymond et al., 2017). A national initiative has recently encouraged tree planting in the region (Edwards et al., 2019) although systematic afforestation is known to reduce river flows (e.g. Hughes et al., 2020). Invasion by non-native conifer tree species into grasslands and shrublands is also widespread (Peltzer, 2018).

Data

All daily river flow time-series observed since 1980 were obtained from the regional authority and the National Institute of Water and Atmospheric Research. All flow measurements conformed to national environmental monitoring standards for open channel flow measurement (National Environmental Monitoring Standards, 2013) and were subject to quality assurance-quality control procedures equivalent to National Environmental Monitoring Standards (2019). Flow time-series for sites without determinable upstream catchments (sites on canals, dam spillways etc.) or downstream of large dams were removed from the dataset after inspecting site names, locations and catchment areas.

Water years were defined as starting on the 1st of October of the previous calendar year following the method of Booker and Woods (2014) to minimise the likelihood of low flow periods crossing years. Seasons were identified as: summer = January-March; autumn = April-June; winter = July-September; and spring = October-December. Legitimate water years included in the analysis were defined as those with no more than 35 missing days and legitimate seasons were defined as those with no more than 35 missing days.

Daily time-series of rainfall (including water from snowfall; mm d^{-1}) and both minimum and maximum temperature (^{o}C) since 1980 were obtained from the Virtual Climate Station Network (VCSN), which is a representation of measured conditions on a 0.05^{o} (approximately 5 km) grid covering all New Zealand. VCSN values at each grid location were derived from a spline interpolation of values recorded at weather stations with available quality-controlled data (Tait and Woods 2007). The mean absolute error of the VCSN data is 0.9°C for maximum daily temperature and 1.2°C for minimum daily temperature (Tait and Macara 2014). The mean absolute error in VCSN daily rainfall for locations below 500 m elevation is approximately 2-4 mm (95% of the range) for rain days (rainfall ≥ 1 mm), whereas the error in areas above 500 m elevation is approximately 5-15 mm (Tait et al. 2012). VCSN minimum and maximum air temperature for each day were averaged to represent mean daily temperature. Daily time-series of rainfall and temperature were spatially averaged across the catchment upstream of each site using two-dimensional distance-weighted linear interpolation.

Models

A five-year training period (typically 1986-1991 depending on data completeness) and a following assessment period (typically 1992-2020) were identified for each site (Figure 3). For each site, models were developed to predict flows during the training period from variables describing concurrent and preceding climate conditions. Each model was then used to predict flows given climate conditions observed during the assessment period. Daily residual flow during the assessment period was calculated as observed flow minus modelled flow. Negative residual flows indicate that observed flows were lower than would be expected given the climate conditions during the assessment period and the landcover and local activities during the training period. Trends in residual flows therefore indicate changes in flows that are attributable to changes in landcover and local activities during the assessment period because they were not accounted for by changes in climate during the assessment period. Daily flow for each site was modelled using generalised least-squares linear regression. Variables representing rainfall and temperature in the catchment of each site were used as potential predictors as follows: a) concurrent rainfall and temperature; b) preceding day's rainfall; c) rainfall and temperature averaged over the preceding week, month, and season; d) number of days since daily rainfall was greater than 10 mm; and f) number of days since temperature was below 1 ^{o}C to distinguish snowfall from rainfall following Clark et al. (2009).

Transformations were applied to the flow (response) and predictor variables to approximate normal distributions where appropriate. Two-parameter Box-Cox transformations (Box and Cox, 1964) were applied to flow and number of days since daily rainfall was greater than 10 mm. Inverse hyperbolic sine transformations (Abramowitz and Stegun, 1972) were applied to concurrent rainfall, preceding day's s rainfall, weekly rainfall, monthly rainfall, number of days since daily rainfall was greater than 10 mm, and number of days since temperature was below 1 ^{o}C. A forwards-and-backwards stepwise reduction procedure used the Bayesian Information Criterion (BIC; Neath and Cavanaugh, 2012) to identify the most parsimonious model for each site. An autocorrelation structure of order one (Box et al., 1994) was applied to account for temporal autocorrelation within the data used to train each model. No interaction terms were applied within the models to simplify interpretation of model coefficients.

Coefficients for each model were inspected for consistency with hydrological principles including higher flows being associated with more rain (including fewer days since high rainfall) and lower flows being associated with higher temperatures due to higher evaporation (Ward and Robinson, 1990). The 95% confidence intervals around each coefficient of each model were calculated following the method of Pinheiro and Bates (2000). Confidence intervals that did not include zero indicated high confidence in direction of effect as indicated by the sign of the coefficient.

A block cross-validation procedure was applied to assess model predictive performance. For each site, data for each season within each year of the training period were removed, each model was refitted using all remaining training data and then used to predict flows for the left-out season. This procedure was equivalent to 20-fold cross-validation but left out each season in turn rather than splitting the data randomly. This method minimised the impacts of temporal autocorrelation by applying the temporal equivalent of the "spatial K-fold CV" procedure described by Ploton et al. (2020).

Because the aim was to identify the presence and direction of trends rather than their absolute magnitude, model performance was assessed using the coefficient of variation of observations versus the cross validated predictions (R^2) as defined in Moriasi et al. (2015). Model performance was assessed against standard performance evaluation criteria suggested by Moriasi et al. (2015): $R^2 > 0.85$ = very good; $0.70 \leq R^2 \leq 0.85$ = good; $0.50 < R^2 < 0.70$ = Satisfactory; and ≤ 0.50 = not satisfactory. Model results for sites whose cross-validated performance was not satisfactory ($R^2 \leq 0.5$) were not used in further analysis.

Trends

Trends in the annual series of seasonal medians were calculated for each of five variables: daily temperature; monthly rainfall; daily observed river flow; daily modelled river flow; and daily residual river flow. Trends were calculated for each season at each site separately to discriminate between-season and between-site patterns. The median monthly (30-day running-average) rainfall rather than median of daily rainfall was used to represent rainfall whilst maintaining consistent treatment of variables and avoid ties caused by zero values.

The non-parametric Mann-Kendall statistic was used to characterise if trends in each annual series were increasing or decreasing and the confidence in those assessments. The Mann-Kendall test p-value was used to calculate confidence that the sign of the S statistic represented the true direction of trend (Choquette et al., 2019). The confidence that the direction of the assessed trend was correct was computed from the two-sided p-value as [1-(p/2)]. Confidence in trend direction was expressed using the categorisation of Hirsch et al. (2015), which followed those used by the Intergovernmental Panel on Climate Change (Mastrandrea and Mach, 2011; Table 1). The categories for increasing trends are the complement of the categories for decreasing trends i.e., a “highly unlikely” decreasing trend is the same as a “highly likely” increasing trend. A correction for underestimation of the variance of Mann-Kendall’s S statistic when data are autocorrelated was applied. After having subtracted Sen’s median slope from the data, significant values of autocorrelation between the ranks of the observations were used to calculate and apply the variance correction factor described by Hamed and Rao (1998).

Table 1
Definitions for descriptive statements of confidence of trends as a function of the posterior mean estimate of the probability of a decreasing trend. After Hirsch et al. (2015).

Descriptor	Range of values for the posterior mean estimate of the probability of a decreasing trend
Highly likely	≥0.95 and ≤1.0
Very likely	≥0.90 and ≤0.95
Likely	≥0.67 and ≤0.90
About as likely as not	≥0.33 and ≤0.67
Unlikely	≥0.10 and ≤0.33
Very unlikely	≥0.05 and ≤0.10
Highly unlikely	≥0 and ≤0.05

For each site, the final model and all 20 models fitted during cross-validation (i.e. models refitted with data for a single season withheld) were used to predict flow on all days with an observed flow following the training period. Trends in modelled flow and residual flow were calculated from the final models and also from each of the 20 models fitted during cross-validation for each site in order to provide an assessment of how uncertainty in flow modelling propagated into trend characterisation. This procedure was similar to a bootstrap assessment of parameter uncertainty obtained by repeatedly refitting to sets of randomly resampled data (Efron and Tibshirani, 1993), but attempted to alleviate the effects of temporal autocorrelation by leaving out each three-month period rather than randomly resampling with replacement from the full dataset.

Results

Data completeness

A total of 38 sites whose flow time-series began before 1991 and with at least 25 legitimate water years (5 for training and 20 for assessment) were included in the analysis (Figure 3). For 33 sites the training period comprised the five legitimate water years up to and including 1991. Many sites had ideal data for this analysis; five consecutive legitimate water years ending 1991 for training and a full set of subsequent water years for trend assessment (Figure 3). For five sites the training period was extended past 1991 because five legitimate water years prior to 1992 were not available (Figure 3).

Flow time-series rarely contained non-legitimate water years due to missing data (e.g. Rakaia at Fighting Hill; Figure 3), but one site contained a six-year sequence of non-legitimate water years (Kakahu at Mulvihills; Figure 3). Flow data for each water year at each site were often either fully complete or fully

missing. Across all sites, 76% of legitimate water years (from both training and assessment periods) had no missing data, and 93% of water years had less than 5% missing data (18 days missing within a year).

Five of the 38 sites were located upstream of another site. Waiau at Malings Pass, Hurunui at Mandamus, Camp Stream at Craigieburn, Selwyn at Whitecliffs, and Rocky Gully at Rockburn had catchment areas that were 4, 42, 0.03, 17 and, 5% of a downstream site respectively. Given the relatively large contrasts in catchments areas for upstream-downstream pairs except those on the Hurunui River, results for all 38 sites were retained in further analysis.

Models

The signs of the regression model coefficients were largely consistent with hydrological principles. Coefficients for all predictors representing rainfall, including days since high rainfall, indicated that more rain was associated with higher flows, and none of these coefficients had 95% confidence intervals that included zero (Figure 4). All coefficients for seasonal temperature and most coefficients for monthly temperature indicated that lower flows were associated with higher temperatures. The direction of coefficients for weekly temperature and days since freezing were not consistent across sites, and several of these coefficients had 95% confidence intervals that included zero (Figure 4). Concurrent temperature was excluded from models for all but 5 of the 38 sites whereas concurrent and preceding day's rainfall were retained for all but 7 and 6 sites respectively. This is consistent with hydrological principles; indicating rapid rises and falls in flow are driven by quickflow following rainfall, and gradual flow recession are driven by temperature-driven increases in evaporation (Ward and Robinson, 1990).

Cross-validation indicated the models performed well for most sites (Figure 3). Cross-validated predictive performance was categorised as satisfactory for 25 sites, good for 11 sites, and very good for one site. Results derived from the model for one site (Avon at Gloucester St Br; a river with a largely urban catchment) were removed from further analysis because predictive performance was not satisfactory.

Trends

Temperatures increased during the assessment period in all seasons and across nearly all sites (Figure 5). Evidence of increasing temperatures were strongest for winter with 92% of sites categorised as “extremely unlikely” to be decreasing (i.e. increasing trends were extremely likely). The direction of rainfall trends was inconsistent across seasons and sites, but 18% of site-by-season combinations were categorised outside the middle three categories (i.e. “likely”, “as likely as not” or “unlikely”).

Trends in observed flows were categorised as either “extremely likely” or “very likely” to be decreasing for 45% of sites in summer and 34% of sites in spring (Figure 5). Consistent trend directions for observed flows were not detected across sites during winter and autumn, with only 11% of site-by-season combinations categorised outside the middle three categories.

Trends in modelled flows often mirrored trends in observed flows (Figure 5). There were decreases in modelled flows for some sites during summer and spring, with trends categorised as either “very likely” or

“extremely likely” to be decreasing for 30% of sites in summer and 46% of sites in spring. Consistent trend directions for modelled flows were not detected across sites during winter and autumn, although 18% of site-by-season combinations were categorised outside the middle three categories.

Direction of, and confidence in, trends in residual flows varied between sites and between seasons (Figure 5). Decreases in residual flows for several sites during summer and spring were detected with confidence categorised as either “extremely likely’ or “very likely” to be decreasing for 38% of sites in summer and 16% of sites in spring. Increases in residual flows were detected with confidence for some sites across all seasons, with trends categorised as either “extremely unlikely” or “very unlikely” to be decreasing for 17% of all site-by-season combinations.

The trend categories derived from the 20 CV models were generally consistent with the final model for each site (Figure 6). Flow trends calculated from CV models spanned only two trend direction confidence categories for 96% of site-by-season combinations. The flow trend direction confidence category calculated from the final model was consistent with the mode category calculated from the CV models for 93% of the site-by-season combinations. Similarly, trend direction confidence for the residual trends derived from the CV models spanned only two categories for 98% of site-by-season combinations. The residual trend category calculated from the final model was consistent with the mode trend category calculated from the CV models for 97% of site-by-season combinations.

Discussion

Practical implications

Detecting trends in flows provides river managers with warnings about potential impacts on water supply, ecosystem health, aesthetic values, and cultural values. Attributing the likely causes of changes in flows to local activities and climate can provide river managers with important information because they can directly influence the former but only anticipate and potentially adapt to the effects of the latter. The approach taken in this study acknowledges the need to account for complex and interrelated dynamics within human-induced hydrological systems that are influenced by climate and local activities (AghaKouchak et al., 2021). This point is illustrated by considering three contrasting result from this study. The first situation represents purely locally driven impacts on flows as indicated by low confidence in trend direction in modelled flows and high confidence in trends in residual flows (e.g. Hurunui at SH1 Bridge). This situation indicates a need for on-going monitoring and evaluation of environmental flows because local activities are potentially influencing in-stream values and reliability of water supply for downstream anthropogenic uses. The second situation represents purely climate-driven impacts on flows as indicated by high confidence in trends in modelled flows and low confidence in trend direction for residual flows (e.g. Pareora at Huts). This situation indicates that climate-driven impacts on flows need to be factored into water resource management because environmental flows may be compromised by changes in the flow regime that are attributable to climate regardless of changes in local activities. The third situation involves high confidence in trends in both modelled and residual flows (e.g. Waimakariri at

Old Highway Bridge). This situation highlights the need to consider future climate-driven impacts on flows alongside local activities in flow management decisions, and also highlights potential for falsely attributing flow regime changes to a single cause when both climate and local activities are influential.

The approach applied in this study attributes changes in flows to climate and local activities and identifies the direction of effect and quantifies the level of confidence. This information is relevant in a region where there have been concerns that abstraction of surface water or shallow groundwater has depleted river flows (e.g. Lennox and Diukanova, 2011), as well as concerns that river flows have been artificially augmented through inter-basin transfers or inefficient irrigation practices (e.g. Dench and Morgan, 2021). Results indicate that flow changes are attributable to both factors and demonstrate that impacts of local activities vary between catchments. Differences in the direction of effect of local activities on flows was expected due to the wide range in climate, landcover, and irrigation practices through time and space. The direction of effect of climate change on hydrology is also likely to be spatially variable due to interactions between topography and predominant weather patterns (Collins, 2021). The hydrological effects of irrigation and landcover change are also likely to vary spatially. For example, Duncan et al. (2016) discussed variability in groundwater recharge depending on irrigation practices, water source, soil types and climatic conditions.

Evidence for trends in residual flows since enactment of the RMA in 1991 was found, but this does not mean that flow regime trends can be attributed directly to the change in regulations. Several local activities with the potential to influence flows have occurred since the early 1990's. Expansion of irrigation and increased water demand may have been driven by a combination of regulatory drivers, technological advancements such as centre pivot irrigation systems (Duncan et al., 2016), or economic incentives associated with increased production (Ma et al., 2020). The situation is further complicated by recent advances that have encouraged efficient irrigation practices in the region (Dench and Morgan, 2021), and the possibility that local activities may themselves be adapting to changes in climate (Cradock-Henry et al., 2020).

Technical aspects

Regression was used to model flow and non-parametric Mann-Kendal tests were used to assess trend direction and confidence. Within the general approach, alternative methods could be used for hydrological modelling and trend analysis. The choice of method for trend assessment depends on whether relative or absolute changes are of primary interest. For example, Chen et al. (2019) applied a linear regression to assess trends. Choice of method for flow modelling might depend on availability of flow data, model set-up data, and computational resources. Simple regression models have several benefits compared to more sophisticated machine learning or physically-based models including: low input data requirements; simple modelling fitting, low computational requirements, and easily interpreted model coefficients.

Some between-site inconsistency in the direction of coefficients for weekly temperature and days since freezing was expected because lower flows can be associated with lower temperatures in catchments

influenced by freezing and snowmelt. However, these patterns could also be an artifact of covariation within predictors because the method did not include interactions between predictors or attempt to reduce covariation by creating synthetic orthogonal predictors. Although correlations between predictors within regression models are ideally avoided because they bias parameter estimates, it is difficult to break covariation of predictors used to represent physical processes within a hydrologic system, and therefore some level of multicollinearity often has to be accepted (Moradkhani and Meier, 2010). A different model specification would be required if models were being used to test hypothesis about independent effects of various predictors, rather than for purely predictive purposes.

A disadvantage of the regression approach applied here was a dependence on relatively long flow, rainfall and temperature time-series for model training and trend assessment. Longer training periods may have produced more representative models but would also increase potential for uncertainties associated with temporal variability in local activities. An assumption of the approach is that local activities are stationary over the training period. The duration of the training period is a trade-off between the validity of this assumption and having adequate data to represent flow-climate relationships for model training and cross-validation.

Model performance was quantified in terms of their ability to predict relative differences in observed daily flows rather than absolute flow. This was acceptable because the subsequent analysis was only concerned with trend direction. Quantification of performance in absolute terms such as root-mean-square-error would have been appropriate had absolute differences in flows been a desired model output (Moriasi et al., 2015).

Training models to predict daily (rather than monthly or seasonal) flow had the advantage of allowing rigorous testing of predicted flow patterns that can subsequently be used to assess trends in various indices representing flow regimes. Seasonal medians were used in this study to represent changes in climate regime and flow regime. The same models could have been used to investigate other aspects of flow regimes such as daily variability, extremes, and seasonality, which are often used collectively to represent flow regimes (Richter et al., 1997). Ability to investigate various aspects of flow regimes is useful because river ecosystem health is linked to a suite of hydrological characteristics that constitute historical flow regimes (Poff, 1997).

Data were available for more sites within the region, but their trends could not be assessed because their observed flow data started too late (e.g. after 1995), ended too early (e.g. before 1991), or contained too much missing data. Length of assessment period in this study was required to be longer than 20-years because shorter periods are likely to be influenced by short-term climatic oscillations (Hannaford and Buys, 2012). Attempting to attribute flow changes to either long-term climate changes or local activities over short time scales is difficult given quasi-periodic climatic variation at these time-scales (Snelder et al., 2021).

Conclusion

This study provides strong evidence for declines in river flows at some, but not all, sites across a region. Declining river flows were more evident during summer and spring than autumn and winter. Evaluating trends in climate variables was insightful for interpreting trends in river flows as there was strong evidence for consistent increases in temperatures across all sites and all seasons. The picture was less clear for rainfall with decreasing trends at some sites across all seasons and increases for some sites during autumn.

Statistical models whose coefficient directions were consistent with hydrological principles were used to represent flows as a function of rainfall and temperature. There was evidence for changes in flows being attributable to changes in climate and to local activities. Overall, the findings demonstrate that water resources managers must be cognisant of purely climate-driven hydrological alterations as well as changes hydrological alterations resulting from local activities (e.g. water abstraction or land cover changes) that may themselves include adaptation to climate variability.

The approach applied in this study could be applied elsewhere to attribute flow regime changes to climate and local activities, and could be adapted to utilise various modelling techniques, utilise various methods for assessing trends and investigate various components of flow regimes.

Declarations

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Availability of data and materials: River flow data that support the findings of this study are available at the following URL addresses: http://data.ecan.govt.nz/RiverRecorderQcEcanDaily.hts and https://www.ecan.govt.nz/data/riverflow/. VCSN data may be requested from the authors or Enquiries@niwa.co.nz.

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Figures

Figure 1

Map showing river flow sites, upstream catchments (grey polygons), and main rivers of the Canterbury region.

Figure 2

Timelines showing: a) some regulations relating to water-land management; b) examples of flow-influencing activities in the Canterbury region (source: http://www.TeAra.govt.nz/en/irrigation-and-drainage); c) maximum allowable rate of abstraction summed across all consents to take water in the Canterbury region (data source: Environment Canterbury); d) annual air temperatures (source: https://data.mfe.govt.nz/data/category/environmental-reporting/atmosphere-climate/temperature/).

Figure 3

For each site (ordered from North to South), training and winter assessment periods (left) and cross-validated predictive performance using the criteria proposed by Moriasi et al. (2015) (right).

Figure 4

For each site, the predictors retained in the model and their directions. Crosses indicate that the 95% confidence intervals around the coefficient included zero. White indicates predictor removed.

Figure 5

Number of sites in each confidence category for seasonal medians of observed 30-day rainfall, observed daily temperature, observed daily flow, modelled daily flow, and residual daily flow (observed median minus modelled median).

Figure 6

Confidence that modelled (right panel) and residual (left panel) trends in median seasonal river flows are decreasing. Residual is observed minus modelled. CV refers to a suite of 20 cross-validated models. Black dot represents final model.