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Precipitation elasticity of streamflow in catchments across the world

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Abstract Estimates of the sensitivity of streamflow to climate are required to make informed decisions for managing water resources and environmental systems to cope with hydroclimatic variability and climate change. The precipitation elasticity of streamflow (ε_P), defined as the proportional change in mean annual streamflow divided by the proportional change in mean annual precipitation, is a measure of the sensitivity of streamflow to precipitation. This paper uses a nonparametric estimator to estimate ε_P for over 500 catchments across the world. The nonparametric estimator calculates ε_P directly from concurrent historical annual catchment precipitation and streamflow data, and is particularly useful for global studies such as this because it does not require the selection of a single hydrological model and calibration criteria that are appropriate for catchments across the world. The results indicate that changes in precipitation are amplified in streamflow. The ε_P estimates generally range from 1.0 to 3.0, that is, a 1% change in mean annual precipitation results in a 1–3% change in mean annual streamflow. The higher ε_P values (greater than 2.0) are observed in southeastern Australia and southern and western Africa, while lower ε_P values (lower than 2.0) are observed in southwestern South America and at mid and high latitudes in the Northern Hemisphere. There is a relatively strong inverse relationship between ε_P and runoff coefficient, with higher ε_P values observed in catchments with lower runoff coefficients. The ε_P value is also generally lower than 2.0 in catchments with high mean annual streamflow (greater than 500 mm) or mean annual precipitation (greater than 1500 mm), and in cold climates (mean annual temperature lower than 10°C).

Key words climate change; elasticity; global; hydroclimatic variability; precipitation; streamflow

INTRODUCTION

Climate is a key driver of hydrological processes. Estimates of the sensitivity of streamflow to climate are required to make informed decisions to manage water resources and environmental systems to cope with hydroclimatic variability and climate change. The sensitivity of streamflow to climate is almost always estimated using calibrated hydrological models by comparing estimates of the modelled streamflow for the present climate and the modelled streamflow for a perturbed climate (e.g. Schaake, 1990; Xu, 1999; Chiew & McMahon, 2002). The results from the modelling studies are likely to be dependent on the hydrological model and calibration criteria used in the studies.

The alternative to the hydrological modelling approach is to estimate the sensitivity of streamflow to climate directly from a set of concurrent climate and streamflow data. This paper presents the precipitation elasticity of streamflow for over 500 catchments across the world, estimated using a nonparametric estimator of elasticity which calculates the elasticity directly from a set of concurrent annual catchment precipitation and streamflow data. The precipitation elasticity of streamflow (ε_P) is defined here as the proportional change in mean annual streamflow divided by the proportional change in mean annual precipitation (Schaake, 1990). An elasticity of 2.0 therefore indicates that a 1% change in precipitation results in a 2% change in streamflow. The nonparametric estimator of elasticity is particularly useful for this global study because it is difficult to define a hydrological model structure that is appropriate for large parts of the world, and to obtain the data required to run such models.

This paper first describes the nonparametric estimator of ε_P and its limitations, followed by a description of the compilation of precipitation, temperature and streamflow data sets for catchments across the world. The paper then presents estimates of ε_P for over 500 catchments and discusses the observed relationships between ε_P and hydroclimatic characteristics.

NONPARAMETRIC ESTIMATOR OF ELASTICITY

The nonparametric estimator of ε_P proposed by Sankarasubramaniam *et al.* (2001) is used here:

$$\varepsilon_P = \text{median}\left(\frac{Q_t - \overline{Q}}{P_t - \overline{P}}\frac{\overline{P}}{\overline{Q}}\right) \tag{1}$$

where $\overline{P}$ and $\overline{Q}$ are the mean annual precipitation and streamflow respectively. To estimate ε_P, a value of $\left(\frac{Q_t - \overline{Q}}{P_t - \overline{P}}\frac{\overline{P}}{\overline{Q}}\right)$ is calculated for each pair of P_t and Q_t in the annual time series, and the median of these values is the nonparametric estimate of ε_P. This nonparametric estimate of ε_P is therefore defined at the mean value of the hydroclimate variable.

Sankarasubramaniam *et al.* (2001) showed, using Monte-Carlo experiments, that this nonparametric estimate of ε_P has low bias and is as robust as ε_P estimated using modelling approaches. Sankarasubramaniam *et al.* (2001) and Chiew (2006) also showed that there is a high correlation between ε_P values estimated using this nonparametric estimator and modelling approaches for catchments in the USA and Australia, respectively, although the hydrological modelling approach gives slightly higher ε_P values.

There are several limitations in the nonparametric estimation approach. As the nonparametric estimator uses annual data, it only provides an estimate of the sensitivity of long-term streamflow to changes in long-term precipitation, and cannot describe the sensitivity of streamflow characteristics, other than the long-term mean, to changes in precipitation characteristics. The estimates, which are derived from historical data, should also be interpreted cautiously in climate change impact studies, because the approach does not consider potential changes in land surface processes and surface-atmosphere feedbacks in an enhanced greenhouse environment.

GLOBAL PRECIPITATION, TEMPERATURE AND STREAMFLOW DATA SETS

To estimate ε_P using the nonparametric estimator, a data set of concurrent (but not necessarily continuous) annual lumped catchment-average precipitation and streamflow data is required. Temperature data are also compiled for catchments with concurrent precipitation and streamflow data.

The streamflow data used in this study are drawn from the global database of monthly streamflow data for over 1200 catchments described in Peel *et al.* (2004). The streamflow data are believed to be unregulated over the period of record in the database. The source of the precipitation and temperature data is the Global Historical Climatology Network (GHCN, Version 2), which contains monthly precipitation and temperature data for over 20 000 and 7000 stations respectively (Peterson & Vose, 1995; Vose *et al*., 2005).

To compile the catchment-average monthly precipitation data, the catchment boundaries are constructed from the HYDRO1k DEM (1 km × 1 km resolution, USGS, http://edcdaac.usgs.gov/gtopo30/hydro/). The catchment is used only if the area defined by the boundary is within 5% of the published catchment area.

For each catchment, precipitation stations within 200 km of the catchment boundary (with more than 50% of data over the period of streamflow data) that contribute to the Thiessen weighting are used to estimate the lumped catchment-average monthly precipitation time series. Figure 1 shows the number of precipitation stations that account for 70% of the Thiessen weighting plotted against the catchment area. Any missing monthly precipitation data for a station (Station A) are infilled using data from stations within 200 km, each time using data from the station (which has data when data from Station A is missing) with the highest precipitation correlation with Station A. Precipitation data infilled using data from a station with precipitation correlation against Station A that is lower than 0.7 are considered to be poor, and catchments with more than 5% of poor (Thiessen weighted) infilled data are not used.

Like precipitation, temperature stations within 500 km of the catchment boundary that contribute to the Thiessen weighting are used to estimate the lumped catchment-average monthly temperature time series. Missing monthly temperature data for a station are also infilled using data from the station with the highest correlation.

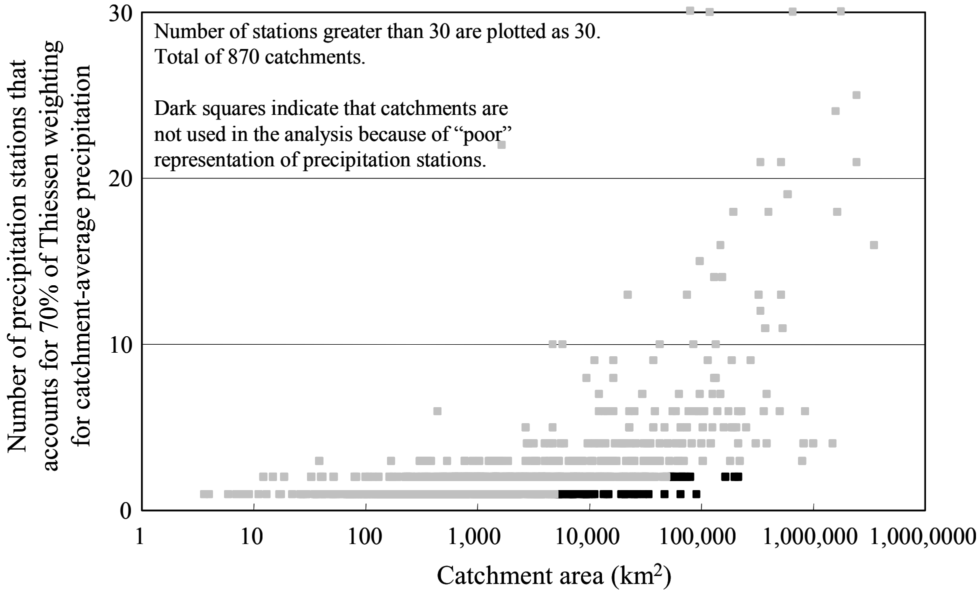

Fig. 1 Number of precipitation stations that accounts for 70% of the Thiessen weighting plotted against the catchment area.

The two biggest sources of error in the data are in the streamflow measurements (particularly the flow-stage rating) and the likelihood of more precipitation stations being located in the lower parts of the catchments where precipitation is usually lower than in the upper parts of the catchments (Milly & Dunne, 2002). The latter problem is highlighted by about 20% of the catchments having runoff coefficients [mean annual runoff (streamflow expressed in mm averaged over the catchment area) divided by mean annual precipitation] greater than one. Other main sources of error include: catchments may not be unregulated as believed and/or may have undergone land-use changes; poor infilling of precipitation data; and insufficient precipitation stations to represent the catchments. The latter two problems are overcome to some degree by removing catchments with more than 5% of "poor infilled data" as described above, and removing catchments larger than 5000 km^2 with only one precipitation station representing 70% of the Thiessen weighting and catchments larger than 50 000 km^2 with only one or two precipitation stations representing 70% of the Thiessen weighting (see Fig. 1).

The monthly precipitation and streamflow data are used to derive concurrent (not necessarily continuous because there can be missing monthly streamflow data) annual precipitation and streamflow data. The annual data are derived for a "water year" (rather than "calendar year"), which starts from the month with the lowest long-term mean monthly streamflow.

This study uses only data from catchments with at least 20 years of concurrent annual precipitation and streamflow data. Catchments with runoff coefficients greater than one and ε_P estimates less than zero are also not used.

Altogether, 521 catchments are used in this study (Fig. 2). They provide a reasonable coverage of different hydroclimatic regions, although they are not evenly distributed across the world. The data length varies from 23 to 64 years (10th to 90th percentile) and the catchment areas range from 100 to 76 000 km^2 (10th to 90th percentile).

RESULTS AND DISCUSSION

The nonparametric estimator is used to estimate ε_P for the 521 catchments across the world. The ε_P values for the 521 catchments are summarized in Fig. 2, and the range of ε_P values and runoff coefficients for the major climatic types (as described by the Koppen climate classification scheme, Henderson-Sellers & Robinson, 1986) are tabulated in Tables 1 and 2 respectively. Figure 3 shows ε_P plotted against various hydroclimatic characteristics. Before discussing the results, it is worth noting that there is no relationship between ε_P and catchment area or data length in the data used here (not shown here).

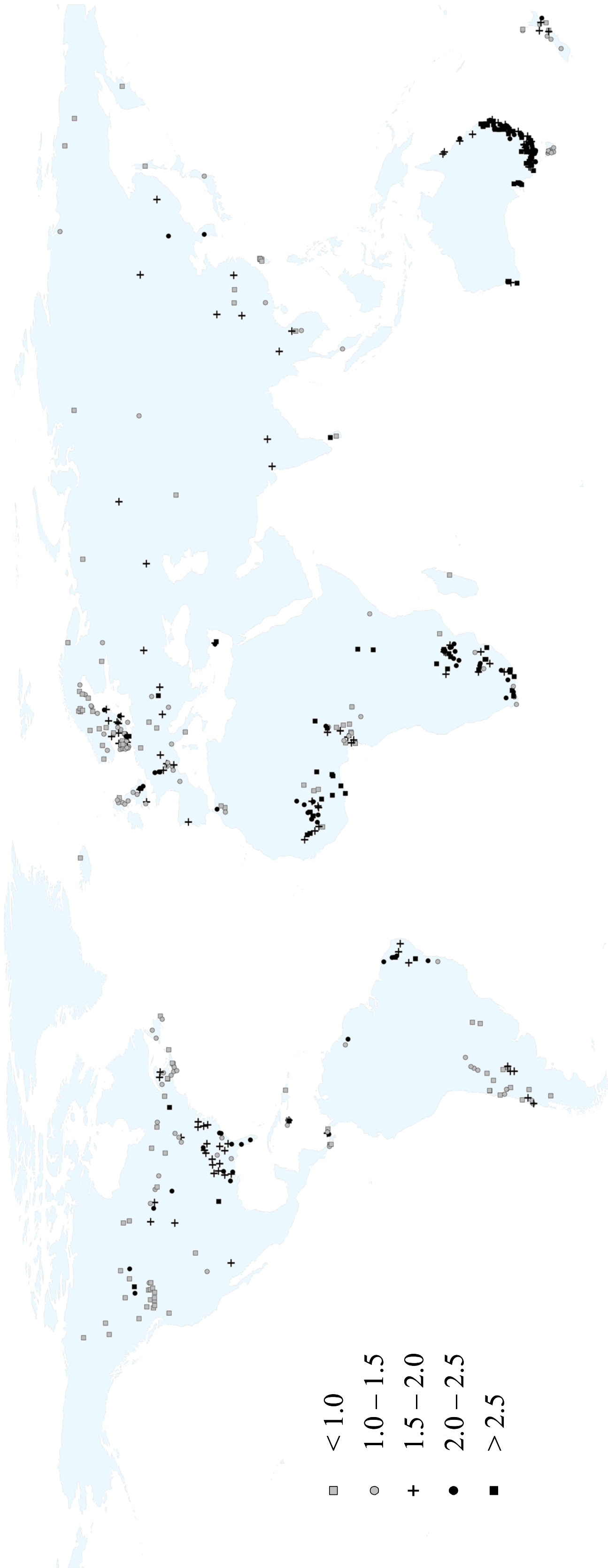

Fig. 2 Estimates of ε_P for 521 catchments across the world.

Table 1 Range of ε_P values for the major climate types.

Climate zone*	Number of catchments	Precipitation elasticity of streamflow: Median	10th and 90th percentiles in brackets
Tropical (A)	**79**	**1.7**	**(0.8 – 3.1)**
Very wet (Af, Am)	20	1.2	(0.8 – 1.9)
Moderately wet (Aw)	59	2.0	(0.9 – 3.3)
Arid (B)	**45**	**1.8**	**(0.4 – 2.9)**
Cold arid (BWk, BSk)	32	1.6	(0.4 – 3.1)
Warm arid (BWh, BSh)	13	2.0	(0.5 – 2.5)
Temperate (C)	**262**	**1.9**	**(0.9 – 3.1)**
Wet winter (Csa, Csb, Csc)	32	2.0	(0.9 – 3.4)
Wet summer (Cwa, Cwb, Cwc)	35	1.8	(0.8 – 2.8)
No seasonality (Cfa, Cfb, Cfc)	195	1.9	(1.0 – 3.1)
Cold (D)	**135**	**1.1**	**(0.5 – 1.9)**

* The climate types are described using the Koppen climate classification scheme (indicated by the letters in brackets).

Table 2 Range of runoff coefficients for the major climate types.

Climate zone	Number of catchments	Runoff coefficient: Median	10th and 90th percentiles
Tropical (A)	**79**	**0.24**	**(0.06 – 0.67)**
Very wet (Af, Am)	20	0.58	(0.34 – 0.83)
Moderately wet (Aw)	59	0.19	(0.05 – 0.40)
Arid (B)	**45**	**0.09**	**(0.02 – 0.45)**
Cold arid (BWk, BSk)	32	0.08	(0.02 – 0.59)
Warm arid (BWh, BSh)	13	0.13	(0.07 – 0.22)
Temperate (C)	**262**	**0.32**	**(0.09 – 0.75)**
Wet winter (Csa, Csb, Csc)	32	0.27	(0.09 – 0.71)
Wet summer (Cwa, Cwb, Cwc)	35	0.14	(0.05 – 0.50)
No seasonality (Cfa, Cfb, Cfc)	195	0.34	(0.12 – 0.77)
Cold (D)	**135**	**0.54**	**(0.21 – 0.82)**

The difficulties in compiling accurate catchment precipitation-streamflow data were discussed in the previous section. Therefore, despite the data used here being the best available global catchment precipitation-streamflow data set, this paper only discusses general trends in the ε_P estimates. For this reason, the upper and lower tenth percentiles of the data points in Fig. 3 are shown as smaller and lighter shaded squares. However, although more accurate estimates of ε_P can be obtained for a particular area using better local data and hydrological models developed and calibrated specifically for a catchment, the results here provide a useful overview of the sensitivity of long-term streamflow to climate in different parts of the world.

The results indicate that 80% of the ε_P estimates are between 0.7 and 3.0. The map in Fig. 2 indicates that the higher ε_P values (greater than 2.0) are in southeastern Australia and southern and western Africa, while the lower ε_P values (lower than 2.0) are in southwestern South America and the mid and high latitudes of the Northern Hemisphere (note that the catchments are not evenly distributed across the world and the catchment elevations are not considered here).

Figure 3(a) shows that there is a reasonably strong inverse relationship between ε_P and runoff coefficient. This is because of the nonlinearity in the precipitation–runoff process, and the same absolute change in streamflow for a given absolute change in precipitation would be reflected as a higher ε_P in a catchment with a lower runoff coefficient. In most cases, the upper limit of ε_P is the inverse of runoff coefficient (when the change in streamflow is the same as the change in precipitation).

The ε_P versus runoff coefficient relationship is also reflected in the ε_P *versus* streamflow relationship (Fig. 3(b)) and to a much lesser extent in the ε_P *versus* precipitation relationship (Fig. 3(c)). Figures 3(b) and 3(c) indicate that ε_P is generally below 2.0 in catchments with high mean annual streamflow (greater than 500 mm) or mean annual precipitation (greater than 1500 mm).

Tables 1 and 2 show that ε_P is generally lower (median ε_P of 1.1 and 90th percentile ε_P of 1.9 in the 135 catchments) and runoff coefficient is generally higher, respectively, in the cold climate

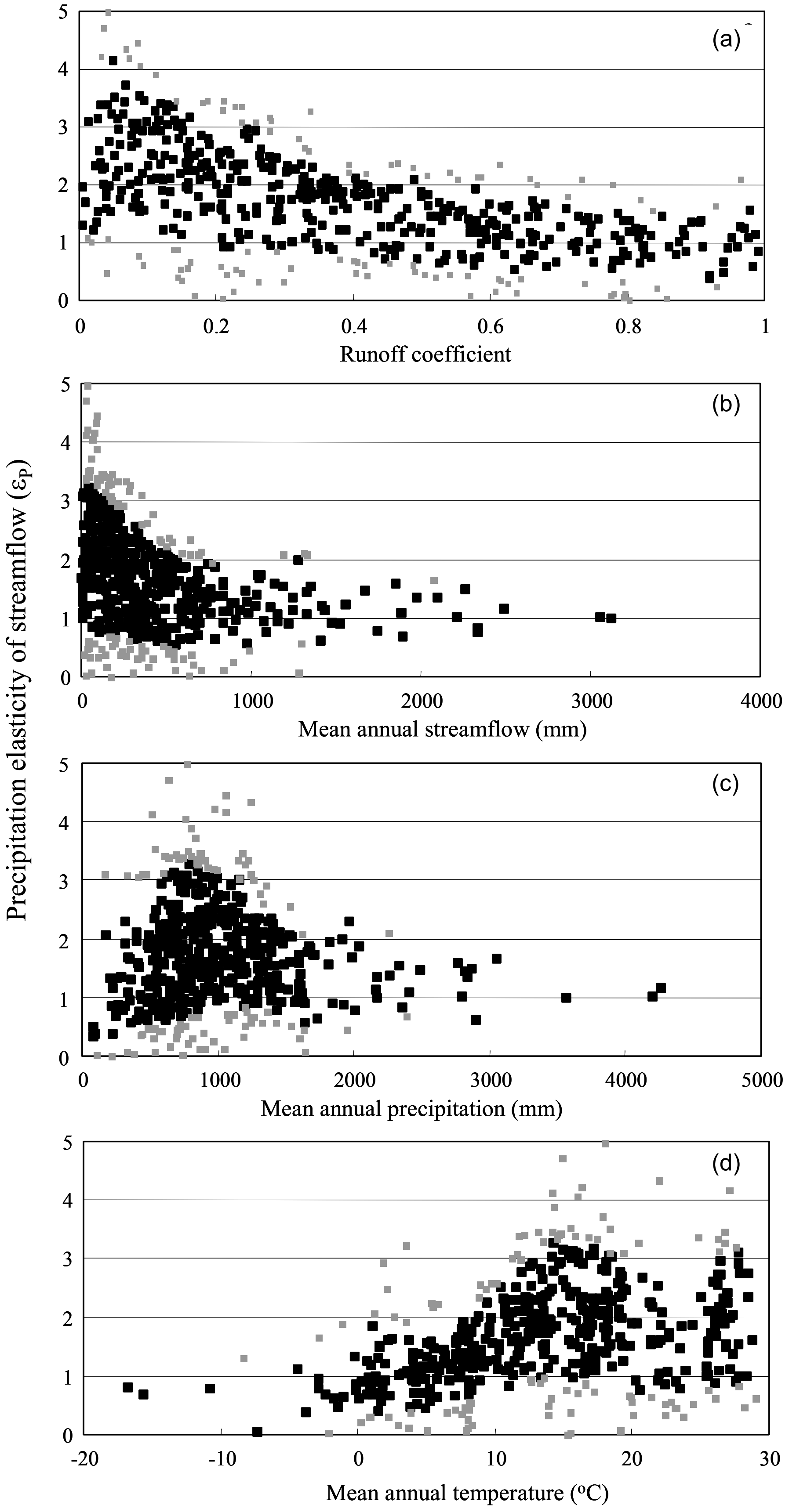

Fig. 3 Relationship between ε_P and various hydroclimatic characteristics.

type compared to the other Koppen climate types. This is also reflected in the ε_P *versus* temperature plot in Fig. 3(d) in which ε_P is generally less than 2.0 where the mean annual temperature is less than 10°C. The runoff coefficient is high in cold climates because of the low amount of energy available for evapotranspiration, and the ε_P value is low in cold climates because of the high runoff coefficient. In addition, where there is significant/permanent snowpack, annual streamflow is also dependent on the temperature which governs the amount of snowmelt and over-year snow storage, which is not considered in the ε_P estimator used here.

Apart from the cold climate type, it is difficult to distinguish the ε_P values in the other three climate types. Nevertheless, the wetter catchments in the tropical climate type generally have lower ε_P and higher runoff coefficient compared to the drier catchments (Tables 1 and 2 respectively). There is also a weak observation that the runoff coefficient in the temperate climate type is higher in catchments dominated by winter rainfall (Table 2), most likely due to lower evapotranspiration losses. It is also interesting to note that although the runoff coefficient is lower in the arid catchments as expected (Table 2), the ε_P values in the arid catchments are similar (and not higher) to the tropical and temperate climate types (although most of the arid catchments in this data set are in colder arid regions).

CONCLUSIONS

The precipitation elasticity of streamflow (ε_P) for 521 catchments across the world, estimated using a nonparametric estimator, is presented in this paper. The nonparametric estimator calculates ε_P directly from concurrent historical annual catchment precipitation and streamflow data, and is particularly useful for global studies such as this because it does not require the selection of a single hydrological model and calibration criteria that are appropriate for catchments across the world.

The results indicate that changes in precipitation are amplified in streamflow. The ε_P estimates generally range from 1.0 to 3.0, that is, a 1% change in mean annual precipitation results in a 1% to 3% change in mean annual streamflow. The higher ε_P values (greater than 2.0) are observed in southeastern Australia and southern and western Africa, while lower ε_P values (lower than 2.0) are observed in southwestern South America and the mid and high latitudes of the Northern Hemisphere. There is a reasonably strong inverse relationship between ε_P and runoff coefficient, with higher ε_P values observed in catchments with lower runoff coefficients. The ε_P value is also generally lower than 2.0 in catchments with high mean annual streamflow (greater than 500 mm) or mean annual precipitation (greater than 1500 mm), and in cold climates (mean annual temperature lower than 10°C).

REFERENCES

Chiew, F. H. S. (2006) Estimation of rainfall elasticity of streamflow in Australia. *Hydrol. Sci. J.* (in press).

Chiew, F. H. S. & McMahon, T. A. (2002) Modelling the impacts of climate change on Australian Streamflow. *Hydrol. Processes* **16**, 1235–1245.

Henderson-Sellers, A. & Robinson, P. J. (1986) *Contemporary Climatology*. Longman Scientific and Technical, London, UK.

Milly, P. C. D. & Dunne, K. A. (2002) Macroscale water fluxes. 1. Quantifying errors in the estimation of basin mean precipitation. *Water Resour. Res.* **38**, 1205, doi:10.1029/2001WR000759.

Peel, M. C., McMahon, T. A. & Finlayson, B. L. (2004) Continental differences in the variability of annual runoff—update and reassessment. *J. Hydrol.* **295**, 185–197.

Peterson, T. C. & Vose, R. S. (1997) An overview of the Global Historical Climatology Network temperature database. *Bull. Am. Met. Soc*. **78**, 2837–2849.

Sankarasubramaniam, A., Vogel, R. M. & Limburner, J. F. (2001) Climate elasticity of streamflow in the United States. *Water Resour. Res.* **37**, 1771–1781.

Schaake, J. C. (1990) From climate to flow. In: *Climate Change and US Water Resources* (ed. by P. E. Waggoner), 177–206. John Wiley, New York, USA.

Vose, R. S., Wuertz, D., Peterson, T. C. & Jones, P. D. (2005) An intercomparison of trends in surface air temperature analyses at the global, hemispheric, and grid-box scale. *Geophys. Res. Lett*. **32**, L18718, doi:10.1029/2005GL023502.

Xu, C. Y. (1999) Climate change and hydrologic models: a review of existing gaps and recent research developments. *Water Resour. Manage.* **13**, 369–382.