

Attribution analysis using the Budyko method

Based on the Budyko hypothesis, the analytical water-energy balance equation is derived at the mean annual time scale, which is expressed as:

$$E = \frac{P \times PET}{(P^n + PET^n)^{\frac{1}{n}}} \quad (1)$$

where E is the mean annual actual evapotranspiration, P is the mean annual precipitation, PET is the mean annual potential evapotranspiration, which is calculated following the guidelines provided by the Food and Agriculture Organization, and the parameter n represents the basin landscape characteristics, which include properties of soil, topography, and vegetation.

Assuming negligible changes in terrestrial water storage and combining the long-term basin water balance with equation (1), we obtain:

$$Q_n = P - \frac{P \times PET}{(P^n + PET^n)^{\frac{1}{n}}} \quad (2)$$

where Q_n is the mean annual naturalized streamflow.

Assuming P , PET , and n are independent variables and introducing the concept of elasticity, we obtain the following:

$$\frac{dQ_n}{Q_n} = \varepsilon_P \frac{dP}{P} + \varepsilon_{PET} \frac{dPET}{PET} + \varepsilon_n \frac{dn}{n} \quad (3)$$

$$\varepsilon_P = \frac{\frac{dQ_n}{Q_n}}{\frac{dP}{P}} = \frac{1 - \left[\frac{\left(\frac{P}{P} \right)^n}{1 + \left(\frac{P}{P} \right)^n} \right]^{\frac{1}{n}+1}}{1 - \left[\frac{\left(\frac{P}{P} \right)^n}{1 + \left(\frac{P}{P} \right)^n} \right]^{\frac{1}{n}}} \quad (4)$$

$$\varepsilon_{PET} = \frac{\frac{dQ_n}{Q_n}}{\frac{dPET}{PET}} = \frac{1}{1 + \left(\frac{P}{P} \right)^n} \frac{1}{1 - \left[\frac{1 + \left(\frac{P}{P} \right)^n}{\left(\frac{P}{P} \right)^n} \right]^{\frac{1}{n}}} \quad (5)$$

$$\varepsilon_n = \frac{\frac{dQ_n}{Q_n}}{\frac{dn}{n}} = \frac{1}{\left[1 + \left(\frac{P}{P} \right)^n \right]^{\frac{1}{n}} - 1} \left[\frac{P^n \ln(P) + PET^n \ln(PET)}{P^n + PET^n} - \frac{\ln(P^n + PET^n)}{n} \right] \quad (6)$$

where ε_P , ε_{PET} , and ε_n represent P , PET , and n elasticity of streamflow, respectively. Based on equation (3), Budyko-simulated changes in naturalized streamflow ($\Delta \widehat{Q}_n$) can be attributed to the CCV-induced change ($\Delta Q_{n,CCV}$) and the LUCC-induced change ($\Delta Q_{n,LUCC}$):

$$\Delta \widehat{Q}_n = \varepsilon_P \frac{Q_n}{P} \Delta P + \varepsilon_{PET} \frac{Q_n}{PET} \Delta PET + \varepsilon_n \frac{Q_n}{n} \Delta n \quad (7)$$

where Δ represents the changes from the pre-1986 period to 1986 onwards. Based on equation (7), the contributions of CCV, LUCC, and WADR to changes in observed streamflow (ΔQ_o), as calculated using the Budyko method, can be expressed as:

$$C_{CCV} = \frac{\Delta Q_{n,CCV}}{\Delta Q_o} \times 100\% \quad (8)$$

$$C_{LUCC} = \frac{\Delta Q_{n,LUCC}}{\Delta Q_o} \times 100\% \quad (9)$$

$$C_{WADR} = \frac{\Delta Q_o - \Delta Q_n}{\Delta Q_o} \times 100\% \quad (10)$$

The Budyko attribution framework is applied through the following steps:

- Step 1: input the 1960-2016 annual mean P , PET , and Q_n into equation (2) to inversely calculate the parameter n for each station.
- Step 2: input the 1960-2016 annual mean P , PET , and the parameter n (obtained in Step 1) into equations (4-6) to calculate ε_P , ε_{PET} , and ε_n .
- Step 3: input the annual mean P , PET , and Q_n for the pre-1986 period and from 1986 onwards into equation (2) to inversely calculate the parameter n for each station in both periods.
- Step 4: input ΔP , ΔPET , and Δn from the pre-1986 period to 1986 onwards, together with Q_n , P , PET , n , ε_P , ε_{PET} , and ε_n in Steps 1 and 2, into the equation (7) to calculate ΔQ_n , $\Delta Q_{n,CCV}$, and $\Delta Q_{n,LUCC}$.
- Step 5: input changes in observed (ΔQ_o) and naturalized (ΔQ_n) streamflow from the pre-1986 period to 1986 onwards, together with $\Delta Q_{n,CCV}$ and $\Delta Q_{n,LUCC}$ obtained in Step 4, into equations (8-10) to calculate contribution rates.
- Step 6: use $\widehat{\Delta Q_n}$ obtained in Step 4 and ΔQ_n to plot fig. S5A. Since Q_n is used in Step 1 to inversely calculate the parameter n in the Budyko model (serving as model calibration), the Budyko-simulated naturalized streamflow exhibits perfect agreement and correlation. This confirms that the Budyko framework effectively quantifies the relationships between P , PET , and Q_n .

ISIMIP3a,

The observation-based forcings used in these models are specified as “obsclim” and “histsoc.”

- 1) “obsclim” refers to observation-based climate-related forcings, consisting of standard atmospheric forcings. ISIMIP3a uses four atmospheric forcings—GSWP3-W5E5, 20CRv3, 20CRv3-W5E5, and 20CRv3-ERA5—each of which is used separately to drive the GHMs.

- 2) “histsoc” represents varying direct human influences during the historical period, including LUCC, variable human water abstraction, and simplified reservoir regulation.

To isolate and identify the contributions of different drivers to streamflow changes, ISIMIP3a transforms observation-based forcings and uses these transformations to rerun the GHMs. The transformations used in this study are “counterclim” and “1901soc”.

- 3) “counterclim” refers to a hypothetical counterfactual climate condition in the absence of observed climate change. This condition is derived by detrending four atmospheric forcings using ATTRICI version 1.1, which removes global mean temperature-related shifts in each grid.
- 4) “1901soc” represents direct human influences that remain constant over time, maintaining land use, human water abstraction, and reservoir conditions identical to those in 1901.

On the basis of the information outlined above, Q_o is reconstructed using GHMs forced by “obsclim + histsoc” (denoted as Q'_o), and Q_n is reconstructed using GHMs forced by “obsclim + 1901soc” (denoted as Q'_n). In addition, GHMs forced by “counterclim + 1901soc” (denoted as Q'_{cn}) are used to distinguish the influence of climate change from climate variability. According to the GHMs participating in ISIMIP3a, as listed in data S2, we downloaded Q'_o , Q'_n , and Q'_{cn} from nine ISIMIP3a outputs.

The contributions of CCV, LUCC, and WADR to the change in Q_o denoted as C_{CCV} , C_{LUCC} , and C_{WADR} , can be calculated as

$$C_{CCV} = \frac{\Delta Q'_n}{\Delta Q_o} \times 100$$

$$C_{LUCC} = \frac{\Delta Q_n - \Delta Q'_n}{\Delta Q_o} \times 100$$

$$C_{WADR} = \frac{\Delta Q_o - \Delta Q_n}{\Delta Q_o} \times 100$$

C_{CCV} can be further divided into the contributions of ACC and NCV, namely C_{ACC} and C_{NCV} , as follows

$$C_{ACC} = \frac{\Delta Q'_n - \Delta Q'_{cn}}{\Delta Q_o} \times 100$$

$$C_{NCV} = \frac{\Delta Q'_{cn}}{\Delta Q_o} \times 100$$

ISIMIP2a, NOSOC, VARSOC experiment

Data Sources

- **Observed streamflow data:** Global Runoff Data Center (GRDC, <https://portal.grdc.bafg.de/applications/public.html?publicuser=PublicUser#dataDownload/Home>)
- **Water consumption data:** Data of different sectors—irrigation, live-stock, electricity generation, domestic, mining and manufacturing from 1970–2010 (<https://doi.org/10.5281/zenodo.1209296>)
- **Future climate projections:** <https://www.isimip.org/>

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