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Climate change to exacerbate the burden of water collection on women's welfare globally

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Climate change is aggravating water scarcity worldwide. In rural households lacking access to running water, women often bear the responsibility for its collection, with adverse effects on their well being through long daily time commitments, physical strain and mental distress. Here we show that rising temperatures will exacerbate this water collection burden globally. Using fixed-effects regression, we analyse the effect of climate conditions on self-reported water collection times for 347 subnational regions across four continents from 1990 to 2019. Historically, a 1 °C temperature rise increased daily water collection times by 4 minutes. Reduced precipitation historically increased water collection time, most strongly where precipitation levels were low or fewer women employed. Accordingly, due to warming by 2050, daily water collection times for women without household access could increase by 30% globally and up to 100% regionally, under a high-emissions scenario. This underscores a gendered dimension of climate impacts, which undermines womens' welfare.

As anthropogenic climate change continues to alter our planet[1], impacts on water resources are set to become increasingly severe[2]. Coupled with increasing urbanization, some estimates forecast that between one-third and one-half of urban populations will face some form of water scarcity by the year 2050[3]. The physical determinants of water availability are changing as global temperatures rise and precipitation patterns shift. On the one hand, rising temperatures fuelled by anthropogenic emissions increase rates of evapotranspiration, which depletes groundwater resources[4]. On the other hand, an intensification of the hydrological cycle[5–8] is shifting patterns of precipitation[1] and intensifying the variability of precipitation at seasonal and interannual timescales[9,10]. These physical drivers are also subject to regional uncertainties[11,12], painting a risk-laden picture of future water availability.

In households without running water, women (and often children) bear most of the burden when collecting this much-needed resource[13]. Domestic water responsibilities are a strong contributing factor to women's well being in such households, even without the additional stress of climate change. The physical burden carries the risk of injury[14], and there is also evidence of potential psychological distress[15,16]. Beyond collection, women also tend to be responsible for water storage, usage and disposal, taking up considerable time during the day[17]. For example, the United Nations estimates that in Malawi, women spend an average of 54 minutes per day collecting water, compared with just 6 minutes for men[18]. As a global collective, women and girls spend up to 200 million hours daily on this task[18], reducing the time available for education, employment, childcare and other daily responsibilities. In extreme cases, women can find themselves locked in a state of 'time poverty'[19], with limited opportunities for activities that could improve overall welfare. Furthermore, regional studies demonstrate that under water scarcity, these negative effects on women's welfare and employment are often exacerbated[20–22], with vulnerabilities often intersecting with other inequities[23]. In the context of a changing climate, the burden of water collection on women's welfare may therefore be an overlooked societal impact that could be exacerbated as water scarcity intensifies.

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Here we contribute a quantitative basis to this issue at a global scale. We use a harmonized database of household surveys on women's welfare[24] and historical observations of temperature and precipitation[25] to provide insights into the effects of climate conditions on self-reported water collection times in over 347 subnational regions across Africa, Latin America, Eastern Europe and Asia over the period 1990 to 2019. We use panel fixed-effects regression to control for time-invariant differences across regions and contemporaneous global shocks, thereby focusing on exogenous temporal fluctuations to identify plausibly causal effects[26,27] (the Methods section provides further details on this causal interpretation). The subnational granularity of the LivWell dataset[24] provides a detailed reflection of the observable heterogeneity in climate and economic conditions, whereas the use of data from a wide variety of geographic locations allows for a richer and more robust understanding of impacts across the globe.

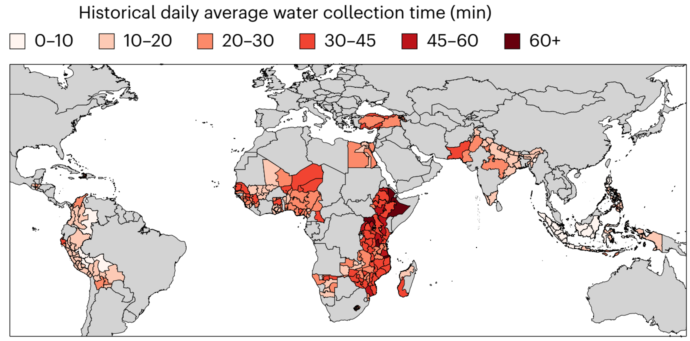

Fig. 1 | Historical averages of self-reported daily water collection time. Map highlighting the historical regional averages of daily water collection time for women in households without water access on site. Data are obtained from LivWell[24], a harmonized dataset of household surveys on women's welfare.

Historical water collection times

Historical averages of self-reported daily water collection time of women vary greatly across space, both within and between countries (Fig. 1). The global average for the period 1990 to 2019 was 22.84 minutes. The minimum regional average was just under 4 minutes—in Jakarta, Indonesia—whereas the maximum of around 110 minutes occurred in the Ethiopian region Afar (Supplementary Table 1; Supplementary Table 2 provides a full list of observations by country, region and year). In general, daily water collection times were highest in eastern and southern Africa, typically between 30 and 60 minutes. Comparatively short daily water collection times were reported for South American and Southeast Asian regions, with women spending anywhere from 0 to 20 minutes per day on average. It is important to note that the water collection times shown in Fig. 1 (and throughout this study) have already been regionally aggregated, meaning that individual water collection times could often be higher.

Moreover, these data and all subsequent results refer to women in households without access to running water. Across the countries of our sample, 49% of households lacked such access in 2020, despite declines in this fraction across most countries (33 from 37) of 14% on average since 2000 (Extended Data Table 1). Across Africa, over 68% of households lacked access in 2020 with declines of 16% since 2000. This highlights the widespread vulnerability of large proportions of the population to water scarcity, which will probably remain considerable even if declines continue in the near future.

Effect of climate conditions on water collection time

Applying fixed-effects panel regression models reveals distinct effects of historical fluctuations in physical climate conditions on water collection times for women in households without access to running water. First, we find that a 1 °C increase in average temperature over the last 60 months corresponds to an increase of about 4 minutes in daily water collection time (Table 1, columns (1) and (2)). Including additional squared terms for temperature does not provide any significant results (Table 1, column (3)), indicating that the effect is predominantly linear. Multiplying this linear coefficient by the within-region variability of observed temperatures shows the average effect of historical temperature fluctuations on water collection times (Fig. 2a,b). In the majority of regions, such a temperature change corresponds with 1 to 2 additional minutes of water collection time, with slightly stronger effects in northern Africa, India and Pakistan.

Defining temperature over shorter timescales (12 and 36 months) reveals very similar results (Supplementary Table 3). Whereas these alternative measures demonstrate the general robustness of our results, we choose to use the 60-month averages of temperature as our main specification for three reasons: they better capture the full climate exposure between survey years, they are more indicative of long-term impacts, which we then aim to project under future climate change, and finally, they are more statistically significant, particularly with respect to temperature.

The analysis also reveals a significant nonlinear effect of precipitation changes on water collection time. Specifically, we find a 10 mm increase in monthly precipitation (last 60 months) reduces daily water collection time by about 1.39 minutes on average, with larger magnitudes in regions with lower average precipitation totals (significant linear and quadratic terms in Table 1, column (1); note that this estimate reflects the marginal effects evaluated using equation (6) as shown in Methods). These results signal that precipitation declines are disadvantageous from the perspective of water collection, and furthermore that regions that already have lower levels of precipitation are more negatively affected (Fig. 3a). For precipitation defined over 12 and 36 months, we find results that support our main findings of a significant nonlinear effect (Supplementary Table 3). For the same reasons as outlined above, we continue to use the variables defined over 60 months as our main specification.

Assessing these results in combination with the historical variability of precipitation (Fig. 2c,d), one can observe that a one standard deviation decrease in precipitation has a stronger effect on water collection time than a similar increase in temperature. Averaged globally, a one standard deviation decrease in precipitation corresponds to a 1.84 minute increase in water collection time, whereas the effects of a one standard deviation increase in temperature less than half at 0.86 minutes. Furthermore, there is greater spatial heterogeneity in the impacts of precipitation, with largest effects in South America and Southeast Asia.

Testing for adaptation

Recent findings on adaptation indicate that financial income and education are important determinants of the capacity to adapt to climate impacts[28–30]. We therefore further test whether regional levels of education (mean years of schooling in that subnational region) and employment (percentage of women working in that region) moderate the effects of changing climate conditions on water collection times by including them as interaction terms with the two climate variables in our panel regression (Methods). For precipitation, we determine a significant interaction effect of levels of employment, with an opposing coefficient to the main term (Table 1, column (5)). This indicates that greater levels of employment can build resilience against increases in water collection time resulting from precipitation declines (Fig. 3b). These moderating effects are sizeable, with the effect of precipitation being reduced to zero at high levels of employment (80%). For temperature, results indicate no significant interaction effects with either the education or employment variable, suggesting that socio-economic conditions are less able to mitigate the effects of temperature changes on water collection times. The current analysis concerns only the

Table 1 | Regression results for the effects of climate conditions on water collection time

Dependent variable	Daily water collection time (min)					
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables						
Temperature (°C)	3.834***	4.065***	1.343	4.824	1.971	3.744**
	(1.441)	(1.520)	(6.233)	(4.141)	(2.247)	(1.502)
Precipitation (mm)	−0.2923***	−0.0976**	−0.2919***	−0.1046*	−0.302**	−0.1007**
	(0.0832)	(0.0382)	(0.0828)	(0.0416)	(0.0534)	(0.111)
Employment (%)						−0.0446
						(0.0357)
Mean years of education						−0.8300**
						(0.4197)
Education × precipitation				0.001		
				(0.0092)		
Education × temperature				−0.145		
				(0.8823)		
Employment × precipitation					0.004*	
					(0.002)	
Employment × temperature					−0.0446	
					(0.0507)	
Precipitation × precipitation	0.0005***		0.0005***			
	(0.0002)		(0.0002)			
Temperature × temperature			0.0567			
			(0.1365)			
Fixed effects						
Region	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,355	1,355	1,355	1,298	1,298	1,355
R^2	0.76847	0.76733	0.76850	0.76875	0.76329	0.76340
Within R^2	0.01592	0.01106	0.01606	0.01710	0.01574	0.01618

Driscoll–Kraay standard errors in parentheses. *P < 0.1, **P < 0.05, ***P < 0.01. Column (1) shows our preferred specification. Column (2) shows a basic model with only linear terms. Column (3) tests nonlinearities in the impacts of temperature and precipitation. Columns (4) and (5) explore the effect of socio-economic variables in mitigating the impacts of climate conditions. Column (6) demonstrates the robustness of the main results to the direct effects of socio-economic variables.

subset of regional households without on-site access to water, within which it is likely that education and employment levels are already relatively low. When considering the entire regional population, these socio-economic indicators may be better determinants of whether a household already has on-site water access, rather than of the heterogeneity of the relationship with climate.

Robustness of empirical results

By using fixed-effects regression models, we are able to isolate variation in climate conditions, which is plausibly exogenous, strengthening the interpretation of causality in the relationships we identify (Methods). To further strengthen the robustness of our results, we report standard errors using the specification proposed by Driscoll and Kraay[31], which controls for heteroscedasticity and cross-sectional dependence within panel data. In doing so, we account for correlated movements in water collection time and climate across different regions, which might otherwise lead us to overstate the statistical significance of our results. Alternatively, clustering standard errors by region indicates similarly significant results (Supplementary Table 4, column R1).

Additionally, results are robust when accounting for household size or number of children (Supplementary Table 5), for temporal changes in levels of education and employment (Table 1) and when removing regions with fewer than four or five observations (Supplementary Table 5). The latter test reduces the risk of type-one errors ('false positives'), which can occur in panel contexts with insufficient time observations[32].

Finally, we test the standardized precipitation and evapotranspiration index (SPEI)[33]- as an alternative independent variable. The metric takes temperature and precipitation as direct inputs such that increases in temperature and decreases in precipitation correspond to reductions in the SPEI. Results indicate that as the SPEI increases, water collection time decreases (Supplementary Table 6), therefore consistent with our main results shown in Table 1. Including temperature, precipitation and SPEI as independent variables together leads all terms to be insignificant, and we therefore continue to use the model with the effects of temperature and precipitation estimated separately (as shown in Table 1, column (1)) as our main specification.

Future climate change to exacerbate water collection times

We combine the coefficients from our main empirical specification with temperature and precipitation projections from an ensemble

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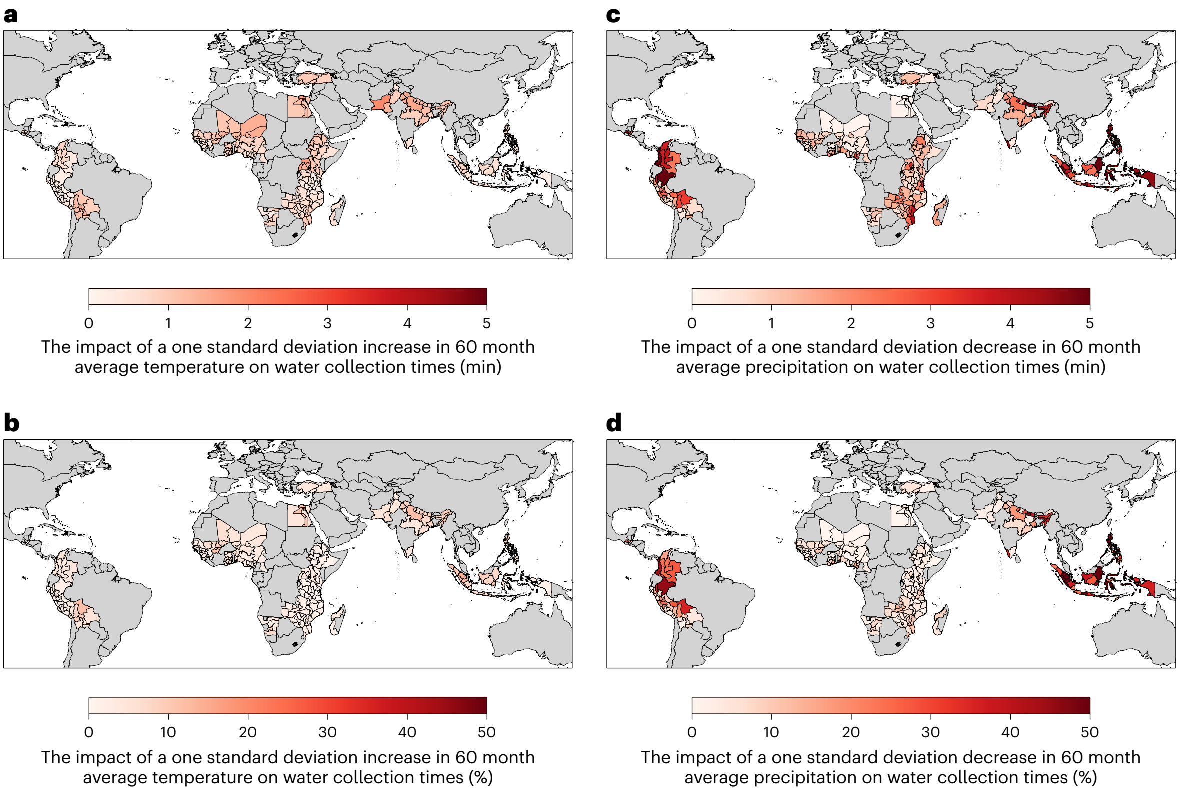

Fig. 2 | The effects of historical fluctuations in temperature and precipitation on water collection times by region. a–d, Maps of the average impact of a one standard deviation increase in monthly temperature (**a**,**b**) or decrease in precipitation (**c**,**d**) on daily water collection time, based on monthly climate averages from the last 60 months and their associated coefficients, as shown in Table 1, column (1). To enable simple comparison, impacts with the same sign were shown, resulting from a decrease in precipitation versus an increase in temperature.

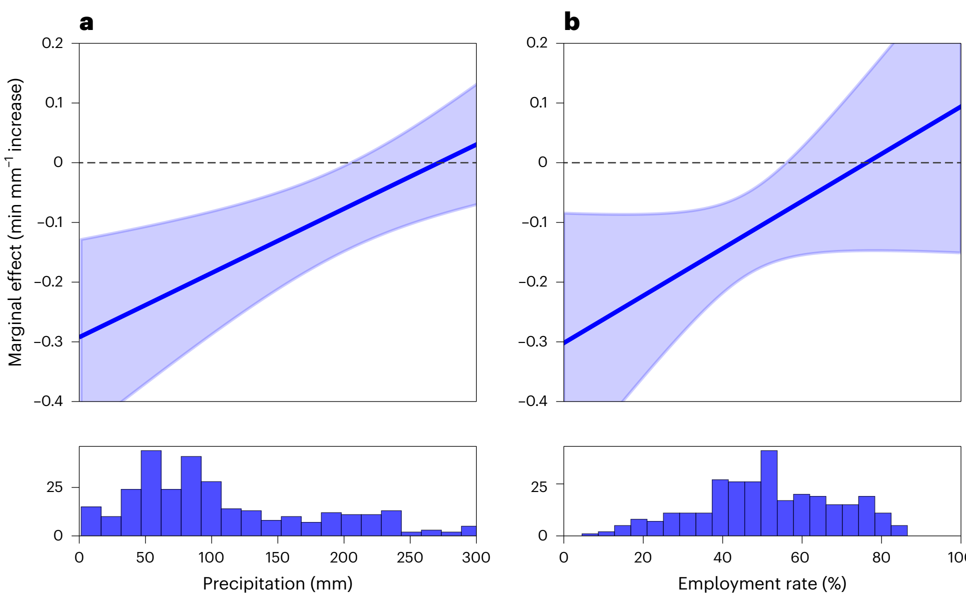

Fig. 3 | Exploring heterogeneity in the effect of climate conditions on water collection times across regions. a, The marginal effects of precipitation on water collection time, which vary based on prevailing precipitation levels via the nonlinearity shown in Table 1, column (1). **b**, The marginal effects of precipitation varying based on prevailing levels of employment as shown in Table 1, column (4). Central lines reflect the mean and shaded area the 95% confidence intervals based on the parameter uncertainty shown in Table 1, column (4). The histograms under each main panel display the distribution of precipitation and employment percentage, respectively.

of bias-adjusted physical climate models from the Coupled Model Intercomparison Project phase 6 (CMIP-6)[34,35] to assess the effects of future changes in climate on daily water collection time (Methods). Temperatures are projected to increase everywhere, which in turn would lead to increases in water collection times across all regions (Fig. 4). Under a high-emissions scenario (representative concentration

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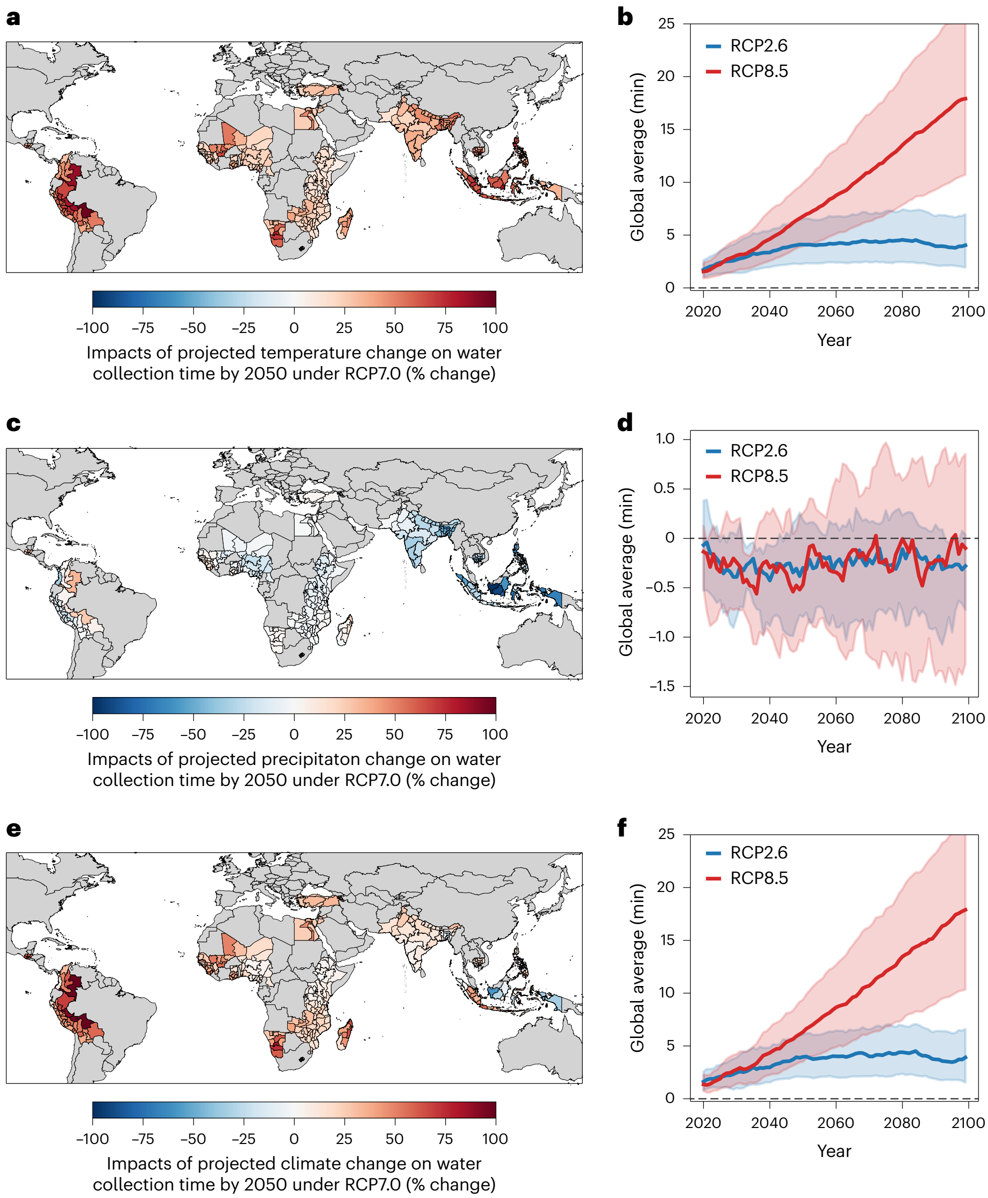

Fig. 4 | The effects of projected changes in temperature and precipitation on daily water collection times. **a**,**c**,**e**, The impacts by region in 2050 under the high-emissions scenario RCP8.5, expressed as a percentage of the historical water collection time. **b**,**d**,**f**, The globally averaged impacts on daily water collection times in minutes for both the low-emissions (RCP2.6) and high-emissions scenario (RCP8.5) over time. Central estimates show the median and shaded areas show the likely range based on the Intergovernmental Panel on Climate Change (IPCC) likelihood classification reflecting a 66% chance. Uncertainty is derived from a Monte-Carlo procedure, which samples from the uncertainty of the empirical regression shown in Table 1 and from the 21 physical climate models from CMIP-6. **a**–**f**, The impacts of temperature (**a**,**b**), precipitation (**c**,**d**) or both temperature and precipitation combined (**e**,**f**). **a**,**c**,**e**, Impacts are estimated from climate changes smoothed with a 30-year running mean to show the impacts of long-term changes. **b**,**d**,**f**, They are shown after smoothing with a 5-year running mean to show variations at shorter timescales (Methods).

pathway, RCP8.5), the global average for water collection time would increase by about 30% by the year 2050, as opposed to 19% in the low-emissions scenario (RCP2.6). Regionally, a high-emissions scenario could increase daily water collection times by up to 100% by 2050—for example, in regions across South America and Southeast Asia. For regions in eastern and central Africa with the highest baseline water collection times, temperature rises in a high-emissions scenario would still cause increases of between 20% and 40%. Despite best tracking recent cumulative emissions and future emissions based on currently stated policies[36], RCP8.5 is a worst-case scenario of future emissions and resulting climate change. Other high-emissions scenarios such as RCP7.0 predict marginally smaller impacts from future temperature changes, which nevertheless constitute 25% globally by 2050 (Supplementary Fig. 1).

Precipitation impacts show greater heterogeneity with regional winners and losers (Fig. 4c). Most regions from our sample benefit, with up to 40% reductions in water collection time under the high-emissions scenario by 2050 for many regions in India, Indonesia and the Philippines. Most regions in Africa appear also to benefit, generally seeing reductions in water collection time between 0 and 20%, with the exception of coastal regions in western Africa (up to 30% increases) and most of Namibia and Zimbabwe (up to 20% increases). In South America, the difference between regional winners and losers is greatest and split distinctly across the Andes mountain range. In the global average, these estimates are marginal compared with those of temperature and show large uncertainty (Fig. 4d). Interestingly, uncertainty is considerably larger under the high-emissions scenario RCP8.5, highlighting the risk posed by precipitation changes, particularly regionally.

The combined impacts of temperature and precipitation show increases in water collection times in almost all regions (Fig. 4e), with the exception of Indonesia, where strong increases in precipitation bring benefits that are larger than the adverse local temperature effects. On global average, however, temperature impacts strongly outweigh the varied effects of precipitation (Fig. 4e).

Discussion

These impacts highlight how climate change may threaten socio-economic development through non-market factors specific to women in the Global South, with particular relevance for United Nations Sustainable Development Goals (SDG) 5 and 6 related to sanitation and women's welfare (https://sdgs.un.org/goals). Although the number of households without access to running water has recently declined (Extended Data Table 1), it remains high in many countries and will probably remain considerable until 2050, particularly in Africa. These results will therefore remain relevant to large numbers of women in the near future. In Extended Data Table 2, we provide conservative 'back-of-the-envelope' estimates of a welfare equivalent of these impacts. To do so, we assume that their economic value is equivalent to the opportunity cost of lost employment at the country-specific minimum wage (Methods). Results indicate that the monetary costs of climate-induced increases in water collection time would be substantial. In most regions, they are tens to hundreds of millions of US dollars per year (at 2017 purchasing power parity) already by 2050 under a high-emissions scenario. Particularly large costs are estimated for India (US$1.4 billion), Turkey (US$1.4 billion) and Pakistan (US$2.1 billion). Emissions mitigation in line with the Paris Agreement (RCP2.6) would substantially reduce these costs, for example, to US$750 million in Turkey, US$1.2 billion in Pakistan and even to net benefits in India (owing to the role of increasing precipitation). Similarly, continued declines in the proportion of households without access to running water at recent rates could substantially reduce impacts, eradicating them entirely in India and reducing them to US$300 million in Turkey. One exception here is Pakistan, where the proportion of households without access to water has actually increased in the past 20 years, and if this trend continues, costs would be exacerbated reaching US$3.7 billion annually. Whereas limited in their underlying assumptions and probably failing to capture the knock-on consequences of lost education and skills for socio-economic development, these simple estimates demonstrate the large welfare losses that these impacts may entail.

Our empirical analysis provides quantitative evidence of the presence and direction of causal effects of climate conditions on water collection times but is not able to shed light on the relevant mechanisms at play and is subject to a number of limitations regarding data availability. We provide a discussion of potential mechanisms and limitations below.

First, with regard to temperature, the simplest mechanism through which temperature rises can increase water collection time is through evapotranspiration. Hotter weather causes more water to evaporate from Earth's surface, reducing the levels of rivers, streams and lakes and rates of groundwater recharge[37]. These effects would naturally cause women to travel further in search of adequate amounts of water. Beyond the physical processes altering water availability, higher temperatures may also increase water collection time simply by making the journey more uncomfortable. Extensive literature finds that high temperatures can lead to heat stress and decrease labour productivity, particularly for work that is done outside[38], making this a potentially relevant mechanism for water collection.

Regarding precipitation, greater rates means that water tables are higher[39] and nearby sources are more likely to contain an adequate supply. Similarly, collecting water from a full well is more efficient when the water table is higher. Moreover, the nonlinearity of our results indicates that in regions that are relatively drier, precipitation changes have stronger effects. In other words, regions with lower precipitation totals benefit more from increased precipitation and also suffer more from decreased precipitation. This underscores the greater vulnerability of women in regions that are already closer to water scarcity.

Whereas our study provides quantitative insights into the effects of climate conditions on water collection times across a large number of subnational regions spanning three decades and four continents, there are a number of limitations regarding the available data. One primary limitation is the unbalanced nature of the available data, with as few as three observations in some regions and up to 11 in others (Extended Data Fig. 1). Whereas our results are robust to the exclusion of regions with a small number of observations (Supplementary Table 5), they will nevertheless be skewed towards regions with a larger number of observations.

Furthermore, surveys are conducted in the same region only once every four to five years, meaning that short-term variations in water collection time remain elusive. We primarily use 60 month climate averages to account for all exposures to climate conditions that occurred between observations, which provide more significant results and better reflect the long-term changes expected under climate change. Nevertheless, other weather events within a region between surveys may affect water collection times in ways that cannot be identified with the current availability of data. For example, short-term shocks from weather extremes such as floods or storms are unlikely to be resolved by our analysis or any such analysis that uses survey data with these time gaps. Finally, survey data themselves may be considered limited in that one relies on self-reported values for water collection time.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-024-02037-8.

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Methods

Water collection data

Daily water collection time estimates are taken from LivWell[24]: a subnational dataset on the living conditions of women and their well being. LivWell contains data for 447 regions in 52 countries and includes a total of 265 different indicators, one of which is our main variable: daily water collection time in minutes. It covers the time period from 1990 to 2019. We only include regions with at least three annual observations for water collection times in our analysis, thus reducing the sample to 347 regions. Many of the variables in LivWell, including water collection time, years of education and employment percentage, originate from household-level questionnaires conducted by the US Demographic and Health Surveys (DHS) programme. Initially, the DHS uses a two-stage clustering process to ensure the sample of households is representative at the national and subnational level. Questionnaires are typically carried out every three to four years in a given country. Interviewed women are those of reproductive age, between 15 and 49. Within LivWell these micro-level data from DHS are aggregated to subnational regions, ensuring harmonization of regions over time by accounting for any changes in regional structure or boundaries[24]. A full description of the aggregation methods can be found in ref. 24. The comprehensive list of the LivWell regions used in the current study and the survey years from which the data originated is given in Supplementary Table 2.

Further data on the proportion of households with access to running water were obtained from the World Health Organization (WHO) and UNICEF Joint Monitoring Programme for Water Supply, Sanitation and Hygiene (JMP) (https://washdata.org/). These are shown in Extended Data Table 1 and are used to estimate a welfare metric equivalent of the climate impacts on water collection times (detailed below and shown in Extended Data Table 2).

Historical climate data

LivWell also contains historical climate data for all regions and their respective time points, including average monthly precipitation and temperature over the last 12, 36 and 60 months. These historical climate data were extracted from the Climate Research Unit gridded time series[25] and aggregated to the specific regions using their administrative boundaries, using an area-weighted average. Temperature is measured in °C, and precipitation is given in mm. Unless explicitly stated otherwise, all references to temperature and precipitation pertain to the 60 month averages.

Fixed-effects panel regression models

Following extensive climate-econometric literature, we used fixed-effects panel regressions as our main method to identify plausibly causal effects of fluctuating climate conditions on water collection times[26,27]. The causal interpretation of such effects rests primarily on two facets. First, that interannual fluctuations in weather conditions are exogenous of socio-economic outcomes such as water collection. This can be understood as assuming that fluctuations in water collection time cannot influence interannual weather fluctuations (otherwise a problem of reverse causality), nor can other socio-economic factors, which may be relevant for water collection times. Second, the use of unit fixed effects removes time-invariant unobserved confounders, allowing the analysis to focus on interannual fluctuations. Together, this enables a quasi-experimental research design in which regions are considered as relatively comparable to themselves across time (after further removing low-frequency temporal variation with year fixed effects) and their experience of different weather conditions in different years thereby interpretable as random treatments from which a plausibly causal response can be measured (reviews of these methods can be found in refs. 26,27).

The following equations represent the various regression models used to examine the relationship between monthly climate averages and daily water collection time. They appear in the same order as shown in Table 1. Our main specification (column (1)) is as follows:

$$W_{ry} = \beta_1 T_{ry} + \beta_2 P_{ry} + \beta_3 {P_{ry}}^2 + \gamma_r + \delta_y + \epsilon_{ry} \quad (1)$$

where W_{ry} represents the averaged daily self-reported water collection time for region r and year y, T_{ry} and P_{ry} represent the average monthly precipitation and temperature, respectively, β_1 and β_2 are their coefficients, ${P_{ry}}^2$ represents the squared monthly precipitation, β_3 its coefficient, γ_r represents the fixed effects for region r, δ_y represents the fixed effects for year y and ϵ_{ry} is the error term.

Initially, we included linear terms only for temperature and precipitation (Table 1, column (2)):

$$W_{ry} = \beta_1 T_{ry} + \beta_2 P_{ry} + \gamma_r + \delta_y + \epsilon_{ry} \quad (2)$$

To arrive at our main specification, we first tested for any nonlinearity in the relationship between the climate variables and water collection by including quadratic terms for temperature and precipitation (Table 1, column (3)):

$$W_{ry} = \beta_1 T_{ry} + \beta_2 P_{ry} + \beta_3 {P_{ry}}^2 + \beta_4 {T_{ry}}^2 + \gamma_r + \delta_y + \epsilon_{ry} \quad (3)$$

where ${P_{ry}}^2$ and ${T_{ry}}^2$ represent the squared monthly precipitation and temperature and β_3 and β_4 represents their coefficients, respectively. We were able to detect a nonlinear relationship for precipitation but not for temperature, so we dropped the ${T_{ry}}^2$ term, which resulted in our main specification shown in equation (1).

We further assessed whether socio-economic conditions modulate the magnitude of impacts from climate conditions, by including the socio-economic variables as interaction terms (columns (4) and (5) in Table 1) that are both represented by the following equation:

$$W_{ry} = \beta_1 T_{ry} + \beta_2 P_{ry} + \lambda_1 (P_{ry} \times M_r) + \lambda_2 (T_{ry} \times M_r) + \gamma_r + \delta_y + \epsilon_{ry} \quad (4)$$

In this instance, λ_1 represents the coefficient for the interaction term between average monthly precipitation and a moderating variable M_r (either employment percentage or average years of schooling in that region) and λ_2 is the coefficient for the interaction term between the same moderating variable and average monthly temperature. Note that the lack of index y indicates that the average of the moderating variables has been taken for each region to explore only the role of regional levels of these variables in altering the impacts of climate conditions, rather than the direct effect of their temporal changes on water collection (which we instead test below).

We further tested the robustness of our results by accounting for the direct effects of these same socio-economic variables on water collection times (Table 1, column (6)):

$$W_{ry} = \beta_1 T_{ry} + \beta_2 P_{ry} + \beta_3 E_{ry} + \beta_4 S_{ry} + \gamma_r + \delta_y + \epsilon_{ry} \quad (5)$$

where E_{ry} and S_{ry} represent the employment percentage and average years of schooling, respectively, for region r and year y.

Marginal effects

Having detected significant nonlinearity for precipitation, the partial derivative of equation (1) with respect to P was used to plot the marginal effects in Fig. 3a:

$$\frac{\mathrm{d}}{\mathrm{d}P_{ry}} W_{ry} = \beta_2 + 2\beta_3 P_{ry} \quad (6)$$

We also determined a significant moderating relationship between our socio-economic variables and precipitation. The marginal effect as shown in Fig. 3b is therefore represented as:

$$\frac{\mathrm{d}}{\mathrm{d}P_{ry}} W_{ry} = \beta_2 + \lambda_1 M_r \tag{7}$$

where β_2 is the coefficient for precipitation, λ_1 represents the coefficient of the interaction term and M_r is the average years of schooling or the average percentage of employment for region r.

Future climate data

Data on future climate conditions stem from an ensemble of 21 climate models from CMIP-6[34]. Data have been bias adjusted to reflect the historical distribution of temperature and precipitation using the trend-preserving method developed by the Inter-Sectoral Impact Model Inter-comparison Project[35] and are originally available on a 0.5 × 0.5° grid. Monthly averages of daily mean surface temperatures and monthly totals of precipitation are calculated to match the data from LivWell. Data are then averaged over each year for the period 1990–2100 under historical (1990–2015) and future (2015–2100) emissions forcing specified by the low-emissions scenario RCP2.6 and high-forcing scenarios RCP7.0 and RCP8.5. Data are available for only 10 of the 21 models for RCP7.0 and are used only as a robustness test in Supplementary Fig. 1. Furthermore, data are then aggregated to the level of the subnational administrative boundaries, using the shapefiles provided by the LivWell database.

Estimating future impacts of climate change

To estimate the impacts on water collection times from future climate change, we evaluate the equation of our preferred regression model (shown in equation (1)) under the temperature and precipitation conditions projected by CMIP-6 ensemble. Specifically, the coefficients of this regression (shown in column (1) of Table 1) are multiplied by future values of temperature, precipitation and precipitation squared. This procedure is done for each future year with the projected temperature and precipitation data from each climate model and future emissions scenario. The effect of climate change on water collection time at a given future date is then estimated as the difference between these values at a given future date and the average over the historical period in which the empirical regressions were estimated (1990–2019). To focus on long-term changes in climate, which are due to human forcing rather than natural variability, we first apply a running mean to the time series of regional temperature and precipitation. This avoids impacts from an anomalously wet or dry year being misattributed to long-term climate change. In the case of the maps shown in Fig. 4, we use a 30-year running mean to focus on long-term climate changes, whereas in the globally averaged time series we use only a five-year running mean to focus on variations over shorter timescales.

To estimate uncertainty in these projected future impacts, we follow extensive climate-econometric literature[26] and use a Monte-Carlo procedure to sample from the uncertainty distribution of the regression (column (1) of Table 1) and from the different physical climate models from CMIP-6. We take 1,000 samples and present the mean average and 13th and 67th percentiles to reflect a 'likely' range (66% chance) as classified by the Intergovernmental Panel on Climate Change.

Welfare valuation of future impacts

We provide simple estimates of a welfare metric equivalent of the effects of future climate change on water collection time. These estimates follow the assumption that their value is equal to the opportunity cost of lost working time at the country-specific minimum wage. We consider these estimates as conservative as they probably do not reflect the knock-on consequences of human capital degradation, which longer water collection times also entail, for example, in terms of lost time in education.

To do so, we combine data on the proportion of households in a country that lack access to running water, WA (Extended Data Table 1), and the proportion of national population that are of working age from the World Bank, WP. Combining these with future population projections, P, under socio-economic scenario SSP1 with low future population growth, we estimate the number of women who are of working age and without access to running water:

$$N = P \times \mathrm{WA} \times \mathrm{WP}/2 \tag{8}$$

The division by two assumes equal proportion of women and men in each country of working age. In all cases we assume the proportion of population of working age to remain fixed, and in two distinct scenarios we assume either that the proportion of households without access to water remains at current levels ('no-progress' scenario) or that it declines at the same rates observed over the past 20 years ('progress' scenario). This allows us to assess the benefits of avoided climate impacts by continued efforts to increase water access.

Finally, we combine these estimates with the annual minimum wage of each country in 2017 purchasing power parity US dollars from the International Labour Organization, MW (https://ilostat.ilo.org/topics/wages/#), with the country-average change in the minutes spent collecting water due to future warming (M, Fig. 4), as a fraction of the number of minutes in an 8 h working day, to estimate annual costs, C:

$$C = N \times \mathrm{MW} \times \frac{M}{480} \tag{9}$$

Data availability

All historical data on women's living conditions and exposure to climate conditions are publicly available from the LivWell dataset (https://zenodo.org/records/5821533). Bias-adjusted projections of future daily climate conditions are publicly available at 0.5 × 0.5° resolution from the Inter-Sectoral Impact Model Inter-Comparison Project (https://www.isimip.org/). Data for reproduction of this study are available via Zenodo at https://doi.org/10.5281/zenodo.11126471 (ref. 40). Source data are provided with this paper.

Code availability

All code used in this analysis and necessary for reproduction is available via Zenodo at https://doi.org/10.5281/zenodo.11126471 (ref. 40).

References

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Author contributions

C.B. collected the data. M.K. proposed the study with R.C., M.K., P.-P.P., H.W. and L.W. contributing to its design.

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R.C., M.K. and L.W. designed the empirical models. R.C. conducted the statistical empirical analyses, and M.K. calculated the future climate impacts and their welfare metric equivalent. R.C., M.K., P.-P.P., H.W. and L.W. contributed to the interpretation of the results. R.C. and M.K. produced the visualizations, and R.C. wrote the manuscript. M.K. and L.W. gave detailed feedback on the manuscript, with P.-P.P. and H.W. providing further feedback.

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Competing interests

The authors declare no competing interests.

Additional information

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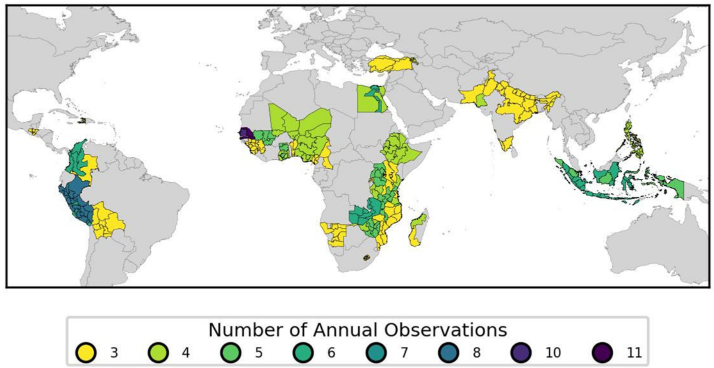

Extended Data Fig. 1 | The total number of observations per region. Map highlighting the total number of observations per region from our sample. Data are obtained from LivWell, a harmonized database of household surveys on women's welfare.

Extended Data Table 1 | The proportion of households with access to water on the premises

Africa	**2000**	**2005**	**2010**	**2015**	**2020**	**Change**
Benin	36.49	35.54	34.47	33.13	31.54	-4.95
Cameroon	9.01	14.45	20.58	27.42	34.96	25.95
Ghana	12.10	17.24	24.86	33.25	42.34	30.24
Kenya	21.51	25.23	29.22	33.45	37.92	16.41
Lesotho	8.85	13.42	18.39	23.54	29.10	20.25
Madagascar	6.93	9.93	13.66	17.90	22.65	15.72
Mali	19.45	22.59	25.81	31.27	38.17	18.73
Mozambique	7.49	9.79	15.07	22.33	31.35	23.86
Niger	9.00	10.78	12.61	14.54	16.76	7.76
Nigeria	12.60	16.36	21.19	26.65	32.72	20.12
Rwanda	3.50	6.20	8.65	11.33	14.38	10.88
Senegal	36.41	43.75	52.36	61.75	71.85	35.43
Sierra Leone	12.45	12.82	13.40	13.94	14.41	1.96
Uganda	2.30	5.03	8.38	12.29	16.75	14.45
Tanzania	1.43	3.03	11.11	22.88	37.56	36.13
Zambia	17.61	20.46	23.69	27.19	31.00	13.40
Zimbabwe	41.34	40.91	37.19	33.66	30.59	-10.75
Asia & Middle East						
Armenia	89.95	92.38	94.98	97.66	99.00	9.05
Bangladesh	63.83	65.78	71.43	76.89	82.10	18.27
Cambodia	41.04	44.04	46.20	47.56	47.89	6.85
Egypt	90.36	92.52	94.65	96.78	97.66	7.29
India	38.68	45.74	53.11	60.76	68.67	29.99
Indonesia	57.65	61.07	64.02	66.52	68.87	11.21
Jordan	98.09	98.15	98.31	98.42	98.46	0.37
Nepal	42.89	49.25	55.75	62.44	69.25	26.35
Pakistan	84.37	84.51	80.16	75.59	70.79	-13.59
Philippines	40.85	48.14	57.54	67.72	78.27	37.41
Turkey	89.40	90.36	91.35	92.24	93.05	3.65
South & Central America						
Bolivia	73.17	76.65	79.95	83.02	85.75	12.58
Colombia	90.61	92.29	93.83	95.24	96.37	5.76
Guatemala	72.62	76.57	80.49	84.44	87.13	14.51
Haiti	18.94	17.45	14.68	11.17	7.83	-11.11
Peru	73.03	76.74	80.10	83.28	86.44	13.41
Sample Average	37.82	40.71	43.98	47.66	51.52	13.70

To illustrate the development of water access over time, we pro- vide national level data for all countries sampled by the current study at 5-year intervals. Values show the percentage of households per country with access to water and the last column indicates the change between 2020 and 2000.

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Extended Data Table 2 | The estimated monetised costs of future changes in water collection time due to climate change

Country	RCP2.6 no-progress	RCP2.6 progress	RCP8.5 no-progress	RCP8.5 progress
Armenia	0	0	0	0
Bangladesh	-7	0	-5	0
Benin	45	50	72	80
Bolivia	66	0	122	0
Cameroon	26	10	79	32
Colombia	14	0	75	0
Egypt	70	0	128	0
Ethiopia	71	51	125	90
Ghana	76	16	122	26
Guatemala	56	0	148	0
Guinea	9	6	85	57
Haiti	72	85	163	192
India	-297	0	1446	0
Indonesia	180	82	785	361
Jordan	7	4	13	8
Kenya	172	104	340	205
Lesotho	14	8	27	15
Madagascar	146	102	227	157
Malawi	102	84	161	133
Mali	83	45	145	79
Mozambique	225	108	394	189
Nepal	42	0	91	0
Niger	74	63	91	78
Nigeria	377	208	413	228
Pakistan	1180	2004	2181	3702
Peru	70	0	140	0
Philippines	4	0	148	0
Rwanda	1	1	2	1
Senegal	35	0	86	0
Sierra Leone	-6	-6	82	80
Turkey	756	161	1409	300
Uganda	3	2	3	2
Tanzania	160	21	307	40
Zambia	105	74	148	105

Estimates show values in millions of US dollars at 2017 purchasing power parity by 2050 under the low- and high-emission scenarios (RCP2.6 and RCP8.5 respectively), as well as across two scenarios which assume that the number of households with access to running water remains at present levels ('no-progress') or continues to change at the rates observed in the past 20 years ('progress'). Estimates reflect a conservative approach which only values impact based on the value of lost working hours for women in developing countries, while neglecting important impacts on human capital for example via lost education. See Methods of the main manuscript for further details.