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Supplemental information

Socio-demographic factors shape mortality risk linked to compound drought-heatwave events under climate change in China

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Supplemental Figures

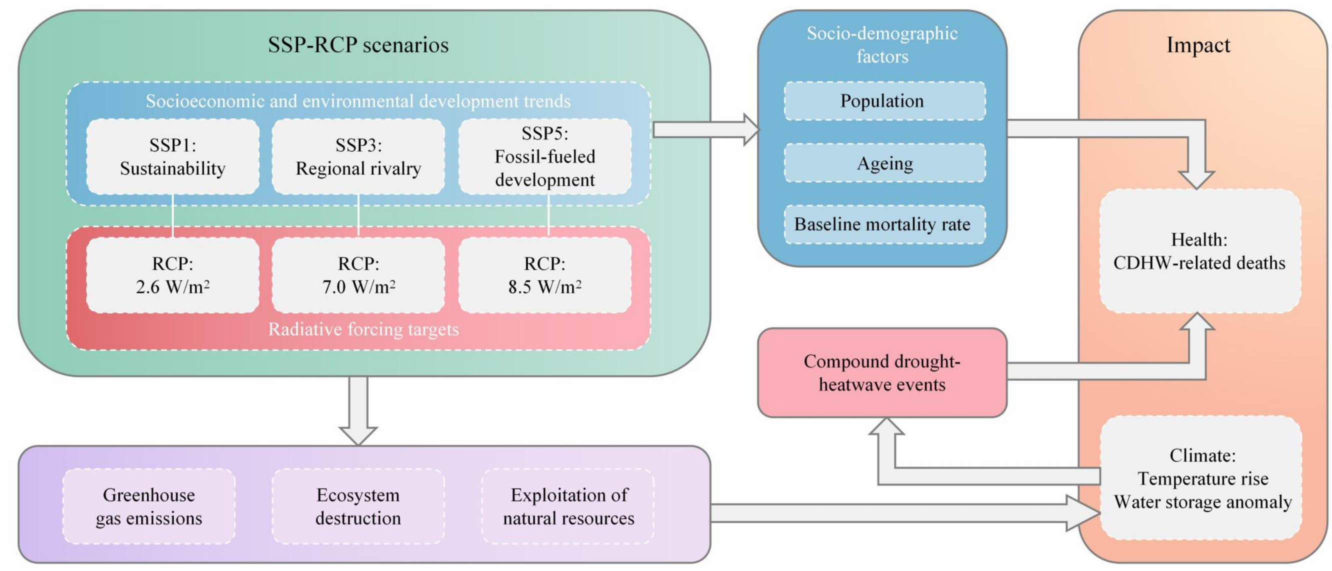

Fig. S1. | **The integrated modeling framework to assess future temperature rise, terrestrial water storage anomaly, and CDHW-related health burden.** We consider three scenarios that vary in socioeconomic trends, greenhouse gas emission control efforts and climate targets, i.e. SSP1-2.6, SSP3-7.0 and SSP5-8.5. For each scenario, we simulate the daily maximum 2 m air temperature (T_{max}) and terrestrial water storage (TWS) at 0.5°×0.5° spatial resolution using ten GCM-GHM coupling models from CMIP6. More detailed descriptions of the scenarios are available in Methods and in Supplementary Note 1.

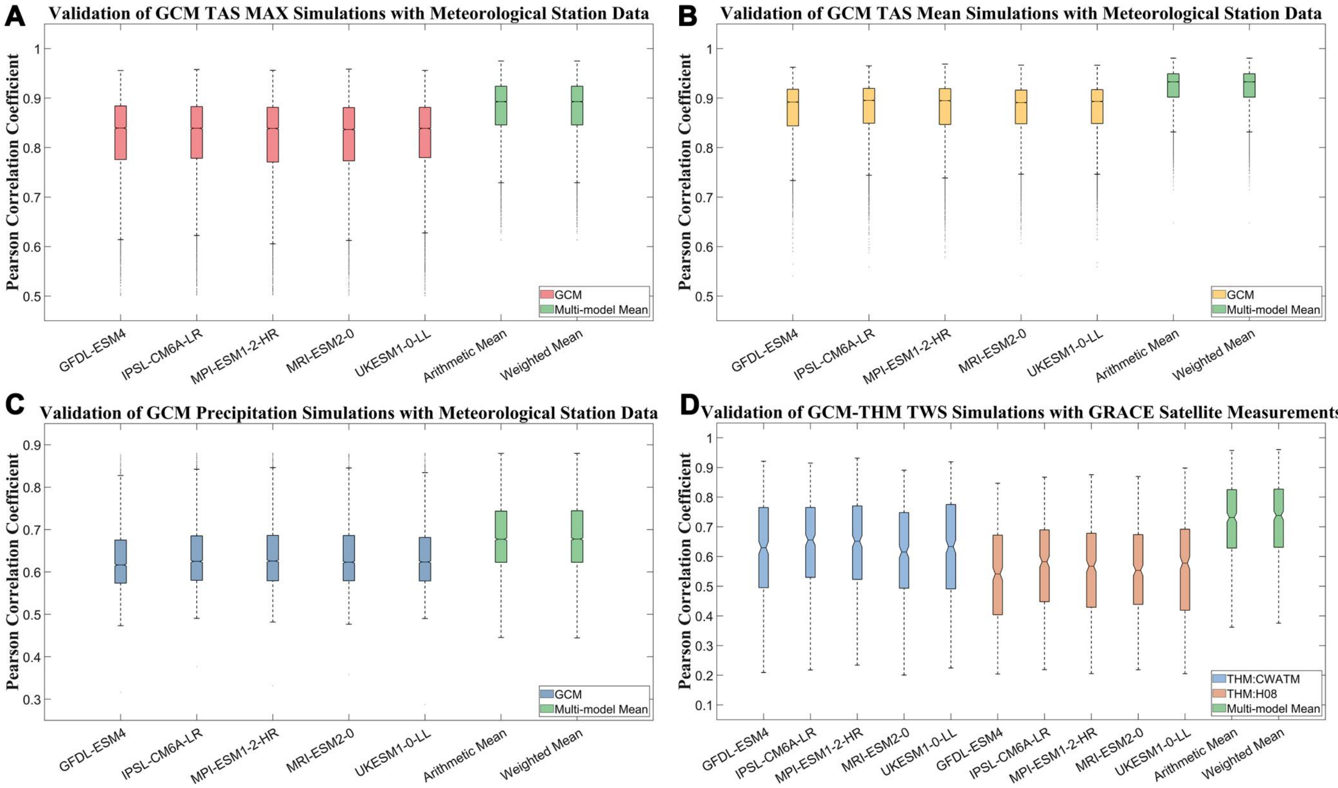

Fig. S2. | **Validation of the GCM-GHM coupling model simulations. A**, validation of GCM T_{max} simulations with meteorological station data. **B**, validation of GCM daily mean temperature simulations with meteorological station data. **C**, validation of GCM daily precipitation simulations with meteorological station data. **D**, validation of GCM-GHM TWS simulations with GRACE satellite measurements. The centre line indicates the median value, the box bounds indicate the 25th/75th percentile values, the whiskers indicate the minimum/maximum values and the points indicate the outliers.

Fig. S3. | **Historical and projected changes in the frequency of CDHWs under different definitions.** Variations in the spatially averaged frequency of CDHWs under different definitions across China for historical (1941 to 1980), recent (1981 to 2014), and future periods (2015 to 2100) based on selected future climate scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5). The asterisks indicate that the change is significant (p<0.05), which is detected by Mann-Kendall trend test. The shading represents the 95% confidence intervals (CIs).

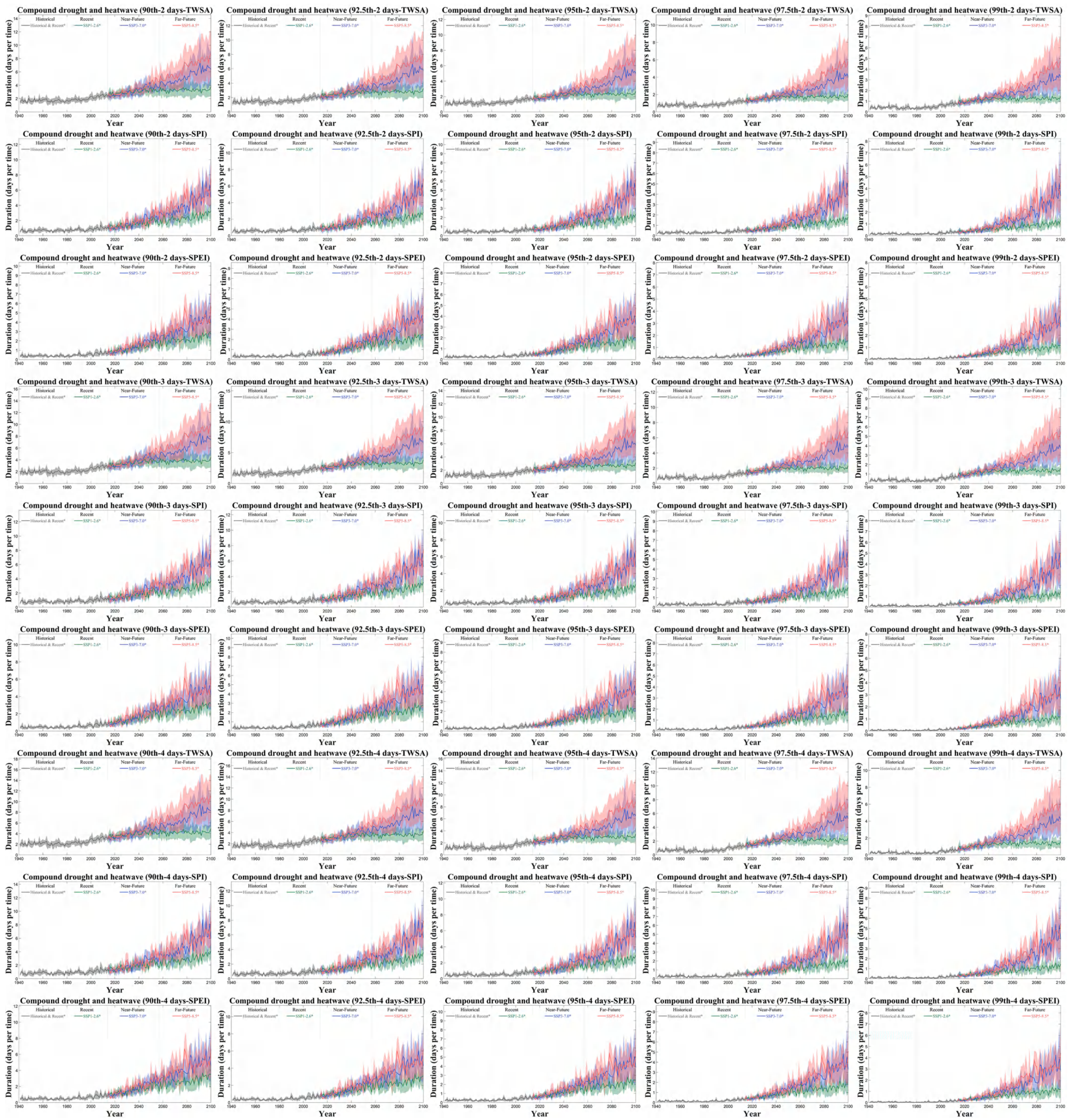

Fig. S4. | **Historical and projected changes in the duration of CDHWs under different definitions.** Variations in the spatially averaged duration of CDHWs under different definitions across China for historical (1941 to 1980), recent (1981 to 2014), and future periods (2015 to 2100) based on selected future climate scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5). The asterisks indicate that the change is significant (p<0.05), which is detected by Mann-Kendall trend test. The shading represents the 95% CIs.

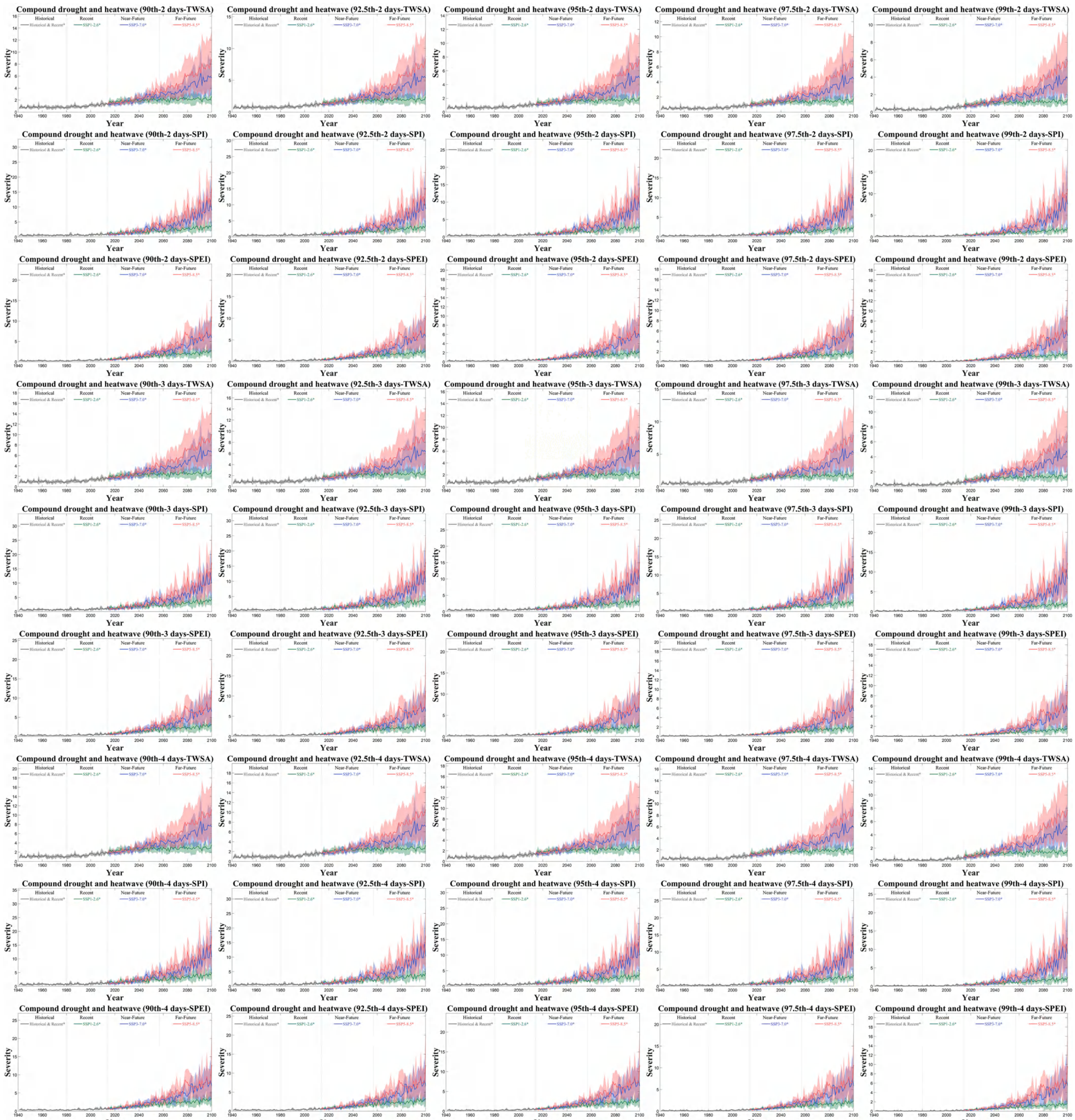

Fig. S5. | **Historical and projected changes in the severity of CDHWs under different definitions.** Variations in the spatially averaged severity of CDHWs under different definitions across China for historical (1941 to 1980), recent (1981 to 2014), and future periods (2015 to 2100) based on selected future climate scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5). The asterisks indicate that the change is significant (p<0.05), which is detected by Mann-Kendall trend test. The shading represents the 95% CIs.

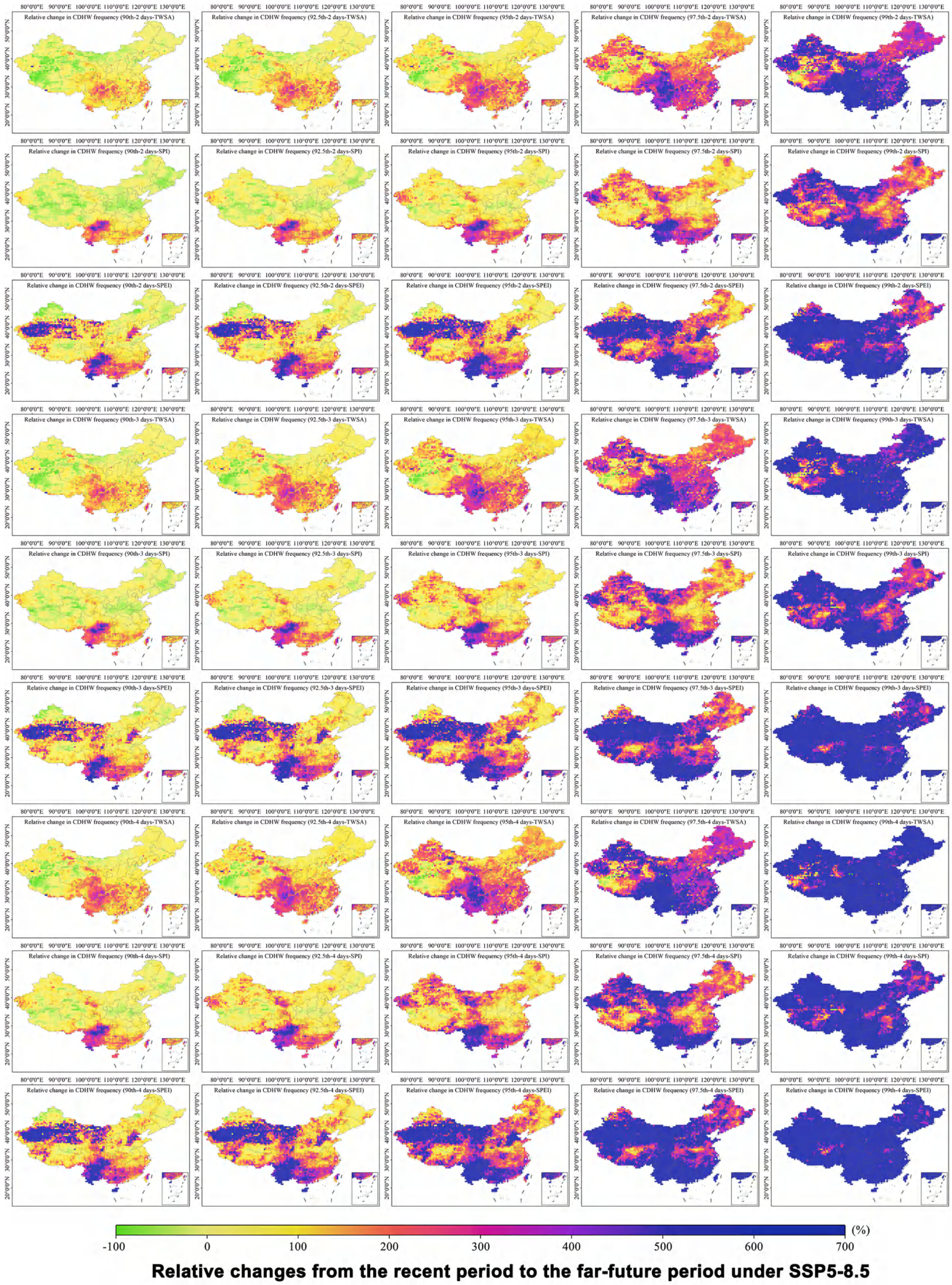

Fig. S6. | **The changes in the frequency of CDHWs under different definitions.** Spatial patterns of relative changes in frequency of CDHWs under different definitions between recent (1981 to 2014) and far-future (2058 to 2100) periods under SSP-5.85 scenarios.

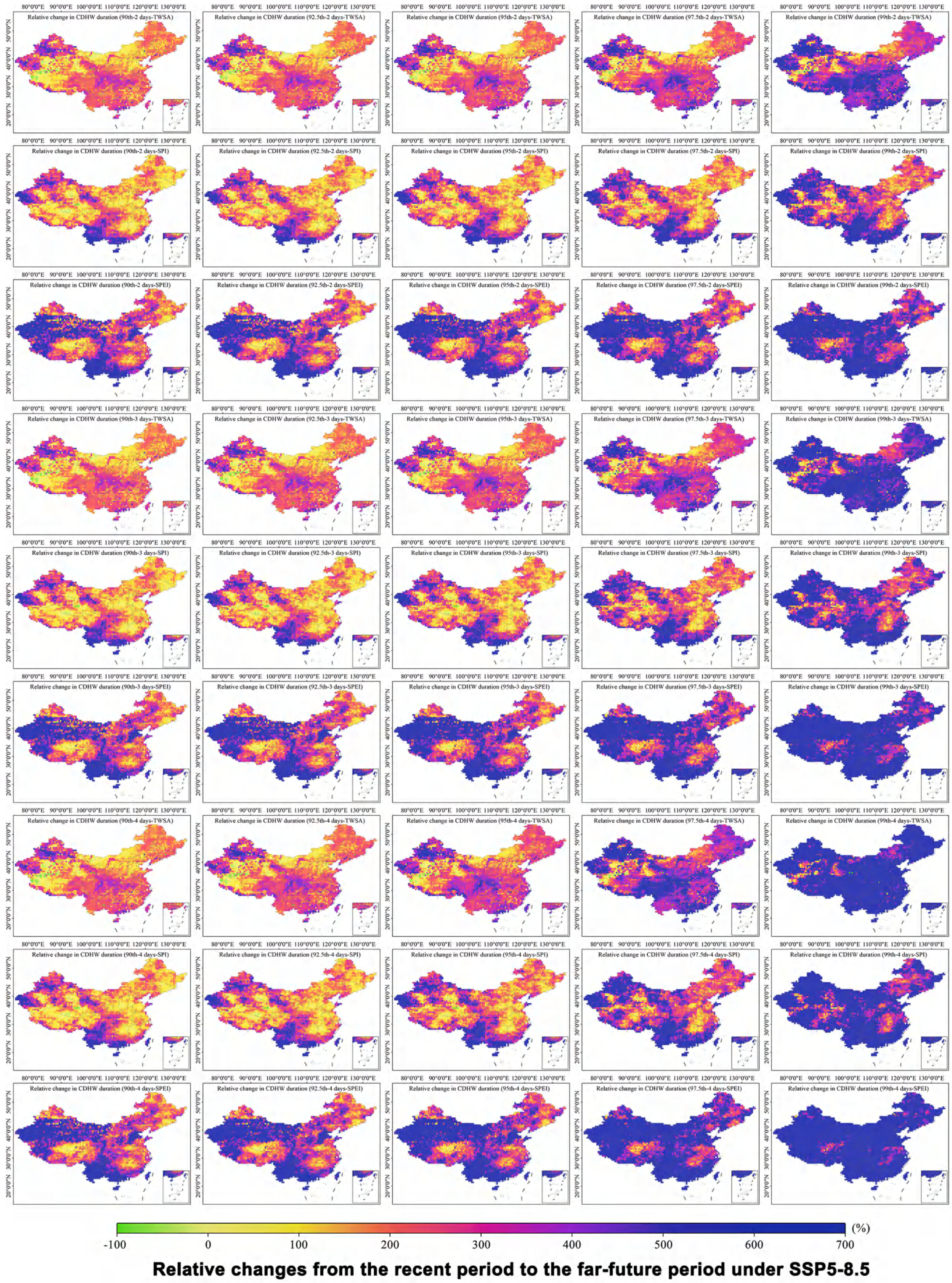

Fig. S7. | **The changes in the duration of CDHWs under different definitions.** Spatial patterns of relative changes in duration of CDHWs under different definitions between recent (1981 to 2014) and far-future (2058 to 2100) periods under SSP-5.85 scenarios.

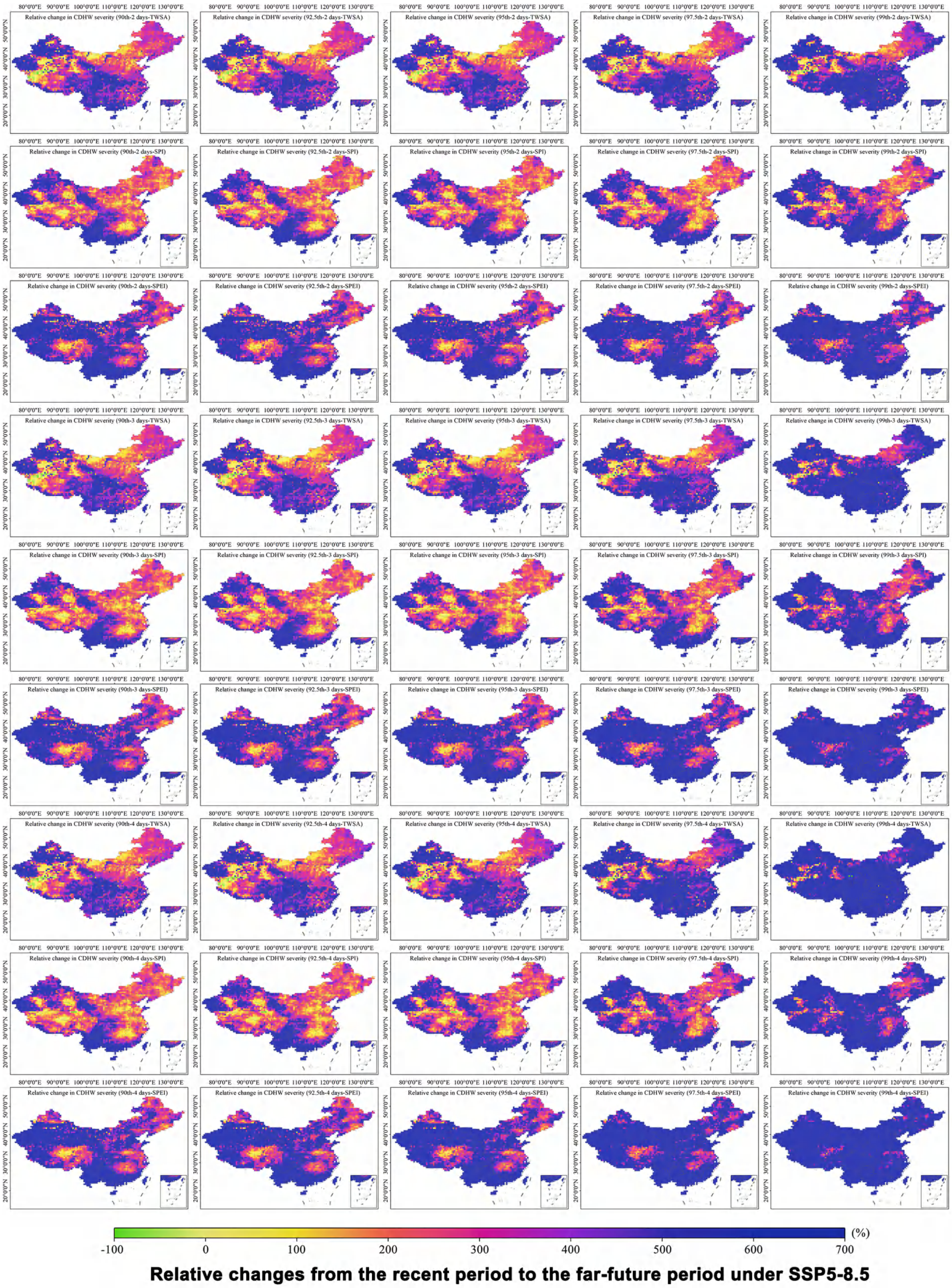

Fig. S8. | **The changes in the severity of CDHWs under different definitions.** Spatial patterns of relative changes in severity of CDHWs under different definitions between recent (1981 to 2014) and far-future (2058 to 2100) periods under SSP-5.85 scenarios.

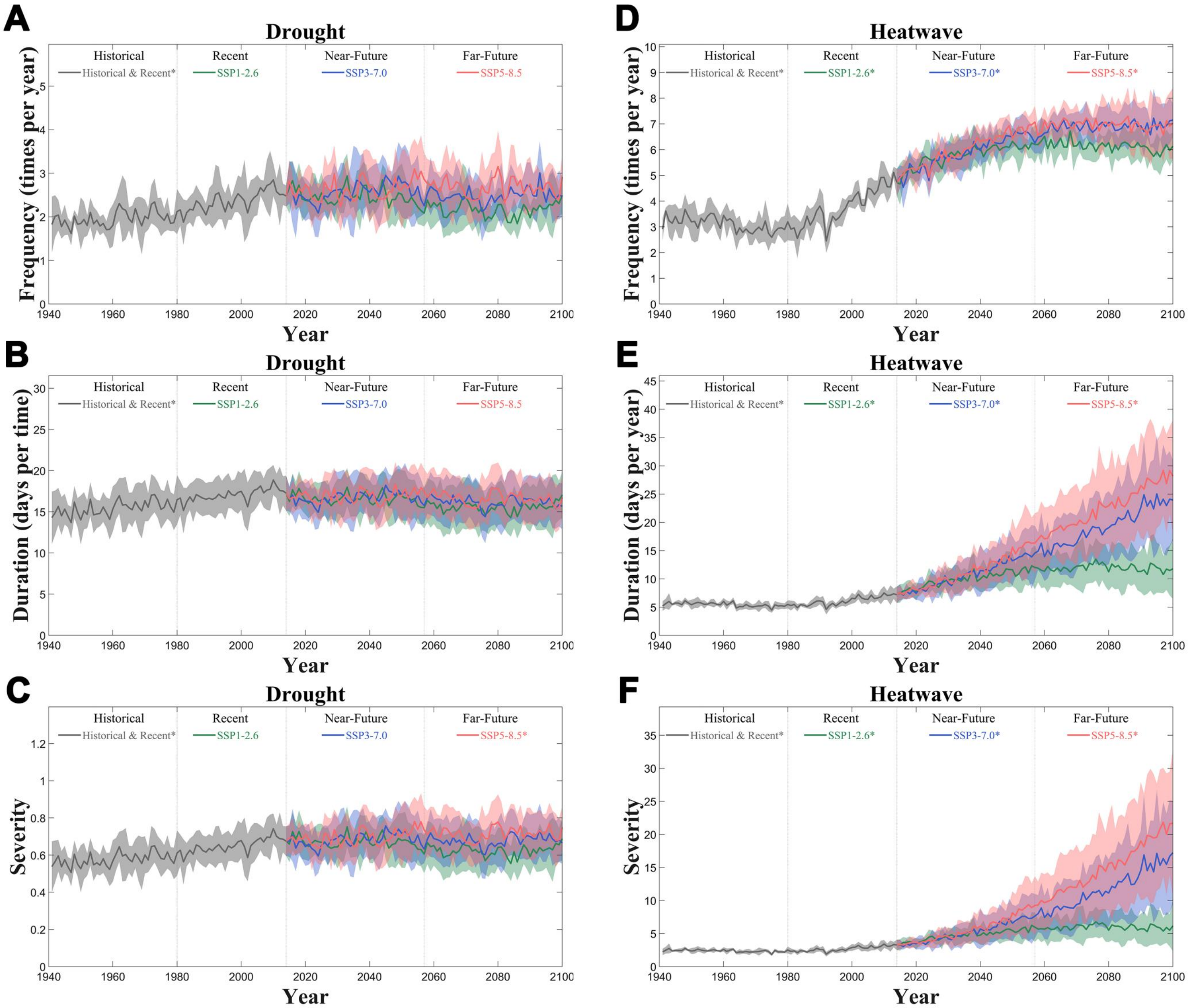

Fig. S9. | **Historical and projected changes in drought and heatwave characteristics.** **A**-**C**, Variation in GCM-GHM-based MME mean projections of drought characteristics—(**A**) frequency, (**B**) duration, and (**C**) severity—spatially averaged over China for historical (1941 to 1980), recent (1981 to 2014) and future periods (2015 to 2100) based on the selected future climate scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5). **D**-**F**, Variation in GCM-based MME mean projections of heatwave characteristics. The asterisks indicate that the change is significant (p<0.05), which is detected by Mann-Kendall trend test. The shading represents the 95% CIs. The droughts in **A**-**C** are all identified based TWS-DSI, and the heatwaves in **D**-**E** are all identified based on the 92.5th percentile temperature threshold and 3-day duration threshold.

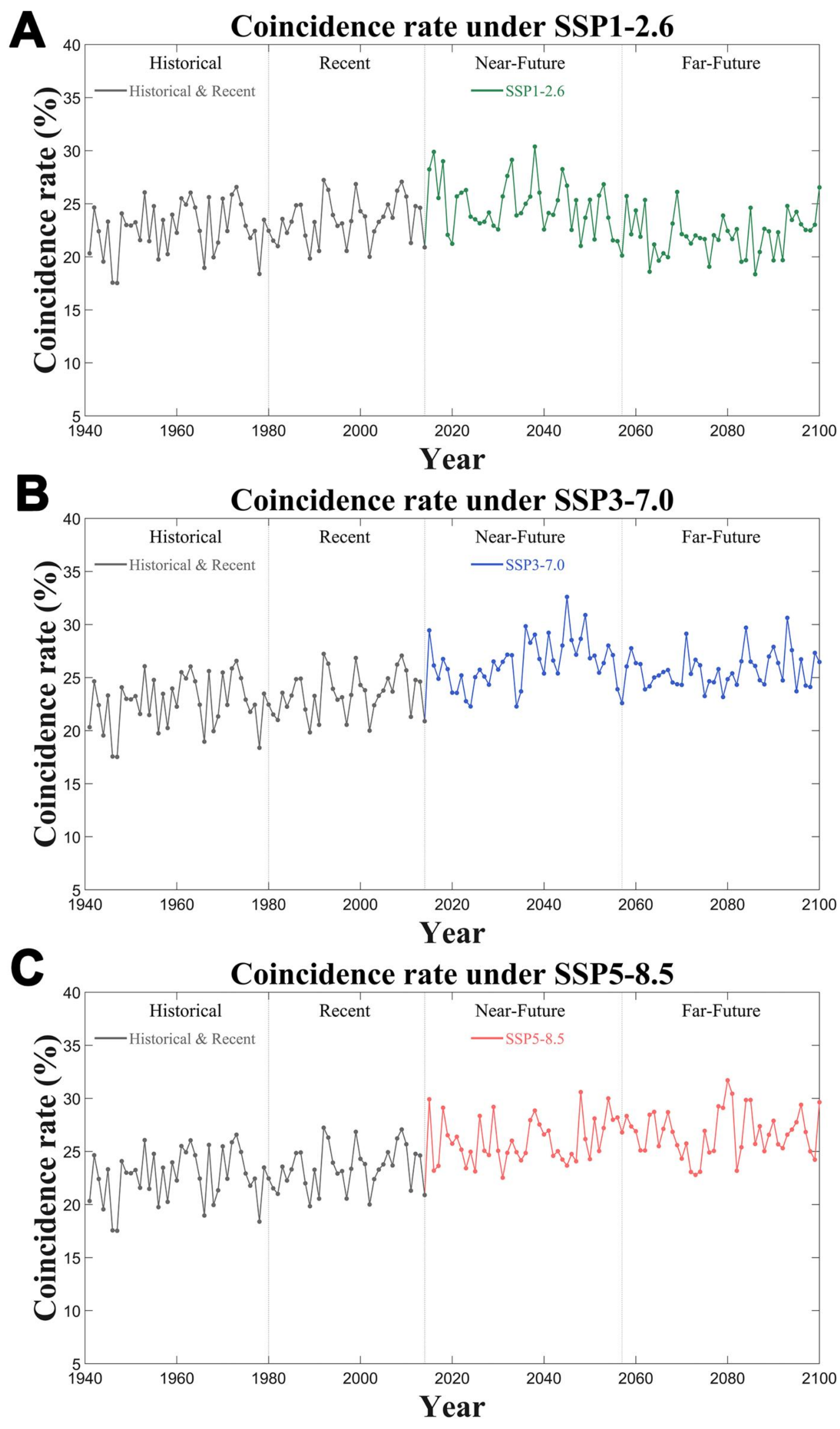

Fig. S10. | **Historical and projected changes in coincidence rate under different scenarios.** Variation in GCM-GHM-based MME mean projections of coincidence rate—spatially averaged over China for historical (1941 to 1980), recent (1981 to 2014) and future period (2015 to 2100) based on the selected future climate scenarios ((**A**) SSP1-2.6, (**B**) SSP3-7.0, and (**C**) SSP5-8.5). The asterisks indicate that the change is significant ($p<0.05$) as detected by the Mann-Kendall trend tests. The CDHWs in **A**-**C** are all identified based on the 92.5th percentile temperature threshold, 3-day duration threshold, and TWS-DSI as the drought index.

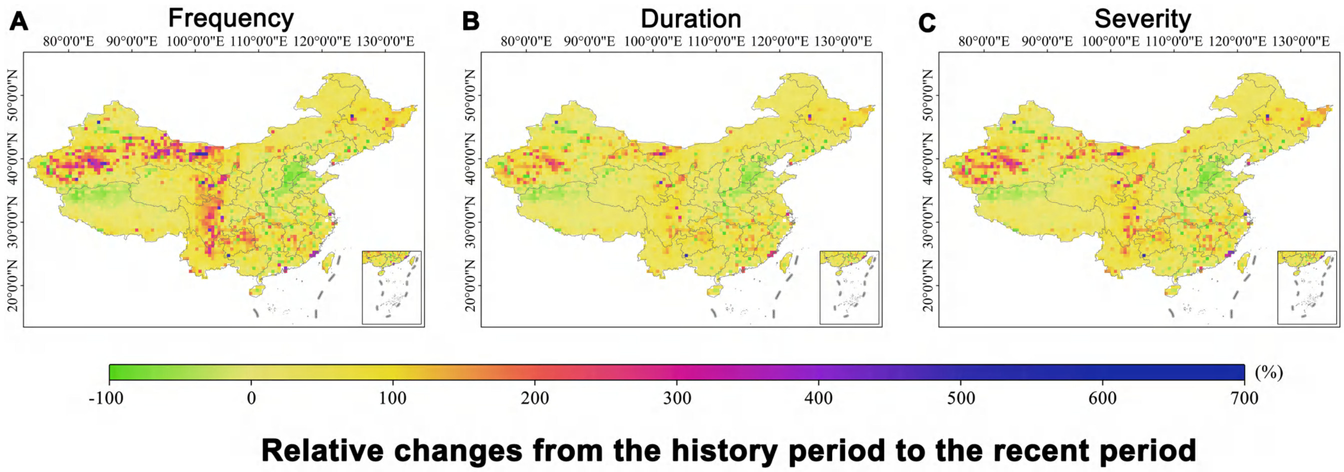

Fig. S11. | **The changes in the characteristics of CDHWs under model simulations.** Spatial patterns of relative changes in (**A**) frequency, (**B**) duration and (**C**) severity of CDHWs between two periods (i.e. historical: 1941 to 1980, and recent: 1981 to 2014). The CDHWs in **A**-**C** are all identified based on the 92.5th percentile temperature threshold, 3-day duration threshold, and TWS-DSI as the drought index.

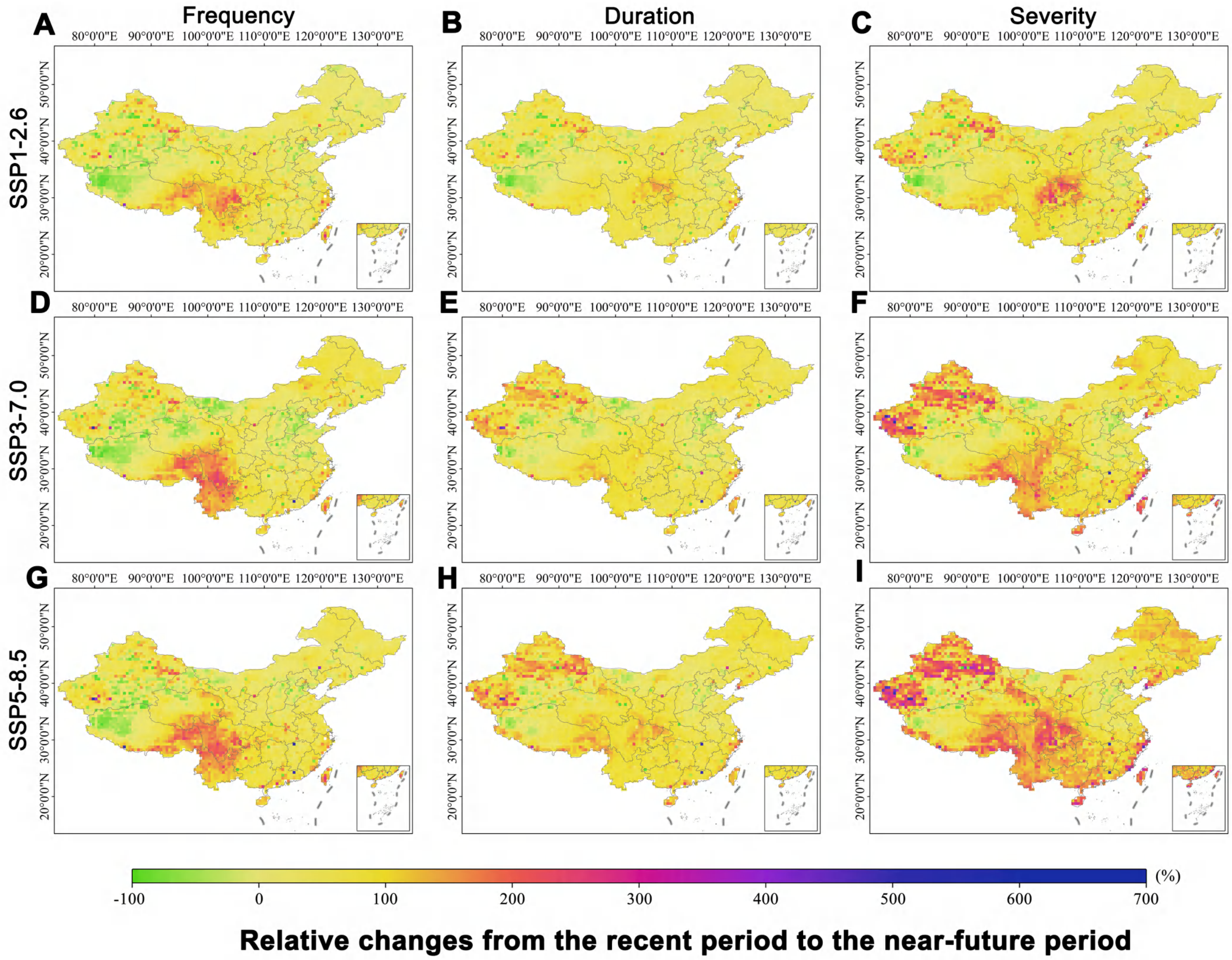

Fig. S12. | **The changes in CDHW characteristics under model simulations.** Spatial patterns of relative changes in CDHW frequency, duration and severity between recent (1981 to 2014) and near-future (2015 to 2057) periods under different SSP-RCP scenarios. The CDHWs in **A**-**I** are all identified based on the 92.5th percentile temperature threshold, 3-day duration threshold, and TWS-DSI as the drought index.

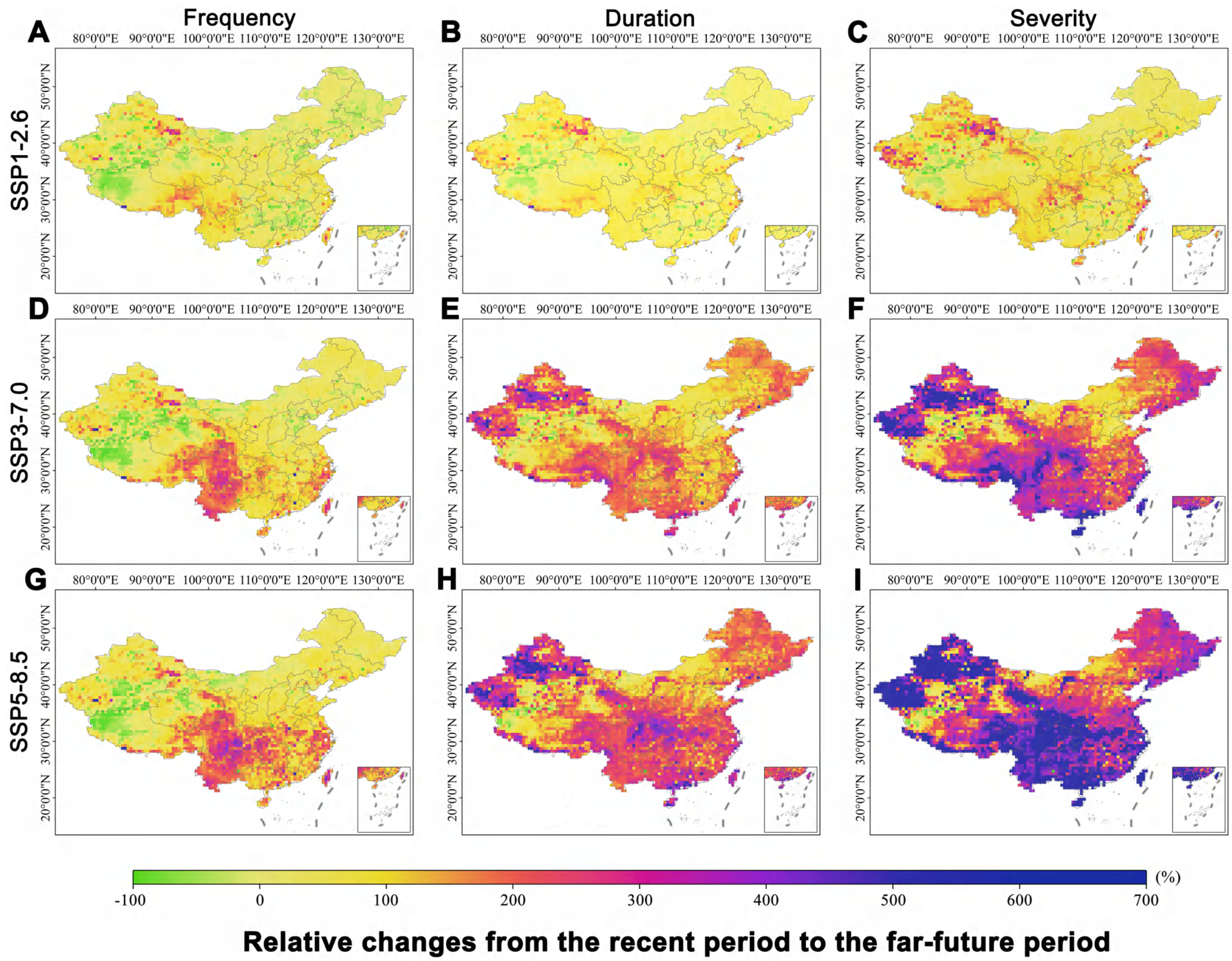

Fig. S13. | **The changes in CDHW characteristics under model simulations.** Spatial patterns of relative changes in CDHW frequency, duration and severity between recent and far-future (2058 to 2100) periods under different SSP-RCP scenarios. The CDHWs in **A**-**I** are all identified based on the 92.5th percentile temperature threshold, 3-day duration threshold, and TWS-DSI as the drought index.

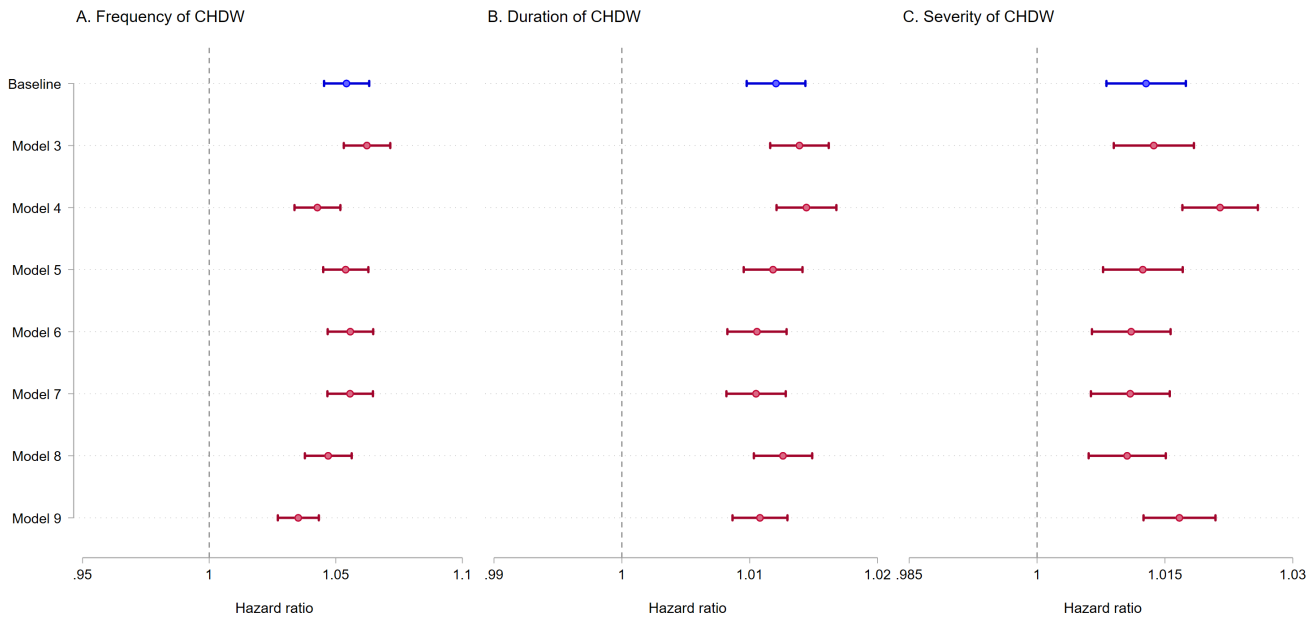

Fig. S14. | **Robustness tests for the baseline regression.** The robustness tests for the baseline of **A**, frequency, **B**, duration and **C**, severity of CDHWs. The first row describes the baseline estimates. The second row excludes older adult samples from Guangxi province which has the highest number of deaths. The third row excludes older adult samples from the year with the highest number of deaths in 2006. The fourth row adds urban-rural residences as an additional control variable. The fifth row adds counties of the older adults as an additional control variable. The sixth row adds urban-rural residences and counties of the older adults as additional control variables. The seventh row adds diseases of the older adults as additional control variables. The eighth row only controls for age and sex. Points and lines represent HR estimates and their corresponding 95% CIs, respectively (please see Supplementary Table 9 for more details).

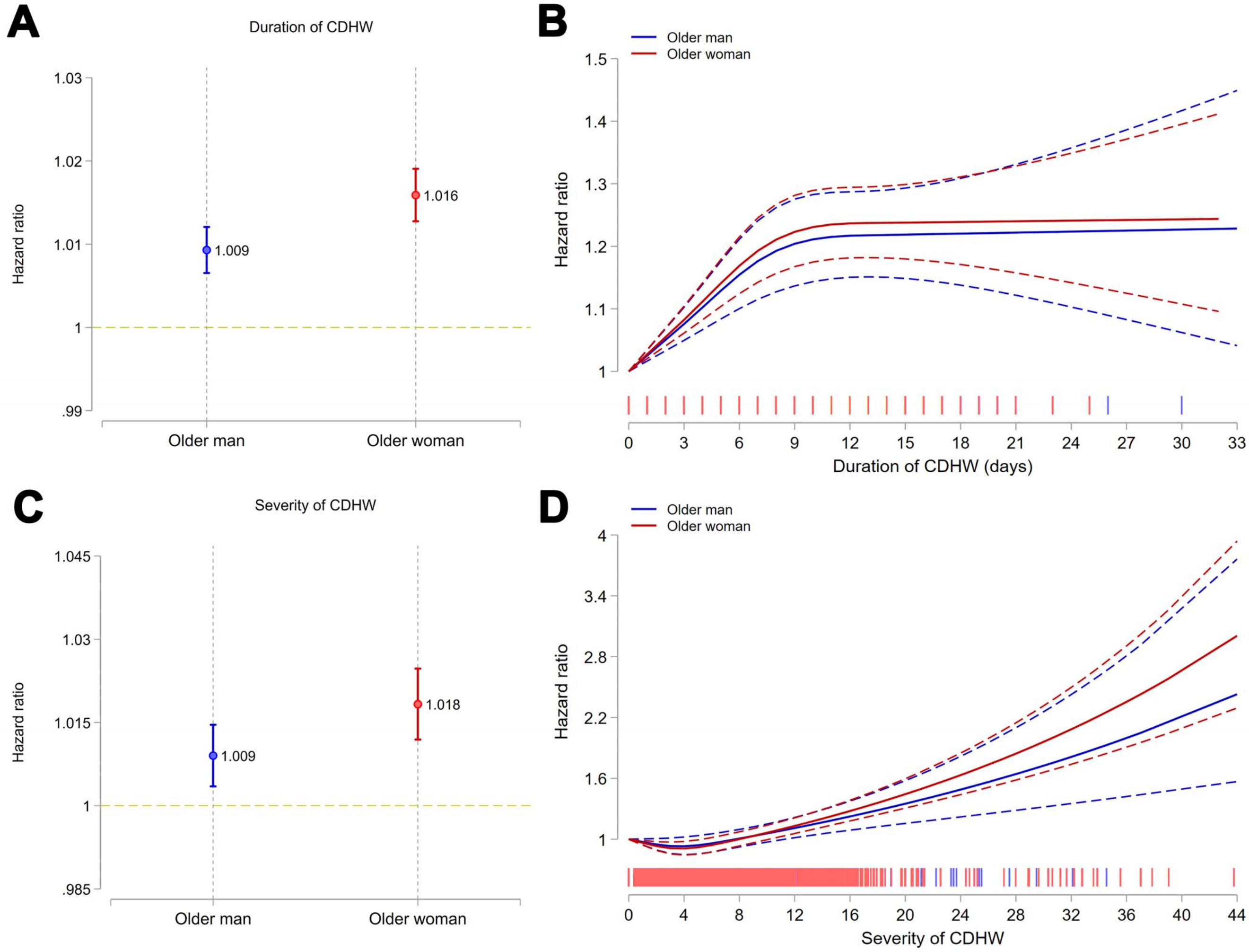

Fig. S15. | **HRs of deaths associated with 1-unit increase in duration and severity of CDHWs by sex subgroup.** **A**, HRs and 95% CIs for the association between all-cause mortality and duration of CDHW exposures by sex sub group for the baseline model. Points and lines represent HR estimates and their 95% CIs, respectively. **B**, HRs and 95% CIs for the association between all-cause mortality and severity of CDHW exposures by sex sub group for the baseline model. Points and lines represent HR estimates and their 95% CIs, respectively. **C**, Curve associations between all-cause mortality and 1-day increase in duration of CDHW by sex sub-group for Model 2. The reference duration is 0. **D**, Curve associations between all-cause mortality and 1-unit increase in severity of CDHW by sex sub-group for Model 2. The reference severity is 0.

Supplemental Tables

Table S1. | Summary of the model simulations under ISIMIP3b.

GHM	SSP-RCP scenario	Historical	SSP1-2.6	SSP3-7.0	SSP5-8.5
	Simulation period / GCM	1941-2014	2015-2100	2015-2100	2015-2100
CWatM	GFDL-ESM4	✓	✓	✓	✓
	IPSL-CM6A-LR	✓	✓	✓	✓
	MPI-ESM1-2-HR	✓	✓	✓	✓
	MRI-ESM2-0	✓	✓	✓	✓
	UKESM1-0-LL	✓	✓	✓	✓
H08	GFDL-ESM4	✓	✓	✓	✓
	IPSL-CM6A-LR	✓	✓	✓	✓
	MPI-ESM1-2-HR	✓	✓	✓	✓
	MRI-ESM2-0	✓	✓	✓	✓
	UKESM1-0-LL	✓	✓	✓	✓

Table S2. | **Information of the used global hydrological models.**

Model name	Evapotranspiration module	Snow module	Groundwater module	Runoff module (surface/subsurface runoff)	River routing module	Reservoir operation	Human water use	Reference
CWatM	Penman-Monteith formulation	Degree-day method	Explicit (single reservoir)	Saturation excess, baseflow	Kinematic water formulation	Yes	Irrigation, domestic, industry, livestock	Burek et al. (2020)(1)
H08	Bulk formulation	Energy balance method	Explicit (renewable and non-renewable reservoirs)	Saturation excess, baseflow	Linear reservoir model	Yes	Irrigation	Hanasaki et al. (2018)(2)

Table S3. | **Statistics of the survey data (Individuals=35,085; Records=86,305).**

Variable	Observation	Mean	Std. Dev.	Min	Max	Missing Observation
Death	86,305	0.247	0.431	0	1	0
Age (years)	86,305	88.105	11.253	65	120	0
BMI	82,599	23.259	5.353	11.718	38.205	3,706
Education (years)	85,858	1.941	3.352	0	25	447
Household income (yuan)	85,567	18575.35	27566.67	0	96752	738
Sex	86,305					0
Woman	36,600 (57.59%)					
Man	49,705 (42.41%)					
Marital status	85,924					381
Currently married, living with spouse	24,125 (28.08%)					
Separated	1,409 (1.64%)					
Divorced	324 (0.38%)					
Widowed	59,193 (68.89%)					
Never married	873 (1.02%)					
Smoking status	85,826					479
Never	57,293 (66.75%)					
Currently	1,307 (1.52%)					
Past	13,328 (15.53%)					
Always	13,898 (16.19%)					
Drinking status	85,694					611
Never	58,803 (68.62%)					
Currently	2,430 (2.84%)					
Past	12,779 (14.91%)					
Always	11,682 (13.63%)					
Physical activity	85,522					783
Never	50,744 (59.33%)					
Currently	7,913 (9.25%)					
Past	11,174 (13.07%)					
Always	15,691 (18.35%)					
Residence	86,305					0
Urban	48,958 (56.73%)					
Rural	37,347 (43.27%)					
Hypertension	82,370	0.208	0.406	0	1	3,935
Diabetes	81,867	0.301	0.172	0	1	4,438
Heart disease	82,126	0.099	0.299	0	1	4,179
Stroke and cerebrovascular disease	82,283	0.067	0.251	0	1	4,022
Bronchitis/emphysema/pneumonia and asthma	82,554	0.124	0.331	0	1	3,751
Tuberculosis	82,253	0.008	0.088	0	1	4,052
Cataracts	82,185	0.127	0.333	0	1	4,120
Glaucoma	79,084	0.025	0.155	0	1	7,221
Cancer	81,399	0.006	0.078	0	1	4,906
Gastrointestinal ulcers	79,032	0.049	0.217	0	1	7,273
Parkinson’s disease	80,184	0.006	0.078	0	1	6,121
Pressure ulcers	79,364	0.008	0.091	0	1	6,941
Arthritis	82,736	0.174	0.379	0	1	3,569
Dementia	82,880	0.034	0.182	0	1	3,425

Table S4. | Testing for co-linearity among variables under different CDHW definitions.

CDHW definition			VIF															
Temperature threshold	Duration threshold	Drought index	Frequency	Duration	Severity	Age	Sex	Smoking status	Drinking status	Exercising status	Household income	BMI	Marital status	Education status	Relative humidity	Ozone concentrations	PM1 concentrations	PM2.5 concentrations	PM10 concentrations
90%	2	SPI	1.56	18.81	17.23	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.12	1.14	11.85	40.84	38.18
90%	3	SPI	1.74	19.61	17.48	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.13	1.14	11.85	40.8	38.21
90%	4	SPI	1.85	19.94	17.65	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.12	1.14	11.85	40.76	38.15
90%	2	SPEI	1.39	15.33	14.81	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.12	1.14	11.83	40.57	38.1
90%	3	SPEI	1.53	14.89	13.87	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.12	1.14	11.83	40.51	38.07
90%	4	SPEI	1.65	15.33	14.02	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.12	1.14	11.82	40.49	38.04
90%	2	TWSA	1.26	5.82	5.59	1.42	1.65	1.45	1.26	1.11	1.05	1.07	1.47	1.34	2.13	1.17	11.86	41.25	38.77
90%	3	TWSA	1.32	6.16	5.77	1.42	1.65	1.45	1.26	1.11	1.04	1.07	1.47	1.34	2.14	1.16	11.85	41.09	38.72
90%	4	TWSA	1.42	6.39	5.85	1.42	1.65	1.45	1.26	1.11	1.04	1.07	1.47	1.34	2.14	1.16	11.84	41.11	38.73
92.50%	2	SPI	1.64	20	18.06	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.13	1.14	11.85	40.83	38.14
92.50%	3	SPI	1.78	20.7	18.34	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.87	40.9	38.17
92.50%	4	SPI	1.76	18.55	16.59	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.87	40.9	38.15
92.50%	2	SPEI	1.48	13.61	12.81	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.12	1.14	11.86	40.5	38.02
92.50%	3	SPEI	1.58	14.3	13.16	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.85	40.55	38.04
92.50%	4	SPEI	1.57	12.38	11.58	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.84	40.5	38.07
92.50%	2	TWSA	1.34	6.64	6.14	1.42	1.65	1.45	1.26	1.11	1.04	1.07	1.47	1.34	2.13	1.16	11.84	41.15	38.74
92.50%	3	TWSA	1.41	6.89	6.29	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.13	1.16	11.84	41.2	38.75
92.50%	4	TWSA	1.48	6.7	6	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.13	1.15	11.84	41.11	38.7
95%	2	SPI	1.62	23.25	21.05	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.93	41.07	38.15
95%	3	SPI	1.8	22.82	20.18	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.96	41.12	38.13
95%	4	SPI	2.09	23.52	20.14	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.91	40.91	38.08
95%	2	SPEI	1.56	13.76	12.7	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.91	40.6	38
95%	3	SPEI	1.72	14.18	12.7	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.89	40.67	37.99
95%	4	SPEI	1.98	14.35	12.43	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.14	11.86	40.5	37.98
95%	2	TWSA	1.39	7.01	6.42	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.13	1.15	11.86	41.17	38.69
95%	3	TWSA	1.49	7.51	6.7	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.13	1.15	11.86	41.3	38.7
95%	4	TWSA	1.6	7.73	6.71	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.14	1.14	11.86	41.13	38.66
97.50%	2	SPI	1.77	25.95	23.42	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.13	1.14	11.89	40.88	38.13
97.50%	3	SPI	2.08	25.89	23.07	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.13	1.14	11.9	40.98	38.06
97.50%	4	SPI	2.45	25.35	22.33	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.13	1.15	11.89	40.81	37.99
97.50%	2	SPEI	1.79	15.65	14.74	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.13	1.14	11.91	40.4	37.9
97.50%	3	SPEI	2.05	15.36	14.67	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.13	1.14	11.9	40.48	37.94
97.50%	4	SPEI	2.45	15.83	14.58	1.42	1.65	1.45	1.26	1.1	1.04	1.06	1.47	1.33	2.12	1.15	11.89	40.41	37.91
97.50%	2	TWSA	1.42	7.32	6.71	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.34	2.13	1.15	11.86	41.15	38.59
97.50%	3	TWSA	1.61	7.71	6.81	1.42	1.65	1.45	1.26	1.1	1.05	1.07	1.47	1.33	2.13	1.15	11.85	41.14	38.5
97.50%	4	TWSA	1.85	8.14	6.95	1.42	1.65	1.45	1.26	1.1	1.05	1.07	1.47	1.33	2.13	1.15	11.84	41.03	38.36
99%	2	SPI	1.84	34.94	32.25	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.15	11.91	40.71	37.96
99%	3	SPI	2.25	31.42	29.25	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.15	11.99	40.85	37.94
99%	4	SPI	3.49	32.55	29.38	1.42	1.65	1.45	1.26	1.1	1.04	1.07	1.47	1.33	2.12	1.15	11.96	40.81	37.97
99%	2	SPEI	2.09	19.09	16.9	1.42	1.65	1.45	1.26	1.1	1.04	1.06	1.47	1.33	2.12	1.15	11.88	40.4	37.93
99%	3	SPEI	2.39	18.18	16.36	1.42	1.65	1.45	1.26	1.1	1.04	1.06	1.47	1.33	2.11	1.15	11.93	40.45	37.88
99%	4	SPEI	3.75	20.47	16.92	1.42	1.65	1.45	1.26	1.1	1.04	1.06	1.47	1.33	2.11	1.15	11.91	40.48	37.93
99%	2	TWSA	1.67	9.9	8.55	1.42	1.65	1.45	1.26	1.1	1.05	1.07	1.47	1.33	2.13	1.15	11.84	40.82	38.24
99%	3	TWSA	2.12	10.41	8.39	1.42	1.65	1.45	1.26	1.1	1.05	1.07	1.47	1.33	2.13	1.15	11.84	40.79	38.15
99%	4	TWSA	2.99	11.73	8.71	1.42	1.65	1.45	1.26	1.1	1.05	1.07	1.47	1.33	2.13	1.16	11.83	40.8	38.16

Notes: VIF stands for Variance Inflation Factor, and if VIF is less than 10, it indicates that there is no co-linearity among the variables.

Table S5. | The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for baseline regressions under different CDHW definitions.

CDHW definition			AIC	BIC
Temperature threshold	Duration threshold	Drought index		
90%	2	SPI	36871.8	36885.8
90%	3	SPI	36821.6	36835.6
90%	4	SPI	36808.7	36822.6
90%	2	SPEI	36943.3	36957.3
90%	3	SPEI	36893.9	36907.9
90%	4	SPEI	36915.8	36929.7
90%	2	TWSA	36775.2	36789.2
90%	3	TWSA	36711	36725
90%	4	TWSA	36778.2	36792.2
92.50%	2	SPI	36868.7	36882.6
92.50%	3	SPI	36819.8	36833.7
92.50%	4	SPI	36854.3	36868.2
92.50%	2	SPEI	36888.2	36902.2
92.50%	3	SPEI	36891.4	36905.4
92.50%	4	SPEI	36866.7	36880.6
92.50%	2	TWSA	36762.8	36776.7
92.50%	3	TWSA	36708.3	36722.3
92.50%	4	TWSA	36819.8	36833.8
95%	2	SPI	36812.4	36826.3
95%	3	SPI	36815	36829
95%	4	SPI	36763.9	36777.8
95%	2	SPEI	36895	36908.9
95%	3	SPEI	36910.5	36924.5
95%	4	SPEI	36887.4	36901.3
95%	2	TWSA	36781.9	36795.8
95%	3	TWSA	36825.1	36839.1
95%	4	TWSA	36845.9	36859.9
97.50%	2	SPI	36719.4	36733.4
97.50%	3	SPI	36759.7	36773.6
97.50%	4	SPI	36820.7	36834.7
97.50%	2	SPEI	36948.4	36962.3
97.50%	3	SPEI	36926.9	36940.8
97.50%	4	SPEI	36900.6	36914.5
97.50%	2	TWSA	36749.7	36763.7
97.50%	3	TWSA	36968.5	36982.5
97.50%	4	TWSA	36995.2	37009.2
99%	2	SPI	36770.6	36784.6
99%	3	SPI	36898.2	36912.2
99%	4	SPI	36928	36941.9
99%	2	SPEI	37027.8	37041.7
99%	3	SPEI	36966	36979.9
99%	4	SPEI	36993.5	37007.4
99%	2	TWSA	36850.2	36864.2
99%	3	TWSA	36951.7	36965.6
99%	4	TWSA	36950.1	36964

Notes: Each row in the table represents a separate regression using cox proportional hazards model. Among them, the combination with the lowest AIC and BIC is highlighted in red font.

Table S6. | Testing for co-linearity among variables of baseline regression model.

Variables	VIF
Frequency of CDHW	1.4
Duration of CDHW	6.87
Severity of CDHW	6.23
Age	1.42
Sex	1.65
Smoking status	1.45
Drinking status	1.26
Exercising status	1.1
Household income	1.04
BMI	1.05
Marital status	1.47
Education status	1.34
Relative humidity	1.48
Ozone concentrations	1.08
PM2.5 concentrations	1.4

Notes: VIF stands for Variance Inflation Factor, and if VIF is less than 10, it indicates that there is no co-linearity among the variables.

Table S7. | HRs of the baseline Cox proportional hazards model.

Variables	Hazard ratio
Frequency of CDHWs	1.05424***
	[0.00455]
Duration of CDHWs	1.01206***
	[0.00117]
Severity of CDHWs	1.01279***
	[0.00238]
Age	1.04797***
	[0.00089]
1.Sex	1.15485***
	[0.02115]
2.Smoking status	1.05114
	[0.05687]
3.Smoking status	1.05880**
	[0.02434]
4.Smoking status	1.20344***
	[0.02485]
2.Drinking status	1.00567
	[0.03912]
3.Drinking status	1.04840**
	[0.02233]
4.Drinking status	1.19327***
	[0.02414]
2.Physical activity	0.80025***
	[0.01980]
3.Physical activity	1.29252***
	[0.02364]
4.Physical activity	0.98454
	[0.01940]
Household income	0.88843***
	[0.00294]
BMI	1.00874***
	[0.00176]
2.Marital status	1.29201***
	[0.07410]
3.Marital status	1.71694***
	[0.19096]
4.Marital status	1.36043***
	[0.02865]
5.Marital status	1.35770***
	[0.10075]
Education	0.99169***
	[0.00276]
Relative humidity	1.00822***
	[0.00125]
Ozone concentration	0.99847
	[0.00102]
PM2.5 concentration	1.00508***
	[0.00103]
No. of subjects	33,971
No. of failures	19,662
Time at risk	236,247
Observations	83,295

Notes: Each column represents a separate regression using the Cox proportional hazards model. The numbers show the HR of each measure on mortality risk of older adults. Standard errors are shown in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table S8. | Schoenfeld residual test for proportional hazards assumption of baseline Cox proportional hazards model.

Variables	rho	chi2	df	Prob>chi2
Frequency of CDHWs	-0.00626	0.97	1	0.3239
Duration of CDHWs	0.00732	1.33	1	0.2487
Severity of CDHWs	0.00801	1.59	1	0.2069
Age	-0.00571	0.81	1	0.3682
Sex	0.00447	0.5	1	0.4812
Smoking status	-0.00199	0.1	1	0.7538
Drinking status	-0.00190	0.06	1	0.8005
Exercising status	-0.00212	0.11	1	0.7383
Household income	0.00168	0.07	1	0.7912
BMI	-0.00237	0.14	1	0.7088
Marital status	-0.00259	0.17	1	0.6832
Education status	-0.00177	0.08	1	0.7803
Relative humidity	-0.00899	2.01	1	0.1566
Ozone concentrations	-0.00189	0.09	1	0.7658
PM2.5 concentrations	0.01098	2.99	1	0.0836

Table S9. | **Robustness checks of the baseline Cox proportional hazards model.**

Variables	**Hazard ratio**							
Frequency of CDHWs	1.05424***	1.06230***	1.04272***	1.05391***	1.05574***	1.05565***	1.04700***	1.03519***
	[0.00455]	[0.00468]	[0.00463]	[0.00455]	[0.00459]	[0.00458]	[0.00472]	[0.00414]
Duration of CDHWs	1.01206***	1.01389***	1.01444***	1.01183***	1.01057***	1.01049***	1.01260***	1.01080***
	[0.00117]	[0.00117]	[0.00119]	[0.00117]	[0.00118]	[0.00118]	[0.00116]	[0.00110]
Severity of CDHWs	1.01279***	1.01369***	1.02147***	1.01241***	1.01104***	1.01093***	1.01057***	1.01670***
	[0.00238]	[0.00240]	[0.00226]	[0.00238]	[0.00235]	[0.00236]	[0.00231]	[0.00215]
Age	1.04797***	1.04769***	1.04902***	1.04791***	1.04758***	1.04756***	1.04516***	1.05300***
	[0.00089]	[0.00091]	[0.00094]	[0.00089]	[0.00090]	[0.00090]	[0.00095]	[0.00074]
1.Sex	1.15485***	1.14401***	1.17338***	1.15788***	1.15163***	1.15261***	1.15006***	1.15818***
	[0.02115]	[0.02140]	[0.02257]	[0.02119]	[0.02115]	[0.02118]	[0.02233]	[0.01640]
2.Smoking status	1.05114	1.05949	1.00671	1.05022	1.05136	1.05108	0.99250	
	[0.05687]	[0.05825]	[0.05886]	[0.05682]	[0.05700]	[0.05698]	[0.05875]	
3.Smoking status	1.05880**	1.07456***	1.04808*	1.05946**	1.06999***	1.07018***	1.03440	
	[0.02434]	[0.02534]	[0.02536]	[0.02434]	[0.02460]	[0.02460]	[0.02560]	
4.Smoking status	1.20344***	1.21657***	1.20038***	1.20086***	1.19452***	1.19378***	1.17064***	
	[0.02485]	[0.02558]	[0.02619]	[0.02481]	[0.02487]	[0.02487]	[0.02596]	
2.Drinking status	1.00567	1.01339	0.98954	1.00483	1.00129	1.00106	0.95646	
	[0.03912]	[0.04003]	[0.04109]	[0.03910]	[0.03903]	[0.03902]	[0.04050]	
3.Drinking status	1.04840**	1.05243**	1.03188	1.04961**	1.04760**	1.04804**	1.04265*	
	[0.02233]	[0.02278]	[0.02330]	[0.02234]	[0.02253]	[0.02253]	[0.02374]	
4.Drinking status	1.19327***	1.19573***	1.19440***	1.19120***	1.19908***	1.19840***	1.15384***	
	[0.02414]	[0.02470]	[0.02545]	[0.02409]	[0.02458]	[0.02457]	[0.02504]	
2.Physical activity	0.80025***	0.80502***	0.77613***	0.79573***	0.80865***	0.80717***	0.73750***	
	[0.01980]	[0.02031]	[0.02043]	[0.01971]	[0.02011]	[0.02008]	[0.01957]	
3.Physical activity	1.29252***	1.29251***	1.28035***	1.28247***	1.28157***	1.27834***	1.20583***	
	[0.02364]	[0.02405]	[0.02492]	[0.02361]	[0.02375]	[0.02384]	[0.02367]	
4.Physical activity	0.98454	0.99517	0.96313*	0.97641	0.98393	0.98131	0.96579*	
	[0.01940]	[0.02022]	[0.02008]	[0.01939]	[0.01949]	[0.01958]	[0.02038]	
Household income	0.88843***	0.88200***	0.89370***	0.88719***	0.88310***	0.88272***	0.88618***	
	[0.00294]	[0.00318]	[0.00301]	[0.00299]	[0.00302]	[0.00306]	[0.00315]	
BMI	1.00874***	1.00864***	1.01023***	1.00870***	1.00885***	1.00884***	1.00863***	
	[0.00176]	[0.00176]	[0.00179]	[0.00176]	[0.00176]	[0.00176]	[0.00178]	
2.Marital status	1.29201***	1.29147***	1.26711***	1.29372***	1.31066***	1.31109***	1.31143***	
	[0.07410]	[0.07726]	[0.07688]	[0.07423]	[0.07632]	[0.07635]	[0.08284]	
3.Marital status	1.71694***	1.74783***	1.72556***	1.71316***	1.71474***	1.71356***	1.54970***	
	[0.19096]	[0.19915]	[0.20495]	[0.19025]	[0.19550]	[0.19515]	[0.18918]	
4.Marital status	1.36043***	1.35609***	1.36978***	1.36108***	1.36343***	1.36359***	1.36032***	
	[0.02865]	[0.02920]	[0.03032]	[0.02865]	[0.02897]	[0.02896]	[0.03021]	
5.Marital status	1.35770***	1.35062***	1.34698***	1.35020***	1.36934***	1.36677***	1.35773***	
	[0.10075]	[0.10579]	[0.10676]	[0.10010]	[0.10125]	[0.10104]	[0.10551]	
Education	0.99169***	0.99161***	0.99058***	0.99084***	0.98939***	0.98912***	0.99103***	
	[0.00276]	[0.00283]	[0.00292]	[0.00276]	[0.00277]	[0.00278]	[0.00289]	
Relative humidity	1.00822***	1.00803***	1.00756***	1.00862***	1.02677***	1.02680***	1.01497***	
	[0.00125]	[0.00126]	[0.00133]	[0.00126]	[0.00164]	[0.00164]	[0.00135]	
Ozone concentration	0.99847	0.99828*	0.99650***	0.99837	0.99115***	0.99116***	1.00034	
	[0.00102]	[0.00103]	[0.00106]	[0.00101]	[0.00106]	[0.00106]	[0.00108]	
PM2.5 concentration	1.00508***	1.00605***	1.00281***	1.00525***	1.01184***	1.01185***	1.00380***	
	[0.00103]	[0.00105]	[0.00109]	[0.00104]	[0.00110]	[0.00110]	[0.00110]	
Model	1	3	4	5	6	7	8	9
No. of subjects	33,971	30,134	33,971	33,971	33,971	33,971	31,331	35,128
No. of failures	19,662	16,754	17,734	19,662	19,662	19,662	16,855	21,341
Time at risk	236,247	207,186	234,034	236,247	236,247	236,247	196,210	255,901
Observations	83,295	79,336	81,517	83,295	83,295	83,295	71,302	89,231

Notes: Each column represents a separate regression using the Cox proportional hazards model. The numbers show the HR of each measure on mortality risk of older adults. Standard errors are shown in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table S10. | **The heterogeneous impacts of CDHW characteristics on mortality risk of older adults in the age subgroup.**

Variables	**Hazard ratio**		
Frequency of CDHWs	1.12641	1.05486***	1.05396***
	[0.08207]	[0.00472]	[0.00456]
Frequency of CDHWs*age_group[65-69]	1.00000		
	[0.00000]		
Frequency of CDHWs*age_group[70-74]	0.97626		
	[0.07654]		
Frequency of CDHWs*age_group[75-79]	0.93529		
	[0.07015]		
Frequency of CDHWs*age_group[80-84]	0.92134		
	[0.06854]		
Frequency of CDHWs*age_group[85-89]	0.93540		
	[0.06901]		
Frequency of CDHWs*age_group[90-95]	0.92256		
	[0.06772]		
Frequency of CDHWs*age_group[95-99]	0.93443		
	[0.06848]		
Duration of CDHWs	1.01196***	1.03494	1.01204***
	[0.00112]	[0.02357]	[0.00116]
Duration of CDHWs*age_group[65-69]		1.00000	
		[0.00000]	
Duration of CDHWs*age_group[70-74]		0.98450	
		[0.02398]	
Duration of CDHWs*age_group[75-79]		0.98950	
		[0.02319]	
Duration of CDHWs*age_group[80-84]		0.98587	
		[0.02301]	
Duration of CDHWs*age_group[85-89]		0.97663	
		[0.02252]	
Duration of CDHWs*age_group[90-95]		0.97745	
		[0.02241]	
Duration of CDHWs*age_group[95-99]		0.97461	
		[0.02230]	
Severity of CDHWs	1.01184***	1.01133***	1.04447
	[0.00237]	[0.00212]	[0.03953]
Severity of CDHWs*age_group[65-69]			1.00000
			[0.00000]
Severity of CDHWs*age_group[70-74]			0.98006
			[0.04130]
Severity of CDHWs*age_group[75-79]			1.00120
			[0.03936]
Severity of CDHWs*age_group[80-84]			0.98686
			[0.03866]
Severity of CDHWs*age_group[85-89]			0.97020
			[0.03741]
Severity of CDHWs*age_group[90-95]			0.96941
			[0.03701]
Severity of CDHWs*age_group[95-99]			0.96509
			[0.03674]
Control variables	✓	✓	✓
No. of subjects	33,971	33,971	33,971
No. of failures	19,662	19,662	19,662
Time at risk	236,247	236,247	236,247
Observations	83,295	83,295	83,295

Notes: Each column represents a separate regression using Cox proportional hazards model. The numbers show the HR of each measure on mortality risk of older adults. Standard errors are shown in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table S11. | The heterogeneous impacts of CDHW characteristics on mortality risk of older adults in the sex subgroup.

Variables	Hazard ratio		
Frequency of CDHWs	1.05595***	1.05512***	1.05419***
	[0.00569]	[0.00508]	[0.00455]
Frequency of CDHWs*sex_group	0.99615		
	[0.00778]		
Duration of CDHWs	1.01178***	1.00930***	1.01203***
	[0.00102]	[0.00141]	[0.00114]
Duration of CDHWs*sex_group		1.00654***	
		[0.00188]	
Severity of CDHWs	1.01278***	1.01285***	1.00902***
	[0.00238]	[0.00243]	[0.00283]
Severity of CDHWs*sex_group			1.00919**
			[0.00373]
1.Sex	1.16220***	1.16247***	1.16189***
	[0.02542]	[0.02549]	[0.02511]
Age	1.04798***	1.04783***	1.04777***
	[0.00089]	[0.00089]	[0.00089]
2.Smoking status	1.05114	1.08440	1.08355
	[0.05685]	[0.05870]	[0.05843]
3.Smoking status	1.05896**	1.10554***	1.10690***
	[0.02434]	[0.02461]	[0.02467]
4.Smoking status	1.20352***	1.24583***	1.25057***
	[0.02485]	[0.02507]	[0.02512]
2.Drinking status	1.00569	1.00248	1.01150
	[0.03911]	[0.03904]	[0.03949]
3.Drinking status	1.04812**	1.06051***	1.07257***
	[0.02234]	[0.02242]	[0.02268]
4.Drinking status	1.19331***	1.21697***	1.21925***
	[0.02414]	[0.02446]	[0.02451]
2.Physical activity	0.80022***	0.80918***	0.80327***
	[0.01980]	[0.01993]	[0.01988]
3.Physical activity	1.29248***	1.30419***	1.29232***
	[0.02364]	[0.02382]	[0.02368]
4.Physical activity	0.98459	0.99666	0.98815
	[0.01940]	[0.01960]	[0.01949]
Household income	0.88844***	0.88955***	0.88819***
	[0.00294]	[0.00295]	[0.00295]
BMI	1.00874***	1.00854***	1.00859***
	[0.00176]	[0.00177]	[0.00177]
2.Marital status	1.29217***	1.29578***	1.28817***
	[0.07407]	[0.07415]	[0.07384]
3.Marital status	1.71661***	1.71944***	1.71484***
	[0.19080]	[0.18673]	[0.18804]
4.Marital status	1.36012***	1.32661***	1.32349***
	[0.02864]	[0.02770]	[0.02766]
5.Marital status	1.35803***	1.39321***	1.37659***
	[0.10069]	[0.10285]	[0.10216]
Education	0.99170***	0.99658	0.99696
	[0.00276]	[0.00268]	[0.00266]
Relative humidity	1.00822***	1.00841***	1.00803***
	[0.00125]	[0.00123]	[0.00125]
Ozone concentration	0.99847	0.99676***	0.99852
	[0.00102]	[0.00101]	[0.00102]
PM2.5 concentration	1.00509***	1.00349***	1.00484***
	[0.00103]	[0.00102]	[0.00103]
No. of subjects	33,971	33,971	33,971
No. of failures	19,662	19,662	19,662
Time at risk	236,247	236,247	236,247
Observations	83,295	83,295	83,295

Notes: Each column represents a separate regression using Cox proportional hazards model. The numbers show the HR of each measure on mortality risk of older adults. Standard errors are shown in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table S12. | **The baseline mortality rates in China (deaths per thousand older adults).**

Year	Sex	Age	GBD 2019 Central Value	GBD 2019 Lower bound	GBD 2019 Upper bound	Our estimates based on IF
2017	woman	65 - 69	58.3479	67.5663	49.6646	60.7113
		70 - 74	106.8721	122.2522	91.9779	111.5928
		75 - 79	179.2183	202.4823	156.2598	171.4418
		80 - 84	317.6486	349.5825	284.7623	330.366
		85 - 89	472.4616	512.4582	429.84	502.2881
		90 - 94	647.5205	683.9867	608.2065	644.6004
		95 - 99	795.9281	823.211	765.9193	852.2263
	man	65 - 69	103.4956	121.6697	86.2603	106.0596
		70 - 74	175.9385	203.395	149.1542	167.8389
		75 - 79	279.5364	315.6121	243.0195	263.252
		80 - 84	451.9994	493.2856	407.5921	475.0367
		85 - 89	746.7031	772.6532	715.7196	766.542
		90 - 94	845.423	865.3247	820.1493	852.4227
		95 - 99	880.4467	893.9098	863.0156	918.9933
2018	woman	65 - 69	57.7524	68.296	48.5671	58.9293
		70 - 74	105.6169	123.1005	89.8699	108.8311
		75 - 79	177.5168	203.7137	153.1191	166.9682
		80 - 84	314.5934	350.3723	279.5667	321.1248
		85 - 89	468.6575	513.3569	423.1024	487.7575
		90 - 94	644.0954	685.084	601.8894	625.1923
		95 - 99	793.641	824.7964	760.7382	825.9211
	man	65 - 69	100.4842	119.8498	83.1126	103.1057
		70 - 74	174.3305	204.0454	146.8407	163.7361
		75 - 79	275.0956	314.1055	237.6298	256.4717
		80 - 84	448.7861	493.5928	402.7613	462.1858
		85 - 89	724.1838	754.5988	690.0785	744.8801
		90 - 94	831.5318	854.3596	803.6104	827.1911
		95 - 99	871.2803	886.7218	849.487	891.0227
2019	woman	65 - 69	57.2218	69.2373	47.1469	57.2174
		70 - 74	104.4596	124.3968	87.1877	106.1088
		75 - 79	176.0077	205.7967	149.1856	162.5258
		80 - 84	311.8367	352.1387	273.2601	311.8335
		85 - 89	465.1583	515.1252	414.5054	473.128
		90 - 94	640.8695	686.3889	593.3419	605.7266
		95 - 99	791.4119	825.101	753.9602	799.6004
	man	65 - 69	99.3482	121.2582	80.0551	100.2731
		70 - 74	172.2942	205.6588	141.7371	159.7495
		75 - 79	272.7037	316.5297	230.8328	249.8816
		80 - 84	445.0924	495.3482	393.3546	449.5387
		85 - 89	719.873	754.3504	681.0377	723.6052
		90 - 94	829.2142	854.797	798.1843	802.5168
		95 - 99	868.3118	884.7486	847.0889	863.753

Table S13. | **Summary of socio-demographic projections consistent with SSPs.**

Year	Sex	Age	Population SSP1-2.6	Population SSP3-7.0	Population SSP5-8.5	Baseline mortality rates SSP1-2.6	Baseline mortality rates SSP3-7.0	Baseline mortality rates SSP5-8.5
2050	woman	65-69	46.1133013	43.06942158	46.13794768	22.7978017	32.93084156	22.54188165
		70-74	40.3763234	36.10414001	40.39537365	48.99963949	68.04519248	49.66547162
		75-79	47.70098134	39.39677599	47.69887374	71.55446415	102.0812858	71.80978784
		80-84	40.71244618	29.61665537	40.70849797	131.9367722	190.9464954	131.9162895
		85-89	23.37165229	14.0242306	23.37176125	200.2511111	291.0168548	199.4798814
		90-94	11.40263106	5.181423302	11.40279665	257.6657446	376.0359813	256.0784846
		95-99	4.444153712	1.412687345	4.444043123	334.475535	491.3896024	331.6077639
	man	65-69	46.28930254	41.48871701	46.29537372	45.05650846	64.15079277	44.5646174
		70-74	38.7316722	32.60175137	38.74121703	82.28642736	109.1877196	84.23564642
		75-79	42.78677326	32.41376002	42.77991392	123.7930193	167.722982	125.7332485
		80-84	33.9912629	21.97292482	33.98513621	214.3374005	296.0308234	216.2352028
		85-89	17.25268978	8.894866741	17.25175124	334.5098163	470.2267377	335.1117715
		90-94	7.399314709	2.804994522	7.399092731	359.3611346	513.5923284	357.5870099
		95-99	2.311261601	0.606140286	2.311142388	378.9850752	546.5827689	375.9032369
2100	woman	65-69	18.31410978	28.31890455	18.34120341	7.742812139	17.00638001	7.350729486
		70-74	20.27507935	27.85616321	20.31045671	19.01358912	39.60766901	19.55894203
		75-79	23.15662667	25.46644602	23.20267578	28.52396794	60.11393377	29.21300373
		80-84	25.91857383	21.27475873	25.97365752	54.10869775	116.2657805	54.59069438
		85-89	26.92591626	14.59543869	26.99383163	84.78500571	183.0813626	85.0462021
		90-94	28.62034158	8.611135716	28.66836036	112.1805626	242.2494816	112.0832789
		95-99	22.76233853	3.322324484	22.79397214	145.3305325	316.4354499	144.6073195
	moman	65-69	20.52232908	29.90303274	20.53313996	16.35609072	36.86830448	15.57156012
		70-74	22.8039897	28.42177601	22.81888322	34.65388684	67.40945779	36.13256193
		75-79	26.02354532	24.55498745	26.04391886	51.95192424	104.0495478	53.38261058
		80-84	28.87099494	18.83437085	28.89366536	89.71363392	184.608421	90.79463366
		85-89	29.56840036	11.54482415	29.59554526	140.122011	295.1297167	141.2116441
		90-94	30.24555027	5.850640011	30.24924365	152.2981587	322.4117007	151.9413353
		95-99	22.24445345	1.863520566	22.24227326	160.1987004	342.1414154	158.8586875

Notes: Population data are sourced from the IIASA SSP population datasets (3), measured in millions. And baseline mortality rates are predicted using the International Futures (IFs) model v7.89 (4), measured in deaths per thousand older adults.

Supplemental Notes

Supplemental Note 1: SSP-RCP scenario framework. The SSP-RCP scenario framework is designed to explore plausible futures of human activities, emissions, and the changing climate, making it an important tool in climate change research and climate model predictions. It consists of two main components: SSPs (Shared Socioeconomic Pathways) and RCPs (Representative Concentration Pathways). The SSPs narrate possible alternative trends in socioeconomic and environmental development (5). The SSPs are divided into five scenarios as follows: (1) SSP1: Sustainable Development, emphasizing social equity and environmental sustainability, with a focus on renewable energy use. (2) SSP2: Continued Development, maintaining existing trends. (3) SSP3: Regional Rivalry, emphasizing regional competition and social inequality. (4) SSP4: Inequality but High Adaptability, focusing on climate change adaptation. (5) SSP5: Fossil-fueled Development, emphasizing economic growth and technological innovation. The distinct differences across the SSPs are driven by the basic SSP elements which are population, urbanization, and GDP (3). In addition, each RCP represents the warming targets for the emission pathways of energy systems and land use, as measured as certain radiative forcing levels (in W/m^2) by the end of the century (6). The IPCC AR5 report presents four distinct RCPs (7), including: (1) RCP2.6: A low-emission scenario (8). (2) RCP4.5: A stabilization scenario (9). (3) RCP6.0: A scenario with climate policy interventions (10). (4) RCP8.5: A scenario without mitigation efforts (11). These RCPs outline various pathways for understanding and assessing future climate change scenarios. The integration of SSPs and RCPs is built upon the framework of Shared Climate Policy Assumptions, including the vital details like the evolution of international climate policies and the overarching goals for long-term climate mitigation. The common SSP-RCP combinations include SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. The aim of this unified scenario framework is to encompass the fundamental traits of global climate policies that extend until the end of the century (12).

The SSP-RCP scenario framework has been widely adopted across research communities in scientific assessments such as CMIP6 (13) and the IPCC AR6 report (14). This study selects three SSP-RCP scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5), which are consistent with the emission scenarios in the IPCC AR6 report (14). The end-of-century warming levels for these scenarios range from a lower limit of 2.6 W/m^2 (approximately 2°C) to an upper limit of 8.5 W/m^2 (close to 5°C).

Supplemental Note 2: Validations of the GCM-GHM coupling model simulations. We validate the T_{max}, daily mean air temperature, and daily precipitation simulations from five GCMs and the TWS simulations from ten GCM-GHM coupling models, as well as the results from the MME means, using T_{max}, daily mean air temperature, and daily precipitation data from Chinese temperature stations for the period 1942-2014 and TWS data from Gravity Recovery and Climate Experiment (GRACE)-constrained reconstruction and reanalysis data during 2002-2014. We construct the multi-model ensemble (MME) mean using two ways. The first way takes the simple arithmetic average of the results from the ten GCM-GHM coupling models. The second way uses Pearson correlation coefficients between each GCM-GHM coupling model and the validation data as weights to calculate a weighted average.

We obtain daily T_{max}, daily mean air temperature, and daily precipitation data by processing 3-hourly temperature and precipitation records from the ground stations in the Chinese region, captured from the National Climatic Data Center (NCDC) of the United States. Due to the extended time span of the data and inconsistent data gaps at different stations, it is a challenge to maintain a complete time series spanning from 1942 to 2014. Consequently, we take the data in each station as an individual time series for each year. We then conduct Pearson correlation analyses between the data in this station and the simulated data for the corresponding grid, aiming to validate the accuracy of the simulated data.

For the validation of the GCM-GHM coupling models TWS, we utilize the surface water anomaly data from the GRACE satellite, which provides complete time series data with a resolution of 1°×1° spanning from 2002 to 2014. We perform a bilinear interpolation of the GCM-GHM coupling models TWS to match the 1°×1° resolution and compute the Pearson correlation coefficient between the interpolated data and the corresponding grid cells of the GRACE satellite data for validation purposes.

The average of Pearson correlation coefficients between T_{max} simulated by individual models and the validation data are around 0.8 (Supplementary Fig. S2a), and around 0.9 for daily mean air temperature (Supplementary Fig. S2b), and around 0.6 for daily precipitation (Supplementary Fig. S2c). and around 0.6 for TWS (Supplementary Fig. S2b). The Pearson correlation coefficients between the MME mean and the validation data indicate a significant improvement compared to the simulations by individual models (Supplementary Fig. S2a-d).

Supplemental Note 3: Adjust administrative codes of the counties. To protect the privacy of the older adults in CLHLS, their exact geographic coordinates are obscured, and we can only match each older adult sample with the CDHW characteristics of their counties of residence. However, between 2005 and 2014, 109 county administrative codes were changed for various reasons. To address this, we reassigned new administrative codes to the older adult samples whose codes changed. Specifically, there are four types:

Firstly, there are 16 counties that have been merged with neighboring counties to form new counties due to the county consolidation policy, and their real geographic locations do not change. For example, in July 2010, the Chinese State Council approved the revocation of Xicheng District (110102) and Xuanwu District (110104) in Beijing, and established a new Xicheng District (110102). We replace the older administrative codes with the new ones of the merged counties.

Secondly, there are 85 counties that have formed new counties due to policies such as "abolishing counties and establishing districts", "abolishing cities and establishing districts", "abolishing districts and establishing counties", "abolishing districts and establishing cities", and "adjusting administrative regions". The administrative regions of these counties do not change significantly or at all. For example, in April 2015, the Chinese State Council approved the abolishment of Xushui County (130625) and the establishment of Xushui District (110102). We replace the original administrative codes of these counties with the new ones after the adjustment.

Thirdly, there are 7 counties where administrative codes were recorded incorrectly during the survey, leading to the inability to match CDHW characteristics. We have corrected the erroneous county codes, such as recording Hetang District (430202) as Hetang District (430220).

Fourthly, there is one county that has been split into multiple counties. For example, the Daxing'anling area (232700) was split into Mohe City (232701), Tahe County, and Huma County. We replaced the original county code with the code of the county with the largest area after the split.

Supplemental Note 4: Control variables. In the baseline Cox proportional hazards model, we include 9 survey indicators as control variables to enhance the description of the model and reduce the interference of confounders. These indicators are comprised of sex, age, smoking status, drinking status, physical activity, body-mass index (BMI), household income, marital status, and education. Among them, sex is a binary categorical variable, where 0 represents females and 1 represents males. Age is a continuous variable obtained by subtracting the older adults' birth date from their survey or death date. Smoking status, drinking status, and physical activity are individually divided into four levels from low to high, namely, "1: never smoked, drank and exercised", "2: currently smoke, drink and exercise", "3: smoked, drank and exercised in the past", "4: always smoke, drink and exercise". BMI is calculated using height and weight. Weight is a continuous variable, and samples with weights below 20 kg or above 200 kg are excluded due to possible data errors. Height is a continuous variable similar to weight, and samples with height below 55 cm or above 200 cm are excluded. Household income is household per capita annual income, which is a continuous variable that reflects the economic status of the older adult family. Marital status includes "1-currently married, living with spouse", "2-separated", "3-divorced", "4-widowed" and "5-never married". Education is the years of education of the older adult samples.

In the robustness tests, we also include other control variables containing urban-rural residence, counties of the older adults, and the diseases suffered from CLHLS older adult samples. Among them, the urban-rural attribute is a binary categorical variable, i.e. 0 indicating living in rural areas and 1 indicating living in urban areas. The diseases include hypertension, diabetes, heart disease, stroke and cerebrovascular disease, bronchitis/emphysema/pneumonia and asthma, tuberculosis, cataracts, glaucoma, cancer, gastrointestinal ulcers, Parkinson's disease, pressure ulcers, arthritis, and dementia. All of the above diseases are binary variables, i.e. 0 indicating the absence of the disease, and 1 indicating the presence of the disease.

Supplemental Note 5: Droughts indices. We use three different drought indices in this study: (1) the terrestrial water storage-based drought severity index (TWS-DSI) to identify terrestrial terrestrial water storage deficits (15), (2) the standardized precipitation index (SPI) to identify precipitation deficits (16), and (3) the standardized precipitation-evapotranspiration index (SPEI) to capture the combined effects of precipitation and evaporative demand on regional water availability (17).

TWS-DSI can capture changes in vertically integrated water storage and is used to identify terrestrial drought conditions (15). A negative TWS-DSI means that the TWS is lower than the average level during the study period. It is used to represent the drought magnitude. The TWS-DSI is calculated by using Eq. [1].

$$\mathrm{TWS} - \mathrm{DSI}_{i,j} = (\mathrm{TWS}_{i,j} - \overline{\mathrm{TWS}_j})/\sigma_j \quad [1]$$

where $\mathrm{TWS}_{i,j}$ refers to the TWS anomalies at year i and month j. and denote the mean value and standard deviation of TWS anomalies at month j. For the GCM-GHM TWS outputs, we determine the same time-mean baseline as the GRACE data, and thus obtain monthly TWS anomalies during 1941-2100 by subtracting the mean value of TWS for 2004–2009. In calculating the mean and standard deviation of TWS for any specified period, we use a common reference period (that is, 1941–2014) to ensure robust comparison of drought events across time periods.

To calculate the 6-month SPI, we fit a gamma distribution to the 6-month cumulative precipitation time series over the 1941-2014 calibration period for each spatial grid cell. Subsequently, the cumulative precipitation value for each month is assigned a probability of occurrence based on the gamma distribution specific to that grid cell. These probabilities are then transformed onto the standard normal distribution (with zero mean and unit variance) to derive SPI values (i.e., z-scores). For SPEI, we estimate potential evapotranspiration using the Thornthwaite equation (18), and repeat this process using precipitation minus potential evapotranspiration to compute SPEI. Similar to TWS-DSI, future SPI/SPEI values (2015-2100) are also calculated using the historical (1941-2014) gamma distributions. The calculations of SPI/SPEI were conducted using the Python climate indices module (19), modified by Deeksha Rastogi et al. (20), enabling SPI/SPEI calculations for future periods based on historical calibration.

Supplemental Note 6: Decomposing the drivers of CDHW-attributable deaths. We dissect the contributions of driving factors including: (1) effect of population size, (2) effect of change in age structure (that is, population ageing), (3) effect of changes in CDHW exposures, and (4) effect of mortality rates independent of exposure to CDHWs (that is, the change in the baseline mortality rate due to changes in access to healthcare, treatment and other risk factors), to the change in attributable deaths to CDHWs using the decomposition method (21). Population and age structure data are sourced from the IIASA SSP population datasets (3), baseline mortality rates are predicted using the International Futures (IFs) model v7.89 (4), and CDHW characteristics are derived from the predictions of the GCM-GHM coupling model used in this study.

This approach estimate the contribution of different factors by sequentially introducing each factor into the AN equation. The difference between each consecutive step provided an estimate of the relative contribution of each factor. For example:

$$\mathrm{AN_{t0}} = \sum_{\mathrm{a}=65}^{99} \mathrm{P_{t0}} \times \mathrm{Age_{t0,a}} \times \mathrm{y^{0}_{t0,a}} \times \mathrm{AF_{t0}} \quad [2]$$

$$\mathrm{A_{t}} = \sum_{\mathrm{a}=65}^{99} \mathrm{P_{t}} \times \mathrm{Age_{t0,a}} \times \mathrm{y^{0}_{t0,a}} \times \mathrm{AF_{t0}} \quad [3]$$

$$\mathrm{B_{t}} = \sum_{\mathrm{a}=65}^{99} \mathrm{P_{t}} \times \mathrm{Age_{t,a}} \times \mathrm{y^{0}_{t0,a}} \times \mathrm{AF_{t0}} \quad [4]$$

$$\mathrm{C_{t}} = \sum_{\mathrm{a}=65}^{99} \mathrm{P_{t}} \times \mathrm{Age_{t,a}} \times \mathrm{y^{0}_{t,a}} \times \mathrm{AF_{t0}} \quad [5]$$

$$\mathrm{D_{t}} = \sum_{\mathrm{a}=65}^{99} \mathrm{P_{t}} \times \mathrm{Age_{t,a}} \times \mathrm{y^{0}_{t,a}} \times \mathrm{AF_{t}} \quad [6]$$

where $\mathrm{AN_{t0}}$ is the attributable deaths in the baseline period t0, which are calculated based on the factors in the baseline period. $\mathrm{A_t}$, $\mathrm{B_t}$ and $\mathrm{C_t}$ are the intermediate variables, which consider the changes in population, age structure, and baseline mortality rate incrementally from the baseline period to target period. $\mathrm{D_t}$ is the attributable deaths in the target period, which consider all the changes in four factors. Using Eqs. [2]-[6], we calculate the percent contribution of each factor as follows.

1)Population size effect (%) = $(\mathrm{A_t}\text{-}\mathrm{AN_{t0}})/\mathrm{AN_{t0}}$.
2)Population ageing effect (%) = $(\mathrm{B_t}\text{-}\mathrm{A_t})/\mathrm{AN_{t0}}$.
3)Baseline mortality rate change effect (%) = $(\mathrm{C_t}\text{-}\mathrm{B_t})/\mathrm{AN_{t0}}$.
4)Exposure change effect (%) = $(\mathrm{D_t}\text{-}\mathrm{C_t})/\mathrm{AN_{t0}}$.
5)Total change (%) = $(\mathrm{D_t}\text{-}\mathrm{AN_{t0}})/\mathrm{AN_{t0}}$.

Notably, the order in which each factor is included can influence the results. That is to say, if the sequence of adding factors is not considered, a large bias may occur. Thus, we estimate the results under all sequence permutations (a total of 24 possible sequences) of the four factors. The final estimation of contributions from different factors is the average of the results for all sequences.

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