

Depth-dependent heat amplification across soil and atmosphere driven by soil moisture-temperature hypersensitive regime

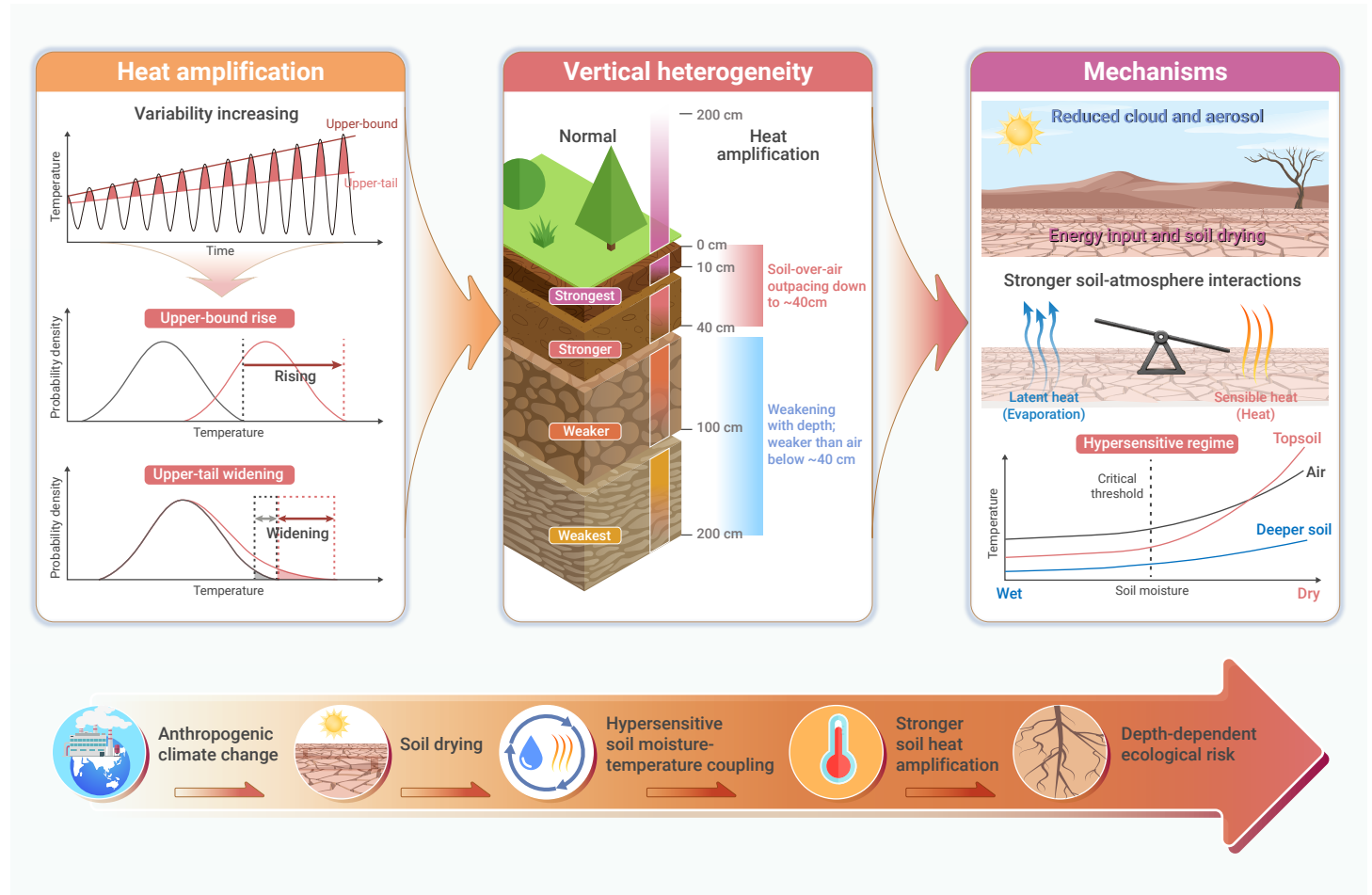
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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Depth-dependent soil heat amplification outpace than near-surface air down to ~40 cm depth.
- Stronger soil heat amplification is driven by hypersensitive soil moisture-temperature coupling regime.
- Both soil heat amplification and its depth dependence are projected to persist in the future.

Depth-dependent heat amplification across soil and atmosphere driven by soil moisture-temperature hypersensitive regime

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Record-breaking heat extremes are increasingly amplified by soil-atmosphere interactions, threatening ecosystems and agriculture. Yet the vertical-heterogeneity of this amplification across air and multiple soil layers and potential mechanisms remain unclear. Here, we integrate multi-source datasets to quantify depth dependence of heat-extreme amplification (i.e., upper-bound rise and upper-tail widening) in soil and atmosphere worldwide over the past four decades. For annual upper-bound rise of air and soil temperatures, we find that soil heat extremes outpace near-surface air across western North America, South America, central Africa, Europe, northeastern Asia, and southern Australia, with this soil-over-air “outpacing” obviously detectable to ~40 cm soil depth. These hotspots also exhibit pronounced, depth-dependent upper-tail widening of soil temperature distributions, which diminishes with depth and becomes weaker than the air counterpart below ~40 cm. Amplification in soil exceeds that in atmosphere because long-term soil drying frequently triggers an unfamiliar hypersensitive soil moisture-temperature coupling regime: once soil moisture drops below a critical threshold, soil temperature responds to drying more rapidly and dramatically than air. Persistent drying also raises soil temperature variability through this hypersensitivity, thereby widening the upper tail of soil temperature distributions. Under the business-as-usual scenario, both soil heat amplification and its depth dependence are projected to persist. These findings imply ecological risk assessment and management must explicitly consider the depth reached by heat amplification, prioritizing the 0–40 cm biotic layer now and systematically extending to deeper soils.

INTRODUCTION

Record-breaking heat extremes have occurred frequently worldwide in recent years, threatening ecosystem stability and food security.^{1–3} Growing evidence shows that many regional heat extremes are amplified by soil-atmosphere interactions.^{4–6} For instance, during the 2021 Pacific Northwest heatwave, such interactions increased event severity by ~40%.⁷ This amplification exerted by soil-atmosphere interactions manifests along two complementary dimensions (Figure 1). First, upper-bound rise: the hottest extremes in annual temperature distribution shift toward warmer values,⁸ making heat records easier to break.⁹ Second, upper-tail widening: larger gap between the hottest and moderate extremes,¹⁰ whereby higher-quantile temperatures increase faster and thresholds for crop desiccation, ecosystem instability, and wildfire ignition are crossed more frequently and abruptly.^{11–13} Observations and simulations alike show that, over recent decades, heat extremes in both the atmosphere and soil have strengthened and been further amplified by soil-atmosphere interactions.^{14–16} However, most studies still treat the soil and atmosphere in isolation, offering neither explicit temperature contrasts between them nor detailed accounts of cross-sphere energy-water exchanges that drive these contrasts. Regional evidence suggests that soil high temperatures have increased faster than near-surface air temperatures,¹⁴ but explanations are typically qualitative. It is unclear why amplification is stronger in soils nor whether this “outpacing” varies with soil

depth. A robust understanding therefore requires a unified assessment from atmosphere to soil to support climate adaptation strategies and strengthen ecosystem resilience.

For the upper-tail widening, whether upper-tail widening of air temperature distributions is widespread under global warming remains contested. Different statistical approaches yield divergent conclusions, with some studies reporting clear tail widening (e.g., in Europe and North America)^{10,17} and other finding extremes that warm in step with the median.¹⁸ The physical mechanisms behind these differences are often underexplained. Extending the lens to the entire soil profile adds further complexity because risks associated with tail widening vary by depth.^{19,20} In topsoil, faster warming at high quantiles can disrupt plant-microbe interactions and increase carbon loss risk.^{21,22} In deeper layers, heat extremes more often reshape root water uptake and the structure and function of deep-rooted plant communities.²³ Whether the soil temperature exhibits robust upper-tail widening, how its strength varies with depth, and to what extent such depth-dependence is controlled by soil-atmosphere interactions remain unassessed at global, long-term, and cross-layer scales. This gap is compounded by sparse and inconsistent soil temperature records across space and depth.²⁴ These limitations constrain soil-layer-aware risk management for agriculture, ecosystem, and wildfire prevention.

To fill these gaps, we synthesize multi-source datasets to provide a global view of heat-extreme amplification in soil and atmosphere from historical observations to future projections, with emphasis on phenomenon, inter-layer differences, mechanisms, and anthropogenic contributions. Specifically, we first compare the rise of annual upper bounds in air and soil temperatures and quantify the depth to which “soil outpaces air”. We then apply two statistical approaches to test for upper-tail widening of soil temperature and its depth dependence. Finally, we clarify how soil-atmosphere interactions drive this amplification and its pronounced vertical heterogeneity.

MATERIALS AND METHODS

Reanalysis and gridded observations

We utilized the land component of the European Centre for Medium-Range Weather Forecasts (ECMWF) fifth-generation reanalysis dataset (ERA5-Land),²⁵ which offers hourly soil temperature (unit: K) and soil moisture (unit: m³·m⁻³) at 0–7 cm, 7–28 cm, 28–100 cm, and 100–289 cm, hourly 2-m air temperature (unit: K), hourly surface net shortwave radiation (unit: J·m⁻²), and hourly surface net longwave radiation (unit: J·m⁻²). Given the variations in the quantity and quality of observations assimilated into ERA5-Land, particularly the incorporation of satellite data since 1979, analyses focus on 1981–2020.

ERA5-Land results were compared with: (a) The China Meteorological Administration global land surface reanalysis dataset (CRA-Land),²⁶ which provides 3-hourly soil temperature (unit: K) at 0–10 cm, 10–40 cm, 40–100 cm, and 100–200 cm and 2-m air temperature (unit: K). (b) The European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Satellite Application Facility on Climate Monitoring (CM-SAF) Land Surface Temperature dataset Meteosat First and Second Generation Edition 1,²⁷ which provides hourly instantaneous land surface temperature (unit: K). We combined this dataset with daily 2-m air temperature from the ENSEMBLES

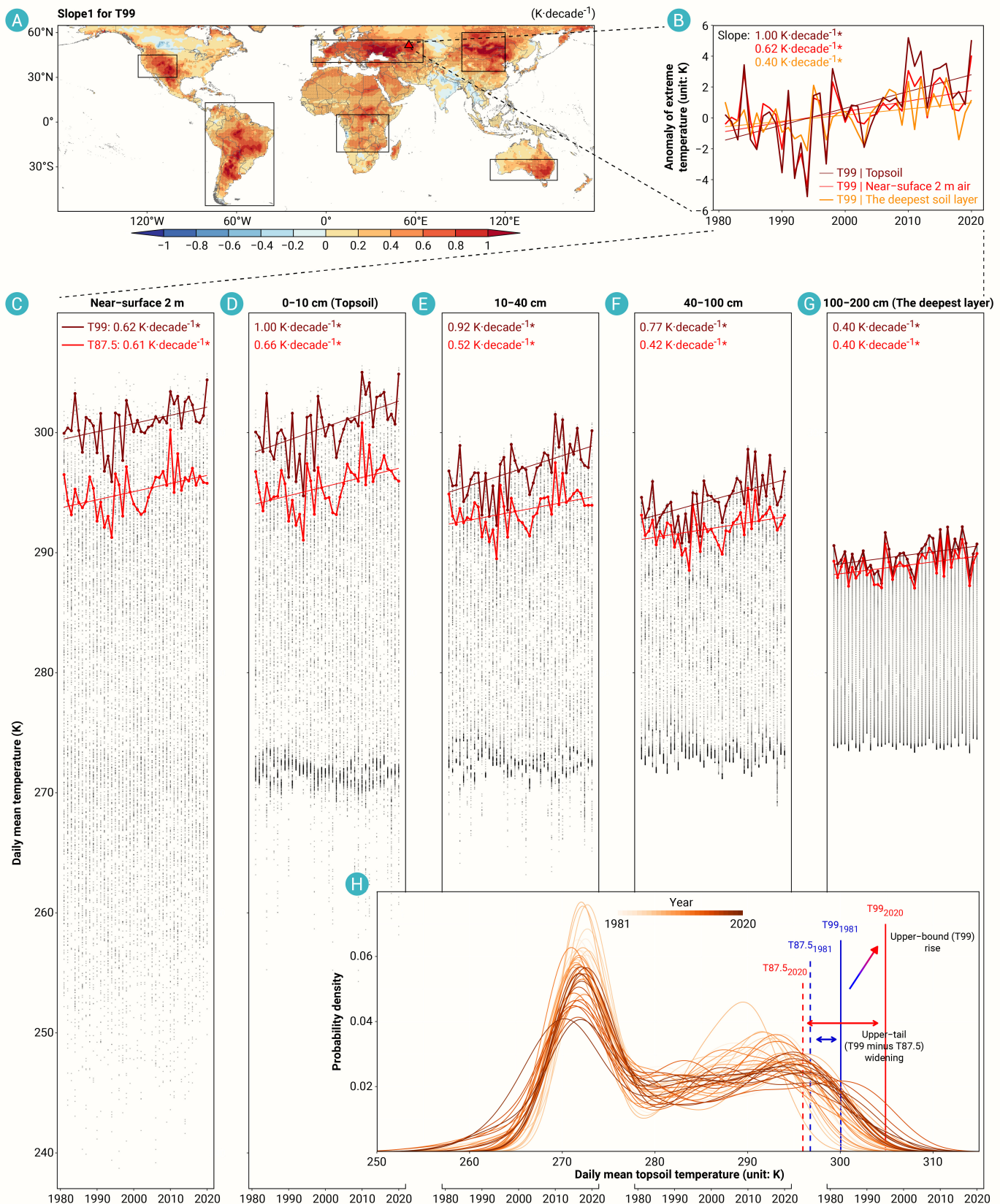


Figure 1. Annual temperature distributions across soil and atmosphere during 1981–2020 based on ERA5-Land (A) Long-term trends in the annual T99 of daily mean temperature in topsoil. Stippling indicates statistically significant trends at the 0.05 significance level (Mann-Kendall test). (B) Anomalies in T99 for topsoil (dark red), near-surface 2-m air (light red), and the deepest soil layer (orange). Solid lines indicate linear trends. (C) Annual T99 (dark red) and T87.5 (light red) for near-surface air, with daily mean temperature shown as black dots. (D–G) Same as (C), but for topsoil, the second (10–40 cm), the third (40–100 cm), and the deepest soil layer. The “*” symbol indicates statistically significant trends at the 0.05 significance level (Mann-Kendall test). (H) Annual probability density functions of daily mean topsoil temperature.

Observations (E-OBS) dataset for Europe²⁸ and from the Berkeley Earth Surface Temperature (BEST) dataset for other land regions.²⁹ (c) The China

daily multilayer soil temperature $0.25^{\circ} \times 0.25^{\circ}$ gridded dataset (TS25) with daily soil temperature (unit: K) at 5 cm, 10 cm, 15 cm, 20 cm, and 40 cm soil

depths,³⁰ paired with 2-m air temperature from CN05.1.³¹

We collected other variables from multi-source datasets: (a) Monthly total cloud cover (unitless) from ERA5;³² (b) Hourly aerosol optical depth (unitless) from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA2);³³ (c) Daily actual evapotranspiration (unit: mm·day⁻¹) and daily potential evapotranspiration (unit: mm·day⁻¹) from the Global Land Evaporation Amsterdam Model (GLEAM);³⁴ (d) Daily precipitation (unit: kg·m⁻²) from the Global Soil Wetness Project Phase 3 (GSWP-3);³⁵ (e) Clay fraction, sand fraction, and silt fraction from the global gridded soil information (SoilGrids) version 2.0;³⁶ (f) Vegetation type from the United States Geological Survey (USGS). For more information including spatial resolution and data sources please see Table S1.

In-situ observations

We collected station-based observations of multi-layer soil temperature and 2-m air temperature from three sources: (a) The Australia hydrological monitoring network (OzNet),³⁷ which provides soil temperature at 2.5 cm and 15 cm depths within the YANCO network at 20-minute intervals, and at 4 cm, 15 cm, 45 cm, and 75 cm depths within the MURRUMBIDGEE, ADELONG, and KYEAMBA networks at 30-minute intervals. (b) The Climate Data Center of the Deutscher Wetterdienst (DWD), which provides soil temperature at 10 cm and 50 cm depths, along with near-surface 2-m air temperature from Germany weather stations. (c) The Fluxnet2015 in North America and Europe,³⁸ which provides near-surface 2-m air temperature, along with multi-layer soil temperature and soil moisture at either 1-hourly or 30-minute intervals. A total of 160 Fluxnet2015 stations were used to identify the soil moisture-temperature coupling regime shift. To ensure depth consistency of soil layers between observational and reanalysis datasets, we selected soil temperature measurements from depths closest to 10 cm (with a tolerance of ±10 cm) and the deepest available measurements to represent temperature in the topsoil and deeper soils, respectively. Only sites with at least 15 valid years from 1981 to the present, with a missing rate in a calendar year of less than 20%, were used in our analysis. Based on these requirements, we selected 15 stations from OzNet, 377 stations from DWD, and 14 stations from Fluxnet2015.

Land surface model outputs

We utilized the Noah Land Surface Model of NASA's Global Land Data Assimilation System (GLDAS-Noah) version 2.0 (1981–2014) and 2.1 (2000–2020),³⁹ providing 3-hourly soil temperature (unit: K) at depths of 0–10 cm, 10–40 cm, 40–100 cm, and 100–200 cm and 3-hourly 2-m air temperature (unit: K) from atmospheric forcing of GLDAS. To ensure consistency, we integrated GLDAS v2.0 and v2.1 by employing the common period of 2000–2014. The cumulative distribution function matching method⁴⁰ was used to correct grid-by-grid biases in soil and air temperature. We also used the Inter-Sectoral Impact Model Intercomparison Project simulation round 3a (ISIMIP3a) outputs of global daily multi-layer soil temperature⁴¹ from two global land surface models [MIROC-INTG-LAND⁴² and ORCHIDEE-MICT⁴³]. Two land surface models are run with two bias-corrected atmospheric forcings (20CRv3-W5E5 and GSWP3-W5E5).^{35,44,45} These atmospheric forcings between 1981 and 2019 were obtained by applying the ISIMIP3 bias adjustment method to ERA5.⁴⁶ All ISIMIP3a simulations considered water consumption sectors (for irrigation, domestic, and industrial purposes), reservoir management, and land-use change under 1901 social and economic scenarios (1901soc) run. For each land surface model, simulations driven by different atmospheric forcings were averaged after calculating trend differences. For more information including atmospheric forcing sources please see Table S2.

Earth system model simulations

We used the CMIP6 simulations covering the historical climate (1851–2014; designated as *historical* in CMIP) and future high-emissions scenario (2015–2100; *ssp585* in the Scenario Model Intercomparison Project, SSP5-8.5) (Table S3).⁴⁷ We combined the simulation from SSP5-8.5 to extend the historical simulations to 2020.⁴⁸ Seven models with daily soil temperature (unit: K) were selected, accompanying variables included daily 2-m air temperature (unit: K), daily surface upward latent heat flux (unit: W·m⁻²), daily

surface upward sensible heat flux (unit: W·m⁻²), monthly total cloud cover percentage (unit: %), daily soil moisture in the upper 10 cm (unit: kg·m⁻²), and monthly ambient aerosol optical thickness at 550 nm (unitless) from these models. To avoid considering variability within each climate model ensemble, one ensemble member per model was used (first member preferred if available). Additionally, unforced pre-industrial control (PiControl) experiments were used to estimate the internal climate variability. We also used the Max Planck Institute for Meteorology Earth System Model version 1.2 (MPI-ESM1-2-LR) 50-member large ensemble.⁴⁹

Identification of amplification in heat extremes

We processed the above data in the following four steps: (a) We excluded Antarctica, northern polar regions (over 65°N), Greenland, and deserts [annual precipitation below 100 mm from GSWP-3⁵⁰]. (b) Sub-daily variables were averaged to daily. In situ days with >10% missing sub-daily values were omitted. (c) Multilayer soil temperature and soil moisture were interpolated to common depths: 0–10 cm, 10–40 cm, 40–100 cm, 100–200 cm,⁵¹ representing the 0–200 cm biologically active profile.^{52,53} (d) All gridded variables were remapped to 1° × 1° resolution (bilinear for temperatures, second-order conservative for fluxes).

The range from the atmosphere to the soil includes the 2-m air and soil layers at depths of 0–10 cm, 10–40 cm, 40–100 cm, and 100–200 cm. Heat-extreme amplification is quantified along two dimensions. The annual upper bound is measured by the 99th percentile of daily mean temperature (T99), which approximates the median of the hottest 2% of days in a calendar year. The upper-tail width is measured by the difference between T99 and the 87.5th percentile (T87.5), where T87.5 represents the median of the upper quartile (75th–100th percentile range) and characterizes the summer-season background of hot days. The significance of differences between two yearly trend series (e.g., T99 difference between air and soil; or T99 minus T87.5) series was assessed using a non-parametric bootstrap method. Specifically, the difference series was resampled 1,000 times with replacement while preserving the temporal order, and a trend was estimated for each iteration. The trend difference was deemed significant if the 5th–95th percentile range of the 1,000 trend estimates was above or below zero. Moreover, this percentile-based methodology eliminates dependence on fixed calendar-based season definitions, enabling consistent cross-regional comparisons while accounting for hemispheric and latitudinal variations in seasonal timing. To test the robustness of upper-tail widening, we additionally applied a rank-based approach. For the 40-year record, ranks range from 1 to 40, with the year exhibiting the largest difference between T99 and T87.5 assigned the highest rank. Accordingly, an upward trend in ranks over time indicates upper-tail widening, vice versa.

Detection of soil moisture-temperature coupling

To quantitatively describe soil-atmosphere interactions, we calculated the soil moisture-temperature coupling intensity (π metric) based on ERA5-Land and GLEAM, defined as:⁵⁴

$$\pi = \left[(R_n - \lambda E') - (R_n - \lambda E_p) \right] \times T \quad (1)$$

where apostrophe denotes standardized anomalies, R_n is surface net radiation, T is near-surface 2-m temperature, E and E_p denote actual and potential evapotranspiration, respectively, and λ is the latent heat of vaporization. Surface net radiation was calculated as the difference between surface net shortwave radiation and surface net longwave radiation. For CMIP6 model simulations, we derived the π metric using the Priestley-Taylor evaporation model and the principle of energy conservation:

$$E = \frac{LE}{\lambda} \quad (2)$$

$$E_p = \frac{a}{\lambda} \frac{\Delta R_n}{\Delta + \gamma} \quad (3)$$

$$R_n = LE + HE \quad (4)$$

where LE and HE denote surface upward latent and sensible heat flux,

respectively, α is the correction factor, Δ is the slope of the vapor pressure, and γ is the psychrometric constant. When the great potential of soil moisture to affect temperature concurs with an anomalously high temperature, the soil moisture associated energy balance is believed to be at play as expressed by a large π value that thereby indicates stronger soil moisture-temperature coupling conditions.

We assessed the shift in the soil moisture-temperature coupling regime. For each station or grid cell, we identified the three warmest calendar months of the recorded period based on 2-m air temperature. Within these three months, a breakpoint is found by piecewise linear regression where topsoil moisture is the independent variable, and topsoil temperature (or near-surface 2-m air temperature) is the dependent variable. We defined the detection of a hypersensitive regime based on the following criteria:⁵⁵ (a) The slopes on both sides of the breakpoint are negative, indicating that temperature increases as soil dries. (b) Relative to the estimated breakpoint, the slope to the left of the breakpoint is steeper than that to the right, suggesting heightened sensitivity of temperature to declining soil moisture, i.e., a hypersensitive regime. (c) The difference in slopes across the breakpoint is statistically significant ($P < 0.05$) using a two-sample Z-test that accounts for autocorrelation. (d) all samples are restricted to days with positive surface net radiation anomalies to reduce cloud-related confounding and better isolate the effects of soil moisture on temperature; and (e) each side contains at least 10 samples.

Calculation of soil temperature variability

To estimate topsoil temperature variability reliably with abundant samples, it was calculated for each 11-year moving window period. For example, the topsoil temperature variability in year 1981 was identified using the period 1976–1986, the year 1982 using to the period 1977–1987, and so forth. As in previous studies,⁵⁶ for each 11-year period, we first removed the linear trend and seasonal cycle from the daily topsoil temperature time series, then estimated summer topsoil temperature variability based on the temporal standard deviation. The summer was defined as June–August in the Northern Hemisphere and December–February in the Southern Hemisphere.

Ridge regression

Ridge regression was used to estimate multiple linear regression model coefficients, particularly in cases where explanatory variables exhibit high multicollinearity. In the ridge regression model, the inter-layer T99 difference (or T99-minus-T87.5) was detrended and normalized as the dependent variable, and yearly summer topsoil moisture, total cloud cover, and aerosol optical depth were detrended and normalized as the independent variables. Multicollinearity was controlled with variance inflation factor < 3 .⁵⁷ The relative contribution (η_j) of each independent variable to the dependent variable is estimated as follows:

$$\eta_j = \frac{|\beta_j|}{|\beta_1| + |\beta_2| + |\beta_3|} \quad (5)$$

where β_j is coefficient of independent variable j .

Climate change detection and attribution

To attribute the soil heat amplification and its depth dependence, we employed two complementary approaches. First, correlation-based method.⁵⁸ yearly time series of inter-layer T99 differences (topsoil vs. deepest soil layer) and topsoil T99-minus-T87.5 were calculated (hereafter the difference series). From 3,000 years of CMIP6 pre-industrial control simulations, 297 overlapping 40-year segments were extracted with a ≥ 10 -year separation between start years, and 2,000 samples were randomly drawn to build a large ensemble of the difference series. Spearman correlations between these control segments and the CMIP6 historical multi-model mean provided the range of internal climate variability. If correlations between ERA5-Land and CMIP6 historical difference series fall outside the 5–95% internal variability range, the ERA5-based results cannot be explained by natural variability alone. Indeed, during 1981–2020, correlations between ERA5-Land and CMIP6 historical simulations significantly exceed those between historical and control simulations, indicating an anthropogenic contribution to the increasing inter-layer differences in T99 and topsoil T99-minus-T87.5.

Second, regularized optimal fingerprinting method:⁵⁹ we detected the anthropogenic fingerprint by regressing the difference series from the ERA5-Land (Y) against that from CMIP6 historical simulations (X):

$$Y = (X - \mu)\beta + \varepsilon \quad (6)$$

where β is the pattern - amplitude, i.e., scaling factor, μ is the sampling uncertainty of X, and ε represents internal climate variability which is estimated using CMIP6 pre-industrial control simulations. If the 90% confidence interval of the scaling factor is above zero, anthropogenic fingerprint is considered detectable in soil heat amplification and its depth dependence. Our analysis shows that the scaling factor is significantly positive, reinforcing the correlation-based evidence. Together, these methods robustly demonstrate that historical anthropogenic forcing has significantly contributed to the observed soil heat amplification and its depth dependence.

RESULTS

Vertical heterogeneity of heat amplification

We used multiple datasets to examine the amplification of heat extremes, including two reanalyses, seven observations, one satellite product, four land-surface model outputs, and seven Earth system model simulations (Tables S1–S3). We focused on near-surface 2-m air (Layer0) and four soil layers (Layer1–Layer4: 0–10 cm, 10–40 cm, 40–100 cm, and 100–200 cm). For each layer, the annual upper bound was defined as the 99th percentile of daily mean temperature (T99). Based on the state-of-the-art reanalysis (ERA5-Land; see MATERIALS AND METHODS), topsoil (0–10 cm) T99 increased over 94.0% of global land during 1981–2020 (Figure 1). The topsoil T99 trend exceeds that of near-surface air and the deepest soil layer (100–200 cm) over 64.5% and 60.5% of global vegetated lands (excluding Antarctica, deserts, Greenland, and high-latitude polar regions), respectively (Figures 2A & B). This "soil-outpacing-air" signal is concentrated in western North America, South America, central Africa, Europe, northeastern Asia, and southern Australia (i.e., hotspots; black rectangles in Figures 2A & B). Along the soil profile, the outpacing weakens with depth, approaching air levels at 40–100 cm and largely vanishing at 100–200 cm (Figure 2F).

To quantify soil-atmosphere interactions, we computed summer soil moisture-temperature coupling intensity, where larger values indicate stronger soil control on surface energy partitioning and temperature increase.⁹ The summer was defined as June–August in the Northern Hemisphere and December–February in the Southern Hemisphere. Regions with stronger interaction align with outpacing hotspots (spatial correlation $r = 0.31$ – 0.37 , $P < 0.05$; Figures 2C–E). Exceptions include southern South America and central Africa, where rainforest-driven evaporative cooling suppresses such interactions.^{60,61} Notably, the spatial patterns of inter-layer T99 trend differences across hotspots are corroborated by additional reanalysis, observations, and satellite product (Figure S1 & S2). By contrast, land-surface models forced one-way by the atmosphere struggle to capture bidirectional soil-atmosphere interactions and thus show large biases for topsoil-vs-air T99 trend differences ($r = 0.11$ – 0.20 ; relative error -2.38 to -1.91 ; Figure S1). The same models reproduce the spatial pattern of topsoil-vs-deepest-soil differences more faithfully ($r = 0.35$ – 0.41 ; $P < 0.05$) but underestimate the magnitude (relative error -0.52 to -0.32 ; Figure S2). These results indicate that soil-air contrasts are most likely driven by soil-atmosphere interactions and can extend to ~ 40 cm depth, whereas within-profile soil differences additionally reflect intrinsic soil processes (e.g., vertical heat conduction and moisture gradients).⁶²

We further examined the existence of upper-tail widening of soil temperatures. Specifically, we defined the annual upper tail as the difference between T99 and a moderate extreme (the 87.5th percentile, T87.5, the upper-quartile bound) and characterized widening by its long-term trend. Across identified hotspots (black rectangles in Figure 3A), ERA5-Land shows a clear signal in the topsoil that T99 increases faster than T87.5. This signal is robust to multi-source datasets (including land-surface models with slightly weaker magnitude) and an alternative rank-based approach (Figures S3 & S4). Tail widening weakens with depth (Figures 3B–D) and, within hotspots, generally remains stronger in soils than in air, though by 10–40 cm it approaches air levels (Figure S5). These hotspots also exhibit increasing trends in soil moisture-

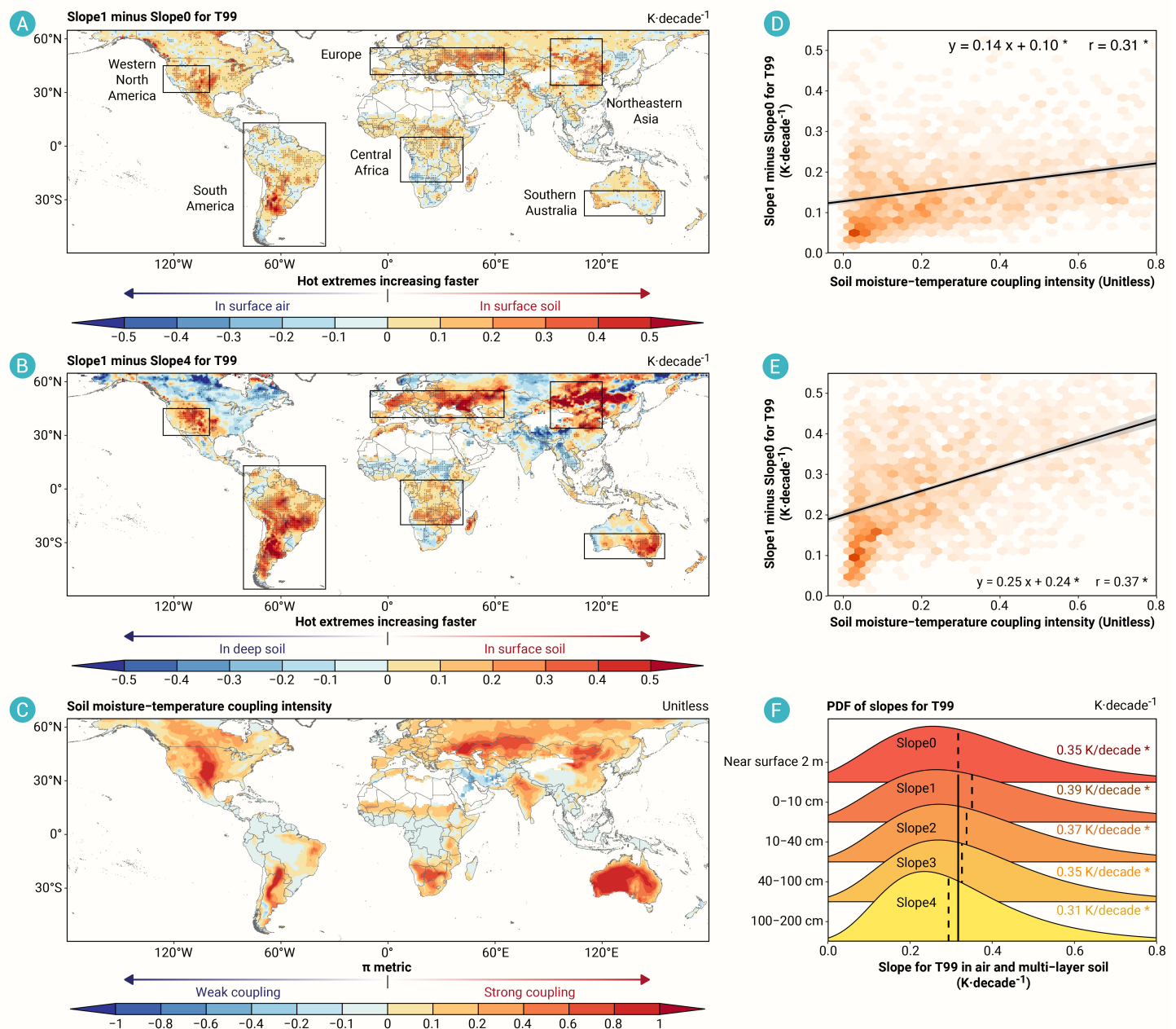


Figure 2. Upper-bound rise of annual temperature distributions and its vertical heterogeneity in soil and atmosphere during 1981–2020 (A) Inter-layer trend difference in the yearly 99th percentile of daily mean temperature (T99) between topsoil (Layer1: 0–10 cm) and near-surface 2-m air (Layer0) based on ERA5-Land. Layer-specific trends are denoted Slope0–Slope4 for Layer0–Layer4. (B) The same as (A), but for the difference between topsoil and the deepest soil layer (Layer 4: 100–200 cm). Stippling indicates that the trend differences are statistically significant at the 0.05 significance level (see MATERIALS AND METHODS). (C) Multi-year mean summer soil moisture-temperature coupling intensity (π metric) based on ERA5-Land and GLEAM. (D) Inter-layer T99 trend difference (y-axis) versus multi-year mean summer soil moisture-temperature coupling intensity (x-axis) for grid cells where topsoil T99 trends significantly exceed those of air. The solid line represents the best-fit linear regression, and the shaded area represents the corresponding 95% confidence interval. The “*” symbol indicates statistically significant trends or correlations ($P < 0.05$; Mann-Kendall test or Spearman correlation test). (E) The same as (D), but for the difference between the topmost and deepest soil layers. (F) Probability density functions (PDF) of T99 trends across grid cells exhibiting upward trends across all continuum layers. Vertical dashed line and colorful text represent the median and area-weighted average of the T99 trends, respectively, while the solid line denotes the median T99 trend for near-surface air.

temperature coupling intensity (Figure 3E). In topsoil, trends in T99-minus-T87.5 significantly correlate with trends in coupling intensity ($r = 0.31$; $P < 0.05$; Figure 3F). This correlation declines with depth (from 0.31 to -0.03) and vanishes in the deepest layer. Overall, upper-tail widening of soil temperatures is associated with strengthened soil-atmosphere interactions and is likely driven by anthropogenic warming that intensifies these interactions.

Mechanisms behind heat amplification and vertical heterogeneity

We quantitatively assessed how soil-atmosphere interactions shape both this heat amplification and its vertical heterogeneity. Mechanistically, under enhanced incoming shortwave radiation, dry soils release more sensible heat, warming near-surface air. Resultant increase in atmospheric evaporative

demand further desiccates soil, reinforcing warming through a positive feedback.⁶⁰ Such interactions are regulated by three key drivers, i.e., soil moisture, clouds, and aerosols. During 1981–2020, summer topsoil moisture and total cloud cover declined over 71.6% and 64.6% of vegetated lands, respectively (Figures 4A & B). Soil moisture deficits are the prerequisite for interactions, while cloud reductions increase surface shortwave radiation and energy input. These long-term declines strongly correlate with temporal changes in the inter-layer T99 difference (topsoil vs. air, $r = -0.88$ to -0.77 ; $P < 0.01$) and in topsoil T99-minus-T87.5 ($r = -0.71$ to -0.56 ; $P < 0.01$; Figure S6 & Table S4). Over the same period, aerosol optical depth decreased across North America, Europe, and Central Asia (Figure 4C), further boosting surface energy input in arid regions.⁶³ In southern hemisphere rainforests, wildfire-

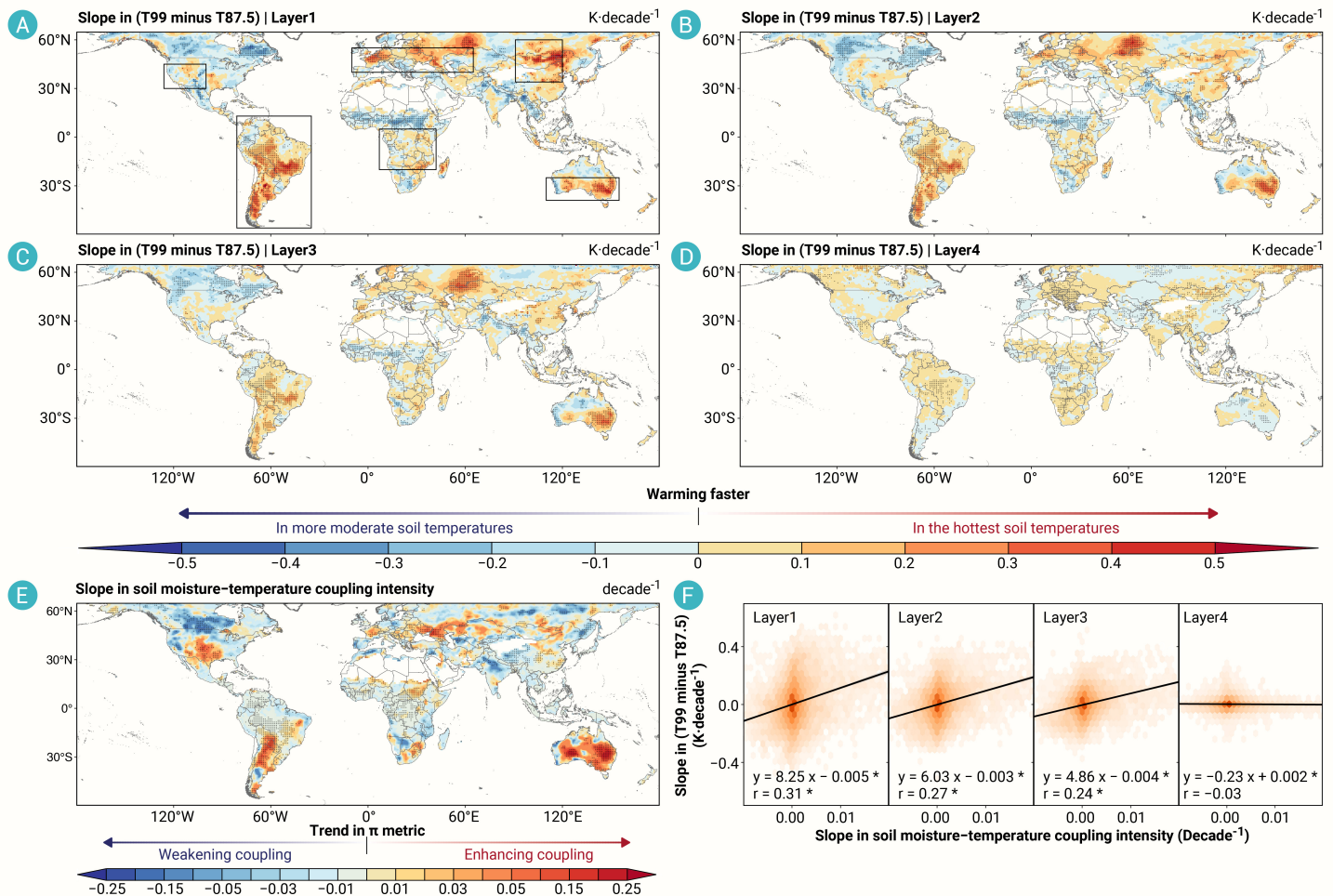


Figure 3. Upper-tail widening of soil temperature distributions and its depth dependence during 1981–2020 (A) Long-term trends in the difference between the yearly 99th (T99) and 87.5th (T87.5) percentiles of daily mean temperature for topsoil based on ERA5-Land. (B–D) The same as (A) but for Layer2 to Layer4. (E) Trends in summer soil moisture-temperature coupling intensity. Stippling indicates that the trend differences (A–D; see MATERIALS AND METHODS) or trends (E; Mann-Kendall test) are statistically significant at the 0.05 significance level. (F) Trends in T99-minus-T87.5 from Layer1 to Layer4 (y-axis) versus the trends in summer soil moisture-temperature coupling intensity (x-axis) in each land grid cell. The solid line represents the best-fit linear regression, and the shaded area represents the corresponding 95% confidence interval. The “*” symbol indicates statistically significant trends (Mann-Kendall test) or correlations (Spearman correlation test) at the 0.05 significance level.

generated aerosols increased and suppressed rainfall.⁶⁴ Together, these patterns indicate that climate-driven long-term soil drying and enhanced surface energy absorption have strengthened soil-atmosphere interactions, thereby amplifying heat extremes.

To explain why soil-atmosphere interactions cause heat amplification in the soil outpacing that in the atmosphere, we identify a rare soil moisture-temperature hypersensitive coupling regime (MATERIALS AND METHODS). When soil moisture drops below a critical threshold, evapotranspiration is curtailed, latent heat collapses, and energy is rerouted into sensible and ground heat fluxes, producing a much stronger warming in topsoil (i.e., hypersensitive topsoil temperature response) than under normal (weak) coupling (Figure 5). Sensible heat is then transferred to the near-surface air, activating a hypersensitive air temperature response to soil dryness. However, energy irreversible dissipation renders the atmospheric amplification weaker than in the topsoil. Reanalysis and observations confirm the occurrence of hypersensitive regime in six hotspots (Figure S7). Once topsoil moisture drops below the breakpoint, topsoil temperature responds more strongly to further drying than air temperature does. Overall, 88.63% of hotspots show a detectable hypersensitive regime for both topsoil and near-surface air (Figure S7 & Table S5). Regional-mean sensitivity of topsoil temperature to topsoil moisture across hotspots is $-149.6 \text{ K} \cdot \text{m}^{-3} \cdot \text{m}^3$ under the hypersensitive regime, compared with $-19.7 \text{ K} \cdot \text{m}^{-3} \cdot \text{m}^3$ under normal conditions, indicating that the temperature response becomes 7.6 times stronger once the hypersensitive regime is triggered. Among hotspots with a detectable hypersensitive regime, 82.06% exhibit a stronger temperature response in topsoil than in near-surface air, further supporting that topsoil

responds more strongly to soil dryness than near-surface air under hypersensitive regime. Long-term drying and increased surface energy make this hypersensitive regime easier to trigger during hot spells, causing the upper bound of soil temperatures to rise faster than that of air. In addition, declining topsoil moisture lowers thermal conductivity, impeding downward heat transfer and trapping heat near the surface (Figure 5). Because soil dryness decays with depth, this warming effect from soil moisture-temperature coupling weakens in deeper layers (Figure 2F). This inherent depth-dependence of moisture and heat dynamics yields a vertical gradient in which soil heat-extreme amplification exceeds that of air near the surface but diminishes with depth.

Soil texture likely modulates the soil moisture-temperature hypersensitive regime by shaping the background hydrological and thermal properties of soils. Spatially, we found that the soil moisture breakpoint for this regime shift decreases with increasing sand fraction, but increases with increasing silt and clay fractions (Figure S8). Consistent with their lower water-holding capacity, weaker capillary retention, and faster drainage,⁶⁵ sandy soils tend to enter the hypersensitive regime only under drier conditions, whereas silt- and clay-rich soils retain more water and sustain evaporative cooling over a wider moisture range,⁶⁵ allowing the shift to occur at relatively higher soil moisture. Together, these results suggest that soil texture facilitates regulating the critical soil moisture threshold for rapid heat amplification and thus conditions where such regime shifts occur.

Strengthened soil-atmosphere interactions, superimposed on long-term warming, exhibit that the soil temperature response to moisture deficits is more sensitive and thus increases soil temperature variability. An upward

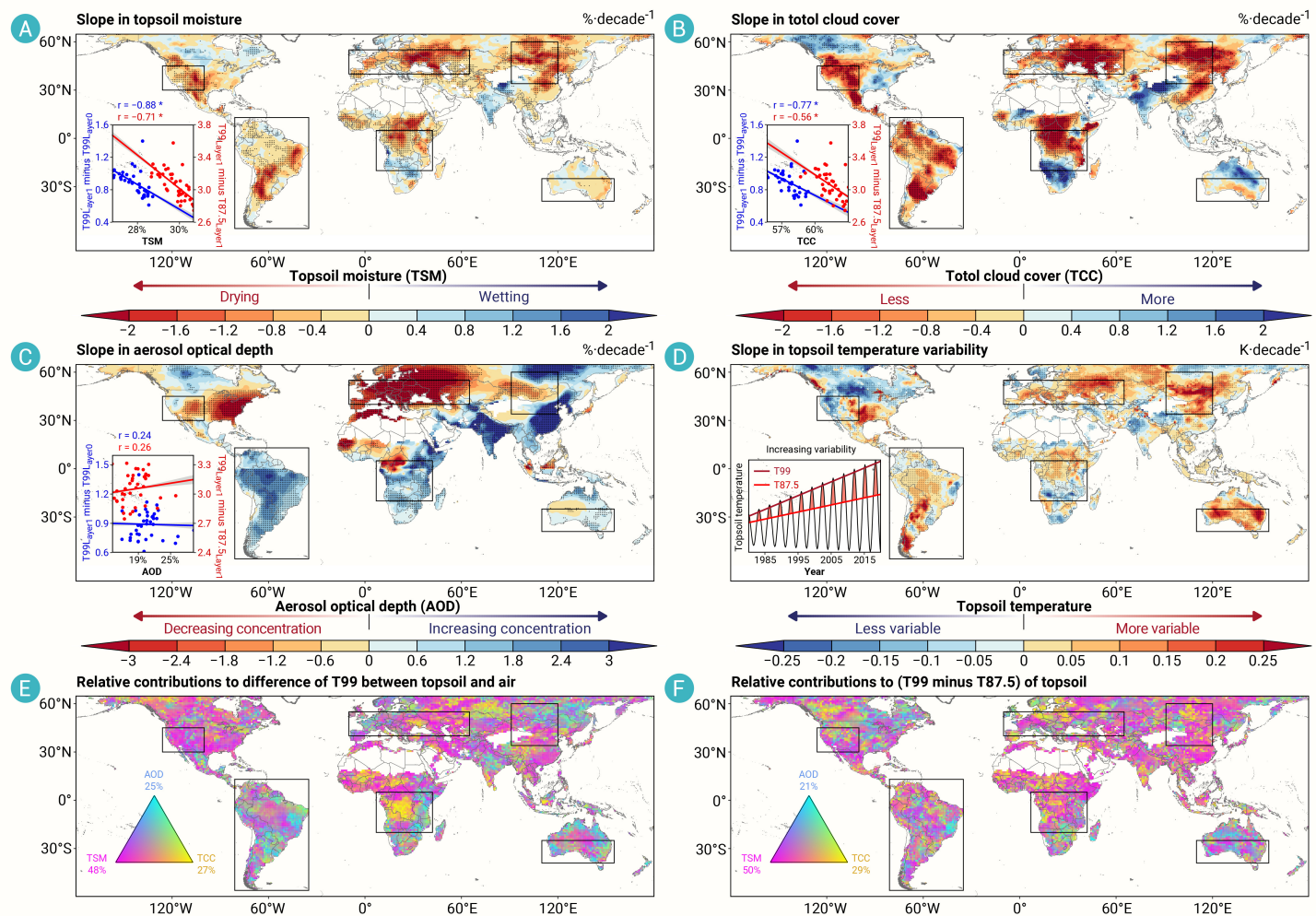


Figure 4. Long-term trends and contributions in drivers behind heat amplification (A) Summer topsoil moisture (TSM) trends during 1981–2020 based on ERA5-Land. Stippling indicates that the trends are statistically significant at the 0.05 significance level (Mann-Kendall test). Dots in the bottom-left subplot accompanying the map (A) represent the annual, area-weighted average T99 difference between topsoil and air across grid cells exhibiting greater T99 trends in the topsoil than near-surface air (red dots; unit: K) or topsoil T99-minus-T87.5 across grid cells exhibiting greater topsoil trends in T99 than T87.5 (blue dots; unit: K) on the x-axis, plotted against annual, area-weighted average summer topsoil moisture (unitless) on the y-axis. The solid line represents the best-fit linear regression, and the shaded area represents the corresponding 50% confidence interval. The “*” symbol indicates a statistically significant correlation at the 0.05 significance level (Spearman correlation test). (B–D) The same as (A), but for summer total cloud cover (TCC; B) based on ERA5, summer aerosol optical depth (AOD; c) based on MERRA2, and summer topsoil temperature variability (D) based on ERA5-Land. The time series in the bottom-left conceptual diagram accompanying the map (D) represent T99 (dark red line), T87.5 (light red line), and soil temperature (black line). (E) Relative contributions of topsoil moisture (magenta), total cloud cover (yellow), and aerosol optical depth (cyan) to the T99 difference between topsoil and air. (F) The same as (E), but for T99-minus-T87.5.

trend in day-to-day summer topsoil temperature variability emerged over 56.6% of vegetated lands (Figure 4D). The increased variability drives upper-tail widening of soil temperatures. We also quantified the soil moisture-temperature coupling intensity under T99 and T99-minus-T87.5 decreases progressively with depth at the global scale (Figure S9). This suggests that the influence of soil-atmosphere interactions shows a gradual downward decay across the soil profile (0–200 cm). Beyond soil-atmosphere interactions, anthropogenic climate change further enhances temperature variability and tail widening by altering vegetation growth and transpiration,^{66,67} atmospheric circulation anomalies (e.g., the weakening of the jet stream),⁶⁸ and shifts in precipitation patterns.⁶⁹ These atmospheric changes are embedded in atmospheric forcing, explaining why land surface models can reproduce the upper-tail widening of soil temperatures.

Finally, disentangling the individual contributions of soil moisture, clouds, and aerosols is nontrivial given their coupled effects (e.g., drying can enhance instability and mesoscale convergence, while aerosols modify cloud microphysics and radiation).^{70,71} Using ridge regression to isolate independent effects, we found that in 60.3% (62.6%) of vegetated land, soil moisture is the dominant factor, explaining 48% of the temporal variations in the inter-layer T99 difference (topsoil vs. air) and 50% of the variations in topsoil T99-minus-T87.5 (Figures 4E–F & Table S6). Thus, both heat amplification and its vertical

heterogeneity are driven primarily by moisture-limited conditions (i.e., topsoil drying) rather than by energy excess alone.

Anthropogenic influences on soil heat amplification

The long-term changes in the three above drivers, along with the increasing variability of topsoil temperature, are closely linked to global warming,^{72–74} underscoring the critical role of anthropogenic climate change. But can anthropogenic fingerprints be explicitly detected in the stronger amplification of heat extremes in the topsoil? To answer this, we analyzed multi-model simulations from the Coupled Model Intercomparison Project Phase 6 (CMIP6). Globally, CMIP6 historical simulations struggle to accurately reproduce the ERA5-based trends from 1981 to 2020 (Figure S10). Across six identified hotspots, while some Earth system models capture the trend tendencies consistent with ERA5-Land, more than 50% underestimate the T99 difference between topsoil and near-surface air. A 50-member large ensemble from MPI-ESM1-2-LR (see MATERIALS AND METHODS) exhibits even greater difficulty in replicating both the trend tendency and magnitude of the inter-layer differences (Figure S10). This discrepancy arises because Earth system models struggle to accurately represent the complex land-atmosphere interactions, as reflected in their weak spatial correlation with soil moisture-temperature coupling intensity based on ERA5-Land (Figure S11). The shift in the soil moisture-temperature coupling regime is

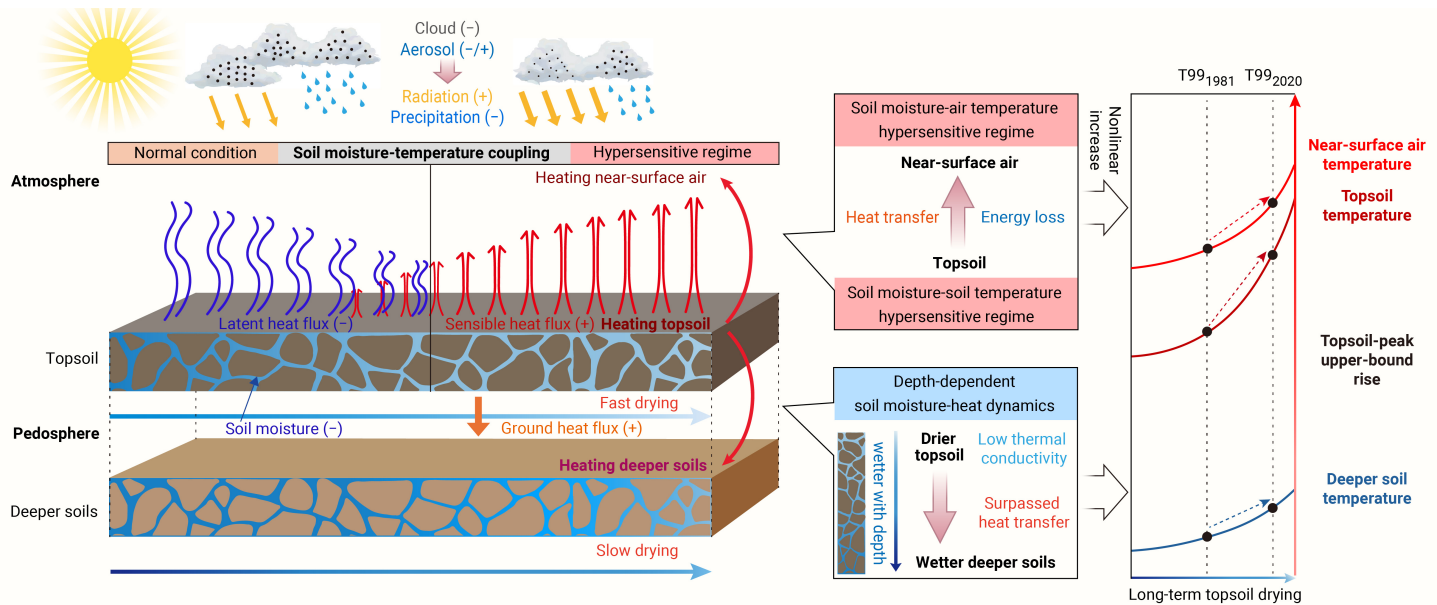


Figure 5. Conceptual diagram illustrating vertical heterogeneity of heat extreme amplification in atmosphere and soil The upper-bound rise in topsoil temperature outpaces that of air due to stronger soil moisture-temperature hypersensitive coupling within soil. With drying, reduced topsoil thermal conductivity suppresses heat transfer to deeper soils, accelerating heat accumulation near the surface and producing a depth-dependent attenuation with depth.

detected in 25.1% of hotspots by at least 60% of the Earth system models (Figure S7 & Table S5), further indicating their failure to detect an anthropogenic fingerprint in the temporal changes of soil-air differences in T99.

Despite these underestimations, CMIP6 models do capture increasing trends in inter-layer T99 difference between the topsoil and the deepest soil layer (ERA5-Land: 1.96×10^{-1} K-decade $^{-1}$; CMIP6: 0.76×10^{-1} K-decade $^{-1}$) as well as in topsoil T99-minus-T87.5 (ERA5-Land: 0.79×10^{-1} K-decade $^{-1}$; CMIP6: 0.25×10^{-1} K-decade $^{-1}$) across identified hotspots during 1981–2020 (Figures 6A & D). Spatially, most hotspots exhibit well-reproduced trends, except for Australia (Figures 7A & D), with further confirmation from the MPI-ESM1-2-LR large-ensemble simulations (Figures S10 & S12). These decreasing trends over southern Australia also reflect a failure of Earth system models to capture the evolving land-atmosphere interactions in this region as the models simulate weakening coupling while reanalyses indicate strengthening.⁷⁵ Nevertheless, these regional-average increasing trends across hotspots lie outside the 95th percentile of those derived from 10,000 overlapping 40-year segments based on CMIP6 pre-industrial control simulations (Figures 6B & E), indicating that amplification of heat extremes peaked in topsoil cannot be fully explained by internal climate variability.

To further quantify the role of anthropogenic climate change, we applied two detection and attribution methods. First, in a correlation-based analysis, we calculated Spearman correlations between the multi-model mean of CMIP6 historical simulations and each of 2,000 overlapping 40-year segments from pre-industrial control simulations, focusing on the time series of inter-layer differences in T99 (the topsoil vs. the deepest soil layer) and topsoil T99-minus-T87.5 during 1981–2020. Temporal changes in these metrics under CMIP6 historical simulations show statistically significant correlations with those derived from ERA5-Land (Figures 6C & F). There is a 95% probability that these correlations exceed those between CMIP6 historical and pre-industrial control simulations, indicating that anthropogenic climate change is the likely cause of the increasing inter-layer differences in T99 (the topsoil vs. the deepest soil layer) and topsoil T99-minus-T87.5. Second, using a regularized optimal fingerprint method, the ERA5-based inter-layer differences in T99 (or topsoil T99-minus-T87.5) were regressed against the multi-model mean of CMIP6 historical simulations during 1981–2020, with a scaling factor applied to align simulated these metrics with that in the ERA5-Land. The anthropogenic signal is detected if the 5%–95% uncertainty range of the scaling factor is above zero. Our detection and attribution analysis reveals that historical anthropogenic forcing significantly contributes to the accelerated rise in the upper bound of and the widening of the upper tail of topsoil temperature distributions, reinforcing the correlation-based evidence.

Overall, both methods suggest that anthropogenic climate change is very likely (more than 90%) responsible for the amplification of heat extremes peaked in the topsoil during 1981–2020.

With the continued anthropogenic emissions, the amplification of heat extremes peaked in the topsoil is expected to persist in the future. Under a high-emissions scenario (SSP5-8.5), hotspots exhibiting heat amplification peaked in the topsoil during 1981–2020 (Figures 7A & D) are projected to maintain this trend during 2061–2100 (Figures 7B & E). Despite the underestimation in Earth system model simulations, increases in inter-layer difference in T99 between the topsoil and the deepest soil layer and topsoil T99-minus-T87.5 are projected to continue during 2021–2100 (Figures 7C & F). The MPI-ESM1-2-LR large ensemble simulations further support these projections, reinforcing the robustness of projected heat amplification peaked in the topsoil (Figure S12). In a warmer climate, this amplification is driven by widespread declines in topsoil moisture, reductions in total cloud cover, and changes in aerosol optical depth—with decrease (increase) in the Northern (Southern) Hemisphere, relative to the historical period (Figure S13).

DISCUSSION

We show that soil-atmosphere interactions amplify heat extremes in both soil and atmosphere by rising the upper bound and widening the upper tail of the annual temperature distribution. Whereas prior regional work confined to Europe reported that soil (0–7 cm) extreme temperatures outpace air counterparts,¹⁴ we extend this pattern both horizontally (across the globe) and vertically (with depth), detecting stronger soil outpacing across western North America, South America, central Africa, northeastern Asia, and southern Australia. In contrast to the ongoing debate over upper-tail widening in air temperature based on different methods,^{10,18} our multi-method analysis reveals a robust widening in soil temperature upper tail. Crucially, both the upper-bound rise and upper-tail widening exhibit pronounced depth dependence, with stronger soil heat amplification relative to air persisting to ~40 cm. Mechanistically, warming-enhanced soil-atmosphere interactions and frequently triggered soil moisture-temperature hypersensitive regimes produce nonlinear warming that is stronger in soil than in air, explaining the soil heat amplification beyond air and its depth dependence.

Our results are not sensitive to the percentile thresholds used to characterize upper-tail width. Sensitivity analyses using alternative percentile combinations, including T99-minus-T95 and T97.5-minus-T90, show spatial patterns highly similar to those of T99-minus-T87.5 across all layers (Figures S14 & S15), with spatial correlations of 0.69–0.80 and 0.78–0.96, respectively ($P < 0.01$). These alternative metrics also consistently show that soil heat amplification

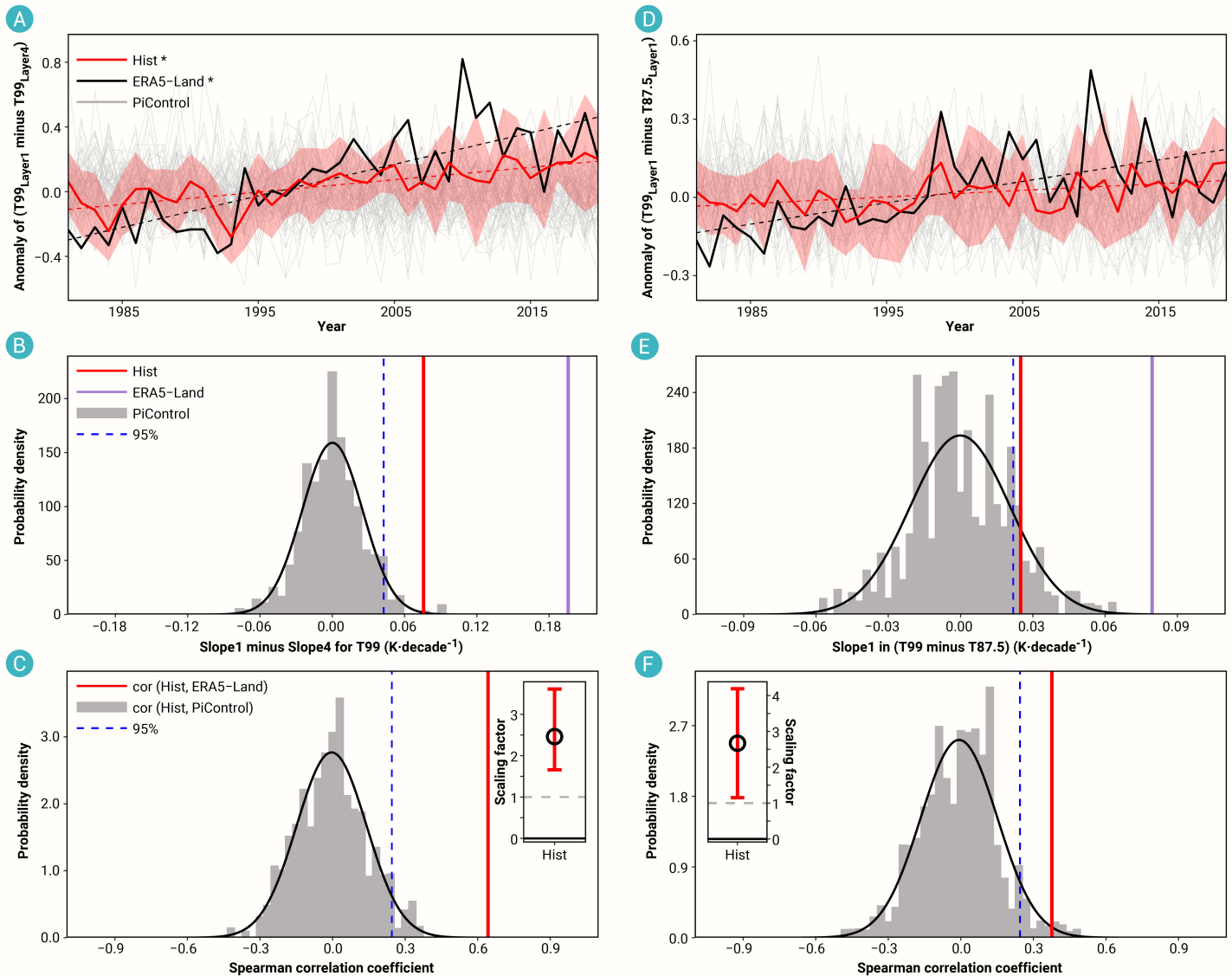


Figure 6. Detection and attribution of soil heat amplification and its depth dependence during 1981–2020 (A) Temporal changes in anomalies of inter-layer T99 difference between topsoil and the deepest soil layer within hotspots (see black rectangles in Figure 2A). The black line represents the ERA5-Land, while the red line shows the multi-model mean of CMIP6 historical simulations (Hist). Thin grey lines in the background represent results from 75 non-overlapping 40-year segments of pre-industrial control simulations (PiControl). Shaded areas indicate the ± 1 ensemble standard deviation range, and the "*" symbol indicates these anomalies have a statistically significant trend at the 0.05 significance level (Mann-Kendall test). (B) The histograms and probability density functions of the trends in these anomalies for inter-layer T99 differences based on 2,000 overlapping 40-year segments from the pre-industrial control simulations. Vertical purple and red lines represent the trends from ERA5-Land and CMIP6 historical multi-model means, respectively. (C) The histogram and probability density function of Spearman correlation coefficients for temporal changes in these anomalies for inter-layer T99 differences between the CMIP6 historical multi-model mean and 2,000 overlapping 40-year segments from the pre-industrial control simulations. Vertical red line represents the Spearman correlation coefficient between the ERA5-Land and CMIP6 historical multi-model mean. The inset box in (C) includes the optimized scaling factors and their 5%–95% confidence intervals from the regularized optimal fingerprint method where the anomalies from ERA5-Land are regressed by the anomalies from CMIP6 historical multi-model mean. (D–F) The same as (A–C), but for topsoil T99-minus-T87.5.

cation stronger than that in near-surface air persists within the upper 0–40 cm soil layer, reinforcing the robustness of our conclusions. We also assessed changes in lower-tail width, defined as T12.5-minus-T1 (Figure S16). Although regional averages over hotspots show increasing lower-tail width across all soil layers, upper-tail widening is more pronounced, with rates approximately 2.2 to 4.5 times those of the lower tail. This indicates that temperature distribution changes are not simply characterized by a uniform shift, but instead by an asymmetric deformation in which the upper tail stretches more strongly than the lower tail.

To provide a globally consistent comparison of soil temperature variability, we quantified boreal/austral summer soil temperature variability. In the tropics, however, temperature variability likely reflects wet-dry seasonality and associated soil moisture depletion.⁷⁶ Nevertheless, the spatial pattern of trends in full-year soil temperature variability is broadly consistent with that for summer (spatial correlation: $r = 0.56$, $P < 0.01$; Figure S17), indicating that our results are not sensitive to the seasonal definition. We also noted that

remapping soil temperature dataset to 1° resolution may smooth fine-scale heterogeneity in topography, vegetation, and soil properties. However, a sensitivity analysis based on native-resolution ERA5-Land dataset (0.1°) shows that the spatial patterns of soil heat amplification remain broadly consistent (Figure S18), suggesting that our results are robust despite the unavoidable loss of local detail.

Under the influence of soil-atmosphere interactions, the soil heat amplification stronger than that in near-surface air can extend downward to at least about 40 cm across hotspots, implying that the 0–40 cm soil layer generally experiences stronger heat extremes than near-surface air. Heat-risk assessments and climate-impact evaluations based solely on near-surface air temperature may therefore underestimate the severity of heat extremes within this depth range, and should incorporate soil temperature within at least the upper 40 cm. Moreover, the ecological impacts of this depth range arise not only from the vertical heterogeneity of heat amplification itself, but also the depth dependence of ecosystem responses to temperature, because

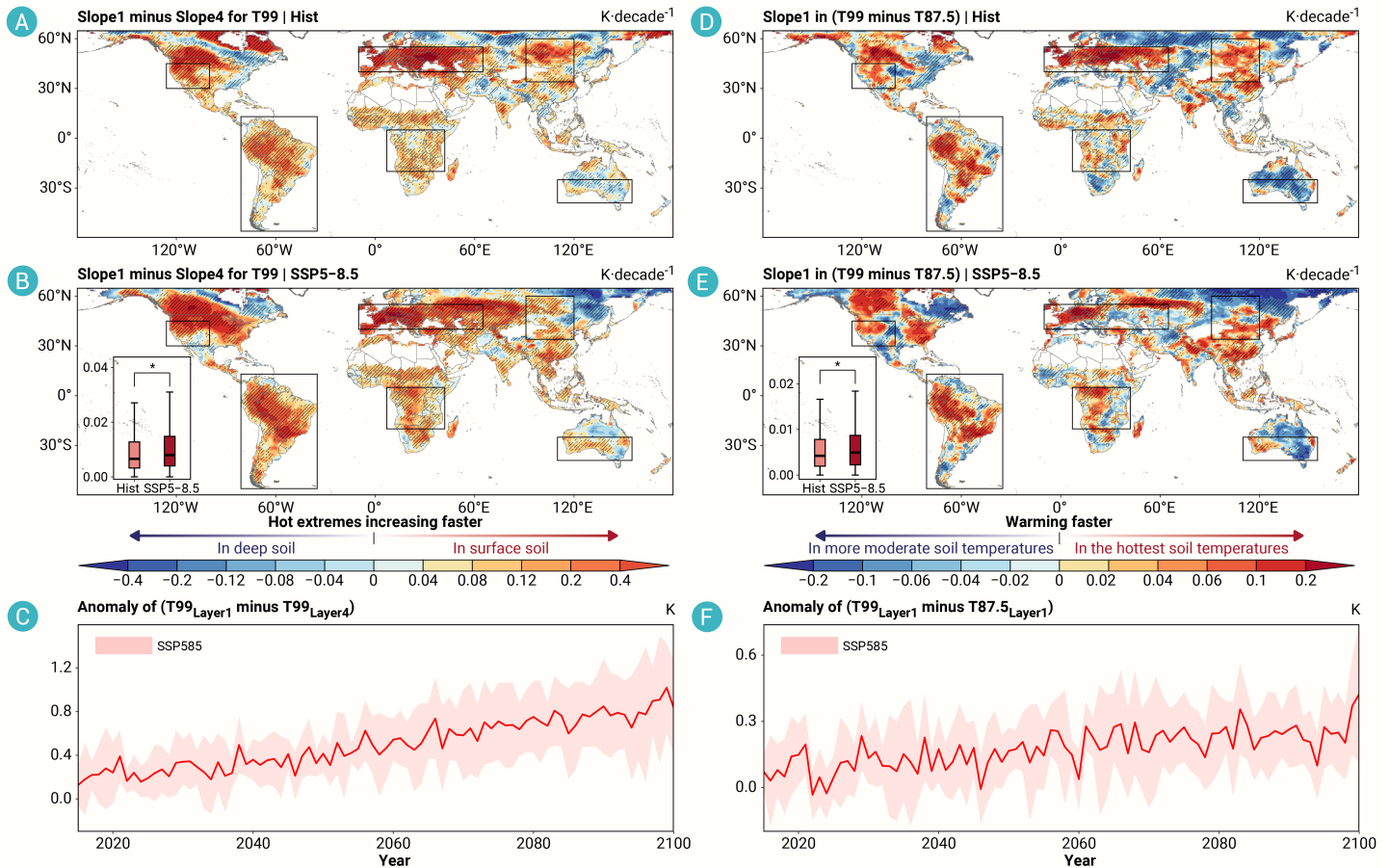


Figure 7. Projected soil heat amplification and its depth dependence (A) The same as Figure 2B, respectively, but based on the multi-model mean of CMIP6 historical simulations during 1981–2020. Hatching shows regions where more than 80% of the models agree on the sign of change. (B) The same as (A), but under SSP5-8.5 during 2061–2100. Boxplots show the trend differences across these grid cells with faster T99 trends in the topsoil than in the deepest soil layer. In the boxplots, the upper whisker represents

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AUTHOR CONTRIBUTIONS

Conceptualization, X.G.; Methodology, X.G.; Formal analysis, X.G.; Data curation, X.G.; Software, X.G.; Visualization, X.G.; Investigation, X.G.; Validation, X.G.; Supervision, X.G.; Project administration, X.G.; Writing – original draft, X.G.; Writing – review & editing, X.G., S.W., Y.G., X.Z., L.L., S.L., R.W., J.L., X.W., C.L., D.K. and L.W. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

All data used in this study are available online. ERA5-Land reanalysis dataset is publicly available at the CDS website (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=overview>). CRA-Land reanalysis dataset is publicly available at the China Meteorological Data Service Centre website (http://www.nmic.cn/data/cdcdetail/dataCode/NAFP_CRA40_FTM_3HOR_NC.html). BEST dataset is publicly available (<https://berkeleyearth.org/data/>). GLEAM dataset is publicly available (<https://www.gleam.eu/>). GSWP-3 dataset is available at the DIAS website (<https://doi.org/10.20783/DIAS.501>). ERA5 reanalysis dataset is publicly available at the CDS website (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels-monthly-means?tab=overview>). MERRA2 reanalysis dataset is publicly available at the GES DISC website (https://disc.gsfc.nasa.gov/datasets/M2T1NXAER_5.12.4/summary?keywords=merra2). CM-SAF satellite dataset is publicly available at the CMSAF website (<https://wui.cmsaf.eu/safira/action/viewHome>). Fluxnet2015 dataset is publicly available (<https://fluxnet.org/>). E-OBS dataset is publicly available the CDS website (<https://cds.climate.copernicus.eu/datasets/insitu-gridded-observations-europe?tab=overview>). DWD dataset is publicly available (https://opendata.dwd.de/climate_environment/). OzNet dataset is publicly available (<https://www.oznet.org.au/>). TS25 dataset can be requested from ref 30. CN05.1 dataset can be requested by from ref 31. CMIP6 simulations are publicly available at the ESGF website (<https://aims2.llnl.gov/search>). GLDAS-Noah dataset is publicly available at the GES DISC website (https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_3H_2.1/summary and https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_3H_2.0/summary). ISIMIP3a simulations are publicly available at the ISIMIP website (<https://data.isimip.org/>). SoilGrids is publicly available at the ISRIC website (<https://www.isric.org/explore/soilgrids>). Land use type is publicly available at the USGS website (<https://lpdaac.usgs.gov/>). All relevant codes used in this study are available, upon request, from the corresponding author.