

1 **Title**

- 2 • Full title: **Summer soil drying exacerbated by earlier spring greening of northern**
- 3 **vegetation**
- 4 • Short title: Inter-seasonal vegetation-soil moisture feedbacks

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One-sentence summary: Extra water loss from earlier spring greening dries soils locally in summer, but can moisten soils in areas downwind.

Abbreviations: AMIP, Atmospheric Model Intercomparison Project; AVHRR, Advanced Very High Resolution Radiometer; CMIP, Coupled Model Intercomparison Project; CRU, Climate Research Unit; GCM, global climate model; GIMMS, Global Inventory Monitoring and Modeling Studies; GLEAM, Global Land Evaporation Amsterdam Model; ET, evapotranspiration; GPCC, Global Precipitation Climatology Centre; IPCC, Intergovernmental Panel on Climate Change; GRACE-REC, reconstructed TWS anomalies from Gravity Recovery and Climate Experiment satellites; IPSL-CM4, Institut Pierre Simon Laplace Climate Model version 4; JJA, June, July and August; LAI, Leaf Area Index; LAI_{obs}^{MAM} , numerical experiment forced with observed MAM LAI; LAI_{clim}^{MAM} , numerical experiment forced with climatological MAM LAI; LMDZ, the Laboratoire de Météorologie Dynamique general circulation model with Zooming capability; MAM, March, April and May; MCA, maximum covariance analysis; MODIS, Moderate Resolution Imaging Spectroradiometer; FLUXNET-MTE, the ET product based on eddy-covariance measurements and the model tree ensemble algorithm; WB-MTE, the ET product based on water mass balance and the model tree ensemble algorithm; NDVI, Normalized Difference Vegetation Index; ORCHIDEE, Organising Carbon and Hydrology In Dynamic Ecosystems; P, precipitation; PFTs, plant functional types; Q, surface runoff; SIF, sea-ice fraction; SST, sea-surface temperature; SVD, singular value decomposition; SWC, soil water content; TRENDY, trends and drivers of the regional scale sources and sinks of carbon dioxide; TWS, terrestrial water storage; TXx, the

73 summer maximum of daily maximum temperature; TX90p, the number of summer days
74 with maximum temperatures exceeding the local 90th percentile of a given base period.
75

76 **Abstract**

77 **Earlier vegetation greening under climate change raises evapotranspiration and**
78 **thus lowers spring soil moisture, yet the extent and magnitude of this water deficit**
79 **persistence into the following summer remain elusive. We provide observational**
80 **evidence that increased foliage cover over the Northern Hemisphere, during 1982-**
81 **2011, triggers an additional soil moisture deficit that is further carried over into**
82 **summer. Climate model simulations independently support this, and attribute the**
83 **driving process to be larger increases in evapotranspiration than in precipitation.**
84 **This extra soil drying is projected to amplify the frequency and intensity of summer**
85 **heatwaves. Most feedbacks operate locally, except for a significant teleconnection**
86 **where extra moisture transpired over Europe is transported to central Siberia.**
87 **Model results illustrate that this teleconnection offsets Siberian soil moisture losses**
88 **from local spring greening. Our results highlight that climate change adaptation**
89 **planning must account for the extra summer water and heatwave stress inherited**
90 **from warming-induced earlier greening.**

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Quantifying this vegetation-soil moisture legacy effect must take full account of the complete loop of soil-vegetation-atmosphere exchanges of water and energy fluxes. Many feedback mechanisms, as summarized in the above paragraph, are essential for accurate assessments of global or regional soil moisture changes, yet are ignored by previous studies (9–12). In particular, without characterising atmospheric feedbacks and including those that are inter-seasonal, it still remains an open question on the extent to which vegetation greening influences summer soil moisture. Here, we first analyse multiple strands of direct observational data to characterise the spring-to-summer vegetation-soil moisture feedbacks. We then perform factorial experiments with a state-of-the-art coupled land-atmosphere climate model to better understand the underlying mechanisms.

Results

Observational Evidence for Summer Drying Induced by Earlier Spring Greening

To examine spatiotemporal connections between recent spring phenological changes (section S1 and fig. S1) and soil water content (SWC) dynamics in the following summer, we first analyse long-term satellite data of spring Leaf Area Index (20) (LAI, as a proxy for vegetation phenology and growth, Methods), and summer values of two observation-driven SWC-related data sets, for the period of 1982–2011. The two SWC-related data include root-zone soil moisture from the Global Land Evaporation Amsterdam Model (21) (GLEAM; Methods) and the long-term reconstruction of terrestrial water storage (TWS) anomalies based on Gravity Recovery and Climate Experiment satellites (22) (GRACE-REC). Our study domain only covers the middle to high latitudes of the Northern Hemisphere (25–90°N), because of their distinctive vegetation seasonality and

particularly pronounced recent changes in springtime LAI phenology (fig. S1). We define spring across the domain as the period from March to May (MAM), and summer as the period from June to August (JJA). We calculate partial correlations between spring LAI and summer SWC (or TWS), whereby covarying effects of summer LAI and climatic variables (i.e. temperature, precipitation and solar radiation) are controlled for (Methods). As potential non-local precipitation feedbacks modulate the local relationship between spring LAI and summer SWC (14, 19), we also implement a lagged maximum covariance analysis (23) (MCA; Methods, section S2). This statistical approach isolates pairs of coupled spatial patterns that explain a maximum fraction of the covariance between two space-time data fields (in our case, spring LAI and summer SWC). Hence, the MCA method has obvious advantages over routine correlation analysis that only partially describes covariability between two fields (i.e. spatial correlation using geographical points only, or temporal correlation using time series only).

Partial correlations between spring greenness and subsequent summer SWC show a widespread negative pattern across most northern lands (64% of land area for GLEAM SWC and 56% for GRACE-REC TWS) (Fig. 1, A and B), including significantly greening regions of Europe, eastern U.S., east Asia and Siberia (fig. S1). For temperate and semi-arid grasslands where LAI is coupled to shallow moisture, this dominance of negative correlation between spring LAI and summer moisture is additionally supported by using microwave-derived summer top-layer soil moisture (fig. S2). The widespread negative correlation indicates that, when effects of inter-annual variations of precipitation are factored out, earlier greening in spring generally results in local soil drying in subsequent summers. On the other side, positive correlation is also apparent over regions including the North China Plain, central and southeastern Europe and the U.S. Great

Plains, especially for TWS that additionally captures storage variations in canopy, snow, streams, lakes and groundwater (Fig. 1, A and B). Many such regions are influenced by intensive agricultural activities, which potentially decouples the relationship between spring LAI and summer SWC observed in natural ecosystems. By averaging land surface undisturbed by cropland management, we find a negative correlation between spring LAI and summer SWC that is statistically significant (-0.44 for GLEAM SWC and -0.40 for GRACE-REC TWS, $p < 0.05$) (fig. S3). However, an increasing fraction of land areas affected by croplands leads to a weakening of this negative correlation, which shifts robustly to being positive when croplands occupy over 50% of local land areas (fig. S3).

Fig. 1, C-F presents the leading first MCA mode characterising spatial patterns of the coupling between spring LAI and summer SWC. This mode in particular includes potential non-local impacts of LAI-induced moisture transport anomalies on SWC at downwind regions. This mode pair explains 46% and 59% of the total squared covariance between the two variables, for GLEAM SWC and GRACE-REC TWS respectively. For both SWC-related products, the first spring LAI mode shows widespread positive anomalies (i.e. earlier greening) in the majority of the Eurasia (> 80%) and eastern U.S., while negative anomalies (i.e. delayed greening, or browning) covers vast areas of central and western North America (Fig. 1, C and E). The patterns of the leading LAI mode generally resemble the trend pattern of satellite-observed spring LAI (fig. S1). As a consequence, the leading summer SWC (or TWS) mode (Fig. 1, D and F) coupled to the spring LAI patterns demonstrates a direct response pattern of summer SWC to the emerging spring greening. The MCA-based annual time series linked to the spring LAI and summer SWC (or TWS) pattern are also highly correlated ($r = 0.86$ for GLEAM SWC, $r = 0.80$ for GRACE-REC TWS, $p < 0.05$ for both; fig. S4). This reiterates the

strong coupling between the two coupled patterns shown in Fig. 1, C-F. Generally, negative summer SWC anomalies (i.e. soil drying) are preceded by spring greening, whereas positive SWC anomalies (i.e. soil wetting) dominate the western North America with spring browning (Fig. 1, D and F versus Fig. 1, C and E). The dominance of negative LAI-SWC coupling, as also seen by partial correlation patterns, implies an impact of earlier spring onset on local summer soil drying. The cropland-dominated central Europe have wetter summers during years with greener springs (Fig. 1, C-F), which is in agreement with the positive correlation between spring greenness and summer soil moisture (Fig. 1, A and B). A notable exception occurs in the Siberia region, where summer SWC increases despite the presence of a clear positive spring LAI anomaly and limited human interventions. This is also in sharp contrast to the negative partial correlations in central Siberia after removing covarying effects of precipitation (Fig. 1, A and B). Such difference implies that altered precipitation patterns driven by spring LAI changes cause extra moisture to be brought into this area.

Simulating the Spring-to-summer Vegetation Feedbacks

Statistical analyses of observation-based data show that summertime soil moisture anomalies negatively co-vary with the preceding spring greening patterns. However, the detection of systematic legacy effects of spring LAI on summer soil moisture within data is partially impacted by noise from weather variability, potential non-linearity in soil moisture responses, different rooting depth and moisture access across ecosystems, and slowly varying drivers of both LAI and soil moisture trends such as vapour pressure deficit and rising atmospheric CO₂. To confirm a causal link between spring greening and summer soil drying, and to better understand the local and non-local mechanisms, we perform further analyses using the IPSL-CM4 coupled land-atmosphere global climate

model (24) (GCM) (Methods). Coupled land-atmosphere models describe explicitly biophysical interactions between the land surface and the atmosphere. This includes local exchanges of water and energy fluxes, and large-scale changes of atmospheric circulation and moisture convergence. Paired time-evolving (i.e. transient) numerical experiments are run with the land surface component of IPSL-CM4, ORCHIDEE (Methods), forced with two contrasting spring LAI conditions. One set of simulations (labelled as “ LAI_{obs}^{MAM} ”) is prescribed with annually varying LAI from satellite observations (20) during all seasons, including MAM. The second set of simulations (labelled as “ LAI_{clim}^{MAM} ”) is also prescribed with annually varying LAI during all seasons, except in MAM when it is fixed to the climatological mean LAI conditions observed during 1982–2011 (Methods). Apart from the spring LAI differences, the two model experiments are forced identically with observed boundary conditions of sea-surface temperature, sea-ice fraction and atmospheric CO₂ concentration. This enables us to account for the vegetation biophysical feedbacks stemming from interactions with changes in oceanic processes or CO₂ radiative/physiological forcings. Multi-member paired ensembles are generated for each coupled-model experiment by performing 30 repeated runs but with different initial conditions (Methods).

Model evaluation against global observational datasets supports the capacity of the IPSL-CM4 GCM to capture the annual and seasonal features of key hydrological variables, including ET and precipitation (fig. S5, A and B, further details in section S3). To avoid systematic biases from the diverging magnitude of modelled and observation-based SWC, SWC changes are instead compared as the fraction of the present-day climatological mean (1982–2011) (25). At the scale of the Northern Hemisphere (25–90°N), the IPSL-simulated SWC shows a negative trend whereas GLEAM SWC shows a

weaker positive trend (fig. S5C). Whilst this sign difference is possibly a concern for global mean changes, we find zonally coherent patterns of the IPSL-simulated SWC trend compared to GLEAM SWC (fig. S5, D-I). The IPSL-simulated SWC broadly captures regions where soil wetting or drying occurs, at both annual and seasonal timescales (fig. S, D-I). This regional consistency strengthens our confidence in examining both the observed zonally different fingerprint of spring greening on summer soil moisture, and the ability of our GCM to explain such changes.

The difference between the two factorial simulations with variable and fixed spring LAI ($LAI_{obs}^{MAM} - LAI_{clim}^{MAM}$) allows us to isolate the fingerprint of observed spring LAI changes on summer soil moisture (δSWC), as well as other important hydrological variables. The symbol “ δ ” hereafter denotes the influence of spring LAI changes on other target variables of interest. Our factorial model simulations confirm a strong coupling between spring LAI and summer δSWC anomalies ($r = -0.51$, $p < 0.01$) (Fig. 2A). Hence, on a year-to-year basis, the observed higher spring LAI values prescribed to our GCM correspond to lower summer SWC estimates. We then examine if there is a robust overall trend of decreasing δSWC , driven by the significantly increasing spring LAI (greening). This effect is more difficult to detect because the inter-annual trend of LAI over the past 30 years is smaller than concurrent climate-driven variabilities. Average summer δSWC across all the northern lands (25–90°N) tends to decrease at a rate of $-0.11 \pm 0.09 \times 10^{-4} \text{ m}^3 \text{ m}^{-3} \text{ yr}^{-1}$ (linear trend: mean $\pm$ one standard derivation, $p = 0.22$) due to the spring LAI changes. This overall summer δSWC trend is negative, in line with our hypothesis that higher green foliage cover is transpiring more in spring and leaving soils drier in summer. The calculated trend is, though, not statistically significant, partly due to the presence of contrasting effects on summer SWC in regions with spring greening (i.e. positive LAI

trends) versus spring browning (i.e. negative LAI trends). When instead considering only regions where spring LAI generally increases, a statistically significant and much stronger summer drying trend in summer δ SWC ($-0.17 \pm 0.07 \times 10^{-4} \text{ m}^3 \text{ m}^{-3} \text{ yr}^{-1}$, $p < 0.05$) is detected (Fig. 2B). On average, including areas with spring browning, this decreasing trend of summer SWC associated with spring LAI changes contributes an additional 16% to the simulated decrease in summer SWC directly caused by climate change during 1982–2011 (overall decrease: $-0.68 \times 10^{-4} \text{ m}^3 \text{ m}^{-3} \text{ yr}^{-1}$ from the $\text{LAI}_{\text{obs}}^{\text{MAM}}$ simulation).

We also perform the MCA analysis on observed spring LAI and IPSL-simulated summer SWC (from simulation $\text{LAI}_{\text{obs}}^{\text{MAM}}$). The coupling patterns between spring LAI and summer SWC for the first mode (fig. S6, A and B) show high accordance with those purely based on observations (Fig. 1, C-F), confirming the ability of our GCM to simulate the inter-seasonal vegetation-soil moisture feedbacks. We further test whether insights based on our GCM-based factorial simulations could be overly influenced by water-stressed regions at low-latitudes. In doing so, we calculate spring LAI and summer δ SWC anomalies weighted by both area and annual mean soil moisture values. Again, a significant negative correlation is found between spring LAI and summer δ SWC (fig. S6, C and D). This spring LAI-induced drying trend of summer SWC ($-0.09 \pm 0.06 \times 10^{-4} \text{ m}^3 \text{ m}^{-3} \text{ yr}^{-1}$) is consistent with that without assigning a lower weight to drier regions (Fig. 2A), partly because earlier greening mainly occurs in regions with favorable moisture conditions. Therefore, our GCM simulations provide robust process-based evidence that the observed overall earlier greening of northern land causes extra decreases in summer soil moisture.

Intra- and inter-seasonal soil moisture anomalies are determined by the balance between changes in ET, precipitation and runoff (Schematic, Fig. 3). To gain more insights into how spring vegetation changes feedback on soil moisture, we further use the paired GCM experiments to examine changes in these major hydrological fluxes. Higher spring LAI levels tend to accelerate water recycling from the land surface to the atmosphere through enhanced plant transpiration. As transpiration dominates total terrestrial ET (26) (average transpiration/ET ratio of IPSL-CM4: 0.47 for spring and 0.76 for summer), a higher spring transpiration directly leads to higher modelled spring ET ($+0.28 \pm 0.06 \text{ mm yr}^{-2}$, $p < 0.01$) (Fig. 2D). We also note that the overall trend of IPSL-simulated spring ET is not statistically significant ($p > 0.05$), which is confirmed by two observation-based ET products (fig. S5A). This is mainly because the significant ET increase in regions with spring greening is compensated by ET decrease in regions with spring browning, when integrated to the hemispheric scale (fig. S7). For this greening-enhanced ET, however, only a proportion (71%) is subsequently recycled as additional land precipitation during MAM ($0.20 \pm 0.09 \text{ mm yr}^{-2}$, $p < 0.01$) (Fig. 2D). During MAM, this imbalance between increasing precipitation and ET due to earlier phenology and LAI development results in a decreasing trend in both soil moisture ($-0.11 \pm 0.09 \times 10^{-4} \text{ m}^3 \text{ m}^{-3} \text{ yr}^{-1}$) and surface runoff ($-0.08 \pm 0.09 \text{ mm yr}^{-2}$). The larger increase in ET than in precipitation is much more pronounced when considering only regions with spring greening, where it causes a strong signal of soil drying (Fig. 2, B and E). However, in regions with spring browning, there is a stronger decrease in ET than in precipitation, thus causing soil wetting (Fig. 2, C and F). These contrasting responses, where ET changes do not balance precipitation changes, suggest a geographical redistribution of the extra atmospheric water vapour from regions with earlier greening, towards regions with browning, within the springtime.

Our factorial model simulations allow further investigation of the soil moisture legacy effects into the summer following a spring with altered phenology and hydrology. We find that the spring soil moisture deficit caused by earlier greening is indeed carried over into the summer months (Fig. 2D, blue bars). The inter-seasonal soil moisture memory propagates this moisture deficit forward, and this also involves additional contribution of soil moisture-atmosphere biophysical feedbacks. Given the short memory of days to weeks of the atmosphere, the atmospheric moisture anomaly from earlier greening is dissipated mainly in the springtime, through extra spring rainfall (Fig. 2D). The lower soil moisture levels in late spring due to a prolonged period of stronger decrease and insufficient rainfall re-supply, become less accessible for plant root uptake and soil evaporation (27), particularly in climatologically water-stressed regimes. Hence, summer δET decreases substantially across the entire study area ($-0.10 \pm 0.05 \text{ mm yr}^{-2}$), and summer δP (precipitation) decreases even more ($-0.19 \pm 0.08 \text{ mm yr}^{-2}$), leading to a slightly strengthened decreasing trend in summer SWC ($-0.11 \pm 0.09 \times 10^{-4} \text{ m}^3 \text{ m}^{-3} \text{ yr}^{-1}$) (Fig. 2D). This summer drying signal is larger and statistically significant in areas with extra spring greening (Fig. 2E). The significantly decreasing spring LAI ($p < 0.05$) in areas with spring browning do not, however, generate significant changes in any of the hydrological fluxes in summer (i.e. ET, P, runoff and SWC; all $p > 0.1$) (blue bars in Fig. 2F). In these browning regions, soil moisture anomalies in spring have little impact on subsequent summer water recycling ($\delta ET \gg 0$) and hence summer rainfall feedbacks. It is noteworthy that both spring greening and browning tend to decrease the amount of summer precipitation (Fig. 2, E and F). This implies that the current spring LAI levels may have evolved to be an optimum that maximizes the precipitation retained on continents in the subsequent summer season.

We further investigated the spatial pattern of the GCM-derived soil moisture trend in δ SWC (Fig. 4; other hydrological fluxes in fig. S8). Generally, the modelled summer δ SWC pattern and observed summer SWC anomalies associated with the first MCA mode (Fig. 1, D and F) are highly similar, providing mechanistic support for our observation-based findings. Besides, the summer δ SWC pattern closely resembles the spring δ SWC pattern (Fig. 4B versus Fig. 4A), implying the dominant role of soil moisture memory in carrying this greening-induced water deficit into the summer. Areas with the highest rates of summer drying ($> 0.1 \times 10^{-3} \text{ m}^3 \text{ m}^{-3} \text{ yr}^{-1}$) occur mainly in Europe, eastern Asia, western Asia and eastern North America (Fig. 4B), where pronounced advances of vegetation greening occur during spring (fig. S1). Conversely, a summer wetting trend of soil moisture dominates regions with spring browning, such as central and northwestern North America (Fig. 4B versus fig. S1). One notable exception is again the central Siberian regions where a strong modelled soil wetting trend occurs in both spring and summer ($> 0.05 \times 10^{-3} \text{ m}^3 \text{ m}^{-3} \text{ yr}^{-1}$) (Fig. 4), despite the presence of a clear spring greening tendency there that generally lowers summer soil moisture elsewhere (Fig. 4 and fig. S1). The GCM simulations show that this trend of regional wetting in Siberia is caused by different mechanisms in the two seasons. In spring, the extra water vapour recycled into the atmosphere in upstream regions (Europe) with strong greening, is carried to Siberia by westerly winds (fig. S9A). This imported extra precipitation moistens local soils and offsets the soil moisture deficit originated from local spring greening (Schematic Fig. 3). During the following summer, when the prevailing westerly winds become weaker (fig. S9B), the Siberian region operates as a more closed system with intensified local water recycling (fig. S8). Consequently, the imported extra soil moisture in springtime helps to sustain local positive feedbacks on summer precipitation and is ultimately retained in the Siberian soils throughout the boreal summer. This

additional summer wetting from the earlier greening of local and remote regions, in total, accounts for over 90% of the overall summer soil wetting trend derived from LAI_{obs}^{MAM} , showing its much more important role for Siberia than the ongoing climate change.

Implications for Near-surface Land Climate in Summer

Lower soil moisture can trigger the occurrence, or amplify the frequency and intensity of heatwaves, by altering the surface energy balance (17, 28, 29). Our finding that earlier greening pre-conditions summer soils to be drier thus implies a shift in the distribution of summer surface air temperature towards even more hot extremes, adding to the warming-induced increase in extreme occurrence. To verify this mechanism with our paired GCM simulations, we calculate two extreme hot temperature indices (30): i) the summer maximum of daily maximum temperature (TXx) and ii) the number of summer days with maximum temperatures exceeding the local 90th percentile of a given base period, here as 1982–2011 (TX90p) (see Methods). We find that earlier spring greening increases both TXx and TX90p (Fig. 5 and fig. S10) across the land regions where it depletes summer soil moisture more strongly (Fig. 4B). Conversely, regions with additional summer soil wetting from spring LAI changes exhibit fewer hot extremes in summer. On average, our paired GCM analysis shows that the overall soil drying causes an additional 23% and 26% increase (increasing rates of $0.8 \text{ days decade}^{-1}$ for summer $\delta TX90p$ and $0.07 \text{ }^{\circ}\text{C decade}^{-1}$ for summer δTXx) in TX90p and TXx, respectively, which exacerbates the summer heatwaves caused directly by background global warming. This finding implies the existence of a positive feedback: human-induced global warming causes earlier spring greening and thus forces lower summer soil moisture. This, in turn, aggravates further the higher frequency and intensity of hot summer extremes driven by rising greenhouse gas concentrations (31).

391

392 **Discussion**

393 Our combined use of satellite observations and model simulations suggest that a more
394 intense water loss from land soils during spring, due to earlier vegetation greening,
395 lowers soil moisture in spring and summer. This moisture depletion further reduces
396 surface evaporative cooling and thus increases the possibility of stronger summer
397 heatwaves. Exacerbated soil water limitation, together with more extreme weather events
398 in summer, may restrain vegetation growth and suppress ecosystem productivity,
399 especially for climatologically arid ecosystems that are sensitive to summer water
400 availability (e.g. western U.S.). Our study has important implications for more accurate
401 predictions of summer weather and climate features. For many parts of the world, climate
402 models and measurements show that surface meteorological conditions are affected by
403 both large-scale atmospheric circulation patterns, as well as by local soil moisture status
404 in some regions with strong vegetation-atmosphere coupling (17, 32). The results of this
405 study highlight the necessity of also accounting for spring plant phenology in weather and
406 climate forecasting of summer months, given their capacity to modulate summer soil
407 moisture levels through the inter-seasonal biophysical feedbacks.

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409 One limitation of our analysis is the examination of diagnostics from an ensemble based
410 on a single climate model. This concern is offset by our findings of modelled spring-to-
411 summer greenness-soil moisture linkages having consistency with results of parallel
412 observation-based analysis (Fig. 1). However, for future studies, we encourage other
413 modelling centres to perform similar factorial experiments to ours, to verify the lagged
414 hydrological impacts of earlier vegetation phenology. This includes independent model
415 evidence of our discovery that precipitation feedbacks can alleviate greening-induced soil

drying for some locations, involving the role of atmospheric teleconnections. Such assessment must rely on high-resolution GCMs that have accurate representations of large-scale atmospheric circulation processes. Furthermore, root-zone soil moisture relevant for deep-rooted plants are not directly measurable at large spatial scales. Hence, currently some uncertainties exist in soil moisture estimates from both observation-driven products and GCMs, in terms of the magnitude, inter-annual variability and trends. Future improvements of root-zone soil moisture may be fulfilled by integrating in situ soil moisture measurements at different depths, microwave-based surface soil moisture and robust surface-to-root-zone scaling approaches (e.g. ref. 33). This will enable additional verification of our identified soil moisture responses to the ongoing earlier greening, and also aid enhanced soil moisture parameterizations in the next generation of CGMs. Whilst we are confident of the broad applicability of our findings, such improved simulations of soil moisture will allow refinement of magnitudes of our discovered feedbacks.

Human land-use changes may have strong imprints on the seasonal linkage between natural plants and soil moisture. The phenology of crops is strongly controlled by management actions, including fertilizer use, cropping calendars, multi-cropping, quick-growing hybrid cultivars, pest control and notably, irrigation. The latter can effectively sustain soil moisture of irrigated croplands throughout the growing season, causing different correlations between crop growth and soil moisture. However, at present, many agricultural practices are not explicitly represented in GCMs, which limits our capacity to simulate the hydrological consequences of cropland managements. As we illustrate how vegetation greening feedbacks can be strongly modulated by human land-use, this demonstrates the importance for the next generation of GCMs to include dynamic crop growth and realistic irrigation schemes. This will enable more accurate simulation of

vegetation-soil moisture interactions with human interventions. In addition, the hydrological feedbacks of afforestation, reforestation and forest management practices over regions like China are not assessed separately from those of natural vegetation greening. Deliberately planted trees are expected to have similar variations in LAI as existing forests, causing similar alterations to the water cycle via changing transpiration and regional to large-scale precipitation patterns. Nonetheless, the ability of plants to transpire water varies with species composition and forest age (34), which should be taken into account in future assessment of hydrological impacts of large-scale afforestation/reforestation.

Materials and Methods

Experimental Design

We utilised satellite-derived measurements of LAI (as a proxy for vegetation “greenness”) and reanalysis-based soil moisture to identify any significant relations between spring vegetation phenology and summer soil moisture, using the Maximum Covariance Analysis (MCA) approach. We also used factorial experiments by the IPSL-CM Earth System Model to provide process understanding of observation-based greenness-to-soil moisture linkages.

Observational Data Sets

Vegetation greenness was characterized using a gridded bi-weekly LAI data set derived from the Global Inventory Monitoring and Modeling Studies (GIMMS) LAI3g at an 8-km spatial resolution and 15-day interval for the period 1982–2011 (20). This global LAI product was generated from the GIMMS Advanced Very High Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (NDVI) 3g data and Moderate

Resolution Imaging Spectroradiometer (MODIS) LAI data using an artificial neural network algorithm (20). The GIMMS LAI3g data have been demonstrated to have good quality through direct comparisons with field measurements and inter-comparisons with other satellite-derived LAI products (35). Monthly LAI maps were obtained by calculating the maximum value of the two composites in each month at the original 8-km resolution, and were then aggregated to each $0.5^{\circ} \times 0.5^{\circ}$ grid cell that was used for our model simulation during the study period.

Besides LAI, other observed boundary conditions prescribed for IPSL-CM include SST and SIC maps and atmospheric CO_2 concentrations, all covering the study period 1982–2011. Monthly SST and SIC data sets were both obtained from the Atmospheric Model Intercomparison Project (AMIP; <https://esgf-node.llnl.gov/news/list/input4mips/>) with a $1^{\circ} \times 1^{\circ}$ spatial resolution. Global annual atmospheric CO_2 concentrations were derived from those used for transient simulations of the TRENDY project (“Trends and drivers of the regional scale sources and sink of carbon dioxide”, <http://dgvm.ceh.ac.uk/node/9>).

Two independent SWC-related data sets covering the period of 1982–2011 were used for detecting coupled patterns of variability with changes in spring LAI and for evaluating modeling results. The first one is the satellite-derived zoot-zone soil moisture from the Global Land Evaporation Amsterdam Model (21) (GLEAM v3.2a). The GLEAM data set fully assimilates reanalysis-based temperature and radiation, and remotely-sensed top-layer soil moisture, L-band vegetation optical depth (VOD) and snow water equivalents from different satellite sensors (21), and also uses multi-source precipitation forcings.

The assimilation of surface soil moisture allows us to diagnose where irrigation in agricultural regions is perturbing the hydrological cycle and the vegetation-soil moisture

491 feedbacks between spring and summer. Meanwhile, the forced precipitation and implied
492 differences in hydrological balance provide data-based indications of where atmospheric
493 teleconnections are transporting extra moisture. In addition, GLEAM incorporates VOD
494 to calculate the effects of water stress, heat stress and phenological constraints on ET
495 (21). In this way, it indirectly accounts for the influence of plant phenological changes on
496 soil moisture. VOD and LAI are intrinsically related, but this does not generate circularity
497 as we test for the link between GLEAM summer SWC and spring LAI measurements
498 from optical satellite data. This is because VOD is controlled not only by plant structure
499 (in part characterized by LAI), but additionally by plant hydraulic strategies (i.e. stomatal
500 and xylem regulation on water use) (36). The seasonal development of L-band VOD and
501 LAI is proven to differ considerably for some biomes, such as woody savannas of which
502 water is mainly stored in stems or branches (36). The GLEAM SWC data have been
503 extensively used in examining land-atmosphere feedbacks and benchmarking climate
504 model simulations (e.g. ref. 16). Note that the GLEAM root-zone soil moisture, of which
505 the maximum depth ranges between 10 and 250 cm depending on local vegetation types,
506 was here treated as a substitute for total soil moisture.

507
508 The other soil moisture-related data is GRACE-REC, a global reconstruction of terrestrial
509 water storage (TWS) anomalies based on the GRACE satellite retrievals (22). The past
510 TWS anomalies are reconstructed using a statistical model forced by daily precipitation
511 and temperature anomalies, but trained with original TWS data from GRACE satellites
512 for 2002-present (22). The TWS anomalies, expressed as the equivalent water thickness
513 (units: cm), include not only soil moisture in the upper layers, but also snowpack, canopy
514 water, riverine and lacustrine water and groundwater. Removing these non-soil moisture

components from the TWS anomalies is technically challenging, so some caution is needed when interpreting the TWS-based results (Fig. 1, B, E and F).

We also obtained a range of observation-based data sets to evaluate model performance for hydrological variables besides SWC (ET and P). No direct observations of global land ET have been reported, so we used two satellite-derived reconstructions of long-term land ET. The first, FLUXNET-MTE, is based on field eddy-covariance measurements (37), and the second, WB-MTE, is based on information for precipitation, river discharge and changes in water mass balance (38). Both ET products use satellite measurements to scale up either site- or catchment-level ET observations to a $0.5^{\circ} \times 0.5^{\circ}$ global grid cell using a machine learning algorithm. Gridded data for global monthly precipitation were obtained from the Global Precipitation Climatology Centre (39) (GPCC) version 6.0 and the Climate Research Unit (CRU) TS3.22 data sets (40).

Model and Experimental Setup

IPSL-CM (24) is a coupled land-atmosphere global climate model (GCM), versions of which continuously contribute to the Coupled Model Intercomparison Project (CMIP) initiatives, thus informing assessment reports of the Intergovernmental Panel on Climate Change (IPCC). We employed the IPSL-CM version 4 GCM, which consists of the atmospheric component LMDZ (the Laboratoire de Météorologie Dynamique general circulation model with Zooming capability) and the land surface component ORCHIDEE (Organizing Carbon and Hydrology In Dynamic Ecosystems (41)). The soil hydrology within ORCHIDEE consists of two moisture layers with a constant total depth of 2 m water content per unit soil volume. Vegetation in this land surface model is described globally with 13 plant functional types (PFTs), each using different governing equations

and taking different parameter values to represent the onset and offset processes of the leafy season (41). Using the IPSL-CM coupled model, changes in hydrological fluxes due to vegetation biophysical feedbacks were determined by replacing the modeled LAI in the ORCHIDEE land surface model with satellite observations prescribed for each of the 13 PFTs.

To investigate how spring vegetation feedbacks modulate summer soil moisture patterns in the last 30 years, we conducted a pair of transient GCM simulations prescribed with different spring LAI conditions. One experiment (abbreviated as LAI_{obs}^{MAM}) was prescribed with satellite-observed annually varying monthly LAI maps for 1982–2011 (including MAM). The other experiment (abbreviated as LAI_{clim}^{MAM}) was also prescribed with satellite-observed LAI maps identically to the LAI_{obs}^{MAM} experiment, except for spring months.

During MAM, the LAI maps for each year were replaced with average monthly values over the entire study period (1982–2011). Spring greening in the real world may affect soil moisture via a coupling to changes in oceanic and atmospheric conditions, hence both experiments were fed additionally with other boundary conditions of sea-surface temperature (SST), sea-ice fraction (SIF) and atmospheric CO_2 concentration. With this numerical experiment design, the fingerprint of earlier greening on summer hydrological variables can be calculated as the difference between the two experiments (i.e. $LAI_{obs}^{MAM} - LAI_{clim}^{MAM}$). The original or MAM-averaged LAI data-based time series (20) were used to prescribe LAI for each GCM grid cell and for each PFT within a grid cell. To reduce the effect of initial conditions uncertainty due to internal climate variability, we conducted an ensemble of 30 simulations for each experiment with different initial conditions. The initial conditions were derived from the model outputs of an undisturbed 60-year run (i.e. with average LAI for all seasons, average SST, SIF and atmospheric CO_2 concentrations):

the first 30 years of the run for the spin-up of the simulation and then each of the last 30 years of the run for providing an alternative initial condition. All our model-based analyses were based on the 30-member ensemble mean of each transient experiment. Only vegetated areas, defined as regions with multi-year (1982–2011) average LAI ≥ 0.1 , were considered to reduce the spurious influence of bare and sparsely vegetated areas on the overall trend in LAI. All quantities averaged over the Northern Hemisphere (25–90°N) are weighted by area, unless otherwise noted.

Indices of Extreme Hot Temperatures

We used two metrics to measure modelled changes in summer extreme hot temperatures due to the earlier spring vegetation onset, following a previous study of extreme-temperature detection (30). One metric measures the frequency of extreme hot temperatures, expressed as the number of summer days with maximum daily temperatures exceeding the 90% percentile of a baseline period (TX90p). The percentiles were calculated for each calendar day over a 15-day moving window using the 30-year simulation forced by observed LAI and other boundary conditions (i.e. LAI_{obs}^{MAM}) (1982–2011). The other metric measures the intensity of extreme hot temperature events, as expressed as the summer maximum of daily maximum temperature (TXx). Both indices were first calculated for both 30-ensemble mean experiments (LAI_{obs}^{MAM} and LAI_{clim}^{MAM}), and changes in TX90p and TXx induced by earlier spring greening were then calculated as the difference between the indices derived from the two simulations with and without spring LAI changes.

Statistical Analysis

We applied partial correlation analysis in this study to evaluate the relationship between spring LAI and summer soil moisture, after statistically controlling for the covarying effects of summer LAI and climatic variables (including summer temperature, precipitation and solar radiation). These climatic variables are all derived from the CRU TS3.22 data sets. We also used the MCA analysis to characterize the coupling patterns between spring LAI and summer SWC. This approach is also known as the singular value decomposition (SVD) (23), which can be considered as a generalization of principle component analysis. MCA has been widely used in environmental sciences to detect teleconnection patterns in the ocean-atmosphere-land system (e.g. ref. 42). The MCA analysis looks for pairs of spatial patterns and associated time series (or called expansion coefficients) that efficiently explain the covariance between two space-time data fields. This is realized by performing SVD on the cross-covariance matrix between the two fields, yielding a set of singular vectors and singular values that are associated with pairs of spatial patterns. The time series for each pattern pair (fig. S4) are calculated by projecting one data field onto the respective singular vector. The correlation coefficient between the time series of the two fields indicates how strongly related the coupled patterns are. Heterogeneous regression maps (Fig. 1, C-F and fig. S6, A and B) are generated by regressing the gridded values of one field to the time series of the pattern amplitude of other. Detailed mathematical basis of the MCA algorithm is described in section S2.

Supplementary Materials

Supplementary Text

Section. S1. Earlier spring vegetation greening revealed by remote sensing

614 Section. S2. Mathematical basis of the MCA analysis

615 Section. S3. Model evaluation using available observations

616 Figures S1-S10

617 Fig. S1. Spatial patterns of the trend in spring vegetation changes for 1982-2011.

618 Fig. S2. Grassland partial correlations between ESA-CCI summer SWC and GIMMS
619 spring LAI during 1982-2011.

620 Fig. S3. Partial correlations between spring LAI and either summer SWC or summer
621 TWS, as affected by agricultural extent.

622 Fig. S4. Time series (or expansion coefficients) of the leading first MCA patterns.

623 Fig. S5. Validation of IPSL-simulated hydrological variables.

624 Fig. S6. Robustness test of the IPSL-simulated relationship between spring LAI and
625 summer SWC.

626 Fig. S7. Comparison of trends of observation-based and IPSL-simulated ET.

627 Fig. S8. Spatial patterns of IPSL-simulated trends in key hydrological variables induced
628 by spring LAI changes.

629 Fig. S9. IPSL-simulated average global prevailing wind at 10-m height.

630 Fig. S10. Spatial patterns of IPSL-simulated trends in summer extreme hot temperature
631 indices induced by spring LAI changes.

634 References and Notes

- 635 1. J. Barichivich *et al.*, Large-scale variations in the vegetation growing season and annual cycle
636 of atmospheric CO₂ at high northern latitudes from 1950 to 2011. *Glob. Chang. Biol.* **19**, 3167–
637 3183 (2013).
- 638 2. S. Piao *et al.*, Leaf onset in the northern hemisphere triggered by daytime temperature. *Nat.*

- 639 *Commun.* **6**, 6911 (2015).
- 640 3. Q. Liu *et al.*, Delayed autumn phenology in the Northern Hemisphere is related to change in
641 both climate and spring phenology. *Glob. Chang. Biol.* **22**, 3702–3711 (2016).
- 642 4. M. D. Schwartz, R. Ahas, A. Aasa, Onset of spring starting earlier across the Northern
643 Hemisphere. *Glob. Chang. Biol.* **12**, 343–351 (2006).
- 644 5. A. Menzel *et al.*, European phenological response to climate change matches the warming
645 pattern. *Glob. Chang. Biol.* **12**, 1969–1976 (2006).
- 646 6. Y. H. Fu *et al.*, Recent spring phenology shifts in western Central Europe based on multiscale
647 observations. *Glob. Ecol. Biogeogr.* **23**, 1255–1263 (2014).
- 648 7. C. D. Keeling, J. F. S. Chin, T. P. Whorf, Increased activity of northern vegetation inferred from
649 atmospheric CO₂ measurements. *Nature*. **382**, 146 (1996).
- 650 8. S. Piao, P. Friedlingstein, P. Ciais, N. Viovy, J. Demarty, Growing season extension and its
651 impact on terrestrial carbon cycle in the Northern Hemisphere over the past 2 decades. *Glob.*
652 *Biogeochem. Cycles*. **21**, 1–11 (2007).
- 653 9. S. Wolf *et al.*, Warm spring reduced carbon cycle impact of the 2012 US summer drought. *Proc.*
654 *Natl. Acad. Sci. U. S. A.* **113**, 5880–5885 (2016).
- 655 10. A. Angert *et al.*, Drier summers cancel out the CO₂ uptake enhancement induced by warmer
656 springs. *Proc. Natl. Acad. Sci. U. S. A.* **102**, 10823–10827 (2005).
- 657 11. W. Buermann, P. R. Bikash, M. Jung, D. H. Burn, M. Reichstein, Earlier springs decrease peak
658 summer productivity in North American boreal forests. *Environ. Res. Lett.* **8**, 24027 (2013).
- 659 12. W. Buermann *et al.*, Widespread seasonal compensation effects of spring warming on northern
660 plant productivity. *Nature*. **562**, 110–114 (2018).
- 661 13. S. Sippel *et al.*, Contrasting and interacting changes in simulated spring and summer carbon
662 cycle extremes in European ecosystems. *Environ. Res. Lett.* **12**, 75006 (2017).
- 663 14. R. J. Van Der Ent, H. H. G. Savenije, B. Schaefli, S. C. Steele-Dunne, Origin and fate of

- 664 atmospheric moisture over continents. *Water Resour. Res.* **46**, W09525 (2010).
- 665 15. Z. Zeng *et al.*, Impact of Earth greening on the terrestrial water cycle. *J. Clim.* **31**, 2633–2650
666 (2018).
- 667 16. Y. Li *et al.*, Divergent hydrological response to large-scale afforestation and vegetation
668 greening in China. *Sci. Adv.* **4**, eaar4182 (2018).
- 669 17. B. Quesada, R. Vautard, P. Yiou, M. Hirschi, S. I. Seneviratne, Asymmetric European summer
670 heat predictability from wet and dry southern winters and springs. *Nat. Clim. Chang.* **2**, 736–
671 741 (2012).
- 672 18. A. Berg *et al.*, Land-atmosphere feedbacks amplify aridity increase over land under global
673 warming. *Nat. Clim. Chang.* **6**, 869–874 (2016).
- 674 19. A. L. S. Swann, I. Y. Fung, J. C. H. Chiang, Mid-latitude afforestation shifts general circulation
675 and tropical precipitation. *Proc. Natl. Acad. Sci. U. S. A.* **109**, 712–716 (2012).
- 676 20. Z. Zhu *et al.*, Global data sets of vegetation leaf area index (LAI)3g and Fraction of
677 Photosynthetically Active Radiation (FPAR)3g derived from Global Inventory Modeling and
678 Mapping Studies (GIMMS) Normalized Difference Vegetation Index (NDVI3g) for the period
679 1981 to 2011. *Remote Sens.* **5**, 927–948 (2013).
- 680 21. B. Martens *et al.*, GLEAM v3: Satellite-based land evaporation and root-zone soil moisture.
681 *Geosci. Model Dev.* **10**, 1903–1925 (2017).
- 682 22. V. Humphrey, L. Gudmundsson, S. I. Seneviratne, A global reconstruction of climate-driven
683 subdecadal water storage variability. *Geophys. Res. Lett.* **44**, 2300–2309 (2017).
- 684 23. C. S. Bretherton, C. Smith, J. M. Wallace, An intercomparison of methods for finding coupled
685 patterns in climate data. *J. Clim.* **5**, 541–560 (1992).
- 686 24. O. Marti *et al.*, Key features of the IPSL ocean atmosphere model and its sensitivity to
687 atmospheric resolution. *Clim. Dyn.* **34**, 1–26 (2010).
- 688 25. A. Berg, J. Sheffield, P. C. D. Milly, Divergent surface and total soil moisture projections under

- 689 global warming. *Geophys. Res. Lett.* **44**, 236–244 (2017).
- 690 26. X. Lian *et al.*, Partitioning global land evapotranspiration using CMIP5 models constrained by
691 observations. *Nat. Clim. Chang.* **8**, 640–646 (2018).
- 692 27. M. Stéfanon, P. Drobinski, F. D’Andrea, N. De Noblet-Ducoudré, Effects of interactive
693 vegetation phenology on the 2003 summer heat waves. *J. Geophys. Res. Atmos.* **117**, D24103
694 (2012).
- 695 28. M. Hirschi *et al.*, Observational evidence for soil-moisture impact on hot extremes in
696 southeastern Europe. *Nat. Geosci.* **4**, 17–21 (2011).
- 697 29. M. M. Vogel *et al.*, Regional amplification of projected changes in extreme temperatures
698 strongly controlled by soil moisture-temperature feedbacks. *Geophys. Res. Lett.* **44**, 1511–1519
699 (2017).
- 700 30. S. E. Perkins, L. V. Alexander, On the measurement of heat waves. *J. Clim.* **26**, 4500–4517
701 (2013).
- 702 31. N. Christidis, G. S. Jones, P. A. Stott, Dramatically increasing chance of extremely hot
703 summers since the 2003 European heatwave. *Nat. Clim. Chang.* **5**, 46–50 (2014).
- 704 32. D. L. Swain *et al.*, Trends in atmospheric patterns conducive to seasonal precipitation and
705 temperature extremes in California seasonal precipitation and temperature extremes. *Sci. Adv.*
706 **2**, e1501344 (2016).
- 707 33. Albergel, C. *et al.*, From near-surface to root-zone soil moisture using an exponential filter: an
708 assessment of the method based on in-situ observations and model simulations. *Hydrol. Earth*
709 *Syst. Sci.* **12**, 1323–1337 (2008).
- 710 34. S. T. Brantley, C. F. Miniati, P. V. Bolstad, Rainfall partitioning varies across a forest age
711 chronosequence in the southern Appalachian Mountains. *Ecohydrology*, **12**, e2081 (2019).
- 712 35. H. E. Beck *et al.*, Global evaluation of four AVHRR–NDVI data sets: Intercomparison and
713 assessment against Landsat imagery. *Remote Sens. Environ.* **115**, 2547–2563 (2011).

- 714 36. F. Tian *et al.*, Coupling of ecosystem-scale plant water storage and leaf phenology observed by
715 satellite. *Nat. Ecol. Evol.* **2**, 1428–1435 (2018).
- 716 37. M. Jung *et al.*, Recent decline in the global land evapotranspiration trend due to limited
717 moisture supply. *Nature*. **467**, 951–954 (2010).
- 718 38. Z. Zeng *et al.*, A worldwide analysis of spatiotemporal changes in water balance-based
719 evapotranspiration from 1982 to 2009. *J. Geophys. Res. Atmos.* **119**, 1186–1202 (2014).
- 720 39. A. Becker *et al.*, A description of the global land-surface precipitation data products of the
721 Global Precipitation Climatology Centre with sample applications including centennial (trend)
722 analysis from 1901–present. *Earth Syst. Sci. Data*. **5**, 71–99 (2013).
- 723 40. I. Harris, P. D. Jones, T. J. Osborn, D. H. Lister, Updated high-resolution grids of monthly
724 climatic observations – the CRU TS3.10 Dataset. *Int. J. Climatol.* **34**, 623–642 (2014).
- 725 41. G. Krinner *et al.*, A dynamic global vegetation model for studies of the coupled atmosphere-
726 biosphere system. *Glob. Biogeochem. Cycles*. **19**, 1–33 (2005).
- 727 42. A. Dai, Increasing drought under global warming in observations and models. *Nat. Clim.*
728 *Chang.* **3**, 52–58 (2013).
- 729 43. S. Piao *et al.*, Plant phenology and global climate change: Current progresses and challenges.
730 *Glob. Chang. Biol.* **25**, 1922–1940 (2019).

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Figure captions

Fig. 1. Coupling between observed spring LAI and summer SWC during 1982-2011.

Spatial pattern of partial correlation coefficients between GIMMS spring LAI and (A) GLEAM summer SWC, or (B) GRACE-REC summer TWS for 1982-2011.

Black stipples indicate regions with a statistically significant correlation ($p < 0.05$). Heterogeneous regression maps of (C, E) GIMMS spring LAI and (D, F) GLEAM summer SWC (or GRACE-REC summer TWS), associated with the first MCA mode for 1982-2011. The squared fractional covariance (SFC) explained by the first MCA mode is 46.3% and 58.9% for the GLEAM and GRACE-REC data sets, respectively.

Fig. 2. IPSL-simulated changes in summer soil moisture induced by spring LAI changes. (A–C) Inter-annual anomalies of the area-weighted average of spring LAI (green dotted lines) and summer δ SWC (blue solid lines) for (A) all northern latitudes (25–90°N), (B) regions with positive LAI trends (i.e. greening) and (C) regions with negative LAI trends (i.e. browning). The red lines indicate the least-squares linear regression of GCM-based δ SWC (straight lines) against time and the 95% confidence intervals (curves). Note that the right axes are reversed, so higher LAI values are towards the bottom of the plots. (D–F) Inter-annual trends in mean spring LAI and resultant changes in the spring and summer hydrological variables of ET, precipitation (P), runoff (Q) and SWC. The subplot maps at the bottom of each main panel display the corresponding averaged areas as gray (the same as panels A–C).

Fig. 3. Schematic of the effect of earlier greening on summer soil moisture. Earlier spring greening influences spring soil moisture by altering land-atmosphere water exchanges (via ET, P and Q) and by the redistribution of atmospheric water vapour by atmospheric circulation. This spring soil moisture anomaly persists later into the following summer due to the carry-over effects of soil moisture. The magnitude of this cross-seasonal vegetation feedback and the role of atmospheric circulation, however, vary geographically. Three typical examples of the circulation-modulated vegetation feedback (Europe, Siberia and eastern China) are displayed at the bottom of the schematic.

Fig. 4. Spatial patterns of IPSL-simulated trends in soil moisture induced by spring LAI changes. Shown are spatial patterns of the linear trends in spring (left) and

summer (right) δ SWC changes. This change in soil moisture induced by earlier spring greening, δ SWC, is obtained as the difference between the two simulations with and without spring LAI changes. (i.e. $LAI_{obs}^{MAM} - LAI_{clim}^{MAM}$). Black stipples indicate regions with a statistically significant linear trend ($p < 0.05$).

Fig. 5. IPSL-simulated changes in summer extreme hot temperature indices related to δ SWC changes. The average linear trend of (A) δ TXx and (B) δ TX90p due to earlier greening for different summer δ SWC trends binned into $0.4 (\times 10^{-4} \text{ m}^3 \text{ m}^{-3} \text{ yr}^{-1})$ intervals. The δ TXx and δ TX90p values are obtained as the difference between the two simulations with and without spring LAI changes ($LAI_{obs}^{MAM} - LAI_{clim}^{MAM}$). The insets are scatterplots of trends in δ TXx (left) and δ TX90p (right) versus trends in δ SWC for 1982–2011. Each colored dot in the scatterplots represents a grid cell in the pattern of trends in δ TXx or δ TX90p (fig. S10).