Here I analyze the observed and projected surface temperature anomalies over land between 50°S-50°N for the period 1950–2099 by large-scale ecoregion and find strongest warming consistently and persistently seen over driest ecoregions such as the Sahara desert and the Arabian Peninsula during various 30-year periods, pointing to desert amplification in a warming climate. This amplification enhances linearly with the global mean greenhouse gases (GHGs) radiative forcing and is attributable primarily to a stronger GHGs-enhanced downward longwave radiation forcing reaching the surface over drier ecoregions as a consequence of a warmer and thus moister atmosphere in response to increasing GHGs. These results indicate that desert amplification may represent a fundamental pattern of global warming associated with water vapor feedbacks over land in low- and mid- latitudes where surface warming rates depend inversely on ecosystem dryness. It is likely that desert amplification might involve two types of water vapor feedbacks that maximize respectively in the tropical upper troposphere and near the surface over deserts, with both being very dry and thus extremely sensitive to changes of water vapor.

The observed global mean surface temperature has increased by 0.85 °C for the period 1880–2012 and this warming has been attributed mostly to the increase in anthropogenic greenhouse gases (GHGs) in the atmosphere1. Global coupled atmosphere-ocean general circulation models (AOGCMs) driven by a set of scenarios of anthropogenic forcings, Representative Concentration Pathways (RCPs), project a further warming up to 4.8 °C for 2081–2100 relative to 1986–20051. Observational and model studies of temperature change, climate feedbacks and variations in the Earth’s energy budget together provide confidence in the magnitude of global warming in response to past and future forcing1.

The positive GHGs-induced radiative forcing is global-scale but can be amplified or dampened by various atmospheric and terrestrial feedbacks2,3. Over land, evapotranspiration (ET) is a primary process driving energy and water exchanges in the interface of hydrosphere, atmosphere and biosphere4. It can largely weaken this positive forcing and thus determine spatial patterns of surface warming among different ecosystems. After analyzing observed land surface air temperature trends in low- and mid- latitudes for the period 1979–2012, Zhou et al.5 found a spatial dependence of observed surface warming on terrestrial dryness, with the strongest warming rate seen over the driest ecoregions such as the Sahara desert and the Arabian Peninsula, suggesting a warming amplification mechanism over deserts (i.e., desert amplification). Based on a comprehensive analysis of observations, reanalysis data and historical simulations for the period 1979–2012, Zhou et al.5 proposed that desert amplification may result mainly from stronger GHGs-enhanced downward longwave radiation reaching the surface associated with water vapor feedbacks over drier ecoregions, rather than from land surface processes as the deserts have too limited amounts of vegetation and soil moisture (SM) to influence ET. This finding, if true, has important implications for understanding climate sensitivity to anthropogenic forcings, uncovering mechanisms of spatio-temporal patterns of climate change, and assessing climatic impacts6.

However, desert amplification was proposed based on the analysis of only 34 years of data (1979–2012), which are too short to detect a climate signal and particularly overlap with the global warming hiatus1. Furthermore, simple linear trends were calculated to estimate the warming rates and the linear trend for a short time series depends strongly on the choice of the beginning and end points of data. This raises an important question of whether this amplification is a true long-term signal of global warming or simply short-term climate variability for the period 1979–2012. Here I analyze observational temperatures and historical and projected simulations of 26 AOGCMs (Table S1) over land for the period 1950–2099 (see Method for detail) to further this amplification at longer time scales. Unlike the previous studies5,7 which estimated the linear trends and analyzed primarily land surface variables, different 30-year average anomalies relative to the same reference period 1961–1990 are used to

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quantify the warming magnitude over different periods and atmospheric profiles are also examined to further the linkage between water vapor and the amplification.

The observations (OBS) are obtained from the ensemble mean of three widely used surface air temperature datasets for the period 1950–2013. There are two groups of historical simulations for the period 1950–2005: one with both anthropogenic and natural forcings (referred to as ALL) and the other with only natural forcings (referred to as NAT). For the projected climate from 2006 to 2099, the simulations under RCP45 and RCP85 are used. These two pathways represent contrasting mitigation efforts between a concerted rapid CO₂ mitigation and a ‘business-as-usual’ scenario (CO₂ concentrations could increase to 538 and 936 ppm by 2100, according to RCP45 and RCP85, respectively)7. As averaging over multiple members enhances the forcing signal and reduces noise from internal variability and errors from individual models1, I simply average available simulations to obtain the multi-model ensemble mean for the period 1950–2099.

I calculate the 9-month (March-November) mean anomalies of observations and CMIP5 simulations relative to the reference period 1961–1990 for every year, and then average the anomalies into five 30-year periods: 1950–1979, 1980–2009, 2010–2039, 2040–2069, and 2070–2099. My primary focus is long-term temperature anomalies and so a fixed reference period makes the comparison of the anomalies consistent over time. A satellite-measured vegetation greenness index, enhanced vegetation index (EVI)8 for the period 2000–2013, is aggregated to create the 9-month mean climatology of EVI. EVI largely reflects the geographical distribution of amount of vegetation and SM and thus ET at large scales9,10. The latitudinal zones beyond 50°N and 50°S and three winter months (DJF) are excluded because polar amplification and albedo feedbacks dominate the high-latitude surface warming5,6.

Desert amplification by large-scale ecoregion
Figure 1a shows the regional mean T₂m anomalies for the period 1950–2099 over the entire study region. OBS shows strong interannual variability in 1950–1979 but a persistent warming trend thereafter. ALL generally reproduces the observed warming with a slightly smaller magnitude and also captures the large-scale cooling associated with volcanic eruptions on shorter time scales1 (Fig. 1d). NAT simulates this short-term variability but exhibits no apparent warming trend. The projected T₂m increases persistently and is 2.8 and 5.6°C warmer in 2099 than the 1961–1990 averages under RCP45 and RCP85, respectively.

Figure 2 shows spatial patterns of 30-year mean T₂m anomalies for two periods: 1980–2009 and 2070–2099, together with the climatology of EVI. The observed and projected T₂m increases everywhere relative to the reference period 1961–1990 and the strongest warming occurs mostly in arid and semi-arid regions such as Northern Africa, Middle East, Northern Asia, and western U.S. Noticeable regional warming is also observed or projected over several non-dry regions such as southern Amazon, Europe, and eastern U.S., likely related to decreased SM11 or dynamical processes linked to changes in circulation and sea surface temperature patterns5,6. Although the warming rate increases with time and is stronger in RCP85 than RCP45, OBS and projections exhibit spatial patterns of T₂m anomalies that are similar to those projected for the later 21st century and are highly correlated with EVI, with a spatial correlation ranging from −0.42 to −0.45 (p < 0.001, n = 1538). Note that T₂m is not a linear function of EVI. Overall the warming is generally strongest over the driest or least vegetated ecologies such as the Sahara desert and the Arabian Peninsula.

To minimize data noise and variability at small scales, I classify the study region into 7 large-scale ecologies from barren deserts to dense rainforests based on the climatological EVI values, and then analyze how the 30-year mean T₂m anomalies vary as a function of EVI by ecoregion via least squares fitting (Fig. 3; Fig. S1). Evidently, the warming rate depends strongly on ecoregions and increases dramatically with decreasing EVI. Four regression lines (exponential, linear, logarithmic, and power) are fit between T₂m and EVI over different 30-year periods, all with R² values that range from 0.77 to 0.98. The corresponding R² value for the linear (exponential) fit is 79% (84%) in OBS 1980–2009, 86% (88%) in ALL 1980–2009, and 88% (90%) in RCP85 2070–2099. To examine whether the T₂m-EVI relationship depends on the ecoregions classified – indicating that the fitted T₂m-EVI relationship remains robust.

Overall the negative power and logarithmic fit describes well the T₂m-EVI relationship by ecoregion in both OBS and projected climate, indicating the strongest warming over the driest ecologies. ALL generally reproduces the observed features of regional mean T₂m anomalies (Fig. 1a), spatial patterns of 30-year mean T₂m anomalies (Fig. 2b), and the spatial dependence of warming on EVI by ecoregion (Fig. 3a; Fig. S1; Table 1). It has slightly weaker warming rates and smaller interannual variability than OBS, which is expected as the multi-model ensemble mean represents primarily the forced signal of GHGs1.

For the power, T₂m = C₀*(EVI)A₀, and logarithmic, T₂m = Aᵦ*ln(EVI)+C½ function, C₀ is the T₂m anomaly for EVI = 1, which approximates the warming rate for dense rainforests. The negative scaling factor, Aᵦ, represents the growth rate of warming from the rainforests to dry deserts, i.e., the magnitude of desert amplification.
Mathematically the negative power and logarithmic fits exhibit the almost identical $T_{2m}$-EVI relationship within the valid range of EVI. Interestingly, the magnitude of fitted coefficients for $T_{2m}$ ($C_0$ and $A_0$) both increases linearly with the global mean GHGs radiative forcing from 1950 to 2099 (Fig. 4a,c), meaning that not only the warming rate over humid rainforests becomes stronger with time, but also the magnitude of desert amplification becomes larger. These results consistently indicate that desert amplification is a persistent signal in a warming climate and it intensifies with the radiative forcing associated with increased GHGs.

**Changes in surface radiation and energy budget**

To understand the above warming patterns, I first examine the changes in surface radiative and non-radiative fluxes (DLR, DSR, ULR, upward solar radiation, net shortwave and longwave radiation, latent and sensible heat). Zhou et al. performed a comprehensive analysis of observations, reanalysis and CMIP5 data from this perspective for the period 1979–2012. They found that GHGs-enhanced DLR is the primary driver for desert amplification, while ecosystem feedbacks associated with SM and vegetation play a secondary role. I perform the same analyses for different 30 periods and obtain similar results, some of which are briefly summarized below.

The warming rate of $T_{2m}$ depends on surface radiative forcing. Figure 1c shows the regional mean anomalies of DLR and DSR over the study region for the period 1950–2099. DLR displays a persistent increasing trend,
Figure 2. Spatial patterns of 30-year mean surface air temperature anomalies (T2m, °C) relative to the 1961–1990 averages for two periods: (a) OBS 1980–2009, (b) ALL 1980–2009, (c) RCP45 2070–2099, and (d) RCP85 2070–2099, and (e) spatial patterns of climatological EVI (unitless) for the period 2000–2013, in 2.5° × 2.5° grid boxes over land. Map was created using CISL’s NCAR Command Language (NCL) (https://www.ncl.ucar.edu/) Version 6.0.0.
while DSR varies slightly after 1991 between $-0.8$ and $+1.1 \text{ W/m}^2$. The DLR anomaly reaches $18.4 \text{ W/m}^2$ under RCP45 and $38.6 \text{ W/m}^2$ under RCP85 in 2099, which are substantially larger than the DSR anomalies. DLR is slightly higher in clear-sky than all-sky while the opposite is true for DSR, due to a small decreasing trend in total cloud cover (Fig. S2). Hence the positive DLR anomalies should dominate the surface radiative forcing, while the DSR forcing is small and has a secondary effect.

The warming rate of $T_{2m}$ also depends on land surface properties and ecosystem feedbacks in response to the surface radiative forcing, particularly upward shortwave and longwave radiation and the partitioning of net radiation between sensible and latent heat \textsuperscript{4,12}. Figure S2 show the regional mean anomalies of related surface fluxes over the study region for the period 1950–2099. ULR displays similar but slightly smaller anomalies than DLR, reaching $16.5 \text{ W/m}^2$ under RCP45 and $34.1 \text{ W/m}^2$ under RCP85 in 2099, while the upward shortwave radiation decreases slightly by $0.8 \text{ W/m}^2$ under RCP45 and $1.0 \text{ W/m}^2$ under RCP85 in 2099. The surface latent heat increases slightly with time after 1980s and its anomaly in 2099 is $1.0 \text{ W/m}^2$ under RCP45 and $1.7 \text{ W/m}^2$ under RCP85. The sensible heat shows similar but slightly larger increases, reaching $2.2 \text{ W/m}^2$ and $4.8 \text{ W/m}^2$ under RCP45 and RCP85 in 2099, respectively.

I then perform similar analyses as done above for $T_{2m}$ to each of the surface fluxes but can only identify two variables (DLR and ULR) showing features similar to $T_{2m}$ at both the grid and ecoregion level (Figs 5, S3 and S4). Note that DLR and ULR resemble $T_{2m}$ because DLR is the primary radiative forcing for surface warming while ULR is mainly a consequence of the warming following the Stefan–Boltzmann law. Compared to other ecoregions, deserts are least opaque to thermal infrared radiation due to least amounts of water vapor and cloud cover in the atmosphere and thus are most effective in emitting terrestrial radiation to space. Consequently, the DLR anomalies are mostly balanced by the ULR anomalies over the driest ecoregions. I also analyze interannual variations of cloud and precipitation anomalies and their spatial dependences on EVI but cannot identify any statistical meaningful relationship with the warming patterns.

For a given forcing, land surface warms less due to more evaporative cooling via ET over ecoregions with more SM and vegetation\textsuperscript{13}. However, desert amplification is most evident over the driest ecoregions where SM and vegetation are too limited to have a noticeable impact on ET\textsuperscript{6}. Furthermore, the Bowen ratio, which is controlled by vegetation and SM, decreases slightly over deserts, with time during different 30-year periods (Fig. S5), indicating its limited role in controlling the surface warming patterns. Again these results suggest that DLR is the primary radiative forcing for desert amplification, while other processes related to SM and vegetation play a secondary role.

**Strong coupling between DLR and atmospheric water vapor content**

Radiative forcing due to increasing GHGs drives much of long-term climate change\textsuperscript{23} and increasing TAWV is closely linked to surface and tropospheric warming\textsuperscript{5,8,14–16}. As DLR depends strongly on near surface humidity and temperature\textsuperscript{17,18}, next I examine its associations with $T_{2m}$, TAWV and $q_{2m}$. Because most of TAWV is confined
near the surface, the changes in TAWV and $q_{2m}$ are very similar at both grid and ecoregion levels. Hence most of my results are shown for TAWV for brevity. TAWV and $q_{2m}$ display a persistent increasing trend along with DLR over the study region for the period 1950–2099 (Fig 1b). The temporal increases in $T_{2m}$, TAWV, $q_{2m}$ and DLR resemble these in the global mean GHGs radiative forcing and the atmospheric CO$_2$ concentration under RCP45 and RCP85 (Fig. 1d). Hence, the positive DLR forcing associated with enhanced GHGs, particularly water vapor, should primarily determine the observed and projected large-scale warming patterns.

Scatter plots of CMIP5 data (Fig. S6) clearly demonstrate a power function of DLR on TAWV as shown in previous studies$^{15-16}$, DLR = $C_0 * (TAWV)^{0.83}$, where $C_0$ varies 156–165 W/m$^2$ among different periods. This function is evident in NAT, ALL, RCP45 and RCP85 despite their differences in atmospheric CO$_2$ concentration. Note that the greenhouse effect is roughly proportional to changes in the logarithm of the GHGs concentrations$^{14-16}$. The derivative of DLR versus TAWV ($\partial$DLR/$\partial$TAWV) resembles a negative power (or logarithmic) function (Table 2), indicating that for a unit amount of TAWV increase, the largest efficiency in increasing DLR will occur over the driest regions with the least TAWV. Therefore, the negative power and logarithmic $T_{2m}$-EVI relationships shown above may result from a warmer and moister atmosphere with increasing GHGs. This can be tested next by analyzing the collective changes in DLR, $q_{2m}$, TAWV, and $T_{2m}$.

First, I examine the spatial patterns of changes in DLR and water vapor at the grid level for three periods: ALL 1980–2099, RCP45 2070–2099, and RCP85 2070–2099. If the increase in DLR and associated water vapor are the primary driver of the warming patterns, one would expect to see a spatial coupling between these variables. As expected, the changes in TAWV and $q_{2m}$ are very similar even at the grid level (Fig. S7), with a spatial correlation of 0.95–0.96 ($p < 0.001$, $n = 1538$). Figure 5 shows the spatial patterns of changes in DLR and fractional changes in TAWV (referred to as FTAWV), with a spatial correlation of 0.55–0.78 ($p < 0.001$, $n = 1538$). The spatial correlation between $T_{2m}$ and DLR is 0.52–0.55 ($p < 0.001$, $n = 1538$). Note that the correlations of DLR-$T_{2m}$ and DLR-FTAWV are lower than the TAWV-$q_{2m}$ correlations because DLR depends nonlinearly on the changes in both atmospheric temperatures and humidity. The driest ecoregions such as the Sahara desert and the Arabian Peninsula where DLR increases most have the largest increases in FTAWV, resembling the spatial patterns of warming of $T_{2m}$. The widespread increase of water vapor in ALL 1980–2099 is consistent with surface synoptic observations and reanalysis data$^3$. As expected, URL (Fig. S4) shows patterns similar to DLR (Fig. 5), with a spatial correlation of 0.62–0.77 ($p < 0.001$, $n = 1538$). These results suggest a stronger linkage between surface warming and increasing water vapor over drier ecosystems.

Second, I analyze the spatial dependence of DLR on EVI by large-scale ecoregion as done for $T_{2m}$. If DLR is responsible for desert amplification, one would expect to see similar features in DLR as shown in $T_{2m}$. As expected, TAWV increases with EVI and thus has the largest increase over dense rainforests (Fig. 6b). However, it

| Ecoregions | $T_{2m}$ = $A_0^* \ln(EVI)$ + $C_0$ | $T_{2m}$ = $C_0^*$(EVI)$^{0.83}$ | $T_{2m}$ = $A_0^* \ln(EVI)$ + $C_0$ | $T_{2m}$ = $C_0^*$(EVI)$^{0.83}$ |
|----------------|-----------------|-----------------|-----------------|-----------------|
|                | $R^2$ ($C_{op}, A_0$) | $R^2$ ($C_{op}, A_0$) | $R^2$ ($C_{op}, A_0$) | $R^2$ ($C_{op}, A_0$) |
| OBS (1980–2009) |     |     |     |     |
| 7               | 0.95(0.23, −0.11) | 0.97(0.27, −0.25) | 0.99(0.29, −0.07) | 0.98(0.30, −0.18) |
| 14              | 0.91(0.23, −0.11) | 0.93(0.27, −0.25) | 0.94(0.29, −0.07) | 0.93(0.30, −0.18) |
| 21              | 0.89(0.24, −0.10) | 0.91(0.27, −0.25) | 0.91(0.29, −0.07) | 0.91(0.30, −0.17) |
| 28              | 0.86(0.24, −0.10) | 0.88(0.27, −0.25) | 0.89(0.29, −0.07) | 0.88(0.30, −0.17) |
| 35              | 0.84(0.24, −0.10) | 0.86(0.27, −0.25) | 0.86(0.29, −0.07) | 0.85(0.30, −0.17) |
| RCP85 (2010–2039) |     |     |     |     |
| 7               | 0.97(1.12, −0.20) | 0.98(1.15, −0.14) | 0.99(1.03, −0.18) | 0.99(1.06, −0.13) |
| 14              | 0.90(1.12, −0.20) | 0.89(1.15, −0.14) | 0.92(1.03, −0.18) | 0.91(1.06, −0.13) |
| 21              | 0.85(1.12, −0.20) | 0.85(1.15, −0.14) | 0.89(1.04, −0.18) | 0.88(1.06, −0.13) |
| 28              | 0.82(1.12, −0.20) | 0.82(1.15, −0.14) | 0.85(1.04, −0.18) | 0.84(1.06, −0.13) |
| 35              | 0.79(1.12, −0.20) | 0.78(1.15, −0.14) | 0.82(1.04, −0.18) | 0.81(1.06, −0.13) |
| RCP45 (2040–2069) |     |     |     |     |
| 7               | 0.98(2.36, −0.39) | 0.99(2.36, −0.13) | 0.98(1.75, −0.27) | 0.98(1.79, −0.12) |
| 14              | 0.92(2.29, −0.39) | 0.91(2.36, −0.13) | 0.91(1.75, −0.28) | 0.90(1.79, −0.12) |
| 21              | 0.89(2.36, −0.39) | 0.88(2.36, −0.13) | 0.88(1.75, −0.27) | 0.87(1.79, −0.12) |
| 28              | 0.85(2.30, −0.39) | 0.84(2.36, −0.13) | 0.84(1.75, −0.27) | 0.83(1.79, −0.12) |
| 35              | 0.83(2.30, −0.39) | 0.82(2.36, −0.13) | 0.82(1.75, −0.27) | 0.81(1.79, −0.12) |
| RCP85 (2070–2099) |     |     |     |     |
| 7               | 0.98(3.79, −0.59) | 0.98(3.87, −0.12) | 0.98(2.16, −0.32) | 0.98(2.20, −0.12) |
| 14              | 0.92(3.78, −0.59) | 0.91(3.87, −0.12) | 0.91(2.15, −0.32) | 0.90(2.20, −0.12) |
| 21              | 0.89(3.79, −0.59) | 0.88(3.87, −0.12) | 0.88(2.16, −0.32) | 0.87(2.20, −0.12) |
| 28              | 0.85(3.79, −0.59) | 0.84(3.87, −0.12) | 0.84(2.16, −0.32) | 0.83(2.20, −0.12) |
| 35              | 0.83(3.79, −0.59) | 0.82(3.87, −0.12) | 0.81(2.16, −0.32) | 0.80(2.20, −0.12) |

Table 1. Fitted coefficients and goodness of fit ($R^2$) of the logarithmic and power functions between 30-year mean $T_{2m}$ anomalies ($^\circ$C) and the climatological EVI by large-scale ecoregion for four different periods from 1980–2099.
Figure 4. Scatter plots of fitted coefficients ($C_0$ and $A_0$ for the logarithmic fit of $T_{2m}$ and DLR) and atmospheric CO$_2$ concentration as a function of the global mean GHGs radiative forcing (W/m$^2$, Fig. 1d) for different 30-year periods: (a) $C_0$ for surface air temperature anomalies ($T_{2m}$ °C), (b) $C_0$ for surface downward longwave radiation (DLR, W/m$^2$), (c) $A_0$ for $T_{2m}$ (d) $A_0$ for DLR, and (e) atmospheric CO$_2$ concentration (ppm). For each period, the arithmetic mean fitted coefficients are obtained from Tables 1–2.
is the fractional change in water vapor (i.e., FTAWV) that matters in the change in DLR. Despite their smallest increases in TAWV, the driest regions have the largest fractional increases in water vapor (Fig. 6c) and thus the strongest increase in DLR (Fig. 6a). ∂DLR/∂TAWV resembles a negative power (or logarithmic) function (Fig. 6d), indicating the strongest sensitivity of DLR to TAWV changes over the driest regions. For example, R² is 95% (94%) for the power (logarithmic) fit in the case of 7 ecoregions. Again, this feature remains consistent under different ecoregion classifications and during different 30-year periods (Table 2). The fitted two coefficients for DLR (C₀ and A₀) both increase in magnitude during all five 30-year periods from 1950–2099, meaning that DLR over humid rainforests and its difference from the deserts become stronger with time. These results resemble those of T₂m (Fig. 4b,d) discussed above.

Third, I analyze the spatial dependence of maximum and minimum T₂m on EVI by ecoregion. Arid regions generally have the deepest well-mixed atmospheric boundary layer (ABL) at daytime but a very shallow and stable (atmospheric stratification) condition at nighttime. For a given DLR forcing, the surface warming rate depends inversely on the ABL depth, indicating the sensitivity of T₂m to changes in DLR is stronger at nighttime when ABL is mostly stable and persistently stratified. My analyses of maximum and minimum T₂m support a much stronger effect of DLR on T₂m at nighttime than at daytime (not shown).

Fourth, I examine the response of T₂m changes to DLR for special cases when water vapor changes little over the study period. The spatial dependence of warming on ecoregion in a warming climate for periods after 1980 are absent from (i) the period 1950–1979 when the warming is small and (ii) NAT when the natural forcings is only considered. The largest increases in T₂m, fractional changes in q₂m, FTAWV, and DLR over the driest regions seen above disappear in these two cases (not shown), pointing to human cause of anthropogenic GHGs in increasing DLR and T₂m over the deserts. This inference is consistent with previous analyses of observations, reanalysis data and AOGCM simulations.

It is worth noting again that the magnitude of fitted coefficients (C₀ and A₀) for both DLR and T₂m increases similarly and linearly along with the global mean GHGs radiative forcing (Fig. 4). Also there is a strong positive correlation between the GHGs forcing versus the atmospheric CO₂ concentration (Fig. 4e), indicating that increasing GHGs warm all ecoregions via enhanced DLR and broaden the differences in T₂m and DLR between the driest and wettest ecoregions.

**Summary and Discussion**

This study analyzes the observed and projected surface temperature anomalies over land between 50°S-50°N for the period 1950–2099 by large-scale ecoregion and finds that the warming rate increases dramatically with decreasing vegetation cover. The strongest warming is consistently and persistently seen over driest ecoregions such as the Sahara desert and the Arabian Peninsula during various 30-year periods, pointing to a fundamental pattern of desert amplification in a warming climate over land in low- and mid- latitudes where surface warming
The strongest warming and moistening effects are seen over the wettest ecoregions in
rainforests and in the near surface LT layers over the driest ecoregions. The large water vapor increases could
primarily balance the increase in DLR as shown above over the deserts. Fig. S8 shows the changes in atmospheric air temperature (T) and
the UT but such effects reverse in the LT. Although wave propagation in the UT reduces the horizontal gradients
or without the temperature increases and thus are a reasonable consequence of warming with a relatively
which in turn warms and moistens the atmosphere most22. Hence, the enhanced DLR is a cascade effect of the
wettest ecoregions where the near surface relative humidity is highest and deep moist convection occurs most,

The increase in DLR is likely a consequence of a warmer and thus moister atmosphere associated with water
vapor feedbacks due to increasing GHGs. This amplification enhances linearly with the global mean GHGs
radiative forcing, meaning that both the warming rates of all ecoregions and the warming differences between
rainforests and deserts intensify with increasing GHGs. My analyses suggest that desert amplification is driven
primarily by a stronger GHGs-enhanced downward longwave radiation forcing that reaches and heats the surface
over drier ecoregions.

rates depend inversely on ecosystem dryness. This amplification enhances linearly with the global mean GHGs
radiative forcing, meaning that both the warming rates of all ecoregions and the warming differences between
rainforests and deserts intensify with increasing GHGs. My analyses suggest that desert amplification is driven
primarily by a stronger GHGs-enhanced downward longwave radiation forcing that reaches and heats the surface
over drier ecoregions.

Table 2. Fitted coefficients and goodness of fit (R²) of the logarithmic and power functions between
30-year mean surface DLR anomalies (W/m²) and the climatological EVI by large-scale ecoregion for four
different periods from 1980–2099.

| Ecoregions | DLR = A₀ ln(EVI) + C₀ | DLR = C₀² (EVI)¹⁰ | DLR = A₀ ln(EVI) + C₀ | DLR = C₀² (EVI)¹⁰ |
|------------|---------------------|---------------------|---------------------|---------------------|
|            | R² (C₀, A₀)        | R² (C₀, A₀)        | R² (C₀, A₀)        | R² (C₀, A₀)        |
| OBS (1980–2009) |               |                   |                   |                   |
| 7          | 0.94(1.97, –0.63)  | 0.95(2.12, –0.20)  |                   |                   |
| 21         | 0.88(1.99, –0.61)  | 0.89(2.13, –0.20)  |                   |                   |
| 28         | 0.85(2.08, –0.60)  | 0.86(2.14, –0.20)  |                   |                   |
| 35         | 0.82(2.08, –0.60)  | 0.84(2.15, –0.19)  |                   |                   |
| RCP85 (2010–2039) |               |                   |                   |                   |
| 7          | 0.86(7.56, –1.51)  | 0.87(7.86, –0.15)  | 0.83(6.99, –1.30)  | 0.83(7.24, –0.14)  |
| 14         | 0.78(7.58, –1.49)  | 0.79(7.88, –0.14)  | 0.76(7.02, –1.28)  | 0.77(7.26, –0.14)  |
| 21         | 0.73(7.60, –1.47)  | 0.74(7.90, –0.14)  | 0.72(7.04, –1.26)  | 0.72(7.28, –0.13)  |
| 28         | 0.70(7.63, –1.46)  | 0.71(7.91, –0.14)  | 0.69(7.08, –1.25)  | 0.70(7.29, –0.13)  |
| 35         | 0.67(7.64, –1.45)  | 0.68(7.92, –0.14)  | 0.66(7.07, –1.25)  | 0.67(7.30, –0.13)  |
| RCP85 (2040–2069) |               |                   |                   |                   |
| 7          | 0.84(15.86, –2.56) | 0.85(16.31, –0.12) | 0.78(11.95, –1.65) | 0.78(12.21, –0.11) |
| 14         | 0.76(15.92, –2.51) | 0.77(16.35, –0.12) | 0.70(11.98, –1.63) | 0.70(12.24, –0.11) |
| 21         | 0.70(15.96, –2.48) | 0.71(16.39, –0.12) | 0.64(12.00, –1.61) | 0.65(12.26, –0.11) |
| 28         | 0.67(16.00, –2.46) | 0.68(16.42, –0.12) | 0.61(12.02, –1.59) | 0.62(12.27, –0.10) |
| 35         | 0.63(16.02, –2.44) | 0.65(16.43, –0.12) | 0.59(12.04, –1.58) | 0.59(12.29, –0.10) |
| RCP85 (2070–2099) |               |                   |                   |                   |
| 7          | 0.82(26.62, –3.70) | 0.82(27.21, –0.11) | 0.77(14.59, –1.79) | 0.78(14.85, –0.10) |
| 14         | 0.74(26.72, –3.63) | 0.74(27.28, –0.11) | 0.70(14.62, –1.76) | 0.70(14.88, –0.10) |
| 21         | 0.67(26.79, –3.58) | 0.68(27.34, –0.11) | 0.64(14.65, –1.74) | 0.64(14.90, –0.10) |
| 28         | 0.64(26.85, –3.53) | 0.64(27.39, –0.10) | 0.61(14.68, –1.72) | 0.61(14.92, –0.10) |
| 35         | 0.60(26.89, –3.51) | 0.61(27.42, –0.10) | 0.57(14.70, –1.71) | 0.58(14.94, –0.09) |

With a substantial surface radiative forcing of DLR, the land surface basically has three ways to balance this
additional energy (i.e., cooling processes) due to the absorption of DLR by latent heat via ET, sensible heat via
convection and turbulence, and thermal emission via ULR. Among these three terms, latent heat is the most effec-
tive way to transfer heat from the surface to the above atmosphere. Over very wet ecoregions, latent heat domi-
nates the surface budget and hence the surface and atmospheric air can be warmed at similar rates via ET. Over
very dry ecoregions, sensible heat and ULR dominates the surface budget and hence the surface needs to warm
much more than the above air to increase the upward transfer of sensible heat, which depends on the surface-air
temperature gradient and near-surface wind speed, and ULR, which is mostly proportional to the fourth power of
surface temperature. The increase in URL is much more effective than sensible heat over the dry regions and
thus primarily balances the increase in DLR as shown above over the deserts.

I speculate that two types of water vapor feedbacks might be involved32. The first is the well-known positive
water vapor feedback that amplifies the GHGs induced warming by moistening the atmosphere, which is defined

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from the perspective of top of atmosphere (TOA) radiation budget. The water vapor feedback is strongest in the tropical UT where the warming profile is close to moist adiabatic and the fractional changes in water vapor concentration are largest with increasing GHGs\textsuperscript{14,15,22,23}. In the UT where the temperature is cold and very dry, TOA radiation budget is very sensitive to water vapor changes. The warmer and thus moister atmosphere enhances

Figure 6. Same as Fig. 3 but for (a) surface downward longwave radiation (DLR, W/m\textsuperscript{2}), (b) total atmospheric water vapor content (TAWV, kg/m\textsuperscript{2}), (c) fractional changes in TAWV (FTAWV, %), and (d) the ratio of changes in DLR to changes in TAWV ($\partial$DLR/$\partial$TAWV, W/kg).
Determined. These two pathways represent contrasting mitigation efforts between a concerted rapid CO₂ mitigation (MODIS) satellite sensor8 for the period 2000–2013, to examine the spatial dependence of observed and projected an optimized vegetation greenness index measured by the MODerate resolution Imaging Spectroradiometer5,6. My study region consists of 1538 land grid boxes. As averaging over multiple members enhances the forcing (DJF) are excluded because polar amplification and albedo feedbacks dominate the high-latitude surface warm-
2010–2039, 2040–2069, and 2070–2099. The latitudinal zones beyond 50°N and 50°S and three winter months tology of M-N mean EVI. I average the yearly M-N anomalies into five 30-year periods: 1950–1979, 1980–2009, 9-month mean anomalies during March to November (M-N). The monthly EVI is aggregated to create the clima-
1950–2099. All variables are spatially re-projected into grid boxes (2.5° by 2.5°). The monthly data are converted to reproduce the observed warming at large scales, especially after the 1950s1. For the projected climate after 2005, simulations are available starting 1850, I focus only on the period 1950–2005 because AOGCMs are generally able (referred to as ALL) and the other with only natural forcings (referred to as NAT). Although the ALL and NAT 

Method

Observed surface temperature datasets. This study uses the ensemble mean of three global gridded monthly surface air temperature (T₂m) datasets: CRU38, GISS2 and NCDC39, for the period 1950–2013. The three datasets have been widely used for long-term temperature variability and trend analysis. Despite sharing some similarities in input data sources, they differ substantially in their data processing approaches49. For example, satellite data is used extensively in GISS, used very limited in NCDC, and not used at all in CRU39. Nevertheless, the three datasets show very similar temperature changes and so their ensemble mean is used to reduce redundancy as done in Zhou et al.58. Although some observations are available starting 1880, here only the data after 1950 is chosen to maximize spatial coverage of in situ measurements.

Satellite measured vegetation greenness data. This study uses enhanced vegetation index (EVI), an optimized vegetation greenness index measured by the MODerate resolution Imaging Spectroradiometer (MODIS) satellite sensor9 for the period 2000–2013, to examine the spatial dependence of observed and projected surface warming rates on large-scale ecoregions. EVI does not saturate, even over dense forests, and correlates highly with ET, particularly at large scales40.

CMIP5 simulations. This study uses historical and projected simulations of 26 global coupled atmosphere-ocean general circulation models (AOGCMs) developed for the Coupled Model Intercomparison Project phase 5 (CMIP5)40. For the historical simulations, there are two groups: one with time-evolving changes in anthropogenic (greenhouse gases and sulfate aerosols) and/or natural (solar and volcanic) forcing agents (referred to as ALL) and the other with only natural forcings (referred to as NAT). Although the ALL and NAT simulations are available starting 1850, I focus only on the period 1950–2005 because AOGCMs are generally able to reproduce the observed warming at large scales, especially after the 1950s1. For the projected climate after 2005, the simulations with data from the Representative Concentration Pathways 4.5 (RCP45) and 8.5 (RCP85) are con-

Data processing. This study analyzes monthly output of observations and CMIP5 simulations for the period 1950–2009. All variables are spatially re-projected into grid boxes (2.5° by 2.5°). The monthly data are converted into monthly anomalies relative to the 1961–1990 reference period and then temporally averaged to generate 9-month mean anomalies during March to November (M-N). The monthly EVI is aggregated to create the climate-
ology of M-N mean EVI. I average the yearly M-N anomalies into five 30-year periods: 1950–1979, 1980–2009, 2010–2039, 2040–2069, and 2070–2099. The latitudinal zones beyond 50°N and 50°S and three winter months (DJF) are excluded because polar amplification and albedo feedbacks dominate the high-latitude surface warm-
ing56. My study region consists of 1538 land grid boxes. As averaging over multiple members enhances the forcing signal and reduces noise from internal variability and errors from individual models1, this study simply averages the available multi-model simulations to obtain the multi-model ensemble mean in NAT, ALL, RCP45 and RCP85.

Analyses by ecoregions. This study evaluates T₂m changes at aggregated large-scale ecoregions to minimize small-scale temperature variability and data noise. The 1538 land grids are classified into 7, 14, 21, 28, and 35 large-scale ecoregions from barren land to dense forests based on the climatological EVI values (referred to as EVI)8 and then analyze how T₂m anomaly varies with EVI by ecoregion via least squares fitting. The goodness of fit (R²) is used to measure how successful the fit is in approximating the fraction of the data variations. Different
classifications are used to test whether the fitted $T_{\text{an}}$–EVI relationship is robust. For each classification, every ecoregion contains about the same number of grid boxes. Same analyses are also performed for other $T_{\text{an}}$-related variables. The regional mean time series is calculated using area-weighted averaging over land grids within each ecoregion. For brevity, only results of 7 and 35 ecoregions, which represent the least and most ecoregions classified, are shown in figures, while those of other classifications are listed in tables.

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