

# Greenhouse Gas Emissions Drive Global Dryland Expansion but Not Spatial Patterns of Change in Aridification

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**ABSTRACT:** Drylands play an essential role in Earth's environment and human systems. Although dryland expansion has been widely investigated in previous studies, there is a lack of quantitative evidence supporting human-induced changes in dryland extent. Here, using multiple observational datasets and model simulations from phase 6 of the Coupled Model Intercomparison Project, we employ both correlation-based and optimal fingerprinting approaches to conduct quantitative detection and attribution of dryland expansion. Our results show that spatial changes in atmospheric aridity (i.e., the aridity index defined by the ratio of precipitation to potential evapotranspiration) between the recent period 1990–2014 and the past period 1950–74 are unlikely to have been caused by greenhouse gas (GHG) emissions. However, it is very likely (at least 95% confidence level) that dryland expansion at the global scale was driven principally by GHG emissions. Over the period 1950–2014, global drylands expanded by 3.67% according to observations, and the dryland expansion attributed to GHG emissions is estimated as ~4.5%. Drylands are projected to continue expanding, and their populations to increase until global warming reaches ~3.5°C above preindustrial temperature under the middle- and high-emission scenarios. If warming exceeds ~3.5°C, a reduction in population density would drive a decrease in dryland population. Our results for the first time provide quantitative evidence for the dominant effects of GHG emissions on global dryland expansion, which is helpful for anthropogenic climate change adaptation in drylands.

**SIGNIFICANCE STATEMENT:** In the past decades, global drylands have been reported to show changes in space and time, based on atmospheric aridity (i.e., aridity index defined by the ratio of precipitation to potential evapotranspiration). Using two detection and attribution methods, the spatial change patterns of atmospheric aridity between 1990–2014 and 1950–74 are unlikely to be driven by greenhouse gas (GHG) emissions, whereas the temporal expansion of global drylands (i.e., 3.67% from 1950 to 2014) is principally attributed to GHG emissions (contribution: ~122%). Quantitative evidence from the detection and attribution analysis supports the dominant role of greenhouse gas emissions in global dryland expansion, which will increase the population suffering from water shortages under future warming unless climate adaptation is adopted.

**KEYWORDS:** Climate change; Climate records; Climate models

## 1. Introduction

About 41% of Earth's land surface is composed of drylands (areas suffering from permanent or seasonal water deficiency;

Lian et al. 2021). Drylands are some of the most sensitive areas to global warming and nurture over 38% of Earth's population (Huang et al. 2016; Yao et al. 2020). About half of dryland residents live under the poverty threshold according to the United Nations (Reynolds et al. 2007; Lian et al. 2021). Therefore, the well-being of people, associated ecosystem services, and societal goods are particularly vulnerable to anthropogenic warming (Huang et al. 2017). Thus, past and future changes in drylands under global warming are a growing cause for concern (Dai 2013; Park et al. 2018; Pokhrel et al. 2021; Vicente-Serrano et al. 2020; Li et al. 2021; Zhang et al. 2017;

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Li et al. 2020; Zhang et al. 2019; Yao et al. 2020). Exploring the driving effects of anthropogenic climate change on changes in global dryland extent can greatly enhance our understanding in dryland evolution under future warming. Detection and attribution analysis separating the anthropogenic climate change signal in global dryland changes will deepen our overall knowledge of human activities on dryland extent and of how that may change with anthropogenic climate change.

Spatial and temporal changes in dryland extent and intensity (aridification) have been extensively examined. Previous studies have assessed changes in the spatial patterns of drylands between the current and future periods (Feng and Fu 2013; Berg et al. 2017; Cheng and Huang 2016; Cheng et al. 2015; Schlaepfer et al. 2017; Greve et al. 2014; Burrell et al. 2020; Gu et al. 2019c; Dai 2013; Pokhrel et al. 2021; Huang et al. 2016; Park et al. 2018). Feng and Fu (2013) expected a drier future over most land areas defined by atmospheric aridity. Dai (2013) projected soil moisture deficit of the top 10-cm layer in North America, South America, Europe, southern Africa, and Australia. Enhanced soil moisture drying occurred in humid transitional regions and then expanded to dry transitional regions (Cheng and Huang 2016). Pokhrel et al. (2021) indicated that many global land areas, especially in the Southern Hemisphere, are likely to witness a future reduction in terrestrial water storage. However, global land areas are also projected to experience wetting when using an ecohydrological index (based on surface soil moisture, transpiration, and leaf area index) as a proxy for drylands (Berg and McColl 2021). Based on the analysis from more than 300 combinations of various precipitation, evapotranspiration, and potential evaporation datasets, Greve et al. (2014) found that the “dry gets drier, wet gets wetter” pattern only occurs in 10.8% of global land areas, and the opposite pattern can be found in 9.5% of global land areas. Despite these studies, it is still unknown whether spatial changes in dryland areas can be attributed to human-induced climate change or natural climate variability.

The results of past and future changes in dryland extent differ in previous studies using different indices to define drylands from atmospheric, hydrological, agricultural, and ecological viewpoints (Huang et al. 2016; Lian et al. 2021; Dai 2013; Pokhrel et al. 2021; Berg and McColl 2021). Based on atmospheric aridity indices, dryland expansion is expected to accelerate, with a 23% increase under a high-emission scenario (Huang et al. 2016; Feng and Fu 2013). The self-calibrated Palmer drought severity index shows an 8% increase of global drought areas from 1950 to 2010 (Dai 2013). Land areas with decreases in terrestrial water storage and dry-season water availability are also expanding (Padrón et al. 2020; Pokhrel et al. 2021). In contrast, Berg and McColl (2021) argued that no expansions in global drylands are projected under greenhouse warming when using an ecohydrological index, which is consistent with greening and enhanced vegetation activity (He et al. 2019; Fensholt et al. 2012; Zhu et al. 2016; Piao et al. 2020). Recently, Lian et al. (2021) reviewed the characteristics of dryland aridity changes using atmospheric, hydrological, agricultural, and ecological indices,

and confirmed that dryland areas are projected to increase in the future except when using the ecology-based index. Nevertheless, current research has not yet provided quantitative evidence to support human-induced dryland expansion or quantified the role of different external forcings.

Since both the spatial patterns and extent of dryland areas are projected to change under future warming, an equally important factor is the potentially affected dryland population. Many studies have estimated the exposure of population to droughts at global and regional scales (Chen et al. 2018; Liu et al. 2018; AghaKouchak et al. 2021; Kasprzyk et al. 2009), but few have focused on changes in dryland population (Koutroulis 2019; Stavi et al. 2021; Huang et al. 2016). For example, Huang et al. (2016) projected dryland population growth by 50% in the future under a high-emission scenario. Koutroulis (2019) estimated that 1.9 billion people could avoid living in drylands if the warming increase is reduced from 4° to 1.5°C. However, these studies did not separate the roles of the spatial evolution of drylands from alterations in dryland population (see Fig. 1). This separation can help us take a closer look at the potential effects of dryland changes on population and provide decision-makers with more specific options for adaptation and mitigation.

In this study, following the protocol that is widely used to define drylands from atmospheric aridity, we employ the aridity index [AI; the ratio of the annual total precipitation (PRCP) to potential evapotranspiration (PET)] to identify drylands as the areas with  $AI \leq 0.65$ . Then, we address the following questions:

- Can spatial patterns of changes in AI be attributed to anthropogenic climate change?
- Is there quantitative evidence to support human-induced dryland expansion, and to what extent does anthropogenic climate change contribute to this expansion?
- What are the separate roles of dryland expansion and population alteration in the changes of residents in drylands?

## 2. Data

### a. Observation-based meteorological data

Long-term monthly precipitation observations are collected from four sources: the Climatic Research Unit (CRU; Harris et al. 2020), TerraClimate (Abatzoglou et al. 2018), Princeton (Sheffield et al. 2006), and the University of Delaware (UD; Willmott and Matsuura 2018). The CRU and TerraClimate also provide long-term monthly PET estimations that are calculated by using the Penman–Monteith (PM) equation (Allen et al. 1998; Ekström et al. 2007; Harris et al. 2020; Abatzoglou et al. 2018). We use the PM equation (Allen et al. 1998) to estimate monthly PET based on the variables in the Princeton dataset, namely downward shortwave radiation, maximum temperature, minimum temperature, wind speed, and specific humidity. Monthly PET is also calculated by using the PM equation for the University of Delaware dataset (Cook et al. 2014; Zhang et al. 2021; Feng and Fu 2013; Huang et al. 2016) based on the data (i.e., wind speed, mean temperature,

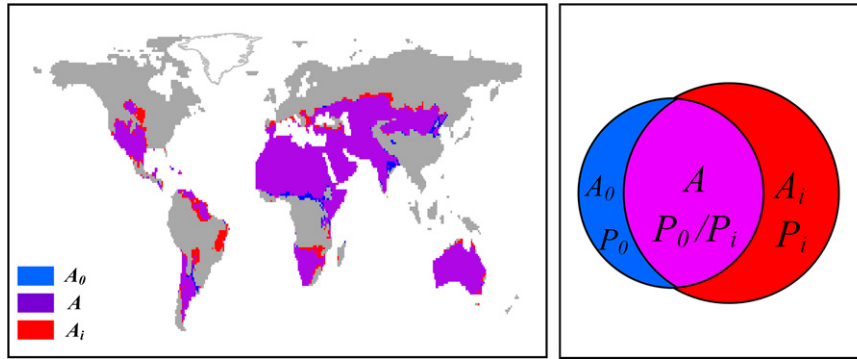


FIG. 1. Schematic diagram of population changes arising from population density and spatial extent of drylands between a warm future (i.e., 20-yr) period and the reference period 1961–90, respectively. (left) The spatial extent of drylands identified during the reference period and a future warming period of  $+3.5^{\circ}\text{C}$  under SSP585. The letters are as follows:  $A$  indicates the shared dryland extent between the two periods,  $A_0$  ( $A_i$ ) is the extent in the 1961–90 reference period (in the future  $i$ th warm period), and  $P_0$  ( $P_i$ ) is the population density in the reference period (in the  $i$ th warm period).

specific humidity, net shortwave radiation flux, and net longwave radiation flux) from the Global Land Data Assimilation System (GLDAS; Rodell et al. 2004; Beaudoin and Rodell 2019; Feng and Fu 2013; Song et al. 2020). Information about these datasets can be found in Table 1. The PET is estimated by the PM equation (Allen et al. 1998):

$$\text{PET} = \frac{0.408\Delta \times R_n^* + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}, \quad (1)$$

where  $T$  is the air temperature ( $^{\circ}\text{C}$ ),  $u_2$  is the wind speed ( $\text{m s}^{-1}$ ),  $e_s - e_a$  is the saturation vapor pressure deficit (kPa),  $\Delta$  is the slope of the vapor pressure ( $\text{kPa } ^{\circ}\text{C}^{-1}$ ), and  $\gamma$  is the

psychrometric constant ( $\text{kPa } ^{\circ}\text{C}^{-1}$ ). Also,  $R_n^*$  is the surface available energy, which can be calculated in two ways: the net radiation minus the soil heat flux density (Sheffield et al. 2006; Hu et al. 2021; M. Liu et al. 2021) or net shortwave radiation flux minus net longwave radiation (Song et al. 2020; Feng and Fu 2013). Due to data availability, the  $R_n^*$  is calculated based on the first (second) way in the Princeton (UD and GLDAS) dataset(s).

Due to the differences in spatial resolution and record length among the four datasets, we used bilinear interpolation (Gu et al. 2019a) to regrid these datasets as a common resolution of  $0.5^{\circ}$ , and extracted data from 1950–2014 as the common study period. The ensemble mean (OBS-EM) of these four

TABLE 1. Observation-based datasets used to calculate the aridity index.

| Datasets      | Variables                                                                                                                                    | Spatial resolution                               | Temporal resolution                               | Sources                                                                                                                                                                                                                                                                                       |
|---------------|----------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------|---------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| CRU (TS4.04)  | Precipitation, potential evapotranspiration                                                                                                  | $0.5^{\circ}$                                    | Monthly, 1901–2019                                | Harris et al. (2020); <a href="https://data.ceda.ac.uk/badc/cru/data/cru_ts/">https://data.ceda.ac.uk/badc/cru/data/cru_ts/</a>                                                                                                                                                               |
| Terra-Climate | Precipitation, potential evapotranspiration                                                                                                  | $1/24^{\circ}$                                   | Monthly, 1958–2015                                | Abatzoglou et al. (2018); <a href="https://data.nkn.uidaho.edu/dataset/monthly-climate-and-climatic-water-balance-global-terrestrial-surfaces-1958-2015">https://data.nkn.uidaho.edu/dataset/monthly-climate-and-climatic-water-balance-global-terrestrial-surfaces-1958-2015</a>             |
| Princeton     | Precipitation, downward shortwave radiation, maximum temperature, minimum temperature, wind speed, specific humidity                         | $1/4^{\circ}$                                    | Daily, 1948–2016                                  | Sheffield et al. (2006); <a href="http://hydrology.princeton.edu">http://hydrology.princeton.edu</a>                                                                                                                                                                                          |
| UD & GLDAS    | Precipitation from UD; wind speed, mean temperature, specific humidity, net shortwave radiation flux, net longwave radiation flux from GLDAS | $1/2^{\circ}$ for UD and $1/4^{\circ}$ for GLDAS | Monthly, 1900–2017 for UD and 1948–2014 for GLDAS | Willmott and Matsuura (2018); <a href="https://doi.org/10.5067/9SQ1B3ZXP2C5">https://doi.org/10.5067/9SQ1B3ZXP2C5</a> ; Rodell et al. (2004); Beaudoin and Rodell (2019); <a href="https://sedac.ciesin.columbia.edu/data/sets/browse">https://sedac.ciesin.columbia.edu/data/sets/browse</a> |

TABLE 2. Model simulations used to calculate the aridity index. An asterisk (\*) indicates that the corresponding model has the data for a given experiment; a long dash (—) indicates that it does not.

| Model name        | AER | GHG | NAT | ALL | CTL<br>(Length: yr) |
|-------------------|-----|-----|-----|-----|---------------------|
| ACCESS-CM2        | —   | —   | —   | *   | 500                 |
| ACCESS-ESM1-5     | *   | *   | *   | *   | 900                 |
| AWI-CM-1-1-MR     | —   | —   | —   | —   | 500                 |
| AWI-ESM-1-1-LR    | —   | —   | —   | *   | 100                 |
| BCC-CSM2-MR       | —   | —   | —   | *   | 600                 |
| BCC-ESM1          | —   | —   | —   | *   | —                   |
| CanESM5           | *   | *   | *   | *   | 1000                |
| CAS-ESM2-0        | —   | —   | —   | *   | 549                 |
| CMCC-CM2-SR5      | —   | —   | —   | *   | 500                 |
| CMCC-ESM2         | —   | —   | —   | *   | —                   |
| CESM2             | *   | *   | *   | —   | —                   |
| EC-Earth3-AerChem | —   | —   | —   | *   | 311                 |
| EC-Earth3-CC      | —   | —   | —   | *   | —                   |
| EC-Earth3-LR      | —   | —   | —   | —   | 201                 |
| EC-Earth3-Veg-LR  | —   | —   | —   | *   | 501                 |
| EC-Earth3-Veg     | —   | —   | —   | *   | 500                 |
| EC-Earth3         | —   | —   | —   | *   | 501                 |
| FGOALS-g3         | *   | *   | *   | *   | —                   |
| FIO-ESM-2-0       | —   | —   | —   | *   | —                   |
| GISS-E2-1-G       | *   | *   | *   | *   | 851                 |
| GISS-E2-1-H       | —   | —   | —   | *   | 801                 |
| GISS-E2-2-G       | —   | —   | —   | —   | 151                 |
| HadGEM3-GC31-LL   | —   | —   | —   | —   | 500                 |
| HadGEM3-GC31-MM   | —   | —   | —   | —   | 500                 |
| INM-CM4-8         | —   | —   | —   | *   | 531                 |
| INM-CM5-0         | —   | —   | —   | *   | 1201                |
| IPSL-CM6A-LR      | *   | *   | *   | *   | 2000                |
| MIROC6            | *   | *   | *   | —   | —                   |
| MPI-ESM-1-2-HAM   | —   | —   | —   | *   | 780                 |
| MPI-ESM1-2-HR     | —   | —   | —   | *   | 500                 |
| MPI-ESM1-2-LR     | —   | —   | —   | *   | 1000                |
| MRI-ESM2-0        | *   | *   | *   | —   | —                   |
| Total counts      | 8   | 8   | 8   | 24  | 15 478              |

datasets is calculated for the following detection and attribution analysis.

#### b. CMIP6 data

The recently released monthly model simulations from phase 6 of the Coupled Model Intercomparison Project (CMIP6) are obtained for the following analyses. The variables provided by CMIP6 are surface upward latent heat flux, surface upward sensible heat flux, wind speed, relative humidity, and minimum/maximum near-surface air temperature under difference forcings: natural (NAT) forcing, greenhouse gases (GHG) forcing, and historical (ALL) forcing (including NAT and anthropogenic forcings). Most of the models under these forcings have simulations ending in 2014. The simulations from the PiControl (CTL) experiments (where the GHG level is set to preindustrial conditions) are also obtained. Results based on the CTL experiments indicate the impact of natural climate variability because they do not include any forcing. Information on the models used in this study can be found in Table 2.

TABLE 3. Model projections used to calculate the aridity index. An asterisk (\*) indicates that the corresponding model has the data for a given experiment; a long dash (—) indicates that it does not.

| Model name        | SSP126 | SSP245 | SSP370 | SSP585 |
|-------------------|--------|--------|--------|--------|
| ACCESS-CM2        | *      | *      | *      | *      |
| ACCESS-ESM1-5     | *      | *      | *      | *      |
| AWI-CM-1-1-MR     | *      | *      | *      | *      |
| CanESM5           | *      | *      | *      | *      |
| CMCC-CM2-SR5      | *      | *      | *      | *      |
| EC-Earth3-AerChem | —      | —      | *      | —      |
| EC-Earth3-CC      | —      | *      | —      | *      |
| EC-Earth3-Veg-LR  | *      | *      | *      | *      |
| EC-Earth3-Veg     | *      | *      | *      | *      |
| EC-Earth3         | *      | *      | *      | *      |
| FGOALS-g3         | *      | *      | *      | *      |
| FIO-ESM-2-0       | *      | *      | —      | —      |
| GFDL-ESM4         | *      | *      | *      | —      |
| IITM-ESM          | *      | —      | —      | —      |
| INM-CM4-8         | *      | *      | *      | *      |
| INM-CM5-0         | *      | *      | *      | *      |
| IPSL-CM6A-LR      | *      | *      | *      | *      |
| MIROC6            | *      | *      | *      | —      |
| MPI-ESM1-2-HR     | *      | *      | *      | *      |
| MPI-ESM1-2-LR     | *      | *      | *      | *      |
| MRI-ESM2-0        | *      | *      | *      | —      |
| Total models      | 19     | 19     | 18     | 15     |

We also obtained projections for 2015–2100 from CMIP6 under four SSP-RCP (shared socioeconomic pathway–representative concentration pathway) scenarios, namely, SSP126, SSP245, SSP370, and SSP585. For example, SSP126 is the combination of SSP1 and RCP26. RCPs represent the radiative forcing paths, with the radiative forcing reaching  $2.6 \text{ W m}^{-2}$  (RCP26),  $4.5 \text{ W m}^{-2}$  (RCP45),  $7.0 \text{ W m}^{-2}$  (RCP70), or  $8.5 \text{ W m}^{-2}$  (RCP85) at the end of the twenty-first century, (Taylor et al. 2012). SSPs represent various global socioeconomic development scenarios, including sustainability (taking the green road; SSP1), middle of the road (SSP2), regional rivalry (a rocky road; SSP3), and fossil-fueled development (taking the highway; SSP5) (Riahi et al. 2017). Populations are projected to increase around 2050, 2060, and 2070 in the SSP1, SSP5, and SSP2, respectively, and then decline by 2100, while this increase in population will persist through 2100 in the SSP3. To ensure the same weight among these models, only the models with realization “r1i1p1fn” are used; for more information, refer to Table 3. The PM equation (Allen et al. 1998; Yang et al. 2019; Scheff and Frierson 2014; Fu and Feng 2014) is used to estimate the PET based on model simulations. Note that  $R_n^*$  is calculated by sensible and latent heat in modeled data (Fu and Feng 2014; Yang et al. 2019; Scheff and Frierson 2014).

#### c. Population data

The yearly population data ( $0.5^\circ$  resolution) are collected from the InterSectoral Impact Model Intercomparison Project (ISIMIP). The ISIMIP provides historical (1861–2005) and future (2006–2100) population data under the SSP1, SSP2, SSP3, and SSP5, respectively. The population data are available at <https://data.isimip.org/>.

### 3. Methods

#### a. Correlation-based attribution approach

Anthropogenic climate change is mainly driven by anthropogenic aerosol (AER) emissions and GHG. Previous studies have consistently shown that effects of the AER forcing on global hydroclimatology were the highest from the 1950s to the 1980s and the relative role of the GHG forcing has grown since then (Marvel et al. 2019; Wu et al. 2013; Wilcox et al. 2013; Polson et al. 2014; Skeie et al. 2011; Padrón et al. 2020). For example, the hydrological cycle was weakened during the 1950s to 1980s because of increased anthropogenic aerosols, and then shifted to enhancement since the 1980s because of increased greenhouse gas emissions (Wu et al. 2013; Wilcox et al. 2013). For changes in global droughts, Marvel et al. (2019) also found that the anthropogenic aerosol forcing signal is detectable during 1950–75 while the greenhouse gas forcing signal is present during 1981–2017. Therefore, we investigate whether there is an anthropogenic climate change signal in changes of spatial aridification patterns between recent (after the 1980s) and past (before the 1980s) periods. Specifically, we investigate changes in spatial aridification patterns based on the difference in AI between two 25-yr periods, 1950–74 and 1990–2014 (Padrón et al. 2020):

$$\Delta AI = AI_{\text{recent}} - AI_{\text{past}}, \quad (2)$$

where  $AI_{\text{recent}}$  ( $AI_{\text{past}}$ ) is the mean of AI during the recent (past) period 1990–2014 (1950–74) in each grid cell. The  $\Delta AI$  is computed in both observations and model simulations under ALL, GHG, and NAT forcings. The CTL simulations available from 24 models have a total of 15478 years, and are divided into 65-yr (the length of the period 1950–2014) nonoverlapping segments (a total of 226 segments), and the  $\Delta AI$  is calculated in each segment in the same way. We also test the sensitivity of  $\Delta AI$  to selected periods (i.e., 1950–74 and 1985–2009, 1955–79 and 1985–2009, and 1955–79 and 1990–2014).

The attribution of changes in the spatial distribution of  $\Delta AI$  to anthropogenic climate change is assessed by following a correlation-based attribution approach (Gudmundsson et al. 2017b; Qian and Zhang 2015; Padrón et al. 2020). We estimate the spatial Spearman correlation of  $\Delta AI$  between observations and model simulations to quantify responses of spatial change to external forcings. The correlations between observations and CTL simulations depict the distribution of impacts only from natural climate variability. The null hypothesis is that there is no signal of anthropogenic forcing in the changes in spatial patterns of AI; that is, these changes are attributed to natural climate change only. The null hypothesis is rejected (an anthropogenic signal is detectable) if the spatial correlations between observations and simulations under ALL/GHG forcing exceed the 95th percentile of correlations between observations and CTL simulations. Furthermore, the presence of an anthropogenic signal is confirmed if the spatial correlations between observations and simulations under NAT forcing are below the 95th percentile.

#### b. The optimal fingerprint method

The spatial extent of global drylands (i.e., areas with  $AI \leq 0.65$ ) is estimated annually based on observations and simulations under different forcings. The Spearman correlations of dryland area extent (time series) between observations and CTL, ALL, GHG, and NAT simulations are estimated, respectively. Similarly, we first employ the correlation-based attribution approach to detect whether an anthropogenic signal is detectable in temporal changes of dryland area extent (Gudmundsson et al. 2017a; Padrón et al. 2020).

We further employ the optimal fingerprinting method (Gu et al. 2019b; Allen and Stott 2003; Kong et al. 2020; Allen and Tett 1999) to quantify the detection and attribution of external forcings to changes in observed dryland area. In this method, observed changes are assumed as the linear sum of responses to external forcings plus natural climate variability (Allen and Stott 2003):

$$y = (\mathbf{X} - \alpha)\boldsymbol{\beta} + \epsilon, \quad (3)$$

where  $y$  is the observed time series of dryland area,  $\mathbf{X}$  is the simulated time series of dryland area from ALL, GHG, and/or NAT forcing,  $\alpha$  is the sampling uncertainty of  $\mathbf{X}$ ,  $\boldsymbol{\beta}$  is the scaling factor that is used to scale  $\mathbf{X}$  and then make  $\mathbf{X}$  match the long-term changes of observations, and  $\epsilon$  is the natural climate variability estimated from CTL simulations. The signal of external forcing is detectable if  $\boldsymbol{\beta}$  is significantly larger than zero. The modeled response is consistent with the observed change if  $\boldsymbol{\beta}$  is around 1. The estimation of  $\boldsymbol{\beta}$  is addressed by using the ordinary least squares (OLS) and total least squares (TLS), respectively. The attribution of the observed change in dryland area to external forcings is quantified as (Allen and Stott 2003)

$$\text{Con} = \text{Slope} \times \beta, \quad (4)$$

where slope is the linear trend in the simulated dryland area under each external forcing, and  $\beta$  is the scale factor of the corresponding external forcing.

#### c. Population assessment in drylands

Changes in dryland population under different warming periods are quantified against the reference period 1961–90:

$$\Delta P = \frac{P_w - P_r}{P_r} \times 100\%, \quad (5)$$

where  $P_w$  is the average population in drylands during a future warming period, and  $P_r$  is the average population in drylands during the reference period 1961–90. From 1991 to 2100 in model simulations (i.e., ALL forcing and SSP scenarios), the warming period is the running 20-yr window, and the warming level is the average temperature during this window minus the average temperature during the base period 1861–1990.

The spatial extent of drylands is expected to change between the future warm period and the historical reference

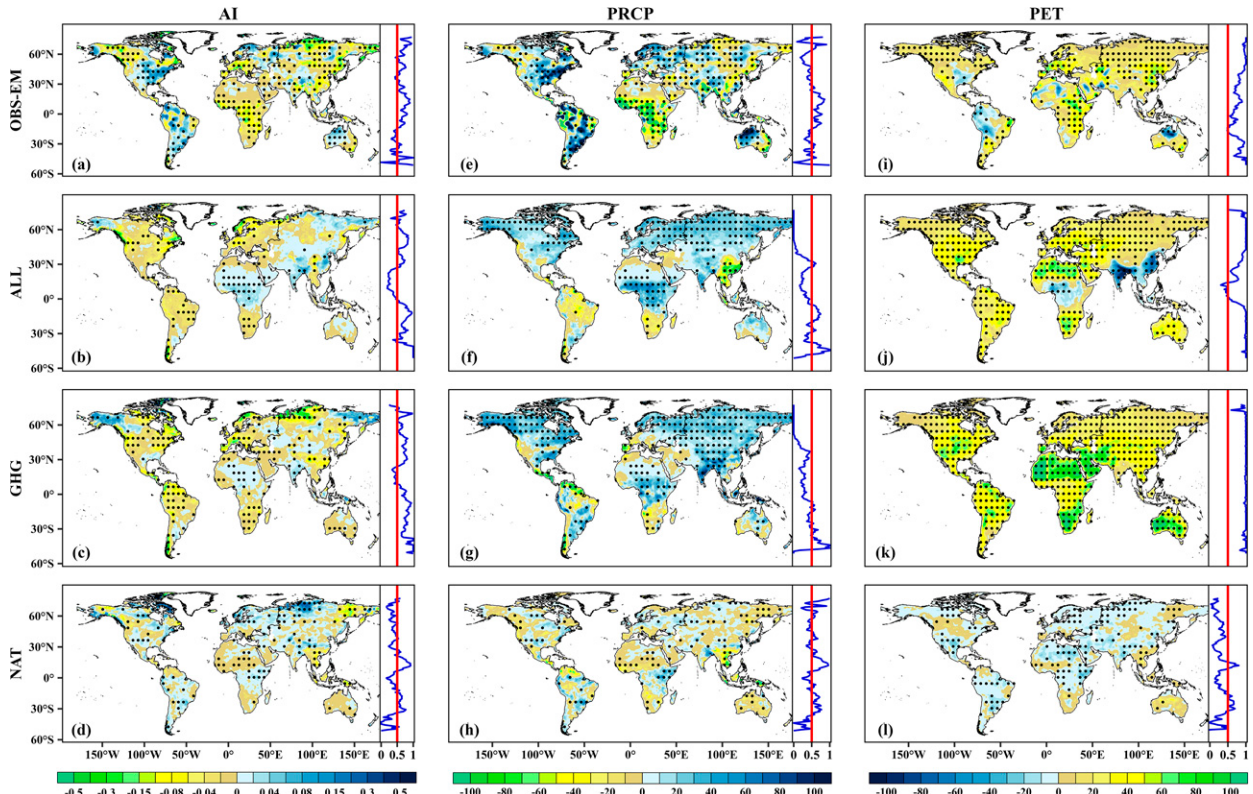


FIG. 2. (a)–(d) Spatial patterns of changes in the mean of aridity index (AI), (e)–(h) annual total precipitation (PRCP; mm), and (i)–(l) annual total potential evapotranspiration (PET; mm) between the two periods (i.e., 1990–2014 and 1950–74, respectively) from multidata mean observations (OBS-EM) and historical simulations (i.e., ALL, GHG, and NAT forcings, respectively). The blue curve on the right side of panels indicates zonal average change. The stippling indicates areas where 75% of the models agree on the sign of the change (observations indicate the agreement of all observed datasets).

period, as is the population density in drylands. Thus, changes in dryland population can be further decomposed as (see Fig. 1 as a schematic):

$$\Delta P = (A + A_i)P_i - (A + A_0)P_0, \quad (6)$$

where  $A$  is the shared dryland area between the two periods,  $A_0$  ( $A_i$ ) is the area found exclusively in the reference period 1961–90 (in the  $i$ th warm period; i.e., a 20-yr window), and  $P_0$  ( $P_i$ ) is the population density in the reference period (in the  $i$ th warm period). Thus,  $\Delta P$  comprises two parts: one from changes in population density in the shared dryland areas (i.e., the common extent between past and future periods), and the other from changes in the spatial extent of drylands. We then quantify relative changes from both components, as shown:

$$\begin{cases} \Delta P_{\text{pop}} = \frac{P_i A - P_0 A}{P_r} \times 100\% \\ \Delta P_{\text{area}} = \frac{P_i A_i - P_0 A_0}{P_r} \times 100\% \end{cases}, \quad (7)$$

where  $\Delta P_{\text{pop}}$  ( $\Delta P_{\text{area}}$ ) is the relative change from changes in population density (spatial extent of drylands).

## 4. Results

### a. Detection of anthropogenic climate change in spatial patterns of change

Figure 2 shows spatial patterns (excluding Antarctica and Greenland) of changes in AI, PRCP, and PET between the mean values during 1990–2014 and 1950–74 from multidata mean observations and multimodel mean simulations under historical forcings (i.e., ALL, GHG, and NAT). Consistent spatial patterns can be found when the periods are 1985–2009 and 1950–74 (Fig. S1 in the online supplemental material), 1985–2009 and 1955–79 (Fig. S2), and 1990–2014 and 1955–79 (Fig. S3). Observations indicate the global land surface has mostly witnessed decreases in AI (62.3% of land grids) during the recent period relative to during the past period (Fig. 2a). Areas with decreases in AI are mainly in the East Asia monsoon region, Africa, and eastern Australia, where a decreasing trend in AI during 1948–2005 was also found by Huang et al. (2016). The observed PRCP shows decreases in only 48% of land grid cells, which are also mainly located in the East Asia monsoon region, Africa, and eastern Australia (Fig. 2e), while increases in observed PET are widespread across the globe (84% of land grids; Fig. 2i). The prominent increases in PET are favorable to decreases in atmospheric aridity. However,

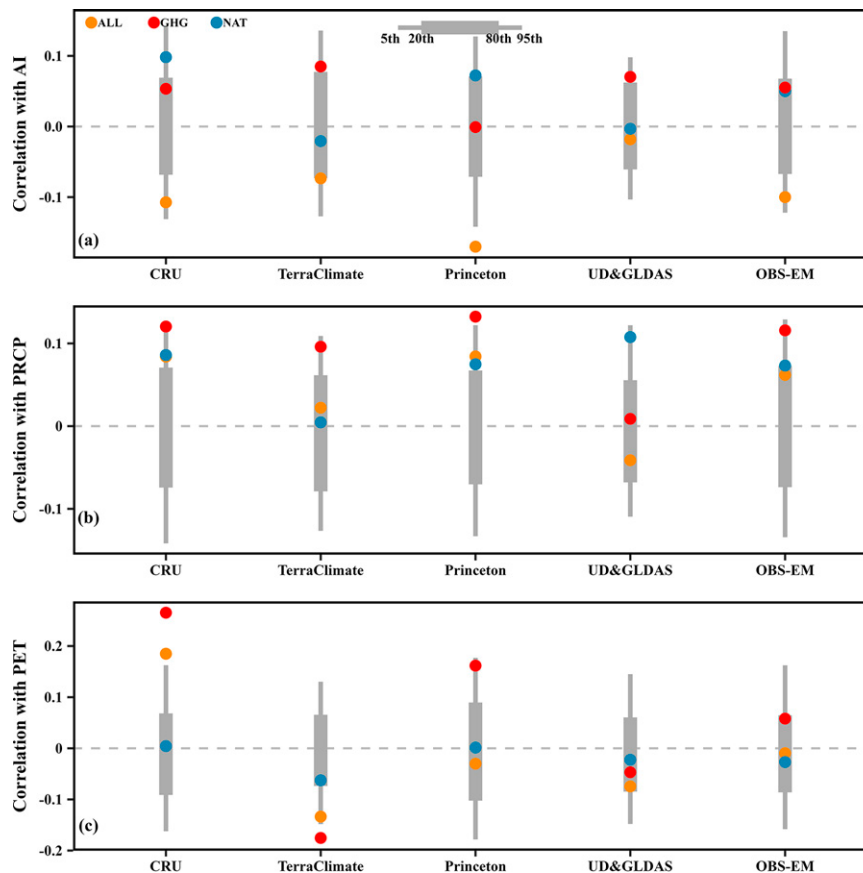


FIG. 3. Correlation-based attribution analyses for changes in spatial patterns of (a) AI, (b) PRCP, and (c) PET (as illustrated in Fig. 2). The gray bars represent the distribution of spatial correlations between observations and all 65-yr nonoverlapping segments from CTL simulations. The orange, red, and blue dots indicate the spatial correlations between observations and the multimodel mean simulations from ALL, GHG, and NAT forcings, respectively.

the spatial patterns of changes in observed AI are more closely controlled by PRCP, as seen by their highly consistent spatial patterns (i.e., 83.2% of land grids have the same change direction; Figs. 2a,e). For observed AI and PET, only 34.5% of the total land grids have the same sign (Figs. 2a,i). Feng and Fu (2013) found that increasing PET dominates the areas with transition from humid to dry subhumid and from dry subhumid to semiarid while increasing precipitation plays a dominant role in the regions with reducing aridity.

There is an agreement in the sign of the changes in PRCP (PET) between observations and simulations under ALL forcing; 55.7% (75%) of land areas have the same direction of change. This agreement in PRCP (PET) is even higher between observations and GHG simulations, and the corresponding percentage is 56.7% (83.6%). However, simulated PRCP (PET) that excludes human-induced impacts under NAT forcing shows much weaker consistency with observations. The above results imply that anthropogenic climate change is likely to be the underlying reason for the observed pattern of change in PRCP and PET. Previous studies have shown that the spatial distribution of long-term changes in precipitation and evapotranspiration at the global scale is well captured by

model simulations (Min et al. 2011; Madakumbura et al. 2021; J. Liu et al. 2021).

Nevertheless, the sign of spatial patterns in changes in observed AI is poorly captured by historical ALL simulations (Figs. 2a,b). Only 47.2% of land grids show consistent directions of change between observed and ALL simulated AI; opposite directions of change are found in North America, South America, northern Africa, and the East Asia monsoon region. The poor consistency of spatial change patterns between observations and ALL simulations was also found in previous studies (Huang et al. 2016; Feng and Fu 2013). The spatial patterns of change are highly similar between ALL- and GHG-simulated AI (Figs. 2b,c), implying that GHG forcing plays an important role in the changes under ALL forcing (which includes GHGs and other external forcings). We notice that the increase of observed AI is captured in simulations under NAT forcing, such as North America and South America (Figs. 2a,d), but not ALL forcing. The possible reasons for the poor ability of models to simulate the spatial patterns of changes in AI are model uncertainties and noises from natural climate variability (Monerie et al. 2020; Fyfe et al. 2021). As natural climate variability affects both observations

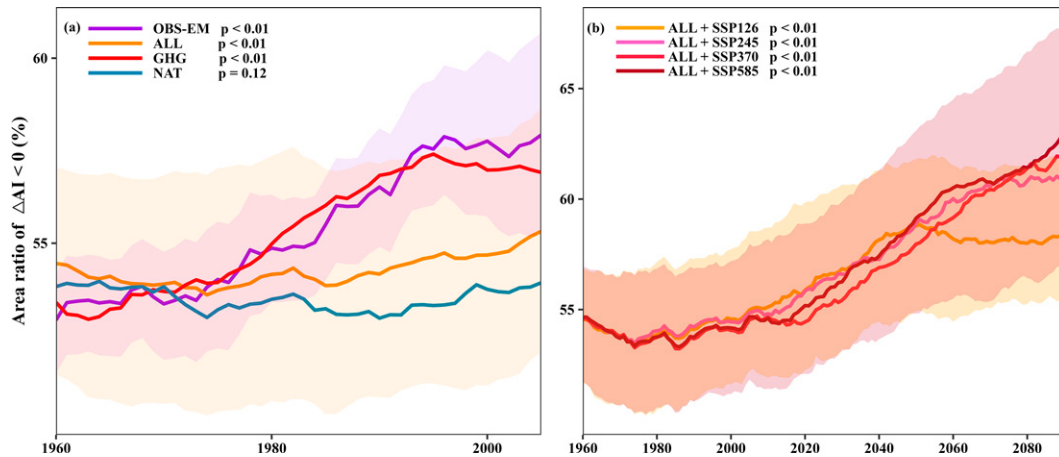


FIG. 4. Temporal evolution of the global proportion of land areas undergoing aridification [ $\Delta AI < 0$ ; see Eq. (1)] based on (a) observations and historical simulations and (b) projections under the four scenarios. Areas with  $\Delta AI < 0$  have drying atmospheric aridity during a running 20-yr window relative to the reference period 1961–90. The purple ribbon for observations indicates the extent of maximum and minimum values from the four observed datasets. The colored ribbons for the models indicate the 25th and 75th percentiles of the multimodel simulations.

and simulations, the agreement of spatial change patterns between them could be reduced by climate noise. On the other hand, the global land is dominated by increases in PRCP and PET under both ALL and GHG forcings, which could lead to mixed changes in  $P/PET$  (i.e., AI).

To formally detect an anthropogenic signal in the spatial change patterns, we assess whether the Spearman correlation of spatial patterns between observations and simulations under external forcings is greater than the correlations obtained from natural climate variability (Fig. 3). We find that the spatial correlation of PRCP (PET) between the ensemble mean of multiple observations (OBS-EM) and GHG simulations (red circle on the far right boxplot) exceeds the 90th (80th) percentile of correlations between observations and the 226 CTL simulation segments (Figs. 3b,c). This finding suggests that the GHG signal is detectable in the spatial patterns of changes in PRCP (PET) at the 90% (80%) confidence level (although both are lower than 95% confidence level). The spatial correlation of PRCP (PET) between OBS-EM and NAT simulations smaller than 80th percentile of correlations between OBS-EM and CTL simulations further confirms the impacts of human-induced climate change.

As shown in previous studies, anthropogenic climate change is detectable in the temporal increases in global precipitation and evapotranspiration (Wu et al. 2013; J. Liu et al. 2021). Based on the Clausius–Clapeyron relationship, anthropogenic warming is expected to increase atmospheric water holding capacity, and thus enhance precipitation totals (Donat et al. 2016; Wu et al. 2013). For global drylands, annual precipitation totals increase by  $\sim 15\%$  per  $1^\circ\text{C}$  of global warming (Donat et al. 2016). Besides the thermodynamic effects (i.e., changes in atmospheric moisture) of global warming, warming-driven dynamic effects also work on precipitation changes (Paik et al. 2020; Pfahl et al. 2017). For example, Pfahl et al. (2017) indicated that the thermodynamics cause a consistent increase in precipitation over most global areas,

while dynamics amplify or weaken this increase depending on regions. Global hydrological cycle is also driven by anthropogenic-induced perturbations to the surface energy budget (Wu et al. 2010, 2013). GHGs can increase net surface radiation by intercepting more outgoing longwave radiation, and then enhance evapotranspiration (Dai et al. 2018; J. Liu et al. 2021). Rising atmospheric  $\text{CO}_2$  can reduce stomatal conductance in plants and lead to a lower transpiration rate, but simultaneously also increase transpiration by expanding plant leaf area (Cui et al. 2020; Ukkola et al. 2016; Yang et al. 2019). Our results indicate that it is likely ( $>80\%$  probability) that GHG forcing is driving not only the observed increases but also the spatial changes of PRCP and PET.

Although a detectable GHG signal is found in spatial changes of PRCP and PET, this signal is not detected in the observed changes in AI (Fig. 3a). The spatial correlation between AI observations and GHG simulations is lower than the 80th percentile of correlations from CTL simulations. There is a very low spatial correlation between AI observations and simulations under ALL forcing, further confirming the poor ability of models to capture observed spatial change patterns (as mentioned above). This weak spatial correlation between observations and simulations under ALL forcing is also found in PRCP and PET. Possible reasons are that 1) model uncertainties may cause a disagreement between observations and simulations (Fyfe et al. 2021; Padrón et al. 2020), 2) the counteracting effect of anthropogenic aerosols and GHG may contribute to a more complex spatial change (Lau et al. 2017; Touma et al. 2021), and 3) the uncertainties among the four observation datasets may affect the response of model simulations to observed spatial patterns (Sun et al. 2018). There is an evident discrepancy in the response of different observational datasets to external forcings, for example, the GHG signal is detectable in the spatial changes of AI based on the UD and GLDAS (TerraClimate) dataset at 80% confidence level (Fig. 3a).

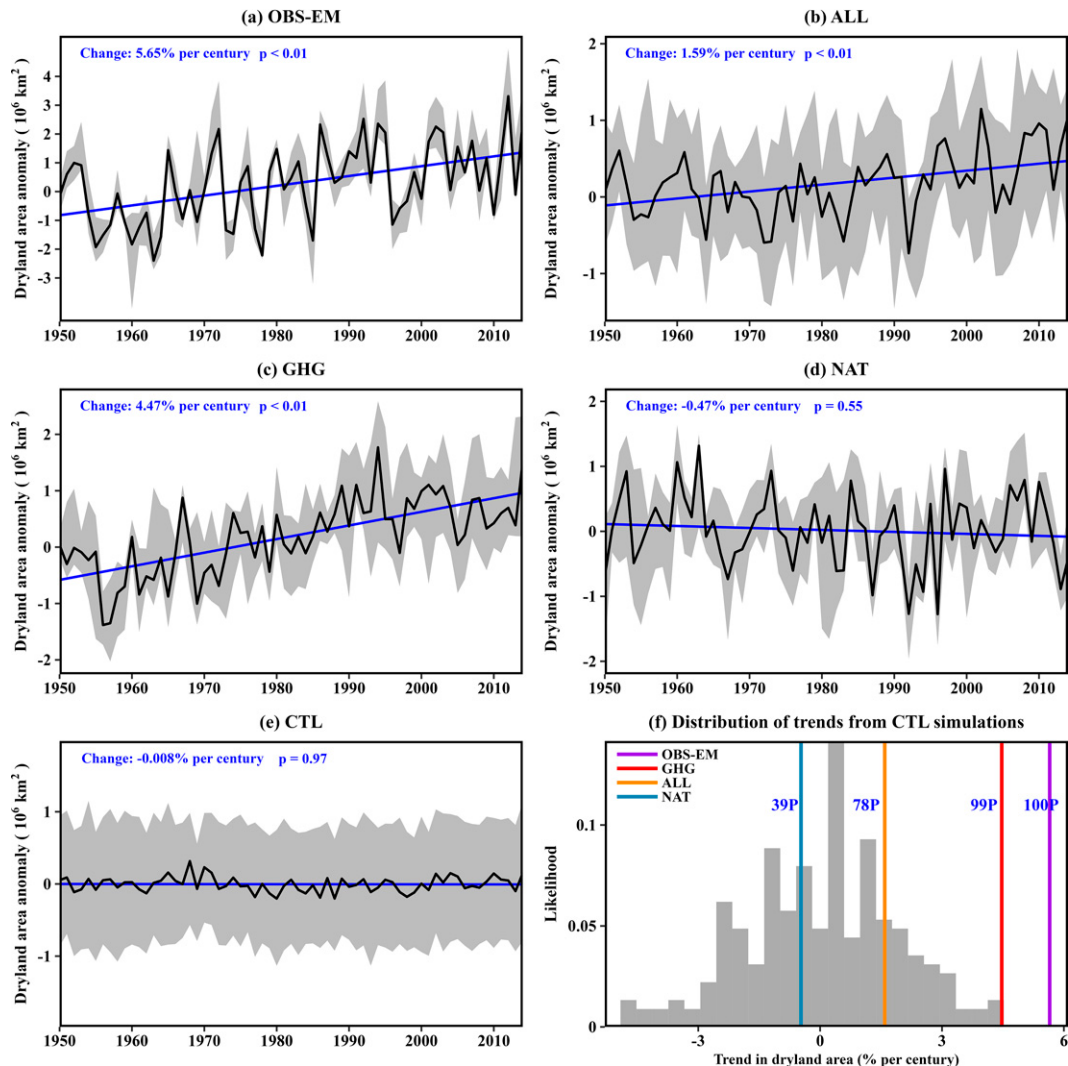


FIG. 5. Long-term changes in dryland areas in observations and model simulations. (a)–(e) The changes estimated from observations and model simulations under ALL, GHG, NAT, and CTL forcings, respectively. In (a), the gray shadow is the spread of maximum and minimum values from the four observed datasets. In (b)–(e), the gray shadow indicates the 25th and 75th percentiles of multimodel simulations. (f) The colored vertical lines show the trends in observations and model simulations under external forcings; blue text is the corresponding percentiles in the probability density distribution of trends in all 65-yr nonoverlapping segments from CTL simulations (see gray bars).

Although models have limited ability to simulate regional patterns of change, they do capture the temporal evolution of global land areas with drying atmospheric aridity ( $\Delta \text{AI} < 0$ ) during a running 20-yr period relative to the reference period of 1961–90 (Fig. 4). In recent decades, observations show a significant increase in the global proportion of land areas with drying atmospheric aridity. The simulations under ALL forcing barely capture this increasing land area; they underestimate the observed increasing rate, which the GHG simulations simulate well. When excluding human-induced forcings (NAT simulations), the increase in land area with drying atmospheric aridity is not detected. These results imply that an increasing proportion of land area is experiencing atmospheric drying, potentially

caused by human-induced climate change. Land areas with drying atmospheric aridity are projected to continue expanding in the future under all four scenarios (although SSP126 may see a decrease in the second half of the twenty-first century).

#### b. Detection and attribution of temporal changes in dryland areas

Following the increase in land areas with drying atmospheric aridity in recent decades (Fig. 4a), we then focus on changes in the extent of dryland areas (i.e.,  $\text{AI} \leq 0.65$ ) in both observations and simulations (Fig. 5). As shown in previous studies (Huang et al. 2016; Dai 2013), the extent of drylands significantly increased at a rate of  $5.65\% \text{ century}^{-1}$  in observations and  $1.59\% \text{ century}^{-1}$  in simulations under ALL forcing

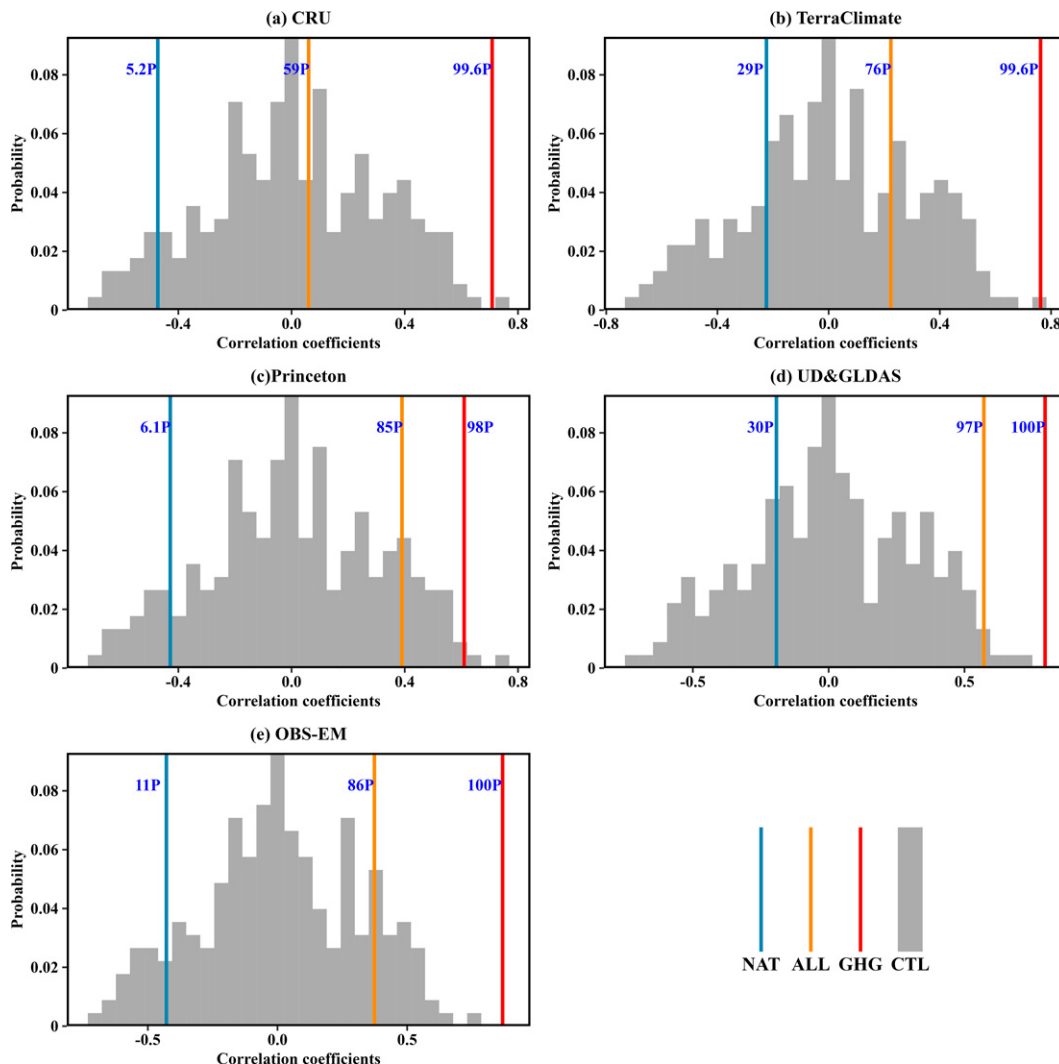


FIG. 6. Correlation-based attribution analyses for long-term changes in dryland extent based on (a) CRU, (b) TerraClimate, (c) Princeton, (d) UD, and (e) multimean observations. The bar plots are the Spearman correlations of dryland area time series between observations and CTL simulations during the period 1950–2014. The colored vertical lines show correlations between observations and model simulations under external forcings; blue texts are the corresponding percentiles in the probability density distribution of correlations between observations and CTL simulations.

during 1950–2014. This increase in dryland extent is more evident in GHG simulations (i.e.,  $4.47\%$  century<sup>-1</sup>) than in ALL simulations. Both NAT and CTL simulations show a slight decrease in dryland area extent (Figs. 5d,e) and therefore do not explain the observed dryland expansion. Additionally, the observed trend and the GHG simulated trend are outside the range or at the high end (i.e., above the 99th percentile) of the trend expected from natural climate variability (see gray bar plots in Fig. 5f), which is quantified from CTL simulations. These results indicate that the GHG emission signal is strong enough to be detected in the observed increase in dryland extent.

We first employ the correlation-based attribution approach (Gudmundsson et al. 2017a; Padrón et al. 2020) to conduct a

quantitative assessment of anthropogenic impacts (Fig. 6). The Spearman correlations of drylands area time series between observations and ALL simulations are relatively high, that is, above the 85th percentile of correlations between observations and the CTL simulations (for the composite observations, Princeton, and UD and GLDAS datasets). This percentile is notably higher (i.e., at least above the 98th percentile) for the correlations between observations and GHG simulations (for the composite observations and all the individual datasets), suggesting that there is a high probability that GHG emissions are driving the observed increase in dryland extent. Furthermore, the NAT simulations are weakly correlated with the observed pattern (i.e., well within the range spanned by CTL simulations), implying that there is a

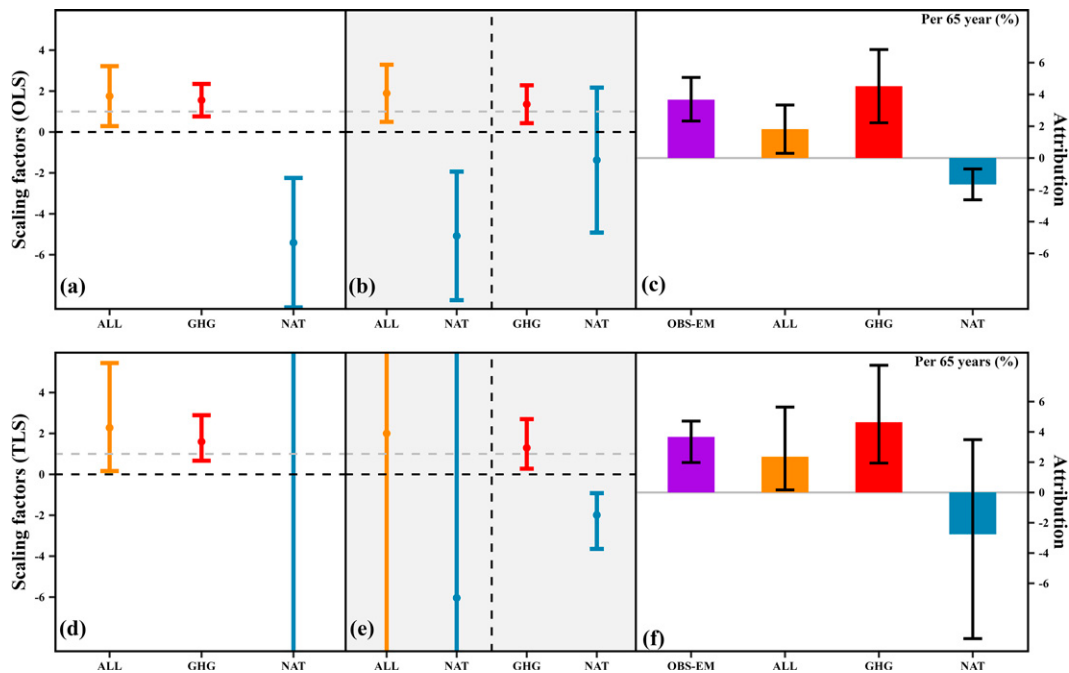


FIG. 7. Detection and attribution of long-term changes in dryland area by using the optimal fingerprint method. The scaling factors estimated from (a),(b) OLS and (d),(e) TLS methods, respectively. The scaling factors based on (a),(d) one-signal and (b),(e) two-signal analysis, and the error bars indicate the 5th and 95th percentile values of the corresponding scaling factor. (c),(f) The corresponding attribution results, except for the purple bar plot, which is the trend in multidata mean observations. The error bars in (c) and (f) indicate the 25%–75% interval of the bar plot values.

low probability that the NAT forcing is driving the observed pattern.

In addition to the correlation analysis, we employ the optimal fingerprinting method to further quantify the contributions of external forcings to the long-term changes in observed dryland extent (Fig. 7). We first regressed the observations on the individual external forcings (i.e., ALL, GHG, and NAT), respectively, and conducted one-signal detection and attribution (Figs. 7a,d). Both the OLS and TLS estimations show that the scaling factors of ALL and GHG forcings are significantly above zero at the 95% confidence level, while this is not the case for the NAT scaling factor. This is consistent with the results from the correlation-based detection, and strengthens the evidence that the signal of GHG emissions is detectable in dryland expansion. Both the scaling factors of ALL and GHG forcings are larger than 1 (i.e., around 2), indicating that model simulations underestimate the amplitude of observed dryland expansion.

The long-term changes in dryland extent show a very strong linear trend in both observations and simulations under ALL and GHG forcings (Figs. 5a–c). If this strong linear trend is distinguishable above the climate noise, this indicates that the one-signal analysis could be dominated by one forcing (Chen and Sun 2017; Gu et al. 2019b). Therefore, we conducted a two-signal analysis by regressing the observations on both ALL and NAT (GHG and NAT) forcings, simultaneously (Kong et al. 2020). As the observed patterns could be affected by several forcings, the two-signal analysis can also tell us

whether the responses of ALL and GHG forcings can be separated from the NAT forcing (Figs. 7b,d). We find that the GHG scaling factor is significantly above zero in both OLS and TLS estimations, but the NAT factor is not. This result indicates that the response of GHG forcing is distinct from the NAT forcing and confirms that the result of one-signal analysis is robust.

We further estimate the contributions of individual external forcings to the observed change in dryland extent (Figs. 7c,f). Over the period 1950–2014, observed dryland areas have expanded by 3.67%. The ALL forcing (including both anthropogenic forcings and NAT forcing) has driven dryland expansion by 2.36% (1.81%) since 1950, according to the TLS (OLS) estimation. In contrast, the dryland expansion attributed to GHG forcing is 4.63% (4.52%) since 1950, which is comparable to the amplitude of change in observations.

### c. Changes in dryland population

Since GHG emissions drive both global warming and dryland expansion, we assess the evolution of dryland extent and population with future warming levels (Fig. 8). All four future emission scenarios project increasing dryland extent with global warming (Figs. 8a,b). The dryland areas are projected to increase by 1%, 2%, and 4.8% relative to the reference period of 1961–90, with warming levels of 1.5°, 2°, and 3.5°C, relative to preindustrial conditions, respectively. This projection is consistent with previous studies (Huang et al. 2016; Koutroulis 2019). Huang et al. (2016) projected 23% and 11%

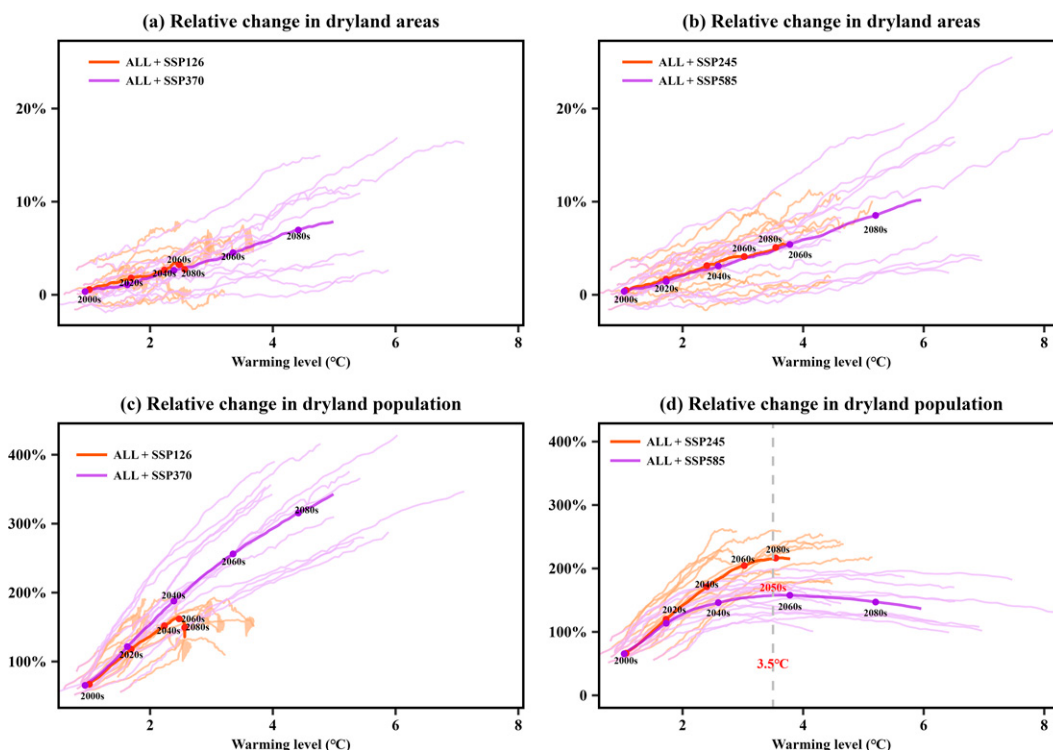


FIG. 8. Projected changes in (a),(b) dryland area and (c),(d) population during future warming periods relative to the reference period of 1961–90 under the four future emission scenarios. The light-colored curves are the projections from individual models and the corresponding dark-colored curves are the projections from multimodel mean.

increases in dryland areas by the end of the twenty-first century under RCP8.5 and RCP4.5 relative to the reference period of 1961–90. Koutroulis (2019) used the outputs of a high-resolution model (i.e., HadGEM3A with a spatial resolution of ~60 km) and projected the areal coverage of drylands would increase by 7% by the end of twenty-first century under RCP8.5.

Both studies (Huang et al. 2016; Koutroulis 2019) also projected increases in the population of drylands during this continued expansion. Koutroulis (2019) indicated that an additional 1.9 billion people would live in dryland areas with an increase in warming from 1.5° to 4°C. However, our projections show that the increases in dryland population persist among all warming levels only under the SSP370 scenario (Figs. 8c,d). The population is projected to increase to 12.6 billion by the end of the twenty-first century in SSP370, which is much higher than other SSPs (i.e., 7 billion for SSP1, 9.4 billion for SSP2, and 7 billion for SSP5; Samir and Lutz 2017; Riahi et al. 2017). Under SSP370, the persistently growing population and dryland expansion lead to continuous increases in relative change in dryland population. For SSP245 and SSP585, we observe a shift in dryland population from increases to decreases when the warming level reaches above ~3.5°C. These changes in dryland population are also found in China where the population exposure to drought is projected to increase up to the 2040s and then decrease until the end of twenty-first century under the four future scenarios, with the exception of SSP370 (Chen et al. 2021).

We hence investigate whether population density and/or the spatial extent of drylands dominate this future shift in dryland population (Fig. 9). The growth in dryland extent is projected to contribute to the increases in dryland population under all four warming scenarios (Figs. 9b,d). Projected increases caused by spatial extent under SSP370, for instance, are 5.1%, 6.4%, and 14.1% at warming levels of 1.5°, 2°, and 3.5°C, respectively. In comparison with dryland expansion, changes in population density play an even greater role in dryland population growth (Figs. 9a,c). For example, the population increases induced by population density under SSP370 are 69%, 106%, and 160% at warming levels of 1.5°, 2°, and 3.5°C, respectively. However, this persistent increase in population induced by changes in population density is found only under SSP370 (Figs. 9a,c). For SSP245 and SSP585, the trajectory is projected to start decreasing beyond a warming level of ~3.5°C, due to the reduction in dryland population density. These results suggest that warming above ~3.5°C under SSP245 and SSP585 could make the dryland areas uninhabitable by humans, and thus lead to a reduction in dryland population.

## 5. Discussion and conclusions

In this study, we conduct a formal detection and attribution analysis of the observed spatiotemporal changes in global dryland extent by comparing multiple observed and simulated datasets using a correlation-related approach and optimal

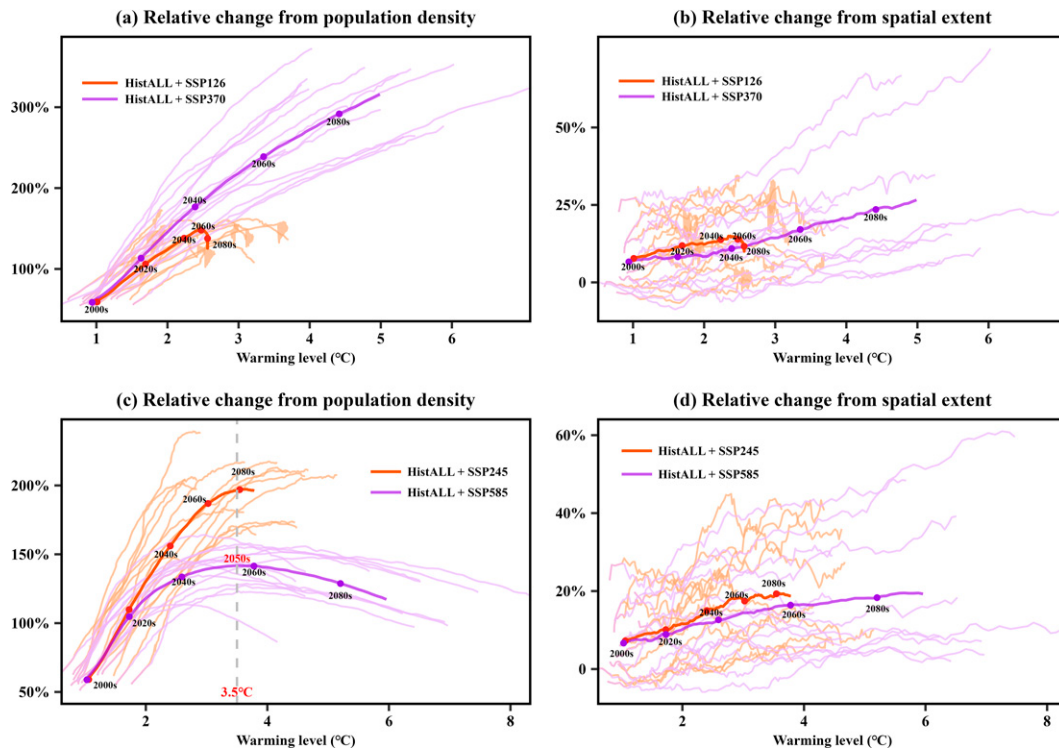


FIG. 9. Projected change in dryland population arising from changes in (a),(c) population density and (b),(d) spatial extent of drylands during a future warming period relative to the reference period 1961–90 under the four future emission scenarios. The light-colored curves are the projections from individual models and the corresponding dark-colored curves are the projections from the multimodel mean.

fingerprint method. Correlation-related attribution analysis shows it is unlikely that the spatial changes of atmospheric aridity (i.e., AI) between the recent period (1990–2014) and the past period (1950–74) are caused by GHG emissions. However, the growing fraction of land areas with increasing atmospheric aridity (i.e.,  $\Delta AI < 0$ ) is captured by model simulations only when the models are forced with GHG emissions, implying that anthropogenic climate change may be driving dryland expansion. Formal detection and attribution analysis further support that a GHG signal is detectable (at 95% confidence level) in the observed expansion of global drylands over the past decades. Specifically, the observed extent of global drylands increased by 3.67% from 1950 to 2014, and a growth of  $\sim 4.5\%$  can be attributed to GHG emissions. Detection and attribution analysis quantitatively supports that anthropogenic climate change is the dominant contributor to global dryland expansion, which will increase population in drylands. In comparison with the increase driven by dryland expansion, changes in dryland population density play a more important role. A reduction in dryland population density is expected to drive a subsequent decrease in dryland population if future warming exceeds  $\sim 3.5^\circ\text{C}$  under the SSP245 and SSP585 scenarios.

As mentioned in the introduction, the spatial patterns of change and dryland expansion differ when using other indices to define drylands. Besides AI, Lian et al. (2021) also used vapor pressure deficit (VPD), soil moisture, runoff, and gross

primary production (GPP) to define drylands and found that VPD- and soil moisture-based drylands show obvious expansion in the future while runoff-based (GPP-based) dryland extent remains stable (significantly decreases). The consistent obvious dryland expansion between AI and VPD and soil moisture implies that the anthropogenic climate change signal may be also detectable in dryland expansion identified based on VPD and soil moisture. Our previous study has detected the influence of human activities on the past decrease in global soil moisture (Gu et al. 2019b). However, no expansion is projected in runoff- and GPP-based global drylands, indicating that greenhouse warming signals may not be detectable in observed dryland expansion. This is because the effects of increasing atmospheric  $\text{CO}_2$  on runoff and vegetation are still ambiguous and debatable (Zhang et al. 2021; Lian et al. 2021; Berg and McColl 2021; Yang et al. 2019). Here, we focus on atmospheric aridity and use the aridity index to define drylands. Other indices based on agricultural, hydrological, and ecological attributes are beyond the scope of our study.

The robustness of our results is mainly affected by uncertainties in observations and model simulations. Spatial changes in the aridity index, precipitation, and potential evapotranspiration exhibit clear differences among the four observed datasets (Fig. S5). The Spearman correlation of spatial change between each pair of the four datasets is within 0.46–0.73 for the aridity index, 0.48–0.87 for precipitation, and 0.11–0.62 for potential evapotranspiration (Fig. S5). Observational uncertainties do

affect the detection of a GHG emissions signal. For example, for the aridity index, a GHG signal is not detectable in the multimean observed changes, but is detected (>90% probability) in the UD and GLDAS dataset (Fig. 3a). In contrast, for precipitation, the GHG signal is detectable (>90% probability) in the multimean observed change, but not in the UD and GLDAS dataset (Fig. 3b). The inconsistencies among these observed precipitation datasets are described in Sun et al. (2018).

We also note the inconsistency of spatial changes in the aridity index between observations and model simulations (see Figs. 2a,b). The poor ability of models to capture spatial changes in the aridity index is also found in Huang et al. (2016). Alongside the changes in AI-based drylands, soil organic carbon storage and emission are also changed; however, these carbon cycle processes are not included in some climate models, which hinders models from accurately reproducing these spatial patterns of change (Huang et al. 2016). The models also underestimate the amplitude of the observed dryland expansion (see the scaling factor of ALL forcing, which exceeds 1 in Figs. 7a and 7d). We use a correlation-based approach and anomalies to reduce the potential impact of biases in the absolute magnitude of simulations on our detection and attribution results (Gudmundsson et al. 2017b; Qian and Zhang 2015), and relative changes in comparison with the reference period to reduce biases in the dryland population estimates.

Human-induced dryland expansion is accompanied by serious land degradation (Reynolds et al. 2007; Burrell et al. 2020). The change of above 5 million km<sup>2</sup> of drylands toward desertification was driven by anthropogenic climate change during 1982–2015 (Burrell et al. 2020). Dryland expansion and degradation mean less water availability, and population growth increase water demand. The interaction between less water availability and growing water use would put great pressure on ecosystems and human settlements in drylands. Therefore, adaptation measures are needed to mitigate the adverse effects of water shortages, such as demand management, water markets, water-saving techniques, and limiting carbon emissions (AghaKouchak et al. 2021). Policymakers and societies should prioritize water demands and uses to minimize the impacts on ecosystems and human settlements. Researchers could focus on the integration of water supplies, needs, and management under climate change, which is important to sustain the development of humans and ecosystems in drylands (AghaKouchak et al. 2021).

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Research and Innovation (MR/V022008/1). The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Data availability statement.** The Climatic Research Unit datasets are available at [https://data.ceda.ac.uk/badc/cru/data/cru\\_ts/](https://data.ceda.ac.uk/badc/cru/data/cru_ts/), the TerraClimate datasets at <https://data.nkn.uidaho.edu/dataset/monthly-climate-and-climatic-water-balance-global-terrestrial-surfaces-1958-2015>, the Princeton datasets at <http://hydrology.princeton.edu>, the University of Delaware datasets at [http://climate.geog.udel.edu/~climate/html\\_pages/download.html#P2017](http://climate.geog.udel.edu/~climate/html_pages/download.html#P2017), and the Global Land Data Assimilation System datasets at <https://doi.org/10.5067/9SQ1B3ZXP2C5>. The simulated data from phase 6 of the Coupled Model Intercomparison Project are available at <https://esgf-node.lnl.gov/search/cmip6/>. Population datasets are available at <https://data.isimip.org/>.

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