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Large-scale photovoltaic deployment in the Taklamakan Desert could intensify regional water stress

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ABSTRACT

Northwest China's arid climate and fragile ecosystems are becoming wetter and greener. However, the rapid expansion of photovoltaic (PV) infrastructure in this region alters land-atmosphere interactions, with potential consequences for local climate and water resources. Here, we use a combined climate and dynamic vegetation modeling approach to assess the effects of hypothetical PV deployment across the Tarim Basin, home to the world's second-largest mobile desert. We find that large-scale PV installations may significantly reduce water resources in populated areas, with over 30% reductions in runoff, precipitation, and aridity index, alongside an 8.5% decline in soil moisture. High-efficiency PV panels increase surface albedo, leading to surface cooling and intensified anticyclonic circulation, which suppresses precipitation and triggers vegetation decline. This vegetation feedback amplifies aridity by modifying albedo and evapotranspiration. These results highlight the critical need to incorporate vegetation feedback in future studies to fully evaluate PV's hydrological impacts and stress the importance of careful planning to mitigate environmental risks associated with large-scale solar projects in Northwest China.

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1. Introduction

Since the 1980s, Northwest China has experienced a “warming and wetting” trend, marked by rising precipitation, runoff, lake levels, and improved vegetation cover [1–3]. This climatic and ecological enhancement has accelerated since the 1990s [4,5], yet the region's arid climate, fragile ecosystems, scarce water resources, and sensitivity to external disturbances remain largely unchanged [6].

Under the “14th Five-Year Modern Energy System Plan”, large-scale photovoltaic (PV) projects are rapidly expanding in Northwest China, including three 10-gigawatt-class renewable energy bases [7,8]. The Tarim Basin, home to the world's second-largest

mobile desert, offers ideal conditions for such projects due to its vast terrain, high solar irradiance, and unique hydrological features [9–11]. However, studies on the environmental impacts of large-scale PV development in this region remain limited. Water resources in the Tarim Basin are highly sensitive to environmental and climatic changes, making them particularly important for human settlements. Most of the population lives along the desert edges, with some communities located in interior areas where water resources are accessible. Therefore, changes in water resources could significantly affect local livelihoods and socio-economic activities. Initiatives such as the “Battle for Blocking the Edge of the Taklamakan Desert” are established, which aim to protect these fragile ecosystems [12]. These factors make the Tarim Basin a critical area for studying the environmental impacts of large-scale PV deployment.

Solar energy, as a clean and renewable resource, plays a crucial role in reducing greenhouse gas emissions and transitioning from

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fossil fuels [13–15]. Desert regions have high solar irradiance and vast expanses of land, making them ideal for large-scale PV installations [16–18]. As the scale of solar projects expands their broader environmental impacts, particularly on climate and terrestrial ecosystems, become non-negligible [19–21]. However, previous field observations, satellite remote sensing, and model simulations have revealed complex but profound effects of desert solar farms [22–24]. For example, some studies show that large-scale PV installations can lead to a “photovoltaic heat island effect”, causing local temperature increase, and they further have a negative impact on desert scrub plant communities, which reduces biodiversity [25–27]. Conversely, other studies suggest that the installation of PV panels significantly lowers the average local temperature, especially during the day, and enhances vegetation resilience in arid regions [28–30]. These contrasting results underscore the complexity of PV panel impacts on regional climate and terrestrial ecosystems, often dependent on local topography, microclimate and solar panel conditions, as well as the limitations of field observations and remote sensing in isolating the specific effects of utility-scale PV installations. Moreover, the feedback effects induced by changes in surface temperature, wind, and humidity further complicate the influence of PV panels on surrounding climate and ecosystem dynamics [31,32]. In response to these challenges, some studies have utilized a fully coupled Earth system model to examine the effects of hypothetical PV panels in the Sahara Desert, showing local benefits like increased precipitation and improved vegetation [33,34] but adverse impacts elsewhere, due to large-scale atmospheric circulation shifts [34]. Although the spatial scale and climate background differ significantly between the Sahara and the Tarim Basin, these global model studies improve our understanding of important climate-ecosystem feedbacks induced by massive desert solar farms. However, their coarse resolution may overlook critical weather details and limit their ability to capture fine-scale interactions between deserts and surrounding regions [35,36]. Moreover, although the climatic and ecological impacts of large-scale PV farms have received widespread attention, their effects on regional water resources remain a critical yet underexplored aspect of sustainability, particularly in arid and semi-arid regions. PV arrays can directly interfere with key hydrological processes—such as evaporation and runoff—by modifying surface energy balance, intercepting precipitation, altering vegetation distribution, and changing soil thermal and moisture conditions [37,38]. Rather than occurring in isolation, these impacts can be amplified through land-atmosphere coupling processes, ultimately propagating to the regional water resource system. Notably, studies that explicitly address the impacts of PV installations on water resources remain limited. A systematic investigation of the mechanisms linking PV-induced climate-ecosystem changes to regional water resources, therefore represents an important scientific question.

In this study, we examine how extensive PV deployments could influence the climate, terrestrial ecosystems and their interactions, and consequently water resources within the Tarim Basin. Compared with previous studies that relied on field observations, remote sensing, or coarse-resolution global climate models, this study advances existing knowledge by adopting a high-resolution, process-based modeling framework that explicitly resolves surface-vegetation-atmosphere interactions at the regional scale. We employ the Weather Research and Forecasting model (WRF) offline coupled with the Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS), a dynamic global vegetation model (DGVM), to simulate the impacts of large-scale PV installations under a suite of realistic present-day, future, and extreme photovoltaic scenarios during 2016–2020. We designed 5 sensitivity experiments based on PV panel reflectivity and efficiency with albedo values of 0.1925 (S19, current low-conversion efficiency of

0.15), 0.335 (S335, future high-conversion efficiency of 0.3), together with three extremes scenarios of 0.62 (S62, extremely high-conversion efficiency of 0.6), 0.905 (S905, extremely high-conversion efficiency of 0.9, or “white panel”), and 0.05 (S05, extremely low-conversion efficiency of 0.05, or “black panel”). These sensitivity experiments were compared with control simulations (Ctrl) to systematically explore the sensitivity and nonlinearity of climate and ecosystem responses to PV deployment. Based on the coupling method (Fig. S1 online), we can quantify the climate/vegetation response only to PV panels in WRF (WRF2)/LPJ-GUESS (LPJ-GUESS2), and also the climate impacts of PV further amplified by vegetation feedbacks in WRF (WRF3) (see more details in Methods). This integrated approach allows us to quantitatively attribute PV-induced changes in climate, ecosystems, and water resources, thereby providing mechanistic insights and policy-relevant guidance for the sustainable deployment of large-scale solar energy infrastructure in arid and semi-arid regions of Northwest China.

2. Data and methods

2.1. Data sources

This study utilized four climate datasets and one vegetation dataset, all covering the period of 2016–2020. The climate datasets include the following: (1) the monthly-resolution CN05.1 dataset (temperature and precipitation), constructed by the China Meteorological Administration through the interpolation of over 2400 ground meteorological stations, with a spatial resolution of $0.25^\circ \times 0.25^\circ$ [39]; (2) CRU TS4.05 dataset (temperature and precipitation) from the Climate Research Unit of the University of East Anglia, featuring a spatial resolution of $0.5^\circ \times 0.5^\circ$ [40]; (3) the GPCC precipitation provided by the Global Precipitation Climatology Centre, at a $0.25^\circ \times 0.25^\circ$ resolution [41]; (4) the hourly-resolution ERA5 reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF), which provided all necessary meteorological forcing data to the WRF model, at a $0.25^\circ \times 0.25^\circ$ resolution. The Global Land Surface Satellite (GLASS) dataset, developed by Beijing Normal University, offers global Leaf Area Index (LAI) data with a spatial resolution of $0.05^\circ \times 0.05^\circ$ and is considered highly reliable [42,43]. The soil properties data (including the fractions of sand, silt, and clay) used to drive the LPJ-GUESS model were obtained from the topsoil layer of the WISE30-min 3.0 global soil dataset [44,45].

2.2. Methods

2.2.1. The climate and ecosystem models

The WRF model (version 4.2.2) demonstrates high accuracy in climate simulations and is widely used in real-time weather forecasting, regional climate research, and idealized numerical simulations [46–48]. In this study, the WRF model was set up with a single-layer grid nesting, covering an area approximately between 35°N and 50°N , and 70°E to 100°E , with a spatial resolution of 9 km and a temporal resolution of 6 h, utilizing 35 vertical layers and the top level at 50 hPa. The ERA5 reanalysis dataset, known for its high resolution and accuracy, was used as the model's initial and boundary conditions. The simulation period spanned from December 1, 2015, at 00:00, to December 31, 2020, at 18:00, with the first month of simulation for model spin-up to allow the model to reach equilibrium. The selected parameterization schemes included the Thompson microphysics scheme, the Rapid Radiative Transfer Model (RRTM) longwave radiation scheme, the Dudhia shortwave radiation scheme, the Monin-Obukhov surface layer scheme, the Noah land surface scheme, the Kain-Fritsch cumulus parameteriza-

tion scheme and the Mellor-Yamada Nakanishi Niino (MYNN) 2.5 level Turbulence Kinetic Energy (TKE) boundary layer scheme.

LPJ-GUESS incorporates individual- and patch-based representations of woody and herbaceous vegetation and includes explicit process-based descriptions of key plant physiological processes [49–51]. It is widely applied in studies on terrestrial ecosystem structure and function [49,52], particularly in arid and semi-arid ecosystems [53,54]. Previous DGVM intercomparison and evaluation studies provide important context for assessing the robustness of LPJ-GUESS simulations. Although substantial inter-model spread exists in dryland ecosystem responses due to differences in process representation and parameterization, these studies consistently indicate that LPJ-GUESS performs in line with other widely used DGVMs in arid and semi-arid regions. Accordingly, despite remaining uncertainties and the absence of a multi-model ensemble, the vegetation responses simulated by LPJ-GUESS in this study fall within the plausible range reported by existing DGVM intercomparison studies, rather than representing an extreme model behavior [53,55,56].

We also validated the accuracy of WRF and LPJ-GUESS in simulating the climate and vegetation characteristics of Northwest China in Ctrl. The results indicate that Ctrl can effectively reproduce the climatic and vegetation changes in the present climate state (Table S1, Figs. S2–S4 online).

2.2.2. The offline coupling method

Since the vegetation in standard WRF is static rather than dynamic, we incorporated dynamically simulated vegetation from LPJ-GUESS into WRF through offline coupling to analyze the climate-ecological effects of solar PV panels. Specifically, the 6-h resolution outputs from the WRF model, including temperature, precipitation, and shortwave radiation, are first subjected to a scale transformation. These transformed WRF outputs are combined with pre-prepared data sets at 9 km spatial resolution, such as latitude and longitude, nitrogen deposition, and soil texture-related data. Together, these variables form boundary conditions to drive the LPJ-GUESS model, allowing us to simulate the vegetation response to initial climate change. Subsequently, the outputs from LPJ-GUESS, including surface albedo, LAI, vegetation fraction of photosynthetically active radiation (FPAR), soil temperature, and land use, are processed and used to replace corresponding input data for WRF. By re-running WRF with these updated parameters, we are able to capture the feedback effects of vegetation on climate, triggered by PV installations. This two-way offline coupling process is illustrated in Fig. S1 (online), where WRF1 and LPJ-GUESS1 represent the Ctrl simulations. One step further, WRF2 and LPJ-GUESS2 represent climate and vegetation changes considering only PV impacts. WRF3 represents regional climate changes under the combined influence of PV and vegetation feedback.

2.2.3. Solar farm simulations

In this study, we selected the largest desert region in China, the Tarim Basin, as the experimental area to simulate the installation of solar PV panels (Fig. S5a online, orange area). The simulation excluded areas unsuitable for PV panel construction based on three geographical constraints (Fig. S5b online) [57]. First, legally protected areas, including nature reserves and their 10-km buffer zones, were excluded. Second, forested lands were also removed. These two constraints were applied to minimize potential ecological disturbance associated with large-scale PV deployment. Third, regions with slopes greater than 30° were excluded to confine PV construction to relatively flat terrain and ensure engineering feasibility. Land-use data were sourced from the European Space Agency (ESA) with a spatial resolution of 300 m, while slope data were extracted from the United States Geological Survey (USGS) elevation dataset, which has a spatial resolution of 1 km. Based

on multiple field investigations at PV sites across the Tarim Basin (Figures not shown), we plausibly assume no vegetation beneath the PV panels, thereby excluding vegetation feedback within PV-covered areas. Nevertheless, vegetation changes in the intermediate LPJ-GUESS2 simulations are still displayed, as they provide valuable insights into PV-induced vegetation responses. Under this assumption, within the offline coupling framework, when output variables from LPJ-GUESS2 are fed back into WRF (WRF3), updates are applied only to non-PV-covered areas, while PV-covered grid fractions retain the baseline land-surface conditions derived from LPJ-GUESS1.

To simulate the impact of PV panel installation on land surface characteristics, we fixed the *effective albedo* in the model to represent the PV panel locations. *Effective albedo* is used to characterize the net fraction of incoming shortwave radiation that does not contribute to heating the land surface in areas covered by PV panels. It represents the combined effect of radiative reflection by the panel and the removal of absorbed solar energy through electricity generation. Specifically, part of the incoming shortwave radiation is directly reflected to the atmosphere, while another part is absorbed by the PV panels and converted into electrical energy, thereby reducing local surface heating. In the WRF model, this effect is represented by modifying the surface albedo to account for the presence of PV installations. This method is straightforward to implement in the model, effectively capturing the primary radiative perturbations induced by PV installations, and is widely used as a simplified model scheme for large-scale solar farms in previous studies [31,33,34].

In this experiment, we assumed a typical reflectivity of solar PV panels to be 0.05 [58]. Six simulation scenarios for different *effective albedo* were designed: Ctrl, S335, S62, S905, S19, S05. The S19 experiment represents the recent typical conversion efficiency of PV panels after degradation (such as dust), which is approximately 0.15 [33,54]. The corresponding *effective albedo* for S19 is calculated as $0.05 + 0.15 \times (1 - 0.05) = 0.1925$, summing the portion of solar radiation which doesn't generate heat locally. With technological advancements, laboratory tests have recorded steadily increasing conversion efficiencies of PV panels, reaching over 0.2 to 0.4. However, in the actual application of PV panels, external factors such as dust or high operating temperature can lead to efficiency losses. Therefore, it is assumed that with further advancements in technology, the actual conversion efficiencies are 0.3 [59,60]. Correspondingly, the *effective albedo* would be 0.335, which represents a near-future scenario (S335). Although most of the areas within the basin are deserts, there are also patches of grasslands, shrubs, and rivers around and within the desert. As a result, the model-simulated annual mean surface albedo within the basin ranges from 0.13 to 0.33, with a regional average of approximately 0.21 [61,62]. Thus, the PV panels with conversion efficiencies of 0.3 and 0.15 result in surface effective albedos that are higher and slightly lower than the background albedo, respectively, providing a basis for comparative analysis. To artificially enhance forcing signals and produce more pronounced climate and ecological impacts from the PV installations, three additional extreme scenarios were designed for comparison with realistic scenarios and understanding of the forcing mechanisms. These include scenarios where the conversion efficiency is as high as 0.6 and 0.9, corresponding to an effective albedo of 0.62 (S62) and 0.905 (S905, “white panel”), respectively. In which S905 is analogous to a nearly fully reflective whiteboard, with almost all solar radiation being reflected into the atmosphere. The final extreme scenario, S05, assumes that all energy is dissipated as heat, resulting in an effective albedo equivalent to the reflectivity of the panel itself (0.05), meaning that 95% of the solar radiation is absorbed by the land surface, akin to a “black panel” absorbing nearly all incoming solar radiation.

2.2.4. Diagnostic methods for hydroclimatic variables

In addition to basic statistical analysis, the study employs other diagnostic methods including the calculation of water vapor flux ($Q = \frac{1}{g} \int_{ps}^{300hPa} qV \cdot dp$), where g is gravity ($m\ s^{-2}$), ps is surface pressure (Pa), V is horizontal velocity ($m\ s^{-1}$), q is specific humidity ($kg\ kg^{-1}$), and Q represent water vapor flux ($kg\ m^{-1}\ s^{-1}$). The aridity index is defined as $AI=P/PET$, where PET is calculated using the FAO Penman–Monteith formulation:

$PET_{fao} = \frac{0.408sR_n + \gamma \frac{900}{T+273} uD}{s + \gamma \{1 + [0.34 + 2.4 \times 10^{-4} ([CO_2] - 300)]\}}$. Here, R_n^* is the available energy ($MJ\ m^{-2}\ d^{-1}$); γ is the psychrometric constant ($Pa\ K^{-1}$); T is the temperature at 2 m height (K); u is the wind speed at 2 m height ($m\ s^{-1}$); D is the vapor pressure deficit of the air at 2 m height (Pa); s is the gradient of saturation vapor pressure related to temperature ($Pa\ K^{-1}$); and the term $2.4 \times 10^{-4} ([CO_2] - 300)$ is the effect of CO_2 concentration on vegetation surface resistance. See Refs. [4,63] for a detailed description of these formulas. Furthermore, we calculated the extreme precipitation indices as defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) [64], including Rx1day (mm, monthly maximum 1-d precipitation), Rx5day (mm, monthly maximum consecutive 5-d precipitation), SDII (mm, simple daily intensity index), R10mm (d, annual count of days when precipitation ≥ 10 mm), CDD (d, maximum length of dry spell), CWD (d, maximum length of wet spell), R95pTOT (mm, precipitation in very wet days).

3. Results

3.1. The comprehensive impacts of photovoltaic and associated vegetation feedbacks on water resources

Following the model evaluation described in Section 2 and the Supplementary Materials, we first analyzed the water resources changes by comparing WRF3 and Ctrl in the year 2019 (the simulated spatial patterns of these changes are similar across all 5 simulation years). The results indicate significant climate and water resource response to the hypothetical large-scale PV panel installations, especially in and around the installation sites. Specifically, in future scenarios with higher conversion efficiency for PV panels (S335), the annual mean precipitation significantly decreases within and surrounding the Tarim Basin (outlined by black curves in Fig. 1) by approximately 50% (Fig. 1a1), with absolute reductions of about $0.2\ mm\ d^{-1}$ inside the basin and over $0.5\ mm\ d^{-1}$ in the surrounding areas (Fig. S6 online). This decline in annual precipitation enhances and expands as the conversion efficiency of PV panels increases in more extreme scenarios (S62 and S905), extending to adjacent regions and stretching eastward toward the arid boundaries in Northwest China (Fig. 1a2, a3), while the precipitation over the eastern Tianshan Mountains gradually increases as the PV conversion efficiency increases. Consistent with the three scenarios with higher conversion efficiency (S335, S62, S905), the precipitation shows an opposing response in the two scenarios with lower conversion efficiency (S19, S05), which are featured by an overall decrease of PV panel albedo. An increasing trend in precipitation is simulated in the basin with hypothetical PV panels, and this magnitude and extent of increased precipitation expand as the conversion efficiency of PV panels decreases (S05, Fig. 1a4, a5). However, it is important to note that in S19 scenario, precipitation changes are neither significant nor consistent with those within the basin, with little variation simulated in most areas. This suggests that the impact of PV on precipitation is relatively small at this conversion efficiency (0.15), which is a common efficiency for current PV panels [33,61]. Similar to the precipitation changes, the surface runoff (Fig. 1c), shallow soil water (Fig. 1d, 0–40 cm) and aridity index (AI, AI represents the degree of water shortage,

typically defined as the ratio of annual precipitation to annual potential evapotranspiration, and it is more appropriate for characterizing long-term trends in aridity variation, Fig. 1b) indicate that there is a decreased surface runoff and soil water, and a drying condition within the basin under the S335 scenario. But the eastern Tianshan Mountain shows an improved condition for water resources (Fig. 1b1–d1). It is noteworthy that in the extreme scenarios of S62 and S905, the basin does not consistently exhibit the same decreased water resources as in S335, except for precipitation. Since these variables are influenced not only by precipitation but also by other factors such as temperature and evapotranspiration, this implies more complex interactions under extreme scenarios, where varying contributions may lead to inconsistent changes.

As vegetation cover expands or shrinks, it can further contribute to regional climate change through surface energy and water exchange processes. For instance, increased vegetation evapotranspiration can lead to an increase in latent heat flux and atmospheric moisture availability, both of which can strengthen the water cycle and increase precipitation [65–68]. To better understand the vegetation feedbacks, we further analyzed the climate response to PV from the simulation with fixed vegetation cover in Ctrl (WRF2, Fig. S7a1–d1 online). It is found that in high conversion efficiency scenarios, the reduction in precipitation, surface runoff, soil water, and AI within the basin was relatively weaker (Fig. 2). This indicates that excluding vegetation feedback leads to an underestimation of the impacts of PV.

The basin selected for PV installation and adjacent regions serve as population centers in southern Xinjiang (Fig. S8a online), where several rivers are present (Fig. 2a). The precipitation, runoff and soil water form crucial water resources essential for human activities. To quantify PV impacts, we averaged these populated areas within the basin with PV installations (Fig. 2a and Fig. S8b online) to analyze water resource changes. We found over 30% reduction in surface runoff (Fig. 2b), precipitation (Fig. 2c) and AI (Fig. 2d), and an 8.47% drop in soil water (Fig. 2e) in WRF3 (including vegetation feedbacks), stronger than those in WRF2. In addition, we calculated the extreme precipitation indices and found that, under the influence of PV installations (S335, S62, S905), the frequency and intensity of extreme precipitation events in this region decrease. Meanwhile, the number of days with extreme drought events increases, and the duration of consecutive wet events noticeably decreases (Figure not shown). The intensified water stress may adversely affect local agriculture, ecosystems, and water supplies. As the conversion efficiency of PV panels increases (S62 and S905) and precipitation response becomes stronger, water resources reduction deepens. In contrast, the lower conversion efficiency scenario (S05) would increase water resources in this region, while water resource changes are minimal in scenario S19. It is noteworthy that under the S05 scenario, vegetation feedbacks do not amplify the climatic effects of PV deployment; instead, the magnitude of moistening decreases when vegetation feedback is included. This may be because, in our model configuration, no local vegetation is assumed beneath PV panels, so the vegetation feedback mainly arises from surrounding areas rather than the PV-covered zone itself. Moreover, as the results highlight the densely populated areas within the basin, this spatial focus may further accentuate the complexity.

We further performed a quantitative comparison between the direct photovoltaic effect and the vegetation effect. The results indicate that for precipitation, AI, and soil water, the PV effect is dominant, accounting for more than 63.77% of the total response, and particularly for soil water, where the PV contribution exceeds 86.29% across all scenarios. In contrast, surface runoff displays a markedly different pattern: the vegetation effect dominates, contributing more than 84.92% in all scenarios (Table S2 online). This

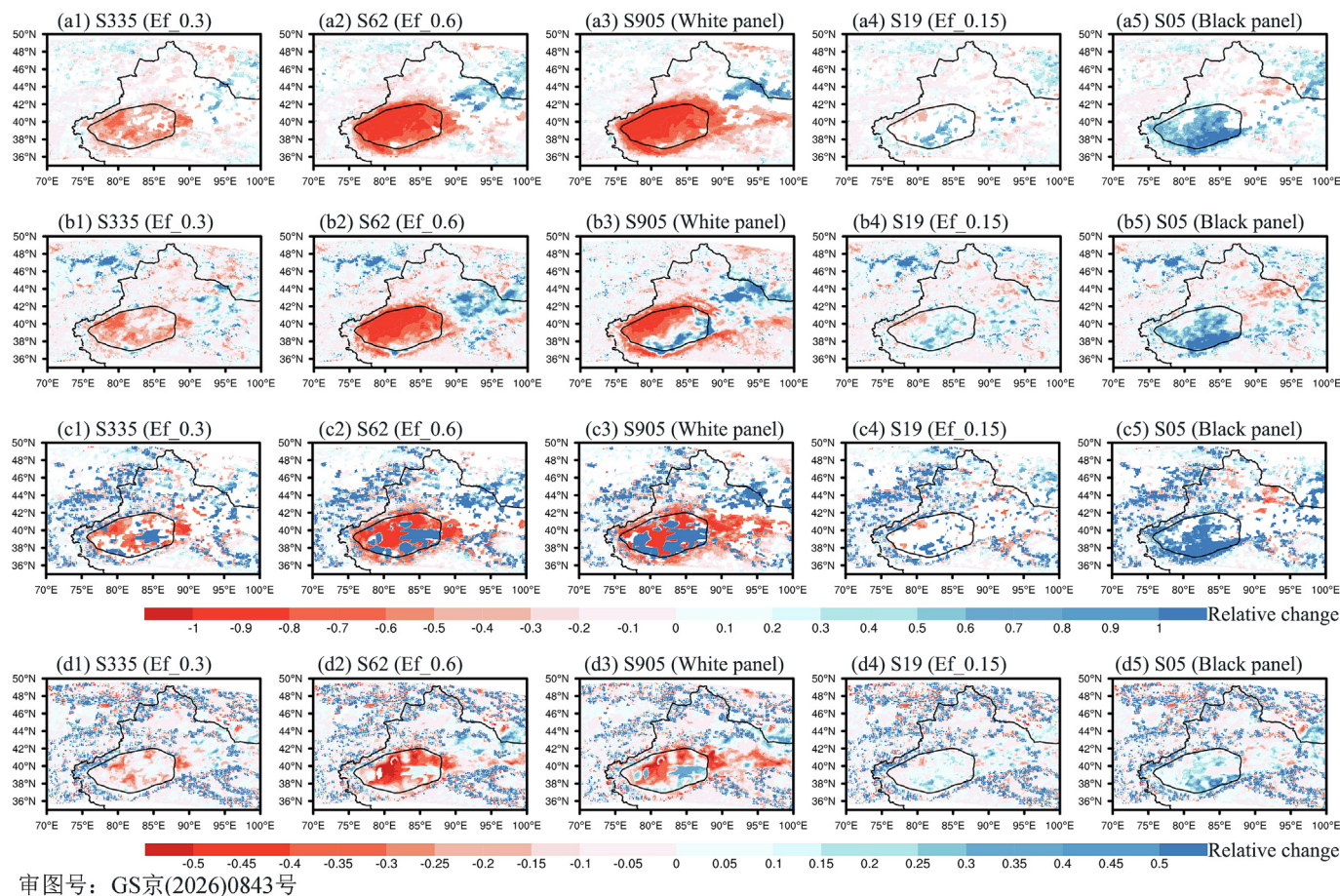


Fig. 1. The water resources affected in different PV farm scenarios. Relative changes in precipitation (a1–a5), aridity index (AI, b1–b5), surface runoff (c1–c5), soil water (0–40 cm, d1–d5) between S335, S62, S905, S19 and S05 compared to the Ctrl of WRF3 (PV impact with vegetation feedback) in 2019. These figures (except Fig. 1b, as significance test is not feasible for the annual AI index) only display results that passed the 90% significance test. The black closed curves indicate the Tarim Basin with hypothetical PV panels.

divergence may be attributed to the spatial distribution of vegetation, which is largely confined to river corridors or runoff-concentrated zones, thereby strengthening the coupling between vegetation dynamics and runoff variability.

We next examine if the natural year-to-year variability in the background climate can amplify or weaken the impacts of solar farms using the five-year simulation period from 2016 to 2020. The suppressed surface runoff, precipitation, soil water and AI in densely populated basin areas in the future scenario (S335) compared to Ctrl is robust throughout the whole period (Fig. 3). Vegetation feedbacks amplify these water resource changes over all the five years, with reductions varying between –25.50% and –51.77% in surface runoff, –29.48% and –44.79% in precipitation, –4.31% and –11.93% in soil water, and –20.06% and –41.07% in AI. The contribution from vegetation feedbacks is generally larger than the interannual natural variability (black bars in Fig. 3), underscoring the importance of involving the relevant processes to more accurately simulate the regional climate change. We also notice that PV systems do not influence the overall trend of averaged changes in water resources, as precipitation, soil water, and AI show a gradual decreasing trend from 2016 to 2020, while runoff exhibits an abrupt increase in 2018 (Fig. S9 online).

3.2. The forcing mechanism of PV impacts on water resources

The effective albedo (0.335) of the PV panels in S335 scenario is higher than the background albedo of the Tarim Basin (Fig. 4a1),

which leads to a significant surface cooling within the basin by approximately 1.5 °C (Fig. 4b1). We found that the surface temperature perturbation can affect local atmospheric circulation, in which cooling within the basin strengthens the low-level (1000–700 hPa) anticyclone and leads to divergence flow in the interior of the Tarim Basin (Fig. 4c1 and Fig. S10a, b online). This reduces the westerly moisture transport from the Tianshan mountain fracture zone into the basin (see the geographical annotations in Figs. 4c and 6 for detailed locations). The anomalous anticyclone also enhances moisture divergence (Fig. S11a1 online) and descending motion (Fig. S11b1 online) in the region, further decreasing convective available potential energy (CAPE), making the atmosphere more stable (Fig. 4d1). As a result, the precipitation significantly decreases within and surrounding the basin (Fig. 1a1). The AI also indicates a drying condition within the basin. In addition, the combined effects of reduced moisture, precipitation, and aridity index may lead to a significant decrease in runoff (Fig. 1c1) and soil water (Fig. 1d1). Under the combined influence of the basin's anticyclonic anomaly and the blocking effect of the Tianshan Mountains and the Tibetan Plateau, the anomalous moisture is transported eastward and northeastward along the basin's edge (Fig. 4c1). The moisture is further influenced by the Tianshan fracture zone, the Turpan Basin, and the high-altitude Gobi region near 95°E, resulting in anomalous moisture transfer to northern and northwestern areas, creating a cyclonic anomaly over the eastern Tianshan Mountains (Figs. 4c1 and 6). The northerly winds in the southern part of this cyclonic anomaly favor increased

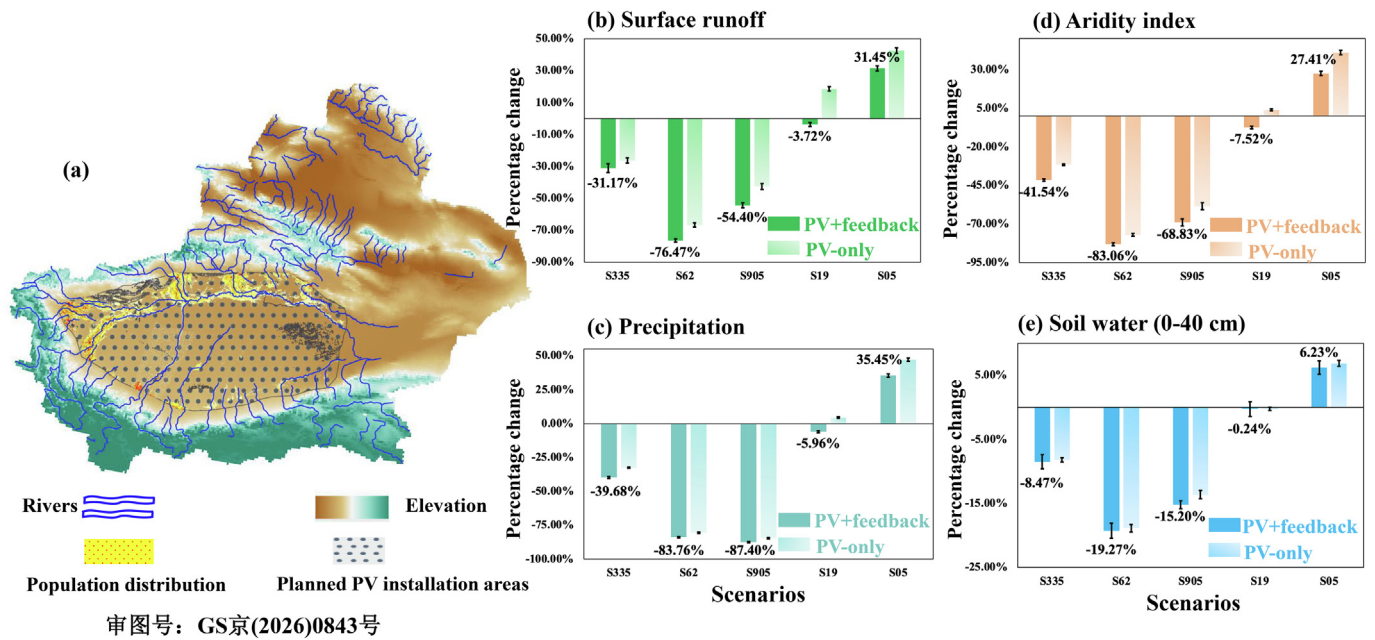


Fig. 2. The percentage changes of water resources in populated areas. Percentage changes in surface runoff (b), precipitation (c), aridity index (d) and soil water (e) between S335, S62, S905, S19 and S05 relative to the Ctrl in populated areas within the basin (yellow shading in (a), orange and red dots represent population distribution, with redder color indicating higher population density) under various scenarios in WRF3 (dark color bars, PV impact with vegetation feedback) and WRF2 (light color bars, PV impact without vegetation feedback) in 2019. The numerical values labeled on the bars indicate the relative percentage change of each variable in the corresponding scenarios of WRF3. Error bars represent the standard error of the annual mean variable calculated at 906 selected grid cells with population ($\text{standard deviation}/\sqrt{n}$, where n represents the sample size of 906). The blue lines in (a) represent rivers, and the background color represents the terrain distribution based on elevation data. The population color (yellow/red) represents population counts, with lighter colors representing lower population and darker colors representing higher population.

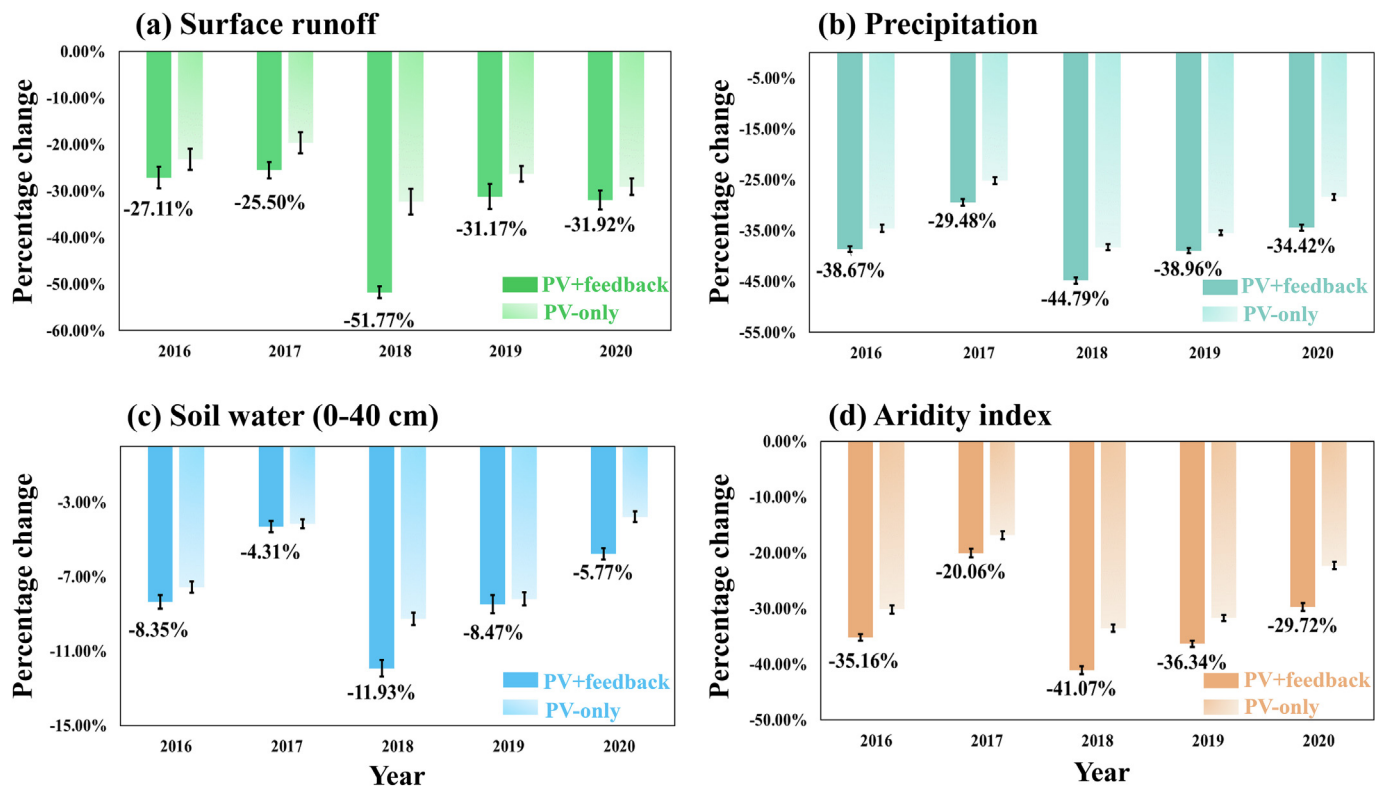


Fig. 3. The water resource response in the whole simulation period of 2016–2020. Percentage changes of surface runoff (a), precipitation (b), soil water (c), aridity index (d) between S335 and Ctrl in WRF3 (dark color bar, PV impact with vegetation feedback) and WRF2 (light color bar, PV impact without vegetation feedback) in populated areas within the basin over 2016–2020. The numerical values labeled on the bars indicate the relative percentage change of each variable in the corresponding year of WRF3. Error bars represent the standard error of the annual mean variable calculated at 906 selected grid cells with population (standard deviation/ $\sqrt{n}$, where n represents the sample size of 906).

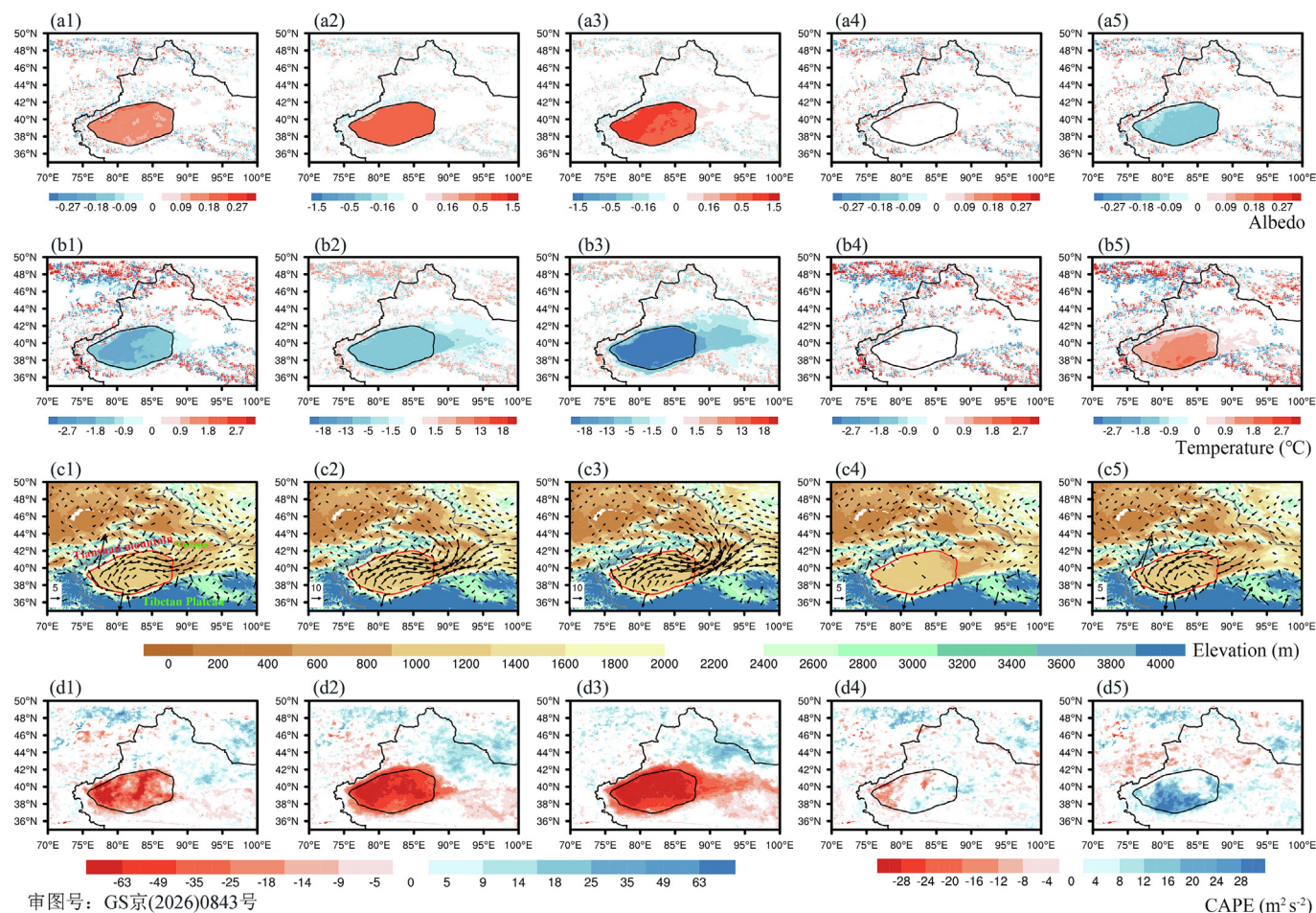


Fig. 4. The forcing mechanisms of PV impacts on water resources. The difference in albedo (a), temperature (b, unit: °C), water vapor fluxes (c, units: $\text{kg m}^{-1} \text{s}^{-1}$) of low-level (1000–700 hPa) and CAPE (d, unit: $\text{m}^2 \text{s}^{-2}$) between S335, S62, S905, S19, and S05 with Ctrl of WRF3 (PV impact with vegetation feedback) in 2019. These figures only display results in shading/vectors that passed the 90% significance test. The shading in c indicates the elevation (unit: m).

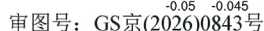
moisture retention over the east segment of the Tianshan Mountains (Fig. 4c1 and Fig. S10a, b online). In addition, the cyclonic anomaly leads to a significant increase in CAPE, indicating atmospheric instability (Fig. 4d1). Therefore, these regional-scale atmospheric circulation changes lead to increased precipitation (Fig. 1a1) and a wetter condition (Fig. 1b1) in the eastern Tianshan Mountains. In the extreme scenarios of S62 and S905, the annual mean surface air temperature decline expands outside the basin region (Fig. 4b2, b3). This further significantly intensifies the moisture and dynamic conditions mentioned above (Fig. 4c2, c3, d2, d3, and Figs. S10c, d, S11a2, a3, b2, b3 online), causing stronger precipitation reduction and drier conditions beyond the study basin. In contrast, with low-conversion efficiency PV panels (S19), where albedo is close to background levels (Fig. 4a4), there is almost no change in temperature, with only isolated areas experiencing warming within the basin (Fig. 4b4) as expected. The warming becomes distinct in the lowest-albedo extreme scenario (S05, Fig. 4b5), and causes overall opposite but stronger climate effects compared to the S335 scenario.

3.3. The forcing mechanism associated with vegetation feedbacks

The simulated climate changes drive robust responses in terrestrial ecosystems, and the vegetation changes feed back to the climate. Within these changes (simulated by LPJ-GUESS), those under PV installations were not fed back into the climate model

(WRF) and are indicated by the hatched areas in Fig. 5a. These hatchings only illustrate the potential vegetation distribution if present, while the actual climate simulations exclude these effects. Under higher-albedo scenarios (S335, S62, S905), both vegetation cover (Fig. S12a1–a3 online) and LAI around the basin areas are decreasing and degrading (Fig. 5a1–a3) due to drier conditions. We also observed the changes in vegetation types: in the basin and surrounding areas, arid vegetation, including dry grasslands and arid shrub/steppe, has turned into deserts; in a few areas, grasslands have degraded into arid vegetation (based on LAI data, Fig. S13 online). Vegetation changes in the two scenarios with lower albedo (S19, S05) exhibit the opposite responses. In S335, vegetation degradation in areas surrounding the basin affected by PV panels led to a significant reduction in latent heat flux (Fig. 5b1). This suppressed the local hydrological cycle, depleting atmospheric water vapor and reducing low cloud cover (Fig. 5c1). These effects eventually contribute to intensified precipitation reduction and a drier climate compared to the simulations without dynamic vegetation.

The vegetation feedbacks are more complicated on seasonal timescales due to phenology. Comparing S335 and Ctrl for a typical year 2019, within the basin, the LAI shows a consistent decreasing response across spring, summer, and autumn. For the entire Northwest China domain, though, the changes in LAI are not consistent across seasons. There is a decrease in LAI during the spring, but an increase in the autumn, and no significant changes during the



winter (Fig. S14a online). Due to the seasonal variation in vegetation, the feedback to the climate further results in different changes in water resource variables. In spring, summer, and autumn, the water resources within the basin show a significant decreasing response, consistent with the vegetation pattern. However, in winter, the changes are much smaller or even show the opposite change, which is similar to previous studies [69,70]. Furthermore, due to seasonal differences outside the basin, the annual average of water resource variables does not demonstrate a clear, consistent response (Fig. S14b–d online). Future studies are needed to further analyze these seasonal differences in more detail.

4. Discussion

types may also contribute to varying climate impacts of PV installations [31–34]. These findings highlight the importance of considering spatial variability when evaluating the broader environmental consequences of large-scale PV deployments.

At utility scales, previous field and unmanned aerial vehicle-based studies mainly focused on small-scale or site-level PV installations, showing that PV panels can increase soil moisture beneath them, as well as enhance ground vegetation cover and species richness [71–74]. However, our research reveals that when PV installations expand in scale and panel conversion efficiency, these positive local effects no longer dominate; instead, local water resources may be depleted, posing potential risks to ecological sustainability. This finding provides a novel perspective and a crucial scientific basis for planning and developing PV technology sustainably, offering key insights into assessing the hydrological impacts of large-scale PV plants. Within the WRF framework, PV deployment is parameterized through modifications in effective albedo, thereby altering net shortwave radiation and the subsequent surface energy balance. From an energy balance perspective, the effective albedo formulation accounts for the fraction of absorbed solar radiation converted into electricity, while also implicitly incorporating the remaining portion that ultimately contributes to local heat release during panel operation. Consequently, although our model does not explicitly resolve panel-scale thermal processes, the primary radiative perturbations associated with PV deployment are accurately represented in the regional energy balance. Another potential limitation in our modelling approach is that it does not explicitly resolve sub-grid structural processes such as drip-line infiltration or panel-scale shading heterogeneity. Therefore, the local positive effects are likely underestimated in our modeling framework, which may partly contribute to the differences between our regional-scale results and previous site-level observations. Nevertheless, based on our own field observations across the Tarim Basin and surrounding oases, most PV-covered

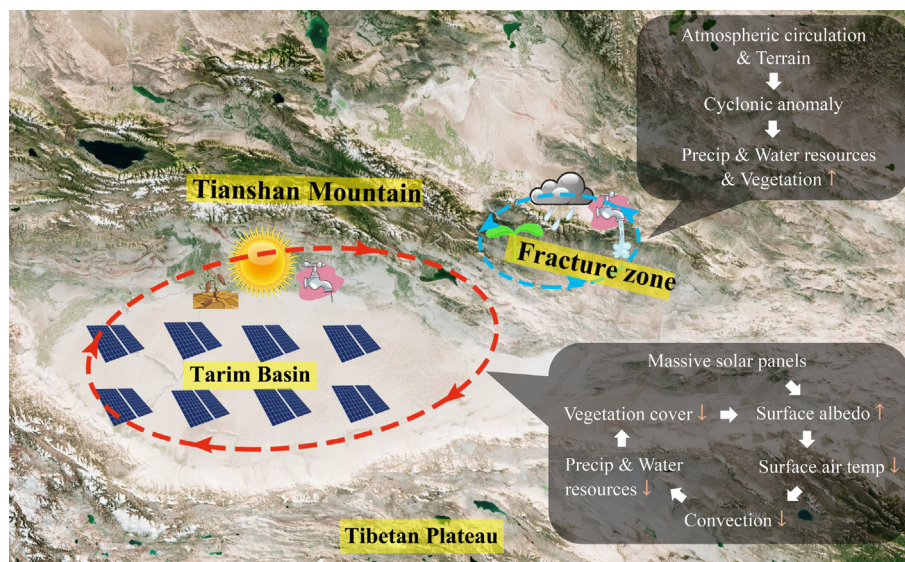


Fig. 6. Schematic diagram of the climate-ecological-water resources affected by PV panels. The red clockwise (blue counterclockwise) circle represents anomalous anticyclonic (cyclonic) circulation in the lower troposphere. The responses of local climate, vegetation cover, and water resources are shown in the cartoon symbols. The processes of impact for the two regions are given in the two callout boxes.

areas remain barren, and vegetation cannot establish without irrigation (Figures not shown). We argue local positive effects such as shading-induced vegetation growth or drip-line infiltration are inherently limited under the hyper-arid environmental conditions of the Taklamakan Desert. Additionally, because the simulated responses are controlled by basin-scale circulation adjustments and vegetation–atmosphere feedbacks, the results are inherently sensitive to the regional topographic and climatic background. The Tarim Basin is characterized by a low-elevation desert basin enclosed by high mountain ranges, with distinct atmospheric circulation and hydrological conditions. The applicability of our findings to other arid environments may differ depending on those conditions, and thus warrants further investigation. Future studies will be necessary to comprehensively explore the climate–ecosystem impacts of photovoltaic installations in other representative arid regions to assess the robustness and broader applicability of our conclusions.

While the higher PV conversion efficiency scenarios reveal clear and spatially coherent impacts, the S19 scenario, representing current commercially available PV technology, exhibits relatively weak and spatially heterogeneous responses. This muted and heterogeneous signal may partly reflect the smaller magnitude of surface energy perturbations associated with present-day PV conversion efficiencies. At the same time, it should be noted that this result may also partly stem from uncertainties in the model and in our modeling framework, such as the simplified representation of PV effects through prescribed albedo changes (see the following discussion on uncertainties), which may limit the model sensitivity under this moderate forcing condition. Therefore, the S19 results likely represent a conservative, lower-bound estimate rather than evidence of an absence of impact. In contrast, as PV efficiency and deployment scale increase, surface energy perturbations become sufficiently strong to trigger more coherent land–atmosphere–vegetation feedbacks, leading to detectable regional-scale responses.

Our offline coupling approach between WRF and LPJ-GUESS may involve several uncertainties that were not accounted for, due to technical issues like delayed effects and timeliness, missing sufficient diurnal variability, the simplification of surface energy balance [75–77], along with the simplified representation of PV

panel effects through prescribed albedo changes. Such parameterizations are widely used in current modeling studies due to the lack of explicit PV modules in most land surface and climate models, but they also constitute a common source of uncertainty when simulating PV–climate interactions. In addition, although 5 sensitivity experiments were designed to span a range of scenarios from realistic to more extreme conditions, all experiments are highly idealized and assume basin-wide PV coverage. This large-scale PV coverage is prescribed to explore the dominant climate–ecosystem mechanisms and to provide the potential upper bound of PV-induced impacts. These factors may introduce uncertainties to our simulations but do not undermine the overall validity of our findings. The fundamental processes involved in land–vegetation–atmosphere interactions triggered by PV panels are comparable with those simulated in fully coupled global models [33,34]. This consistency in the underlying physical and biogeophysical mechanisms in the arid regions strengthens the reliability and robustness of our results.

Our current simulations assume that the entire basin is covered with PV panels, resulting in an estimated annual power generation of 25 TW in S335 scenario (Text S2 online)—surpassing the recent global electricity consumption of 18 TW [78]. However, although the future PV deployment plan remains uncertain, in terms of the solar power capacity, different conversion factors used in our study somehow represent partial coverages. For example, the electricity generation in the fully covered (by solar panels) S19 scenario is similar to the half-covered S335 scenario, yet their climate and water resource effects are nearly opposite. This emphasizes that the panel albedo, in addition to its conversion efficiency, should be an important consideration for future PV designs for its comprehensive climate impacts. We also acknowledge that water consumption associated with cleaning PV panels in such arid and dusty regions is an important practical issue that is not included in the current modeling framework. However, this additional water demand would likely increase regional water stress and thus potentially reinforce the main conclusions of this study. Future studies should also explore various and more realistic installation strategies, including partial coverage scenarios and different values of PV panel albedo, to better understand the potential climate and ecological impacts of PV installations in the real-world

applications. Additionally, we should explore the impacts of PV installations in other representative regions of Northwest China to determine whether the effects are consistent across various landscapes and climate zones. Nevertheless, our pilot study highlights the importance of considering installation area, layout, and potential environmental consequences when planning and deploying large-scale solar energy projects in Northwest China. Such considerations are vital to ensuring long-term sustainability and mitigating unintended hydroclimatic risks.

Conflict of interest

The authors declare that they have no conflict of interest.

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Author contributions

Zhengyao Lu, Wei Huang, and Fahu Chen conceived the study. Tingting Xie performed the simulations with input from Zhengyao Lu, Jing Tang, and Tinghai Ou. Tingting Xie analyzed the data. Tingting Xie and Zhengyao Lu wrote the first draft of the manuscript with contributions from all authors. All authors reviewed the manuscript.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scib.2026.05.005>.

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