SUPPLEMENTARY INFORMATION:

Promoting sustainable development by optimizing city-level PV deployment

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S.1 Influencing factors of city PV deployment

The factors selected are presented in Table S1.1. On the one hand, we take into account the factors affecting solar photovoltaic (PV) cost-efficiency defined as maximum power generation at minimum cost. On the other hand, we take the necessity of developing PV in cities into account by including the state-of-art resource, environment, and social performance of each city, which indicates the perceived urgency of each city to deploy PV. The cities government have incorporated mandatory environmental targets into the performance appraisal system to incentive effective measures (e.g. PV installation) to alleviate the pressures. The cities with high urgency in sole SDG goal consistent with the central government priority would be inspired to deploy PV under the financial and policy support from the central government to harvest better policy benefits.

Table S1.1. Indicators affecting PV deployment under different scenario

Cost-efficiency factors	Indicator of measuring necessity to deploy PV
● PV generation potential	Carbon emission (Million tons, Mt)
● electricity demand	Average annual concentration of $PM_{2.5}$ (ug/m^3)
● transmission line density	Water Stress Index (WSI)
● LCOE	Disposable income per capita (CNY)

PV generation potential, as directly related to the total output of utility-scale PV (USPV) and distributed-scale PV (DSPV) projects, is vital to the PV deployment. The assessment of USPV generation potential of each city is referred to Yang et al.,[1] which is performed at grid level using ArcGIS software, and finally aggregated to the city scale. Firstly, we started by determining the areas where photovoltaic power plants can be physically installed, and the protected areas and unsuitable land cover types are excluded. Secondly, the potential installed capacity is estimated as a function of PV suitability land and land conversion factors by different slope and latitude categories. Finally, we combine the solar radiation and system efficiency data to calculate the PV power generation potential, see Equation (S1):

$$USPVGi=\sum_{l=18}^{50}\sum_{s=1}^{3}\frac{LA}{LCF}\times 10MW\times GHI\times GSR\times PR\times(1\text{-}SF) \qquad (S1)$$

where, US*PVGi* indicates the USPV technical potential in city *i*, *l* refers to geographic latitudes and *s* refers to three categories of slope ranges. *LA* refers to available land area suitable for USPV. *LCF* refers to land conversion factors for PV plants, which vary between different latitudes and slope. The LCF is also derived from the research of Yang et al. [1] GHI refers to Global Horizontal Irradiance. According to Nuria,[2] the standard values for generator to system ratio (GSR) in China is 0.8, performance ratio (PR) is 0.8, and shading factor (SF) is 0.05.

The assessment of DSPV generation potential is based on Yu et al., [3] considering available land area and solar radiation. According to the *Code for Classification of Urban Land-use* and *Planning Standards of Development Land*, the available land resources for DSPV development include the rooftops of residential, industrial, and commercial buildings, roads, and green spaces at the city level.[4] We estimate the potential DSPV installed capacity after calculating available land of each city using GlobCover 2009 data, obtained from the European Space Agency (ESA) GlobCover Portal. [5] Then, solar radiation and system efficiency data are used to calculate the DSPV generation potential. As shown in Equation (S2):

$$DSPVGi = Qi \times GHI \times E_f \times C_o \qquad (S2)$$

where *Qi* refers to available land area suitable for DSPV in city *i*, which includes the rooftops of residential, industrial, and commercial buildings, roads, and green spaces. E_f is the module efficiency (%) assumed to be 17%;[3] C_o is the comprehensive coefficient reflecting the temperature variations and soiling of the modules, which is assumed to be 80%.[3]

Electricity demand. There is a spatial mismatch between the high solar energy resource endowment and power demand among Chinese regions. The aggressive solar PV installation in Northwest China in recent years has led to high curtailment rate issues. The cities with large electricity demand can afford more PV power, considering that China's current PV utilization strategy emphasizes local consumption. And cities with high electricity consumption face greater pressure on power supply and power sector transition. Therefore, the total electricity consumption is chosen as one of the most crucial influencing indicators for PV deployment.

Transmission line density is also an important factor to be considered in PV deployment. Utilization within broader regions tends to be restricted by insufficient transmission capacity, High transmission line density avoids the additional cost of infrastructure construction and reduces energy loss due to power transportation. Therefore, Transmission line density is selected as one influencing indicator for PV deployment.

Finally, the *levelized cost of electricity (LCOE)* of PV generation is selected as one indicator for PV deployment which indicates the cost per KWh in the PV life cycle, and the lower LCOE with higher revenue gains would be more competitive compared with thermal power.

S.2 Benefits assessment for PV deployment

S.2.1 Carbon emission mitigation

The avoided carbon emissions of PV are determined by that emitted from the same amount of coal power considering the ignorable emissions of PV power's operation process. We adopted the widely applied Intergovernmental Panel on Climate Change (2006) sectoral approach to calculate the average CO_2 emissions of coal power generation of each city,[6] considering varied types of coal sources and combustion efficiency. Then, the avoided carbon emissions could be derived from Equation (S3).

$$CEi = EGi \times CCRi \times NCVi \times EFci \times Oi \qquad (S3)$$

where *CEi* represents the avoided CO_2 emissions of PV in city *i*, *EGi* represents the maximum solar power generation of each city under the allocated PV capacity. *CCRi* indicates the average plants-level coal consumption rate per unit of coal electricity generation in each city (g/kWh). The plant-level *CCR* is calculated by dividing the plant thermal power generation with the coal consumption amount of each plant from the Electric Power Industry Statistical Information Compilation in 2018.[7] The *NCVi*, average net caloric value of coal (J/t), *EFi,* emission factor of coal (tonne CO_2/J), and *Oi*, oxygenation efficiency of coal (%) of each city is equal to the proportion of different types of coal multiplied by the corresponding factor of different types of coal (as shown in Table S2.1). The proportion of different coal types used by coal power in each city is derived from the energy balance table of each province.

Table S2.1 Emission coefficient of different coal types

Coal types	NCV(PJ/10^4t)	CE Mt CO2/TJ	O(%)
raw coal	0.21	96.51	92%
cleaned coal	0.26	96.51	92%
washed coal	0.15	96.51	92%
Briquettes	0.18	96.51	92%
Coke	0.28	115.07	92%

S.2.2 Avoided air pollutants emissions

Similar to the CO_2 emissions mitigation calculation, the avoided SO_2 (NO_X) emissions of PV in each city is estimated using Equation (S4):

$$SEi = EGi \times CCRi \times EFi \times (1 - \rho i) \tag{S4}$$

$$EF_{si} = 2 \times SCC_i \times (1 - S_{ri}) \tag{S5}$$

where, *SEi* represents the avoided SO_2 or NOx emission in city *i*. *EFi* is the unabated emission factor, in g kg^{-1} of coal, which is estimated via the sulfur mass balance approach using Equation (S5). *SCCi* is the average sulfur content of different types of coal, and S_{ri} is the fraction of sulfur retention in ash. The parameter ρ_i is the average SO_2 or NOx removal efficiency of the abatement equipment. We collected the installation types of air pollution abatement equipment in each power plant, and calculated the proportion of different types of air pollution abatement equipment in each city. Then, we assume that all coal-fired power plants will be equipped with air pollution abatement equipment in 2030, and the average removal efficiency depends on the existing abatement equipment installation types and proportions. The removal efficiency of different abatement equipment Technology types are presented in Table S2.2.

Table S2.2 Removal efficiencies of different control technologies for SO_2 and NOx

Technology	SO2 removal efficiencies	Technology	NOx removal efficiencies
Wet Limestone-Gypsum FGD	98.35%	SCR	80%
Ammonia Process	97.35%	SNCR	55%
Seawater desulfurization	97%	SCR+SNCR	70%
Circulating Fluidized Bed FGD	95.50%		
Dual Alkali Process	90%		
Semi-dry Process	90%		
Magnesium oxide flue gas desulfurization	95%		

S.2.3 Water savings

For solar PV, water is mainly used for panel cleaning in the operation stage, differently, water is required for cooling in the coal power generation. Thus, when generating the same amount of electricity, the amount of water saving was obtained as shown in Equation (S6):

$$Wi = EGi \times (WCFti - WCFpi) \qquad (S6)$$

where Wi represents the amount of water saving in city i. $WCFpi$ represents the water consumption (L/kWh) per unit PV power generation, and $WCFti$ represents the water consumption (L/kWh) per unit coal power generation.

S.2.4 Job creation

For the employment assessment of the PV installation, we adopt the employment factor method established by Rutovitz,[8] which covers the employment in the construction and operation & maintenance employment (O&M) stage. The construction and O&M employment refer to the jobs created during the construction and installation of PV, and that related to the operation and maintenance during the operating life of the power plant, respectively, as shown in Equations (S7)~(S9):

$$Jobs\ in\ region = \text{Con jobs} + \text{O\&M jobs} \qquad \text{(S7)}$$

$$\text{Con job} = IC \times \frac{1}{L} \times Con\ EF \times Regional\ job\ multiplier \times DF \qquad (S8)$$

$$O\&M\ jobs = IC \times O\&M\ EF \times Regional\ job\ multiplier \times DF \qquad (S9)$$

where, the construction or O&M employment factor (EF) we adopted represents the national average level factor. To reflect the labor productivity level differences in regions, the regional employment multiplier was introduced. Moreover, technological innovation, learning by doing effect and economies scale effect contributed to the employment savings, which is expressed as the decline factor (DF). The *Con* jobs could be viewed as temporary jobs, and we could covert it to constant jobs by introducing the service life L of PV as shown in Equation (S8).

S.3 Four steps for calculating SDG scores in cities

Step 1: indicator selection. We selected indicators from a combination of the United Nations' official list of global Sustainable Development Goal indicators[9], the 2018 SDG Index and Dashboards Report[10] (as shown in Table S3.1). The 2018 SDG Index and Dashboards Report provides a robust, quantitative and transparent method of measuring SDG baselines that has been widely used in the evaluation of sustainable development goals.[11-12]

Step 2: indicator bound. we identified upper and lower bounds for each SDG indicator in order to minimize the potential effects of skewed data distributions on the standardized values during normalization. The upper and lower bounds represent the range of SDG scores from 100 (worst performance) to 0 (worst performance). Our method for setting bounds is similar to the approach used in the 2018 SDG Index and Dashboards report. For SDG6.4.2 and SDG11.6, the upper bound was set as the top 2.5th-percentile value, and the lower bound was defined as the SDG indicator value (one data point) located close to the value of the bottom 2.5th-percentile value. For other indicators, we adopted the bounds used in the 2018 SDG Index and Dashboards report.

Step 3: individual SDG score calculation. After establishing the lower and upper bound for each indicator, we used the following formula to normalize SDG indicator values.

$$Scores = \frac{s - lower(s)}{upper(s) - lower(s)} \times 100 \qquad (S10)$$

where *s* is the original data value of each SDG indicator, *upper/lower* represents the upper/lower bounds for the best/worst performance, and *Scores* is the normalized individual score for a given SDG indicator.

Step 4: weighting and aggregation. we opted for equal weight to every SDG to reflect policymakers' commitment to treat all SDGs equally and as an "integrated and indivisible" set of goals. We first estimate scores for SDG6.4 using the arithmetic mean of SDG6.4.1 and SDG6.4.2. Then, these four SDG scores are averaged to obtain the SDG Index score of the evaluated SDG in each city.

Table S3.1. SDG indicators and indicator bound

SDG targets	SDG indicators	upper bound	lower bound
SDG 6.4 Ensure sustainable withdrawals and supply of freshwater.	6.4.1 Freshwater withdrawal as % total renewable water resources	12.5	100
	6.4.2 water-use efficiency 10^4 yuan per cubic meter)	1183.5	15.5
SDG8.5 Achieve full and productive employment and decent work.	Unemployment ratio (%)	0.5	25.9
SDG11.6 By 2030, reduce the adverse environmental impact of cities.	Production-based SO2 emissions per capital (kg/capita)	0.5	28.8
SDG13.2 Integrate climate change measures into national policies, strategies and planning.	CO2 emissions per capita (tCO2/capita)	0	23.7

S.4 Additional figures and tables

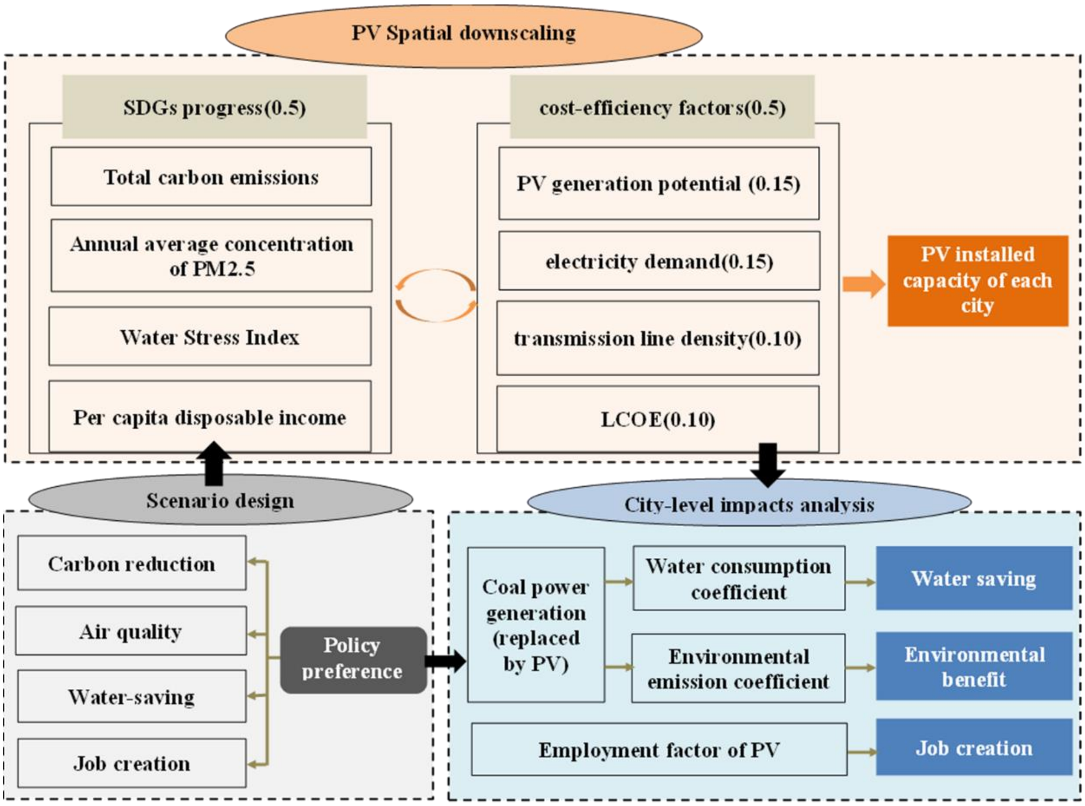

Figure S4.1. The framework of the study. Note: values in the parentheses indicate the weights of each factor.

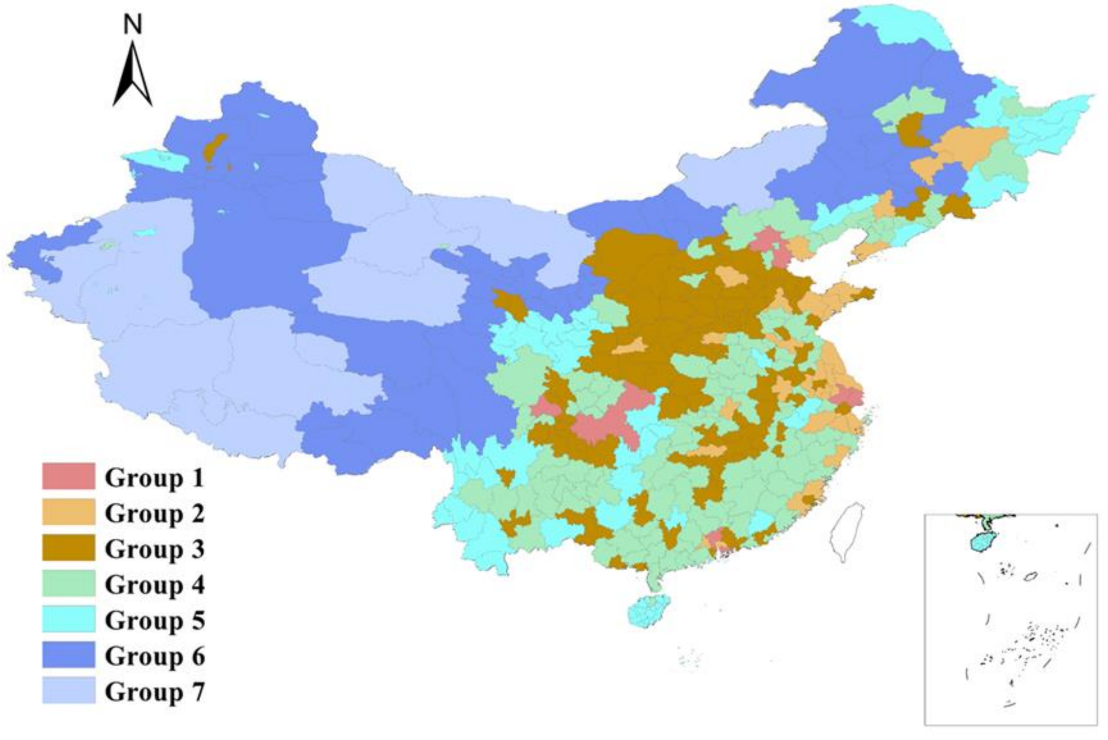

Figure S4.2. Spatial distribution of seven city groups. Colors on the map indicate the city categorization.

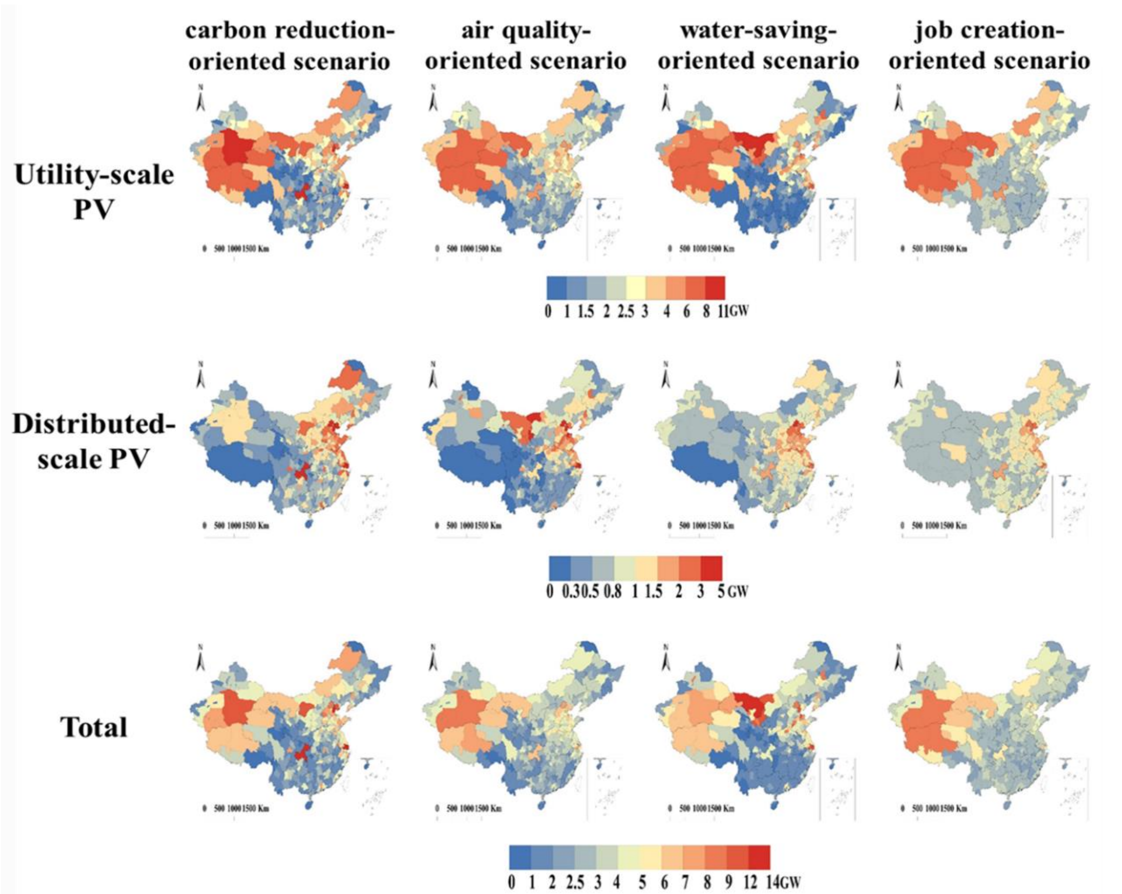

Figure S4.3. The spatial distribution of different PV types under different scenarios.

Table S4.1. Key data sources in the study

Summary of Data sources for key factors influencing PV spatial downscaling	
Indicators	**Data sources**
carbon dioxide emission	Chen, J., et al., 2020[13]
annual concentration of $PM_{2.5}$	Urban Statistical Yearbook (2018)
water scarcity index	Provincial Water Resources Bulletin (2017)
disposable income per capita	Provincial Statistical Yearbook (2018)
electricity demand	Provincial Statistical Yearbook (2018)
transmission line density	China Power Yearbook (2017)
LCOE	China New Energy Power Generation Report (2020) [14]
Summary of Data sources for environmental-resource-social benefits assessment	
Factors	**Reference**
carbon emissions factors	Liu et al., 2015[15]
SO_2 and NOx emission factors	Tang, et al., 2019[16] & Liu et al., 2015[17]
water consumption (L/kWh) per unit of coal power generation	Xie et al., 2020[18]
Employment factor	Rutovitz et al., 2015[19]

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