

The compulsory use of dust-proof nets led to significant environmental, health and economic benefits in China

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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- China mandated dust-proof nets (DPNs) on construction sites to combat air pollution.
- We used satellite data and machine learning to find DPNs use surged after the 2017 policy.
- This policy helped avoid over 26,836 premature deaths from 2017 to 2021.
- DPNs are a cost-effective clean air tool with great potential for wider use.

The compulsory use of dust-proof nets led to significant environmental, health and economic benefits in China

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In 2017, China launched a regulation on the compulsory coverage of construction wastes with dust-proof nets (DPNs) to mitigate air pollution resulting from urban construction activities. Challenges exist in quantifying how its implementation has mitigated airborne particulate matter (PM) pollution in China. Here we developed a framework combining high-resolution satellite images, machine learning, and an air quality model to identify DPNs and associated PM mitigation across China from 2016 to 2021. The total national DPN area surged significantly since 2017 and peaked in 2019, 9.78 times of that in 2016, especially in North China Plain (NCP). With a simultaneous increase of coverage duration, DPNs caused national PM emission reduction in 2019 was 23 times larger than 2016. Based on the extracted DPN dataset, we employed WRF-Chem regional air quality model to simulate the effects of DPNs on the PM-reduction across China. Next, we calculated that the use of DPNs helped a total of 253.8 million of people exposure to notably improved air quality and 26,836 people (95% CI: 23,630–30,041) avoided premature mortalities from 2017 to 2021. Accordingly, we quantified the economic benefits from DPNs use across China reached 20.7 billion based on the Value of Statistical Life (VSL) model. Large potential remains for DPN use in China. The national DPN coverage could additionally increase by 3.3 times if DPN coverage rate in NCP would transfer to the entire country.

INTRODUCTION

Since 2013, deteriorated airborne pollution has become one of the most pressing environmental concerns in China,¹ posing a severe threat to public health and crop growth,^{2,3} incurring substantial economic costs due to healthcare expenditures and lost productivity,⁴ and hindering sustainable urban development. The United Nations' Sustainable Development Goal (SDG) 3.9 also calls for a significant reduction in the number of deaths and illnesses caused by hazardous chemicals and air, water, and soil pollution.⁴ To comprehensively improve air quality, China has implemented a series of emission-cut policies, including the restricted use of coal and automobiles,⁵ the promotion of vehicle electrification,⁶ prohibitions on agricultural straw burning⁷, and the closure of environmentally unqualified factories. These efforts have proven effective in mitigating PM_{2.5} pollution, resulting in a 33% decrease in PM_{2.5} concentrations in China during 2013–2017.⁸ Meanwhile, natural and anthropogenic dust contributed significantly to air pollutants.⁹ Amidst rapid urbanization in China, anthropogenic dust emissions and other pollutants produced in urban construction sites have been recognized as one major source of airborne particulate pollution in China.^{10,11} In response, China launched a regulation in 2017 that all construction wastes, including construction muck, piles, and exposed land, should be covered with dust-proof nets (DPNs).¹² However, several critical knowledge gaps persist in understanding the effectiveness of China's DPN policy. First, the spatial and temporal dynamics of DPN implementation across China remain poorly characterized, primarily due to limitations in large-scale monitoring methods. Second, quantitative assessments of DPN's contribution to air pollutant reduction at the national scale are notably absent from the literature. Given China's substantial and ongoing efforts to improve air quality, addressing

these knowledge gaps regarding the effects and benefits of DPNs was crucial for ensuring that these efforts could effectively promote public health and well-being (SDG 3.9) and contribute to building sustainable and healthy urban communities (SDG 11.6).

Accurately determining the spatial distribution of DPNs is essential for evaluating their effectiveness in controlling particulate matter (PM) pollution. Some studies have explored the integration of machine learning with Earth observation data to detect construction wastes.^{13,14} However, these limited studies on DPN extraction were mainly confined to specific cities and DPN types using discrete remote sensing images.^{15,16} Given the diversity of DPN shapes and colors across China and the fact that DPNs on construction sites may simply last for weeks, existing DPN extraction methods cannot support large-scale applications and may cause severe omissions when temporal variation is not considered. Automatic and reliable DPN extraction on a national scale remains urgent and challenging.

In this study, we tackle these challenges in order to assess inter-annual variations of DPN areas across China and their effects on national air quality from 2016 to 2021. We first developed a framework utilizing Google Earth Engine and machine learning techniques to automatically identify DPNs across China through the analysis of the Sentinel-2 time series data. With the identified DPNs, we quantified PM (PM_{2.5} and PM₁₀)-reduction attributable to DPN implementation and employed WRF-Chem regional air quality model to simulate the effects of DPNs on PM-reduction across China. Next, we integrated the Global Exposure Mortality Model (GEMM) and the Value of Statistical Life (VSL) to calculate the total number of populations that gained the benefit of improved air quality, the total avoided premature deaths, and the resulting economic benefits. We addressed three key questions: (a) What were the spatiotemporal dynamics of national DPN implementation between 2016 and 2021? (b) How much did DPN implementation reduced air pollutant emissions and concentrations in China? (c) What health and economic benefits resulted from DPN implementation? This research not only demonstrated the substantial multifaceted benefits and cost-effectiveness associated with DPN use in China but also highlighted their considerable potential as a practical tool for contributing to key SDGs (particularly SDG 3 and SDG 11). These results provided valuable lessons for future national and global "clean air" actions.

MATERIALS AND METHODS

Data sources

Sentinel-2 data for DPN extraction. The Sentinel-2 data provided observed remote sensing images for DPN extraction. Sentinel-2 surface reflectance (SR) (2019–2021) and top-of-atmosphere (TOA) reflectance (2016–2018) data were procured using the GEE platform. Sentinel-2 is capable of providing four 10m spatial resolution bands (bands 2,3,4,8), six 20m spatial resolution bands (bands 5,6,7,8A,11,12), and three 60m spatial resolution bands (bands 1,9,10). In this study, all bands were resampled to a 10-meter resolution to ensure spatial resolution consistency. Compared with Landsat or MODIS data the improved spatial resolution of Sentinel-2 makes it a more suitable source for better identifying DPNs without causing severe omissions. To ascertain data quality, the quality assurance (QA) band was

employed to detect and eliminate subpar observations, including those affected by clouds and cloud shadows.^{17,18} Only images with less than 10% cloud cover were chosen for analysis. Both Sentinel-2A and Sentinel-2B satellites possess a revisit cycle of 10 days. In scenarios where the datasets from these two satellites are complementary, the optimal temporal resolution of Sentinel-2 data sources can be up to 5 days. We divided China into $2^\circ \times 2^\circ$ grids and established the time series by considering all qualified high-quality images that could cover these grids from 2016 to 2021 (Supplementary Figure S1).

ESA WorldCover data for DPN extraction. This data set was used to generate high-quality non-DPN samples when constructing the DPN extraction model. The ESA WorldCover data is a global land cover map with a 10m resolution, produced by the European Space Agency (ESA) based on Sentinel-2 and Sentinel-1 data. The ESA WorldCover data provides 11 land cover categories, and a detailed description of this product is included in Supplementary Table S1. We used the 2020 ESA WorldCover data for China with an overall classification accuracy of 74.4%. Compared with other land cover products, it possesses advantageous spatial resolution and classification precision, thus garnering widespread use.^{19,20}

Land cover type data for air quality simulation. This data set serves as a ground cover benchmark for air quality simulations. Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (MCD12Q1) Version 6 data product was employed to improve the land use category contained in the air quality simulation model. The MODIS MCD12Q1 Version 6 data provides 17 types of land cover categories (the detailed description of this product can be found in Supplementary Table S2) at a 500-meter resolution, and it has been extensively validated.²¹⁻²³ In this study, the MODIS MCD12Q1 Version 6 data for the years 2016 and 2019 was employed.

Emission inventory data for air quality simulation. This data set provides annual emissions of air pollutants for air quality simulations. Various types of emission inventories were used to mitigate the uncertainty in model simulations. The pollutant emission data for five macro emission sectors in China (i.e., power, industry, traffic, agriculture, and residence) in 2016 and 2019 were obtained from the MEIC emission inventory.^{1,24} The agricultural NH_3 emissions over China are refined based on Chen et al.²⁵ For the region out of China in the modeling domain, the 2010 MIX Asia emission inventory is adopted.²⁶ Other emissions including biogenic emissions and biomass burning emissions are also considered in the model. The biogenic emissions are calculated from the Model of Emissions of Gases and Aerosols from Nature (MEGAN).²⁷ The hourly biomass burning emission inputs for the model are based on the Fire Inventory from NCAR (FINN) version 1.5.²⁸

Global Urban Boundary (GUB) data for determining urban and non-urban regions. The urban areas mentioned in this study refer specifically to the scope of the built-up regions within the cities, the boundary of which is derived from the most recent Global Urban Boundary (GUB) dataset from 2018.²⁹ The GUB data were extracted through a hierarchical approach using Landsat data with a 30m resolution. Compared to other urban boundary datasets, the range determined in the GUB data provides an effective reflection of the edges of cities.²⁹ The GUB data, due to its outstanding accuracy with correlation coefficients of 0.82-0.87 in identifying urban boundaries, has thus seen wide application.^{19,30} Similarly, the non-urban areas were extracted as areas beyond the scope of the GUB data.

China's population data for PM exposure assessment. WorldPop provided annual population data at a 1 km resolution from 2016 to 2020. To match the resolution of PM concentrations simulated by WRF-Chem model, we aggregated the WorldPop 1 km annual population data to a 27 km spatial resolution.

Extraction of DPNs

The types of DPNs vary significantly across regions, posing a major challenge for automatically and reliably identifying a diversity of DPNs across China. Without a comprehensive consideration of the various types and temporal variations of DPNs, current studies majorly conducted at the local scale caused severe omissions.^{15,16,31} To fill this gap, we developed a framework for identifying the main DPN types in China based on time-series Sentinel-2 data, Google Earth Engine, and Random Forest (RF). The proposed

method consists of four steps: a. image pre-processing, b. feature extraction and classifier training, c. time-series remote sensing image classification and post-processing, and d. determination of the duration of DPN presence.

Firstly, cloud contamination poses a negative impact on the identification of DPNs based on remote sensing images. To address this, we implemented a median composite of images over a specified time period, producing cloud-free, high-quality imagery for the given period. To minimize the constraints of temporal resolution introduced by the median compositing, we manually checked the shortest continuous time intervals that were capable of generating cloud-free, high-quality imagery from January 1st of each year, and thus created a qualified time-series of Sentinel-2 data for DPN extraction.

The incorporation of feature sets is crucial for DPN extraction. DPNs are commonly made of plastic material with distinctive coloring, which makes them easily distinguished from other land covers.^{15,32} Therefore, sets of spectral features are required to differentiate DPNs from other land cover types. Since the spectral bands of Sentinel-2 data can highlight corresponding land covers and suppress others,^{33,34} comprehensive spectral indices have become a key feature set for identifying DPNs.^{35,36} Certain spectral indices were employed to preclude some disturbing land cover types. To distinguish natural vegetation from DPNs, three typical vegetation indices were considered: the Normalized Difference Vegetation Index (NDVI), the most widely used vegetation index; the Ratio Vegetation Index (RVI), which amplifies the radiometric distinction between vegetation and soil; and the Enhanced Vegetation Index (EVI), which enhances the vegetation signal by correcting the influence of soil and aerosol scattering. To distinguish water bodies from DPNs, the Normalized Difference Water Index (NDWI) was used to extract water-related information. For artificial land covers, the Normalized Difference Building Index (NDBI) and Index-based Built-up Index (IBI) were used to distinguish artificial land covers from DPNs. The Bare Soil Index (BSI) was selected to enhance the spectral difference between bare soil and DPNs. Finally, the Normalized Difference Snow Index (NDSI) was used to identify the spectral differences between snow/ice and DPNs. These spectral indices are calculated as follows:

$$\text{NDVI} = \frac{R_{\text{NIR}} - R_{\text{Red}}}{R_{\text{NIR}} + R_{\text{Red}}} \quad (1)$$

$$\text{RVI} = \frac{R_{\text{NIR}}}{R_{\text{Red}}} \quad (2)$$

$$\text{EVI} = \frac{2.5 \times (R_{\text{NIR}} - R_{\text{Red}})}{R_{\text{NIR}} + 6 \times R_{\text{Red}} - 7.5 \times R_{\text{Blue}} + 1} \quad (3)$$

$$\text{NDWI} = \frac{R_{\text{Green}} - R_{\text{NIR}}}{R_{\text{Green}} + R_{\text{NIR}}} \quad (4)$$

$$\text{NDBI} = \frac{R_{\text{MIR}} - R_{\text{NIR}}}{R_{\text{MIR}} + R_{\text{NIR}}} \quad (5)$$

$$\text{IBI} = \frac{\frac{2 \times R_{\text{SWIR1}}}{R_{\text{SWIR1}} + R_{\text{NIR}}} - \left(\frac{R_{\text{NIR}}}{R_{\text{NIR}} + R_{\text{Red}}} + \frac{R_{\text{Green}}}{R_{\text{Green}} + R_{\text{SWIR1}}} \right)}{\frac{2 \times R_{\text{SWIR1}}}{R_{\text{SWIR1}} + R_{\text{NIR}}} + \left(\frac{R_{\text{NIR}}}{R_{\text{NIR}} + R_{\text{Red}}} + \frac{R_{\text{Green}}}{R_{\text{Green}} + R_{\text{SWIR1}}} \right)} \quad (6)$$

$$\text{BSI} = \frac{(R_{\text{SWIR1}} + R_{\text{Red}}) - (R_{\text{NIR}} + R_{\text{Blue}})}{(R_{\text{SWIR1}} + R_{\text{Red}}) + (R_{\text{NIR}} + R_{\text{Blue}})} \quad (7)$$

$$\text{NDSI} = \frac{R_{\text{Green}} - R_{\text{SWIR1}}}{R_{\text{Green}} + R_{\text{SWIR1}}} \quad (8)$$

where R_{Red} , R_{Green} , R_{Blue} , R_{NIR} , and R_{SWIR1} are the surface reflectance in the red, green, blue, near-infrared, and short-wave infrared bands, respectively.

The RF algorithm, characterized by its remarkable flexibility, uses random sampling to construct multiple decision trees, generating classification outcomes through a majority voting process.³⁷ A well-trained RF model is capable of implementing pixel-wise classification in remote sensing data with both high precision and robustness.^{37,38} Moreover, RF has been integrated into GEE. With powerful and freely accessible computational resources

provided by GEE, national-scale land cover mapping can be conducted.³⁹ Currently, no existing algorithms are specifically designed for extracting DPNs. To fill this gap, inspired by previous research, which successfully identified other types of objects similar to DPNs (e.g., plastic canopies and mulches) according to their unique shapes and spectral reflectance characteristics, we employed GEE-provided RF model to map the national distribution of DPNs, according to highly differentiable features between DPNs and other land covers.

The RF model is an integrated classifier that uses a set of decision trees for classification and prediction purposes.⁴⁰ Each node undergoes splitting based on the number of features (Mtry). The Classification And Regression Tree (CART) algorithm is used for tree construction until the forest achieves a user-defined quantity of trees (Ntree).⁴¹ Finally, the classification decision is acquired from the arithmetic mean of the class assignment probabilities determined by all trees. During the training process, approximately two-thirds of the training samples are utilized to train the RF classifier.⁴⁰ The remaining one-third of the training samples, referred to as out-of-bag (OOB) samples, are used to calculate the OOB error, which reflects the generalization capability of the RF model. A well-trained RF model is used to classify all pixels on the Sentinel-2 images to map the DPNs.

The first step is to deploy an RF model that involves the preparation of reliable training samples. In this study, DPNs and other samples were generated by a semi-automatic labeling method. We manually collected 3,000 DPN samples through random sampling in Beijing, Shanghai, Chengdu, Guangzhou, and Zhengzhou, five megacities located in different parts of China that have undergone extensive infrastructure development and a rapid increase of various DPN types. The sampling periods were in 2018 and 2021, as they facilitated the acquisition of spectral reflectance data for DPNs in both TOA and SR datasets. For non-dust-proof-net samples, an automatic sampling method was used. Specifically, we generated 3,000 random sampling points within each grid based on ESA WorldCover data. For ESA WorldCover data, DPNs were categorized as built-up areas. Accordingly, our randomly generated sample points corresponding to non-built-up areas were retained, while those associated with built-up areas were further checked to remove erroneous non-DPN samples. Finally, training samples for each grid were created by combining non-DPN samples with the collected DPN samples.

We employed a total of 20 features mentioned above to train the RF model, including spectral bands 1–12, NDVI, RVI, EVI, NDWI, NDBI, IBI, BSI, and NDSI of Sentinel-2 data. Mtry and Ntree are the two key parameters determining the performance of the RF model. Existing empirical and theoretical studies indicated that the commonly employed parameter-setting strategies for classification were to set Mtry as the square root of the number of features and Ntree as 500.³⁷ Accordingly, in this study, Mtry and Ntree were set as 4 and 500, respectively. We provided further discussion regarding the rationale for the model parameters in Supplementary Text 1. Next, local adaptive RF models were trained within each grid. Compared with the global training, this approach yielded improved classification results,³⁸ as land cover types within individual grids generally presented some variations. With the acquired final RF model for each grid, the time series of Sentinel-2 images was classified to produce an initial distribution map of DPNs across China from 2016 to 2021. Some post-processing strategies were used to further improve the classification accuracy. Firstly, the majority filter method was applied to eliminate isolated error pixels and mitigate the “hole phenomenon” within areas with DPNs.⁴² Following this, to further remove the influence of falsely identified small DPNs, we set the minimum size of extracted DPNs as 500 m² and removed those DPNs below this threshold for the following reasons. Although these areas may contain small DPNs, it is highly possible that they are mainly used for covering discarded materials, instead of construction waste, and have a slight influence on PM emissions.

As described, our method entails the detection of DPNs at multiple times throughout the year, allowing for the acquisition of the duration of DPN presence (ΔT). Due to cloud contamination and the limited temporal resolution of Sentinel-2, the observation duration of DPN presence (ΔT) could be several days earlier or later. However, this issue exerted a limited influence on our simulation outputs. Firstly, large-scale construction usually takes months, which can usually cover the potential omission during this period. Secondly,

the following simulation was conducted based on monthly emission inventories, and thus as long as the existence of DPNs was identified, the potential bias of several days led to slight simulation uncertainty. In this case, the spatial resolution, quality, and temporal resolution jointly make time series Sentinel-2 data an ideal source for mapping national DPNs on a weekly and monthly basis.

Calculation of PM_{2.5} and PM₁₀ reduction attributable to DPNs

We estimated PM_{2.5} and PM₁₀ emissions using the empirical formulae from the U.S. Environmental Protection Agency (U.S. EPA) Emission Factor Guidance Manual (AP-42),^{43,44} which was used to estimate dust emissions from construction activities. The method was recommended by the Ministry of Ecology and Environment of the People's Republic of China (MEE) and has been widely used in China. PM_{2.5} and PM₁₀ emissions were calculated as follows:

$$Wi = Ei \times A \times \Delta T \times fi \quad (9)$$

$$Ei = 2.69 \times 10^{-4} \times (1 - \eta) \quad (10)$$

In the equation (9), Wi denotes the emission of PM_{*i*}; Ei denotes the average emission factor of PM_{*i*}; A denotes the area of construction activity regions; ΔT denotes the duration of DPN coverage; fi denotes the proportion of the particle size coefficient for PM_{*i*}. In this study, we employed the particle size coefficients for TSP, PM₁₀, and PM_{2.5} recommended by the MEE, as 1.0 for TSP, 0.49 for PM₁₀, and 0.1 for PM_{2.5}.

In the equation (10), η represents the dust removal rate with control technology. In this study, the dust removal rates of DPNs recommended by the MEE were used. The maximum and minimum PM₁₀ removal rates for DPNs are 20% and 10% while the maximum and minimum PM_{2.5} removal rates are 17% and 8%. To calculate DPN caused PM emission reductions, we respectively calculated PM_{2.5} and PM₁₀ emissions with or without DPN coverage. The first scenario considered PM_{2.5} and PM₁₀ emissions with the intervention of DPNs and different PM removal rates (The actual scenario). For the second scenario, we simulated PM_{2.5} and PM₁₀ emissions under the non-DPN hypothesis. The DPN caused PM_{2.5} and PM₁₀ emission-reduction were calculated as the difference between PM emissions in the first and second scenarios.

Furthermore, we estimated the potential DPN caused PM emission-reduction if the coverage rate of DPNs in NCP was transferred to the entire China, while the coverage duration of all DPNs was regarded as the national area-weighted average duration of DPNs for each year. Specifically, the DPN coverage rate in NCP was calculated annually based on equation (11). By considering the annual national construction area and the DPN coverage rate in NCP, we acquired the national potential DPN area for each year based on equation (12). The additional DPN area was calculated as the difference between the national potential and actual DPN area. According to equation (9) and equation (10), the additional PM emission-reduction from national additional DPNs were calculated. The average coverage duration of additional DPNs was assumed to be the same to that of the actual DPNs. The overall DPN's potential of PM emission-reduction for each year was the sum of PM emission-reduction caused by the additional and actual DPN.

$$Ri = \frac{A(NCP, DPN, i)}{A(NCP, Construction, i)} \quad (11)$$

$$PotentialA(National, DPN, i) = Ri \times A(National, Construction, i) \quad (12)$$

Where Ri denotes the NCP's DPN coverage rate in the year i ; $A(NCP, DPN, i)$ denotes the NCP's DPN area in the year i ; $A(NCP, Construction, i)$ denotes the construction area in the year i ; $PotentialA(National, DPN, i)$ denotes the national potential DPN area in the year i ; $A(National, Construction, i)$ denotes the national construction area in the year i .

The WRF-Chem model simulations

The Weather Research and Forecasting (WRF) model coupled with Chemistry (WRF-Chem) version 3.6.1 was used to simulate the PM_{2.5} and PM₁₀

concentrations from 2017 to 2021.⁴⁵ WRF-Chem integrates meteorological and chemical simulations, offering reliable modeling outcomes,^{46,47} and has been widely used and verified in various studies,^{48,49} especially for simulating PM concentrations.⁵⁰ The simulation domain covered the entire China using 186 (west-east) × 153 (south-north) grid cells with a horizontal spatial resolution of 27 km and 37 vertical layers extending from the surface to 50 hPa. The horizontal resolution of WRF-Chem facilitates the analysis of PM_{2.5} and PM₁₀ concentration variations at the urban scale. The National Center for Environmental Prediction Final (FNL) Analysis data with 1° spatial resolution and 6 hours temporal resolution were used to drive and re-initiate the meteorological initial and lateral boundary conditions every two days. This helped to reduce the drifting errors between simulated and actual meteorological fields.

The chemical initial and lateral boundary conditions were created from the output of the Community Climate Model with chemistry (CAM-Chem).⁵¹ The Carbon-Bond Mechanism version Z (CBMZ) gas-phase chemical mechanism coupled with the 4-bin sectional Model for Simulation Aerosol Interactions and Chemistry (MOSAIC-4 bins) aerosol scheme was utilized as the model chemical kinetics kernel.⁵² To improve the PM_{2.5} simulation, an improved scheme of heterogeneous sulfate formation reactions was adopted in the model.⁵³ MODIS MCD12Q1 Version 6 data product was additionally employed to improve the land use category contained in the modeling static geographical data. Anthropogenic emissions considered in the model were a combination of several emission inventories, as introduced in the data section.

To quantify the impacts of construction waste emissions, PM_{2.5} and PM₁₀ emissions from construction wastes for each year were added to the MEIC emission inventory in the model. Similar to previous studies,^{54,55} three sets of WRF-Chem simulations (Base, Min, and Max) were conducted for January, April, July, and October in each year. The "Base" scenario represents PM emissions without DPN intervention, the "Min" scenario represents PM emissions at the maximum PM removal rate, and the "Max" scenario represents PM emissions at the minimal PM removal rate. The average concentration of these four months' simulation was considered as the annual mean PM concentration. Through this controlled experiment, the meteorological conditions and emission inventory from other sectors were set unchanged and we could simply compare the with-DPN and No-DPN scenarios and isolate and quantify the sole impact of DPNs on PM variations.

Estimation of health effects attributable to DPN use

We used WorldPop population data to estimate the annual population benefiting from PM-reduction. After unifying the resolution, the WorldPop population data matched the resolution of PM reduction concentrations simulated by WRF-Chem model. We calculated the population benefiting from areas with PM_{2.5} or PM₁₀ reductions by more than 0.5 µg m⁻³ and 1 µg m⁻³ from 2017 to 2021. In areas where DPN caused a continuous PM-reduction over multiple years, we only calculated the number of beneficial population once to avoid double counting. The annual beneficiary population in China is the sum of the populations in areas with PM reduction concentrations greater than 0.5 µg m⁻³ and greater than 1 µg m⁻³, calculated as follows:

$$\text{Population}_{y,c} = \sum_{i=0} \text{Pop}_{i,y} \times T, c = (0.5, 1) \quad (13)$$

$$T = \begin{cases} 0, & \text{PM}_{i,y} < c \\ 1, & \text{PM}_{i,y} \geq c \end{cases}$$

Where $\text{Population}_{y,c}$ represents the population benefiting from a PM-reduction exceeding c . $\text{Pop}_{i,y}$ represents the population of grid i in year y . $\text{PM}_{i,y}$ represents the reduction in PM_{2.5} or PM₁₀ concentration in grid i in year y .

We used the Global Exposure Mortality Model (GEMM) to calculate the avoided premature mortalities attributed to the reduced PM_{2.5} and PM₁₀ concentrations. GEMM describes the connection between PM_{2.5} and the risks associated with non-communicable diseases and lower respiratory infections (NCD+LRIs), using data from global epidemiological cohort studies. It is extensively employed to assess the health consequences of PM pollution.⁵⁶⁻⁵⁸ The estimated reduction in premature mortalities attributable to the DPN-caused PM concentration reductions is as follows:

$$\Delta \text{Morti} = \text{Pop}_i \times \text{Base}_i \times \left(\frac{1}{\text{RR}_i(\text{CDPN})} - \frac{1}{\text{RR}_i(\text{CBase})} \right) \quad (14)$$

Where ΔMorti is the avoided premature mortalities between the DPN scenario and the baseline scenario within age group i ; Pop_i is the population within age group i . Base_i is the national baseline mortality rate for age group i ; RR_i is the relative risk of air-pollution-induced premature mortalities for age group i ; CDPN and CBase are national average air pollutant concentrations in the DPN scenario and the baseline scenario, respectively. The national population and baseline mortality rate with different age group are obtained from the Global Burden of Disease (GBD) database (<http://ghdx.healthdata.org/>). The estimated number of avoided premature mortalities is related to the baseline mortality rate of the year, the reduction in PM concentration, and the population. Therefore, the reduction in PM concentration may not correspond directly to the number of premature mortalities avoided.

According to GEMM, the relative risks (RR) of NCDs and LRIs linked to exposure to PM_{2.5} are computed for adults aged 25 years and older. Age groups are divided into 5-year intervals ranging from 25 to over 80 years, as outlined below:

$$\text{RR}(c) = e^{\frac{\theta \times \log(\frac{c}{c_0} + 1)}{1 + e^{\frac{c - \mu}{\nu}}}}, c = \max(0, c - 2.4) \quad (15)$$

Where c represents the national annual average PM_{2.5} and PM₁₀ concentration in µg m⁻³ (with no observed health impact for PM_{2.5} concentrations below 2.4 µg m⁻³ and for PM₁₀ below 15 µg m⁻³);⁵⁹ θ , α , μ and ν represent parameters governing the shape of the RR curves. The value α of, μ and ν remain constant, while θ varies across different age groups. We referred to previous studies that estimated the health benefits of PM reduction to establish the values for these parameters.^{57,60} We used the same method to estimate the avoided premature mortalities attributed to the PM_{2.5} and PM₁₀ reduction.

In addition, we also estimated reduced years of life lost (YLL) attributed to improved air quality. YLL was calculated as follows:

$$\text{YLL} = \sum_{i=1} (\text{Agelimit} - \text{MidAge}_i - 0.5) \times \text{Morti} \quad (16)$$

Where Agelimit is the upper limit of age, which is set at 80 years;⁵⁷ MidAge_i is the mid-point of the class interval of each age group i ; Morti is the premature mortalities of age group i .

Estimation of the economic benefits

Admittedly, assigning economic benefits of human health attributed to reduced PM emissions involves considerable uncertainties and debates. Currently, one mainstream approach for Monetizing air quality is the Value of Statistical Life (VSL), which was frequently employed in recent studies.^{56,57,61} VSL is a measure of people's willingness to pay to reduce their mortality risk, which is widely used for monetizing the benefit of human health. Therefore, we monetized the avoided premature mortalities attributed to improved air quality on the basis of the VSL in China. The economic value is calculated as follows:

$$E = \text{VSL}_i \times \Delta \text{Morti} \quad (17)$$

Where E is the economic benefits of human health associated with reduced PM emissions; ΔMorti is the total reduced premature mortalities associated with reduced PM_{2.5} and PM₁₀. The VSL is estimated as follow:

$$\text{VSL} = \text{VSL}_{\text{base}} \times \left(\frac{\text{pcGDP}_{\text{China}}}{\text{pcGDP}_{\text{base}}} \right)^{\eta} \quad (18)$$

Where VSL_{base} is the VSL in China in the survey year; $\text{pcGDP}_{\text{China}}$ and $\text{pcGDP}_{\text{base}}$ represent per-capital GDP for China and baseline GDP from the country of each study; η is the income elasticity, set as 0.4 in this study. Estimates of the VSL exhibit significant variation across countries, age demographics, and income brackets. While extensive research on VSL has been conducted in developed nations, studies focusing on developing countries are relatively scarce. We comprehensively referred to China's VSL study and considered the 2015 VSL in China (US\$ 550,000) as the VSL_{base} to estimate

the values for other years,⁶²⁻⁶⁴ which is a benchmark commonly used in many studies.^{56,61}

Accuracy assessments

First, we verified the accuracy of DPN extraction outputs in 2016 and 2019, respectively, to avoid the uncertainty caused by single-year verification. We selected seven $2^\circ \times 2^\circ$ grids in China as validation areas to comprehensively evaluate the reliability of our model across regions. Four major urban agglomerations, including: Beijing-Tianjin-Hebei (BTH), the Yangtze River Delta (YRD), the Pearl River Delta (PRD), and the Sichuan Basin (SCB), are contained within these seven grids with dimensions of $2^\circ \times 2^\circ$. Therefore, the accuracy assessment can generally demonstrate the reliability of nationwide DPN extraction. For each grid, the shortest continuous time intervals that were capable of generating cloud-free, high-quality imagery from January 1st of each year were determined to generate a qualified time-series of Sentinel-2 data. The generated Sentinel-2 time series were used to ensure that the accuracy of DPN extraction at different times within the year could be fully verified.

Validation samples that were independent of the training dataset were utilized to evaluate the accuracy of DPN extraction outputs. Specifically, within each grid, 500 DPN validation samples were selected through manual interpretation to maximally ensure the accuracy of these samples. By establishing a fishnet within each grid and conducting random sampling, 3,000 non-DPN samples were randomly selected. We computed the error matrix of the extraction outputs to evaluate the accuracy of DPN extraction at the pixel level. Generally, our method for extracting national DPNs displayed a high precision level, with the overall accuracy of the DPN extraction results in 2016 ranging from 91.07% to 97.50%, and the overall accuracy in 2019 ranging from 96.07% to 99.73% (see details in Supplementary Table S3 and Figure S2).

Additionally, we evaluated the accuracy of simulated $PM_{2.5}$ and PM_{10} concentrations in 2016 and 2019. Ground-based observations of $PM_{2.5}$ and PM_{10} concentrations were employed to verify the accuracy of the WRF-Chem simulation. $PM_{2.5}$ and PM_{10} concentration data in 2016 and 2019 were sourced from the China Environmental Monitoring Center (CEMC). We examined the data gaps throughout the year for each station and excluded stations with missing observations exceeding 25% of the total observations.⁶⁵ The observed concentrations at the retained stations aligned well with the simulated concentrations. For the year 2016, the R^2 of simulated and actual $PM_{2.5}$ and PM_{10} concentrations were 0.76 and 0.69, respectively. Meanwhile, for 2019, the corresponding R^2 was 0.78 for $PM_{2.5}$ concentration and 0.66 for PM_{10} concentration (Supplementary Figure S3). Moreover, we assessed the simulation precision of $PM_{2.5}$ and PM_{10} concentrations in terms of the Mean Fractional Bias (MFB) and Mean Fractional Error (MFE). The concepts of these two metrics are delineated as follows:

$$MFB = \frac{1}{N} \sum_{i=1}^N \left(\frac{SIMi - OBSi}{\frac{SIMi + OBSi}{2}} \right) \quad (19)$$

$$MFE = \frac{1}{N} \sum_{i=1}^N \left(\frac{SIMi - OBSi}{\frac{SIMi + OBSi}{2}} \right) \quad (20)$$

Where N represents the number of retained observation stations; $SIMi$ denotes the simulated concentration at station i ; $OBSi$ denotes the observed concentration at station i .

Uncertainty

Our analyses face uncertainties in extracting large-scale DPN, estimating PM emission-reduction, and simulating PM concentrations. Concerning DPN extraction, these uncertainties were majorly caused by the image quality of Sentinel-2. The emission factors of construction dust and particulate size proportions of TSP, PM_{10} , and $PM_{2.5}$ in construction dust were major contributors to the uncertainties in estimating the DPN caused PM emission-reduction. The uncertainties in anthropogenic emission inventories are the main reasons for the uncertainties in PM concentrations simulations (More details

concerning uncertainty are explained in Supplementary Text 2). The combined influence of multiple uncertainty sources can be understood through accuracy assessment.

RESULTS

Inter-annual variations of the total area of DPNs across China

Between 2016 and 2021, we identified and calculated the total area of DPN across China during multiple periods within each year (The details are explained in Methods), as shown in Figure 1. Based on the multi-year accuracy assessment, the average overall accuracy of extracted DPNs was over 97% (details of the accuracy assessment are presented in Supplemental Information), making it a reliable data source for the following analysis.

The total area of identified DPNs achieved its peak in 2019 (1,253.2 km²), 9.78 times of that in 2016, and then experienced a slight decline in 2020 and 2021, mainly due to the reduction of construction activities in the COVID-19 pandemic (Figure 2).⁶⁶ Meanwhile, the total construction area across China in 2019 was only 14.02% larger than that in 2016.^{67,68} So the soaring use of DPNs majorly resulted from the released regulation that required compulsory coverage of construction wastes.

Spatially, DPNs are predominantly distributed in China's four major urban clusters: the North China Plain (NCP), the Yangtze River Delta (YRD), the Sichuan Basin (SCB), and the Pearl River Delta (PRD). The increased DPNs majorly concentrated in the NCP, one of the most polluted areas in China (Figures 1B–C). In 2019, the DPN coverage in NCP amounted to 1052.1 km², 83.95% of China's total DPN coverage, and 11.4 times of the combined DPN coverage in the YRD, SCB, and PRD regions. PRD, with the smallest DPN coverage area among the four major urban agglomerations (6.2 km²), represented only 0.5% of national DPN coverage. The DPN area in NCP exhibited the most rapid growth, with its total area in 2019 being 22.7 times that in 2016, reflecting its strictest implementation of compulsory coverage policy (Figure 2). Similarly, the total area of DPNs in YRD, PRD, and SCB demonstrated continuous growth from 2016 to 2018 and distinct fluctuations since 2019 (Figure 2).

Despite a remarkable increase in DPNs, the implementation and effects of this policy demonstrated notable spatial variations across China. In 2019, the total construction area in NCP only accounted for 19.36% of the national construction area,⁶⁸ while the total area of DPNs in NCP accounted for 83.95% (Figure 1F). As a comparison, the construction area in YRD accounted for 37.28% of the national total, while DPN coverage in YRD only accounted for 6.00% (Figure 1F and Table S4). A common misunderstanding is that PM-reduction in regions with relatively good air quality has much weaker influence on public health than that in heavily polluted regions.^{69,70} Therefore, the stricter implementation of DPN policy across China, especially in YRD remained highly necessary and urgent, and this policy still holds substantial potential in future "clean air" actions. Assuming that the nationwide implementation level of DPNs is benchmarked against that in NCP, the coverage area of national DPNs in 2019 could further increase by 3.3 times (Figure 3).

Reduced PM emissions attributable to DPN use

Based on the identified total area of DPNs and comprehensive consideration of emission coefficients, we estimated the total PM-reduction from 2016 to 2021 due to the use of DPNs (The details are explained in Methods), as shown in Figure 4. From 2016 to 2019, DPNs caused national $PM_{2.5}$ and PM_{10} emission-reduction increased from 346.8 (± 124.9) tons and 2,039.5 (± 679.8) tons to 8,308.7 ($\pm 3,052.7$) tons and 48,844.3 ($\pm 16,651.0$) tons, respectively, characterized with an approximate increase of 23 times (Figure 4A). Clearly, the magnitude of emission-reduction far exceeded the magnitude of DPN increase (8.8 times). This disparity was mainly attributed to the fact that not only the total area, but also the average duration of DPN coverage (see Methods) had increased dramatically.

Based on official national data for total emission reductions, we found that the relative contribution of DPN use to the total PM-reduction has increased notably since 2016.⁷¹⁻⁷⁴ In 2017, DPN caused $PM_{2.5}$ and PM_{10} emission-reduction only accounted for 0.07% ($\pm 0.02\%$) and 0.4% ($\pm 0.1\%$) of the total PM-reduction due to all control measures in China. As a comparison, DPN caused $PM_{2.5}$ and PM_{10} emission-reduction in 2019 accounted for 1.9% ($\pm 0.7\%$) and 11.2% ($\pm 3.8\%$) of the total PM-reduction.

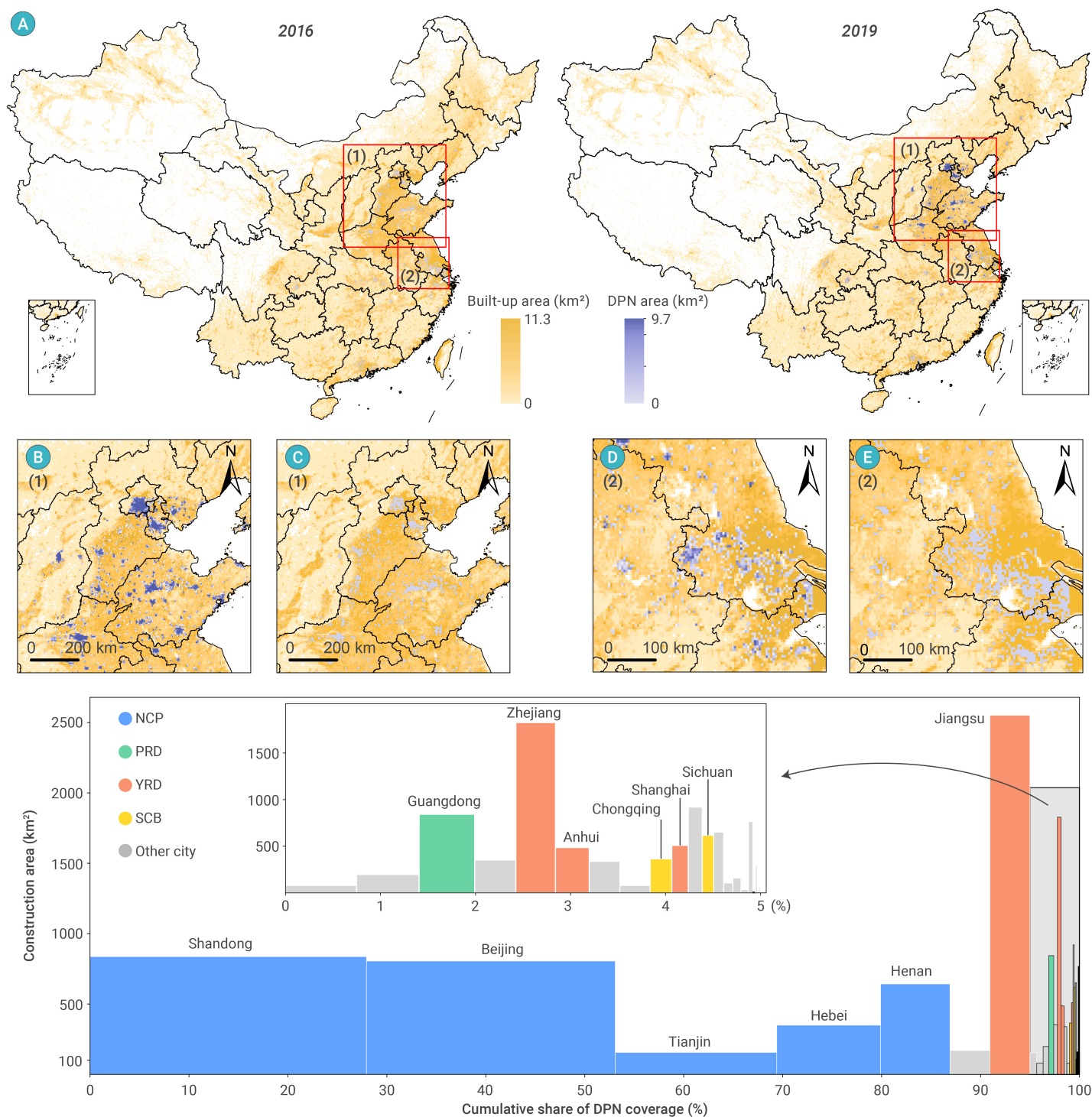


Figure 1. Spatial distribution of DPNs (A) The spatial distribution of DPNs in China for the years 2016 and 2019. (B)–(E) Examples of the DPN distribution in 2016 and 2019 at locations (1) and (2) in (A). The statistical chart in the bottom row shows the relationship between the cumulative share of DPN coverage and the total construction area across provinces in China in 2019.

The compulsory use of DPNs is playing a more and more important role in the current and future national “clean air” actions. Since 2017, the rate of PM-reduction from industries, which were the major pollution sources, has slowed down notably (Figure 4A). In 2019, the total PM-reduction from industrial sources were 230,000 tons.²⁴ Therefore, DPNs induced PM_{2.5} and PM₁₀ emission-reduction accounted for 3.6% ($\pm 1.3\%$) and 21.2% ($\pm 7.2\%$) of the total industrial emission-cut (Figure 4). From 2016 to 2021, the total PM-reduction from DPN even exceeded the total PM-reduction from residential sources by 77,000 tons during the same period.^{71,72}

At the regional scale, the average DPN caused PM_{2.5} or PM₁₀ emission-

reduction in the four major urban agglomerations accounted for 91.2% of the national DPN caused PM_{2.5} or PM₁₀ emission-reductions in 2019, while the NCP region alone accounted for 84.8% (Supplementary Figure S4).

Given the relatively low DPN coverage in other regions, DPN caused PM-reduction could be further enhanced significantly. If the ratio of DPN coverage in NCP could be transferred to the entire country, the DPN's potential PM-reduction from 2018 to 2021 could be 4.3 times of the actual PM emission reductions (see Methods). Specifically, DPN caused PM_{2.5} and PM₁₀ emission-reduction in 2019 could account for 8.2% ($\pm 3.0\%$) and 48.2% ($\pm 16.3\%$) of the total national PM-reduction (Figures 4A–B). This suggests that the use of

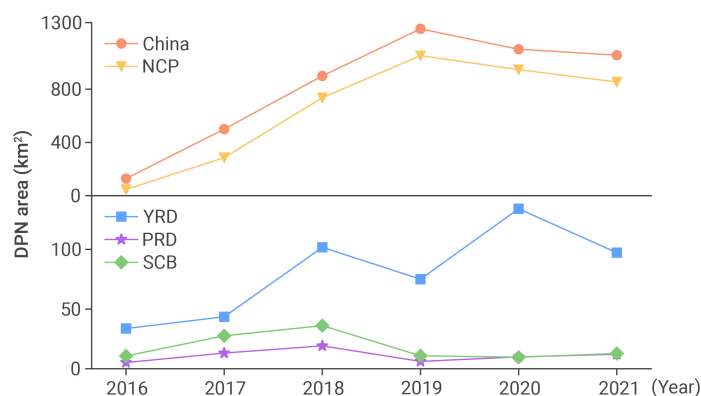


Figure 2. The DPN area from 2016 to 2021.

DPNs has become one major approach for PM-reduction. Especially under the background that the national air quality had been largely improved, DPNs may become the most important approach for PM mitigation in the future if DPN coverage could be largely promoted across the country.

The effects of DPN use on PM-reduction across China

We employed WRF-Chem to simulate the effects of DPNs on PM concentrations across China from 2016 to 2021. The WRF-Chem model comprehensively consider the influence of various meteorological and anthropogenic factors on PM concentrations and can isolate the relative contribution of specific-emission sources by setting control experiments (more details see Methods). The Mean Fractional Error (MFE) for the simulated national $PM_{2.5}$ and PM_{10} concentrations reached the error standard of recommended by the U.S. Environmental Protection Agency,⁷⁵ indicating a reliable simulation outcome (more details see Methods). A comparison with related studies also illustrates that simulation outputs achieved a relatively high level of accuracy.^{56,75,76}

Our simulation indicated that the increased use of DPNs could notably reduce PM concentrations in urban areas, especially in those areas with massive coverage of DPNs (Figures 5–6). In 2016, the limited application of DPNs yielded a modest reduction in PM concentrations. 6.4% of urban areas exhibited $PM_{2.5}$ -reduction exceeding $0.2 \mu g m^{-3}$ and 5% of urban areas exhibited PM_{10} -reduction exceeding $0.4 \mu g m^{-3}$. With the significant expansion of DPN applications, the role of DPN in improving air quality has continuously increased. In 2019, 18.9 % of urban areas exhibited $PM_{2.5}$ -reduction exceeding $0.2 \mu g m^{-3}$, and 20.0% of urban areas exhibited PM_{10} -reduction exceeding $0.4 \mu g m^{-3}$, respectively, achieving similar results to those in 2020 and 2021. Changes in non-urban areas are still weak. In 2019, only 2.0% of non-urban areas exhibited $PM_{2.5}$ -reduction exceeding $0.2 \mu g m^{-3}$ and 1.8% of non-urban areas exhibited PM_{10} -reduction exceeding $0.4 \mu g m^{-3}$.

The regions where DPNs made the principal contribution underwent dynamic changes during the study period (2016–2021). Overall, the region with the largest contribution from DPNs shifted from PRD in 2016 to NCP in 2019. In 2019, the average contribution of DPNs to $PM_{2.5}$ and PM_{10} reduction in NCP was $0.14 \mu g m^{-3}$ and $0.31 \mu g m^{-3}$. These levels substantially exceeded those observed in other key regions during the same period; for instance, they were 2.4 and 3.5 times higher, respectively, than the contributions observed in the SCB. For comparison, the average contribution of dust-proof nets to $PM_{2.5}$ and PM_{10} concentration reduction was $0.04 \mu g m^{-3}$ and $0.06 \mu g m^{-3}$ in the PRD and $0.05 \mu g m^{-3}$ and $0.07 \mu g m^{-3}$ in YRD in 2019. Spatially, the PM reduction attributed to DPNs in 2019 exhibited a pattern of decline from core urban areas towards rural regions (Figures 5B & 6B). This pattern was consistent across the four analyzed urban agglomeration regions. The spatial extent of PM_{10} reduction attributed to DPNs exceeded that of $PM_{2.5}$ reduction, indicating a more pronounced mitigation effect of DPNs on PM_{10} .

Within all analyzed key regions, the contribution of DPNs was consistently characterized by substantially higher levels in urban areas compared to rural areas, forming a clear urban-rural gradient. Within the four regions, the contribution of DPNs was generally much larger in urban areas than in non-urban areas. In NCP and SCB, the average contribution of DPNs to $PM_{2.5}$ -

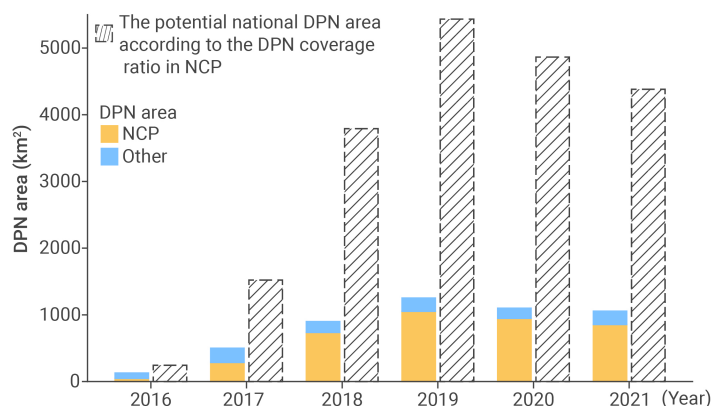


Figure 3. The actual DPN area and potential DPN area in the NCP and other regions from 2016 to 2021.

reduction in urban areas in 2019 was $0.28 \mu g m^{-3}$ and $0.14 \mu g m^{-3}$, which was 2.4 and 1.8 times of the contribution in non-urban areas, respectively. This disparity was even more pronounced for PM_{10} . In NCP, the average contribution of DPNs to PM_{10} -reduction in urban areas was $0.65 \mu g m^{-3}$, approximately 3.6 times of that in non-urban areas (Supplementary Figure S5). Specifically, reductions in $PM_{2.5}$ and PM_{10} concentrations can be notably observed in localized areas within cities. $PM_{2.5}$ -reduction and PM_{10} -reduction at some urban locations within NCP could reach up to $2.54 \mu g m^{-3}$ and $7.23 \mu g m^{-3}$ in 2019. Spatially, this urban-rural gradient manifested as high DPN contribution zones concentrated within urban built-up areas and rapidly diminishing towards surrounding rural regions (Figures 5B & 6B), suggesting an association with more intensive urban activities.

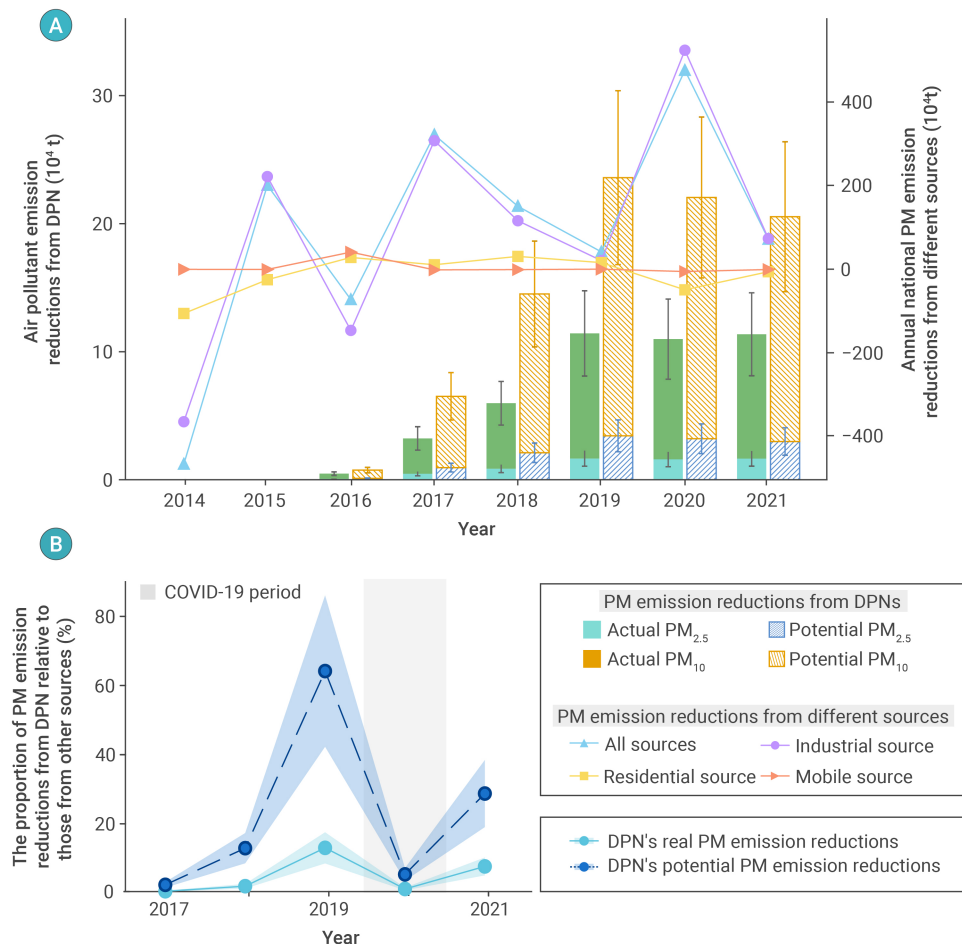
Health benefits of DPN use across China

Based on the epidemiological exposure-response curves (details see methods), we estimated the total number of populations that benefited from a mitigated PM level and the total number of avoided premature mortalities attributable to DPN use from 2017 to 2021 (Figure 7). Since the avoided premature mortalities was determined not only according to the mitigated $PM_{2.5}$ and PM_{10} concentrations, but also the exposed PM level,^{69,70} reducing the same amount of PM concentrations could cause a large difference in the number of saved lives under different PM levels. Therefore, it is noted that the number of avoided premature mortalities was not linearly correlated with the total DPN coverage. We set relevant parameters according to inter-annual China's baseline mortality rates provided by the Global Burden of Disease (GBD) database (<http://ghdx.healthdata.org/>).

From 2017 to 2021, the total population, exposure to $PM_{2.5}$ (PM_{10}) concentrations mitigated by more-than- $0.5 \mu g m^{-3}$, reached 84.8 (253.8) million. The total population, exposure to $PM_{2.5}$ (PM_{10}) concentrations mitigated by more-than- $1 \mu g m^{-3}$, reached 32.2 (119.1) million. Here for those areas with DPN caused PM reduction in multiple years, we simply calculated for once to avoid repeated calculation. In 2019, the total population benefiting from more-than- $0.5 \mu g m^{-3}$ PM-reduction reached 108.6 million, while those benefiting from more-than- $1 \mu g m^{-3}$ PM-reduction was 53.9 million, approximately 11 times and 7 times of that in 2017. Across all urban areas nationwide, people within the NCP benefited the most from $PM_{2.5}$ and PM_{10} reduction, accounting for more than half of the national beneficiary population.

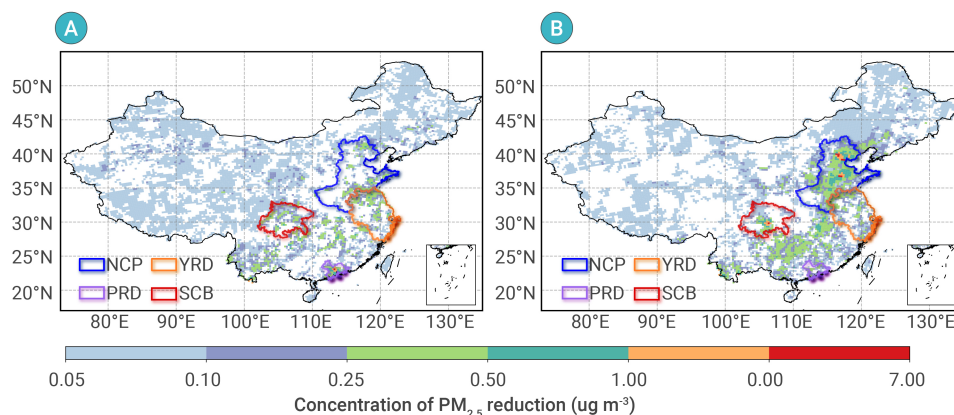
More importantly, the nationwide implementation of DPN policy from 2017 to 2021 avoided 26,836 cases (95% CI: 23,630–30,041) of premature mortalities. Specifically, the exposure to reduced $PM_{2.5}$ concentrations avoided 11,644 (95% CI: 10,306–12,981) premature mortalities, while the exposure to reduced PM_{10} concentrations avoided 15,192 (95% CI: 13,323–17,060) premature mortalities. The total number of avoided premature mortalities was largest in year 2018, as 6,193 cases (95% CI: 5,456–6,930). Furthermore, we calculated the numbers of avoided premature mortalities and Years of Life Lost (YLL) across different age groups. As shown in Supplementary Table S5 and Supplementary Table S6, the majority of avoided premature mortalities occurred in the aged group of 80 and above (comprising 34% of

Figure 4. The PM emission reductions from DPNs and other sources (A) The DPN's actual and potential PM-reduction and the PM-reduction from other sources. (B) The proportion of DPNs caused PM-reduction in the national total PM emission reductions.



reached 5.0 billion dollars, approximately 2.7 times of that in 2017, suggesting a continuous and rapid increase of economic benefits from DPN use. Considering the cheap price of DPNs,⁷⁸ we calculated the total cost of DPN implementation across China from 2017 to 2021 was approximately 300 million, simply 1.4% of its economic benefits. Here we also compared the cost-effectiveness of other major measures for mitigating airborne pollution. Liang et al.⁵⁶ estimated that fleet electrification could avoid 17,456 premature mortalities by 2030, which is 2.8 times of that attributable to DPN use in 2018. Nevertheless, the total cost of implementing fleet electrification at the national scale is about 100 times of DPN implementation. The mean cost of one avoided premature mortalities attributable to DPN use was 11,341 ($\pm 1,355$) dollars. As a comparison, from 2013 to 2017, the most important "clean air" measure was emission-cut in the industrial sector avoided an estimated 339,500 (95% CI: 322,000–357,000) premature mortalities,⁸ with the mean cost of one avoided premature mortalities as 1.3 (± 0.1) million dollars.^{67,79–82} Meanwhile, another key policy for improving air quality, "coal to gas

Figure 5. Contribution of DPNs to the reduction of $PM_{2.5}$ concentrations (A) $PM_{2.5}$ concentration reductions in 2016. (B) $PM_{2.5}$ concentration reductions in 2019.



cases), while most YLL were related to individuals above 60. Considering that China has become an aging society, the large number of avoided premature mortalities and YLL, especially for the older groups, proved the substantial health benefits from the DPN use.

Economic benefits of DPN use across China

Here we employed Value of a Statistical Life (VSL) model (see Methods), which has been widely employed in recent studies,^{57,58} to roughly estimate the economic benefits from DPN use from 2017 to 2021. VSL model estimates the economic benefits of the policy of compulsory DPN use from the perspective of avoided premature mortalities (labor loss) due to PM-reduction. Some key parameters of VSL were set according to various baseline studies in China.^{61,62,77}

From 2017 to 2021, the increased use of DPNs generated massive economic benefits by 20.7 billion dollars. In year 2021, DPN caused economic benefits

(electricity) for clean heating" avoided 49,200 (95% CI: 46,600–51,600) premature mortalities,⁸ with the mean cost of one avoided premature mortalities up to 5.6 (± 0.3) dollars.^{67,79–82} Clearly, while the compulsory use of DPNs could also avoid thousands of premature mortalities and lead to billions of economic benefits annually, the implementation of this policy is much more cost-effective.

DISCUSSION

Despite a robust DPN extraction method and WRF-Chem model employed, some uncertainties remain. Firstly, although we managed to extract DPNs at multiple times throughout the year, there remains a possibility that a small proportion of DPNs were missed, potentially leading to an underestimation of their coverage area and related PM-reduction. Since the temporal resolution of Sentinel-2 images is up to five days and most DPNs last for weeks, such omissions were relatively limited. Secondly, in past decades, some abandoned DPNs without covering construction wastes may be recognized and disturb our simulation of DPN caused PM-reduction. In recent years, the government released strict rules that DPNs should be cleared soon after the completion of construction activities and thus the abandoned DPNs became very rare, causing very limited influence to our outputs. Thirdly, it is inevitable that there were some uncertainties in meteorological data and emission

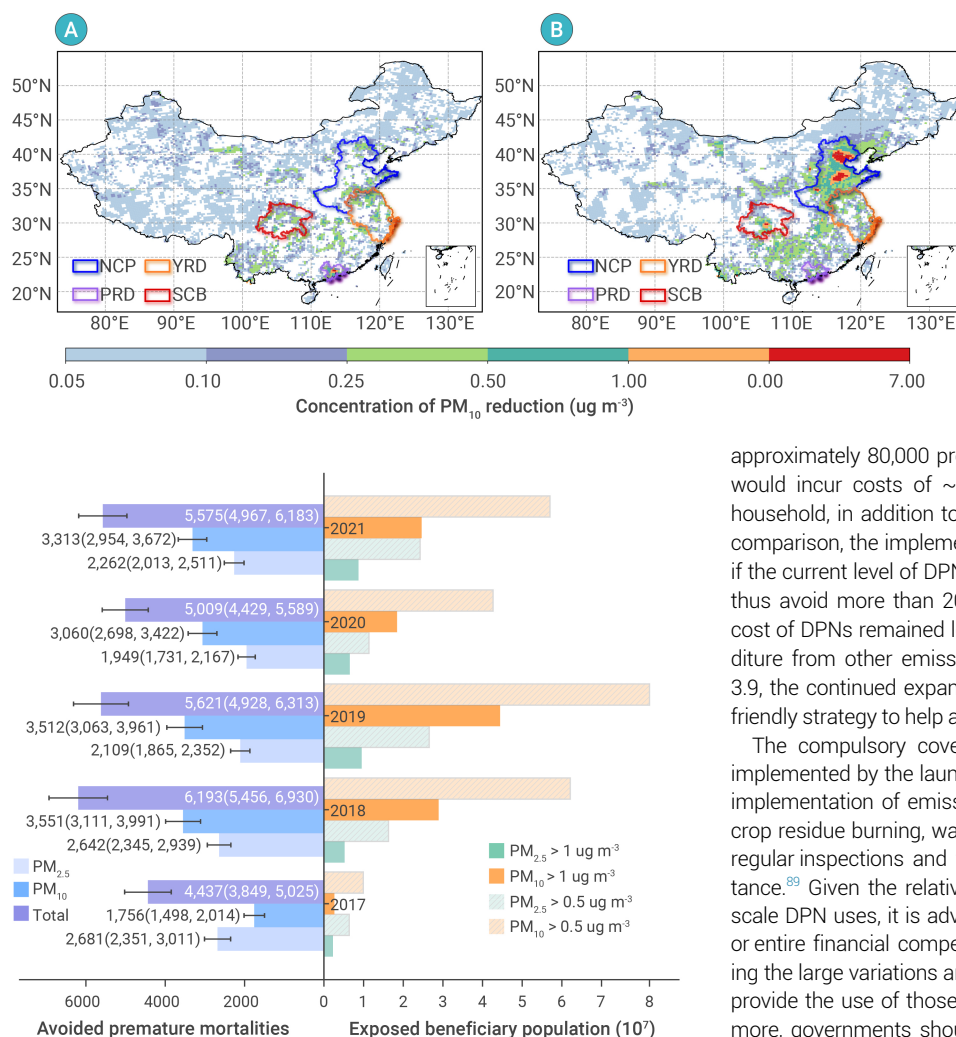


Figure 7. The population benefited from PM-reduction and avoided premature mortalities attribute to DPNs from 2017 to 2021.

inventories involved in the WRF-Chem model. To effectively reduce such uncertainties, we employed control experiments, which made sure the meteorological conditions and other emission sources unchanged and thus isolated the influence of DPNs on PM-reduction. Due to the limited effects of these potential uncertainties, the satisfactory accuracy of DPN extraction and WRF-Chem simulation generally suggested the reliability of our findings.

To mitigate severe airborne pollution, China launched the national "clean air actions", which included a series of regional or national measures targeting industrial, vehicle, and residential emissions.^{5,6,8} Those major emission sources had been controlled as the initial focus. Hundreds of heavily polluted industrial factories were shut down temporally or permanently.⁸ The emission standard for automobiles had been largely enhanced. The commonly used coal, one major trigger for PM_{2.5} pollution in the Beijing-Tianjin-Hebei region in winter, had been gradually replaced with gas and electricity.⁵⁸ The impact of these strong emission control measures was evident over 2013–2017, as national mean PM_{2.5} and PM₁₀ concentrations dropped significantly from 72 ug m⁻³ and 118 ug m⁻³ to 43 ug m⁻³ and 75 ug m⁻³, respectively.^{83,84} However, recent studies revealed that China experienced persistent and unexpected haze episodes since 2020^{85–87} which highlighted the difficulty and uncertainty in long-term effective airborne pollution mitigation under the combined effects of complicated meteorological conditions and anthropogenic emissions. Recently, Yue et al.⁸⁸ suggested that even the current largely-reduced PM_{2.5} level, would pose an increasing threat to China's aging society, and further emission-reduction remained highly necessary and urgent. Similarly, the United Nations' Sustainable Development Goal (SDG) 3.9 also calls for a continued reduction in deaths attributable to air pollution.

Figure 6. Contribution of DPNs to the reduction of PM₁₀ concentrations. a PM₁₀ concentration reductions in 2016. b PM₁₀ concentration reductions in 2019.

Since anthropogenic emissions from major sources have already been restricted with high priority, achieving additional urban emission cuts may require substantial additional efforts. For instance, under scenarios of high electrification rates, fleet electrification will avoid approximately 17,000 premature mortalities in 2030, yet this would cost a government investment more than 5 billion dollars.⁵⁶ Likewise, under high levels of clean heating,

approximately 80,000 premature mortalities will be avoided in 2030, yet this would incur costs of ~978–1,792 (~2,769–4,073) dollars per urban (rural) household, in addition to billions of investment from the government.⁵⁸ As a comparison, the implementation of DPN was much easier and cheaper. Even if the current level of DPN coverage could be enhanced by multiple times and thus avoid more than 20,000 premature mortalities accordingly, the annual cost of DPNs remained less than 0.4 billion dollars,⁷⁸ far less than the expenditure from other emission-cut measures. Under the requirements of SDG 3.9, the continued expansion of DPN usage in the future is an economically friendly strategy to help achieve this goal.

The compulsory coverage of construction wastes has been effectively implemented by the launch of relevant environmental laws. In past years, the implementation of emission-reduction in other domains, such as restricting crop residue burning, was also promoted by the government using laws and regular inspections and further supported by financial and technical assistance.⁸⁹ Given the relatively small expenditure and notable effects of large-scale DPN uses, it is advisable for governments to consider providing partial or entire financial compensation to companies that adopt DPNs. Recognizing the large variations among different DPNs, governments should require or provide the use of those materials with high PM-filtering efficiency. Furthermore, governments should encourage technical innovation or improvement on advanced DPNs, which can better filter PM_{2.5} and PM₁₀. With large reductions in emissions from conventional sources, continuous emission-reduction would be increasingly difficult and thus the development of new pollutant-reduction materials would become a key solution for the next stage of industrial, vehicle, and residential emission-reduction efforts.

Despite a largely promoted urbanization rate, the annual new construction area for China remained high and the airborne pollutants from construction wastes remained one major urban pollution source.^{10,11} Notably, even with the increased use of DPNs, the potential for further PM reduction remains substantial. Increasing emphasis should be placed on the implementation of DPN coverage in cities where regional air quality is relatively good and this policy received insufficient emphasis. Specially for Yangtze River delta with massive new construction areas, yet very limited DPN coverage, the stricter implementation of DPN coverage could led to massive environmental, health and economic benefits. Similarly, the use of DPNs in non-urban areas should also be largely promoted. As discussed earlier, if the DPN coverage rate in NCP could be extended nationwide, the national DPN coverage be further enhanced by 4 times, making DPN the most important and cost-effective PM-reduction measure. Moreover, advancing stricter and more extensive DPN implementation within these areas represented a feasible approach to contribute to SDG 11, specifically SDG 11.6 concerning the reduction of the adverse per capita environmental impact of cities, including air quality. Beyond its impact in China, the use of DPNs holds significant potential for countries undergoing rapid urbanization and facing heavy airborne pollution, such as India,⁹⁰ by effectively reducing the airborne pollutants caused by large-scale construction.

CONCLUSION

Our study conducted a detailed assessment of the spatio-temporal dynamics of DPNs in China from 2016 to 2021 and evaluated their resulting

environmental, health, and economic benefits. We found that the area covered by DPNs increased 8.78-fold between 2016 and 2019, indicating the widespread implementation of policies mandating their use. This expansion led to substantial PM mitigation benefits; the total emission reductions attributed to DPNs increased 23-fold over this period, causing widespread decreases in PM_{2.5} and PM₁₀ concentrations nationwide. These air quality improvements were estimated to have averted 26,836 (95% CI: 23,630–30,041) premature deaths, generating an associated economic benefit of 20.7 billion dollars. Our research also highlighted the substantial remaining potential for DPN deployment, which is critical for mitigating construction-related pollutant emissions amid ongoing urbanization.

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AUTHOR CONTRIBUTIONS

C.Z., Z.C., X.J. and Z.L. conceived and designed the research; Z.C., X.J. and W.J. performed data analysis; C.Z., Z.C., X.J., Z.L., Z.C., W.Q., and Y.L. wrote the manuscript; and L.M., G.B., L.Q. and Y.J. contributed ideas to data analysis, interpretation of results or manuscript revisions. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Sentinel-2 data is available on Google Earth Engine (<https://developers.google.com/earth-engine/datasets/catalog/sentinel-2>). ESA WorldCover data is available on Google Earth Engine (https://developers.google.com/earth-engine/datasets/catalog/ESA_WorldCover_v100). MODIS MCD12Q1 Version 6 data product is available at <https://www.earthdata.nasa.gov/>. The MEIC emission inventory and DPEC emission inventory used in this study can be found at <http://meicmodel.org.cn>. All other data needed to run WRF-Chem model are available from corresponding references. Global Urban Boundary (GUB) data is available at <https://data-starcloud.pcl.ac.cn/zh>. Worldpop population data is available at <https://www.worldpop.org/>

SUPPLEMENTAL INFORMATION

It can be found online at <https://doi.org/10.59717/j.xinn-geo.2025.100160>