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Satellite evidence on the trade-offs of the food-water–air quality nexus over the breadbasket of India

Mrinal Singha[a], Jinwei Dong[a,*], Quansheng Ge[a,*], Graciela Metternicht[b], Sangeeta Sarmah[a], Geli Zhang[c], Russell Doughty[d], Sharachchandra Lele[e], Chandrashekhar Biradar[f], Sha Zhou[g], Xiangming Xiao[h]

[a] Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
[b] School of Biological, Earth and Environmental Sciences, University of New South Wales, Sydney, NSW 2052, Australia
[c] College of Land Science and Technology, China Agricultural University, Beijing 100193, China
[d] Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA 91125, USA
[e] Centre for Environment & Development, Ashoka Trust for Research in Ecology & The Environment, Bengaluru 560064, India
[f] International Center for Agricultural Research in Dry Areas (ICARDA), CGIAR Research Center, Cairo 11742, Egypt
[g] Lamont-Doherty Earth Observatory of Columbia University, Palisades, NY 10964, USA
[h] Department of Microbiology and Plant Biology, University of Oklahoma, Norman, OK 73019, USA

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ABSTRACT

Access to food, water, and good air quality is indispensable for human life, as reflected in various United Nations Sustainable Development Goals (SDGs); however, pursuing food security may pose threats to water security and/or air quality. An important case is northwest India including the Punjab and Haryana states, which is the 'breadbasket' of India with a significantly increasing paddy rice area. The rapid expansion of rice farming has stressed groundwater resources and impacted air quality. Satellite observations have the potential to provide data for better decisions on food security, water storage, and air pollution, which would be vital for regional sustainable development. Based on observations from multiple satellites from 2001 to 2018, we found that paddy rice expansion (+22%) increased groundwater depletion (−1.50 cm/yr), residue burning (+500%), and air pollution (+29%, $PM_{2.5}$) in the breadbasket of India. Moreover, satellite observations showed changes in these interactions after the enactment of a groundwater protection policy in 2009, which decelerated groundwater depletion (−1.20 cm/yr) due to delayed rice planting and harvest dates (~15d); the latter elevated air pollution in November (+29%, $PM_{2.5}$). Our finding stresses the need to reconcile the trade-offs and consider the interactions among SDGs 2 (food), 3 (good health), 6 (clean water), and 11 (air quality in cities), in policy-making for sustainable development. An efficient crop residue ultilization and management system, bottom-up groundwater use regulations, and cropping system shift towards less water-consuming crops are critically required to resolve the trade-offs of the food-water–air quality nexus in the northern India. Our study also showcases remote sensing approaches and methods to support and aid the achievement of the SDGs and track their progresses to support regional sustainable development.

1. Introduction

To feed arapidly growing population and accommodate for its dietary shifts, global crop production increased threefold in the last five decades (FAO, 2013; Roser et al., 2013). The growth in crop production was mainly achieved through the "Green Revolution" that combined (a) development of high yield crop varieties, (b) agricultural intensification driven by increased cropping intensity (Ray and Foley, 2013), chemical fertilization (Lu and Tian, 2017), mechanization, irrigation (Siebert et al., 2015), and (c) expansion of croplands (FAO, 2019). The increase of crop yield and productivity through the combination of the aforementioned approaches is a common strategy for promoting human development and improving food security, matching with the aspiration of the United Nations Sustainable Development Goal 2 (SDG 2, viz.,

* Corresponding authors.
E-mail addresses: dongjw@igsnrr.ac.cn (J. Dong), geqs@igsnrr.ac.cn (Q. Ge).

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ending hunger and achieving food security) (Aguilar-Rivera et al., 2019). However, to achieve sustainable development, it is necessary to account for aspects of environmental impacts such as water and air quality (SDG 3, SDG 6) (Nilsson et al., 2018) as well as soil and plant health (SDG 15) that such a strategy might impose.

Research consistently points to the trade-offs and co-benefits that can arise from the implementation of the SDGs (Allen et al., 2019; 2017; Messerli et al., 2019). The nexus of water-food-energy first identified during the World Economic Forum (Waughray, 2011) has been investigated (Bleischwitz et al., 2018; Simpson and Jewitt, 2019) to propose coherent policy options underpinned by integrative resource planning (Daher and Mohtar, 2015) that minimize trade-offs. The latter requires careful analysis of the connections among the SDGs and targets (Allen et al., 2019), and frameworks have been proposed to that end (Griggs et al., 2017; Nilsson et al., 2018). For instance, the SDG interaction framework (ICSU), presents a typology and scoring of interactions on a 7-point scale (ranging from −3, when actions for one target make it impossible to reach another target, to + 3 when targets are inextricably linked, and actions for one target led to the achievement of another target). Analysis of the SDGs and their associated targets using this typology provides a method to assess whether progress on a SDG target has a negative, positive or neutral impact on the progress of another target. The implementation of these frameworks is important for policy design and implementation, where indicators are needed to assess performance. In this regard, historical time series of satellite observation and Big Earth Data can provide evidence —in the form of indicators or essential variables— to evaluate whether policy and strategies (Dong et al., 2019) designed to advance the SDGs create co-benefits among the targets or produce negative impacts on subsets of SDG targets.

We selected the 'breadbasket' of India, namely the Indian States of Punjab and Haryana (northwest India), as a test case for our study. This region produces two-thirds of the nation's grain food (Balwinder-Singh et al., 2019; Jethva et al., 2018) and was the epicenter of the Indian green revolution. Paddy rice has significantly increased in these two states during 2000–2015 in an effort to enhance the nation's food security (Zhang et al., 2020). Such rapid expansion of rice farming has stressed groundwater resources and has impacted air quality. Previous studies have investigated the increase in rice paddy area (Zhang et al., 2017), depletion of groundwater (Rodell et al., 2018; 2009), and residue burning and air pollution (Jethva et al., 2018) in the region. The Punjab and Haryana Preservation of Subsoil Water Act (GW Act) enacted in 2009 slightly improved groundwater storage (Bhanja et al., 2017) but may have posed additional pressure on air pollution in northwest India, including the megalopolis of Delhi (Balwinder-Singh et al., 2019; Jethva et al., 2018). However, there is limited understanding of the co-benefits and trade-offs arising from the interactions of these three components —food security, groundwater sustainability, and clean air. Quantitative evidence on the relationship among them, as proposed in this research, is essential to understand interactions amongst policy objectives around food security (SDG 2), groundwater depletion (SDG 6), and air pollution (SDG 3 &11), to anticipate how these interactions constrain or counteract progress in achieving SDG targets (Griggs et al., 2017; Tremblay et al., 2020), for policy design and implementation.

Here, we seek to demonstrate the potential of time-series of satellite observations to gather the information that can evidence impact (positive, enabling or reinforcing, or negative, as in constraining, counteracting or canceling) sectoral policies on national commitments of advancing the SDG targets related to food security (Supplementary Table 1). We focus on the links between food security (SDG targets 2.3 and 2.4), sustainable water management using groundwater withdrawal as a proxy, and good health and well-being using air quality as a proxy (SDG targets 3.9 and 11.6). Although none of the SDGs mentions groundwater explicitly, 53 of the 169 targets have clear links to groundwater, particularly SDG targets 6.6 and 6.4 which highlights the importance of groundwater for achieving SDG targets (Guppy et al., 2018). We used a satellite-based framework and correlative analyses of time series measurements to identify interactions among changes in paddy rice planting areas, groundwater depletion, agricultural burning, and air pollution. Our study aimed to identify long-term changes in paddy rice planting areas (a proxy for food production) and their trade-offs with groundwater storage, agricultural burning in northwest India (Punjab and Haryana), and air pollution of neighboring urban areas such as Delhi. Our framework also facilitated the assessment of the impacts of the 2009 Water Act on groundwater preservation, the paddy rice calendar, groundwater depletion rate, and air quality in northwest India. Additionally, we estimated the number of people exposed to high levels of $PM_{2.5}$, which is used to track the progress of SDG target 11.6. This target is focused on reducing the adverse per capita environmental impact of cities, including air quality.

The specific objectives of this study were to: (1) quantify the interactions connecting paddy rice expansion, groundwater storage, residue fires, and air quality, using observations from multiple satellites; (2) investigate the impacts of groundwater conservation policy on annual groundwater trends, paddy rice harvest time and residue fires and regional air-quality; and (3) estimate the number of people exposed to poor outdoor air quality in rural and urban areas neighboring the agriculture residue burning sites.

2. Data and methods

2.1. Study area

The two states Punjab and Haryana are situated in northwest India, extending between 27°03'38" to 32°08'35" N latitude and 73°01'54" to 77°05'36" E longitude. These regions are major rice and wheat producer characterized by double cropping patterns on the irrigated lands and utilize modern mechanical equipment and large amounts of fertilizer. These two states alone constitute more than 70% of the total crop residue fires in the Indo-Gangetic Plains. The region has a subtropical monsoon climate with very hot summer and very cold winter. The mean monthly temperature varies between 5°C to 40°C, and the average annual rainfall is about 633 mm. Recently, these two states were in the limelight due to agricultural fires and declining groundwater tables. Here we analyzed the environmental consequences of intensifying paddy rice cropping and unsustainable agriculture practices and related air quality in the megacity Delhi.

2.2. Data

2.2.1. MODIS surface reflectance data and vegetation indices

We used Moderate Resolution Imaging Spectroradiometer (MODIS) surface reflectance data to map paddy rice planting areas. The MOD09A1 land surface reflectance product version 6 is an 8-day interval and 500-m spatial resolution composite generated from daily observations and is atmospherically corrected for gases, aerosols, and Rayleigh scattering. The data quality flags included in the MOD09A1 dataset were used to exclude pixels with cloud cover (cloudy and mixed), internal clouds, cloud shadows, high aerosols, high cirrus, and snow (Supplementary Fig. 1). Three spectral indices, including the Normalized Difference Vegetation Index (NDVI) (equation (1)), Enhanced Vegetation Index (EVI) (equation (2)), and Land Surface Water Index (LSWI) (equation (3)), were calculated for paddy rice mapping.

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (1)$$

$$EVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + 6 \times \rho_{red} - 7.5 \times \rho_{blue} + 1} \quad (2)$$

$$LSWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}} \quad (3)$$

where ρ_{NIR}, ρ_{red}, ρ_{blue}, and ρ_{SWIR} are the surface reflectance values of near-infrared (NIR), red, blue, and shortwave-infrared (SWIR) bands from MOD09A1, respectively.

2.2.2. Satellite-based fire and burned area data

The Fire Information for Resource Management System (FIRMS) dataset was used to analyze the fire dynamics, which contains near real-time (NRT) active fire locations. The dataset was processed by using the MODIS MOD14/MYD14 Fire and Thermal Anomalies product. Each fire location represents the centroid of a 1 km pixel that contains one or more fires within pixel (Giglio et al., 2015). Daily fires were estimated by counting the active fire pixels within the study area. The FIRMS dataset likely underestimates the number of actual fires because most residue fires are small and short in duration. Also, multiple fires could occur within a single pixel (Balwinder-Singh et al., 2019). The burned area data were from MODIS Terra and Aqua combined MCD64A1 version 6 monthly global gridded 500-m product (MCD64A1.006). Time series of burned area maps were generated after removing the invalid pixels using the quality assurance (QA) data layer.

2.2.3. Satellite-based total water storage (TWS) data from GRACE

The Gravity Recovery and Climate Experiment (GRACE) Tellus Monthly Mass Grids provide monthly gravitational anomalies (1° resolution). We used the monthly GRACE TWS dataset produced by Centre for Space Research of University of Texas to estimate the groundwater storage according to (Chen et al., 2014).

2.2.4. Satellite-based aerosol optical depth (AOD) data and $PM_{2.5}$ data

The aerosol optical depth (AOD) data were derived from the MODIS Terra and Aqua combined MCD19A2 version 6 daily product (MCD19A2.006), which was derived from MODIS using the Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm. This dataset is available at 1-km spatial resolution. MAIAC generated MODIS AOD has reasonable accuracy for long-term AOD trend analysis over northern India (Jethva et al., 2019).

The rise of particulate matter of a diameter less than or equal to 2.5 μm ($PM_{2.5}$) (Dey et al., 2012) is another important indicator for air pollution. Global annual $PM_{2.5}$ grids were obtained from the NASA Socioeconomic Data and Applications Center (SEDAC) (Van Donkelaar et al., 2016). This dataset was generated by combining AOD from MODIS, Multi-angle Imaging Spectroradiometer (MISR), and the Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) satellites. The GEOS-Chem chemical transport model was used to estimate the near-surface $PM_{2.5}$ concentration (micrograms per cubic meter) with dust and sea-salt removed. The annual $PM_{2.5}$ values were generated using geographically weighted regression techniques (Van Donkelaar et al., 2016). The dataset is available for 1986–2016 at 0.01-degree resolution.

The ground-level air quality data in Delhi were also obtained from the US Embassy & Consulate of New Delhi. The hourly $PM_{2.5}$ data is available from 2015 to 2019 and was collected using a MetOne BAM 1020 particulate monitor at the US Embassy in New Delhi. The MetOne BAM 1020 instrument measures the $PM_{2.5}$ concentration of ambient air on an hourly basis using the Beta attenuation method. The annual average $PM_{2.5}$ was calculated using daily hourly data collected at the US Embassy in New Delhi. The dataset is publicly accessible from the following URL https://in.usembassy.gov/embassy-consulates/new-delhi/air-quality-data/.

The PM $_{2.5}$ data from 2002 to 2018 were acquired from the Open Government Data (OGD) platform (https://data.gov.in/). These datasets were collected under the National Air Quality Monitoring Programme (NAMP) of the Government of India from the air quality monitoring stations across Delhi. The data was collected by the Central Pollution Control Board (CPCB) using the $PM_{2.5}$ Gravimetric measurement method and FRM or FEM equipment. The $PM_{2.5}$ data were usually collected twice a week, and annual average $PM_{2.5}$ concentration was calculated from these datasets.

2.2.5. Population data

Population data were derived from the Gridded Population of the World Version 4 (GPWv4) (CIESIN, 2016). It included population estimates for the year 2015 and was calculated for every 1 km^2 cell (~30 arc-seconds) using the proportional allocation of populations from census and administrative units. This dataset is appropriate to assess the pollution exposure to urban and rural population (Leyk et al., 2019).

3. Methods

3.1. Paddy rice mapping

The annual paddy rice maps between 2001 and 2018 were generated using the phenology and pixel-based algorithm from MODIS data at a 500-m spatial resolution. Paddy rice is the only crop that is transplanted in flooded fields, and the flooding signal during the transplanting phase is the unique feature for the identification of paddy rice areas (Xiao et al., 2005). Time series remote sensing indices are capable of identifying the flooding signals from the water-soil mixture fields of paddy rice based on the relationship between the Enhanced Vegetation Index (EVI) and Land Surface Water Index (LSWI) using the following equations, $LSWI + 0.05 \geq EVI$. This algorithm has been applied successfully in previous studies in Asia (Dong et al., 2016; Zhang et al., 2020).

To reduce the commission errors in the paddy rice maps, several non-croplands masks were generated, including permanent water bodies, forest area, bare land, built-up, evergreen vegetation, and high slope lands. Final annual paddy rice maps were generated after excluding these non-cropland areas. The derived paddy rice maps were validated using the higher resolution Landsat-based paddy rice maps (Dong et al., 2016). The validation showed that derived paddy rice maps were reliable and spatially consistent with the higher spatial resolution Landsat-derived products.

3.2. Groundwater extraction from GRACE

Groundwater anomalies were derived after removing surface water storage (soil moisture, snow water, and surface reservoirs) from GRACE TWS. The storage changes in surface water, snow, ice, and biomass are minor relative to the total regional water storage and thus are usually neglected (Breña-Naranjo et al., 2014).

We used an estimate from GLDAS (Rodell et al., 2009) to remove the surface water storage to create annual groundwater storage from 2002 to 2016. The total groundwater anomalies were calculated from the processed monthly GRACE landmass grid dataset. The groundwater storage anomalies ($dGWS/dt$) are typically approximated as:

$$dGWS/dt = dTWS/dt - dSMS/dt \tag{4}$$

where TWS is total water storage and SMS is soil moisture storage. The yearly mean groundwater storage was calculated from the monthly groundwater values to analyze long-term changes.

3.3. Derivation of paddy rice phenology

We derived the start of the season (SOS) from the MODIS EVI time series data using the double logistic (DL) model. The DL model uses the sigmoid function to estimate the SOS, and its model parameters represent the physical characteristics of vegetation growth. To extract the SOS, the DL model was fit to the EVI time series using the following equation:

$$f(t) = a_1 + a_2\left(\frac{1}{1+e^{-p_1(t-n_1)}} - \frac{1}{1+e^{-p_2(t-n_2)}}\right) \tag{5}$$

where $f(t)$ is the fitted EVI value at day t, and a_1 and a_2 are the background and amplitude of EVI, respectively. p_1, n_1, and p_2, n_2 are the pair-parameters that trace the green-up (SOS) and senescence time of vegetation growth, respectively (Li et al., 2019). The SOS was defined as the time or date when the derivative of EVI reaches the maximum during the growing period, and the half-maximum criteria were used to derive it from EVI (Li et al., 2019). To accurately extract the SOS, we initially smoothed the EVI time series using a moving average of continuous observations within two days, which helps normalize the abnormal acquisitions, preserves the inherent seasonal pattern of EVI, and minimizes the uncertainty of parameter estimation of the double logistic model (Li et al., 2019). The DL model parameters were estimated according to *Li et.al* (Li et al., 2019).

3.4. Interannual variation and trend analyses of paddy rice area, groundwater, residue burned area, $PM_{2.5}$ and AOD

We investigated the spatial pattern of changes in various variables (paddy rice area, groundwater, residue burned area, ambient $PM_{2.5}$, and AOD) using the least square linear regression method. The slope a of the regression indicated the trend of temporal change at the pixel level, $a > 0$ denoted increasing trend, and $a < 0$ denoted decreasing trend. The pixels with slopes that were statistically significant at the 95% confidence level ($p < 0.05$) were selected for our analysis. We calculated a spatially explicit map of the linear trend for the mentioned variables during the 2001–2018 period for the respective datasets. We calculated standard anomaly (Std. anomaly) for the groundwater, residue burned area, $PM_{2.5}$, and AOD between 2002 and 2018 for the respective variables using the following equation:

$$Std.anomaly = \left(X - \overline{X}\right) \Big/ \sigma \tag{6}$$

Where X is the value at a year, and $\overline{X}$ and σ are the average and standard deviation values, respectively.

3.5. Estimation of population-weighted exposure to $PM_{2.5}$ pollution

We estimated human exposure to $PM_{2.5}$ using the Gridded Population Count of the World (GPW) dataset for both rural and urban areas. The annual mean values of $PM_{2.5}$ were used to model the population exposure to $PM_{2.5}$, as the long term mean $PM_{2.5}$ concentration is important from the human health perspective (WHO, 2018). We have used the population-weighted exposure (PE) method to estimate the individual exposure to $PM_{2.5}$ for both urban and rural areas. The urban and rural areas were distinguished using the MODIS-derived urban area gird (Schneider et al., 2009) (https://www.naturalearthdata.com). The population-weighted exposure (PE) (Aunan et al., 2018) to $PM_{2.5}$ was estimated for 2015 using the mean $PM_{2.5}$ concentration and the Gridded Population count of the World (GPW) for the same year. The population-weighted exposure (PE) was calculated using the following equation:

$$PE = \frac{1}{P}\sum_{i} P_i . C_i \tag{7}$$

where P is the population, C is the $PM_{2.5}$ concentrations, i represents pixels or regions.

3.6. Air mask back trajectories analysis

During the post-monsoon burning season, the air flows from Punjab and Haryana towards Delhi, carrying all the aerosol particles with it and creates a high level of $PM_{2.5}$ in and around Delhi (Liu et al., 2018; Martin et al., 2019). We used the Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT) (Stein et al., 2015) to estimate the airsheds to determine the impact of the neighboring region's outdoor burning on Delhi's air quality. The HYSPLIT analysis evidence that post-monsoon increases in $PM_{2.5}$ were driven more by residue burning than any other source (Supplementary Fig. 2). Compared to October, air pollution dispersion is lower in November due to weaker wind and fog. Consequently, the $PM_{2.5}$ level is significantly higher in November and December than any other months (Supplementary Fig. 3), indicating that rice residue burning contributes more to the rise of air pollution rather than any other sources post-monsoon season.

The transport of smoke particles from the source to the receptor primarily depends on the wind direction, speed, and transport altitude along the transportation path. To trace the source locations of smoke particles over Delhi, five-day air mask back trajectories were calculated at an altitude of 100-m for every 6 h starting at 1:30 pm local time of Delhi using the HYSPLIT model (Stein et al., 2015). The back-trajectories were calculated during the crop burning months of October and November in 2018. The HYSPLIT model was fed with the NCEP and NCAR reanalysis meteorological datasets from (National Oceanic and Atmospheric Administration (NOAA) to compute the back-trajectories. Several previous studies have used HYSPLIT back trajectories to determine the influence of agriculture fires on nearby city's air quality (Bikkina et al., 2019; Jethva et al., 2018; Liu et al., 2018).

4. Results

4.1. Nexus of paddy rice cultivation, groundwater depletion, and air pollution

Food production, water, and air quality are interconnected in northwest India. In an effort to increase food production, the paddy rice cultivated area has been rapidly increased in recent years. Continuous and excessive extraction of groundwater to irrigate the extensive paddy rice fields has depleted groundwater storage. Furthermore, increased paddy rice farming has generated more rice residues. To manage and prepare the croplands for the next crops, the rice residues are burned in the fields, which causes air pollution throughout the region. We first investigated each component of this interconnected system and then provided a comprehensive assessment of this system involving food, water, and air quality.

The spatial distribution, trends, and anomalies of the groundwater, fire events, AOD, and $PM_{2.5}$ are analyzed to investigate the trade-offs of the food-water–air nexus. Extensive expansion of paddy rice fields occurred in both Punjab and Haryana (Fig. 1), where the paddy rice area increased from approximately 3.5 million hectares (Mha) in 2001 to 4.3 Mha in 2015 according to the government statistical data, at a rate of ~ 1.5% per year (Fig. 1). The most dramatic increase occurred in Punjab where our remote sensing-based analyses showed an increased rice proportion from 25% in 2001 to 57% in 2018 (Fig. 1B).

A historical negative feedback loop exists between food security and sustainable water withdrawal in northwestern India. Most of the croplands in Punjab and Haryana are irrigated (Supplementary Fig. 4), especially paddy rice, which is kept inundated until 7–10 days before harvest. The net irrigated area increased from 6.9 million hectares in 2009 to 7.1 million hectares in 2014 (Fig. 2A). The consistent withdrawal of groundwater has led to the persistent depletion of groundwater storage in these regions (Figs. 2 and 3). Our analysis of the Gravity Recovery and Climate Experiment (GRACE) satellite datasets show that Punjab and Haryana experienced a significant depletion of groundwater at a rate of −1.50 cm/yr from 2002 to 2016 (Fig. 2B), a finding which is well supported by previous studies (Asoka et al., 2017; Rodell et al., 2018; 2009).

Another negative feedback loop occurs between air quality and rice-residue management. The burning of rice residues in the fields is a common management practice (Ahmed et al., 2015) for clearing harvested rice fields and preparing the fields for subsequent wheat cultivation in Punjab and Haryana. The post-monsoon airshed of Delhi extends from northwest to Punjab and Haryana where most of the rice paddies are located (Supplementary Fig. 2). Residue burning occurs during the post-monsoon season when the dispersion of air pollution is low (Methods, Supplementary Fig. 2), especially in November and December, which triggers annual spikes in air pollution in these states

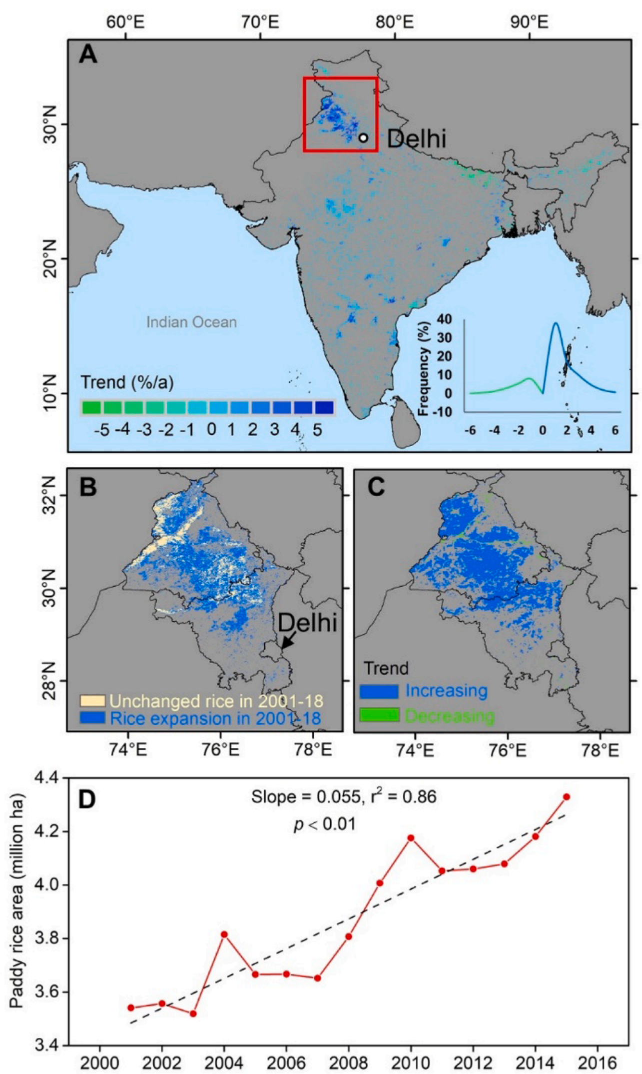

Fig. 1. Spatial distribution and trend of paddy rice area in India. (A) the spatial trends of paddy rice area during 2000–2015, derived from the MODIS data; the inset figure is the frequency diagram of Figure A; (B) spatial distribution of unchanged and expanded paddy rice from 2001 to 2018; (C) trend of paddy rice area; (D) annual changes and trend of paddy rice areas from 2001 to 2015 derived from official statistical data.

and the neighboring capital city of Delhi (Supplementary Fig. 3) (Jethva et al., 2019, 2018; Liu et al., 2018). As the paddy rice area expanded and the rice residues increased due to the higher mechanization, the number of fire incidents increased substantially from 35,426 in 2002 to 57,918 in 2018 (Fig. 2C), and the burned area increased from 500 km^2 in 2002 to 15,780 km^2 in 2018 (Fig. 3B).

We also found that $PM_{2.5}$ distinctly increased in the post-monsoon season (October, November, and December) (Supplementary Fig. 3), with annual mean $PM_{2.5}$ increased from 127.69 μg/m^3 in 2002 to 167.97 μg/m^3 in 2018 (Fig. 2F), which coincided with the time of rice residue burning in Punjab and Haryana. Similarly, satellite-based aerosol optical depth (AOD) had an upward trend (Fig. 3), with the annual maximum AOD increasing from 0.93 in 2002 to 1.21 in 2018 in winter (Fig. 2E), and so did ground-based $PM_{2.5}$ observations during 2002–2018 with a peak in 2018 (1546 μg/m^3) (Fig. 2D). To curb the post-monsoon pollution in Delhi, the local government implemented an ‘odd and even license plate numbers’ automobile driving policy in 2016. According to this policy, private vehicle use was restricted and split into the odd- and even- days according to the license plate number. However, this policy did not decrease $PM_{2.5}$ values (Chowdhury et al., 2017), which suggests that residue burning practices have the most substantial impact on urban air quality during winter.

Both the negative rice-groundwater feedback loop and the rice-air quality feedback loop affect the nexus of food-water–air. Because of the effort to achieve food security and the policies supporting the price of rice, the paddy rice planting area increased substantially during 2001–2018 and irrigation intensified. The extensive and constant groundwater withdrawals for irrigation have depleted groundwater storage at a steady rate that outpaces natural groundwater recharge. Along with the increase in paddy rice planting areas, rice biomass and residues in the fields have also increased. These residues are usually burned in the field in preparation for the next crop. The residue burning activities have increased $PM_{2.5}$ concentrations during the post-monsoon season. The impact of residue burning is not limited to agricultural areas, but also affects other adjacent, densely populated regions in the airshed such as Delhi. The correlations among the paddy rice areas, residue burning, AOD, and $PM_{2.5}$ are presented in Supplementary Tables 2 and 3; the correlation coefficients indicate the respective positive and negative relationships.

In short, paddy rice expansion caused the depletion of groundwater through increased irrigation; meanwhile, increased paddy rice planting area generated more residues that are being burned following the heightened air pollution (Figs. 2 and 3). Additionally, the GW Act led to the more concentrated rice harvest timing and residue burning, which further contributed to the degraded air quality of the northwest region of India-including Delhi (Fig. 4), as we discussed further in the following section. Over the period of 2001–2018, paddy rice cultivation area increased by 22%, crop residue fires increased by 500%, and AOD and $PM_{2.5}$ increased by 30% and 29%, respectively. Intensive irrigation of paddy rice fields contributed to the depletion of groundwater by −1.5 cm/year. The groundwater conservation policy slowed down groundwater depletion from −1.5 cm/year to −1.2 cm/year. The groundwater conservation policy shifted the rice harvest time towards the winter season by 15 days and increased the winter air pollution by 29%.

4.2. *Unintended negative consequences of sectoral policy responses*

The food, water, and air quality in the northwestern India are closely interconnected. This system is affected by external factors that either elevate or reduce the stress between them. For example, in northwestern India the groundwater conservation policy had negative impacts on the regional air quality.

Over the past decades, paddy rice fields were inundated with irrigation water from groundwater sources before the monsoon season arrives, which caused groundwater depletion. To protect the groundwater resources, the GW Act was enacted in 2009, which precludes farming of paddy rice until the arrival of the monsoon (20th June). Fig. 5 provides satellite-based evidence of the effectiveness of this policy on groundwater protection. It is worth noting that the rate of groundwater depletion decreased from −1.82 cm/yr during 2002–2008 to −1.20 cm/yr during 2009–2016 in Punjab and Haryana (Fig. 5F). The policy had remarkable effectiveness, given the similar precipitation trends before and after the GW Act (Bhanja et al., 2017) (Supplementary Fig. 5).

We also found unintended negative consequences of this policy on air pollution. Our results show that 2009–2010 was the turning point for the interannual variation in the groundwater, residue fires, and air quality (Fig. 3). The rice harvest dates became more concentrated and shifted by ~ 15 days from late September to October (Fig. 5). The shifted harvest dates forced residue burning activities into a narrower time window in early November. Before the GW Act, fire counts peaked in October with 37,573 fire incidents, but after the GW Act, the fire count peaked in November with 54,955 fires. Consequently, both the AOD and $PM_{2.5}$ increased in November. The mean AOD in November increased from 1.10 in 2002–2008 to 1.95 in 2009–2018, while $PM_{2.5}$ in November also increased from 827.12 to 1110.16 μg/m^3 during the

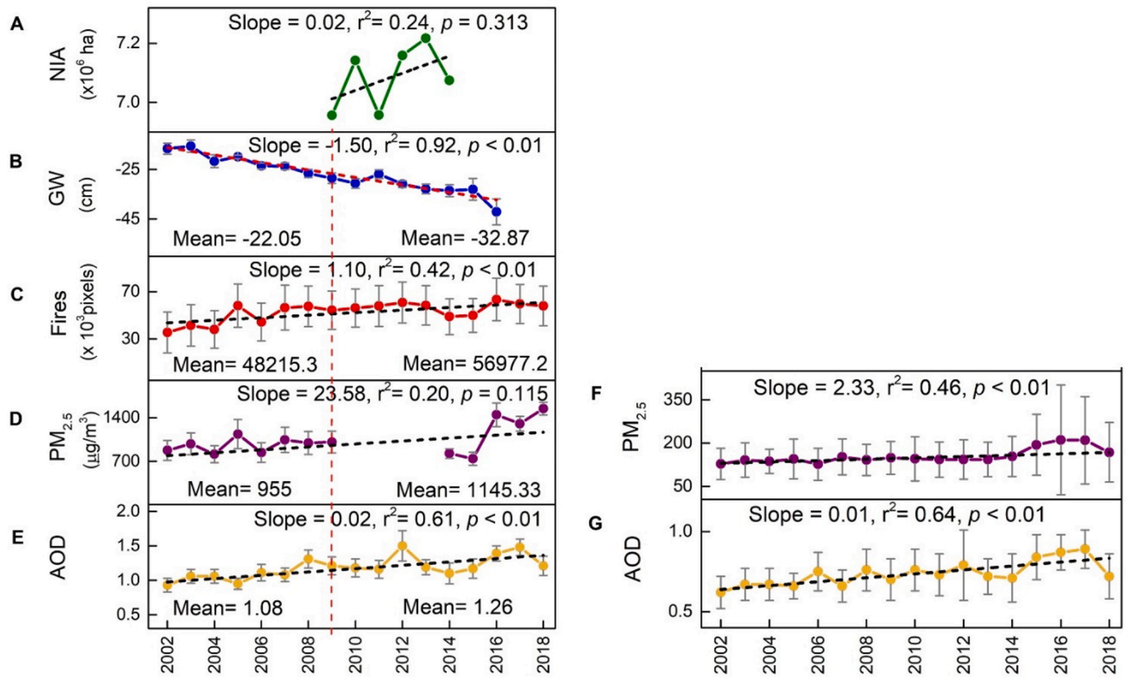

Fig. 2. Interannual variability. (A) net irrigated area; (B-E) represents the interannual variability of yearly maximum values of groundwater storage, residue fires, $PM_{2.5}$, and AOD, respectively; (F, G) represents the interannual variability of yearly mean values of $PM_{2.5}$, and AOD, respectively. The dotted vertical line represents the GW Act implementation year (2009). The presented mean values are for the periods before and after the GW Act. In Figure D, the $PM_{2.5}$ data were missing from 2010 to 2013 as the data were unavailable.

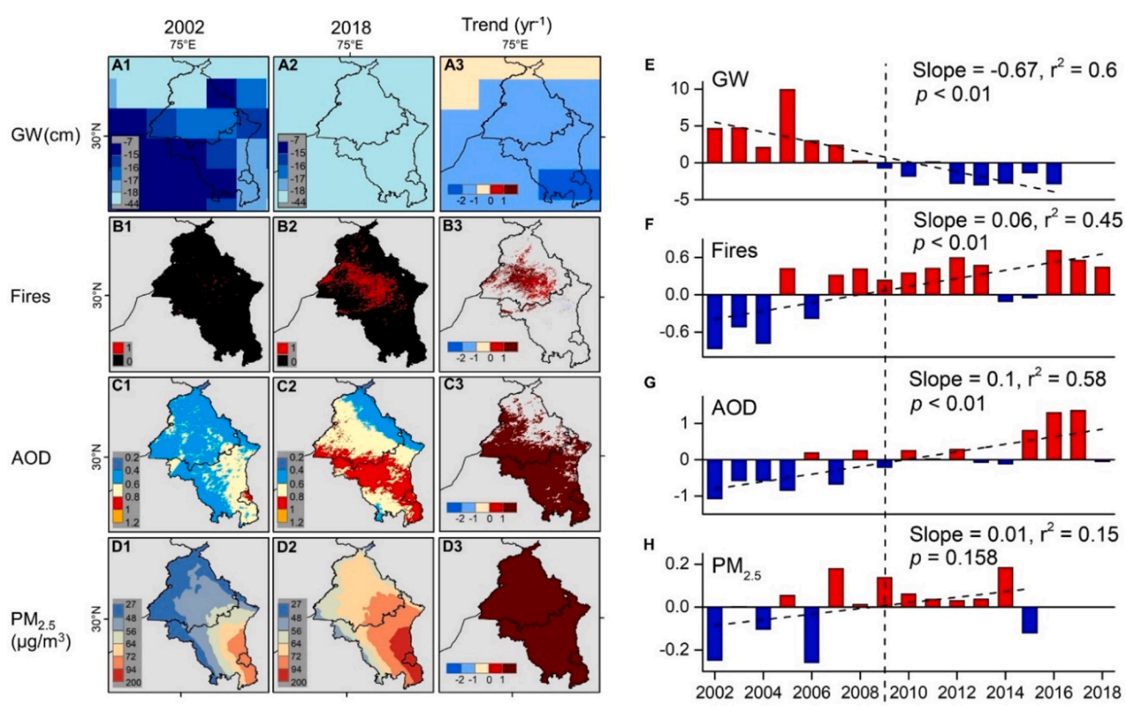

Fig. 3. Spatial distribution, trend, and interannual variability of groundwater storage, fires, AOD, and $PM_{2.5}$. Groundwater storage (A1, A2, A3); residue fires (B1, B2, B3); AOD (C1, C2, C3); and $PM_{2.5}$ (D1, D2, D3). In the figures (A, D) from left to right, each column represents the spatial pattern in 2002, the spatial pattern in 2018, and the trend from 2002 to 2018, respectively. (E-H) represents the interannual variability (Std. anomaly) of groundwater storage, residue fires, AOD, and $PM_{2.5}$, respectively. The dotted vertical line on the graph (right panel) shows the turning point after the GW Act implementation in 2009. The units of A1 and A2 are cm; B1and B2 are m^2; C1 and C2 are unitless; D1and D2 are micrograms per cubic meter.

same time period (Fig. 5J). Overall, the GW Act proved to be effective in slowing groundwater depletion, but it shifted the rice harvest dates to October that has reflected in November with the increase in residue burning and subsequent AOD and $PM_{2.5}$ increase.

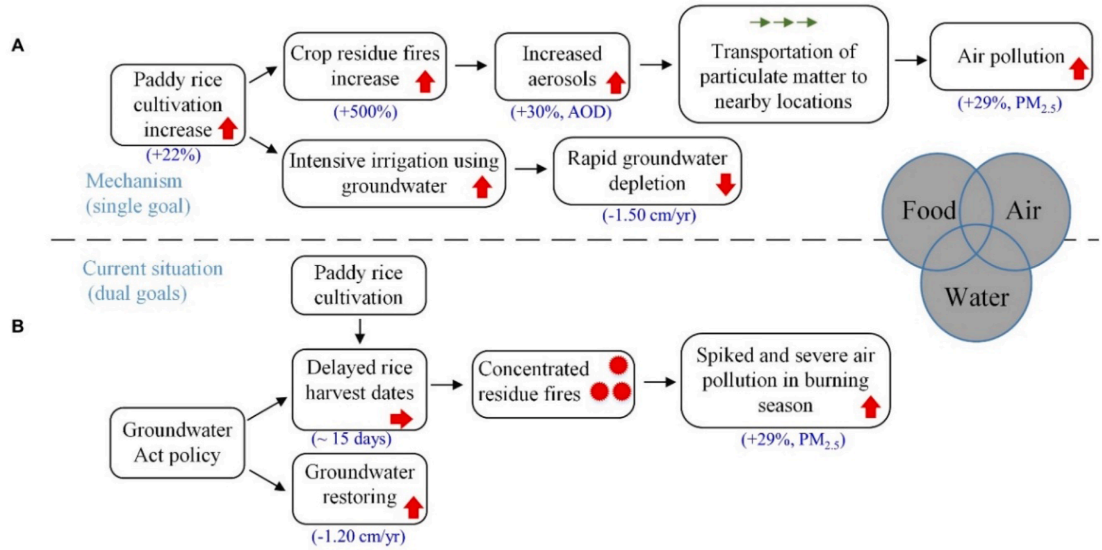

Fig. 4. A typical food, water, and air quality connection in northwest India. The top panel (A) represents the single goal (target of achieving only food production) and mechanism of the nexus. The bottom panel (B) shows the current situation while trying to achieve the dual goals of food production and groundwater conservations. The inset symbols in the red color of Figure A and B represent the following; upward arrow: constant increasing trend; downward arrow: constant decreasing trend; forward arrow: consequences and spiky circle: concentrated reside fires locations. The green color forward arrow represents the transportation of aerosols.

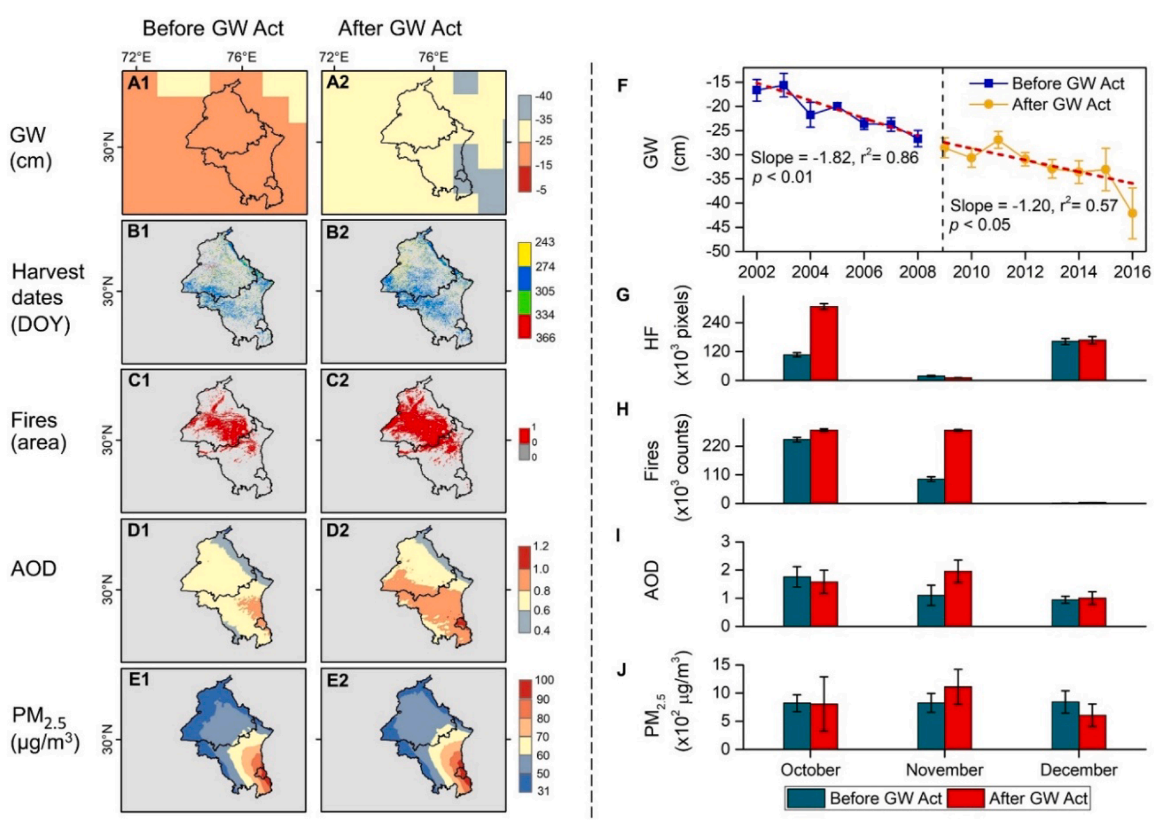

Fig. 5. Impact of the Groundwater (GW) Act implementation. (A1, B1, C1, D1, E1) represents before the GW Act, and (A2, B2, C2, D2, E2) represents after the GW Act. The spatial changes are present in (A1, A2) groundwater (GW); (B1, B2) rice harvest date; (C1, C2) residue fires; (D1, D2) AOD; (E1, E2) $PM_{2.5}$. (F-J) represents the monthly changes of groundwater, harvest date frequency (HF), fire, AOD, and $PM_{2.5}$ before and after the GW Act, respectively. The period before the GW Act is 2002–2008, and after the GW Act is 2009–2016. The annual mean values were used to create the maps (A-F), monthly mean was used for the figure (G-J).

4.3. Higher population exposure to $PM_{2.5}$ inrural than in urban areas

According to the World Health Organization (WHO), the safety level for human exposure to $PM_{2.5}$ is approximately 10 μg/m^3. The exposure to $PM_{2.5}$ in megacity Delhi, where there are 19 million inhabitants, received enormous attention from the government, media, and the public (Bhalla et al., 2019). Over the year, the $PM_{2.5}$ concentration level has been higher in urban areas than in rural areas. Delhi's topography (trough-like, being situated between the Himalayan Mountains to the north and the Central Highlands to the south) and meteorological conditions (wind speed and directions), combined with highly polluting human activities (agricultural burning, transport) have made this city one of the most polluted cities in the world (Bikkina et al., 2019; Chowdhury et al., 2017; Dey et al., 2012; Martin et al., 2019). The annual mean $PM_{2.5}$ values in the urban areas of Delhi, Haryana, and Punjab were 111.2 μg/m^3, 82.5 μg/m^3,and 68.3 μg/m^3, respectively higher than that in the rural areas of Haryana (79.2 μg/m^3) and Punjab (66.5 μg/m^3). Noteworthy is that the peak in asthmatic patients in hospitals of northwest India co-occurs with the rice residue burning season (Singh and Sidhu, 2014), especially in Delhi.

However, human exposure to $PM_{2.5}$ in rural areas was not widely discussed and investigated (WHO, 2018). Agriculture is the primary sector of employment in northwest India, and most of its population works outdoors for farming activities, and thus the outdoor exposure to high concentrations of $PM_{2.5}$ is a threat to human health in the rural areas. Given the fact that India is still a country with a larger population in rural areas than in urban areas, more rural people were likely to be exposed to air pollution. Our results show that in the urban areas of our study area, approximately 7 million people were exposed to 90–120 μg/m^3 level of $PM_{2.5}$, while another 9 and 0.5 million people were exposed to $PM_{2.5}$ level of 60–90 μg/m^3 and 30–60 μg/m^3, respectively (Fig. 6). In the rural areas, approximately12 and 20 million people were exposed to $PM_{2.5}$ levels of 90–120 and 60–90 μg/m^3, respectively (Fig. 6). These results suggested that more people are exposed to air pollution in rural areas than in urban areas; this has been neglected in the past. Our finding that air pollution due to $PM_{2.5}$ is just as harmful in rural areas as in urban areas could substantially impact how pollution is viewed in India. Presently, India is focusing its attention on addressing air pollution in the cities, but our results suggest that policymakers need to also focus on air pollution in rural areas.

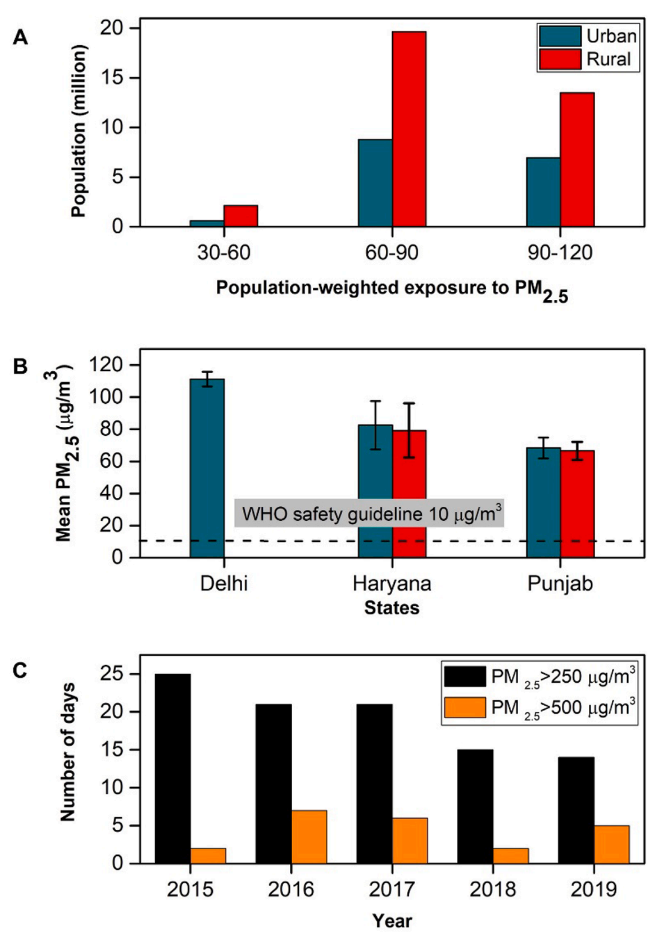

Fig. 6. The exposure ofpollution to air pollution. (A) population-weighted exposure to $PM_{2.5}$ for urban and rural populations in northwest India; (B) mean $PM_{2.5}$ concentration for urban and rural regions in northwest India during 2016; (C) number of days with very unhealthy $PM_{2.5}$ concentrations in November. Note that the WHO safety guideline for $PM_{2.5}$ level is 10 μg/m^3.

5. Discussion

5.1. Trade-offsamong food security (SDG 2),air quality (SDG 3, 11), and sustainable water withdrawal (SDG 6)

A comprehensive understanding of the interlinkages between rice production (SDG 2), water resource depletion (SDG6), and air quality (SDG 3 and SDG 11) is beneficial for coherent policy design that avoids clashes amongst SDG targets, and overcomes barriers to achieve other SDG targets. The complex interactions among the food supply, water, and good air quality are highlighted using a simplified flower diagram (Foley et al., 2005) which is useful to understand the challenges regarding the trade-offs between the SDGs (Supplementary Fig. 6).

In this regard, our results illustrate the prevalence of two situations in the region (Supplementary Fig. 6). First, before 2009 the single goal of food security caused groundwater depletion and air pollution. The increased paddy rice cultivation was favorable for the nation's food security. However, groundwater withdrawals, which are needed to support this crop cultivation, caused groundwater depletion. This phenomenon can be traced to the Indian Green Revolution, which saw the tripling of total irrigated area from 0.21 million km^2 to 0.63 million km^2 between 1950 and 2009, when the total share of groundwater use for irrigation increased from 28% to 61% (Gandhi and Bhamoriya, 2011). Continuous withdrawal has led to a substantial depletion of groundwater resources in these regions (Famiglietti, 2014; Rodell et al., 2018; 2009), and at present groundwater abstraction is about 70% above the annual recharge (Tripathi et al., 2016), which is largely driven by the need to irrigate rice.

Second, the GW Act of 2009 reflects a conversion from a single goal of food security to the dual goals of food production and groundwater protection. However, this conversion further exacerbated air pollution after 2009. The goal of groundwater conservation under the GW Act and the desire to increase rice production have shifted rice harvest dates to later in the year and concentrated residue burning into a narrower time window. Higher rice production has increased rice residue burning, which has contributed substantially to extreme levels of air pollution in northern India (Sembhi et al., 2020). The amount of residue burned is approximately 1.5–2.5 times higher than the actual grain yield (Jethva et al., 2019). In turn, this has increased the levels of air pollution in Delhi; the peak of $PM_{2.5}$ in this megalopolis significantly coincides with the peak of residue burning in Punjab and Haryana (Supplementary Fig. 3). In summary, whereas the groundwater conservation policy has shown success in reducing groundwater depletion, it has intensified air pollution in northwest India by concentrating residue burning in the winter season when meteorological conditions are conducive to poor air quality (Supplementary Fig. 3). Our results indicated an urgent need for sustainable and effective crop residue management practices to curb current trends of air pollution. If ignored, the current burning practices will further deteriorate the air quality and increasingly threaten public health in the region (Fig. 6C).

5.2. Reconciling the three targets for sustainable development in northwest India

We provided satellite-based evidence of the need for policy coherence, interventions that reconcile food security, water security, and air quality, as the contest between food production, groundwater conservation, and air quality will not be a zero-sum game (Fig. 7). Trade-offs occur when an ecosystem is managed to increase a single service such as food production, which causes the reduction of other ecosystem services like the groundwater or regional air quality. Governmental policy needs to focus on sustainable development and reconciling different targets, rather than only maximizing one or two goals. To balance the trade-offs, reasonable approaches are needed, such as moving towards planting less water-consuming and short-duration crops and adopting new methods to manage residues other than burning.

The burning of rice residue is a conscious decision made by farmers due to the unavailability of affordable and effective residue removal methods. Thus, farmers usually opt for on-site burning of residue as an active management strategy to clear and prepare the land for winter wheat (Jethva et al., 2019). Though the local government imposes penalties on residue burning, millions of tons of residues are still burned every year. The practice of rice residue burning will likely continue unless inexpensive technological advances become available to reduce the current cost of residue removal.

The Punjab and Haryana regions have benefited from the expansion of rice paddies through increased farmer income and enhanced national food security, and have become the largest contributor to the state's gross domestic product (GDP) with a 30% share of the agricultural sector. However, the benefits gained from the expansion of the rice area has come at a cost to ecosystems and the environment (Jimmy et al., 2017). For instance, the Indio-Gangetic plain and northwest India have experienced significant depletion of groundwater resources in the last 20 years (Chen et al., 2014; Mishra et al., 2018; Rodell et al., 2009). Overexploitation of groundwater for human uses has led to a persistent decrease in groundwater storage and has left a long-lasting impact on streamflow, lakes, and wetlands (Hanasaki et al., 2008; MacDonald et al., 2016). Due to the prolonged process of groundwater recharge, extremely depleted groundwater resources may not be restored to normal levels in the future, given that the Indian summer monsoon is weakening (Asoka et al., 2017; Chen et al., 2014). Thus, persistent groundwater depletion may lead to severe regional water crises. In these two states, the current groundwater extraction rate exceeds the total annual groundwater recharge rate, which has caused rapid declines in groundwater storage. The trend in groundwater depletion remains persistent despite normal precipitation and temperature patterns reported by the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Supplementary Fig. 7).

5.3. *Human and policy dimensions of the interlinkages among food-water–air quality*

Food, water, and air quality in northwest India interact across multiple scales, from national and local. To meet the national demand of food production, the local challenge of sustainable water availability is frequently ignored. To simultaneously achieve national food security, water security, and cleaner air, frequently fostered local production of food and consumption of water without paying sufficient attention to local-scale impacts and consequences. Moreover, to address localized sustainable water supply issues, regional problems that lead to poor air quality have been overlooked.

Therefore, northwest India needs approaches that consider the interlinkages of food, water and air quality to address the national challenge of food security, water resources conservation and air pollution with in-depth exploration of the process involving the institution and policy framework that influence decision making at local, regional and national levels. The extensive groundwater extraction for rice cultivation can lead to severe water scarcity in the region. Although this issue was well recognized locally, it was merely considered a factor in regional policy. Local decision-makers may have the limited institutional capacity to address such an issue when the central government pursues food security as a national interest. Our results indicated that the decision by local authorities to conserve groundwater resources did not hurt national interests around food security, but impacted regional air quality. This trade-off demonstrates that to maintain an adequate supply of food, preserve water, and air quality, more comprehensive analysis and management policies are needed that involve vertical cooperation and coordination amongst local, regional, and national decision-makers.

The demand for food production will increase with the growing population, which also relies on water and non-polluted air for survival. Understating the fundamental trade-off and synergy among food, water, and air quality is a key first step to enabling more coherent policy-making, but this will also require thinking through the multi-level policy dimensions in the nexus. Ways of reconciling policies across scales could include fiscal transfers from the National Capital Region (NCR) (affected by air pollution) to Punjab and Haryana for subsidizing

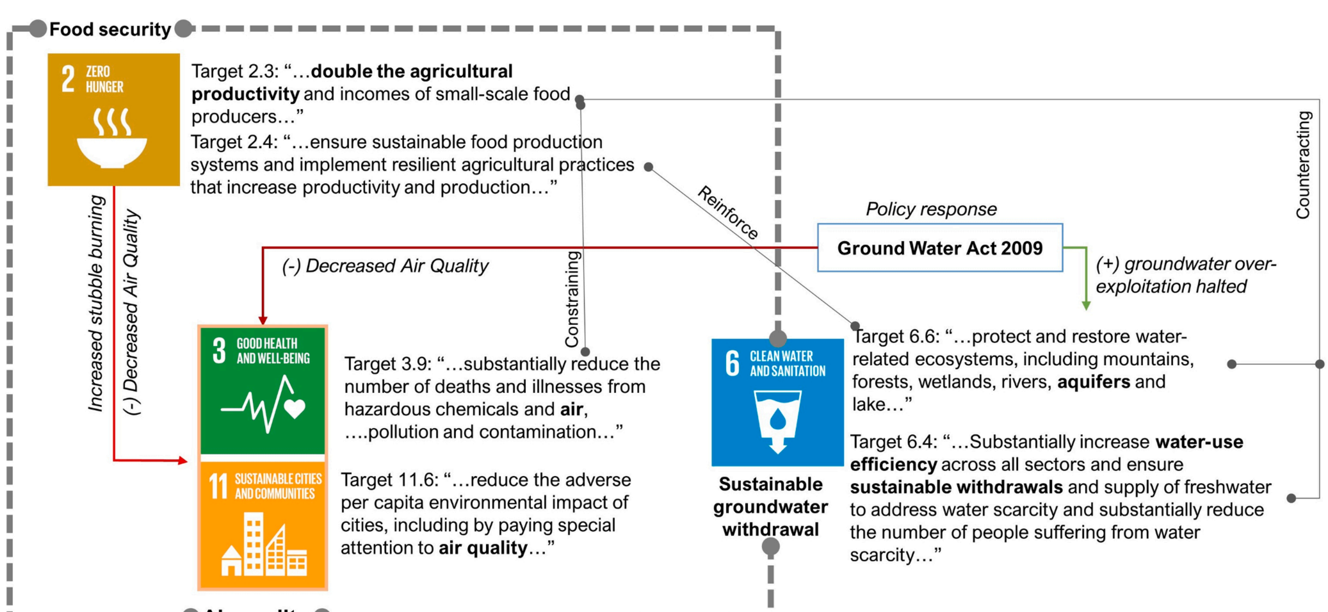

Fig. 7. Summary of SDG target and nexus. A schematic of interactions among the various SDG targets, their nexus, and policy impacts in northwest India.

changes in crop residue management, incorporating the implications of groundwater decline into inter-state water sharing agreements (Srinivasan and Lele, 2017), and changes in national price support and procurement policies to encourage a shift away from rice-wheat overproduction.

5.4. Recommendation and way forward

Handling the trade-offs of the complex interplay among food, water, and air quality requires a holistic approach and frameworks. However, the development of a detailed framework is beyond the scope of this paper. Some nexus analysis tools in prior research, such as the water-energy-food (WEF) nexus Tool 2.0 (Daher and Mohtar, 2015), could be coupled with the satellite-based approach for monitoring and modeling interactions among food, water, and air quality. This kind of tool requires several data inputs such as the percentage of food products grown in open agriculture conditions, yield of different food products, and water requirements. Satellite-based products can provide valuable data for such a nexus tool, given the rapid, multi-temporal, and large-scale coverage of remote sensing observations.

A few actions could be taken at the multiple levels of the government to minimize trade-offs. The first action could be to reduce rice residue burning (Lohan et al., 2018; Shyamsundar et al., 2019). Rice residue can be utilized for many other purposes, such as bioenergy, livestock feed and bedding, compost for mushroom cultivation, and bedding for various vegetables, or can be mulched back into the soil itself. In order to reduce rice residue burning, it is essential to raise awareness among farmers about the impacts of residue burning on their health, alternative uses of rice residues and the importance of environmental sustainability. Additionally, the government could motivate farmers not to burn rice residue instead of imposing a simple burning ban. Encouraging the farmers to use technologoically advance 'happy seeder' machine (Sidhu et al., 2007) that can plant wheat seeds without residue burning could be an alternative solution. The government could provide a financial subsidy for farmers to purchase the 'happy seeder' (Shyamsundar et al., 2019). Corporations and vendors could be mandated to establish after-sale service centers so that farmers do not opt out of using the machine when it needs repair.

The second action is to reduce groundwater use. Raising the price of the energy used for pumping water and limiting the number of water pumps for large farms, could help prevent excess groundwater withdrawals. But these will not succeed or will not be adopted till groundwater regulatory institutions are redesigned to function bottom-up, as suggested by the Planning Commission in 2012 (Shah, 2013), and integrated with surface water allocation institutions.

The long-term solution, although perhaps the most difficult one, is to change the cropping systems towards less water-consuming crops that also do not require stubble burning. Small changes such as a shift to aerobic rice (Bouman et al., 2002) may be possible through a combination of awareness campaign, training and handholding. However, there are deeper issues that need to be addressed if a significant shift is to occur. Farmers in the Punjab-Haryana regions are habituated to a rice–wheat production cycle that is environmentally harmful because of the high prices guaranteed by a procurement policy that has outlived its original objective of providing assured calories to the wider Indian population. But they are also facing indebtedness and rising health issues. Yet, these farmers are agitating for continued price support because they do not see a way out of the current system without a major drop in incomes. Diversifying procurement to include other (water-efficient) crops that also happen to be more healthy, coupled with improved functioning of agricultural markets and providing crop insurance could be a way out.

Some policies are already in place to safeguard water resources or air quality, and others are being contemplated, including those suggested above. However, identifying the 'right' mix of policies and implementing them is a complex and challenging task. The trade-offs we show are not just between sectory but between the lives and livelihoods of real people in those sectors, whether farmers, other groundwater users (or future users), urban residents in the Delhi and National Capital Region (NCR), or the millions of Indians dependent upon the rice and wheat that is procured from this region and channeled through the public distribution system. The process of policy-making is inherently political, as it involves reconciling the conflicting interests of multiple stakeholders. The extant political process can either ignore, amplify or ameliorate these conflicts. Processes that build trust between decision-makers and stakeholders are missing at the moment. Equally challenging is the implementation of policy decisions through a bureaucratic framework (such as agricultural extension or groundwater pumping regulation) or even through imperfectly functioning market instruments, such as electricity princing.

The kind of anlaysis we have provided, and additional analysis of the socio-economic implications of alternate policies, can only inform the stakeholders and their representatives involved in this process. Developing scenario-building and exploration tools that are more participatory and transparent and enable stakeholders to better understand and visualize the trade-offs might be ways for scientists to nudge the process forward. Such transdisciplinary science is a necessary, but by no means sufficient, step in the resolution of these interlinked and highly contentitous environmental problems.

6. Conclusion

To our knowledge, the linkages between paddy rice area expansion, groundwater depletion, crop residue burning, and air pollution in northern India have not been quantified previously. Using long-term time series satellite measurements, we demonstrated a strong connection among them over northern India.We found that the expansion of rice cultivation (+22%) triggered unsustainable groundwater depletion (-1.50 cm/yr) and increased residue fires (+500%), which caused rising air pollution (+29%, $PM_{2.5}$) during 2001–2018. The expansion of the paddy rice planting area has improved India's food security (SDG 2) but has negatively impacted groundwater storage (SDG 6) and regional air quality (SDG 3 and 11), affecting millions of people via water shortage and hazardous air quality. Our results confirm that the GW Act of 2009 reduced the overexploitation of groundwater, but it hampered progress on other SDG targets for air quality and the improvement of human health. This study provides scientific evidence that coherent policy design and implementation are needed to foster changes in farming practices to address these problems and sustain the wellbeing and livelihoods of northern India's population.

CRediT authorship contribution statement

Mrinal Singha: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Jinwei Dong:** Supervision, Conceptualization, Writing – review & editing. **Quansheng Ge:** Conceptualization. **Graciela Metternicht:** Data curation, Writing – review & editing. **Sangeeta Sarmah:** Formal analysis. **Geli Zhang:** Validation. **Russell Doughty:** Writing – review & editing. **Sharachchandra Lele:** Writing – review & editing. **Chandrashekhar Biradar:** Writing – review & editing. **Sha Zhou:** Writing – review & editing. **Xiangming Xiao:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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