Earth's Future

Supporting Information for

A systems framework for analyzing sustainability impacts of agricultural policies in India

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Introduction

This Supporting Information document provides additional details about the HTE framework applied to study sustainability challenges and interventions in the rice-wheat cropping system of Punjab, India. It includes:

- Text S1-S2 (Table S1-S2) on detailed quantitative model set-up and model evaluation results
- Text S3-S4 (Table S3-S4) on methods used to evaluate the impacts of interventions on interactions, specifying direct (structural) and indirect (quantitative) changes as well as sustainability benefits using the inclusive wealth approach.
- Text S5 on expert interviews conducted to inform choice of policy options analyzed in this work

Text S1. Quantitative model set-up

We develop a quantitative model (using R) based on the qualitative representation of system components and interactions outlined, and use it to estimate the impacts of the rice-wheat cropping system and policy interventions on sustainability metrics for the period 2019-2029. We first specify the values of attributes of institutional and knowledge components that form the landscape within which human, technical and environmental components interact in 2019. We also specify the initial values of attributes of human, technical and environmental components in 2019 (see Supp. Data Tables S3-S6).

Component	**Attribute**	**No New Policy scenario**	**Intervention 1: Effective ban on residue burning**	**Intervention 2: Use of residues in power plants**	**Intervention 3: Promote wide-scale use of Happy Seeder**	**Intervention 4: Input (power or fertilizer) subsidy reform**	**Intervention 5: Government procurement of pulses**
Institutional							
Ban on residue burning	Investment in awareness campaign (INR/landholding)	0	14 INR[1]	0	0	0	0
	Fine for burning (INR/ha)	6175[2]	6175	6175	6175	6175	6175
	Payment to farmers (INR/ha)	0	6500[3]	0	0	0	0
	Compliance level (%)	10%[3]	100%	10%	10%	10%	10%
Market for agricultural residues	Market price for residues (INR/ton)	0	0	5500[4]	0	0	0
	Cofiring share in coal power plants (% of installed GW)	0	0	10%[5]	0	0	0
	Biomass power plants (installed number of plants)	0	0	80 (7.5 MW each)[6]	0	0	0
Market for Happy Seeder	Market supply of HS (number of machines)	15,000[7]	15,000	15,000	45,000	15,000	15,000

Happy Seeder subsidy	Subsidy rate (%)	50%[7]	50%	50%	50%	50%	50%
	Investment in farmer training (INR)	0	0	0	150000000 INR[8]	0	0
Power subsidy	Rationed or unrationed power (categorical)	Unrationed	Unrationed	Unrationed	Unrationed	Rationed	Unrationed
	Availability of power (fraction of a day)	0.6[9]	0.6	0.6	0.6	1	0.6
Fertilizer subsidy	Subsidy reform to enable optimal use of urea (categorical)	False	False	False	False	True	False
Government crop procurement program	Crop types procured (categorical)	Rice, wheat	Rice, wheat	Rice, wheat	Rice, wheat	Rice, wheat	Rice, wheat, pulses (pigeon pea)
	Minimum Support Price for crops procured (INR/kg)	Rice = 19.25, Wheat = 20.25[10]	Rice = 19.25, Wheat = 20.25	Rice = 19.25, Wheat = 20.25	Rice = 19.25, Wheat = 20.25	Rice = 19.25, Wheat = 20.25	Rice = 19.25, Wheat = 20.25, Pigeon pea= 62.4[10]
Public distribution program (PDS)	Foodgrain availability quota per PDS beneficiary (kg/month)	Rice = 5 kg/month[11]	Rice = 5 kg/month	Rice = 5 kg/month	Rice = 5 kg/month	Rice = 5 kg/month	Rice = 3kg/month; Pulses= 1kg/month
	Leakage (% procured crops diverted illegally or wasted)	20%[12]	20%	20%	20%	20%	20% (0% tested as alternate value)
	PDS selling price of foodgrains (INR/kg)	Rice = 3; Wheat = 2[12]	Rice = 3; Wheat = 2	Rice = 3; Wheat = 2	Rice = 3; Wheat = 2	Rice = 3; Wheat = 2	Rice = 3; Wheat = 2; Pulses =10% of Minimum Support Price (MSP) paid to farmers
Knowledge							
Awareness about residue burning	Awareness amongst farmers about health impacts of	Low	High	Low	Low	Low	Low

	residue burning? (categorical)						
Monitoring data for residue burning	Data available to the government to monitor residue burning (categorical)	False	True	False	False	False	False
Awareness about Happy Seeder	Awareness amongst farmers about benefits of using Happy Seeder? (categorical)	Low	Low	Low	High	Low	Low

Table S1: Summary of institutional and knowledge attributes used in the model
[1](Thakur et al. 2016) [2](Bhuvaneshwari et al. 2019) [3](Jain et al. 2014; Bhatt 2020; Jitendra et al. 2017) [4] (Ghosal 2017; Special Correspondent 2017) [5](TERI 2018) [6](J. Singh 2015; TERI 2018) [7](Anon 2019; Goyal 2019) [8](Government of India 2019) [9](Sidhu et al. 2020) [10](Punjab Agricultural University 2020) [11](Puri 2017)

We follow the interaction pathways described in Fig.1 and quantify the human-technical-environmental interactions that occur within the institutional and knowledge landscape as follows.

1. **Pathway I): Residue burning releases greenhouse gases (GHGs) and $PM_{2.5}$ which cause health damages to residents of India**

i) Quantifying interaction T1-T2 Crop harvesting creates residues:

Residues generated by crop type:

$$\sum_{crop} Residues_{generated,crop} = P_{crop} * RPR_{crop} \qquad \text{...... Equation 1}$$

Where,
P_{crop} = Production of crops (tons)
RPR_{crop} = Residue to product ratio of each crop
See Supp. Data Table SD3 for above attributes of crops

ii) Quantifying interaction H1-T2 Farmers burn residues:

Residues burnt:

$$Residues_{burnt} = \left(\sum_{crop} Residues_{generated,crop} * R_{frac_{unused,\ crop}} * (1 - Ban)\right) - (P_{rice\ on\ HS\ land} * RPR_{rice}) - Residues_{industry}$$

...... Equation 2

Where
$Residues_{generated,\ crop}$ = see Equation 1
$R\_frac_{unused,\ crop}$ = Fraction of unused residues of each crop type available for burning
$P_{rice\ on\ HS\ land}$ = Production of rice on HS used land = Yield of rice x Land on which HS is used
See Supp. Data Table SD3 for above attributes of crops
$Residues_{industry}$ = Residues used in industry, currently at 0 tons
Ban = Level of ban compliance (%), currently at 10% (see Table 3 for attributes of institutional components)

iii) Quantifying interaction T2-E1 Residue burning emits GHGs to air

GHG emissions from residue burning:

$$GHG_{residue\ burning} = \sum_{species} (emf_{species,residue\ burning} * Residues_{burnt}) * GWP_{species}$$

...... Equation 3

where,
$GWP_{species}$ = Global warming potential of GHGs
$emf_{species,residues,burning}$ = emissions (CO_2, CH_4, N_2O) per kg residues burnt
$Residues_{burnt}$ = total residues burnt (see Equation 2)
(see Supp. Data Table SD5 for emission factors and GWP)

iv) Quantifying interaction T2-E1 Residue burning emits fine particulate matter ($PM_{2.5}$) to air

$$PM2.5_{residue\ burning} = emf_{PM2.5,residue\ burning} * Residues_{burnt}$$ ...... Equation 4

where,
$emf_{residue\ burning}$ = primary $PM_{2.5}$ emissions per kg residue burnt (see Supp. Data Table SD5 for attributes of residues)
$Residues_{burnt}$ = total residues burnt (see Equation 2)

v) Quantifying interaction E1-H2 Air pollution affects the health of residents of India

Mean annual per capita $PM_{2.5}$ exposure level z (ug/m^3) due to agricultural residue burning (or other agricultural activities) in Punjab is estimated from the following relation:

$$z = Sensitivity * \ Emissions/Population \qquad \text{...... Equation 5}$$

where,
Sensitivity = sensitivity of exposure to emissions (27,300 ppl-ug/m^3 per kg of emissions (Lan 2021)). This is the change in total exposure across India due to 1 kg of $PM_{2.5}$ emissions in Punjab.
Emissions = $PM_{2.5}$ emissions in Punjab from residue burning (see Equation 4) (or other agricultural activities, assuming $PM_{2.5}$ emissions due to activities other than residue burning such as power production, diesel use and fertilizer production, occur within Punjab)
Population = exposed population > 25 years of age in India (675,000,000 using World Bank population estimate for 2019 and age group proportions from Census 2011)

We estimate $PM_{2.5}$ exposure level z (ug/m^3) due to agricultural residue burning in Punjab was 9.7 ug/m^3 in 2019.

To estimate premature mortality attributable to agricultural residue burning (or other agricultural activities) in Punjab, we use:

$$\Delta M = P \quad * \frac{Y_{baseline}}{RR_{baseline}} * \ (RR_{obs} - RR_{obs\ minus\ z}) \qquad \text{....... Equation 6}$$

where,
P = population exposed to observed mean annual $PM_{2.5}$ concentration in 2019

$Y_{baseline}$ = baseline mortality rate of 685 per 100,000 people available for the year 2010 from WHO.

$RR_{baseline}$ = Relative risk of non-communicable diseases and lower respiratory infections (NCD + LRI) when $PM_{2.5}$ exposure level changes from theoretical minimum risk z_0 to the exposure level in the baseline year of 2010

RR_{obs} = Relative risk of non-communicable diseases and lower respiratory infections (NCD + LRI), when $PM_{2.5}$ exposure level changes from theoretical minimum risk z_0 to observed exposure level in 2019

$RR_{obs\ minus\ z}$ = Relative risk associated with observed concentration minus the concentration z attributable to the agricultural system in 2019

RR_{obs}, $RR_{obs\ minus\ z}$ and $RR_{baseline}$ are estimated using the Global Exposure Mortality Model (GEMM) equation (Burnett et al. 2018):

$$RR = \exp\left(\theta * \log\left(1 + \frac{x}{\alpha}\right) * \frac{1}{1+\exp\left(-\frac{x-\mu}{\nu}\right)}\right. \qquad \text{...... Equation 6a}$$

where

$\theta = 0.143$ for age > 25 , $\alpha = 1.6$, $\mu = 15.5$, $\nu = 36.8$ (parameter estimates for NCD + LRI in GEMM (Burnett et al. 2018)) and x = mean annual $PM_{2.5}$ exposure per capita in ug/m^3 . We use 3 values for x = baseline value in 2010 (per capita exposure level for 2010 in India = 76.7 ug/m^3(Health Effects Institute 2019)) , observed value in 2019 (per capita exposure level for 2019 in India = 83 ug/m^3 (Health Effects Institute 2019)), and observed minus concentration attributable to agricultural activities in Punjab in 2019 (estimated as 73.3 ug/m^3 using Equation 5 and per capita exposure level for 2019 in India (Health Effects Institute 2019)).

2. **Pathway II): Incorporating residues into the soil using a Happy Seeder (HS) prevents residue burning and provides social and environmental benefits**

i) Quantifying interactions H1-T11, T11-T2 (Farmers use HS to incorporate residues into soil); T2-E4, E4-T3 (Incorporated residues improve soil health and reduce fertilizer requirement); T11-E3 HS reduces crop water requirement; T11-T1 HS increases crop (wheat) yield:

See Supp. Data Tables SD3 and SD4 for attributes of wheat sown using HS (cropped land area, water and fertilizer requirements, yield)
See Equations 9 and 10 for calculations of total fertilizer quantity used and total groundwater extracted respectively

ii) Quantifying interaction T11-H1 HS rental increases farming cost

Cost associated with Happy Seeder (HS) rental:

$$HS_{cost\ per\ ha} = \left(HS\ rental * \frac{Area_{HS}}{Total\ wheat\ sown\ area}\right) + Manual\ spreading$$

…… Equation 7

where,
HS rental = subsidy*unsubsidized rental cost of HS per hectare= 0.5*3300 INR/ha (Shyamsundar et al. 2020)
$Area_{HS}$, Total wheat sown area = Supp. Data Table SD3 for attributes of crops
Manual spreading = Cost of manually spreading residues before using Happy Seeder to incorporating them into soil= 550 INR/ha (Shyamsundar et al. 2020)

iii) Quantifying interaction T11-T7 HS (and other farm machinery) increase diesel use:

Diesel used in a HS:

$$Diesel_{HS}(litres) = Diesel_{HS\ per\ ha} * Area_{HS}$$ …… Equation 8a

where,

$Diesel_{HS\ per\ ha}$ = diesel required by a Happy Seeder mounted tractor per hectare (14 litres (Shyamsundar et al. 2020))
$Area_{HS}$ = area over which Happy Seeder is used (hectares) (Supp. Data Table SD3 for attributes of crops)

Diesel required for mechanized residue management:

$$Diesel_{residue\ management}(litres) = Diesel_{conventional} * \sum_{crops}\left(Area_{crop} - Area_{HS}\right)$$

…… Equation 8b

where
$Diesel_{conventional}$ = Diesel required per hectare for residue management (using stubble shaver, disc, tine , planker, seeder) (40 litres/ha (Shyamsundar et al. 2020))

iv) Quantifying interaction E3-T6, E3-T7 Groundwater extraction determines energy used (electricity and diesel) for irrigation: see Equations 11-13 for calculating energy used for irrigation

v) Quantifying interactions T3-E1, T6-E1, T7-E1 Power generation, diesel combustion and fertilizer production emit pollutants to air: see Equations 14-15 for calculating emissions of GHG and PM2.5 from direct and indirect energy use

vi) Quantifying interactions T2-E1 Residue burning emits pollutants to air: see Equation 4

vii) Quantifying interactions E1-H2 Air pollution causes adverse human health impacts: See Equations 5-6

viii) Quantifying interactions T3-H1, T6-H1, T7-H1 Agricultural inputs affect farming costs: see Equation 16

3. Pathway III): Excess use of agricultural inputs presents environmental challenges

i) Quantifying interaction H1-T3 Farmers use excess fertilizer

Total quantity of fertilizer used by type is given by:

$$Fertilizer_{type} = \sum_{crops} Area_{crop} * \ Fert\ per\ ha_{type,crop} * \ Excess$$

......Equation 9

where

$Area_{crop}$ = Cropped area by crop type (hectares)
$Fert\ per\ ha_{type,\ crop}$ = Fertilizer type (urea, DAP, MOP) required by crop type as recommended by Punjab Agricultural University (tons/hectare)
Excess = fraction in excess of recommended/required usage
See Supp. Data Tables SD3 and SD4 for above attributes of crops

ii) Quantifying interaction H1-E3 Farmers pump excess groundwater

Total groundwater extracted in cubic metres:

$$Water\ =\ Tubewell_{share} * \sum_{crops} Area_{crop} *\ CWR_{crop} *\ Excess$$

…... Equation 10

where
$Tubewell_{share}$ = Share of irrigation requirement met by groundwater extraction using tubewell (73% and the rest is canal irrigation (Grover et al. 2017))
$Area_{crop}$ = Cropped area by crop type (hectares)
CWR_{crop} = water required by crop type per hectare (metres)
Excess = fraction in excess of recommended/required usage
See Supp. Data Tables SD3 and SD4 for above attributes of crops

Depth of groundwater table in metres:

$$Water\ table\ (t+1) = Water\ table\ (t) + \left[(1 - Recharge) * \frac{Water}{\sum Area_{cropped}}\right]$$

…… Equation 10a

where,
t = 1…10 years
Water table(t) = depth of water table at time t (metres) (25m in 2019 (Grover et al. 2017)
Recharge = annual recharge of water table as a fraction of groundwater withdrawal (60% (Central Ground Water Board 2018))
Water = Annual groundwater extraction (m3) (see Equation 10)
$Area_{cropped}$= Cropped area by crop type (hectares) (see Supp. Data Table SD3 for attributes of crops)

iii) Quantifying interactions E3-T6, E3-T7 Groundwater extraction determines energy used (electricity and diesel) for irrigation:

Annual electricity usage in irrigation pumps:

$$kWh =\ Water *\ Share_{electric} *\ Avail *\ H *\ 99 * \frac{9.8}{(3.6\ x\ 10^6) *\ (Eff_{electric} *\ Eff_{T\&D})}$$

…… Equation 11

where
$Water$ = annual groundwater extraction (cubic metres) (Equation 10)
$Share_{electric}$ = share of groundwater requirement met by electric pumps (85% (Sidhu et al. 2020))
Avail = Power availability expressed as share of required power that is available (0.6) (Sidhu et al. 2020)
H= dynamic head (metres) , see Equation 11a
$Eff_{electric}$ = efficiency of electric irrigation pumps (30% (Dhillon et al. 2018; Patle et al. 2016)
$Eff_{T\&D}$ = efficiency of power transmission and distribution system (75% (Dhillon et al. 2018; Buckley 2015))
997 = density of water (kg/m^3)
9.8 = g (m/s^2)
3.6 x 10^6 = conversion factor between Joule to kWh

Dynamic head (total height water needs to be pumped through) (Dhillon et al. 2018; Patle et al. 2016):

$$H = Water\ table\ (t) + Drawdown + Friction \qquad \text{...... Equation 11a}$$

where,
Water table(t) = depth of water table at time t (metres) (25m in 2019 (Grover et al. 2017); see Equation 10a)
Drawdown = lowering of water table near pump (metres) (3m (Dhillon et al. 2018; Patle et al. 2016))
Friction = accounting for frictional losses in pipe (about 20% of water table depth and drawdown (Dhillon et al. 2018; Patle et al. 2016))

Annual diesel use in irrigation pumps in litres:

$$Diesel_{pumps} = Water * (1 - Share_{electric}) * Avail * H * 997 * \frac{9.8}{(E * 10^6) * Eff_{diesel}}$$

...... Equation 12

where,
Eff_{diesel} = efficiency of diesel irrigation pumps (12%(Dhillon et al. 2018; Patle et al. 2016))
E = energy density of diesel =38 MJ/litre
10^6 = conversion factor between Joule and Megajoule
Other variables as specified above

Diesel requirement in generators to compensate for unavailable electricity that is required for electric pumps:

$$Diesel_{gen}(litres) = (1 - Avail) * \left(\frac{kWh}{Avail}\right) * \frac{3.6 * (Eff_{electric} * Eff_{T\&D})}{E * Eff_{diesel}}$$

...... Equation 13

See Equations 11-12 for explanations of variables.

iv) Quantifying interactions T3-E1, T6-E1, T7-E1 Power generation, diesel combustion and fertilizer production emit pollutants to air

GHG emissions from energy use:

$$GHG_{energy\ use} = \sum_{species} \{(emf_{species,power} * kWh) + (emf_{species,diesel,use} * Diesel_{uses}) + (emf_{species,fertilizer,type} * Fertilizer_{type})\} * GWP_{species}$$

...... Equation 14

where,
$GWP_{species}$ = Global warming potential of GHGs
$emf_{species,\ power}$ = emissions (CO_2, CH_4, N_20) per kWh
$emf_{species,\ diesel,\ use}$ = emissions (CO_2, CH_4, N_20) per litre diesel for used in pumping, generator sets for pumps, residue management and Happy Seeder
$emf_{species,\ fertilizer,\ type}$ = emissions (CO_2, CH_4, N_20) per kg fertilizer manufactured (urea, DAP, MOP)
(see Supp. Data Table SD5 for all emission factors and GWP)
kWh, $Diesel_{uses}$, $Fertilizer_{type}$ and $Residues_{burnt}$ from equations above

$PM_{2.5}$ emissions from energy use:

$$PM\ 2.5_{energy\ use} = (emf_{power} * kWh) + \sum_{use} (emf_{diesel,use} * Diesel_{uses}) + \sum_{type} (emf_{fertilizer,type} * Fertilizer_{type})$$

...... Equation 15

where
emf_{power} = primary $PM_{2.5}$ emissions per kWh
$emf_{diesel,\ use}$ = primary $PM_{2.5}$ emissions per litre diesel for used in pumping, generator sets for pumps, residue management and Happy Seeder
$emf_{fertilizer,\ type}$ = primary $PM_{2.5}$ emissions per kg fertilizer (urea, DAP, MOP)
(see Supp. Data Table SD5 for all emission factors)
kWh, $Diesel_{uses}$, and $Fertilizer_{type}$ from equations above

v) Quantifying interaction E1-H2 Air pollution causes adverse human health impacts: See Equations 5-6

vi) Quantifying interaction T3-H1,T6-H1,T7-H1 Agricultural inputs affect farming costs: see Equation 16

4. **Pathway IV) Crops grown in Punjab are procured by the Government of India for the Public Distribution System (PDS)**

i) Quantifying interactions T1-T3, T1-T4, T1-E3 (crops grown determine use of agricultural inputs) and T1-T2 (crops grown determine residue burning)

See Supp. Data Tables SD3 and SD4 for attributes of crops grown in Punjab (yield, production, proportion of residues generated and burnt, water, fertilizer and pesticide requirements)
See Equations 1 and 2 for calculations of residues burnt, Equations 9 and 10 for fertilizer and groundwater used for irrigation and Equations 11-13 for energy used for irrigation

ii) Quantifying interactions T2-E1, T3-E1, T6-E1, and T7-E1 Residue burning, fertilizer production , power generation and diesel combustion emit pollutants to air

See Equations 3 and 4 for emission of air pollutants from residue burning and Equations 14 and 15 for emission of air pollutants from power generation, diesel combustion and fertilizer production.

iii) Quantifying interaction E1-H2 Air pollution causes adverse human health impacts: See Equations 5-6

iv) Quantifying interaction T1-H1 (Sale of crops provides income to farmers), T3-H1, T4-H1, T6-H1, T7-H1 (agricultural inputs determine farming costs) and T11-H1 (HS rental adds to farming cost)

Farmer income (per hectare of cropped land) is estimated as the difference between income from sale of crops (through public procurement) and expenses on farming inputs and residue management

$$\begin{aligned}
&Income\ per\ ha \\
&\quad = \left(\sum_{crop} Yield_{crop} \ * \ MSP_{crop}\right) \\
&\quad - \left(\sum_{fert\ type} Fertilizer_{type} * \frac{Cost_{fert\ type}}{\sum_{crop} Area_{crop}}\right) \\
&\quad - \left(\sum_{crop} Pesticide\ cost_{crop,per\ ha} \ * \frac{Area_{crop}}{\sum_{crop} Area_{crop}}\right) \\
&\quad - \sum_{uses} Diesel_{uses} * \frac{Cost_{diesel}}{\sum_{crop} Area_{crop}} - Other_{inputs} \\
&\quad - HS_{rental\ per\ ha} - Residue\ management
\end{aligned}$$

…… Equation 16

where,
$Yield_{crop}$ = yield per hectare
$Area_{crop}$ = Area cropped by crop type
$Pesticide\ cost_{crop}$ = Pesticide expenditure by crop type
See Supp. Data Tables SD3-SD4 for above attributes of crops
$Fertilizer_{type}$ = total fertilizer use by fertilizer type (urea, DAP, MOP) (see Equation 9)
$Diesel_{uses}$ = Diesel used in pumping, generator sets for pumps, residue removal and Happy Seeder (litres) (Equation 12-13)
$HS_{rental\ per\ ha}$ =see Equation 7

MSP_{crop} = minimum support price (MSP) for crops procured by the government
$Cost_{fert\ type}$ = Subsidized cost of fertilizer by fertilizer type
See Table S1 for above attributes of institutional components

$Cost_{diesel}$ = Cost of diesel (55 INR/litre (Shyamsundar et al. 2020))
$Other_{inputs}$ = Costs of harvesting operations (13,000 INR/ha) and seeds (3000 INR/ha) (Government of India n.d.)
Residue management = Rental, labour and diesel costs associated with conventional residue management before burning residues (stubble shaver, disc, tine, plank, seeder – 6550 INR/ha (Shyamsundar et al. 2020))

v) Quantifying interaction T1-H3 Crops in the PDS influence protein availability in low-income households:

Protein available through crops grown in Punjab and supplied through Public Distribution System,

$$P = \frac{(\sum_{crop} Protein_{crop} * P_{crop}) * (1 - Leakage)}{(\sum_{crop} P_{crop}) * (1 - Leakage)}$$ …… Equation 17

where,
$Protein_{crop}$ = protein content (grams per ton) (Supp. Data Table SD3 for attributes of crops)
Leakage = diversion of grains supplied through the PDS illegally or wastage (20% (Puri 2017))

Using Equation 17, we estimate that protein constitutes 8.5% of the macro-nutrient content of Punjab's foodgrains supplied through PDS.

In addition to quantifying the interactions in the system, we quantify the public expenses associated with the rice-wheat cropping system in Punjab. This includes expenses on agricultural subsidies (fertilizer, electricity, machinery) and the consumer subsidies on foodgrains through the Public Distribution System.

Public expenses on crop production and residue management are calculated as the sum of the agricultural subsidies provided for Happy Seeders, fertilizers and power in addition to expenses on interventions:

$$Public\ expenses_{subsidies} = (HS_{count} * HS_{subsidy\ rate}) + (\sum_{type} Fertilizer_{type} * Fert\ subsidy_{type}) + (kWh * Cost_{per\ kWh}) + Intervention$$

…... Equation 18a

where
HS_{count} = Happy Seeders on the market
$HS_{subsidy\ rate}$ = subsidy on each Happy Seeder (subsidy calculated for year = 1)
$Fert\ subsidy_{type}$ = subsidy on urea, DAP, MOP
(See Table S1 for above attributes of institutional components)
$Cost_{per\ kWh}$= cost of power production in Punjab (4.2 INR/kWh (Commission 2020; Grover et al. 2020))
$Fertilizer_{type}$ = see Equation 9
kWh = see Equation 11
Intervention = additional public expenses on interventions 1-5 (Equations 19 – 24) outlined below (0 INR for the current institutional and knowledge landscape)

Annual consumer subsidy on foodgrains sold through the Public Distribution System and guaranteed to low-income households is estimated as:

$$Public\ expenses_{per\ cap\ PDS} = \sum_{crop} Consumption_{\ crop} * (MSP_{crop} - (PDS\ price_{crop} * (1 - leakage)))$$

…... Equation 18b

where,
$Consumption_{crop}$ = annual per capita consumption of foodgrains through the PDS
MSP_{crop} and PDS $price_{crop}$ = procurement and PDS selling prices of foodgrains respectively
Leakage = diversion of foodgrains procured by the government intended for PDS
(See Table S1 for above attributes of institutional components)

Text S2: Quantitative model evaluation

We use data available from other studies and government reports for previous years to evaluate our estimates of system components' key attributes (summarized in Table S2).

We evaluate our quantitative model estimates for the year 2019 since the model dynamics for 2019-2029 are based on attributes in the base year of 2019.

a) Residues burnt: Using Equations 1 and 2, we estimate 14.9 million tonnes of rice residue was burnt in 2019. Estimates for rice residues burnt in 2018 range from 13 million tonnes (Davis et al. 2018) to 17 million tonnes (TERI 2018). Our estimate of total residues burnt in Punjab in 2019 is 21.6 millon tonnes compared to official estimates of 19.7 million tonnes in 2010 (Ministry of Agriculture 2014).

b) Emission of GHGs: We estimate (using Equation 3) that burning 21.6 million tonnes of residues in Punjab in 2019 emitted 29.6 million tonnes of CO2. Jain et al. (2014) estimate that burning 98.4 Mt of residue across India in 2009 emitted 141.15 Mt of CO2 (equivalent to emissions of 31 Mt of CO2 on burning 21.6 Mt of residues).
We estimate (using Equation 14) that the whole rice-wheat cropping system in Punjab was responsible for 76 Mt of GHGs (CO2e) but could not find equivalent estimates from other studies for validation.

c) Emissions of PM2.5: We estimate (using Equation 4) about 177.5 Gg of primary PM2.5 was released in 2019 due to residue burning in Punjab which is in close agreement with the estimate of 137 Gg PM2.5 released in 2018 (T. Singh et al. 2020), given the uncertainty range of emission factor of PM2.5 from residue burning (+/- 34%) (Pandey et al. 2014).

d) Premature mortality due to PM2.5 exposure attributable to agricultural residue burning in Punjab: We estimate (using Equation 5 and 6) that PM2.5 emissions from residue burning in Punjab was responsible for 68,000 premature deaths in 2019. This is comparable to the Global Burden of Diseases estimate of 66,000 premature deaths in 2015 from all-India residue burning and within the 95% confidence interval of 65,000 – 78,000 premature deaths in 2015 (GBD MAPS Working Group 2018) .

e) Total nitrogen fertilizer used : Our estimate (using Equation 9) of 2.2 million tonnes of annual urea usage in the rice-wheat cropped land in Punjab, is lower than official estimates of 3.0 million tonnes used in Punjab in 2015 (Grover et al. 2018). This may be due to a few reasons: we consider lower fertilizer application on wheat-cropped land sown with Happy Seeder (Government of India 2019), but this may not be the case in practice; the estimates of per hectare application of fertilizers used in our analysis may be conservative; and we only consider rice-wheat cropped land and not all crops grown in Punjab.

f) Annual groundwater extracted and impact on water table: Our estimate of 37 billion cubic metres of groundwater extracted in 2019 (using Equation 10) is 5% higher than annual groundwater extraction of 35 billion cubic metres for 2012-2016 by the Central Ground Water Board (Central Ground Water Board 2018). We estimate an average annual water table decline of 0.22m (using Equation S10a), while estimates from other studies are 0.2m - 0.6m annually (Patle et al. 2016; S. Singh 2020), depending on the 'block' studied in Punjab (blocks are local administrative units within the state).

g) Electricity used for irrigation: Our estimate (using Equation 11) of 11.3 TWh electricity used in 2019 for irrigation of rice-wheat system in Punjab is 2% less than estimates for 2015 and 2016 from other studies (Dhillon et al. 2018; India 2016) and 6% higher than estimates for 2014 (Grover et al. 2020).

h) Diesel used for irrigation and other agricultural activities: We estimate (using Equations 12 and 13) about 327 litres of diesel is used annually per hectare of rice-wheat cropped land in Punjab in 2019. This is higher than estimates of 300 litres of diesel used per hectare (156 litres/ha for rice and 144 litres/ha for wheat) for 2012 by Punjab Agricultural University (Grover et al. 2015), and this may be because we account for diesel use in Happy Seeders in 2019.

i) Farmers' income: By our estimates (using Equation 16), farmers earn about 75,000 INR/ha annually (not accounting for fixed costs of cultivation such as rent for land). This is in agreement with other estimates of 80,000-82,000 INR/ha for rice and 60-65000/ha for wheat (Grover et al. 2015) and 60,000-70,000 INR/ha using conventional residue management or Happy Seeder use (Shyamsundar et al. 2020). Including fixed costs related to rent is expected to drive down income by about 40000 INR/ha (Shyamsundar et al. 2020; Government of India n.d.), with net income equal to about 35,000 INR/ha.

j) Public expenses on crop production and residue management in Punjab: By our estimates (using Equation 18a), power subsidy to farmers cost the government about 44 billion INR in 2019 (compared to other estimates of 61-71 billion INR (Bajwa 2019; Rambani 2020) and 45 billion INR in 2015 (Grover et al. 2020)) and fertilizer subsidy to farmers costs about 41 billion INR (compared to estimates of 35-46 billion INR for the period 2010-2015 (Gulati & Banerjee 2015)) .
Public expenses on the Public Distribution System: We estimate (using Equation 18b) that the government spends about 1050 INR per beneficiary annually, only accounting for subsidies on rice, while other estimates are about 1400 INR per capita annually for the Public Distribution program (World Bank 2019).

Attribute evaluated	**Our model estimate for 2019**	**Estimate from other studies and reports**
Rice residues burnt in Punjab	14.9 million tonnes	13 million tonnes (Davis et al. 2018) to 17 million tonnes (TERI 2018) in 2018
Total residues burnt in Punjab	21.6 million tonnes	19.7 million tonnes in 2010 (Ministry of Agriculture 2014)
Emission of CO_2 due to residue burning in Punjab	29.6 million tonnes of CO_2 emitted due to burning 21.6 million tonnes of residues	Burning 98.4 Mt of residue across India in 2009 emitted 141.15 Mt of CO2 (equivalent to emissions of

		31 Mt of CO2 on burning 21.6 Mt of residues) (Jain et al. 2014)
Emission of primary PM2.5 due to residue burning in Punjab	177.5 Gg of primary PM2.5	137 Gg PM2.5 released in 2018 (T. Singh et al. 2020) (uncertainty range of emission factor of PM2.5 from residue burning is +/- 34% (Pandey et al. 2014))
Premature mortality due to PM2.5 exposure attributable to agricultural residue burning in Punjab	68,000 premature deaths	66,000 premature deaths in 2015 from all-India residue burning (95% confidence interval of 65,000 – 78,000) (GBD MAPS, 2018)
Total nitrogen fertilizer (urea) used in Punjab	2.2 million tonnes on rice-wheat cropped land in Punjab	3.0 million tonnes used in Punjab in 2015 (Grover et al. 2018).
Annual groundwater extracted and impact on water table	37 billion cubic metres of groundwater; average annual water table decline of 0.22m	35 billion cubic metres annually for 2012-2016(Central Ground Water Board 2018); average annual water table decline of 0.2m - 0.6m annually (Patle et al. 2016; S. Singh 2020)
Electricity used for irrigation in Punjab	11.3 TWh	11 TWh for 2015 and 2016 from other studies (Dhillon et al. 2018; India 2016) and 10.6 TWh for 2014 (Grover et al. 2020).
Diesel used for irrigation and other agricultural activities	About 327 litres of diesel used per hectare of rice-wheat cropped land in Punjab in 2019.	300 litres of diesel used per hectare (156 litres/ha for rice and 144 litres/ha for wheat) for 2012 (Grover et al. 2015)
Farmers’ income	About 75,000 INR/ha annually (not accounting for fixed costs such as rent).	80,000-82,000 INR/ha for rice and 60-65000/ha for wheat (Grover et al. 2015); 60,000-70,000 INR/ha for rice-wheat cropping using conventional residue

		management or Happy Seeder use (Shyamsundar et al. 2020).
Public expenses on crop production and residue management in Punjab	Power and fertilizer subsidies for farmers cost the government about 44 billion INR and 41 billion INR respectively in 2019.	Power subsidy: 61-71 billion INR in 2015(Bajwa 2019; Rambani 2020) and 45 billion INR in 2015 (Grover et al. 2020) Fertilizer subsidy: 35-46 billion INR annually for the period 2010-2015 (Gulati & Banerjee 2015)
Public expenses on the Public Distribution System	1050 INR per beneficiary annually, only accounting for subsidies on rice	About 1400 INR per beneficiary annually for the Public Distribution program (World Bank 2019).

Table S2: Evaluation of quantitative model estimates for key attributes for the year 2019

Text S3: Evaluation of impacts of interventions

We use our quantitative model to examine the impact of five interventions on sustainability metrics. (see Table S3 for attributes of institutional and knowledge components for interventions). For each intervention: we characterize direct structural changes and indirect quantitative changes in the system (see Table S3); and we calculate Equations 1 – Equation 18 for a period of 10 years (2019-2029) and estimate quantitative impacts on capital stocks (see Text S4 for details on estimating monetary impacts on capital stocks and Supp. Data Tables SD7-SD14 for detailed estimates of quantitative impacts on sustainability).

a) Intervention 1: Effective ban on residue burning (Interaction Pathway I)

Complete ban compliance requires awareness amongst farmers regarding the impacts of residue burning and alternate residue management options, and monetary compensation to farmers for residue removal (Dutta 2018; Slater 2018; Ellis-Petersen 2019; Yadav 2019).

We estimate the annual public cost of ensuring 100% ban compliance:

$$Ban_{public\ cost} = \left(Payment * Area_{crop}\right) + (Landholdings * Campaign)$$

…… Equation 19

where,
Payment = annual payment (INR/ha) to farmers to not burn residues at the end of summer cropping season
Campaign = expenses incurred for conducting a door-to-door awareness campaign in Punjab, only included in the year(s) of conducting awareness campaign
(see Table 3 for attributes of institutional and knowledge components)
$Area_{crop}$ = summer cropped land area (hectares) (see Supp. Data Table S3 for attributes of crops)
Landholdings = total landholdings in Punjab (1,100,000 in 2019 from Ministry of Agriculture, Government of India)

We estimate system impacts due to complete compliance to ban on residue burning (0% residues burnt) using Equations 1-5 (where Ban=1 and $Residues_{burnt}$=0 in Equation 2) and account for direct payment to farmers in estimating farmer income using Equation 16.

b) Intervention 2: Use of rice residues in the power sector (cofiring in coal power plants and in biomass power plants) (Interaction Pathway I)

Residues are used for cofiring in coal power plants if the Government of India mandates a cofiring share (5-10%) for agricultural residues to be used in state-owned (National Thermal Power Corporation) coal power plants (TERI 2018) and farmers are paid 5500 INR per ton of residues (Ghosal 2017; Special Correspondent 2017).

Residues used in cofiring:

$$Residues_{cofiring} = Share_{cofiring} * Installed\ Capacity_{coal} * Hours * \frac{3600}{Eff_{coal} * LHV}$$

…… Equation 20

Where, $Share_{cofiring}$ = cofiring share in coal power plants (% of installed coal power capacity; see Table 3)
$Installed\ Capacity_{coal}$ = installed coal power capacity (44GW all-India from NTPC)
Hours = annual operating hours of coal power plants (6500 hours) (J. Singh 2015)
3600 = conversion factor from MWh to MJ
Eff_{coal} = coal power plant thermal efficiency (33 %(CEA 2013))
LHV = Lower heating value of agricultural residues (15540 MJ/ton (J. Singh 2015))

Capital cost of residues utilization in coal power plant for cofiring is estimated using:

$$Cofiring_{cap\ cost} = \left(Cap\ cost_{cofiring} * Share_{cofiring} * Installed\ capacity_{coal}\right)$$

…… Equation 21

where

$Cap\ cost_{cofiring}$ = Cost of retrofitting a coal power plant for cofiring (6750000 INR/MW (J. Singh 2015; Griffin et al. 2014))
See above for other variables

Alternately, residues are used to generate power in biomass power plants if there is sufficient installed capacity for utilization of residues (planned 600 MW of biomass power in Punjab (TERI 2018)) and farmers are paid 5500 INR per ton of residues (Ghosal 2017; Special Correspondent 2017).

Residues used in biomass power generation:

$$Residues_{bio\ power} = Installed\ Capacity\ _{biomass} * \ Hours * \frac{3600}{Eff_{biomass} * LHV}$$

…… Equation 22

$Installed\ capacity_{biomass}$ = biomass power capacity (=number of plants x average size of power plant; see Table 3)
Hours = annual operating hours of biomass power plants (6500 hours (J. Singh 2015))
3600 = conversion factor from MWh to MJ
$Eff_{biomass}$ = biomass power plant thermal efficiency (20 % (J. Singh 2015))
LHV = Lower heating value of agricultural residues (15540 MJ/ton (J. Singh 2015))

Capital cost of biomass power plant that utilizes residues:

$$Biomass_{cap\ cost} = \left(Cap\ cost_{biomass} * Size_{biomass\ power} * N\right)$$ …… Equation 23

where
Cap cost = capital cost of biomass power plant (45000000 INR/MW (J. Singh 2015; J. Singh 2016))
$Size_{biomass\ power}$ = Size (in MW) of average biomass power plant
N = number of biomass power plants set up (see Table 3)

We estimate the impacts of residue use in industry on residue burning (and associated effects) using Equations 1-5 (where $Residues_{industry}$= $Residues_{cofiring}$ or $Residues_{bio\ power}$ in Equation 2).

We modify Equation 8b ($Diesel_{residue\ management}$) to include additional diesel use in balers for residue removal in $Diesel_{residue\ management}$ as follows:

$$Diesel_{baling,total}(litres) = \ Diesel_{baling} * \sum_{crops} Area_{crop} * \left(\frac{Residues_{industry,crop}}{Residues_{generated,crop}}\right)$$

…… Equation 8b (addition)

where
$Diesel_{baling}$= Diesel required per hectare for baling (6 litres/ha (Verma et al. 2019))
$Residues_{generated,crop}$ = Residues generated minus residues on Happy Seeder used land (these residues are not removed but incorporated into the soil) (see Equation 1)

$Residues_{industry,crop}$ = Residues used in industry (see Equation 20 and Equation 22)

We modify Equations 14 and 15 to include GHG and PM2.5 emissions respectively from residue use in industry as follows:

$$GHG_{residue,industry} = \sum_{species} \{(emf_{residues,power} * Residues_{cofiring}) + (emf_{residues,power} * Residues_{biomass\ power})\} * GWP_{species}$$

…… Equation 14 (addition)

where,
$GWP_{species}$ = Global warming potential of GHGs
$emf_{species,\ residues,\ power}$ = emissions (CO_2, CH_4, N_2O) per kg residues used in power plants
(see Supp. Data Table SD5 for all emission factors and GWP)
$Residues_{cofiring}$ *and* $Residues_{biomass\ power}$ = Residues used in industry for cofiring in coal power plants and in biomass power plants respectively (see Equations 20 and 22)

$$PM2.5_{residues,industry} = (emf_{residues,power} * Residues_{cofiring}) + (emf_{residues,power} * Residues_{biomass\ power})$$

…… Equation 15 (addition)

where,
$emf_{residues,\ power}$ = primary $PM_{2.5}$ emissions per kg residues used in power plants
(see Supp. Data Table SD5 for all emission factors)
$Residues_{cofiring}$ *and* $Residues_{biomass\ power}$ = Residues used in industry for cofiring in coal power plants and in biomass power plants respectively (see Equations 20 and 22)

We modify Equation S16 to include additional income earned through sale of residues and baling costs in calculating net farmer income as follows:

$$Additional\ net\ income\ per\ ha = \left(Residues_{ind,per\ ha} * Price_{residue}\right) - Baling$$

…… Equation 16 (addition)

where,
$Residues_{ind,\ per\ ha}$ = residues used in industry per hectare of cropped land (see Equations 20 and 22)
$Price_{residue}$ = Market price of residues
Baling = Costs of renting baling machines (including diesel and labour) per hectare for residues used in industry = $Baler_{rental}$*$Residues_{industry}$/$Residues_{generated}$ where, $Baler_{rental}$= 3700 INR/ha (Jaidka et al. 2020; Shyamsundar et al. 2020; Kurinji & S. Kumar 2020). See Equation 1 for $Residues_{generated}$, and Equations 20 and 22 for $Residues_{industry}$

c) Intervention 3: Widespread Happy Seeder (HS) use (Interaction Pathway II)

As of 2019, about 15,000 Happy Seeders were sold either to individual farmers or to farmer cooperatives. We assume that farmers have access to 45000 Happy Seeders in this intervention, through farmers' cooperative societies for machinery rentals, to cover about 80% of rice-cropped land in Punjab (each machine covers 61 hectares (Shyamsundar et al. 2020)). Farmers need to be aware of the benefits of using a Happy Seeder, the associated subsidy, as well as have adequate knowledge on changes in farming inputs when using the machine (lower water requirement as the incorporated residues add moisture to the soil and lower fertilizer requirements (Tallis et al. 2018; Gupta 2011; TERI 2018)).

Public cost of incentivizing widespread use of Happy Seeder by farmers:

$$HS_{public\ cost} = (Subsidy * Market\ price\ of\ HS) + Farmer\ training$$

…… Equation 24

where
Subsidy = Government subsidy (% of total market price) provided to farmers' cooperative societies
Farmer training = Government of India budget for farmer training camps
(see Table 3 for attributes of institutional and knowledge components)

Wheat-cropped area on which Happy Seeder is used,

$$Area_{HS} = N\ x\ Land$$

..…. Equation 25

N = No. of Happy Seeder machines in the market (45,000 in this scenario)
Land = Land covered by each machine in the 25-day period between cropping seasons (61 hectares (Shyamsundar et al. 2020))

We estimate the impact of widespread Happy Seeder use on residue burning and associated effects on air pollutants and human health using Equations 1-6 (where in Equation 2 land on which Happy Seeder is used = $Area_{HS}$) and impacts of HS use on agricultural inputs and associated effects using Equations 7-16.

d) Intervention 4: Reform of subsidy schemes for power and fertilizers (Interaction Pathway III)

We use Equations 9-13 to estimate fertilizer use (optimal levels as prescribed by Punjab Agricultural University) and irrigation energy use (33% less groundwater use for rice relative to current levels) in this intervention, Equations 14-16 to estimate associated impacts on emission of air pollutants and income, and Equation 5-6 to estimate human health impacts. We estimate public expenses on fertilizer and power subsidies using Equation 18a and our revised estimates of fertilizer and power consumption.

e) **Intervention 5: Government procurement of pulses from Punjab at Minimum Support Prices (MSPs) (Interaction Pathway IV)**

Farmers' shift cultivation from rice to pulses if they are procured at guaranteed Minimum Support Price (MSP) by Government of India (announced MSP for pigeon pea, a locally grown pulse, for 2019 = 62.4 INR/kg (Punjab Agricultural University 2020)). We test a 50% shift from rice to pulses in this intervention scenario (S. Singh 2020).

We use Equations 1-17 to estimate the impacts of shifting 50% rice cultivation to pulses on residue burning and associated effects, use of agricultural inputs and associated effects and farmers' income. We estimate public expenses on fertilizer and power subsidies using Equation 18a and per capita consumer subsidy on foodgrains using Equations 18b. By our estimates using Equation 18b, annual public expenses reduces by INR 35 per beneficiary (or 28 billion INR given an estimated 800 million Indians access the PDS (Puri 2017; World Bank 2019)) if leakage in the PDS system (either through diversion of food or through wastage of grain due to poor quality storage) is reduced from 20% to zero.

In our quantitative model, pulses are sold through the PDS at 10% of MSP (as is the case with rice and wheat), and each PDS beneficiary buys 3kg rice and 1kg pulses each month (as opposed to 5kg of rice as each beneficiary is entitled to receive (Press Information Bureau 2013)). This would keep consumer expenses constant and public expenses on PDS would increase by 25% (from 1010 INR to 1260 INR/capita).

Table S3 presents the direct and indirect changes in system interactions due to each intervention.

Intervention	**Direct structural changes**	**Indirect quantitative changes**
Intervention 1 : Effective ban on burning	Farmers do not burn rice residues (H1-T2)	Rice residues are not burnt and emit fewer GHGs (T2-E1)
	Storage facilities established for residues (T13-T2)	Rice residues are not burnt and emit fewer air pollutants (PM2.5) (T2-E1)
		Lower emission of PM2.5 leads to lower adverse health impacts (E1-H2)
Intervention 2: Residues used in power plants	Farmers do not burn rice residues (H1-T2)	Rice residues are not burnt and emit fewer GHGs (T2-E1)

	Farmers rent baling machines (H1-T10)	Rice residues are not burnt and emit fewer air pollutants (T2-E1)
	Storage & processing facilities established for residues (T13-T2, T14-T2)	Lower emission of air pollutants leads to lower adverse health impacts (E1-H2)
	Power plants set up to use residues (T12-T2)	Farmers earn income from sale of residues (T2-H1)
Intervention 3: Wide-scale Happy Seeder use	Farmers use Happy Seeders (H1-T11)	HS incorporates rice residues into the soil (T11-T2)
		Happy Seeder use increases crop yield (T11-T1) and income (T1-H1)
		Incorporated residues improve soil health and reduces fertilizer use (T2-E4; E4-T3)
		Happy Seeder use reduces groundwater extraction (T11-E3) and lowers irrigation fuel (electricity/diesel) consumption (E3-T6, E3-T7);
		Happy Seeder use increases tractor diesel consumption (T11-T7)
		Residue burning and agricultural inputs determine emission of air pollutants (PM2.5 and GHG) (T2-E1, T3-E1, T6-E1, T7-E1).
		Lower emission of PM2.5 leads to lower adverse health impacts (E1-H2)
		Agricultural inputs and Happy Seeder rental affect

		farming costs (T3-H1, T6-H1, T7-H1, T11-H1)
Intervention 4: Input subsidy reform	Farmers extract less groundwater (H1-E3)	Lower groundwater extraction reduces electricity/diesel consumption (E3-T6, E3-T7)
		Lower diesel use reduces farming costs (T7-H1)
		Agricultural inputs (electricity, diesel) determine emission of air pollutants (PM2.5 and GHG) (T6-E1, T7-E1)
		Lower emission of PM2.5 leads to lower adverse health impacts (E1-H2)
	Farmers use less fertilizers (H1-T3)	Lower fertilizer use reduces emission of GHG and PM2.5 (T3-E1)
		Lower emission of PM2.5 leads to lower adverse health impacts (E1-H2)
		Lower nitrogen fertilizer use improves soil health (T3-E4)
Intervention 5: Procurement of pulses	Farmers shift 50% of cultivation from rice to pulses (H1-T1)	Crop yield influences farmers' income (T1-H1)
	Milling facilities are established for pulses (T15-T1)	Crops grown determine protein availability in low-income households who access the PDS (T1-H3)
		Crops grown determine use of agricultural inputs (groundwater, fertilizer, electricity, diesel, pesticides) (T1-E3, T1-T3, T1-T4, T1-T6, T1-T7) and

		farming costs (T3-H1, T4-H1, T6-H1, T7-H1)
		Farmers do not burn all residues (H1-T2)
		Fewer residues are burnt and emit fewer GHGs/PM2.5 (T2-E1)
		Agricultural inputs (fertilizer, electricity, diesel) determine emission of air pollutants (PM2.5 and GHG) (T3, T6-E1, T7-E1)
		Lower emission of PM2.5 leads to lower adverse health impacts (E1-H2)

Table S3: Direct and indirect changes in the system due to interventions
Human, technical and environmental component categories are represented by H,T and E respectively, and numbers represent the components (see Table 1 in manuscript for component numbers). E.g., interaction H1-T1 is an interaction between farmers (human component 1) and crops (technical component 1), where the human component (H1) influences the technical component (T1).

Text S4: Using inclusive wealth as a measure of sustainability

We estimate the changes in inclusive wealth as the sum of changes in capital stocks (human and natural capital and carbon damages) over the period 2019-2029. We calculate this by multiplying the change in stock as estimated by our model with marginal values of stocks. We use marginal values of carbon emissions and human and natural capital from previous studies to provide high-level estimates of the agricultural system's impacts on capital stocks, recognizing the significant uncertainty associated with the shadow prices of stocks (see Supp. Data Tables SD7-SD14 for detailed estimates for 2019-2029).

Human capital: We estimate the change in human capital by accounting for the value of health impacts and farmers' income (Aly & Managi 2018). Health impacts include lives lost due to air pollution exposure from residue burning and other agricultural activities in Punjab and lives saved by increasing protein consumption through subsidizing pulses for low-income households. Farmers' income is estimated as net income earned by farmers through sale of crops and residues, accounting for the cost of agricultural inputs.

$$\Delta Human\ capital = Health_{air\ pollution} + Health_{protein\ availability} + Income$$

…… Equation 26

Health impacts: The value of a statistical life (VSL) can be defined as the monetary worth of a human life or the amount individuals are willing to pay collectively to save a human life. VSL has been estimated and used in practice extensively in developed countries with little focus on estimating it specifically for developing countries (Majumder & Madheswaran 2018). Majumder and Madheswaran (2018) estimate VSL in India as INR 44.69 million (0.62 million USD) (based on Indian labour market data for 2010 – 2017), while Viscusi and Masterman (2017) estimate the VSL for India as 1.009 million USD, based on VSL for US and an income elasticity of 1. We use an income elasticity of 1 (Viscusi & Masterman 2017; Masterman & Viscusi 2018) and expected GDP growth rate of 5%(Bank 2020) to estimate VSL for India for the 10-year period of model run (2019-2029).

We estimate the health capital impact of air pollution due to air pollution exposure from residue burning and other agricultural activities (diesel use in farm machinery, power production and fertilizer manufacturing) in Punjab as:

$$Health_{air\ pollution} = Premature\ mortality\ estimate\ x\ VSL$$ …... Equation 27

The impact of increasing protein intake depends on a number of factors such as the kind of protein and whether protein is over consumed, among others (Naghshi et al. 2020). Naghshi et al. (2020) conducted a systematic review and meta-analysis of cohort studies from different countries (this list of countries excludes India) between 2000 and 2019 to show that, based on a linear dose-response analysis, an additional 3% increase in daily energy from plant protein reduces all-cause mortality risk by 5%. In our analysis, a 50% shift in cultivation area from rice to pulses in Punjab can increase protein intake by an additional 1.2% for about 142 million people (assuming individuals buy 1kg of pulses a month and 3kg rice a month, as opposed to 5kg of rice as entitled by the National Food Security Act (Puri 2017), to keep consumer expenses on foodgrains constant. We also assume that low-income individuals rely on the Public Distribution System for most of their caloric and protein requirement).

We estimate the health capital impact of increasing protein consumption as :

$$Health_{protein\ availability} = Protein\ impact * \ Premature\ mortality\ rate * \ Population * \ VSL$$
..…. Equation 28

Where
Protein impact = 2% reduction in mortality due to 1.2% additional daily energy from plant protein (estimated from linear dose-response relationship in (Naghshi et al. 2020))
Premature mortality rate = 691 per 100,000 people (estimated from the relation: $Y_z/RR_z = Y_{baseline}/RR_{baseline}$ where $Y_{baseline}$= 685 per 100,000 in 2010 (WHO 2011), and relative risk estimated for annual mean exposure to $PM_{2.5}$ in 2010 and 2019 using Equation 21)

Population = 142 million people who are enabled to buy pulses at a subsidized cost through the PDS (see above)
VSL = 0.62 (Majumder & Madheswaran 2018) – 1.009 million USD (Viscusi & Masterman 2017)

Our estimate of the health capital impact of increasing protein consumption is based on a few assumptions: individuals will increase consumption of pulses if it is made available through the PDS; low-income households derive most of the calorific and protein requirement through subsidized foodgrains (Rampal 2018); and Naghshi et al.'s (2020) linear dose-response relationship, between protein consumption and premature mortality, is applicable to the Indian population.

Farmers' income: Income underpins the ability to gain skills and education that constitute human capital (Managi & P. Kumar 2018), however the decadal time scale of our analysis makes it challenging to estimate long-term impacts on farmer's skills and education with each intervention. We include changes in farmers' net income from sale of crops and residues in our estimate for changes in human capital (Aly & Managi 2018). We do not consider changes in support prices provided by the government to farmers over the 10-year period of model run (2019-2029) and assume that support prices do not rise in real terms.

We estimate total farmer income from the rice-wheat cropping system in Punjab as

$$Income = Income_{per\ ha} * \ Area \qquad \text{...... Equation 29}$$

where,
$Income_{per\ ha}$ = annual farmer income per hectare of land cropped (see Materials & Methods Section 2 and Equation 16)
Area = total area cropped annually (see Supp. Data Table S3)

Natural capital: Natural capital includes natural resources such as oil, timber, land, water etc. We estimate changes in natural capital as changes in groundwater stock due to the agricultural system of Punjab, assuming total cropped area remains constant with each intervention. The value of groundwater can be estimated by calculating the value of foregone production due to groundwater extraction but needs careful application of discount rate (discount rates for natural capital are controversial) and marginal human impact on groundwater stock (e.g., how human action such as varying rates of pumping affect groundwater stock) (Fenichel & Abbott 2014; Fenichel et al. 2016). We estimate of the value groundwater stock as the value of foregone rice and wheat production due to groundwater extracted:

$$\Delta Natural\ capital = (\textstyle\sum_{rice,wheat} MPP * \ MP * \ Ratio\ of\ water\ usage) * Groundwater \qquad \text{...... Equation 30}$$

Where,
MPP = marginal physical production of rice and wheat estimated by Srivastava et al. (2015) as 195 kg/ha-m and 1056 kg/ha-m respectively (using a log-linear regression

model for Punjab with yield of rice or wheat as the dependent variable). This represents the additional output of rice or wheat for an incremental unit of groundwater (1 ha-m).
MP = marginal price of rice and wheat. We assume the minimum support prices (19.25 INR/kg for rice and 20.24 INR/kg for wheat (Punjab Agricultural University 2019; Punjab Agricultural University 2020)) at which rice and wheat were procured in 2019 as the marginal prices
Ratio of water usage = By our model estimates, irrigation of rice accounts for about 66% of annual groundwater extraction in Punjab's rice-wheat cropped area and wheat accounts for remaining 34%
Groundwater = groundwater extracted for irrigating rice and wheat in 2019

We estimate the value of foregone future production of rice and wheat due to pumping an additional hectare-metre of groundwater at present at 135 USD (compared to 57 USD and 138 USD estimated by Fenichel (2016) using a 7% and 3% discount rate respectively for Kansas, USA). We do not discount the value of future crop production to emphasize on inter-generational equity in the long-term sustainability of the agricultural sector of Punjab. We also assume that groundwater is available as required in the future (there is no discontinuity in the availability of groundwater) and the future foregone production is due to incremental unavailability of groundwater.

Carbon damages: Climate change is a global externality and the available estimates of social cost of carbon (SCC) provide a measure of the marginal cost of global damages caused by CO_2 (Greenstone et al. 2013). Estimates for SCC vary widely due to uncertainties in economic harm expected from CO_2 (damage function) and in the sensitivity of the climate system's response to CO_2, among other factors (Ricke et al. 2018; Stern & Stiglitz 2021). Studies provide a range of SCC estimates (in 2019 terms): 32.5 USD/t CO_2 in 2020 growing at 1.9% per year (Greenstone et al. 2013); 42 USD/tCO_2 in 2020 growing at 3% per year (EPA 2016); US administration's latest announced value at 51 USD/tCO_2 (Chemnick 2021); a range of 32.5 – 95 USD/tCO_2 in 2025 depending on emissions reduction target (Kaufman et al. 2020); and as high as 409 USD/tCO2 in 2020 (Ricke et al. 2018). Ricke et al. (2018) specify country-level SCCs or the marginal damage caused in each country due to an additional unit of CO_2 emitted – India has the highest country-level SCC at 86 USD/tCO_2 (range of 49-157 USD/tCO_2) in 2020.

We use a conservative value of 32.5 USD/tCO_2 (Greenstone et al. 2013) and the country-level SCC of 86 USD/tCO_2 (Ricke et al. 2018) to highlight the uncertainty in damages caused by GHG emissions. We estimate the damage caused by GHG emissions using the following relation:

$$\Delta Carbon\ damages \quad = GHG\ x\ SCC \qquad \text{….. Equation 31}$$

where,
GHG = Total GHG emissions in CO_2 equivalent

SCC = Social cost of carbon estimated at 32.5 USD/tCO_2 in 2020 or 86 USD/tCO_2 (see above)

The social and environmental costs of nitrogen pollution from fertilizer application are site-specific and challenging to estimate; they include the warming impacts of N_2O emitted into the atmosphere, nitrate pollution in groundwater and soil, and emissions of ammonia which lead to acid rain, soil acidification, and other effects (Good & Beatty 2011; Keeler et al. 2016). We estimate only the damages caused by N_2O as a GHG emitted through fertilizer application since the social cost of carbon is spatially generalizable, accounting for the higher global warming potential of N_2O (GWP = 296(Venkataraman et al. 2016)) using Equation 31.

1% of nitrogen in fertilizers applied is emitted as N_2O (1 tonne of nitrogen fertilizer releases = 0.01*44/28=15.7 kg N_2O; ratio of mol. Weights of N_2O and N = 44/28) and each tonne of nitrogen fertilizer releases 7.22 kg of N_2O through atmospheric ammonia oxidation (Good & Beatty 2011). This results in a total of 23 kg N_2O released with the application of 1 tonne of nitrogen fertilizer.

Table S4 presents the estimated changes in inclusive wealth (monetary values of capital stocks) due to interventions over the period 2019-2029, relative to a No New Policy scenario (see Table 4 for estimated changes in inclusive wealth in the No New Policy scenario). See Supp. Data Tables SD7-SD14 for detailed estimates of quantitative impacts of interventions on sustainability metrics (changes in physical and monetary values of stocks) for the period 2019-2029.

Interventions	**Change in human capital**	**Change in natural capital**	**Carbon damages**
Effective ban on residue burning : by paying farmers and raising awareness	376 - 613	-	13 - 36
Use of residues in power plants: 600 MW biomass power plants	118 - 190	-	2 -5
Use of residues in power plants: Cofiring 10% (or 4.4GW) of state-owned coal power plants	372 - 596	-	3 - 8
Fertilizer subsidy reform : Optimal use of urea	2 - 3	-	2 - 8

Power subsidy reform: guaranteed but rationed power to reduce groundwater extraction for rice by 33%	-0.3 to 1.7	1.1	-0.2 to -0.7
Promote wide-scale use of Happy Seeder (HS): HS use tripled	379 – 614	0.1	14 - 40
Government procurement of pulses: 50% shift from rice to pulses	466 - 762	1.1	13 - 35

Table S4: Cumulative changes in capital stocks relative to base case (No New Policy) 2019 -2029 *(all values in billion USD; range of values depicts range of marginal values of capital stocks)*

Text S5: Details on expert interviews

We conducted four semi-structured interviews with researchers who specialize in different aspects of the agricultural sector of Punjab, India. The policy interventions considered in this work are widely discussed in policy, academic and development circles but have not been implemented on a large scale yet. Our interview questions were aimed at understanding existing institutional barriers to effective policy implementation and helped inform our selection of policy options in this work.

We conducted interviews with the following experts:

Researcher at University of British Columbia's Institute for Resources, Environment & Sustainability, who conducted extensive interviews with farmers in Punjab to understand their perspectives on agricultural residue management. (Interview date: December 14, 2020).

Researcher at University of British Columbia's Institute for Resources, Environment & Sustainability, whose research focuses on irrigation policies that can reduce the adverse environmental impact of the cropping system in India, particularly in Punjab. (Interview date: February 12, 2021)

Researcher at the Council on Energy, Environment & Water (India), working on air pollution and crop residue burning in north India, with a particular focus on technological alternatives to residue burning such as use of residues in power plants. (Interview date: February 24, 2020) .

Researcher at Pennsylvania State University whose work focuses on agricultural markets in India, and particularly on policy issues related to the economics of crop diversification in Punjab. (Interview date: December 1, 2020).

Data Set S1. Data Tables SD1-SD14

Data Set S1 includes the following tables:
Data Table SD1: List of system components and their attributes
Data Table SD2: Detailed interaction matrix between system components
Data Table SD3: Attributes of crops and residues: crop production, protein content and residue generation
Data Table SD4: Attributes of crops: use of agricultural inputs for crop production
Data Table SD5: Attributes of technical components: Emission factors and GWP
Data Table SD6: Values of system components' attributes at t=1 (year=2019)
Data Tables SD7-SD14: Detailed quantitative impacts of interventions on sustainability metrics