Essays on Air Pollution, Global Warming and Agricultural Productivity

Ridhima Gupta

Thesis submitted to the Indian Statistical Institute

in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

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Introduction: Motivation and Main Results

This dissertation consists of three chapters, each of which deals with a particular aspect of environmental policy. The first chapter focuses on the determinants of open-field burning of rice-residue with the aim of analysing possibilities for its regulation. Open field burning is the second-largest contributor to black carbon in South Asia, the second most important greenhouse agent after carbon dioxide. Thus, dealing with the problem of burning of rice residue will tackle a significant proportion of the black carbon emissions released into the atmosphere. The third chapter proposes a new approach for estimating the contribution of agricultural fires to atmospheric aerosols. This approach exploits the recently available satellite data on agricultural fires and AOD to conduct regression analysis.

The second chapter of this dissertation deals with the impact of pollution and global warming on wheat yields in India. Relationships between wheat yield and daily maximum temperature and daily minimum temperature and solar radiation were evaluated by analysing data from 208 districts of India covering the period 1981-2009. The estimated weather parameter from the estimated regressions were used to assess the impact of recent climate trends and the impact of future climate change on wheat yields.

I will now discuss each of these essays in brief by outlining the motivation and major results. In the chapters that follow, we discuss each of them in greater detail.

1.1 Low-hanging fruit in black carbon mitigation: crop residue burning in South Asia

Biomass burning in South Asia is a significant contributor to global emissions of black carbon, the second most important greenhouse agent after carbon dioxide. Emissions from domestic fires are the largest contributor to biomass burning but may be costly to mitigate. Open field burning is the second-largest contributor to black carbon in South Asia. This chapter uses primary field data to identify the determinants of emissions from open-field burning of crop residue with the aim of analysing possibilities for its regulation. The effectiveness of a new seeding machine that lets farmers plant their crops without having to burn the residue from the previous crop is assessed. A comparison of the new machine with conventional practice shows that the new technology decreases field preparation costs but does not significantly impact crop yield and profits. The use of plot-level data with farmer fixed effects enables reliable identification of the impacts of the technology. Given the considerable adverse effects on mortality and health of pollution from burning, these results imply that this source of black carbon can be mitigated at zero private cost and negative social cost. Since farmers have no strong private incentive to adopt the new technology, extension and subsidies to accelerate adoption would be a high net-benefit policy.

1.2 Global warming and local air pollution have reduced wheat yields in India

Regression analysis on data from all major wheat growing districts of India was used to examine the effect of temperature, solar radiation (affected by pollution from aerosols), and rainfall on wheat yields in India. Estimates from models with district fixed effects and time trends indicates that a 1°C increase in average daily maximum and minimum temperature tends to lower yields by 2-3% each. Solar radiation has a one-for-one positive effect on yields indicating that pollution reduction that reduces solar dimming could raise yields. The estimated weather parameters from these regressions were used to assess the impact of recent climate trends and the impact of future climate change on wheat yields. The maximum and minimum temperature during the wheat-growing season has increased by 0.7°C and 1°C over the period 1981-2009. Wheat yields in India would have been higher in 2009 by 4.8% (95% CI: [2.4, 7.4])if this temperature increase had not occurred. Results of the estimation of the impact of future climate change predict even higher losses ranging from 12.3% for mid-term climate change (2010-2040) and up to 17.4% by 2070.

1.3 Fires and Aerosol Pollution In India

Open burning of agricultural fields is a major and neglected source of aerosol pollution in South Asia. Current knowledge of the magnitude of the emissions from field-burning is based on data on crop production, waste to grain ratios,and emission coefficients reported in the literature. Here, we introduce a new approach of estimating these emissions by using satellite data on fires and aerosol optical depth (AOD). Regression analysis was conducted on this data to estimate the contribution of agriculture fires to aerosol pollution over the period 2001-2008. Compared to previous methods, we found a small effect of fire count on AOD. We cannot rule out the possibility that this was because the satellite data on fires fails to detect the small-scale agricultural fires. The contribution of our study is that its methodology can be applied to higher resolution data which is expected to become available and would give a better measure of the fire counts.

2

Low-hanging fruit in black carbon mitigation : crop residue burning in South Asia

2.1 Introduction

Biomass burning in South Asia is a significant contributor to global emissions of black carbon, the second most important greenhouse agent after carbon dioxide. Emissions from domestic fires are the largest contributor to biomass burning but may be costly to mitigate. Open field burning is the second-largest contributor to black carbon in South Asia (Bond, Doherty, Fahey, Forster, Berntsen, DeAngelo, Flanner, Ghan, Kärcher, Koch et al., 2013). This source contributes about 20% of carbonaceous aerosol emissions in South Asia (Venkataraman, Habib, Kadamba, Shrivastava, Leon, Crouzille, Boucher, and Streets, 2006). Previous studies have focused on estimating emissions from open burning of agricultural fields or on analysing its impact on climate and public health. Thus, it is widely recognised to be a key environmental problem facing this region. Yet policy makers have done little to solve it as mitigation strategies for dealing with this problem remain unexplored. Consequently, residue burning goes unchecked in Asia. This study attempts to fill this gap. I use primary field data to identify the determinants of emissions from open-field burning of crop residue with the aim of analyzing possibilities for its regulation. Curbing emissions of black carbon has an immediate payoff because black carbon is quickly washed out and can be eliminated from the atmosphere if emissions stop (Bond et al., 2013).

Reductions in emissions of black carbon are warranted from considerations of regional climate change and human health. For example, in the Himalayan region, warming from black carbon at higher elevations has as large an effect on the melting of snow packs and glaciers as warming due to greenhouse gases (Ramanathan and Carmichael, 2008). This not only has implications for the hydrological cycle, it also intensifies warming. As the glaciers melt, darker areas beneath them get exposed that in turn absorb more sunlight.

Black carbon being a component of particulate matter (PM) has a large adverse impact on public health. Lim, Vos, Flaxman, Danaei, Shibuya, Adair-Rohani, AlMazroa, Amann, Anderson, Andrews et al. (2013) attribute 6% of all deaths in India in 2010 to ambient particulate matter pollution. Preventing black carbon can prevent on average 0.7-4.6 million premature deaths annually from outdoor air pollution world-wide by 2030, particularly in Asia (UNEP, 2011).

Open burning of agricultural residue contributes to the creation of the Atmospheric Brown Cloud, a layer of air pollution that covers large parts of South Asia (Gustafsson, Krusa, Zencak, Sheesley, Granat, Engstrom, Praveen, Rao, Leck, and Rodhe, 2009). Atmospheric Brown Cloud consists of aerosols such as black carbon, organic carbon, dust, sulfates and nitrates. Ramanathan, Chung, Kim, Bettge, Buja, Kiehl, Washington, Fu, Sikka, and Wild (2005) attribute the observed decrease in all India averaged monsoon rainfall since 1950's (June-September) to Atmospheric Brown Clouds. Auffhammer, Ramanathan, and Vincent (2006) found that joint reductions in brown clouds and greenhouse gases had complementary, positive impacts on rice harvests in India over the period 1972-1998. Harvest reductions attributed to brown cloud pollution are estimated to have grown from 3.94% during the 1966-84 period to 10.6% during the 1985-1998 period.

The impact of black carbon on regional climate, in conjunction with its health impacts provides a strong rationale for reducing black carbon emissions in developing countries like India where they have been rising overtime. Between 1996 and 2010, black carbon emissions increased by 41% in India (Lu, Zhang, and Streets, 2011). Estimates from (Venkataraman et al., 2006). indicate that farmers in India burned 116 million metric tonnes of crop residue in 2001, but with strong regional variation. Open burning of cereal residue was estimated to account for about 14% of black carbon and organic matter, and 10% of carbon monoxide emissions, 9% of PM2.5 (particulate mass in particles smaller than 2.5 microns in diameter), 6% of carbon dioxide emissions, and about 1% of sulphur dioxide emissions in India. Field burning in the major agricultural states of Punjab, Haryana and Western Uttar Pradesh was the largest contributor to these emissions. Yang, He, Lu, Chen, and Zhu (2008) estimated the emissions from crop residue burning in the Suqian region of the Jiangsu Province of China. Their results suggest that farmers burnt about 82% of the wheat straw and 32% of the rice straw in the field during the period 2001-2005. Gadde, Bonnet, Menke, and Garivait (2009) estimate that farmers annually burn about 10 million tons of rice straw in Thailand and 10 million tons of rice straw in Philippines.

Biomass regulation from open burning of agricultural residue, therefore, becomes both a national and an international priority. Here, I investigate the following questions: what factors explain the open-field burning of rice residue in India and what are the available alternatives to this practice? Understanding why farmers resort to burning is essential for policy makers to arrive at suitable mitigation policies which would reduce rice residue burning in the region.

Burning of rice residue is a part of the 'rice-wheat cropping system' (RWCS) that is the dominant cropping system in the Indo-Gangetic Plains of South Asia. Rice is grown in summer and wheat in winter. Uttar Pradesh, Punjab, Haryana, Bihar, Madhya Pradesh and Himachal Pradesh have the largest areas under this system among the Indian states (Hobbs and Morris, 1996). Rice residue is the biggest contributor to emissions from open-field burning of crop residue in this region (Badarinath, Chand, and Prasad, 2006). In fact, the Indo-Gangetic plains have been identified as a regional hotspot of Atmospheric Brown Clouds (Ramanathan, Li, Ramana, Praveen, Kim, Corrigan, Nguyen, Stone, Schauer, Carmichael et al., 2007).[1]

In this chapter, I use farm-level data to address the possibility of mitigating emissions from open-field burning of rice residue in Punjab, India. Punjab is the largest producer of wheat

[1]ABC hotspots are defined as regions where the annual mean anthropogenic aerosol optical depth (AOD) exceeds 0.3 and the percentage of contribution by absorbing aerosols exceeds 10 percent (absorbing AOD > 0.03).

and the third largest producer of rice among Indian states. Rice and wheat are grown on an agricultural area of more than 2 million hectares and more than 80% of the 24 million tonnes of rice stubble is burnt each year (Tiwana, Jerath, Ladhar, Singh, Paul, Dua, and Parwana, 2007).

My survey of a representative sample of farmers collected information on the method of residue disposal and its determinants for the purpose of identifying the factors that explain open-field burning of rice residue. I find that the use of coarse (as opposed to higher-priced Basmati) varieties of rice increases the likelihood of farmers harvesting rice using the combine-harvester, which in turn scatters residue and therefore makes the burning of biomass almost certain.

A second survey examined a new seeding machine called the Happy Seeder, which obviates the need to burn rice residue. I conclude that it has the potential to reduce emissions from residue burning in Punjab. The Happy Seeder is a tractor-mounted machine that cuts and lifts the rice straw, sows wheat into the bare soil, and deposits the straw over the sown area as mulch.[2] Farmers can therefore sow wheat immediately after the rice harvest, without having to burn the rice residue.

A comparison of the Happy Seeder with conventional practice shows that that the new technology decreases field preparation costs but does not significantly impact crop yield and profits. Adoption of the Happy Seeder technology may therefore be slow since it has no strong advantage from the viewpoint of profits. Given the considerable adverse effects on mortality and health of pollution from burning, these results imply that there are net private benefits from mitigating this source of black carbon. Accordingly, there is a strong case for promoting the machine through extension and subsidies in order to reduce residue burning, the costs of which are mostly external to the farmer.

[2]Mulch refers to a protective cover placed over the soil to retain moisture, reduce erosion, provide nutrients, and suppress weed growth and seed germination.

The rest of the chapter is organized as follows. The following Section describes the sampling design. Section 3 discusses the factors that explain rice residue burning in Punjab. Section 4 analyses the profitability of the Happy Seeder technology and Section 5 concludes with policy implications.

2.2 Study Area and Sampling

My study area is the state of Punjab in India. I chose Punjab for the study because, at the time the research was done in 2010, the Happy Seeder technology was available only in that state. The empirical analysis uses two samples, the first, a representative sample of farmers and the second a sample of users of the Happy Seeder machine. The representative sample of farmers was selected from the districts of Amritsar, Ludhiana and Sangrur. These districts were purposively chosen to capture the geographical variation that exists across Punjab. The villages were chosen using probability proportional to size sampling procedure. Thirty villages and ten households were randomly surveyed within each village. The data collected includes information on costs incurred by 300 farmers in preparing the field for the wheat crop by conventional tillage.[3]

The second survey gathered information for the assessment of the Happy Seeder machine. Data was collected from all 92 Happy Seeder users spread across the 7 districts of Punjab. Most users experimented with it on only a part of their farms.

The two surveys were conducted between January and April in 2010, with a follow-up via telephone during June 2010 in order to obtain data on the yield of the wheat crop for all

[3]Since there would be people who did not engage in any farming activity in each village, forty households were randomly selected from each voter list. If the first household among the forty households was a farm household, I included it in the survey. If that was not the case, I dropped it and contacted the second household. This procedure was followed until the enumerator was able to complete nine interviews. In order to find out if farmers with large landholdings behaved differently from farmers with small landholdings, I included one farmer with large landholdings from each village in the sample. This was accomplished by asking the respondents to provide the names of the five largest landowners in their village. I randomly selected one farmer from this list for the interview.

respondents.

2.3 Determinants of Rice Residue Burning

Presently, four options are available to the farmers for the disposal of residue, namely, the complete burning of residue, the partial burning of residue, the incorporation of residue into the soil and removal of the residue from the field.

The mode of harvesting strongly influenced the choice of crop residue disposal. Farmers burnt 1% of the area that they manually harvested while they burnt 90% of the area that was harvested by the combine-harvester (see Table 2.1). This is because manual harvesting allows for easy retrieval of the rice residue since the rice plant is cut close to ground level and collected into bundles for subsequent threshing. The recovery of stalks and stubble after harvesting by a combine-harvester, on the other hand, is more problematic since the cut residue (loose residue) is scattered all over the harvested fields. So additional labour is required to collect the loose residue.

There is an active rental market for machines in the study area. Thus, farmers can access the combine-harvesters and other machinery at modest rates.

Table 2.1 also shows that the rice variety grown by the farmers, the choice of coarse or Basmati (fine grain) varieties[4], in turn drives the choice of the mode of harvesting. I observed that farmers were more likely to harvest Basmati varieties manually. Two factors explain this observed difference, the most striking being the price differential between Basmati and coarse varieties with the former fetching between two and three and a half times the price of the latter.

[4]The districts of Amritsar, Tarn Taran, and Gurdaspur, comprise the Basmati belt of Punjab. This is because the agro-climatic conditions of this region are conducive to growing Basmati varieies

Table 2.1: Variety-wise and Mode of Harvesting-wise disaggregation of the Method of the Residue Disposal in Punjab, 2010

Variety of Rice - Basmati				
	Manually Harvested		Combine Harvested	
	% of the Area	Area in Hectares	% of the Area	Area in Hectares
Fully Burnt	1	2	57	53
Partially Burnt	0	0	16	15
Incorporated	0	0	18	17
Removed	99	175	9	9
Total	100	177	100	94
Variety of Rice - Coarse				
Fully Burnt	–	0	76	657
Partially Burnt	–	0	16	141
Incorporated	–	0	4	33
Removed	–	0	4	38
Total	–	0	100	869

Given that the use of the combine-harvester results in a loss of grain and given that the price of Basmati rice far exceeds the price of coarse rice, farmers prefer to opt for manual harvesting of Basmati varieties in order to minimize this loss. On the other hand, it is also much cheaper and quicker to use combine-harvesters than to employ labor. These time savings are dear to the farmers as there is only a short time period between rice harvesting (mid October-early December) and the sowing of wheat, which takes place between November and early December. Any delay in planting reduces the productivity of the wheat crop (Gupta, Sahai, Singh, Dixit, Singh, Sharma, Tiwari, Gupta, and Garg, 2004). Consequently, combine-harvesters are popular with farmers for coarse varieties.

The above findings are confirmed by a recursive bivariate probit model with the methods of harvesting and residue burning as the two dependent variables with the method of harvesting being an explanatory variable in the residue burning equation. Absence of a market for rice residue in the surveyed districts suggests that the method of residue disposal does not influence the choice of the method of harvesting. Thus, in terms of profits, the residue disposal decision is not as important as the choice of the mode of harvest. Hence, I do not control for the method of residue disposal in the equation on the mode of harvesting.

The control variables used in this study to explain the choice of the method of residue disposal and the mode of harvesting come out of the profit maximizing exercise of the farmer. Even though profits are not modeled explicitly, the preceding discussion seeks to identify which heterogeneous characteristics of farmers and their growing conditions influence their choice of harvesting and residue disposal. This discussion implies that the mode of harvesting, proxies for scale of operation and technical ability of the farmer, family size, age of the farmer and farm location explain the choice of the method of residue disposal. Farm location enters this equation owing to the enforcement of a ban on burning rice residue in Amritsar prior to the rice-harvesting season. The punishment given out to violators of the ban was the permanent disconnection of the power supply by the Punjab State Electricity Board.

Turning to the explanatory variables in the equation on the mode of harvesting, these are, the rice variety farmers sow on a plot, ownership of livestock, farm size, family size, rental rate of a combine-harvester in the village, rental rate of contract labor in the village, age and education of the farmer, proxies of technical ability of the farmer and farm location. The rice variety that farmers sow has direct implications for the mode of harvesting (manual or combine). Small-scale farmers may be more inclined to use their own labor or employ labor to harvest Basmati varieties. Farmers who own livestock are more likely to harvest the crop manually. However, I allowed for this effect to vary with the rice variety that farmers sow since they prefer the residue of the Basmati variety for the purpose of feeding livestock. The location of the farm may influence the mode of harvesting even after controlling for the rice variety that farmers grow. This is because farmers in Amritsar plant high quality Basmati varieties that are more likely to be harvested manually. The descriptive statistics of the variables are shown in Table 2.2 and the results are shown in Table 2.3 and Table 2.4.

Table 2.2: Description of the variables used in the analysis

Variables	Description	Unit of Measurement	Variables	
			Mean	S.D.
Burnt	Indexes the method of residue disposal on a plot. 1= residue is burnt ,0 otherwise	% of Plots	0.64	0.48
Combine	Whether or not farmer used a Combine to harvest rice on a plot. 1= Combine machine is used ,0=otherwise	No. of Plots	0.74	0.44
Coarse	Variety of rice sown by the farmer on a plot. 1=coarse,0=Basmati	No. of Plots	0.64	0.48
Farm Size	Size of a farm unit	Hectares	5.03	5.51
Livestock per hectare of farm area		Number	2.46	1.96
Watch	Whether or not farmer watched a television programme on farming. 1=Watches,0=Does not watch	No. of Farmers	0.56	0.50
Contact with Extension	Whether or not an extension agent visited the farmer in the year preceding the survey 1=Yes,0=No	No. of Farmers	0.24	0.43
Reads Magazines	Does the farmer read agricultural magazines. 1=Yes,0=No	No. of Farmers	0.20	0.40
Age of the farmer		No.	51.73	14.21
Education of the farmer		No.	8.16	4.1
Number of persons $\geq$ 15 years of age in the household per hectare of farm area sown to rice		No.	2.71	2.91
Rental rate of combine-harvester in Village		Rs. per Hectare	1889.55 ($16.34)	400.05
Rental rate of Contract Labour in Village		Rs. per Hectare	5882.72 ($50.84)	1460.73
Amritsar	Dummy variable that equals 1 if plot is located in Amritsar	No. of Plots	0.32	0.47
Number of Plots	No.	No.	604	
Number of Farmers	No.	No.	268	

Table 2.3: Marginal Effect of the Variables on the probability of using a combine-harvester

Variables	Probit Method (Marginal Effect)	Linear Probability Model with: Farmer Fixed Effects (Marginal Effect)	Linear Probability Model with: Village Fixed Effects (Marginal Effect)
Coarse	.6275***	.5036***	.5123***
	(17.98)	(8.38)	(7.42)
Livestock per hectare	-.0254***	–	-0.0535***
	(-2.75)	–	
Livestock per hectare *Coarse	.0710**	.0669***	.0537***
	(2.33)	(3.46)	(3.07)
Farm Size	.0009	–	.00103
	(0.48)	–	(0.55)
Number of Persons ≥ 15 years of Age in the Household	.0226	–	.00009
	(0.42)	–	(0.01)
Rental rate of Contract Labour in village	-.00003***	–	–
	(-3.42)	–	–
Rental rate of combine-harvester in Village	-.00004	–	–
	(-1.44)	–	–
Watch	-.0008	–	-.00009
	(-0.03)	–	(-0.00)
Contact with Extension	.0374	–	.0193
	(1.51)	–	(0.76)
Reads Magazines	-.0689***	–	-.0421
	(-2.95)	–	(-1.53)
Age of Farmer	.0016**	–	.0019*
	(2.23)	–	(1.92)
Education of Farmer	.0013	–	.0017
	(0.40)	–	(0.46)
Amritsar	-.1191***	–	–
	(-3.34)	–	–
Number of Plots	736	736	736
Number of Farmers	300	300	300

Variables	Probit Method (Marginal Effect)	Linear Probability Model with: Farmer Fixed Effects (Marginal Effect)	 Village Fixed Effects (Marginal Effect)
Log Likelihood	-151.01	–	–
R Squared	–	0.51	0.49
Psuedo R Squared	0.64		

Notes: Dependent variable is Combine. Combine=1 if the farmer used a combine-harvester on a plot and 0 otherwise. Figures in parenthesis are t-ratios. For probit regression the standard errors are clustered at the farmer level and robust standard errors are reported for the farmer and village fixed effects. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Table 2.4: Marginal Effect of the Variables on the probability of burning crop residue

Variables	Probit Method (Marginal Effect)	Linear Probability Model with: Farmer Fixed Effects (Marginal Effect)	Linear Probability Model with: Village Fixed Effects (Marginal Effect)
Combine	.7960***	.7747***	.7102***
	(27.26)	(18.19)	(14.48)
Farm Size	-.0009	–	.0020
	(-0.34)	–	(0.65)
Number of Persons Equal to or Above 15 years of Age in the Household	-.0175*	– 0	-.0202**
	(-1.92)	–	(-2.20)
Watch	-.0098	–	-.0122
	(-0.37)	–	(-0.40)
Contact with Extension	.0084	–	-.0147
	(0.28)	–	(-0.62)
Reads Magazines	-.0417	–	-.0537*
	(-1.23)	–	(-1.75)
Age of Farmer	.0012	–	.0012
	(1.22)	–	(1.38)
Education of Farmer	-.0002	–	-.0022
	(-0.05)	–	(-0.58)
Amritsar	-.2332***	–	–
	(-4.79)	–	–
Number of Plots	736	736	736
Number of Farmers	300	300	300
Log Likelihood	-190.957	–	–
R Squared	–	0.70	0.50
Psuedo R Squared	0.60		

Notes: Dependent variable is Burnt. Burnt=1 if the farmer burnt residue on a plot and 0 otherwise. Figures in parenthesis are t-ratios. For probit regression the standard errors are clustered at the farmer level and robust standard errors are reported for the farmer and village fixed effects. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

As expected, the use of a combine-harvester exerted the most substantial effect, on average, on the probability that farmers will burn residue on a plot whereas choice of the mode of harvesting was driven by the variety of rice that the farmer sold. Plots located in Amritsar on average were less likely to get burnt than plots situated in Ludhiana and Sangrur due to the ban on burning rice residue in this region. Farmers in this area were also significantly less likely to use a combine-harvester opting for manual harvesting of the high quality Basmati varieties. These findings are consistent with the results obtained from the models that include farmer-fixed effects and village-fixed effects (see columns 2-3 of Table 2.3 and Table 2.4.). The model with the village fixed effects is the most well-identified model as it control for village-specfic unobservable characteristics. It is worth pointing out that these estimated effects are not causal but descriptive. This is because farmers may chose to plant the basmati varieties on better quality plots. Since I do not control for plot quality, there may be a correlation between the probability of using a combine-harvester and the rice-variety sown on a plot.

2.4 Examination of an Available Alternative to the Problem of Burning: The Happy Seeder Technology

The results imply that the most important determinant of the decision to burn rice residue is the use of a combine-harvester. Its prevalence is not amenable to policy intervention because the advantages that combine-harvesters offer in terms of savings in money and time as well as reduced supervision of labor have made them immensely popular with farmers. At present farmers use combine-harvesters mainly to harvest coarse varieties of rice in Punjab. However, farmers who face a labor shortage may resort to mechanical harvesting even in the case of the Basmati varieties. Labor scarcity will therefore lead to an increase in the use of combine-harvesters among farmers. Although a strict ban on burning rice-residue may make the problem of residue burning less severe, in the absence of any economically viable alternative to burning, the ban will not succeed in eradicating emissions from the open burning of rice fields.

It is possible to make a modification to the combine-harvester enabling the residue to be collected separately. However, this raises questions about the utilization of residue. Given that rice residue is of limited value to the farmers, whether as livestock feed or non- feed use, it remains to be seen whether uses can be found for rice residue outside the agricultural sector. The Government has introduced balers in the district of Amritsar. In addition, a sugar mill in the district is also using the baled residue to generate electricity in this district. However, the baling of residue may not be a viable mitigation strategy as the supply of baled residue may outweigh its demand.

Another viable alternative is to develop machines that allow farmers to plant wheat into the loose residue. The Happy Seeder technology performs this function in the context of rice residue. Engineers of CSIRO Griffith at Punjab Agricultural University developed the first prototype of the Happy Seeder in July 2001. At the time of the field survey, a manufacturer at Ramdass in the district of Amritsar in Punjab was manufacturing the Happy Seeder which had been first sold to a farmer in the district in 2007. The Happy Seeder technology is currently undergoing modifications in its design and engineers continue to test its performance.

Thus, an important research question is whether the Happy Seeder technology is a viable alternative to open-field burning of rice residue. I address this question in the next section.

2.4.1 Comparison of Profits from the Happy Seeder and conventional technology

2.4.1.1 Comparison of Yields

To determine the impact of the Happy Seeder technology on wheat yields in comparison with conventional tillage, I ran regressions of yield on various covariates that included farmer fixed effects. Plot level data collected from the users of the Happy Seeder was used to conduct these regressions. The farmer fixed effects eliminate any unobservable factors among farmers that might simultaneously affect yield and the performance of the Happy Seeder technology.

The explanatory variables include a set of plot-level and farmer-level characteristics (the size of the plot, soil type, quantity of fertilizers applied to a plot, age and education of the farmer and variables that measure the technical ability of the farmer such as whether the farmer watched a television program related to farming, etc.), and a dummy variable for the Happy Seeder.

It is not possible to control for the mode of irrigation as all farmers in the sample use a tube-well for irrigation. Since the government gives farmers electricity for free in Punjab, they are unable to provide information on the expenditure incurred on irrigation or the quantity of water used for irrigation. However, the farmer-fixed effect captures the effect of the quantity of water used for irrigation.

For the coefficient on the Happy Seeder variable to have a causal interpretation, any unobserved determinants of yield must remain uncorrelated with the Happy Seeder variable. Since farmer-fixed effects account for any potential confounding farmer-level characteristics, conditional on the other independent variables, any correlation between yield and the error term must be on account of unobserved plot-level characteristics. If the wheat variety that farmers sow on a plot affects yield and correlates with the Happy Seeder variable, the estimated coefficient on the Happy Seeder variable will be biased. Focus group discussions with farmers suggest that the wheat variety that farmers sow does not significantly affect the yield of wheat. The yields differ at most by a magnitude of 1-2 quintals per acre across varieties. However, to rule out the possibility of correlation between the wheat variety that farmers sow and the Happy Seeder variable, I control for the variety of wheat sown in the yield and the profit regressions. There may also be a plot-specific selection effect as farmers may choose to use the Happy Seeder on plots that they believe are more suited for this technology. I control for the type of soil in a plot to account for this effect. Moreover, Happy Seeder is a new technology so farmers are unlikely to be aware of the plot characteristics that are appropriate for this technology. Hence, I can assume plot selection to be random.

2.4.1.2 Comparison of Costs

The second question that I investigate in this section is whether the Happy Seeder technology was a low or high cost alternative to conventional field preparation. For this purpose, I estimate regressions taking the cost incurred per hectare in establishing the wheat crop as the dependent variable. The independent variables in these regressions include the controls in the yield regressions, the output of the wheat crop in a plot, and the mean price per kg of fertilizer paid by the farmer.[5]

A prerequisite for using the Happy Seeder is that the loose rice straw left by the combine-harvester should be spread uniformly on the field. Farmers mostly employed labor for spreading this residue as combine-harvesters with a spreader attached to them are not widely available. In addition, farmers incurred expenditure on the purchase and application of weedicide and fertilizers. Farmers who had utilized their own labor or equipment for field preparation were assigned the prevailing rate of that activity in their village.

The cost per hectare to prepare the field using the Happy Seeder machine comprised the cost of hiring the Happy Seeder, the cost of the diesel to run it and the costs of purchasing and applying weedicide and fertilizers. The cost per hectare of establishing wheat with conventional tillage was calculated in the same manner with the cost of hiring farm equipment replacing the cost of hiring the Happy Seeder machine.

2.4.1.3 Comparison of Profits

I also ran regressions taking profit per hectare from wheat production as the dependent variable to see whether the Happy Seeder technology is a profitable alternative to conventional tillage. The controls in these regressions are similar to the controls in the cost regression except that I do not control for the yield of the wheat crop. The descriptive statistics of the variables used in the analysis are reported in Table 2.5.

[5]Nine respondents had purchased the Happy Seeder implement and consequently did not incur any expenditure to hire it. They were assigned the average cost of hiring the Happy Seeder that prevailed in their district. If village level rates were not available, district level estimates were used to impute these rates.

Table 2.5: Comparison of plot characteristics across users of Happy Seeder

Variables	Unit	Means (Standard Errors in Parenthesis)			
		Plots sown with CT	Plots sown using Happy Seeder	Entire Sample	T-test Difference in Means
Yield per hectare	Quintals	43.81 (0.474)	43.31 (0.710)	43.57 (0.419)	0.50 (0.841)
Cost per hectare	INR	7288.54 (291.70)	6225.3 (141.67)	6780.32 (171.44)	1063.24 (333.69)
Profit per hectare	INR	40024.4 (583.73)	40548.27 (762.23)	40274.81 (473.89)	-523.87 (950.79)
Happy Seeder	No. of plots	—	—	(0.48) (0.04)	–
Plot Size	Hectares	6.039 (0.632)	5.342 (0.646)	5.706 (0.451)	0.70 (0.905)
Fertilizer	Kg	473.09 (9.65)	461.00 (11.14)	467.28 (7.32)	12.03 (14.67)
Price of Fertilizer	Price per Kg	–	–	7.14 (0.022)	–
Age	No.	48.92 (1.44)	49.83 (1.43)	49.35 (1.01)	-0.91 (2.03)
Education	No.	10.30 (0.293)	10.05 (0.375)	10.18 (0.235)	0.25 (0.471)
Watch	No. of farmers	0.57 (0.055)	0.59 (0.057)	0.58 (0.04)	-0.03 (0.079)
Contact with Extension	No. of farmers	0.69 (0.051)	0.65 (0.055)	0.67 (0.038)	0.04 (0.075)
Reads Magazines	No. of farmers	0.48 (0.055)	0.49 (0.058)	0.48 (0.04)	-0.005 (0.08)
%of plots		52	48	100	
No. of Farmers		66	66	66	

Notes : CT refers to conventional tillage. The Happy Seeder technology was made available to 22 respondents free of cost whereas 1 farmer could not be contacted for obtaining the data on the yield of the wheat crop. 3 farmers burnt the rice stubble prior to using Happy Seeder. This reduced the sample size to 66 farmers for the profitability analysis.

2.4.2 Results

Table 2.6 contains estimates of the effect of Happy Seeder on yield per hectare, cost per hectare and profit per hectare of wheat sown. Columns 1 to 3, report the results of the regression model which has yield per hectare as the dependent variable. Column 1 shows the results of the random-effects model. The coefficient on the Happy Seeder variable was negative about -0.5, small compared to the mean of 43 and standard deviation of 5 tonnes/ha, and statistically insignificant. Thus, I do not find any impact on the yield from using the Happy Seeder. The results in column 2 of Table 2.6 are estimates of the farmer-fixed effects model. I continue to find no effect on the yield of the wheat crop from operating the Happy Seeder. Column 3 presents the results of the pooled least squares estimation. The least squares results also imply that the Happy Seeder technology had no effect on the output of the wheat crop relative to conventional tillage.

Columns 4 to 6 display the results of the equation with the cost incurred per hectare to prepare the field of wheat as the dependent variable. The results from all the models indicate that on average the Happy Seeder technology was a significantly lower-cost alternative compared to conventional tillage. Since the fixed-effects model controls for confounding factors at the farmer level, the result strongly indicates that among farmers who used the Happy Seeder technology, the plots that they cultivated using the Happy Seeder technology, on average, incurred a lower cost than those prepared by conventional tillage. This cost saving amounted to INR 1055 per hectare (USD 23).

Columns 7 to 9, present the results of the model that estimates the effect of Happy Seeder technology on profitability. The results show that on average the Happy Seeder is a not a more profitable alternative to conventional tillage, a finding that is consistent across specifications.

Table 2.6: Estimates of Yield, Cost and Profit per hectare from Wheat Production in Punjab in 2009-2010

Variables	Yield per Hectare			Cost per Hectare			Profit per Hectare		
	RE (1)	FE (2)	OLS (3)	RE (4)	FE (5)	OLS (6)	RE (7)	FE (8)	OLS (9)
Happy Seeder	-0.509 (-0.70)	-0.692 (-0.95)	-0.385 (-0.49)	-1063.0*** (-3.04)	-1054.5*** (-3.13)	-997.1**** (-2.61)	571.2 (0.57)	598.6 (0.61)	466.1 (0.44)
Yield per Hectare	–	–	–	18.65 (0.59)	4.704 (0.10)	24.31 (0.81)	–	–	–
Plot Size	0.0950* (1.94)	0.0661 (1.29)	0.110* (2.12)	38.68 (1.28)	-36.06* (-1.87)	113.7*** (3.19)	11.84 (0.20)	64.97 (1.29)	-52.70 (-0.67)
Fertilizer	0.0654*** (3.35)	-0.00405 (-0.05)	0.0673*** (3.60)	–	–	–	–	–	–
Fertilizer Squared	-0.00001*** (-3.33)	-0.00002 (-0.35)	-0.00008*** (-3.52	–	–	–	–	–	–
Price of Fertilizer	–	–	–	449.2** (2.09)	–	636.5** (2.60)	-3452.0*** (-2.93)	–	-3805.4*** (-2.91)
Age	0.005 (0.13)	–	0.0008 (0.02)	-7.065 (-0.42	–	-10.68 (-0.55)	-34.52 (0.64)	–	25.96 (0.47)
Education	-0.421** (-1.98)	–	-0.446** (-2.08)	32.82 (0.62)	–	25.61 (0.39)	-97.98 (-0.45)	–	-86.62 (-0.38)
Watch	0.553 (0.50)	–	0.184 (0.16)	730.6 (1.36)	–	508.5 (0.91)	-1598.1 (-1.16)	–	-1790.6 (-1.36)
Contact with Extension	-0.933 (-0.75)	–	-1.345 (-1.11)	170.1 (0.38)	–	319.3 (0.60)	-279.5 (-0.20)	–	-739.5 (-0.51)
Reads Magazines	-0.200 (-0.17)	–	-0.077 (-0.06)	-272.0 (-0.58)	–	-458.9 (-0.89)	-438.9 (-0.30)	–	249.4 (0.17)
Number of Plots	223	223	223	159	159	159	159	159	159
R^2	0.10	0.13	0.20	0.14	0.19	0.22	0.05	0.09	0.14

Notes: Figures in parenthesis are t-ratios. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

These findings, of course, are based solely on the existing users of the Happy Seeder technology. The question that is of greater relevance to policy is whether the Happy Seeder technology will work for the general population of farmers. In order to investigate whether the users of the Happy Seeder machine are comparable in farm characteristics to representative farmers, I compared the means of farm characteristics between the two samples.

Table 2.7 shows the means of plot level characteristics between the users and non- users of the Happy Seeder. The table also reports the t-test statistics for the difference in means across plots in the two samples (see columns 4, 5 and 6). The numbers in Table 2.7 indicate that the mean output of the wheat crop is similar across the three types of plots, i.e., those that were conventionally tilled and those that were cultivated using Happy Seeder technology. This is a noteworthy feature of the estimates. It means that the general population of farmers is as productive as the Happy Seeder sample.

Table 2.7: Mean Differences between the plots of Users of Happy Seeder and Representative Farmers

	Means, Plots Sown using Conventional Tillage by Representative Farmers	Means, Plots Sown using Conventional Tillage Users of Happy Seeder	Means, Plots Sown using Happy Seeder	T-test, Differences between Means in Column 1 and Column 2	T-test, Differences between Means in Column 1 and Column 3	T-test Differences between Means in Column 2 and Column 3
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristics						
Yield Per Hectare	43.84	43.67	43.65	0.169	0.194	0.025
	(0.269)	(0.468)	(0.736)	(0.566)	(0.662)	(0.844)
Quanity of Fertilizer Applied per hectare	505.31	472.91	456.86	32.40***	48.45***	16.05
	(4.80)	(7.92)	(9.22)	(10.02)	(10.94)	(12.08)
Per Hectare Expenditure on weedicide	1115.09	980.73	899.39	134.37***	215.71***	81.33
	(19.97)	(33.54)	(47.13)	(41.66)	(47.23)	(56.24)
Number of Plots	438	122	101			
Number of Farmers	267	70	88			

Notes: Figures in parenthesis are standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Table 2.8 reports the statistics on farmer characteristics across the two samples. The users of the Happy Seeder were more educated and may be more technically able (as measured by indicators such as viewership of television programs on farming and subscription to agricultural magazines) than non-users of the Happy Seeder. They were better connected with the agricultural extension network. This is not surprising as the agricultural adoption literature highlights that a farmer's education and his connectivity with the extension network play a crucial role in his decision to adopt a new technology (Rahm and Huffman, 1984). However, what is important is that the general population of farmers are as productive as the pioneer

Happy Seeder users. So I have no reason to think that they will do any worse with the Happy Seeder.

Table 2.8: Descriptive Statistics and Mean Differences between the Users of Happy Seeder and Representative Farmers

	Means, Sample of Representative Farmers that used Conventional Tillage (1)	Means, Sample of Farmers that used Happy Seeder (2)	T-test, Differences between means in column 1 and column 2 (3)
Age of the farmer	51.81	49.36	2.45
	(0.87)	(1.34)	(1.70)
Number of Years of Education of the Farmer	8.16	9.95	-1.80***
	(0.25)	(0.36)	(0.48)
Number of Farmers that Watched a Television Programme on Farming	0.55	0.61	-0.06***
	(0.03)	(0.05)	(0.06)
Number of Farmers that were contacted by an Extension Agent	0.24	0.64	-0.40***
	(0.03)	(0.05)	(0.05)
Number of Farmers that read Agricultural Magazines	0.19	0.47	-0.27***
	(0.02)	(0.05)	(0.05)
Number of Farmers	267	88	

Notes: Figures in parenthesis are standard errors.

*** Significant at the 1% level

2.4.3 Benefit Analysis of the Happy Seeder Technology

How large is the social benefit of using Happy Seeder Technology across Punjab? I quantify the benefit of using the Happy Seeder technology by estimating the number of premature deaths that could be avoided if the air pollution associated with rice-residue burning was eliminated.

This calculation adopts the methodology prescribed in Ostro et al. (2004).

Ostro et al. (2004) summarize the health burden of short term exposure to PM 10 as follows: a 1 $\mu g/m^3$ increase in particulate matter increases the all-cause mortality risk by 0.0008 (central estimate), with a 95% confidence interval of [0.0006-0.0010]. Most of the all-cause mortality resulting from exposure to PM is associated with cardiovascular and pulmonary disease.

Since data on particulate matter (PM) for rural areas in Punjab is available for PM 2.5 but not for PM 10 , I use the value of 0.5 for the PM2.5/PM10 ratio for developing countries Ostro et al. (2004). Data derived from satellite images on fine particulate matter (PM 2.5) for 2001-2010 for Punjab was kindly provided by Professor Sagnik Dey, Department of Atmospheric Sciences, Indian Institute of Technology, Delhi (Dey, Di Girolamo, van Donkelaar, Tripathi, Gupta, and Mohan, 2012). According to these estimates the annual average of PM 2.5 for 2001-2010 was 50% higher for the month of October than for September (70 $\mu g/m^3$ compared to 46 $\mu g/m^3$). I attribute this difference to open-field burning of rice residues. This is not an unreasonable assumption.Venkataraman et al. (2006) found that emissions from crop residue burning peaked during the month of May and October in the western Indo-Gangetic plains corresponding with the two major harvesting seasons for rice and wheat.

The deaths attributable to outdoor air pollution caused by burning of rice-residue are estimated by using the average concentration of PM 10 in the month of September of 92 $\mu g/m^3$ as the baseline value and the the average concentration of PM 10 of 141 $\mu g/m^3$ in the month of October as the current value.

Using these values, the relative risk, (the risk of developing a disease in the exposed group relative to the risk of developing a disease in the unexposed group) was 1.0397. Thus, the percentage of all deaths that can be attributed to short-term outdoor air pollution i.e. the attributable fraction was 3.82%. [6]

[6] In general, relative risk is calculated by dividing the incidence rate among those exposed to the pollutant

The expected total number of cases of premature mortality from short-term exposure to PM10 due to burning of rice residue was calculated by multiplying the attributable fraction with the average per person monthly all-cause mortality rate in Punjab and its population. All-cause mortality data were obtained from the Indian Ministry of Health and Family Welfare for 2005-2010. The annual mortality rate is .0684 deaths per person. The Census of India, 2011, estimated a population of 27.70 million for Punjab. In the absence of monthly data on mortality, I assume that the health effects of short-term exposure to air pollution depend on cumulative exposure throughout the year. Thus, an estimate of the expected number of cases of premature mortality from short-term exposure to PM 10 is 606 with a 95% confidence interval of [461-752].

The Value of Statistical Life (VSL) estimates for India from Bhattacharya, Alberini, and Cropper (2007) were used to determine the value of the benefit from reduced mortality from using the Happy Seeder technology. Bhattacharya et al. (2007) report a preferred VSL estimate of INR 1.93 million (2010 rupees) based on a stated preference study of Delhi residents. Other estimates of VSL for India are 14-29 times higher than this estimate (Shanmugam, 2001; Madheswaran, 2007). Hence, the estimated social benefit of INR 1170 million (USD 25 million) is a lower bound on its value. The 95% confidence interval of the benefit ranges from INR 889- 1451 million (USD 19-31 million).

The social benefit of using this technology is much higher because the other health and climate benefits from stopping the burning of rice residue are expected to be substantial though they have not been quantified here. On the other hand, profits with Happy Seeder are equal to profits with the conventional technology as shown in section 4.2.

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by the incidence rate among those not exposed to the pollutant.

$$\text{Relative Risk} = e^{0.0008}(141.32 - 92.69)$$

$$\begin{aligned}\text{Attributable Fraction} &= \frac{\text{Incidence of disease in exposed} - \text{Incidence of disease in unexposed}}{\text{Incidence of disease in exposed}} \\ &= \frac{\text{Relative risk -1}}{\text{Relative Risk}}\end{aligned}$$

2.5 Conclusions and Policy Implications

Emissions from domestic fires are the largest contributor to biomass burning but may be costly to mitigate. Open field burning is the second-largest source of black carbon in South Asia. Bans on burning have been instituted to deal with this pollution but in the absence of any economically viable alternative to burning, they have been rendered ineffective. Hitherto, such alternatives were missing. This chapter highlights a new technology that makes it possible to incorporate rice residues. I conclude that this technology has the potential to reduce emissions from rice residue burning in Punjab, India. Given the considerable adverse effects on mortality and health of pollution from burning, the results imply that there are net private benefits from mitigating this source of black carbon. In fact, it is one of the few mitigation options that are presently available to stop agricultural fires. Since black carbon is a short lived pollutant, fast actions on cutting down its emissions will reap immediate climate and health benefits.

My results indicate that there is a strong link between combine harvesters and biomass burning. Combine-harvesters scatter crop residue as they harvest. As a result, rice residue left behind by a combine-harvester is more likely to be burnt than residue left after a rice crop has been harvested using manual labour. Yang et al. (2008) also attribute the open-field burning of cereal residues in China to the practice of mechanized harvesting of rice crop by a combine-harvester. Farooq, Sharif, and Erenstein (2007) too associate agricultural residue burning with the use of the combine-harvester to harvest crops in the Punjab province of Pakistan. Hence, the Happy Seeder technology may offer a solution to the problem of residue burning in these countries as well.

Another technological innovation that could boost the uptake of Happy Seeder machines is combine-harvesters fitted with a spreader to evenly distribute loose residue. Using these attachments therefore removes one cost element from the use of the Happy Seeder machine. It can also improve wheat crop yields (Singh, Dhaliwal, and Tejpal-Singh, 2006). However, the decrease in cost may not be large enough to motivate farmers to switch to the Happy Seeder technology. Agricultural research finds that reliance of farmers on weed control measures may decrease with the use of the Happy Seeder as the mulch suppresses weeds (Singh et al., 2006). My study supports this finding because the operators of the Happy Seeder applied lower quantities of fertilizer and weedicide to the wheat crop. It is indisputable that lower quantities of fertilizer and weedicide have desirable external benefits.

The results suggest that the Happy Seeder has no strong advantage from the point of view of the private profitability of the farmer. This means that, on its own, the Happy Seeder technology will spread only slowly since farmers are often resistant to taking on new methods and prefer to stick with the tried-and-tested status quo. However, as the machine offers a viable way to tackle the residue burning problem, it makes good policy sense to promote the machine to secure the pollution control benefits it can bring to society as a whole.

The findings indicate that a two-pronged approach of accelerating the adoption of Happy Seeder and prohibiting the burning of rice residue can prevent the burning of rice residue. The state agricultural department has already been successful in spreading the use of the Rotavator across Punjab. Rotavator is a tractor drawn machine that costs nearly the same as the Happy Seeder (INR. 1,15,000 or USD 2638). A combination of subsidies, recommendations by scientists at the state agricultural university, demonstrations by extension agents helped to accomplish this[7]. A similar approach may be tried for promoting the Happy Seeder. This will have benefits to society at large and also to the natural environment both of which are affected by the pollution from residue burning with wider applicability elsewhere in Asia.

[7]Personal Communication with Prof. Peter Hobbs at the Department of Crop and Soil Sciences, University of Cornell

3

Global warming and local air pollution have reduced wheat yields in India [1]

3.1 Introduction

With annual production greater than 92 million tonnes, wheat is India's second largest crop, and is about 14% of global wheat supply. The log of the wheat yield was regressed on average daily maximum and minimum temperature and solar radiation using district-level data from India over the period 1981-2009. The 208 districts in the data account for over 90% of Indian wheat production and cover much of the Indo-Gangetic plains.

Wheat yield was regressed on district-level weather measures and district fixed effects and linear trend. The weather parameters are therefore identified from deviations from district specific variations in weather from the district mean weather. Since variations in weather between years in a district are mostly random, they are uncorrelated with other unobserved determinants of yields thereby avoiding the bias caused by omitted variables. The time trends control for unobserved factors such as technical progress that were common to all districts over the study period.

The results (from models with district fixed effects and linear or quadratic time trends) indicate that high daily maximum and minimum temperatures measurably reduce wheat yields

[1] This chapter is based on a paper co-authored with Prof. E. Somanathan, Planning Unit, Indian Statistical Institute, New Delhi and Professor Sagnik Dey, Centre for Atmospheric Sciences, Indian Institute of Technology, Delhi.

while solar radiation increases yields roughly one-for-one. Moreover, a reduction in aerosol pollution that increases solar radiation reaching the ground would raise yields because the direct effect of an increase in solar radiation outweighs its indirect effects via higher maximum temperatures and lower minimum temperatures.

The estimated weather parameters from these regressions were used to assess the impact of recent climate trends and the impact of future climate change on wheat yields. The maximum and minimum temperature during the wheat-growing season have increased by 0.7°C and 1°C respectively over the period 1981-2009. Wheat yields in India would have been higher in 2009 by 4.8% (95% confidence interval of [2.4, 7.2]) if these increases had not occurred.

Climate change predictions derived from the Reg CM4.3 model for the RCP8.5 high emission scenario were used to forecast future yield declines. These are estimated to be 12% for mid-term (2010-2040) climate change, 17% by 2070, and 27% by the end of the century.

Two other recent studies, Lobell, Schlenker, and Costa-Roberts (2011) and Krishnamurthy (2011) have used observational data to study the impact of climate trends on wheat yields. Lobell et al. (2011), using country-level data covering the period 1980-2008, found that wheat yields are negatively associated with mean temperature and maximum temperature. Using a regression model that is quadratic in temperature, they estimate a yield decline in India of about 8-9 percent per degree increase in temperature.[2] The effect of climate change on Indian wheat may be different from that estimated from this model for several reasons: Indian wheat production is largely irrigated which is not the case globally, Indian wheat is grown at the higher end of the global temperature range, and the model does not control for solar radiation. Given the positive correlation between solar radiation and maximum temperature, this could result in an underestimate of the negative impact of maximum temperature on wheat yields.

The study by Krishnamurthy (2011) is closer to our analysis as it examined the effect of climate change on district-level crop yields in India over the period 1971-2006. Using a

[2]Estimated marginal effects vary by country since their model is non-linear in temperature.

quantile regression framework, Krishnamurthy (2011) found an inverted U-shaped relationship between growing degree day and wheat yield, but the marginal effects of increases in average growing-season temperatures are not reported.

The rest of the paper is organised as follows. The following Section describes the data sources and summary statistics. Results of the effects of weather on wheat yields are presented in Section 3. Section 4 discusses the impact of past temperature trend on wheat yields. Section 5 contains the predicted impacts of climate change on future yields and Section 6 concludes with policy implications.

3.2 Data and Summary Statistics

3.2.1 Agricultural Data

We use district-level data on agricultural outcomes primarily from two sources, the Indian Harvest database from the Centre for Monitoring the Indian Economy (CMIE) and the statistics released by the Directorate of Economics, Ministry of Agriculture (MOA) [3]. The MOA reports district-level area, production and yield and irrigated area for all major crops beginning from the year 1999. Hence prior to 1999 the observations are from the CMIE database. These data are a compilation of the official statistics published by the state governments and the Ministry of Agriculture. Other data sources are the ICRISAT VDSA (Village Dynamics in South Asia) unapportioned Meso database[4] and the statistics complied by the Fertilizer Association of India. These data are from the same original state government sources. Thus, missing data from either MOA or the CMIE were replaced by data from these sources.

The states of Punjab, Haryana, Uttar Pradesh, Uttarakhand, Bihar, Rajasthan, Madhya Pradesh, Maharashtra and Gujarat comprise the study area. We exclude districts from the newly created states of Chattisgarh and Jharkhand because data on the area of the wheat

[3] `http://eands.dacnet.nic.in/LUS_1999_2004.htm`

[4] `http://www.icrisat.org/vdsa/vdsa-index.htm`

crop that is irrigated was largely missing for these states.

Indian district boundaries change periodically as larger districts have been split into smaller ones. We have dealt with this by merging new districts into their 'parent' (1981) districts in order to have a balanced panel so that within-district variation is preserved. Variables are area-weighted averages of the new districts comprising a parent district.

3.2.2 Weather Data

Daily gridded ($1° \times 1°$) resolution data on temperature and rainfall were obtained from the Indian Meteorological Department (IMD). To create daily district-level data, we construct the area-weighted average temperature and rainfall of all the grid cells intersecting a 1981 district.

Reliable data on surface solar radiation for most of India is not available. Ground based measurements of solar radiation are available from as few as 12 weather stations across the country. The Surface Radiation Budget (SRB) dataset[5] suffers from a wide data gap. We collected daily-level reanalysis data on surface solar radiation from the MERRA database at the ($2/3° \times 1/2°$) resolution.[6] District-level solar radiation was generated in the same way as temperature and rainfall.

The daily temperature and solar radiation variables were averaged over the growing season in each year and the rainfall summed over the growing season in each year. The growing season of wheat varies across the states, being slightly longer in the northwestern Indo-Gangetic plains (Punjab, Haryana and western Uttar Pradesh) than in the eastern Indo-Gangetic plains (eastern Uttar Pradesh and Bihar). Wheat is planted about a month earlier in the west. Information on sowing dates and the length of the growing season was obtained from the crop calendars published by the Agricultural Meteorological Division of the IMD and data provided by the regional centres of the Indian Agricultural Research Institute.

[5] `http://www.gewex.org/srbdata.htm`
[6] `http://disc.sci.gsfc.nasa.gov/mdisc/`

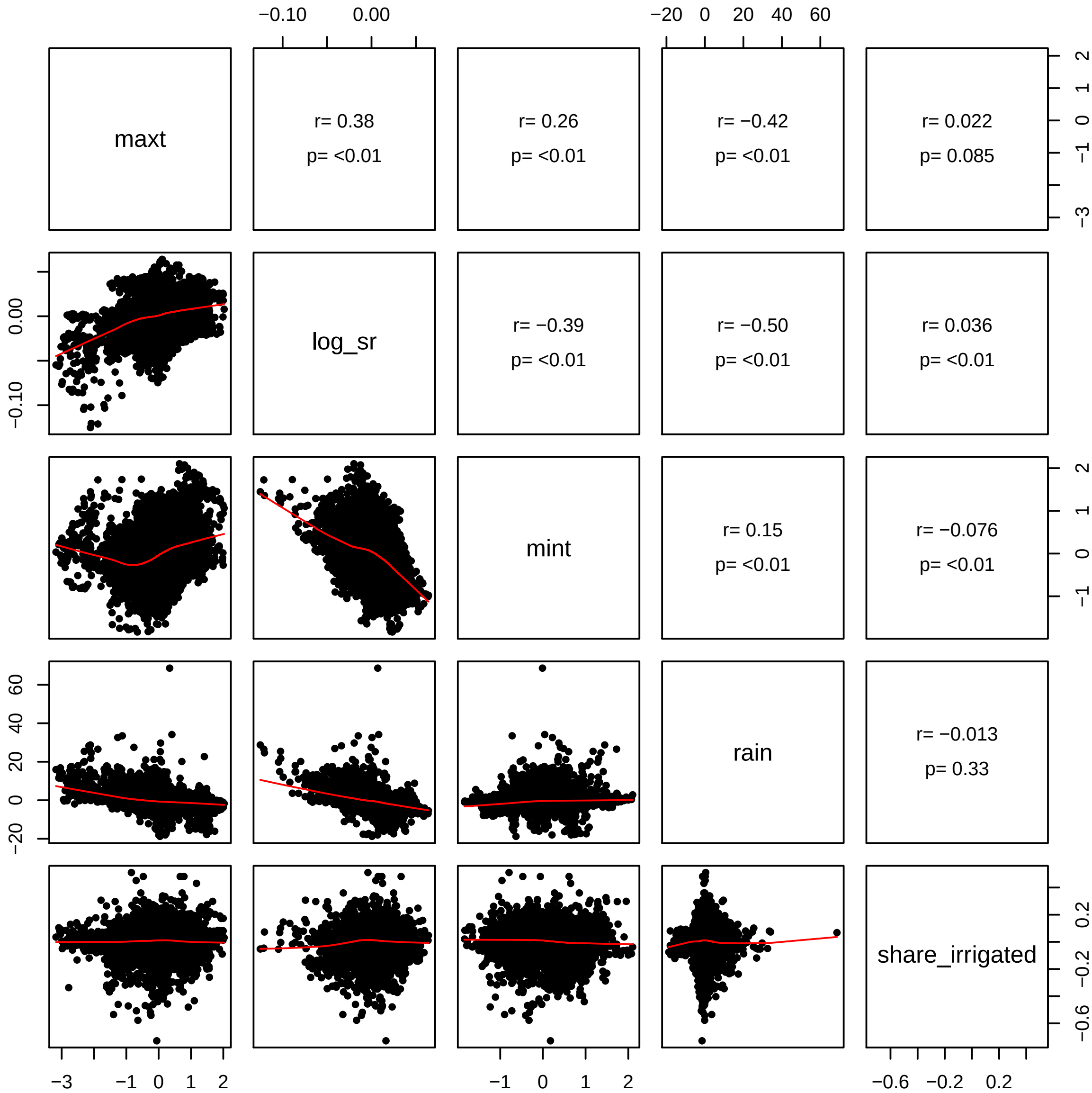
3.3 Regression Model and Results

TableA3.1 in the Appendix reports summary statistics of the key variables of interest. Following the literature our dependent variable in the regression models is the log yield in tonnes per hectare. The variables of interest include the average daily maximum and average daily minimum temperature measured in degrees celsius, total growing season rainfall in centimetres, and the natural log of daily average solar radiation in hectowatt per meter squared.

Pairwise residual correlations and scatterplots of the control variables after removing district fixed effects and a linear time trend are shown in Figure 3.1. Log solar radiation's correlation with maximum temperature was 0.38 and with minimum temperature was -0.39.[7] Clouds and pollution-related haze result in less solar radiation reaching the ground during the day, lowering the maximum temperature. Clouds and haze also block outward radiation of heat from the ground into space at night, thus raising the minimum temperature. These correlations suggest that a failure to account for solar radiation could bias the estimates on the temperature variables. This is discussed further below.

[7] These refer to season averages of daily variables.

Figure 3.1: Correlations among the variables



Notes: Correlations were calculated using residual variation in the variables after removing the influence of district fixed effects and overall linear time trend. Number of observations = 5920. P values are listed below the correlation coefficients.

All the models contain district fixed effects and time trends to control for common trends in the data. The model is of the form

$$\begin{aligned}\log(Y_{it}) = c_i + \gamma_s t + \delta_s t^2 + \beta_1 MaxT_{it} + \beta_2 MinT_{it} + \beta_3 \log(SR_{it}) \\ + \beta_4 Rain_{it} + \beta_5 ShareIrrigated_{it} + u_{it}\end{aligned} \tag{3.1}$$

where the subscripts i, s and t refer to districts, states, and years respectively, $MaxT$ and $MinT$ are daily maximum and minimum temperatures averaged over the growing season, $log(SR)$ is average log solar radiation, $rain$ is the total rainfall in a growing season, $ShareIrrigated$ is the fraction of the wheat crop that is irrigated and u is the error term. By imposing restrictions on the γs and δs, constrained models are obtained, for example, setting $\delta_s = 0$ and $\gamma_s = \gamma$ for all s gives a model with a single linear time trend.

Error terms may be spatially correlated across districts within a state in a year because yields may be spatially correlated. Geographic regions may also have similar errors in nearby years. Therefore, we adjust the standard errors to allow for both the spatial and time-series dependence using the method of Conley (2008) as implemented by Hsiang (2010).[8]

Multiple regression estimates for different specifications of the regression model are shown in Table 3.1. Column 1 of Table 3.1 shows the results for the model that controls for an overall linear time trend. A 1°C increase in maximum temperature tends to lower yields by 2.6% while the same increase in minimum temperature lowers yields by 2.9%. Using country-level data over the period 1980-2008, Lobell et al. (2011) found that wheat yields in India declined by 9% in response to a 1°C increase in maximum temperature and by 4% in response to a 1°C increase in minimum temperature showing that the cross-country data over-estimate temperature impacts for Indian wheat. As mentioned in the introduction, this could be because Indian wheat is exceptional in being largely irrigated and grown at high temperatures, and

[8]Spatial dependence between two observations vanishes as the distance between two districts reaches a specified cut-off. Similarly, observations across time cease to be dependent as the temporal period between the observations equals a specified cut-off. Throughout the analysis, we fix the distance at 300 Kilometres and the temporal period at 2.

because the cross-country study did not control for solar radiation.

Table 3.1: Results of Weather Variables Effect on Wheat Yields

	Dependent Variable-log of yield of wheat in tonnes per hectare			
	(1)	(2)	(3)	(4)
MaxT	-0.02624***	-0.02262***	-0.02558***	-0.02132***
	(0.009)	(0.008)	(0.009)	(0.008)
log_SR	0.95265**	0.82854**	0.71138*	0.63683
	(0.427)	(0.405)	(0.425)	(0.422)
MinT	-0.02933**	-0.01958	-0.03410***	-0.02081*
	(0.013)	(0.012)	(0.013)	(0.012)
Rain	0.00096	0.00090	0.00005	0.00009
	(0.001)	(0.001)	(0.001)	(0.001)
Share_Irrigated	0.37459***	0.33424***	0.44760***	0.36370***
	(0.055)	(0.053)	(0.056)	(0.054)
Linear Trend	Yes	No	No	No
Quadratic Trend	No	Yes	No	No
Linear Trend by State	No	No	Yes	No
Quadratic Trend by State	No	No	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,920	5,920	5,920	5,920
R-squared	0.947	0.950	0.949	0.952

Notes: Standard errors have been corrected for spatial and auto-correlation. Figures in parentheses are standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

The estimated parameters were quite stable when the linear trend was replaced by a quadratic trend (Column 2 of Table 3.1) or by state-specific time trends (Columns 3-4). Our preferred specification is therefore Model 1 since it absorbs the least amount of weather variance.

The estimates in Table 3.1 suggest a near one-to-one relation between solar radiation and yields. This is consistent with evidence from crop simulation models (Chameides, Yu, Liu, Bergin, Zhou, Mearns, Wang, Kiang, Saylor, Luo et al. (1999)). We examine the role of solar radiation in more detail in Table 3.2. Comparing the estimated coefficients on maximum and minimum temperature in Columns 2 and 3 of this table shows that the omission of solar radiation biases these coefficients.[9] Omitting solar radiation halves the magnitude of the marginal effect of maximum temperature on the yield and considerably exaggerates the marginal effect of minimum temperature. This is important for two reasons. First, solar radiation reaching the ground is decreased by aerosol pollution.

A reduction in aerosol pollution would increase solar radiation and the direct effect of this on yields appears to be beneficial and large. The increase in solar radiation reaching the ground during the day would increase maximum temperature. The reduction in aerosol pollution would also lead to more radiation escaping the ground during the night. This lowers minimum temperature with consequent indirect effects on the yield via these variables. A 10% increase in solar radiation is associated with an increase in maximum temperature of 1.5°C and a decrease in minimum temperature of 1.1°C.[10] Using the marginal effects of maximum and minimum temperature reported above, it can be seen that the indirect effect of a 10% increase in solar radiation on yields would be near zero (about +0.7%) while the direct effect would be close to 10%. We conclude that the indirect effect of pollution reduction on yields via temperature effects would be negligible while the direct effect would be positive and considerable. This suggests a possible role for pollution reduction in raising wheat yields that needs further study.

The second reason that the biases caused by the omission of solar radiation are of importance is that global warming is likely to raise temperatures but not via increased solar radiation. So the omission of solar radiation from estimates will give a misleading picture of the effects of maximum and minimum temperatures on yields.

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[9]The inclusion of rainfall and share of wheat crop that is irrigated do not change the parameter estimates of the temperature and the radiation variables by much.

[10]Regressions of $MaxT$ and $MinT$ on $\log(SR)$ with district fixed effects and a linear time trend gave coefficient estimates of 14.7 with a Conley standard error of 2.95 and -11.3 with a Conley standard error of 1.48 respectively.

Table 3.2: Effect of Excluding Solar Radiation

	Dependent Variable-log of yield of wheat in tonnes per hectare				
	MaxT only	add MinT	add log_SR	add Rain	add Share_Irrigated
MaxT	-0.02346**	-0.01376	-0.02516***	-0.02332**	-0.02624***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
MinT		-0.04999***	-0.03480***	-0.03550***	-0.02933**
		(0.013)	(0.013)	(0.013)	(0.013)
log_SR			0.84227*	0.92101**	0.95265**
			(0.433)	(0.444)	(0.427)
Rain				0.00113	0.00096
				(0.001)	(0.001)
Share_Irrigated					0.37459***
					(0.055)
Linear Trend	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,920	5,920	5,920	5,920	5,920
R-squared	0.944	0.945	0.945	0.945	0.948

Notes: Standard errors have been corrected for spatial and auto-correlation. Figures in parentheses are standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

3.3.1 Alternative Models

3.3.1.1 Model with Mean Temperature

Next, we estimate a model controlling for mean temperature instead of maximum and minimum temperature (Table 3.3). The estimated marginal effect of a 1-degree increase in mean temperature is approximately equal to the sum of the marginal effects of maximum and minimum temperature reported earlier while the marginal effect of solar radiation is unchanged. So if maximum and minimum temperatures were to rise by the same amount, the model with mean temperature would give equivalent results. Since unirrigated and irrigated wheat can respond differently to weather shocks, we re-estimate this model for the subsample of irrigated wheat. A district in a given year is defined as irrigated if at least 80% of the wheat area is irrigated. The estimated coefficient on mean temperature (Column 2 of Table 3.3) is about the same, while the coefficient on solar radiation is somewhat smaller and no longer significant in this smaller sub-sample. Rainfall has a small negative effect in this irrigated subsample. The estimated impact of mean temperature is at the upper end of the range of impacts reported by recent simulation studies on wheat yields in India. These studies suggest a 2 to 5% decrease in yield potential of wheat for a mean temperature rise of 0.5°C to 1.5°C in India (Cruz, Harasawa, Lal, Wu, Anokhin, Punsalmaa, Honda, Jafari, Li, and Ninh, 2007).

Table 3.3: Results of Weather Variables Effect on Wheat Yields Controlling for Mean Temperature

	Dependent Variable-log of yield of wheat in tonnes per hectare	
	Full Model (1)	Sub-sample of Irrigated wheat (2)
MeanT	-0.05508***	-0.05746***
	(0.012)	(0.013)
Log_SR	0.98593**	0.74385
	(0.408)	(0.459)
Rain	0.00090	-0.00377***
	(0.001)	(0.001)
Share_Irrigated	0.37536***	
	(0.055)	
Linear Trend	Yes	Yes
District Fixed Effects	Yes	Yes
Observations	5,920	4,050
R-squared	0.948	0.967

Notes: Standard errors have been corrected for spatial and auto-correlation. Figures in parentheses are standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

3.3.1.2 Non-Linear Modelling of Temperature

So far the yield response to temperature has been restricted to be linear. To allow for a non-linear relationship between temperature and yields, we model mean temperature using restricted cubic splines.

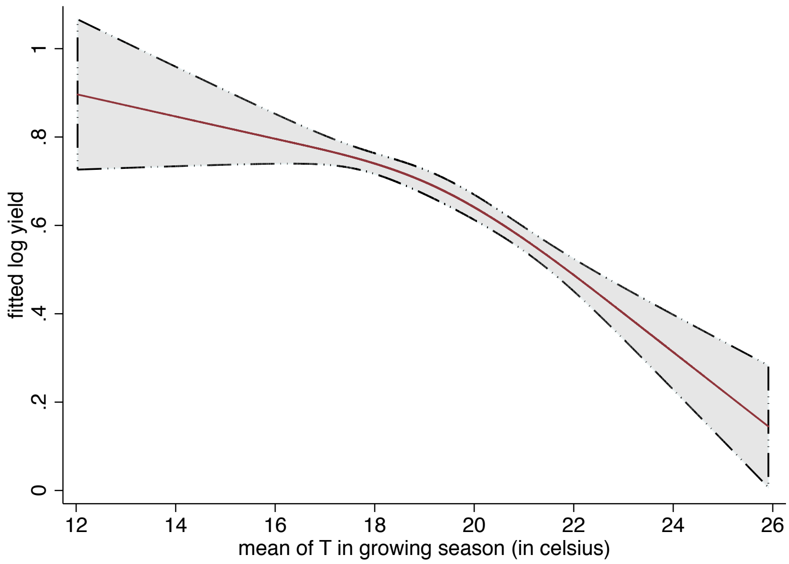
Stone (1986) has shown that the location of knots in a restricted cubic spline model is not very crucial, the fit is influenced much more by the number of knots. We used 3 knots and following Harrell (2001) placed them at the 10^{th}, 50^{th} and 90^{th} percentile of the predictor's marginal distribution. The resulting specification is as follows

$$\begin{aligned} \log(Y_{it}) = & \, c_i + \gamma t + \beta_2 MeanT_{it} + \beta_1 RCS(MeanT_{it}) + \beta_3 \log(SR_{it}) \\ & + \beta_4 Rain_{it} + \beta_5 ShareIrrigated_{it} \end{aligned} \tag{3.2}$$

where c_i is a district fixed effect and γ is the linear trend coefficient

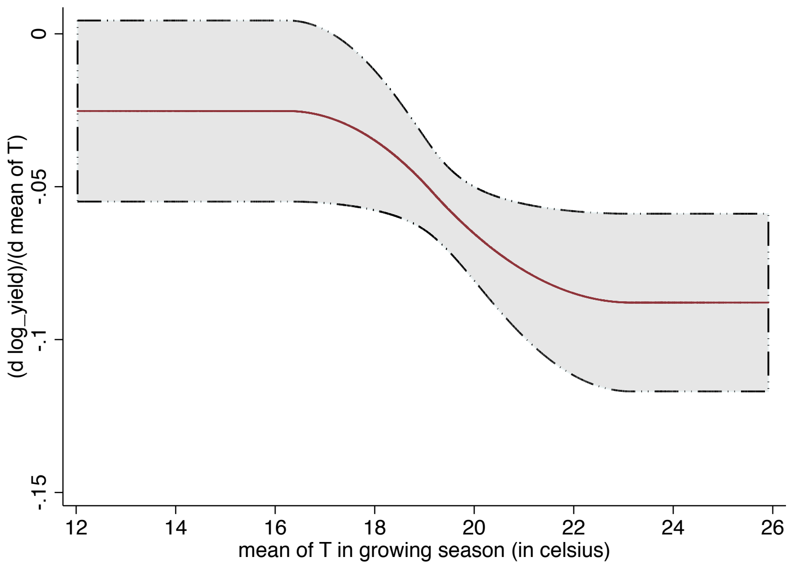
The test for linearity in mean temperature rejected the null hypothesis of linearity. The relationship between mean temperature and predicted log yield suggests that higher temperatures are more harmful for plant growth (Figure 3.2). The difference in slopes at the lower end and higher end of the temperature distribution shown in Figure 3.3 is statistically significant at the 5% level of significance. This is consistent with experimental studies that find that temperature increases are more harmful for wheat productivity at higher temperatures (Rane and Nagarajan, 2004; Jenner, 1991). Robustness checks indicated that the fit was not sensitive to a change in the number or location of knots.

Figure 3.2: log yield as a restricted cubic spline of daily mean temperature averaged over the growing season and the other controls entered linearly as in Equation 3.2.



Notes: The shaded region denotes the 95% confidence intervals. The model controls for district and year fixed effects. Standard errors have been clustered by agro-climatic zones.

Figure 3.3: Change in log yield for a unit change in mean temperature from the restricted cubic spline in Figure 3.2.



Notes: The shaded region denotes the 95% confidence intervals. The model controls for district and year fixed effects. Standard errors have been clustered by agro-climatic zones.

3.3.1.3 Modelling Temperature in terms of GDD (Growing Degree Days)

The nonlinear model above suggests that the negative impact of temperature on yields is higher at higher temperatures. We now re-examine this possibility by modelling the log of yield as a piece-wise linear function of degree days as in Schlenker and Roberts (2009). Temperature is now measured in terms of total growing degree days (GDD) and heating degree days (HDD) in a growing season. These are measures of accumulated exposure to a given range of temperatures through the growing season. Growing degree days are given by

$$\int_{\underline{s}}^{\bar{s}} g(T(s))ds$$

where $\underline{s}$ and $\bar{s}$ denote the starting and ending times of the growing season, $T(s)$ is the temperature at time s, and

$$g(T) = \begin{cases} 0 & \text{if } T \leq 5 \\ T - 5 & \text{if } 5 < T \leq 27 \\ 22 & \text{if } 27 < T \end{cases}$$

while heating degree days are given by

$$\int_{\underline{s}}^{\bar{s}} h(T(s))ds$$

where

$$h(T) = \begin{cases} 0 & \text{if } T \leq 27 \\ T - 27 & \text{if } 27 < T. \end{cases}$$

We now model the log of yield as a linear function of GDD and HDD instead of maximum and minimum temperature with the other controls as before. This allows the response of yield to temperature to change whenever the crop is exposed to a temperature above the threshold of 27°C at any time during the growing season. The lower threshold of 5°C was chosen following conversations with scientists that specialise in wheat breeding at the Indian Agricultural Research Institutes. Following Schlenker and Roberts (2009), the upper threshold of 27°C was determined by looping over several possible thresholds and choosing the one with the highest

R squared.

Table 3.4: Results of Degree Day Variables Effect on Wheat Yields

	Dependent Variable-log of yield of wheat in tonnes per hectare		
	Linear Trend (1)	Quadratic Trend (2)	Linear Trend (3)
GDD	-0.36271***	-0.30015**	
	(0.140)	(0.136)	
HDD	-0.71102	-0.43398	
	(0.449)	(0.421)	
DD			-0.42064***
			(0.095)
log_SR	1.07135***	0.83401**	0.99784**
	(0.396)	(0.390)	(0.409)
Rain	0.00092	0.00097	0.00088
	(0.001)	(0.001)	(0.001)
Share_Irrigated	0.37224***	0.33151***	0.37320***
	(0.055)	(0.052)	(0.055)
F statistic for testing GDD = HDD	0.41	0.07	
Prob > F	0.52	0.80	
District Fixed Effects	Yes	Yes	Yes
Observations	5,920	5,920	5,920
R-squared	0.947	0.950	0.947

Notes: Degree days are measured in 1000 days. Standard errors have been corrected for spatial and auto-correlation. Figures in parentheses are standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

The results are reported in Table 3.4 for models with linear and quadratic time trends. The estimated coefficients on heating degree days are larger in magnitude than those on growing degree days, consistent with our finding above of an increasing negative effect of temperature on yields. However, the F test for testing the equality of coefficients on GDD and HDD did not reject the null hypothesis of equality. This may be because of the small number of observations in the extreme right of the temperature distribution.

The last column in (Table 3.4) reports the results of a model in which the coefficients on GDD and HDD are constrained to be equal. The variable of interest is called *dday* and it measures accumulated exposure to temperatures exceeding the low developmental threshold temperature of 5°C. By multiplying the coefficient on *DD* by the average number of days in the growing season, we obtain the marginal effect of a 1°C increase in mean temperature to be 5.4%. This is very close to the estimated impact of mean temperature in the linear model reported in Table 3.3. The coefficient on solar radiation is also quite similar in the different models.

3.3.1.4 Separating effects by stages in the growing season

In all models described so far, the weather effects are time separable. Thus, the effect of a very hot day on yields is independent of the timing of its occurrence over the growing season. For checking the validity of this assumption, we implement the approach of Welch, Vincent, Auffhammer, Moya, Dobermann, and Dawe (2010). The growing season is divided by agronomists into three growth phases – vegetative, reproductive and ripening. The agronomic literature (Sofield, Evans, Cook, and Wardlaw, 1977; Wardlaw and Moncur, 1995; Stone and Nicolas, 1998; Rane and Nagarajan, 2004) emphasises the negative effects of high temperatures (temperatures greater than 30°C) that prevail during the grain-filling stage at the end of the growing season. In this subsection, we allow for the weather estimates to vary across each of the three growth phases by constructing the weather variables for each phase and including them all as regressors. The null hypotheses of equality of the effects of the temperature and radiation variables across the plant's different growth stages was not rejected (Table 3.5), indicating that modelling time separability in this manner is not required.

Table 3.5: Equality tests of weather coefficients across the three growth stages

Null Hypothesis	P values	
	w\ linear trend	w\ quadratic trend
	(1)	(2)
MaxT equal for all 3 stages	0.12	0.48
log_SR equal for all 3 stages	0.50	0.76
MinT equal for all 3 stages	0.80	0.80
Rain equal for all 3 stages	0.28	0.49
District Fixed Effects	Yes	Yes
Observations	5,920	5,920

3.3.1.5 Controlling for Year Fixed Effects

We now report models with year fixed effects, an even more flexible way to control for yield trends that are unrelated to climate and weather, albeit at the cost of removing considerable variation from the data.[11] Year fixed effects account for the possibility that modelling yield trends in a linear or quadratic fashion is insufficient to capture unobservables affecting yield that are correlated with the weather variables. The coefficient of maximum temperature increases in magnitude by about 2 percentage points as compared to the models with linear or state-specific linear trends (Table 3.6). Minimum temperature and log solar radiation, however, are no longer significant, and the estimated coefficient on minimum temperature decreases by roughly the same amount as the increase in the maximum temperature coefficient. Our conclusion from the earlier models including the one with mean temperature, that a one-degree increase in all temperatures over the growing season would lower yields by about 5.5% still seems to be the most likely conclusion from this model. However, with the estimated coefficient on solar radiation now about 0.6 and no longer statistically significant, the earlier conclusion regarding the positive effect of aerosol pollution reduction on yields, is not robust to this model.

[11] State-by-year fixed effects remove even more of the variation in weather.

Table 3.6: Results of Weather Variables Effect on Wheat Yields Controlling for Year Fixed Effects

	Dependent Variable-log of yield of wheat in tonnes per hectare
	Year Fixed Effect (1)
MaxT	-0.04547***
	(0.014)
log_SR	0.61384
	(0.492)
MinT	-0.01105
	(0.014)
Rain	0.00165
	(0.001)
Share_Irrigated	0.34772***
	(0.048)
District Fixed Effects	Yes
Observations	5,920
R-squared	0.953

Notes: Standard errors have been corrected for spatial and auto-correlation. Figures in parentheses are standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

3.4 The impact of past climate change on current yields

Over the study period, the production weighted maximum temperature and minimum temperature in the wheat growing region increased by 0.7°C and 1°C. There was no statistically significant trend in solar radiation over this period.[12] This section assesses the impact of this increase in temperature on wheat yields. Thus, we attempt to answer the question of how

[12]Padma Kumari, Londhe, Daniel, and Jadhav (2007) analysed observational data on monthly mean solar radiation from 12 stations located in urban India for the period 1984-2004.They found a reduction of $0.86Wm^{-2}/yr^{-1}$ in the amount of solar radiation reaching India, a phenomenon known as solar dimming . Using the re-analysis data, however, we do not evidence for solar dimming over the wheat growing region of India and for the wheat growing season.

wheat growth would have evolved without this trend. Maximum and minimum temperature were de-trended by fitting a linear time trend separately for each district. For each district-year observation, we compute the difference between predicted yields with observed weather and predicted yields with de-trended temperature for the year 2009. Predicted yields were calculated by using the estimated parameters from the specification in Column 1 of Table 3.1.

To arrive at the national effect, we take a production weighted average of these differences. The results indicate that by the year 2009 wheat yields may have declined by $2\pm1\%$ and $2.9\pm 2.5\%$ relative to what would have been achieved without the trend in maximum temperature and minimum temperature over 1981-2009. The combined effect of the trend in maximum and minimum temperature on wheat yields was a decline of 4.8% with a 95% confidence interval of $[-7.2, -2.4]$.

We repeated this analysis for mean temperature using the regression estimates from the linear model and the restricted cubic spline model. The results from the linear model were close to the combined effect of the trend in maximum and minimum temperature. The restricted cubic spline model gave a lower yield loss of 3.35% with a 95% confidence interval of $[-5.5, -1.2]$.

3.5 The impact of predicted climate change on future yields

Climate change predictions are made from the Reg CM4.3 model. This is the latest version of the regional climate model of International centre for Theoretical Physics (ICTP). As the name suggests, regional climate models provide climate simulations over a finer spatial resolution, therefore they are sufficiently accurate for assessing the impact of climate change. Details of the model physics and dynamics are discussed in Giorgi, Coppola, Solmon, Mariotti, Sylla, Bi, Elguindi, Diro, Nair, Giuliani et al. (2012).

We obtained monthly model output on both maximum temperature and minimum temperature. The gridded data was converted to the district-level data using the approach employed to convert the historical gridded data. We used the RCP8.5 emission scenario. This is a high emission scenario. We compute climate change impacts for three time periods, near-future (2040), mid-future (2070) and distant future (i.e. end of the century).

Climate change predictions were made as follows. We calculated the production-weighted predicted yield per acre for each district-year observation after climate change and at the observed weather using the estimated parameters from the specification in Column 1 of Table 3.1. These yield outcomes were summed across all the districts in the sample for each year. We then computed the percentage change in average yield per acre after climate change and at the current climate (i.e. average over the 1981-2009 period). Results are shown in Table 3.7.

Consistent with the literature on climate change, the Reg CM4.3 model predicts greater increases in minimum temperature than maximum temperature in India (Table 3.8). Thus, significant impacts of maximum temperature were outweighed by significant impacts of minimum temperature. Column 3 of Table 3.7 that captures the total effect of changes in both maximum and minimum temperature predicts that wheat yields will be lower by about 12% by 2040 increasing to a decline of 27% by the end of the century (relative to 1981-2009).

Column 4 and Column 5 of Table 3.7 show the results with mean temperature where mean temperature is the average of maximum and minimum temperature. Underlying the impact in Column 4 is the regression with mean temperature entered linearly, the results of which are shown in Column 1 of Table 3.3, whereas Column 5 is based on the regression model with mean temperature fitted as a restricted cubic spline. The predicted changes in yields from all the three models do not diverge by much except for the end-of-the-century forecast from the restricted cubic spline model which predicts a yield decline of about 33%. This is not surprising as the largest increases in mean temperature are projected to occur towards the end of the century.

Table 3.7: Impact of Climate Change on Wheat Yields

Percentage decline in Yield				
Near Future- 2040				
MaxT Effect (1)	MinT Effect (2)	Total Effect (3)	MeanT Effect (4)	Non-Linear MeanT Effect (5)
3.24***	9.33**	12.27***	13.04***	11.88***
(1.08)	(3.86)	(3.56)	(2.72)	(2.50)
Mid Future- 2070				
3.34***	14.54**	17.39***	17.83***	17.55***
(1.11)	(5.84)	(5.43)	(3.62)	(4.99)
Distant Future- 2099				
10.88***	18.57**	27.43***	27.89***	32.72***
(3.48)	(7.28)	(6.22)	(5.29)	(6.04)

Notes: Underlying these impacts are regressions shown in Column 1 of Table 1 and Column 1 of Table 4 and regression with mean temperature modelled as a cubic spline. Predicted impacts of climate change have been calculated as the percentage change in average yield per acre after climate change and at the current climate (i.e. average over the 1981-2009 period. Standard errors have been corrected for spatial and auto-correlation. Figures in parentheses are standard errors. Sample has 5920 observations from 208 districts over the period 1981-2009 *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

3.6 Caveats to the impact of predictions of past and future climate change on yields

We mention some caveats that go with the predictions. The district fixed effects and time trend used to control for unobservable factors wipe out a great deal of variation in temperature (TableA3.2). Hence the predicted impacts for large changes in climate that are expected to occur in the coming decades (TableA3.3) depend on functional form assumptions . Another consideration is the absence of days with maximum temperature exceeding 33°C in the data. If days with temperatures exceeding this bound are expected to occur with climate change then the estimated parameter of the impact of maximum temperature can no longer be applied to infer about the effect of such hot days on wheat yields. Finally, the estimated parameters of our models capture only within-season adaptation, and not long-run adaptation to a changing climate.

3.7 Conclusion

The principal findings from this paper are that global warming over the period 1981-2009 has reduced wheat yields and that reductions in aerosol pollution that decrease solar dimming could raise yields. Our preferred specification, the model with a linear time trend (all our models include district fixed effects) provides an estimated reduction in yield of 4.8% over this period. This is less than that from the recent cross-country panel study by Lobell et al. (2011) . The estimated reduction falls to 3.35% if we use a model that allows for a non-linear relation between temperature and yield.

The conclusion about the potential gains from local air pollution reduction has to be qualified by the somewhat smaller and noisier estimates of the marginal effect of solar radiation on yields when using models with state trends or a quadratic trend. These models reduce the variation in the data, and are probably not required for identifying the weather effects of concern, so we believe the model with the overall linear trend is the most suitable.

Results of the estimation of the impact of future climate change predict losses ranging from 12.3% for medium-term climate change (2010-2040) and up to 27% by 2099 under the RCP8.5 high-emission scenario. The non-linear model yields a higher forecasted loss of 33% at the end of the century.

These findings assume no long-term adaptation and rely on functional form assumptions. If farmers are able to switch to heat resistant varieties then damages would be less. On the other hand, yield losses may be higher due to the increased occurrence of extreme temperature events that is expected to occur with climate change. Data limitations did not allow us to reliably estimate the impact of hot days on wheat yields.

3.8 Appendix

Table A3.1: Descriptive Statistics

Variable	Unit	Mean	Std. Dev	Min	Max
Yield	tonnes per hectare	2.11	0.90	0.16	5.73
log_Yield		0.65	0.46	-1.81	1.75
MaxT	celsius	27.45	2.76	17.94	33.54
MinT	celsius	11.64	2.24	6.01	19.48
MeanT	celsius	19.34	2.48	12.03	25.91
GDD	In 1000 days	1.74	0.22	0.99	2.35
HDD	In 1000 days	0.07	0.05	0.00	0.24
SR	hectowatt per meter squared	2.17	0.15	1.74	2.63
log_SR		0.77	0.07	0.55	0.97
Rain	cm	4.75	6.18	0.00	73.04
Share_Irrigated		0.82	0.24	0.01	1.00
Number of Districts		208	208	208	208
Number of Observations		5920	5920	5920	5920

Notes: Values were calculated across the period 1981-2009 and the growing season.

Table A3.2: Residual Variation in Temperature Variables

	Proportion of observations differing from predicted value by more than				
	Maximum Temperature				
	0.5°C	1°C	1.5°C	2°C	2.5°C
Removed linear trend	0.46	0.18	0.05	0.03	0.01
Removed quadratic trend	0.47	0.19	0.05	0.02	0.01
	Minimum Temperature				
	0.5°C	1°C	1.5°C	2°C	2.5°C
Removed linear trend	0.41	0.09	0.01	0	0
Removed quadratic trend	0.42	0.07	0.01	0	0
	Mean Temperature				
	0.5°C	1°C	1.5°C	2°C	2.5°C
Removed linear trend	0.37	0.06	0.01	0	0
Removed quadratic trend	0.39	0.05	0	0	0

Notes: Entries are averages over the 208 districts over the period 1981-2009.

Table A3.3: Changes in temporal means of temperature variables between 1981-2009 and future time periods for the wheat growing region of India

Maximum Temperature (°C)

High Emission Scenario		
Near Future (2040)	Mid Future (2070)	Distant Future (2099)
1.25	1.30	4.39

Minimum temperature

High Emission Scenario		
Near Future (2040)	Mid Future (2070)	Distant Future (2099)
3.04	5.36	7.1

Mean temperature

High Emission Scenario		
Near Future (2040)	Mid Future (2070)	Distant Future (2099)
2.54	3.57	5.94

Notes: Projections are from the Reg CM4.3 model for the high emission scenario. Entries are the changes in production weighted averages between historical temperature and future temperature for the wheat growing region of India.

4

Fires and Aerosol Pollution in India [1]

4.1 Introduction

Biomass burning of agricultural field residue is a significant contributor to aerosols in South Asia (Streets, Yarber, Woo, and Carmichael, 2003; Gadde et al., 2009; Venkataraman et al., 2006; Bond et al., 2013). Aerosols have important consequences for global climate (Charlson, Schwartz, Hales, Cess, Coakley, Hansen, and Hofmann, 1992; Schwartz, 1996), ecosystem processes (Ramanathan et al., 2005; Ramanathan and Carmichael, 2008), and human health (Long, Tate, Neuman, Manfreda, Becker, and Anthonisen, 1998; Awasthi, Singh, Mittal, Gupta, and Agarwal, 2010; UNEP, 2011). Thus, it is becoming increasingly important to understand the contributions that fires make to aerosols in the atmosphere.

Few studies (Streets et al., 2003; Venkataraman et al., 2006; Gadde et al., 2009; Kanabkaew and Oanh, 2011) have been conducted to measure the impact of agricultural fires on emissions of gases and particles. These studies first estimate the amount of crop waste that is burnt using data on crop production and waste to grain ratios reported in the literature. The estimated crop waste is then multiplied by aerosol emission factors for crop waste burning prevalent in the literature. Thus, uncertainty in the emissions from crop waste burning is introduced at two stages. The waste to grain ratios for example have an uncertainty range of 12-62% (Venkataraman et al., 2006).

Satellite data provides another opportunity for estimating the emissions from crop residue burning. Satellites have been used to record fires on a global scale, providing a variety of data

[1] This chapter is based on a paper co-authored with Prof. E. Somanathan, Planning Unit, Indian Statistical Institute, New Delhi

products with differing spatial and temporal resolutions. Satellites can also provide data on aerosol optical depth (AOD). An important characteristic of aerosols is their ability to influence the amount of solar radiation passing through the atmosphere. Aerosol optical depth (AOD) is a quantitative measure of the extinction of solar radiation by aerosol scattering and absorption between the point of observation and the top of the atmosphere. It is a measure of the integrated columnar aerosol load. In this paper, we combine satellite data on fires and Aerosol Optical Depth (AOD) to determine the impact of agricultural fires on Aerosol Optical Depth (AOD) in India over the period 2001-2008.

Aerosol optical depth (AOD) was regressed on two measures of fires, total fire-count and total fire radiative power (FRP) and weather variables and grid fixed effects. The grid fixed effects control for unobserved factors that varied across space such as type of crop sown that may be correlated with burning of crop residue. The inclusion of these fixed effects increased the likelihood that the impacts that we identified were indeed caused by fires and not variables omitted from the regression models.

We find a small effect of agricultural fires on AOD. Further, after accounting for spatial correlation, this effect was not statistically significant at the conventional levels of significance. We cannot rule out the possibility that this was because the satellite data on fires fails to detect the small-scale agricultural fires. The contribution of our study is that its methodology can be applied to higher resolution data which is expected to become available and would give a better measure of the fire counts (Chang, Liu, and Tseng, 2013; Liu, Tseng, and Chen, 2013). This is the first study that uses satellite data to estimate the contribution of agriculture fires to aerosol pollution.

The rest of the paper is organised as follows. The following section describes the data sources. Results of the effects of fire on AOD are presented in Section 3 and Section 4 concludes.

4.2 Data

4.2.1 Data on Observed Fires

We use daily data on fire locations from the Moderate-Resolution Imaging Spectroradiometer (MODIS) from the National Aeronautic and Space Administration (NASA). MODIS is one of the most important data sources for global mapping of both fire locations and burned areas. MODIS sensors are mounted aboard two satellites, the Terra spacecraft launched in December 1999 and the Aqua spacecraft launched in May 2002. The Terra satellite crosses the equator at approximately 10:30am and 10:30pm each day while Aqua passes over the equator at approximately 1:30am and 1:30pm. Thus, both satellites make up to two fire observations per day since July 2002.

The detection algorithm identifies pixels with one or more actively burning fires that are commonly referred to as 'fire pixels'. Each detected fire represents the centre of an (approximately) 1km pixel that contains one or more fire hotspots. Thus, the fundamental unit of observation, the 'fire pixel' does not necessarily correspond to a single fire, but indicates instead that one or more fires, or portions of larger fires, are contained within the pixel at the time of the satellite overpass (Giglio, Csiszar, and Justice, 2006). The detection criteria are based on the temperature of each potential fire pixel and the difference between the temperature brightness of the fire pixel and its background temperature (Giglio et al., 2006).

The detection probability of active fires depends on a number of factors, among others on fire temperature and satellite viewing angle. MODIS active fires can detect flaming fires ($\sim$ 1000 Kelvin, K) as small as $100m^2$ under ideal conditions (near nadir, homogeneous land surface) with a 50% detection probability, or a 1000–2000 m^2 smouldering fire ($\sim$ 600K) (Giglio, Descloitres, Justice, and Kaufman, 2003; Remer, Kaufman, Tanré, Mattoo, Chu, Martins, Li, Ichoku, Levy, Kleidman et al., 2005; Hawbaker, Radeloff, Syphard, Zhu, and Stewart, 2008). Detection rates will be higher when the daily peak fire activity will coincide with the time of satellite overpass (Schroeder, Prins, Giglio, Csiszar, Schmidt, Morisette, and Morton, 2008).

The data we use is referred to as the global monthly fire location product (MCD14ML). It contains daily data on the location of a fire pixel, the emitted energy in Megawatt (MW) of the fires in the pixel (fire radiative power), the confidence level of fire detection assigned to that pixel in percent and the temperature brightness of the pixel measured in kelvin (K).

We arrived at the total number of fires and total fire radiative power (FRP) in a $1^\circ \times 1^\circ$ grid by summing across all the fire locations that fall inside a grid from both the Aqua and the Terra satellites.

4.2.2 Data on Aerosol Optical Depth

Daily $1^\circ \times 1^\circ$ gridded data on Aerosol Optical Depth at 550nm was obtained from the GIOVANNI database (Goddard Earth Sciences Data and Information Services Center (GES DISC)[2].

Aerosols typically reside in the atmosphere for days to weeks. Therefore they can be transported by surface and upper air winds over thousand of kilometres before being washed out by rain. Our analysis focuses on Aerosol Optical Depth at the surface of the earth. Surface AOD was calculated from columnar AOD using the following relation:

$$AOD(z) = AOD(0) \int_0^{TOA} \exp^{-z/h} dz$$

where AOD(z) is columnar AOD, AOD(0) is the surface AOD, z is the height at the top of the atmosphere(TOA) in kilometres and h is the scale height in kilometres. We used 8 kilometres as the upper value of z as above 8 kilometres from the surface aerosols are hardly found. Scale height values were provided by Dr. Sagnik Dey at the Indian Institute of Technology, Delhi.

[2] `http://disc.sci.gsfc.nasa.gov/mdisc/`

4.2.3 Weather Data

Daily gridded $1° \times 1°$ resolution data on temperature and rainfall was obtained from the Indian Meteorological Department (IMD). Daily gridded $2.5° \times 2.5°$ resolution reanalysis data on relative humidity was taken from the NOAA-CIRES Climate Diagnostic Centre (Kalnay, Kanamitsu, Kistler, Collins, Deaven, Gandin, Iredell, Saha, White, Woollen et al., 1996). To create $1° \times 1°$ resolution data, we construct the area-weighted average relative humidity of all the grid cells intersecting a $1° \times 1°$ grid.

Global hourly station-level data on surface-wind was downloaded from the National Climatic Data Centre (NCDC) of United States, the dataset is called DS 3505[3].

Data on all the aforementioned variables was collected for the period 2001-2008.

4.3 Results

The dependent variable is Aerosol Optical Depth (AOD). We assume that the AOD in a grid cell depends on AOD in that cell on the previous day. Since AOD gets washed away by rain, the influence of lagged AOD will depend on the occurrence of rain. Thus, we interact lagged AOD with rain. The other controls are relative humidity (RH) and dummy variables that capture seasonal variation in temperature.

The data permits the analysis of two measures on observed fires i.e. total fire radiative power (FRP) and the total number of fires (fire count) in a $1° \times 1°$ grid. FRP measures the radiant heat output of detected fires. The confidence level of fire detection was used to create a high-confidence and a nominal-confidence FRP and fire count variable. If the confidence level exceeded 80% then the fire was considered to be a high-confidence fire and if the confidence level exceeded 30% then the fire was considered to be a nominal-confidence fire.

[3] `http://www.ncdc.noaa.gov/cdo-web/datasets`

We selected only those grid cells with cropland. This was done by overlaying a shapefile on the $1^\circ \times 1^\circ$ that contained information on the type of land. Table 4.1 reports the summary statistics of the key variables of interest.

Table 4.1: Descriptive Statistics

Variable	Unit	Mean	Std..Dev.	Min	Max
AOD		0.34	0.33	0	6.68
Lag_AOD		0.33	0.33	0	6.68
Fire_Power_High	$100W/m^2$	0.09	0.82	0	88.42
Fire_Power_Nom	$100W/m^2$	0.19	1.59	0	154.65
Fire_Count_High	100	0.00	0.02	0	2.42
Fire_Count_Nom	100	0.01	0.07	0	6.99
Rain	cm	0.03	0.24	0	14.33
Lag_AOD_Rain		0.01	0.11	0	9.95
RH	100%	0.42	0.19	0	1.00
Winter		0.25	0.43	0	1.00
Spring		0.25	0.44	0	1.00
Summer		0.25	0.43	0	1.00
Number of Grids		214	214	214	214
Number of Observations		296211	296211	296211	296211

Notes: Values were calculated across the period 2001-2008. ‘Winter’ represents the months of December and January, ‘Spring’ represents the months of February and March, ‘Summer’ represents the months of April and May.

All the models contain grid fixed effects. The model is of the form

$$AOD_{it} = c_i + \beta_1 Lag\_AOD_{it} + \beta_2 Lag\_AOD\_Rain_{it} + \beta_3 Rain_{it} + \beta_4 Fire\_Count_{it} + \beta_5 RH_{it} + \beta_6 Winter_{it} + \beta_7 Spring_{it} + \beta_8 Summer_{it} + \mu_{it}$$

where c_i is a grid fixed effect, Lag_AOD_{it} and $Lag\_AOD\_Rain_{it}$ are the lagged AOD and lagged AOD's interaction with rainfall in grid i on day t, $Rain_{it}$ is the daily rainfall in a grid, $Fire\_Count_{it}$ is the total number of fires, RH is relative humidity in percent and $Winter$, $Spring$ and $Summer$ are seasonal dummies and μ_{it} is the error term.

The introduction of a lagged dependent variable as a regressor biases the coefficients on all the regressors in a dynamic panel data model but Nickell (1981) has shown that these biases tend to zero as the time period of the cross-section tends to infinity. Since we have daily data for eight months and eight years, the time period is large. Thus, our estimated parameters are consistent. The standard errors though need to be adjusted for spatial correlation of an unknown form. This is because due to common unobservable disturbances aerosol concentrations tend to be spatially correlated. Thus, we adjust the standard errors to allow for both spatial and time-series dependence following the methodology of (Driscoll and Kraay, 1998).

Multiple regression estimates for different specifications of the regression model with fire count as the explanatory variable are shown in Table 4.2. Columns 1 and 2 of Table 4.2 show the results for the high-confidence fires and columns 3 and 4 display the results for the nominal-confidence fires.

The estimated parameters are nearly identical without the inclusion of the year fixed effects (columns 1-2 and columns 3-4 of Table 4.2). This implies that unobserved factors that vary over the years were uncorrelated with the variables in the analysis. Nominal confidence fires had a significant effect (at the 10% level of significance) on AOD but this effect vanished when fires were restricted to be detected with a high confidence. The marginal effect of 700 agricultural fires, about the maximum value of fire count observed in the data, would be to increase AOD by 0.2. Thus, we find a small effect of fire-count on AOD.

Table 4.2: Effect of the Fire Count Variables on AOD

	Dependent Variable-Aerosol Optical Depth			
	(1)	(2)	(3)	(4)
Lag_AOD	0.62073***	0.61805***	0.62051***	0.61785***
	(0.011)	(0.012)	(0.012)	(0.012)
Lag_AOD_Rain	-0.12093***	-0.12075***	-0.12078***	-0.12061***
	(0.024)	(0.024)	(0.024)	(0.024)
Rain	0.04066***	0.04070***	0.04062***	0.04067***
	(0.007)	(0.007)	(0.007)	(0.007)
Fire_Count_High	0.04368	0.03597		
	(0.042)	(0.043)		
Fire_Count_Nom			0.03154*	0.02991*
			(0.017)	(0.017)
Winter	0.07444***	0.07530***	0.07480***	0.07566***
	(0.006)	(0.006)	(0.006)	(0.006)
Spring	-0.00671	-0.00650	-0.00643	-0.00623
	(0.006)	(0.005)	(0.006)	(0.005)
Summer	0.01210**	0.01221**	0.01248**	0.01256**
	(0.006)	(0.006)	(0.006)	(0.006)
RH	0.08582***	0.08693***	0.08633***	0.08749***
	(0.014)	(0.014)	(0.014)	(0.014)
Year Fixed Effects	No	Yes	No	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes
R_squared	0.44	0.45	0.45	0.45
Observations	296,211	296,211	296,211	296,211
Number of grids	214	214	214	214

Notes: Standard errors have been corrected for spatial and auto-correlation. Figures in parentheses are standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level'Winter' represents the months of December and January, 'Spring' represents the months of February and March, 'Summer' represents the months of April and May and the omitted category is 'Autumn' that represents the months of October and November.

We cannot rule out the possibility that our estimated impact of fire-count is downward biased due to a failure to detect agricultural fires. As mentioned above, the satellite records fires within an area of $1km^2$. The size of agricultural fields in India is much smaller ranging from half an hectare to several hectares leading to an under-count of the actual number of fires. Hawbaker et al. (2008) compare satellite data on fires from MODIS with 361 referenced fires ($\geq$18 hectares) that had been delineated using pre- and post-fire Landsat imagery to assess satellite detection rates in the United States. The size at which 50% of the fires were detected was 105 hectares. Thus, the authors' assert that most small fires that are less than 1 hectare remain undetected with MODIS active-fire data.

All the other variables had expected signs and magnitude. Previous day's AOD contributed the most to current AOD but this influence was diminished by rain. Compared to autumn, aerosol concentrations are higher in winter and summer due to transport of aerosols from the Thar desert over the Indo-Gangetic plains during this period.

Since current AOD is a function of lagged AOD, any reduction in the burning of agricultural residue would have an impact on future AOD. The cumulative effect of a reduction in agricultural fires on AOD is as follows:

$$\begin{aligned} \Delta AOD_{it} &= \Delta Fire\_Count_{it} \\ \Delta AOD_{it+1} = \beta_2 \Delta AOD_{it} &= \beta_2 \beta_1 \Delta Fire\_Count_{it} \\ \Delta AOD_{it+2} = \beta_2 \Delta AOD_{it+1} &= \beta_2^2 \beta_1 \Delta Fire\_Count_{it} \end{aligned}$$

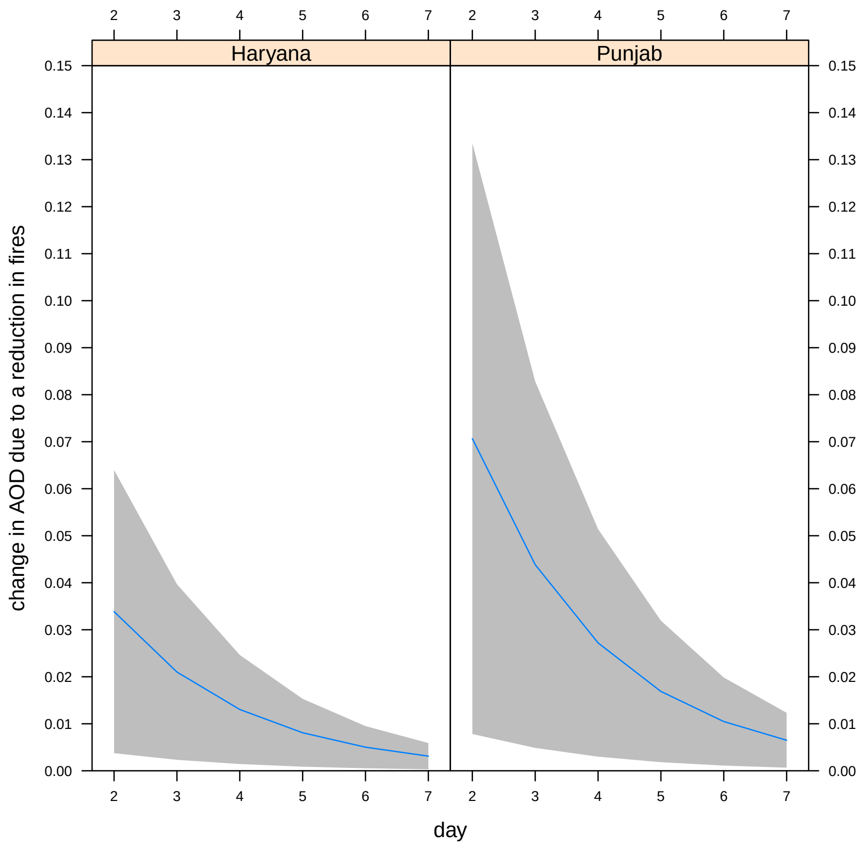
where β_1 is the estimated coefficient on the fire count variable and β_2 is the estimated coefficient on the lagged AOD variable from the specification in Column 3 of Table 4.2. Figure 4.1 shows the effect on AOD of a reduction in the average number of fires detected with nominal confidence in a week during the peak of the burning season in Punjab and Haryana.

Next, we estimate a model that controls for fire radiative power (FRP)[4]. The estimated

[4]We fitted a model with quadratic terms for the fire-count and fire radiative power variables (FRP). The

effect of FRP was close to zero and statistically significant at the 10% level only in the specification that controls for FRP of the nominal confidence fires and grid fixed effects (Table 4.3).

Figure 4.1: Cumulative effect of a reduction in agricultural fires on AOD



Notes: For Punjab, the average number of fires observed during a week of the peak of the burning period was 361 and for Haryana, it was 173. We calculated the decrease in AOD that would result if these fires were eliminated. Standard errors have been corrected for spatial and auto-correlation.The shaded region denotes 90% confidence intervals. The model controls for grid fixed effects.

results are similar to the linear model and therefore we do not report the results.

Table 4.3: Effect of Fire Radiative Power on AOD

	Dependent Variable-Aerosol Optical Depth			
	(1)	(2)	(3)	(4)
Lag_AOD	0.62071***	0.61804***	0.62056***	0.61790***
	(0.011)	(0.012)	(0.012)	(0.012)
Lag_AOD_Rain	-0.12091***	-0.12074***	-0.12081***	-0.12064***
	(0.024)	(0.024)	(0.024)	(0.024)
Rain	0.04067***	0.04070***	0.04064***	0.04068***
	(0.007)	(0.007)	(0.007)	(0.007)
Fire_Power_High	0.00148	0.00126		
	(0.001)	(0.001)		
Fire_Power_Nom			0.00131*	0.00121
			(0.001)	(0.001)
Winter	0.07447***	0.07534***	0.07473***	0.07559***
	(0.007)	(0.006)	(0.006)	(0.006)
Spring	-0.00668	-0.00647	-0.00649	-0.00629
	(0.006)	(0.005)	(0.006)	(0.005)
Summer	0.01212**	0.01222**	0.01236**	0.01244**
	(0.006)	(0.006)	(0.006)	(0.006)
RH	0.08591***	0.08702***	0.08630***	0.08745***
	(0.014)	(0.014)	(0.014)	(0.014)
Year Fixed Effects	No	Yes	No	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes
R_squared	0.44	0.45	0.44	0.45
Observations	296,211	296,211	296,211	296,211
Number of grids	214	214	214	214

Notes: Standard errors have been corrected for spatial and auto-correlation. Figures in parentheses are standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level'Winter' represents the months of December and January, 'Spring' represents the months of February and March, 'Summer' represents the months of April and May and the omitted category is 'Autumn' that represents the months of October and November.

So far we have not accounted for the influence of surface winds that may transport aerosols from one region to the other. Winds were incorporated into the analysis by constructing a variable called 'neighbour' that measures the amount of AOD that was transported into a cell from its neighbouring cells on the previous day. The procedure followed to construct this variable is listed in the appendix. Essentially, by using data on wind-speeds, we determined the location of the air in each grid on the previous day and thus its intersection with its neighbours.The area of the grid falling in each of the four neighbouring grids was then multiplied by the AOD value on the previous day of the corresponding neighbouring grid. These values were then summed up to create the 'Neighbour' value for each grid.

Table 4.4 shows the results of the model with fire-count as the independent variable and with the lag of the AOD being replaced by the 'Neighbour' variable. As evident from comparing Table 4.2 and Table 4.4, the estimated parameters on the fire-count variable are almost identical although not statistically significant in this smaller sample, after we allow for the influence of surface-winds. The coefficient on the 'Neighbour' variable was similar to the coefficient on lagged AOD. This suggests that most of the AOD in a cell on a day came from the same cell on the previous day. These findings also apply to fire radiative power (FRP). Thus, we can ignore the transportation of aerosols by surface-winds in our analysis.

Table 4.4: Effect of the Fire Count Variables on AOD

	Dependent Variable-Aerosol Optical Depth			
	(1)	(2)	(3)	(4)
Neighbour	0.63935***	0.63619***	0.63909***	0.63595***
	(0.013)	(0.013)	(0.013)	(0.013)
Neighbour_rain	-0.11753***	-0.11755***	-0.11733***	-0.11736***
	(0.023)	(0.023)	(0.023)	(0.023)
Rain	0.04155***	0.04162***	0.04149***	0.04156***
	(0.008)	(0.008)	(0.008)	(0.008)
Fire_Count_High	0.03599	0.02829		
	(0.046)	(0.046)		
Fire_Count_Nom			0.02754	0.02593
			(0.017)	(0.017)
Winter	0.07442***	0.07523***	0.07478***	0.07559***
	(0.006)	(0.006)	(0.006)	(0.006)
Spring	0.00024	0.00031	0.00052	0.00059
	(0.006)	(0.006)	(0.006)	(0.005)
Summer	0.01212**	0.01193**	0.01250**	0.01228**
	(0.006)	(0.005)	(0.006)	(0.005)
RH	0.09136***	0.09209***	0.09191***	0.09271***
	(0.015)	(0.014)	(0.015)	(0.014)
Year Fixed Efects	No	Yes	No	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes
R_squared	0.45	0.45	0.45	0.45
Observations	236,332	236,332	236,332	236,332
Number of groups	211	211	211	211

Notes: Standard errors have been corrected for spatial and auto-correlation. Figures in parentheses are standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level'Winter' represents the months of December and January, 'Spring' represents the months of February and March, 'Summer' represents the months of April and May and the omitted category is 'Autumn' that represents the months of October and November.

4.4 Conclusion

Open burning of agricultural fields is a major and neglected source of aerosol pollution in South Asia. Current knowledge of the magnitude of the emissions from field-burning is based on data on crop production, waste to grain ratios, and emission coefficients reported in the literature. In this paper we propose a new approach for estimating the contribution of agricultural fires to atmospheric aerosols. This approach exploits the recently available satellite data on agricultural fires and AOD to conduct regression analysis. We regressed AOD on two measures of fires, total fire-count and total fire radiative power (FRP) and weather variables and grid fixed effects. Our analysis is restricted to agricultural fires that occur in India and covers the period 2001-2008.

For both the fire measures, we found a small effect of fires on AOD compared to previous methods. This may be because the satellite data on fires fails to detect the small-scale agricultural fires. Moreover, agricultural fires are short-lived thus they are more likely to be missed in between satellite passes (Schroeder et al., 2008).

The contribution of our study is that its methodology can be applied to higher resolution data which is expected to become available and would give a better measure of the fire counts (Chang et al., 2013; Liu et al., 2013). The estimated impact of fires from this data would reduce the uncertainty in the magnitude of emissions from open-field burning and therefore provide a more reliable estimate of the economic and climatic benefits from mitigating these fires.

4.5 Appendix

This Appendix outlines the steps followed to create the 'Neighbour' variable. First, we converted the station-level hourly data on wind speed and wind direction into daily gridded data. This conversion was performed by the 'interp' function in the package 'akima' of the open source software 'R'. The interp function implements bivariate interpolation onto a grid for irregularly spaced input data. To use 'interp', the x and y wind component of each observation was derived from its corresponding value of wind speed and direction. These components were then averaged over 24 hours to arrive at daily measures of the x and y component of the wind vector. The latitude, longitude and the x and y component values were then supplied to the interp function to obtain gridded data on wind speed in the XY direction.

The wind speeds were used to compute the location of a cell during the past 24 hours. Next, we determined the intersection of each of the transported cell with the original grid and the area of the intersection. Clearly, each cell can intersect at most four cells. Thus, the AOD in a cell on a day that came from its neighbouring cells was an area-weighted average of the AOD in these four cells. The value of this weighted average for each cell is the value of the variable ‘Neighbour’ .

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