



## Revisiting the crop yield loss in India attributable to ozone

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### HIGHLIGHTS

- Revised estimates of crop yield loss over India using WRF-Chem regional model.
- Higher losses here than observation based estimates due to differing rural chemistry.
- Estimated economic losses are on the higher side, higher crop price also a factor.

### ARTICLE INFO

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### ABSTRACT

Crop Yield Loss (CYL) due to surface ozone substantially affects the Indian economy and the food availability for a billion residents. Nevertheless, the incurring losses over India remain uncertain due to limited measurements and significant uncertainties in the surface O<sub>3</sub> simulated by chemistry-transport models, amongst other causes. Here, we revisit the ozone-attributable CYL using WRF-Chem model, with a set up previously shown to better reproduce the observed ozone variations over the contrasting chemical environments across the Indian region. WRF-Chem simulated ozone fields are converted to Accumulated Ozone above a Threshold of 40 ppbv (AOT40) for two primary crop growing seasons in India, i.e. Kharif (mid-June to mid-September), and Rabi (December to February). Relative Yield Losses (RYL) for wheat are found to be higher (~21–26%) than those in a recent study based on observations (~15%), as the model accounts for the rural chemistry which can be different from urban/suburban/high altitude environments where measurements are largely conducted. Additionally, RYL for rice estimated here (~6%) is 3 times greater than a previous study using this model at a relatively coarser resolution to derive average surface ozone with a set of simulations with varying emission inventories, not evaluated in detail before deriving crop losses. The economic losses due to CYL estimated in this study (~5 billion USD for wheat and 1.5 billion USD for rice) are on the higher side, when estimations from various studies are inter-compared (0.6–4.3 billion USD for wheat, and 0.5–1.5 billion USD for rice), for which increasing crop prices is also a contributing factor. Our study highlights an urgent need to conduct strategic ozone observations especially over agricultural fields, and the development of yearly regional-emission database to support policy making in India.

### 1. Introduction

Elevated ozone concentrations near the surface are shown to significantly reduce the crop yields (Krupa et al., 1998; Rai et al., 2007; Emberson et al., 2009; Ainsworth et al., 2012). This is crucial for Indian region as the country's economy and the food security for about a billion people residing here depends strongly on the agricultural productivity. The tropospheric chemistry over this region is constantly intensifying as a result of rapid increase in the regional anthropogenic

emissions (e. g. Akimoto, 2003; Ohara et al., 2007, Gurjar et al., 2016). Together with this, the intense tropical solar radiation and the ample availability of water vapor result in elevated surface ozone levels (e.g. Naja and Lal, 1996; Saraf et al., 2003; Ojha et al., 2012; Sharma et al., 2017; Lal et al., 2017) imposing a threat to the food security in this region (Ghude et al., 2014; Lal et al., 2017). Such impacts are expected to be further enhanced with feedback of climate warming on ozone formation (Coates et al., 2016) in the future.

To assess the impact of ozone on crop yields, different exposure-

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**Table 1**  
Comparison of estimated relative yield loss (%) for wheat and rice with previous studies.

Study	Method	Wheat (%)	Rice (%)	Remarks
Ghude et al. (2014)	WRF-Chem model	5	2	$0.5^{\circ} \times 0.5^{\circ}$ horizontal resolution
Present work	WRF-Chem model	21	6	$0.3^{\circ} \times 0.3^{\circ}$ horizontal resolution and crop growing seasons taken same as in Ghude et al. (2014)
Debaje (2014)	Observations	21	–	
Lal et al. (2017)	Observations	15	6	
Present work	WRF-Chem model	26	8	Crop growing seasons assumed same as in Lal et al. (2017) and Debaje (2014)
Van Dingenen et al. (2009)	TM5 global model	28	8	$1.0^{\circ} \times 1.0^{\circ}$ horizontal resolution
Avnery et al. (2011)	MOZART-2 global model	30	–	$2.8^{\circ} \times 2.8^{\circ}$ horizontal resolution
Sinha et al. (2015)	Observations	18–27%	12–14%	For states of Punjab and Haryana and using same AOT40 relationship as used in other studies here but for 4–4.5 month growing period
Present work	WRF-Chem model	16	11	For states of Punjab and Haryana

response functions have been developed through intensive field studies under varying climatic conditions (Heck et al., 1987; Legge et al., 1995; Fuhrer et al., 1997; Van Dingenen et al., 2009). Various metrics were developed such as seasonal mean daytime 7 h and 12 h surface ozone concentrations (M7 and M12 respectively), and accumulated ozone above a threshold of 40 ppbv (AOT40) (Emberson et al., 2009). AOT40 is the most widely used metric as it allows greater weightage of elevated ozone levels (Fuhrer et al., 1997; Emberson et al., 2009). Further, it is suggested that Indian wheat and rice cultivars are equally (or more) sensitive to ozone than US and European cultivars (Aunan et al., 2000; Van Dingenen et al., 2009; Sinha et al., 2015) so slightly conservative estimates are anticipated by usage of exposure–response functions developed for western cultivars.

Numerous studies have attempted to estimate the crop yield losses based on AOT40 metric over India using global models (Van Dingenen et al., 2009; Avnery et al., 2011), regional models (Ghude et al., 2014) and observations (Debaje, 2014; Lal et al., 2017) especially for wheat and rice, two important staple crops in Asian region (Emberson et al., 2009). Van Dingenen et al. (2009) used a global chemistry transport model (CTM) TM5 at horizontal resolution of  $1^{\circ} \times 1^{\circ}$  to simulate ozone fields and estimated associated crop yield losses of  $\sim 28\%$  for wheat and  $\sim 8\%$  for rice in India for the year 2000. Similarly, Avnery et al. (2011) estimated crop yield loss of  $\sim 30\%$  for wheat in India by simulating ozone using another global CTM: Model for Ozone and Related Chemical Tracers version 2.4 (MOZART-2) for the year 2000. However, global models show limitation in simulating ozone variations due to several factors including coarse horizontal resolution (Kumar et al., 2012b; Ojha et al., 2012). The limitations are addressed to an extent by incorporating regional-scale models, which are better able to resolve topography and different environments at relatively higher resolutions (Kumar et al., 2012b). Ghude et al. (2014) used a regional model Weather Research and Forecasting with Chemistry (WRF-Chem) (Grell et al., 2005; Fast et al., 2006), incorporating six different emission inventories to simulate average ozone fields at  $0.5^{\circ} \times 0.5^{\circ}$  horizontal resolution and estimated crop yield losses of  $\sim 5\%$  for wheat and  $\sim 2\%$  for rice due to ozone exposure in India for the year 2005. The estimates are significantly lower as compared to global model estimates, and observation-based estimates as discussed later. Recently, we showed that modelled ozone is sensitive to the choice of emissions inventory and chemical mechanism in WRF-Chem (Sharma et al., 2017), especially in daytime hours on which the ozone metrics (e.g. M7, M12 and AOT40) are dependent.

Crop yield loss estimate based on observations have been reported by Debaje (2014) for wheat at  $\sim 21\%$  using the AOT40 metric for the period 2002–2007. Recently, Lal et al. (2017) reported yield loss of  $\sim 15\%$  for wheat and  $\sim 6\%$  for rice using observations from 17 sites in India for the period 2011–14. The observations used in these studies included urban, suburban and high altitude stations as well, where ozone chemistry could be different than that in agricultural rural areas. In rural areas, ozone titration by NO in the evening is slower (because of lower NO levels) than that the urban regions (e. g. Naja and Lal,

2002; Ojha et al., 2012). This could lead to higher ozone over rural agricultural areas (e.g. Chand and Lal, 2004). This suggests that the assessment of crop losses based on surface ozone measurements away from agricultural rural areas might result in lower estimates. Nevertheless, the observation-based yield losses are higher than the regional model estimates mentioned before (especially for wheat). This again substantiates the fact that the regional model fields need improvement in reproducing observed ozone variations. In addition, Sinha et al. (2015) estimated a crop yield loss of 18–27% for wheat and 12–14% for rice in the states of Punjab and Haryana during 2011–2013 period based on observations at Mohali (a suburban site in Punjab) and ozone exposure–response relationship from Mills et al. (2007), as used in aforementioned studies, but calculating AOT40 metric for 4–4.5 month period instead of 3-month period adopted in other aforementioned studies. Although Sinha et al. (2015) also reported crop yield losses using a newly derived ozone exposure–response relationship we only adopt the estimates based on functions in Mills et al. (2007) for a consistent comparison with all the aforementioned studies. The estimates of Sinha et al. (2015) are also higher than the regional model-based estimates by Ghude et al. (2014) for wheat and rice for the states of Punjab and Haryana together.

Clearly, there exists large uncertainty in the CYL estimations in the literature for the Indian region with differences up to 30 times between the different estimates. All these estimates from modeling and observation studies are also provided in Table 1. Regional models like WRF-Chem can provide a comprehensive picture of spatial and temporal variation of pollutants like ozone even over rural areas thus compensating for limited observations especially in developing countries like India. Also, these can serve as a worthier tool compared to global models to investigate the current and future scenarios and support policy making due to their higher resolution. Considering the lower crop loss estimates over India in Ghude et al. (2014) compared to other studies, it is important that the pollutant levels in the regional models are improved by utilizing a suitable configuration of spatial resolution, physics parameterizations, emissions and chemical mechanisms before assessing the crop losses. In the present study we estimate crop yield losses using ozone fields from WRF-Chem by incorporating a setup of a recent regional emission inventory and chemical mechanism shown to better reproduce the observed ozone variations over contrasting chemical environments across Indian region (Sharma et al., 2017). We utilize slightly finer horizontal model resolution of  $0.3^{\circ} \times 0.3^{\circ}$  compared to  $0.5^{\circ} \times 0.5^{\circ}$  used in Ghude et al. (2014) in order to resolve topography and emissions fields better. We also incorporate physics parameterizations that have been tested in several previous modeling studies over India (Kumar et al., 2012b; Ojha et al., 2016; Girach et al., 2017; Sharma et al., 2017).

## 2. Methodology

In this study we use WRF-Chem, a regional chemistry transport model to simulate ozone levels over Indian region for the year 2014–15.

The resulting surface ozone mixing ratios are used to calculate accumulated ozone above a threshold of 40 ppbv (AOT40) during respective crop growing period as follows:

$$\text{AOT40} = \sum_{i=1}^n ([\text{O}_3]_i - 40), \text{ for } \text{O}_3 \geq 40 \text{ ppbv} \quad (1)$$

where  $n$  is the number of daylight hours during the crop growing season.

Exposure-response functions based on AOT40 metric are used to calculate the relative yield losses (RYLs) for wheat and rice, which are subsequently used to estimate crop production losses (CPLs) and associated economic cost losses (ECLs). Here we provide further details about the model including various parameterizations and chemical mechanism incorporated to simulate ozone and the subsequent calculations involved in estimating crop yield loss.

### 2.1. Regional chemistry transport model

WRF-chem (version 3.8.1) is run over domain centered at 22°N and 83°E with 92 points in east-west direction and 118 points in north-south direction. The model domain defined on Mercator projection is shown in Fig. 1a. The horizontal resolution of the model is  $\sim 0.3^\circ \times 0.3^\circ$  with 51 vertical levels from the surface up to 50 hPa. Initial and boundary conditions for meteorology are provided from ERA-interim reanalysis ([www.ecmwf.int/en/research/climate-reanalysis/browse-reanalysis-datasets](http://www.ecmwf.int/en/research/climate-reanalysis/browse-reanalysis-datasets)). Various physics and chemistry options incorporated in the model are given in Table S1. Further, we incorporate Four-dimensional data assimilation (FDDA) technique at all vertical levels with nudging coefficients of 0.0006 for temperature, horizontal winds, and water vapor mixing ratio (Kumar et al., 2012a; Ojha et al., 2016).

Anthropogenic emissions of ozone precursors over are included from a recent regional inventory: Southeast Asia Composition, Cloud, Climate Coupling Regional Study (SEAC4RS) inventory (Lu and Streets, 2012), prepared as a part of NASA SEAC4RS field campaign. The annual emissions in the inventory are available at spatial resolution of  $0.1^\circ \times 0.1^\circ$  for the year 2012. The north western parts of the domain, not covered by SEAC4RS, were filled in using the Hemispheric Transport of Air Pollution (HTAP) inventory (Janssens-Maenhout et al., 2015). The spatial distribution of nitrogen oxides ( $\text{NO}_x$ ) emissions in the SEAC4RS inventory is shown in Fig. 1b. Since SEAC4RS inventory provides total annual emissions, we incorporated the seasonality derived from the Reanalysis of Tropospheric chemical composition (RETRO) inventory ([https://gcmd.gsfc.nasa.gov/records/GCMD\\_GEIA\\_RETRO.html](https://gcmd.gsfc.nasa.gov/records/GCMD_GEIA_RETRO.html)) as shown in Fig. S1. Biomass-burning emissions are included through the Fire Inventory from NCAR (FINN) version 1.0 (Wiedinmyer et al., 2011). The biogenic emissions are taken from the Model of Emissions of Gases and Aerosols from Nature (MEGAN) (Guenther et al., 2006). Initial and boundary conditions for chemistry are provided from the Model for Ozone and Related Chemical Tracers (MOZART-4/GEOS5) (<http://www.acom.ucar.edu/wrf-chem/mozart.shtml>). Model chemistry is based on the Regional Acid Deposition Model – 2nd generation

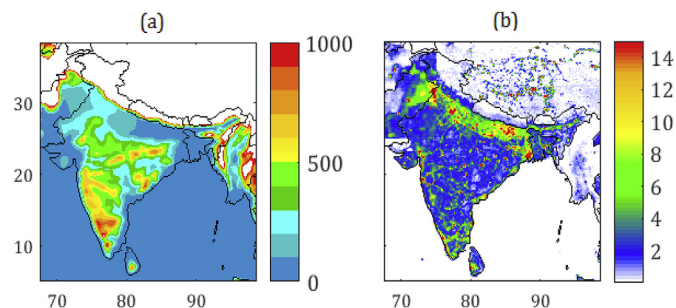


Fig. 1. (a): Terrain height (meters), and (b) anthropogenic  $\text{NO}_x$  emissions ( $\text{mol km}^{-2} \text{h}^{-1}$ ) over the Indian region used in the study.

(RADM2) chemical mechanism (Stockwell et al., 1990), which has been used in several studies over India previously (Michael et al., 2013; Ojha et al., 2016; Girach et al., 2017) and was found to compute ozone in better agreement with observations over India during pre-monsoon when ozone photochemistry is more intense (Sharma et al., 2017).

Model simulation is performed for the period February 19th, 2014–March 1st, 2015 with first 10 days considered as the model spin up. Surface ozone mixing ratios obtained from the model are used to calculate AOT40.

### 2.2. Crop damage and economic losses

We use crop production data for wheat and rice available on district level from “Special Data Dissemination Standard Division, Directorate of Economics and Statistics, Ministry Of Agriculture and Farmers Welfare, Government Of India” (<https://aps.dac.gov.in/APY/Index.htm>). Rice is grown in Kharif (usually June–October) and Rabi season (usually November–April) in India, whereas, wheat is grown primarily as a Rabi crop in the region. In order to calculate crop damage we take 90 days ozone exposure period, as usually adopted in other similar studies, which in the present study is mid June – mid September for Kharif, and December–February for Rabi, as also considered in Ghude et al. (2014). Following exposure-response functions from Mills et al. (2007), as in other studies listed in Table 1, are used to calculate relative yield (RY) losses.

$$\text{For wheat: RY} = -0.0000161 \times \text{AOT40} + 0.99 \quad (2)$$

$$\text{For rice: RY} = -0.0000039 \times \text{AOT40} + 0.94 \quad (3)$$

The functions are scaled to have RY value of 1 at zero value of AOT40 (Van Dingenen et al., 2009; Ghude et al., 2014). Relative yield values from above functions are used to calculate relative yield losses (RYLs) for crops ( $\text{RYL} = 1 - \text{RY}$ ). Subsequently, these RYL values are used to calculate the crop production losses (CPL) after converting district level crop production (CP) data to gridded format having same horizontal resolution as that of the model ( $0.3^\circ \times 0.3^\circ$ ). For each grid cell  $i$ ,  $\text{CPL}_i$  is calculated from  $\text{RYL}_i$  and  $\text{CP}_i$  as (following Van Dingenen et al., 2009; Avnery et al., 2011, Ghude et al., 2014)

$$\text{CPL}_i = \frac{\text{RYL}_i}{1 - \text{RYL}_i} \times \text{CP}_i \quad (4)$$

Following the methodology of Avnery et al. (2011), the crop production loss from all grid cells within the country (or a state) are added to obtain nationwide (statewise) losses. Further, nationwide (statewise) RYL is calculated as nationwide (statewise) CPL divided by the total theoretical nationwide (statewise) CP without any injury due to ozone exposure ( $\text{CP} + \text{CPL}$ ). The economic cost loss (ECL) is calculated by multiplying CPL with the corresponding minimum support price (MSPs) for a crop decided by Government of India for the year 2014–15 (<http://cacp.dacnet.nic.in/ViewContents.aspx?Input=1&PageId=36&KeyId=0>).

## 3. Results

### 3.1. Spatial distribution of modelled surface ozone and AOT40

The spatial distribution of 24 h average surface ozone during the Kharif and Rabi seasons is shown in Fig. 2. During the Kharif season, Indo-Gangetic plain (IGP) generally experiences elevated levels of ozone (40–60 ppbv) due to high pollution loading, intense solar radiation and less precipitation (e. g. Ojha et al., 2012). Surface ozone mixing ratios are mostly found to be lower (below 40 ppbv) in the rest of the Indian region, especially in the south. On the other hand, during the Rabi season, surface ozone mixing ratios are found to be below 45 ppbv along most of the IGP, except eastern part where the levels are mostly above 45 ppbv. The low ozone levels along western and central

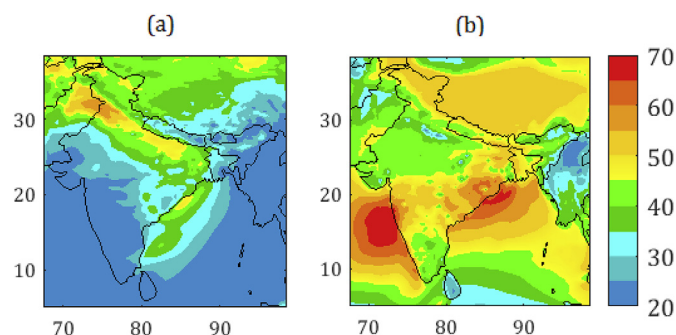


Fig. 2. Average surface ozone (in ppbv) during (a) Kharif (mid June - mid September), and (b) Rabi growing season (December–February).

IGP are due to less intense solar radiation, coupled with increased  $\text{NO}_x$  titration resulting from stronger emissions in the region during this period (Kumar et al., 2012b). Rest of the Indian region experiences high levels (40–60 ppbv) of surface ozone during this period. Elevated ozone levels (above 50 ppbv) are seen in part of Arabian Sea region included in the domain and north part of the Bay of Bengal. Similar spatial distribution of surface ozone over India have been reported in earlier studies (e.g. Kumar et al., 2012b; Ojha et al., 2012).

WRF-Chem has been shown to better reproduce ozone as compared to global models when evaluated against ground based, balloon-borne, aircraft-based, and satellite-based observations (e.g. Kumar et al., 2012b; Ojha et al., 2016; Sharma et al., 2017). Spatial distribution of ozone simulated in the present study is also found to be similar to aforementioned modeling studies over India (e.g. Kumar et al., 2012b; Ojha et al., 2012). Nevertheless, we compare the WRF-Chem simulated seasonal variation in surface ozone with observations at several sites in different regions of India (Supplementary material–Section S1 and Figs. S2 and S3). The evaluation is performed using Normalized Mean Bias (NMB) and fraction of modelled values within 0.5–2 times of the observed values (FAC2) (e.g. Derwent et al., 2010; Dore et al., 2015). We find that for all the sites NMB and FAC2 values are within the recommended range (NMB < 0.2; FAC2 > 0.5) with FAC2  $\geq$  0.9 at all the sites indicating an adequate model performance for its subsequent use to analyze the crop losses. The spatial distribution of AOT40 derived from hourly values of surface ozone during Kharif and Rabi seasons is shown in Fig. 3. Similar to the distribution of ozone, the AOT40 distribution pattern also shows high values (15000 ppbv h) along the IGP during Kharif season, and in eastern IGP, central India and coastal regions during Rabi season. These AOT40 values are used to calculate relative yield loss (RYLs) for the crops as discussed in the next section.

### 3.2. Spatial distribution of CP, RYL and CPL

Fig. 4 shows the gridded distributions of total wheat production (CP for wheat), percentage relative yield loss (% RYL) derived using AOT40 for the regions of wheat production, and crop production loss (CPL) for

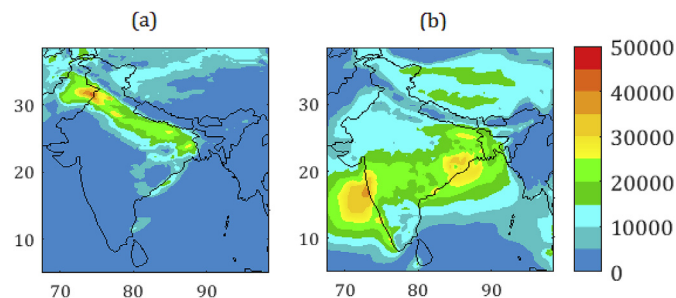


Fig. 3. AOT40 during (a) Kharif; and (b) Rabi crop growing season. Units are in ppbv h.

the year 2014–15 (also see Fig. S4 in the Supplement for locations of different states in India which are part of subsequent discussion). The major wheat producer states are in the IGP (Punjab, Haryana and Uttar Pradesh/UP) with significant contribution from states of Madhya Pradesh (MP), Rajasthan and Bihar (Fig. 4a). Over most of the high wheat producing regions RYL generally varies between 15 and 30% (Fig. 4b). Though the high values of RYL are seen in the eastern IGP and lower western region of India (> 30%), the contribution of these regions to total wheat production is comparatively less which also results in less contribution to total crop damage. The resulting crop damage (Fig. 4c) shows high loss intensity (tonnes/model grid area) in Punjab, Haryana, eastern UP, western Bihar and some parts of MP.

Fig. 5 shows the CP, %RYL and CPL for rice in the year 2014–15 for both Kharif and Rabi rice production aggregated. Major contributors to total annual rice production are in the IGP region (Punjab, UP, Bihar and West Bengal/WB) and states of Orissa and Andhra Pradesh (AP) as seen in Fig. 5a. The relative yield loss (% RYL) distribution in Fig. 5b shows losses of up to 20% in the north west IGP (in the state of Punjab). Over rest of the IGP region %RYL is generally between 6 and 12%. In other regions of India, the %RYL values are seen to be less due to lower AOT40. Fig. 5c for resulting crop damage shows highest loss density along IGP belt especially in north western (Punjab) and eastern IGP (state of West Bengal).

### 3.3. Nationwide and statewide RYL and comparison with other studies

Fig. 6a shows the %RYL for wheat at national level (also see Table 1), and for the high wheat producing states. The total nationwide RYL for wheat is 21% which is substantially higher than the value of ~5% reported in Ghude et al. (2014). Our estimates are similar to the RYL reported by Debaje (2014) based on observations and higher than the value of 15% reported by Lal et al. (2017). Here it should be noted that wheat growing season is considered as January–March in Debaje (2014) and Lal et al. (2017) as compared to the December–February period in the present study following Ghude et al. (2014). To make a consistent comparison with these studies we also present the wheat loss estimate for January–March period in Table 1. RYL for wheat (~26%) during this period is found to be higher than observation-based estimates because in the model differing chemistry over rural areas is accounted for as compared to urban/suburban stations where measurements were generally conducted. To illustrate this further we present distribution of percentage relative yield loss (%RYL) for wheat during Rabi season in the present study along with observation sites used to calculate RYL, for north India, in Lal et al. (2017) in supplementary figure (Fig. S5). Here the yield losses at the measurement sites are seen to be lower than the surrounding rural areas. This is also shown based on ozone diurnal variations at Delhi (urban site), Mohali (suburban site) and over entire Punjab and Haryana regions together after spatial averaging, thus accounting for ozone levels in surrounding rural areas also (Fig. S6). It is seen that the regional ozone levels in the two leading wheat producing states are higher than Mohali throughout the daytime and Delhi towards the end of the day. The higher ozone levels in rural areas translate to higher AOT40 values leading to enhanced crop yield losses. Therefore, it is suggested that the assessments of ozone impact on crops in rural agricultural areas by deriving yield losses from measurements made in various stations (including urban/suburban) might lead to an underestimation. All these RYL estimates for wheat including in the present study are lower than the global modeling-based estimates of 28% and 30% reported in Van Dingenen et al. (2009) and Avnery et al. (2011) respectively. This is attributed to an overestimation of ozone by global models over Indian region leading to high yield losses.

From Fig. 6, the RYL estimates in some leading wheat producing states are ~21% in UP, 16% in Punjab and Haryana each, 19% in Rajasthan and 23% in MP. The RYL estimate of 16% for states of Punjab and Haryana together is lower than the observation based estimate of 18–27% in Sinha et al. (2015) (also see Table 1). Higher estimate in

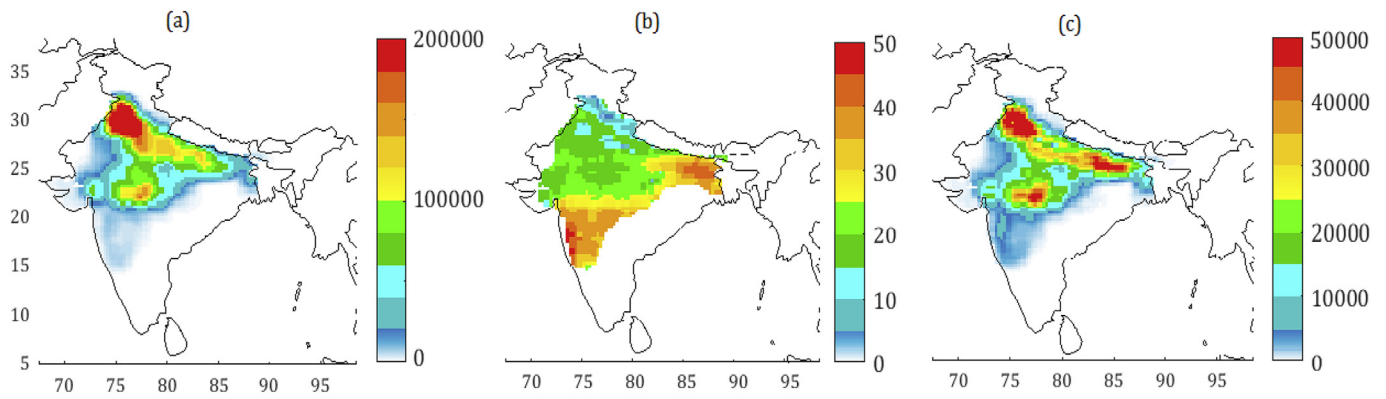


Fig. 4. (a) Total Wheat production (Rabi growing season) in tonnes/model grid; (b) Percentage relative yield loss (%RYL); and (c) Crop production loss (CPL) for wheat in tonnes/model grid in each model grid.

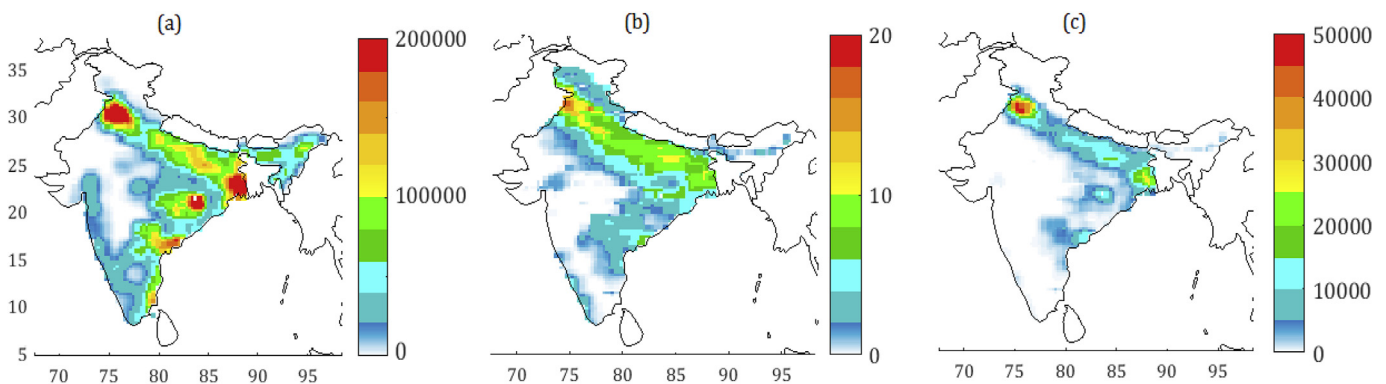


Fig. 5. (a) Total Rice production (both Kharif and Rabi growing seasons) in tonnes/model grid; (b) Percentage relative yield loss (%RYL); and (c) Crop production loss (CPL) for rice in tonnes/model grid in each model grid.

Sinha et al. (2015) is due to the fact that the study took ozone exposure period for wheat as 4–4.5 months as compared to 3 months generally adopted. Nevertheless, estimates in the present study and in Sinha et al. (2015) are significantly higher than the estimates reported in Ghude et al. (2014) for Punjab and Haryana as discussed in section 1 also.

Fig. 6b shows the %RYL estimates for rice at national level (also see Table 1) and for some leading rice producing states. Our nationwide RYL estimate of rice (~6%) is higher than the value of ~2% reported by Ghude et al. (2014). Although the estimate is similar to the losses

reported in observation based study by Lal et al. (2017) but the crop growing periods again differ in two studies. For the same rice growing season as assumed in Lal et al. (2017) our estimates are slightly higher (8%) as shown in Table 1. This is because the model captures the rural chemistry and measurements used in Lal et al. (2017) include data from urban/suburban/high altitude sites. The state wise estimates for some states are ~9% for UP, 11.5% for Punjab, 9% for Haryana, 7% for WB and 4% for Orissa (Fig. 6). The combined RYL estimate for Punjab and Haryana together is ~11% in the present study which is slightly lower

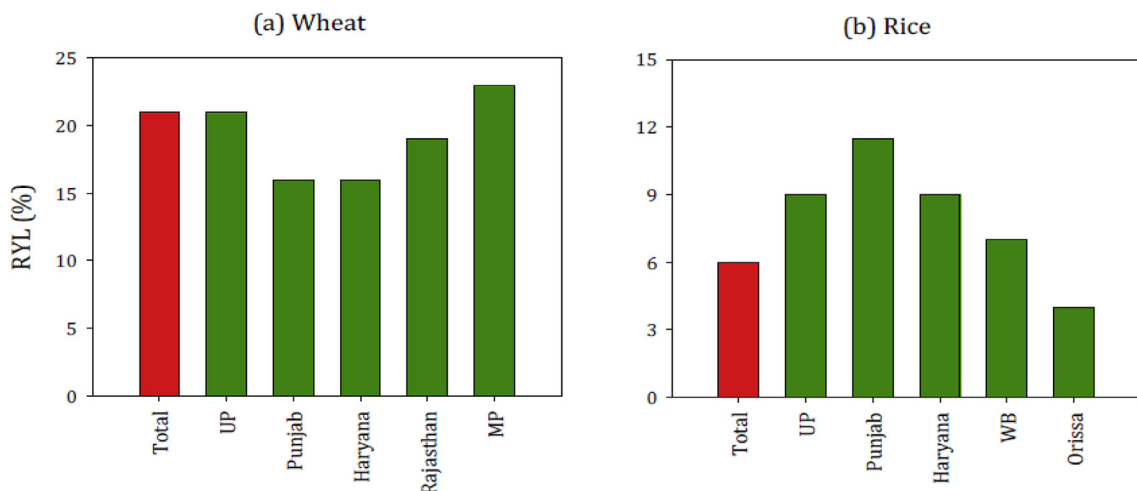


Fig. 6. Relative yield loss (%) for (a) Wheat; and (b) Rice in several respective crop growing states of India (green) due to surface ozone exposure for the year 2014–15. National average relative yield loss is also added in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

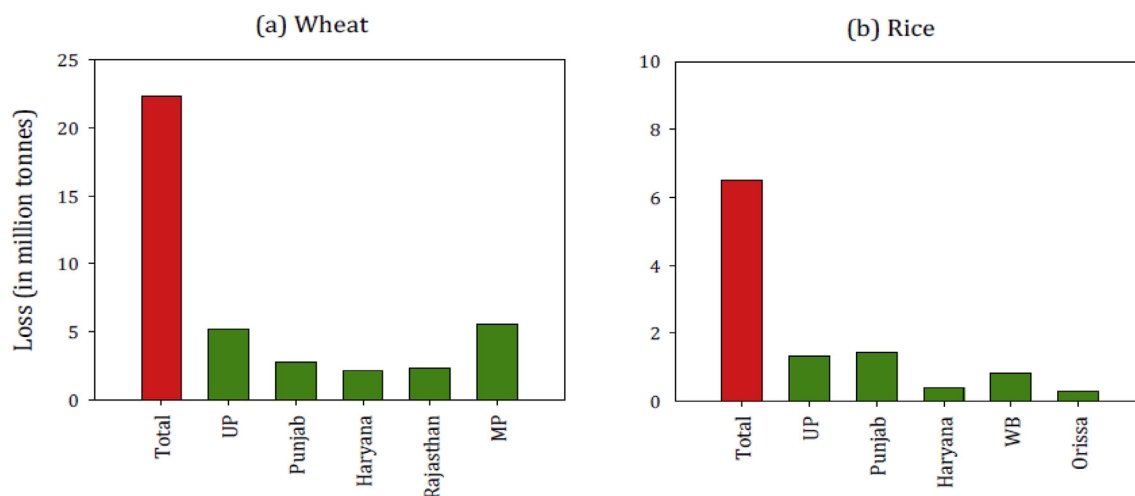


Fig. 7. Crop production loss (in million tonnes) for (a) Wheat; and (b) Rice in several respective crop growing states of India (green) due to surface ozone exposure for the year 2014–15. National average crop production loss is also added in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

than the estimate of 12–14% in [Sinha et al. \(2015\)](#) (also see [Table 1](#)) due to the fact that the latter study took ozone exposure period for rice as 4 months as compared to 3-month period in the present study. Overall the RYL estimates for wheat and rice in the present study are higher than the estimates in several observations based studies and also show an improvement over the estimates in a previous regional modeling study.

The estimates in this study are not free of uncertainties, which may be due to uncertainties in model simulated ozone and exposure-response functions incorporated to name few. Nevertheless, we employed a model setup, which has demonstrated the better ozone build up over differing chemical environments in India. Further, as the Indian wheat and rice cultivars are equally or more sensitive to ozone than western cultivars so using western derived exposure-response functions might have led to conservative results.

### 3.4. Nationwide and statewide CPL and ECL

The total nationwide CPL for wheat in the present study is ~22 million tonnes ([Fig. 7a](#)) in the year 2014–15. Out of this, states of UP and MP bear the most losses at ~5 and 5.5 million tonnes respectively. Other than these, the estimates of CPL are ~3 million tonnes in Punjab and ~2 million tonnes in Haryana and Rajasthan each. [Fig. 7b](#) shows the nationwide CPL for rice as ~6.5 million tonnes in the year 2014–15 with the states of UP and Punjab bearing the most losses at ~1 and 1.5 million tonnes respectively. We also find that more than half of the nationwide crop production losses (CPLs) for wheat and rice due to ozone exposure occur in the IGP region (consisting of states of Punjab, Haryana, UP, Bihar and WB) which is due to the combined effect of higher crop production and exposure to elevated pollution loading in the region.

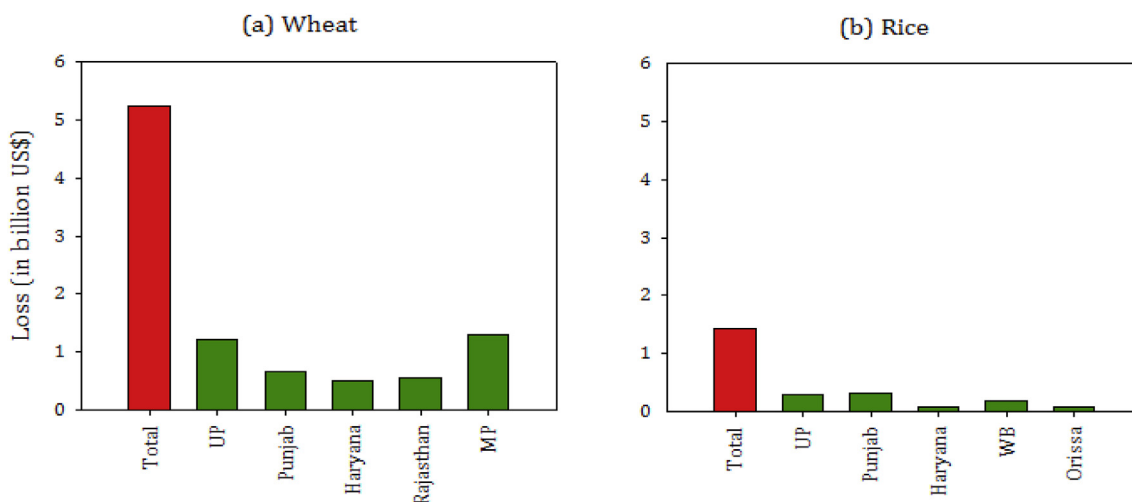
Economic cost losses (ECL) are calculated using minimum support prices for the year 2014–15 ([Fig. 8](#)). The nationwide ECL is estimated at ~5 billion USD and ~1.5 billion USD for wheat and rice respectively in the year 2014–15. States of UP and MP sustain losses of more than 1 billion USD each for wheat, while, for rice the losses are highest in UP and Punjab at ~0.3 billion USD each. The economic losses in the present study are compared with the estimates in various previous studies in [Fig. 9](#). The current estimates (~5 billion USD for wheat and 1.5 billion USD for rice) are on the higher side as compared to previous estimates (0.6–4.3 billion USD for wheat and 0.5–1.5 billion USD for rice) which is also a result of increasing crop prices in India. On the other hand, the total economic losses in Punjab and Haryana (~1.1

billion USD for wheat and 0.4 billion USD for rice) are on the lower side as compared to estimates in [Sinha et al. \(2015\)](#) (~1.3–2.1 billion USD for wheat and 0.4–0.5 billion USD for rice) primarily because of different ozone exposure periods taken in the two studies as mentioned before.

## 4. Summary and conclusions

In this study, we used regional chemistry transport model WRF-Chem to simulate hourly surface ozone mixing ratios to derive AOT40 over India, which was subsequently used to estimate the crop yield losses for wheat and rice and resulting economic loss in the year 2014–15. Our estimates reveal a nationwide relative yield loss (%RYL) of about 21% for wheat and 6% for rice. We also estimate RYL of about 16% for wheat and 11% for rice for the states of Punjab and Haryana together. These estimates are found to be substantially higher than those in previous regional modeling estimates (just 5% for wheat and 2% for rice) over India. Our estimates are also higher than the losses reported by several observation-based studies as the model does account for differing ozone chemistry in rural agricultural fields away from some of the urban (and semi-urban) monitoring stations. Total crop production losses are estimated to be about 22 million tonnes for wheat, with UP and MP states alone suffering losses of about 5 and 5.5 million tonnes respectively. For rice the estimated total crop production loss is 6.5 million tonnes with states of UP and Punjab sustaining losses of about 1 and 1.5 million tonnes respectively. More than half of the nationwide crop production losses (CPLs) for wheat and rice due to ozone exposure is found to occur over the IGP region (consisting of states of Punjab, Haryana, UP, Bihar and WB) due to the combined effects of higher crop production and exposure to elevated ozone levels. The associated economic losses due to CYL estimated in this study (~5 billion USD for wheat and 1.5 billion USD for rice) are on the higher side when estimates from various studies are inter-compared (0.6–4.3 billion USD for wheat and 0.5–1.5 billion USD for rice) for which increasing crop price is also a contributing factor.

[Kumar et al. \(2018\)](#) showed that the surface ozone levels are bound to increase in the future (2045–2054) with maximum enhancement over the IGP belt which is an important agricultural region. This may translate to higher RYL estimates in the future thus posing threat to the food security of the country unless effective pollution mitigation measures are adopted. Development of ozone resistant cultivars is an alternative which needs to be explored in the future. Our study highlights a need to conduct long-term ozone observations near agricultural fields,



**Fig. 8.** Economic cost losses (in billion USD) for (a) Wheat; and (b) Rice in several respective crop growing states of India (green) due to surface ozone exposure for the year 2014–15. National average economic cost loss is also added in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and development of yearly emission database to provide further assessments required for policy making in India.

**Declaration of interest statement**

The authors declare that they have no conflict of interest.

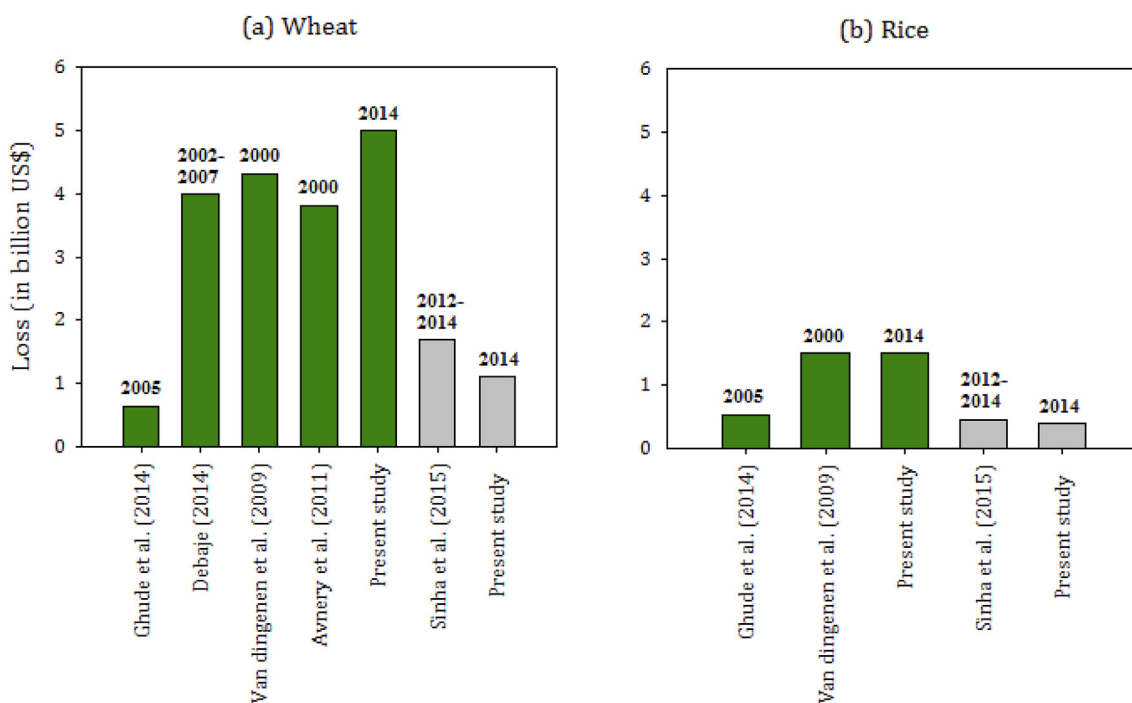
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obtained from [http://edgar.jrc.ec.europa.eu/htap\\_v2/486index.php?SECURE=123](http://edgar.jrc.ec.europa.eu/htap_v2/486index.php?SECURE=123). Initial and boundary conditions for chemical fields are obtained from MOZART-4/GEOS5 output, which is acknowledged. The pre-processors and inputs for biogenic and biomass-burning emissions were downloaded from NCAR Atmospheric Chemistry website (<http://www.acd.ucar.edu/wrf-chem/>). Usage of the High Performance Computing resources HYDRA (<http://www.mpcdf.mpg.de/services/computing/hydra>), and Vikram ([https://www.prl.res.in/prl-eng/hpc/vikram\\_hpc](https://www.prl.res.in/prl-eng/hpc/vikram_hpc)) are acknowledged. Constructive comments and suggestions from two anonymous reviewers are gratefully acknowledged.

**Appendix A. Supplementary data**

Supplementary data to this article can be found online at <https://>



**Fig. 9.** Comparison of Economic cost losses (in billion USD) for (a) Wheat; and (b) Rice in the present study with previous estimates in literature. The time period of estimates in all studies in shown above respective bars. Bars in green represent nationwide losses whereas bars in grey represent total losses in Punjab and Haryana. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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## References

- Ainsworth, E.A., Yendrek, C.R., Sitch, S., Collins, W.J., Emberson, L.D., 2012. The effects of tropospheric ozone on net primary productivity and implications for climate change. *Annu. Rev. Plant Biol.* 63, 637–661.
- Akimoto, H., 2003. Global air quality and pollution. *Science* 302, 1716–1719. <https://doi.org/10.1126/science.1092666>.
- Aunan, K., Bernsten, T.K., Seip, H.M., 2000. Surface ozone in China and its possible impact on agricultural crop yields. *Ambio* 29, 294–301.
- Avnery, S., Mauzerall, D.L., Liu, J., Horowitz, L.W., 2011. Global crop yield reductions due to surface ozone exposure 1: year 2000 crop production losses and economic damage. *Atmos. Environ.* 45, 2284–2296.
- Chand, D., Lal, S., 2004. High ozone at rural sites in India. *Atmos. Chem. Phys. Discuss.* 4, 3359–3380. <https://doi.org/10.5194/acpd-4-3359-2004>.
- Coates, J., Mar, K.A., Ojha, N., Butler, T.M., 2016. The influence of temperature on ozone production under varying NO<sub>x</sub> conditions – a modelling study. *Atmos. Chem. Phys.* 16, 11601–11615. <https://doi.org/10.5194/acp-16-11601-2016>.
- Debaje, P.K., 2014. Estimated crop yield losses due to surface ozone exposure and economic damages in India. *Environ. Sci. Pollut. Res.* 21, 7329–7338.
- Derwent, R.D., Fraser, A., Abbott, J., Jenkin, M., Willis, P., Murrells, T., 2010. Evaluating the Performance of Air Quality Models. Report Prepared for the UK Department for Environment, Food and Rural Affairs. Issue 3/June 2010 Defra, London Available from: [https://uk-air.defra.gov.uk/assets/documents/reports/cat05/1006241607\\_100608\\_MIP\\_Final\\_Version.pdf](https://uk-air.defra.gov.uk/assets/documents/reports/cat05/1006241607_100608_MIP_Final_Version.pdf) 22.04.18.
- Dore, A.J., Carslaw, D.C., Braban, C., Cain, M., Chemel, C., Conolly, C., Derwent, R.G., Griffiths, S.J., Hall, J., Hayman, G., Lawrence, S., Metcalfe, S.E., Redington, A., Simpson, D., Sutton, M.A., Sutton, P., Tang, Y.S., Vieno, M., Werner, M., Whyatt, J.D., 2015. Evaluation of the performance of different atmospheric chemical transport models and inter-comparison of nitrogen and sulphur deposition estimates for the UK. *Atmos. Environ.* 119, 131–143.
- Emberson, L.D., Buker, P., Ashmore, M., Mills, G., Jackson, L., Agrawal, M., Atikuzzaman, M., Cinderby, S., Engardt, M., Jamir, C., Kobayashi, K., Oanh, N., Quadir, Q., Wahid, A., 2009. A comparison of North-American and Asian exposure-response data for ozone effects on crop yields. *Atmos. Environ.* 43, 1945–1953.
- Fast, J.D., Gustafson Jr., W.I., Easter, R.C., Zaveri, R.A., Barnard, J.C., Chapman, E.G., Grell, G.A., Peckham, S.E., 2006. Evolution of ozone, particulates, and aerosol direct radiative forcing in the vicinity of Houston using a fully-coupled meteorology-chemistry aerosol model. *J. Geophys. Res.* 111, D21305.
- Fuhrer, J., Skärby, L., Ashmore, M.R., 1997. Critical levels for ozone effects on vegetation in Europe. *Environ. Pollut.* 97, 91–106.
- Ghude, S.D., Jena, C., Chate, D.M., Beig, G., Pfister, G.G., Kumar, R., Ramanathan, V., 2014. Reduction in Indian crop yield due to ozone. *Geophys. Res. Lett.* 41, 51971. <https://doi.org/10.1002/2014GL060930>.
- Girach, I.A., Ojha, N., Nair, P.R., Pozzer, A., Tiwari, Y.K., Kumar, K.R., Lelieveld, J., 2017. Variations in O<sub>3</sub>, CO, and CH<sub>4</sub> over the Bay of Bengal during the summer monsoon season: shipborne measurements and model simulations. *Atmos. Chem. Phys.* 17, 257–275. <https://doi.org/10.5194/acp-17-257-2017>.
- Grell, G.A., Peckham, S.E., McKeen, S., Schmitz, R., Frost, G., Skamarock, W.C., Eder, B., 2005. Fully coupled 'online' chemistry within the WRF model. *Atmos. Environ.* 39, 6957–6975.
- Guenther, A., Karl, T., Harley, P., Wiedinmyer, C., Palmer, P.I., Geron, C., 2006. Estimates of global terrestrial isoprene emissions using MEGAN (model of emissions of gases and aerosols from nature). *Atmos. Chem. Phys.* 6, 3181–3210. <https://doi.org/10.5194/acp-6-3181-2006>.
- Gurjar, B.R., Ravindra, K., Nagpure, A.S., 2016. Air pollution trends over Indian megacities and their local-to-global implications. *Atmos. Environ.* 142, 475–495. <https://doi.org/10.1016/j.atmosenv.2016.06.030>.
- The NCLAN economic assessment: approach, findings and implications. In: Heck, W.W., Taylor, O.C., Tingey, D.T. (Eds.), *Assessment of Crop Losses from Air Pollutants*. Elsevier Applied Science, London.
- Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Dentener, F., Muntean, M., Pouliot, G., Keating, T., Zhang, Q., Kurokawa, J., Wankmüller, R., Denier van der Gon, H., Kuenen, J.J.P., Klimont, Z., Frost, G., Darras, S., Koffi, B., Li, M., 2015. HTAP\_v2.2: a mosaic of regional and global emission grid maps for 2008 and 2010 to study hemispheric transport of air pollution. *Atmos. Chem. Phys.* 15, 11411e11432. <https://doi.org/10.5194/acp-15-11411-2015>.
- Krupa, S.V., Nosal, M., Legge, A.H., 1998. A numerical analysis of the combined open top chamber data from the USA and Europe on ambient ozone and negative crop responses. *Environ. Pollut.* 101, 157–160.
- Kumar, R., Naja, M., Pfister, G.G., Barth, M.C., Brasseur, G.P., 2012a. Simulations over south Asia using the weather Research and forecasting model with chemistry (WRF-Chem): set-up and meteorological evaluation. *Geosci. Model Dev. (GMD)* 5, 321–343.
- Kumar, R., Naja, M., Pfister, G.G., Barth, M.C., Wiedinmyer, C., Brasseur, G.P., 2012b. Simulations over south Asia using the weather Research and forecasting model with chemistry (WRF-Chem): chemistry evaluation and initial results. *Geosci. Model Dev. (GMD)* 5, 619–648.
- Kumar, R., et al., 2018. How will air quality change in South Asia by 2050? *J. Geophys. Res.: Atmosphere* 123, 1840–1864. <https://doi.org/10.1002/2017JD027357>.
- Lal, S., Venkataramani, S., Naja, M., Kuniyal, J.C., Mandal, T.K., Bhuyan, P.K., Maharaj Kumar, K., Tripathi, S.N., Sarkar, U., Das, T., Swamy, Y.V., Rama Gopal, K., Gadhavi, H., Kottungal, M., Kumar, S., 2017. Loss of crop yields in India due to surface ozone: an estimation based on a network of observations. *Environ. Sci. Pollut. Res.* 24 (26), 20972–20981. <https://doi.org/10.1007/s11356-017-9729-3>.
- Legge, A.H., Grunhage, L., Noal, M., Jager, H.J., Krupa, S.V., 1995. Ambient ozone and adverse crop response: an evaluation of north American and European data as they relate to exposure indices and critical levels. *J. Appl. Bot.* 69, 192–205.
- Lu, Z., Streets, D.G., 2012. The Southeast Asia composition, cloud, climate coupling regional study emission inventory. available at: <http://bio.cgrer.uiowa.edu/SEAC4RS/emission.html>.
- Michael, M., Yadav, A., Tripathi, S.N., Kanawade, V.P., Gaur, A., Sadavarte, P., Venkataraman, C., 2013. Simulation of trace gases and aerosols over the Indian Domain: evaluation of the WRF-Chem model. *Atmos. Chem. Phys. Discuss.* 13, 12287–12336.
- Mills, G., Buse, A., Gimeno, B., Bermejo, V., Holland, M., Emberson, L., Pleijel, H., 2007. A synthesis of AOT40-based response functions and critical levels of ozone for agricultural and horticultural crops. *Atmos. Environ.* 41, 2630–2643.
- Naja, M., Lal, S., 1996. Changes in surface ozone amount and its diurnal and seasonal patterns, from 1954–1955 to 1991–1993, measured at Ahmedabad (23°N), India. *Geophys. Res. Lett.* 23, 81–84.
- Naja, M., Lal, S., 2002. Surface ozone and precursor gases at Gadanki (13.5°N, 79.2°E), tropical rural site in India. *J. Geophys. Res.* 107 (D14), 4197. <https://doi.org/10.1029/2001JD000357>.
- Ohara, T., Akimoto, H., Kurokawa, J., Horii, N., Yamaji, K., Yan, X., Hayasaka, T., 2007. An Asian emission inventory of anthropogenic emission sources for the period 1980–2020. *Atmos. Chem. Phys.* 7, 4419–4444. <https://doi.org/10.5194/acp-7-4419-2007>.
- Ojha, N., Naja, M., Singh, K.P., Sarangi, T., Kumar, R., Lal, S., Lawrence, M.G., Butler, T.M., Chandola, H.C., 2012. Variabilities in ozone at a semi-urban site in the Indo-Gangetic Plain region: association with the meteorology and regional process. *J. Geophys. Res.* 117, D20301. <https://doi.org/10.1029/2012JD017716>.
- Ojha, N., Pozzer, A., Rauthe-Schöch, A., Baker, A.K., Yoon, J., Breninkmeijer, C.A.M., Lelieveld, J., 2016. Ozone and carbon monoxide over India during the summer monsoon: regional emissions and transport. *Atmos. Chem. Phys.* 16, 3013–3032. <https://doi.org/10.5194/acp-16-3013-2016>.
- Rai, R., Agrawal, M., Agrawal, S.B., 2007. Assessment of yield losses in tropical wheat using open top chambers. *Atmos. Environ.* 41, 9543–9554.
- Saraf, N., Beig, G., Schultz, M., 2003. Tropospheric distribution of ozone and its precursors over the tropical Indian Ocean. *J. Geophys. Res.* 108, 4636. <https://doi.org/10.1029/2003JD003521>.
- Sharma, A., Ojha, N., Pozzer, A., Mar, K.A., Beig, G., Lelieveld, J., Gunthe, S.S., 2017. WRF-Chem simulated surface ozone over south Asia during the pre-monsoon: effects of emission inventories and chemical mechanisms. *Atmos. Chem. Phys.* 17, 14393–14413. <https://doi.org/10.5194/acp-17-14393-2017>.
- Sinha, B., Sangwan, K.S., Maurya, Y., Kumar, V., Sarkar, C., Chandra, B.P., Sinha, V., 2015. Assessment of crop yield losses in Punjab and Haryana using 2 years of continuous in situ ozone measurements. *Atmos. Chem. Phys.* 15, 9555–9576.
- Stockwell, W.R., Middleton, P., Chang, J.S., Tang, X., 1990. The second generation regional Acid Deposition Model chemical mechanism for regional air quality modelling. *J. Geophys. Res.* 95, 16343–16367.
- Van Dingenen, R., Raes, F., Krol, M.C., Emberson, L., Cofala, J., 2009. The global impact of O<sub>3</sub> on agricultural crop yields under current and future air quality legislation. *Atmos. Environ.* 43, 604–618.
- Wiedinmyer, C., Akagi, S.K., Yokelson, R.J., Emmons, L.K., Al-Saadi, J.A., Orlando, J.J., Soja, A.J., 2011. The Fire Inventory from NCAR (FINN): a high resolution global model to estimate the emissions from open burning. *Geosci. Model Dev. (GMD)* 4, 625–641. <https://doi.org/10.5194/gmd-4-625-2011>.