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The use of air quality forecasts to assess impacts of air pollution on crops: Methodology and case study

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Abstract

It has been reported that ambient ozone (O_3), either alone or in concurrence with acid rain precursors, accounts for up to 90% of US crop losses resulting from exposure to all major air pollutants. Crop damage due to O_3 exposure is of particular concern as ambient O_3 concentrations remain high in many major food-producing regions. Assessing O_3 damage to crops is challenging due to the difficulties in determining the reduction in crop yield that results from exposure to surface O_3, for which monitors are limited and mostly deployed in non-rural areas. This work explores the potential benefits of using operational air quality forecast (AQF) data to estimate rural O_3 exposure. Using the results from the first nationwide AQF as a case study, we demonstrate how the O_3 data provided by AQF can be combined with concurrent crop information to assess O_3 damages to soybeans in the United States. We estimate that exposure to ambient O_3 reduces the US soybean production by 10% in 2005.
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1. Introduction

The association between ambient ozone (O_3) exposure and its detrimental effects on agricultural crops is well established (Heck et al., 1982; Krupa et al., 2006; EPA, 1996; Morgan et al., 2006; US Environmental Protection Agency (EPA), 2006). Other air pollutants that may adversely affect plants include sulfur dioxide (SO_2), nitrogen oxides (NO_x), peroxyacetyl nitrate (PAN), and many volatile organic compounds (VOCs) (EPA, 1999). While these other air pollutants may inflict incremental stresses on crop plants, ambient O_3, either alone or together with acid rain precursors, accounts for up to 90% of crop losses in the United States resulting from exposure to all major air pollutants (Heck

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et al., 1982; Adams et al., 1986). O_3 damages plants primarily by entering plant leaves through the opening of the stomata. Once inside the plant tissue, O_3 can react to produce byproducts that cause crop losses via a reduction in either photosynthesis because of stomatal closure, or in carbohydrate used to produce detoxification systems (Andersen and Rygiewicz, 1991; EPA, 1996).

In an effort to address crop damages caused by O_3 exposures, the Clean Air Act (CAA) and its amendments (CAAAs) included air pollution damage to vegetation as one of the criteria by which the secondary National Ambient Air Quality Standards (NAAQS) are set and evaluated. In 1971 the EPA set the secondary NAAQS for O_3 at 0.12 ppmv for 1-h daily maximum. In 1997, EPA revised the secondary O_3 NAAQS to 0.08 ppmv for 8-h average daily maximum. Regardless of these regulatory measures, O_3 levels remain high in many areas of the United States (EPA, 2007). Furthermore, O_3 damages to crops are expected even in regions that comply with the O_3 standards. The current US secondary O_3 standard is the same as the health-based primary standard (EPA, 1999), which is considerably higher than the critical levels above which O_3 is believed to have detrimental effects on plants. As a result, there could be a substantial effect of air pollution-induced crop losses on societal welfare.

Over the past two decades, a number of economic assessment studies have been conducted to estimate O_3-induced crop losses in the United States (e.g., Adams and Croker, 1989; Hertstein et al., 1995; EPA, 1999; Murphy et al., 1999; Felzer et al., 2004). Adams and Croker (1989) estimated that a 25% decrease in surface O_3 levels would provide benefits to agriculture of 1–2 billion dollars per year. Murphy et al. (1999) estimated that the benefits to the agricultural sector from eliminating emissions from mobile sources ranged between 3.5 and 6.1 billion dollars annually. The annual agricultural benefits of the CAAA in 2010 are projected to range between 7.5 millions and 1.1 billion dollars (EPA, 1999). The majority of these studies have adopted monitor-based approaches that extrapolate monitor data for O_3 concentrations to rural areas where measurements are unavailable. While this approach has numerous strengths, some of its limitations could be addressed through air quality modeling.

This paper presents the potential advantages and limitations of utilizing the US EPA/National Oceanic and Atmospheric Administration (NOAA) air quality forecasting (AQF) system to estimate crop exposure to surface O_3 in rural areas. The AQF system is based on the National Centers for Environmental Protection (NCEP) Eta model and the EPA's Community Multiscale Air Quality (CMAQ) model (Otte et al., 2005). It generates hourly forecasts of O_3 concentrations at a 12-km horizontal resolution. The O_3 data provided by the continent-scale AQF system thus present a new resource to assist in quantifying O_3 damages to agricultural crops at rural locations that often lack monitoring programs. As a case study, this paper uses results of the first experimental nationwide AQF to estimate soybean exposures to O_3 and resulting yield losses in the United States for the year of 2005. Section 2 reviews existing crop exposure assessment approaches and discusses their limitations. Section 3 describes the methodology that is built around the AQF data to estimate crop exposures to surface O_3. Section 4 presents the results of estimated O_3 damages to soybeans in the United States in 2005.

2. Review of approaches and their limitations of crop exposure assessment

Estimating crop exposures to O_3 is the first step in the procedure to perform an economic assessment of O_3-induced crop loss. A number of approaches exist to estimate crop exposure to ambient O_3. These approaches generally fall into two categories: (1) the monitoring-based approach that determines O_3 exposure based on measurements at discrete locations and spatial interpolations between locations; (2) the modeling-based approach that uses global chemical transport model (CTM) to calculate O_3 exposure.

Majority of studies on air pollution-induced crop loss have employed monitoring-based method to estimate crop exposure to O_3 (e.g., Adams and Croker, 1989; Hertstein et al., 1995; EPA, 1999; Felzer et al., 2004). Except EPA (1999), which utilized a regional CTM to determine spatial and temporal variations between monitors, most studies using the monitor-based approach have relied on spatial interpolation techniques to extrapolate monitor data to locations without O_3 measurements. These spatial interpolation techniques, such as kriging, are based on the assumption that the spatial variation in O_3 concentrations is statistically homogeneous throughout the surface. In fact, O_3 concentrations are very sensitive to changes of environmental parameters, such as precursor

emissions (particularly of NO_x), humidity, and topography. Therefore, the hypothesis of spatial homogeneity, which is fundamental to the interpolation techniques, may not be valid for interpolating surface O_3 distribution. It has been demonstrated that ambient O_3 mixing ratios have a spatial scale of 15 km (Rao et al., 1997). This raises questions about using sparse monitor data to estimate O_3 exposures on a large scale.

Another shortcoming of the monitor-based approach is the representativeness of existing monitor sites for being used to estimate rural O_3 exposure. Air quality monitors for regulatory purposes are primarily deployed in urban and suburban areas with high air pollution and large population densities. In urban areas, which have large O_3 precursor sources, O_3 levels have a large diurnal variation, rising sharply to a short-lived afternoon maximum and then dropping to near zero at night (Chameides et al., 1998). In contrast, O_3 levels are less variable in rural areas, which are removed from large NO_x sources. There is a smaller maximum in the afternoon but a higher minimum in the morning and at night (Chameides et al., 1998). Thus, observations obtained from urban and suburban monitors are unlikely to be representative of rural O_3 concentrations, both in levels and duration (EPA, 2006). Previous studies show that the addition of urban sites actually decreases the interpolated O_3 concentrations in the affected regions (Lefohn and Runeckles, 1987; Felzer et al., 2004).

Recognizing the limitations imposed by the monitor-based approaches and the particular dearth of air quality data in developing countries, Chameides et al. (1994) used a three-dimensional global CTM to estimate O_3 exposure on a continental scale by simulating the physical and chemical processes that regulate the fate of air pollution. Their model predicted that about 10–35% of the world's grain production might occur in regions where crop yields might be reduced by O_3 exposures. A similar approach was adopted by Aunan et al. (2000) to estimate the regional scale O_3 exposure in China. More recently, Wang and Mauzerall (2004) used a global CTM to characterize distributions of ambient O_3 and its impact on grain production in eastern Asia. The advantages of such an approach include the ability to cover a large spatial area and time period, and to take into account the actual processes that determine the spatial and temporal variability in O_3 concentrations at locations without measurements. However, the modeling approach is based on O_3 simulations at the global scale with coarse horizontal resolutions (e.g., $2.8^\circ \times 2.8^\circ$ in Wang and Mauzerall (2004) and $2.8^\circ \times 2.8^\circ$ in Aunan et al. (2000)), which are inadequate for capturing local O_3 peaks. Coarser model resolution generally leads to higher average and lower peak concentrations, as dilution across the grid cell increases O_3 production efficiency and hence higher average concentrations, while local maxima cannot be adequately resolved (Jang et al., 1995). Accurate capture of high O_3 concentrations is important for crop exposure assessment as many exposure indices emphasize both exposure duration and peak O_3 concentrations (Mauzerall and Wang, 2001).

We explore in this study the possibility of using regional AQF data to alleviate some of these limitations. Regional air quality models have been used before to estimate relative changes in crop exposures to surface O_3 (EPA, 1999; Murphy et al., 1999). Such applications generally provide only a short temporal coverage due to computational expense and availability of model input data, such as meteorology and source emissions. The continuous operation of an AQF model, however, is able to provide long-period coverage, including real-time forecast of O_3 distribution. In addition, the advantages of using air quality forecasts to estimate O_3 exposures include (1) the ability to cover a large region including areas devoid of O_3 monitors; (2) high spatial and temporal resolutions making it possible to better capture peak O_3 and duration; (3) the ability to reproduce spatial heterogeneity based on detailed information of emission sources and topography, and through full implementation of chemical and physical processes. The air quality modeling system is also run in conjunction with the real-time weather forecast system, which could additionally provide meteorological parameters needed to calculate flux-oriented exposures to O_3 (Grünhage et al., 2001; Ashmore, 2005). Efforts are also underway to develop reanalyzed pollution surfaces by combining modeled and measured data, which could potentially help address the shortcomings of the individual approaches.

3. Methodology

In order to utilize air quality model estimates in crop exposure assessment, we adopted an integrated assessment approach built around the Eta-CMAQ AQF model (Otte et al., 2005). This integrated

approach follows the consequences of air pollution emissions by predicting rural concentrations, crop exposures, and resulting yield losses. The integrated assessment approach includes the following steps: (1) predict surface O_3 concentrations; (2) couple O_3 concentrations and crop distribution to calculate exposure; (3) incorporate dose–response functions to estimate yield loss (EPA, 1999; Wang and Mauzerall, 2004).

3.1. Predicting surface O_3 concentrations

We use the Eta-CMAQ modeling system (Otte et al., 2005) to predict surface O_3 concentrations on a national scale. In the AQF system, meteorological parameters to drive transport and chemistry were based on the Eta model. The operational domain for the model covers the continental United States with a horizontal resolution of $12 \times 12\,km^2$. Hourly meteorological data, including wind speed and direction, temperature, humidity, pressure, solar radiation and mixing height, from Eta are converted into CMAQ compatible form using a preprocessor for CMAQ, "PREMAQ" (Otte et al., 2005). Anthropogenic emissions of NO_x, VOCs, SO_2, CO and NH_3 are based on the EPA county level National Emissions Inventory (NEI) with adjustments for the current year based on projected energy consumption. The 1995 Canadian and 1999 Mexican Big Bend Regional Aerosol and Visibility Observational Study (BRAVO) emissions inventories are combined with the US NEI to form the continental dataset.

The CMAQ model uses the meteorology and emission inputs to predict hourly concentrations of air pollutants over space and time (Byun and Ching, 1999; Byun and Schere, 2006). The AQF system began operation in September 2004 and provided forecasts of O_3 concentrations over the northeastern United States initially (Eder et al., 2006). The operational forecast domain was expanded to cover the eastern United States in 2005. Experimental forecast simulations over the entire continental US were initiated in June 2005 and have been in continuous operation for the rest of the year. This study uses summertime O_3 forecast data from the model's lowest layer of 22 terrain-following vertical layers to estimate soybean exposure to O_3.

3.2. Crop exposure

Most previous assessments of crop damage from O_3 exposure in the United States are based on concentration–yield loss relationship, or dose–response function, derived from the National Crop Loss Assessment Network (NCLAN) research (Adams and Croker, 1989; EPA, 1999; Murphy et al., 1999). The NCLAN research is the sole comprehensive, large scale field study conducted in the United States (Heagle, 1989). The NCLAN study provides dose–response functions for six major crops (p. 94, EPA, 1999). Dose–response functions also exist for many other US crops from reanalysis of NCLAN results or other separate efforts (Kats et al., 1985; Adams and Croker, 1989). This case study focuses on O_3 impacts on soybean production. Soybean occupies more land than any other dicotyledonous crop in the world (FAO-UN, 2003). Among the major US crops, soybean is one of the most susceptible to O_3, making it a model species for studying the responses of C_3 annual plants in general to rising ambient O_3 level (Ashmore, 2002; Morgan et al., 2003).

The spatial distribution of soybeans is obtained from county estimate survey data collected by the USDA National Agricultural Statistics Service (http://www.nass.usda.gov/). The county-level data are developed from crop yields reported by individual farmers per county. Soybean exposure to O_3 is calculated using exposure indices consistent with the concentration–response functions from which yield losses are derived. Both seasonal mean and cumulative exposure indices have been used at different stages of US NCLAN studies, but the use of cumulative O_3 exposure indices has been favored in most previous assessment studies (Lefohn and Foley, 1992; EPA, 1999; Wang and Mauzerall, 2004). To be consistent with EPA's O_3 NAAQS benefits analysis and the cost benefit analysis of the CAA, we use in this study the exposure index SUM06, which is defined as (EPA, 1999)

$$\mathrm{SUM06(ppmv\text{-}h)} = \sum_{i=1}^{n} [C_{O_3}]_i \quad \text{for } C_{O_3} \geqslant 0.06\,\mathrm{ppmv}, \tag{1}$$

where C_{O_3} is the hourly O_3 concentration (ppmv), i is the hour index and n is the total number of hours in 3 consecutive months of a growing season for which the sum of hourly concentrations greater than or equal to 0.06 ppmv is the highest. For this study, we calculate SUM06 from July to

September 2005. These months are typically characterized by the highest surface O_3 during the growing season in the continental United States. SUM06 emphasizes both exposure duration and O_3 concentrations over a critical level, but weighs all high concentrations equally. There are also other exposure indices that weigh O_3 levels differently (e.g., W126) or adopt a different critical level (e.g., AOT40). The AQF system predicts hourly O_3 concentrations for each location, making it feasible to calculate both mean and accumulative exposure indices. As crop production data are available at county level, the lowest level of aggregation that could be used for calculating O_3 indices is also at the county level. We average O_3 concentrations of all related grid cells in one county, weighed by area, to represent mean O_3 level in that county.

3.3. Crop yield loss

The relationship between crop yield and O_3 exposure, or dose–response function, is usually expressed based on a Weibull distribution (Wang and Mauzerall, 2004)

$$Y = A * e^{[-(X/B)^C]}, \tag{2}$$

where Y is the estimated mean yield, X is the O_3 exposure index (SUM06 in this case as defined in Eq. (1)), A is the theoretical yield at reference O_3 level, B is the scale parameter for O_3 exposure and C is the shape parameter affecting the change in the predicted rate of loss.

Relative yield loss (RYL) due to O_3 exposure above the reference level can be derived from Eq. (2)

$$\mathrm{RYL} = 1 - e^{(X_{ref}/B)^C - (X/B)^C}, \tag{3}$$

where X_{ref} is the estimated mean yield at the reference exposure level. We rely on the original sources of the exposure–response functions for the reference level. The reference level (X_{ref}) is 0 ppmv-h for SUM06 (EPA, 1996). The values of scale and shape parameters, B and C, are given by the chosen dose–response functions derived from field research (Table 1).

4. Results

4.1. Evaluation of model prediction of surface O_3 using measurement data

Prior to using the predicted O_3 data from the AQF model, it is critical to evaluate the ability of the AQF model to capture the spatial variability in O_3 concentrations. We compare model prediction of O_3 concentrations to observations from the AIRNOW monitoring network in the United States (http://airnow.gov). The model was found to be able to capture the 8-h daily maximum O_3 with a mean bias (MB) of 7.2 ppbv, a normalized mean bias (NMB) of 14.7%, and a normalized mean error (NME) of 23.3% when compared against 1150 surface O_3 monitors. Although these monitors cover rural areas, they are mostly urban and suburban stations.

Table 1
O_3-induced soybean yield losses in the United States in 2005

Exposure-response functions	Scale factor (B in Eq. (3))	Shape factor (C in Eq. (3))	County (number)	Range of RYL at different US counties[c] (%)	National sum of yield losses (million bushels)	Percentage to total soybean production (%)
Minimum response[a]	299.7	1.547	3184	0–9	54	2
Median response[b]	101.5	1.452	3184	0–39	308	10
Maximum response[a]	131.4	1	3184	0–38	439	14

For each county, a relative yield loss (RYL) value is calculated based on the minimum, median, and maximum exposure–response functions. The exposure index used here is SUM06.

[a]Adopted from EPA (1999).

[b]Adopted from Wang and Mauzerall (2004).

[c]A RYL value of 0% means O_3 concentrations are below 60 ppbv anytime over this county.

Table 2
Model evaluation statistics for hourly ozone (O_3) concentrations at rural locations in summer 2005

O_3 levels (cut-off value)	Number of data pairs	OBS_{mean} (ppbv)	MOD_{mean} (ppbv)	RMSE (%)	MB (ppbv)	NMB (%) ($\pm$5–15)	NME (%) (30–35)	*R*
All rural [O_3]	811,156	34.7	44.1	17.8	9.3	26.9	40.9	0.67
[O_3] > 25 ppbv	608,563	44.9	50.0	14.2	5.1	11.5	24.7	0.57
[O_3] > 40 ppbv	302,756	55.4	58.6	12.9	3.1	5.7	17.7	0.47
[O_3] > 60 ppbv	61,341	71.4	72.9	11.9	1.6	2.2	12.2	0.33
Daily 1 h max [O_3]	36,830	56.5	61.4	14.7	4.9	8.7	19.9	0.66

Data pairs of measurements and predictions are obtained from the AIRNOW network and from corresponding grid boxes in CMAQ. Where [O_3] is hourly ozone concentration, OBS_{mean} is the mean of counted ozone observations, MOD_{mean} is the mean of predicted ozone values, RMSE is the root mean-square error, MB is mean bias, NMB is normalized mean bias, NME is normalized mean error, and R is correlation coefficient. The definition of these statistical matrices can be found at Eder et al. (2006).

As the focus of this study is on O_3 exposures in agricultural areas, we further compare model prediction against observations sorely from rural sites to examine the capability of the AQF model to reproduce rural O_3 concentrations (Table 2). As many crop exposure indices are based on a critical level or threshold, we apply three cut-off values of 25, 40 and 60 ppbv for all data pairs (i.e., model-observation data pairs containing measured concentrations below the cut-off value were not used in the analysis). These cut-off values were chosen to examine model performance at O_3 levels corresponding to background, AOT40 and SUM06 critical levels, respectively. We found that CMAQ can reproduce O_3 concentrations above the background level (25 ppbv) at rural sites with a NMB value of 11.5% and a NME value of 24.7%. For O_3 concentrations above the European critical level (40 ppbv), the model can match measurements with NMB of 5.7% and NME 17.7%. For O_3 concentrations above the SUM06 critical level (60 ppbv), the model can perform even better, with NMB of 2.2% and NME 12.2%.

4.2. Spatial variability in O_3 concentrations and O_3 exposures (SUM06)

Fig. 1 presents the seasonal mean of model-predicted O_3 concentrations between 0900 and 1600 h (local time) from 1 July to 30 September 2005. The 7-h averaging period is used here because this time period was frequently chosen to derive exposure–response functions in NCLAN studies (EPA, 1996). High O_3 concentrations are predicted in both western and eastern United States. The eastern high O_3 region includes large areas in the middle and upper eastern US, and the western high O_3 region extends from southern California to Rocky Mountain region. Fig. 1 also shows that O_3 concentrations in most urban centers across the nation are relatively lower than surrounding areas. The low O_3 concentrations at urban areas result from titration of surface O_3 by freshly emitted NO_x (Ryerson et al., 2001; Tong et al., 2006). There also exist large concentration gradients around the titrated areas, from which ambient O_3 concentrations can vary considerably within a short distance. The considerably lower O_3 level in urban areas than neighboring regions suggests that urban monitors may be inadequate to represent O_3 on a large scale, especially in rural areas absent of urban emissions. Thus, there is clearly a benefit to use the high-resolution AQF data to calculate crop exposure to O_3 in rural areas.

Fig. 2a displays the spatial distribution of SUM06 calculated from hourly O_3 concentrations in each grid cell for the 3 consecutive months. While the spatial pattern of SUM06 is similar to that of daytime O_3 concentrations, there are significant differences. Unlike the average O_3 which takes into account contributions from each hour equally, SUM06 emphasizes both exposure duration and peak O_3 concentrations (Eq. (1)). Since the crop data are compiled at a county level, we have converted the grid-based SUM06 into county-average data using a geographical information system software arcMap. The county-level O_3 data are computed from concentrations of individual grid cell using an area-weighing method. The county-level map (Fig. 2b) shows a similar spatial pattern to the grid-level map, although the spatial variation in O_3 exposures has been smoothed out due to averaging over a larger area.

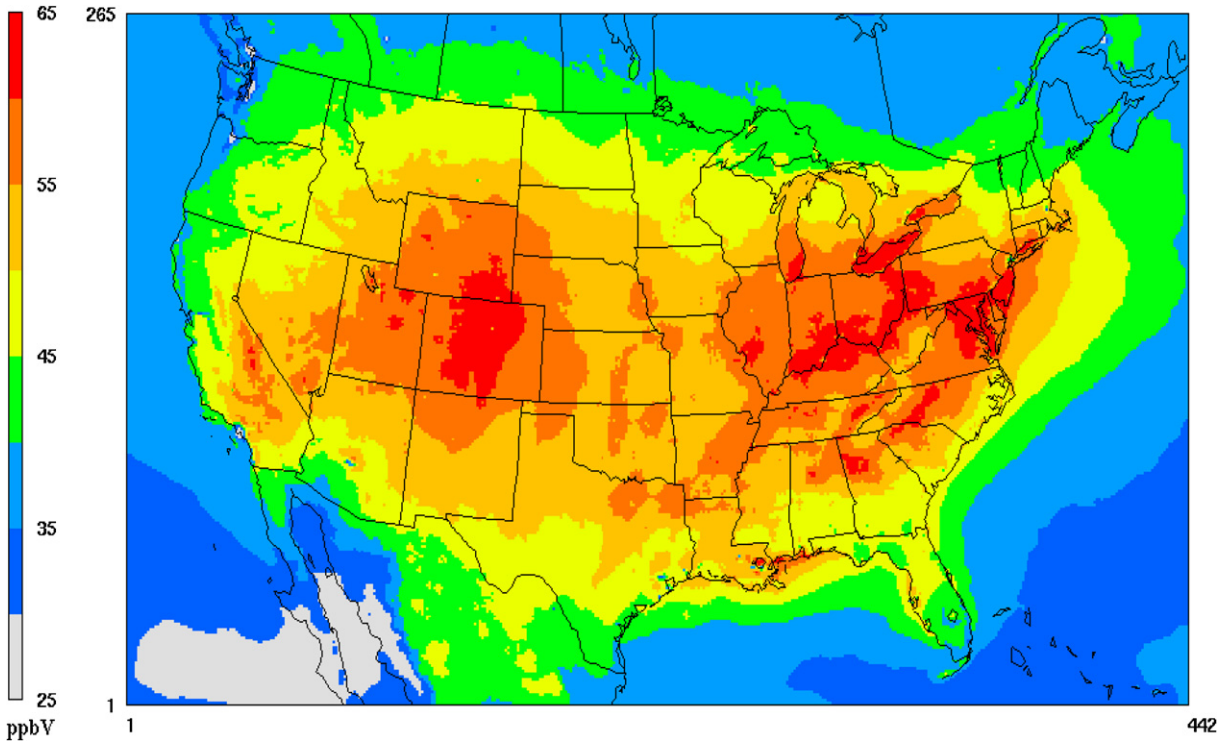

Fig. 1. Seasonal mean of ambient O_3 concentrations between 09:00 and 16:00 h (local time) over the continental United States from 1 July to 31 September 2005.

While we demonstrated here only the spatial distribution of SUM06, similar maps can be generated for other mean or accumulative exposure indices, either by grid or by county, from hourly O_3 data provided by the AQF system.

It should be noted that, in addition to horizontal variability in O_3 concentrations, consideration must also be given to variations in the vertical profile of O_3 in the surface layer (EPA, 2006). The O_3 concentrations in the lowest model grid cells represent a volume average in the bottom layer, which extends from surface to 38 m above ground. There can be substantial gradients in the surface layer above the plant canopy (Joseph Pinto, US EPA, personal communication, 2007), due to deposition to the surface, uptake by crops, and reactions with NO emitted from soil and hydrocarbons from biogenic sources. Horvath et al. (1995) reported that O_3 concentrations decrease by 7% in going from a height of 4 m down to 0.5 m above ground during unstable atmospheric conditions. Using volume-average concentrations from the CMAQ surface layer may lead to an overestimate of crop exposures to O_3. The same overestimate is also applicable to monitor-based approaches; inlets to ambient monitors are typically at heights of 3–5 m.

4.3. Relative yield loss (RYL) and yield losses

In this section we will use the calculated O_3 exposures to estimate O_3-induced yield losses in soybean production. Table 1 shows the RYLs for soybeans in 2005 calculated for all contiguous counties using the calculated SUM06 values and the three dose–response functions. RYL values vary from 0% to 8.5% for the minimum response function, which predicts the minimum damages in response to a given level of O_3 exposure, and from 0% to 38% for the maximum response function. Larger RYL values are found at locations with higher SUM06 values, as RYL almost monotonically increases with SUM06, although the relationship is not linear in any of the dose–response functions (Fig. 3). On a national average, O_3 exposures cause a yield loss ranging from 2% to 14% for counties in which soybeans are planted.

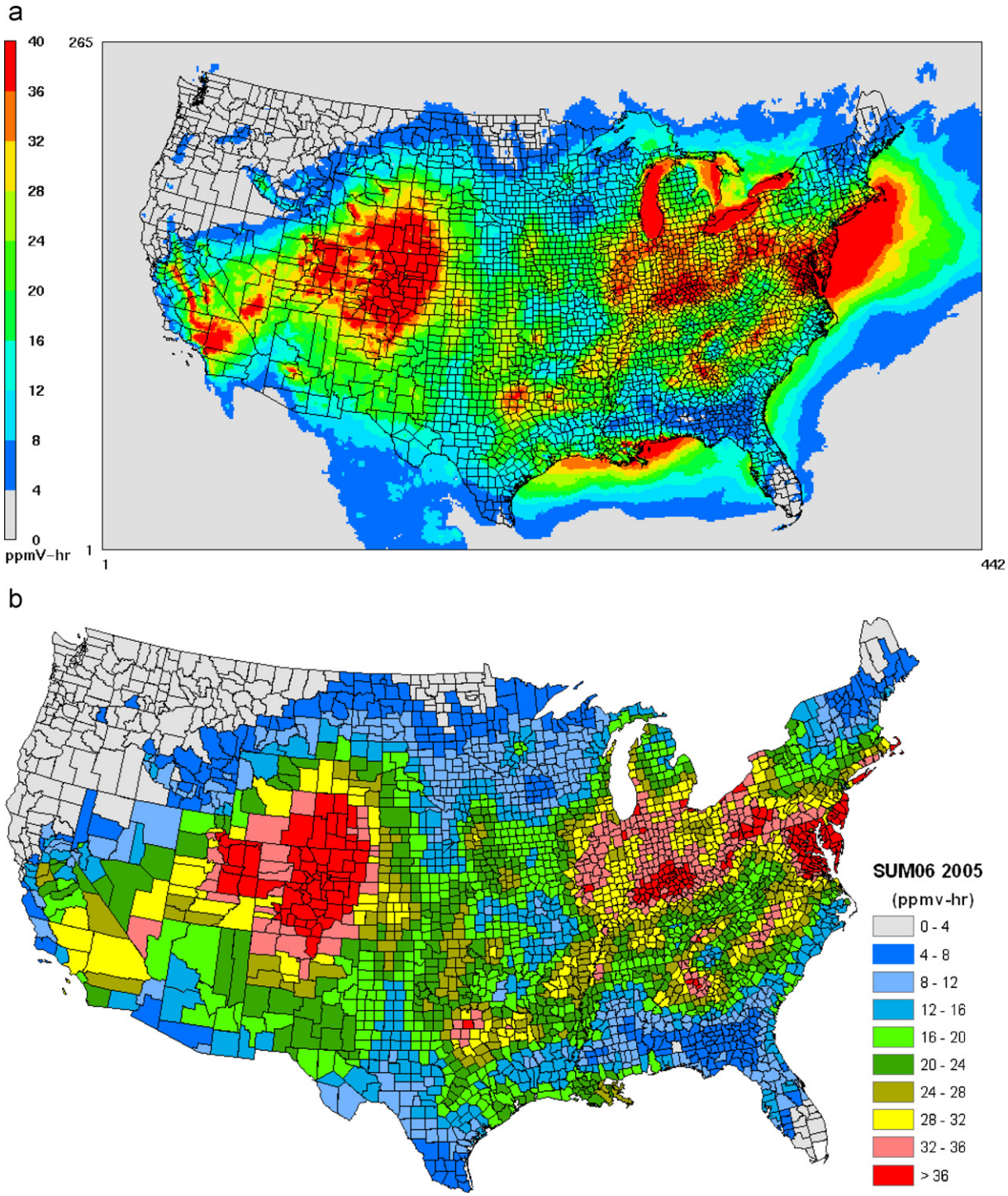

Fig. 2. Spatial distribution of SUM06 calculated from hourly O_3 concentrations for the 3 consecutive months by grid (top) and county (bottom).

Table 1 also shows that, for the range of SUM06 values, a calculated RYL from the maximum response function can be smaller than that from the median response function. The median function is taken from Wang and Mauzerall (2004) in which a single exposure–response function was

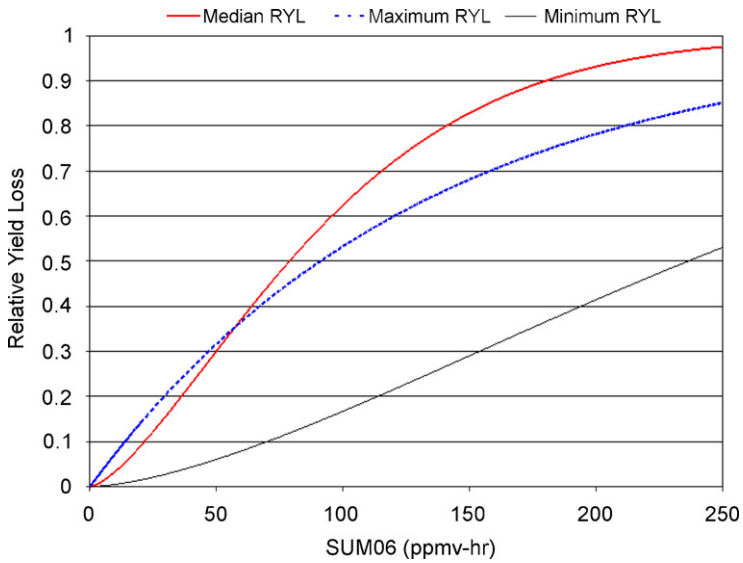

Fig. 3. Relationship between relative yield loss (in percentage) and O_3 exposure levels (indicated by SUM06).

constructed from the median Weibull parameters of all studied cultivars. The derived median curve fits between the minimum and maximum functions provided by EPA (1999) (Fig. 3), but ascends atop the maximum curve once the SUM06 exceeds a certain level (58 ppmv-h). The SUM06 exposure response functions for soybeans are developed by reanalyzing the original experimental data from NCLAN studies (EPA, 1999). While these functions fit well under experimental conditions, they are not necessarily representative of the full range of variability in O_3 exposures and crop response. By extending the range of SUM06 to higher values, Fig. 3 shows the derived maximum function does not yield the highest response. For the maximum SUM06 value calculated for a US county (62 ppmv-h), the RYL calculated from the median response actually is larger than that from the maximum response, although the latter does give larger RYL values for the national average and for counties with a SUM06 value below 58 ppmv-h.

Next, we combine the calculated RYL and crop production to derive the actual yield loss. The actual yield loss is determined by the collocation of both RYL and crop production. Fig. 4 depicts the spatial distribution of soybean production in the United States in 2005. Soybeans are planted primarily in the Midwest and eastern United States; they are rarely planted in the Western US counties. Therefore, although high O_3 exposure index was predicted in the Rocky Mountain region, there is no actual exposure to soybean in this region due to crop absence. The collocation of high exposure level and soybean production in the Midwest, however, leads to large losses of crop yields in this region. As shown in Fig. 5, the largest O_3-induced yield losses occur in the Midwest and the Mississippi Valley regions. Although with high crop density, soybean yield losses from O_3 exposures in North and South Dakota are small due to much lower ambient O_3 levels.

Table 1 also presents aggregate O_3-induced soybean production losses in the United States based on different response functions. By aggregating each county of the contiguous states, we estimate a loss of 53.8 million to 438 million bushels in soybean production, which account for 1.7–14.2% of total US soybean production in 2005.

5. Discussion and conclusions

Optimistic predictions of the impacts of a changing environment on agriculture have been made that rising carbon-dioxide levels are likely to increase food production. Such conclusion was drawn based on the impacts of global warming, implying an increase in crop yields resulting from longer growing seasons, higher temperatures, and more active photosynthesis. Much of the work, however, has ignored the potential damage of air pollution to agricultural crops. This work explores the potential benefits of using the long-term operational AQF data archives to estimate rural O_3 exposure, which is critical to assessing the impacts

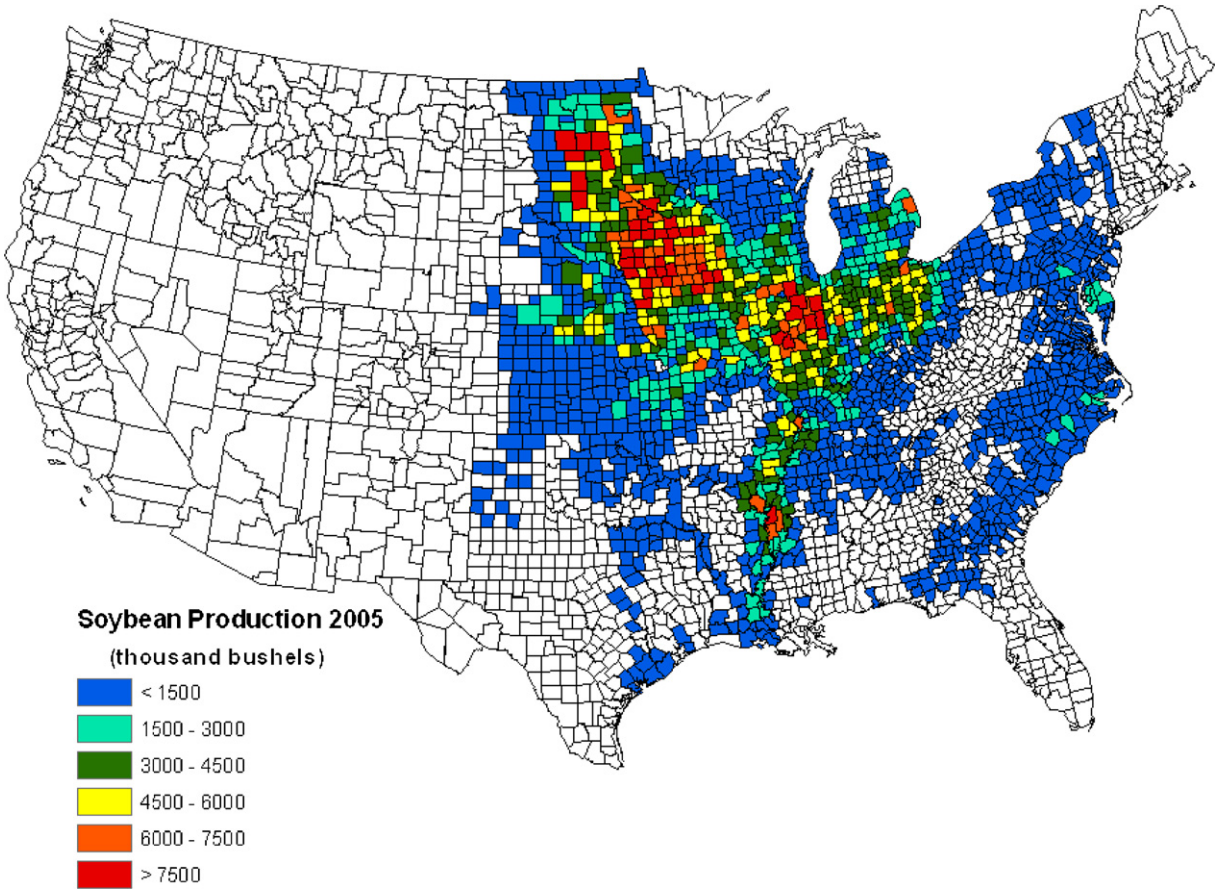

Fig. 4. Total soybean production in the United States in 2005.

air pollution has on crop production. We demonstrate how the AQF data can be combined with concurrent crop information to assess O_3 damages on soybeans in the United States. Exposure to ambient O_3 is estimated to have reduced US soybean production by 10% on a national average in 2005.

Similar assessment studies on O_3-induced crop damages have been conducted in the United States. However, it is difficult to directly compare our estimates to these studies because of considerable variability in the sources and levels of O_3 pollution, the covered crops, adopted dose–response functions, and the assumed economic environmental conditions. The exposure–yield functions used in this study are based the NCALN field experiments, which employed an open-top chamber approach. Concerns have been raised that alternations in microclimate and rainfall within open top chambers could modify plants responses to elevated O_3 (Elagoz and Manning, 2005). A recent study using the free-air gas concentration enrichment (FACE) technology, which minimizes alternation of microclimate and the soil–plant–atmosphere continuum, has validated previous chamber studies (Morgan et al., 2006). In fact, their results suggest that when treated under open-air conditions yield losses may be even greater than the large losses already reported in earlier chamber studies.

Using AQF data to estimate rural O_3 exposure can alleviate several important limitations faced by existing approaches that rely primarily on data from monitoring networks. These monitor-based approaches generally use spatial interpolation techniques to estimate O_3 concentrations at locations without monitor data. Such estimates, however, are highly uncertain for areas at large distances from monitors, particularly for chemical species such as surface O_3 whose ambient concentrations can vary considerably within a short distance (Rao et al., 1997). In addition, most of the O_3 monitors in the US are deployed in urban/suburban areas or near

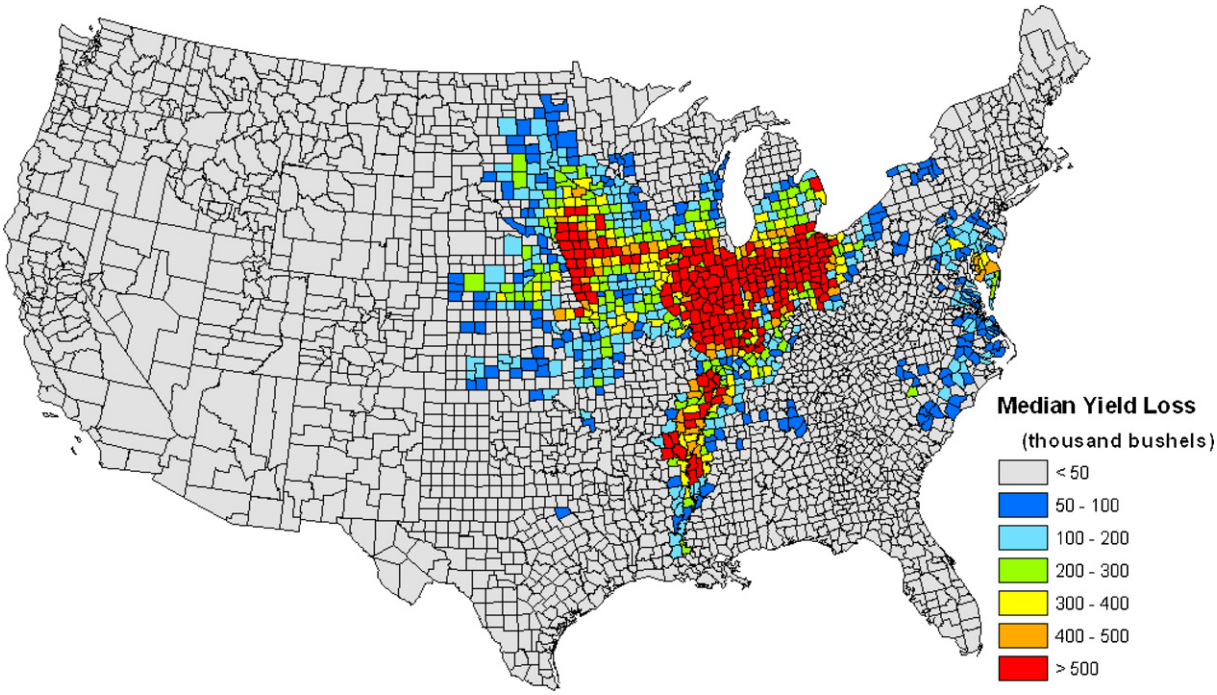

Fig. 5. O_3-induced soybean yield losses in the United States in 2005.

major emission sources. As a result, observations obtained from urban monitors may not be representative of ambient O_3 levels and duration in rural areas (Chameides et al., 1998), making it questionable to use urban-monitor dominated networks to estimate rural O_3 concentrations. Advantages of using data from AQF include its ability to reproduce spatial heterogeneity through full implementation of chemical and physical processes. The high spatial and temporal resolutions of AQF simulations also make it possible to capture peak O_3 and duration, which is important to assessing crop exposure to O_3.

The availability of real-time prediction of crop exposure to O_3 could be used to improve US crop forecasts. Each month the USDA publishes crop production forecasts in the United States (US Department of Ariculture (USDA), 1999). As the largest producer of many main crops, the United States exports a large amount of agricultural products into the world market (Adams and Croker, 1989). Accurate and timely forecasts of US crop production are important for both domestic and international stakeholders to make decision about marketing and investing. Currently, the USDA crop forecast is based on planted acres and yield forecast variables that include number of fruit and weight per fruit. While information of acreage and number of fruit is collected from farm operations and field observations, the weight per fruit for a crop is adopted from historic average data. The forecast is adjusted by significant changes in weather conditions, such as a killing freeze, serious heat waves and beneficial rains (USDA, 1999), but does not take into consideration the impact of air pollution on crop production prospects. As shown in this study, exposures to air pollutants can reduce soybean production by 10% on a national average; high O_3-induced yield losses have also been reported for other crops at different locations (e.g., EPA, 1996; Nali et al., 2002; Felzer et al., 2004; Wang and Mauzerall, 2004; Wang et al., 2005). As demonstrated in this work, the availability of real-time O_3 forecast data can be used to include O_3 impacts in the agricultural forecast system. Incorporating O_3 impact in crop production forecasts can potentially improve the results of agricultural forecast by capturing the fluctuation in yield losses due to air pollution.

Recently there has been extensive debate about the possibility of replacing the current critical-level-based exposure indices (level 1), such as SUM06 and AOT40 (assuming damages only when O_3 concentrations higher than 40 ppbv), by flux-orientated

limiting values (level 2) (Ashmore, 2005). There exists strong evidence that incorporating the effects of variable irradiance, temperature and vapor pressure deficit on O_3 uptake is necessary in order to obtain a stronger relationship (Ashmore, 2005). This argument is supported by the fact that O_3 flux to the leaf surface is significantly lower on days with high O_3 concentrations, due to lower atmospheric conductivity, and lower stomatal conductance resulting from higher vapor pressure deficit (Grünhage and Jäger, 1994). The level 2 approach would include consideration of parameters such as soil moisture conditions, vapor pressure deficit (VPD), and temperature, which are critical in converting O_3 exposure to O_3 dose (Wang and Mauzerall, 2004). The air quality forecast model is driven by meteorology data generated by a real-time weather forecast system. The combination of weather and air quality forecasts has the advantage of providing information for not only level-1 values, but also potential parameters required to estimate level-2 values.

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