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An investigation of widespread ozone damage to the soybean crop in the upper Midwest determined from ground-based and satellite measurements

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A B S T R A C T

Elevated concentrations of ground-level ozone (O_3) are frequently measured over farmland regions in many parts of the world. While numerous experimental studies show that O_3 can significantly decrease crop productivity, independent verifications of yield losses at current ambient O_3 concentrations in rural locations are sparse. In this study, soybean crop yield data during a 5-year period over the Midwest of the United States were combined with ground and satellite O_3 measurements to provide evidence that yield losses on the order of 10% could be estimated through the use of a multiple linear regression model. Yield loss trends based on both conventional ground-based instrumentation and satellite-derived tropospheric O_3 measurements were statistically significant and were consistent with results obtained from open-top chamber experiments and an open-air experimental facility (SoyFACE, Soybean Free Air Concentration Enrichment) in central Illinois. Our analysis suggests that such losses are a relatively new phenomenon due to the increase in background tropospheric O_3 levels over recent decades. Extrapolation of these findings supports previous studies that estimate the global economic loss to the farming community of more than $10 billion annually.

1. Introduction

The impact of elevated ozone (O_3) concentrations on vegetation has been well documented in both chamber studies and at field sites where concentrations can be experimentally controlled (Booker et al., 2009; Heagle, 1989; Heck et al., 1983; Morgan et al., 2006; US EPA, 2006). The onset of injury in a number of O_3-sensitive plants has been observed with seasonal daytime average concentrations as low as 40 ppbv (parts per billion, by volume; US EPA, 2006), and concentrations above this level are commonplace during the growing season in many food-producing regions of the world (Fowler et al., 1999; Morgan et al., 2006; Tong et al., 2007). Nationally, the seasonal 8-h average O_3 concentration ranges from 50 to 55 ppbv during the summer, although diurnal and day-to-day concentrations vary widely (http://www.epa.gov/airtrends/ozone.html). Ozone monitoring stations, however, are predominately located in urban areas and are sparse in most rural locations worldwide, making estimates of potential O_3 impacts on crop production less certain. Furthermore, recent analyses of O_3 measurements entering the U.S. from East Asia source regions show an increase of 0.46 ppbv yr^{-1} since 1984 (Cooper et al., 2010), implying that background O_3 concentrations may continue to rise despite the enactment of pollution control measures in the U.S. The Cooper et al. (2010) findings likewise support the Intergovernmental Panel on Climate Change (IPCC) projection that O_3 concentrations will increase by 25% over the next 30–50 years (Forster et al., 2007; Meehl et al., 2007), exacerbating the negative impacts of O_3 on yield and biomass production (Royal Society, 2008).

Several meta-analyses and other multi-study compilations of O_3 experiments with important agronomic crops such as rice, soybean and wheat showed that chronic exposure to moderate levels of O_3 (30–60 ppbv) was sufficient to reduce seed yield by approximately 5–15% compared with clean-air treatments ($\leq$26 ppbv) (Ainsworth, 2008; Feng and Kobayashi, 2009; Feng et al., 2008; Heagle, 1989; Jäger et al., 1992; Mills et al., 2007; Morgan et al., 2003). Increasing

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the season-long O_3 concentration by 12 ppbv in a free-air experiment in Illinois reduced soybean yield by an additional 15–25% (Morgan et al., 2006), and Emberson et al. (2009) point out that concentration–response models developed in North America and Europe for several major crops may even underestimate the influence of ambient O_3 on rice and wheat varieties grown in Asia.

Despite the implied agricultural and economic outcomes of current and future tropospheric O_3 concentrations, actual measurements of O_3 impacts are difficult because of the highly dynamic nature of O_3 levels as well as the wide range of variable factors that influence productivity (Ainsworth et al., 2008). These variables include both physical parameters, such as precipitation, temperature and solar insolation, and also management practices, including variations in the way crops are cultivated, fertilized and irrigated, and which specific cultivars are used (Lobell and Asner, 2003; Lobell and Field, 2007). In this study, we have developed a statistical model that includes factors that influence crop yield and have devised a methodology that isolates and quantifies the impact of ambient O_3 concentrations. The O_3 data used in the study were from both ground monitors and satellite observations. The results show that these two sets of O_3 data were consistent with each other, as well as being consistent with the impacts of O_3 on yield predicted by previous controlled environment, greenhouse and field studies in which quantifiable O_3 treatments were applied. Our findings also suggest that the satellite information is potentially a better predictor for estimating yield losses since the location and number of ground O_3 monitoring sites currently in use tend to be biased toward urban locations (Tong et al., 2007). Furthermore, satellite observations are available for farmland in countries where no *in situ* O_3 monitoring network is in place to provide important insight into the global extent of this problem.

2. Materials and methods

2.1. Synthesis of data for use in this study

Our study region encompassed the contiguous tri-state domain of Iowa, Illinois, and Indiana, three of the largest soybean-growing states in the U.S; the 2007 value of the soybean crop was \$4.8 billion in Iowa, \$3.9 billion in Illinois, and \$2.2 billion in Indiana (http://www.nass.usda.gov/). Fig. 1 depicts the counties in each of the three states used in this study and the locations of both the O_3 ground monitors (blue triangles) and surface meteorological stations (red diamonds). As a first attempt to establish a relationship between O_3 and crop yield, we calculated the linear regression between crop yield and surface O_3 concentrations for the 50 counties in which monitors were located. If the yields and O_3 concentrations are normalized by the average yield and average concentration for each year, the resultant regression line produces a statistically significant relationship with a correlation coefficient of −0.46 and a slope of -57.4 kg ha^{-1} ppbv^{-1}. This value, normalized to -1.73% ppbv^{-1}, is consistent with previous studies (e.g., Morgan et al., 2006; Tong et al., 2007), but the integrated loss to the entire crop in this type of a calculation is critically dependent on determining the concentration (i.e., a threshold value) at which this relationship can be applied. Furthermore, this simple linear relationship cannot be solely attributed to elevated O_3 concentrations since there also exists a strong relationship between crop yield and moisture, as well as between O_3 and temperature. Thus, the actual impact of O_3 on crop yield can only be examined through the use of a multiple linear regression model (MLR; Montgomery et al., 2001), which takes all of these variables into account at the same time.

One of the immediate challenges of constructing such a model is normalizing these variables into a common spatial scale. Since we also want to see if satellite data can be used as a surrogate for surface measurements, the analysis was built around the resolution of the satellite information using the archived tropospheric O_3 residual (TOR; Fishman et al., 2003). The units of TOR are Dobson Units (DU) and refer to an amount of O_3 integrated throughout the depth of the troposphere. These data are available as monthly averages (http://asd-www.larc.nasa.gov/TOR/data.html) with the same level-3 grid resolution as the archived Total Ozone Mapping Spectrometer (TOMS) dataset. Although the TOR dataset is nearly global in scope and consists of 28,800 grid cells each month, this study used only a small subset that encompassed the tri-state region of Iowa, Illinois and Indiana (Fig. 2). The tri-state region was divided into 40 grid cells, each with a size of 1°-latitude by 1.25°-longitude (~100 km by ~125 km).

2.2. Crop yield data

Annual soybean yields for the 2002–2006 growing seasons (June–September) were obtained from the National Agriculture Statistics Service (NASS) of the U.S. Department of Agriculture (USDA) on a county-by-county format (http://www.nass.usda.gov/). County yield data at the resolution shown in Fig. 1 was mapped onto a TOR grid cell (dashed red lines in Fig. 1) based on a weighted percentage of the county in the grid cell. Two of the five years of data used in this study are presented in Fig. 2a, illustrating both the interannual variability (generally higher yields in 2002 versus 2003) as well as the regional gradients in soybean seed yield. (Graphical depictions for all five seasons of crop yield data as well as all monthly depictions for each of the five years of the other datasets used for this study can be found at http://asd-www.larc.nasa.gov/TOR/data.html.).

2.3. Temperature and moisture data

Surface temperatures were calculated for the growing season (June–August) for each station where information was available (see Fig. 1). The temperature data were then mapped onto the TOR grid cells by averaging the available county data for each cell. Weekly averages of the Palmer Crop Moisture Index (PCMI) and hourly averages of surface temperature were obtained from the National Climatic Data Center (NCDC; http://www.ncdc.noaa.gov/ao/ncdc.html). Weekly values of PCMI data are archived at NCDC and organized by climate division. There are nine climate divisions for each of the three states used in our study. A seasonal average PCMI value for the growing season (July–August) was calculated for each climate division in each year of the study. PCMI values were mapped onto the TOR grid based on a weighted estimate calculated on percent occupation of each grid. Moisture index values between −0.99 and 0.99 indicate adequate soil-water content for crop growth. Values less than −1 indicate abnormally dry conditions, and values greater than 1 indicate abnormally wet conditions (Palmer, 1968). Since only a small percentage of the soybean crop is irrigated in these three states (0.3% in Iowa, 2% in Illinois, and 3% in Indiana; data from http://www.agcensus.usda.gov/Publications/2007/Full_Report/Volume_1,_Chapter_1_State_Level/index.asp), we assume that the PCMI data accurately represents the amount of water available for plant growth in a grid cell. PCMI and temperature fields for 2002 and 2003 are depicted in Fig. 2b and c.

2.4. Surface O_3 data

Surface O_3 measurements for 2002–2006 were obtained for our study region from the EPA Air Quality System (http://www.epa.gov/ttn/airs/airsaqs/detaildata/) and consisted of 90 or more sites each year. Seasonal surface values were derived from monthly average values for June–August; the monthly averages,

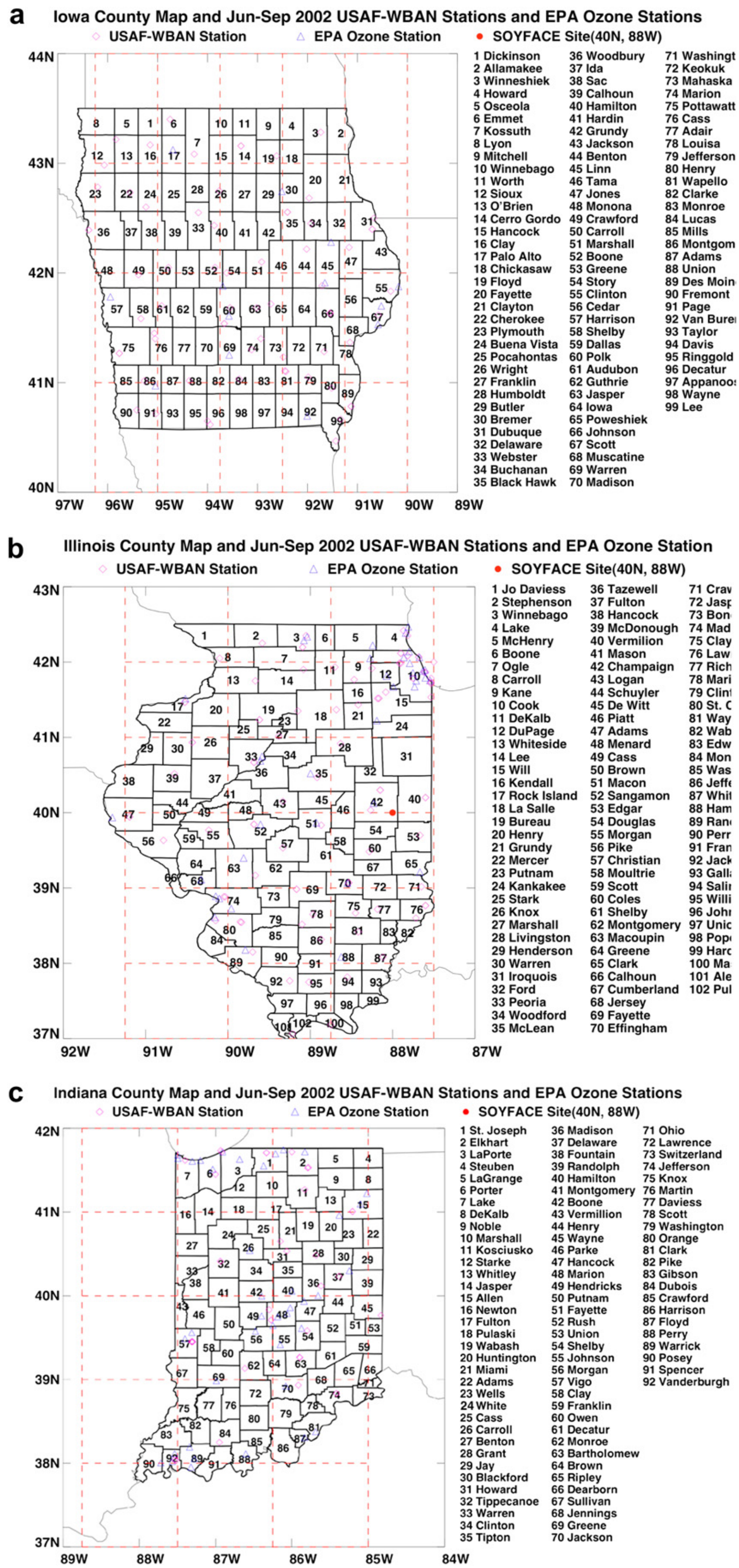

Fig. 1. Location of EPA O_3 monitoring stations (blue triangles) and meteorological sites (red diamonds) used in this study. Also shown are the county boundaries and red dashed grid lines that define the resolution at which satellite data are available. The figure consists of three panels: a) Iowa; b) Illinois; and c) Indiana. The location of the SoyFACE facility (solid red circle) is shown in Fig. 1b in Champaign County.

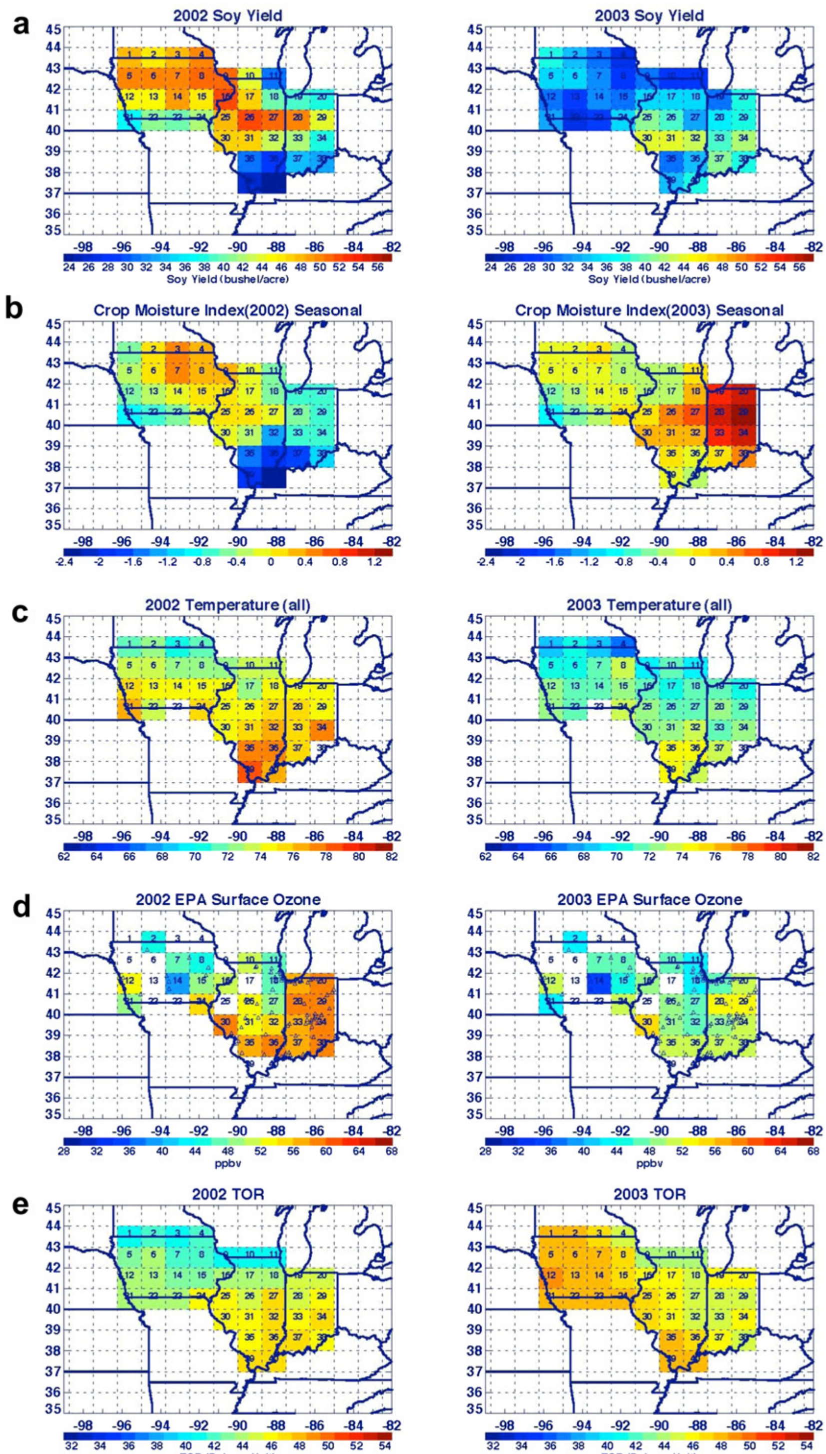

Fig. 2. Data used for the current study for two years, 2002 (left) and 2003 (right). Number in each box represents the numbering system for the grid boxes used in our analyses. (a) soybean yield from USDA NASS website in bushels acre^{-1}; (b) Palmer Crop Moisture Index; (c) average daytime temperature (1000–1800 LST) in °F; (d) surface O_3 concentration daytime average (1000–1800 LST), obtained from measurements denoted by the triangles, in parts per billion volume (ppbv); (e) satellite-derived tropospheric O_3 residual (TOR) in Dobson Units (DU).

in turn, were derived from daytime averages (using the hourly values from 1000 to 1800 LT). The seasonal average EPA surface estimates were then mapped onto the TOR grid. Wherever there was more than one EPA monitoring location within a grid cell, an average value for all stations was used. Within our study region, O_3 monitors were found in 27 of the 40 grid cells (see Fig. 2d). This network was skewed toward urban centers, with as many as eight sites in the grid cell near Chicago (#18). A number of other grid boxes, however, contained only one station that in some cases was near the perimeter of the grid cell and thus may not be fully representative of the surface O_3 value of the entire grid cell (e.g., #10 and #27). It should also be noted that Fig. 1 shows the location of EPA sites operating during 2002. Throughout the five years of our study, some of these sites ceased to operate whereas several others came on line, often near where a station was taken offline.

2.5. Satellite-derived tropospheric O_3

More than two decades (1979–2005) of tropospheric O_3 residual (TOR) satellite data are available on a monthly basis from the TOR website using the TOMS instrument (on four different satellites) as the means of calculating the TOR (Fishman and Balok, 1999; Fishman et al., 1990, 2003). Units of the TOR are Dobson Units (DU) and refer to a column depth of O_3, where 1 DU = 2.68×10^{16} molecules O_3 cm^{-2}; a typical column depth of O_3 is ~300 DU with ~90% of the O_3 located in the stratosphere. An example of this dataset for 2002 and 2003 is depicted in Fig. 2e. Since 2005, total O_3 amounts have been derived from the Ozone Monitoring Instrument (OMI) on the Aura satellite, launched in 2004, and are used to calculate TOR values in 2005 and 2006. Analyses of the TOR data for 2005 (the only complete year of overlap for the operation of the two instruments) have been conducted to compare the differences in the derived TOR product using the two instruments and methodologies. Our analysis showed that the two methods of calculation over our study region were in good agreement and that no obvious systematic or offset biases are present (Fishman et al., 2009). For the monthly averages presented in this study, we also considered only days during which time less than 20% cloud cover was present when the satellite overpass occurred, a criterion that generally excluded ~25% of the days.

2.6. The relationship between surface O_3 and TOR: a historical perspective

Since surface monitoring networks provide much better information near urban areas than in rural regions dominated by farmland, we wanted to see whether or not satellite data could be used to as a surrogate for monitoring sites in non-urban regions. Comparing measurements between the two approaches, however, is not straightforward due to differences in the units employed (DU versus ppbv).

The first nearly global distribution of seasonal maps of tropospheric O_3 derived from satellite measurements was published by Fishman et al. (1990) using the TOMS total O_3 measurements with concurrent stratospheric O_3 profiles derived from Stratospheric Aerosol and Gas Experiment (SAGE) instruments aboard two satellites in the 1970s and 1980s. All satellite-derived tropospheric quantities relate to a column-integrated amount of O_3 between the surface and the tropopause. Validation of these integrals has been conducted through analyses of O_3 profiles derived from ozonesonde measurements (Fishman et al., 1990; Morris et al., 2006; Ziemke et al., 1998). If the assumption is made that a "representative" concentration of O_3 is present throughout the tropospheric column, then such a concentration could be defined by dividing the ozone column (in molecules cm^{-2},) by the depth of the troposphere (which ranges between 10 and 18 km), and then dividing that quantity by the average molecular density of that column. Under such assumptions, the conversion factor between Dobson Units (DU) and concentration (in ppbv) is on the order of 1.5–1.6 ppbv per DU (Fishman and Brackett, 1997; Fishman et al., 1990; Ziemke et al., 2006). Fishman et al. (1990) compared TOR values with average concentrations at a pressure altitude of 500 hPa (often referred to the "middle" of the atmospheric column from a density perspective) and reported a ratio of ~1.6 between volume mixing ratio (in ppbv) and integrated O_3 in DU.

In addition to the unit-conversion issue described above, other factors, such as temporal and spatial scaling differences, also complicate a comparison of surface O_3 concentrations with satellite-derived quantities. Thus, in the analyses presented in this study, we describe a set of surface observations that are comparable to the spatial resolution of the satellite measurements by assuming that these measurements are representative of the entire grid cell. In terms of temporal resolution, we used data that were averaged over either an entire month to acquire a better statistical sample (see discussion in Fishman et al., 2003) or over the entire growing season, which is the shortest temporal scale related to crop productivity.

3. Results from the multiple linear regression model

3.1. Isolating the effect of surface O_3

Dry conditions and high temperatures are most conducive for high O_3 concentrations, and can also have negative effects on crop yield. Therefore, to assess the impact of O_3 on soybean yield, we designed an MLR model in which the interannual variability in soybean seed yield could be modeled along with seasonal temperature, soil moisture (PCMI) and tropospheric O_3 concentration across 100-km by 125-km grid cells encompassing the major soybean-growing region in the U.S. When the statistics of this MLR model were calculated over the entire region, a weak negative relationship between soybean yield and O_3 was found. If, however, the entire domain was divided into specific sub-regions for analysis, the calculations provide significant insight into the impact of O_3 on crop yield that support prior manipulative experiments.

We divided the dataset into three regions as a function of latitude with the northern, central, and southern regions being defined by 42°–44°, 40°–42°, and 37°–40°, respectively, and found that the O_3-soybean yield relationship was considerably more pronounced for the southern region (see Fig. 3) and nearly flat for the other two regions (not shown). For the remainder of the discussion, we focus on the southern region. The MLR determined different intercept terms based on year. By using different intercepts, the model assumed that yield varied by year, but that the coefficients on the explanatory variables (i.e., O_3 concentration, temperature, and crop moisture) remained constant over the 5-year period. Graphically, this appears as the five parallel lines for the fit of the model.

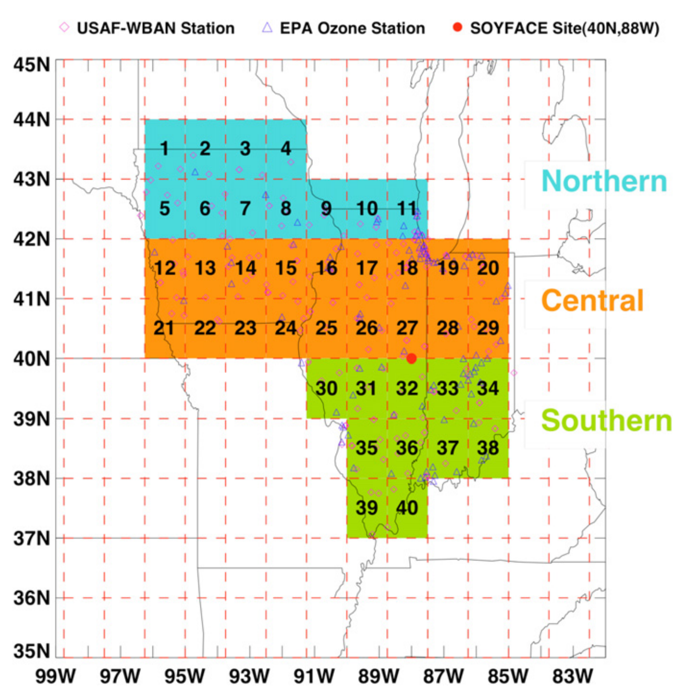

Fig. 3. Map showing the geographical extent of the "Northern," "Central" and "Southern" regions defined for this study.

The fact that the overall negative yield-O_3 relationship was dominated by the data in the southern region was consistent with the observation that there were relatively higher O_3 concentrations in this region. During this 5-year period, the average daytime concentration was 54 ppbv in this region compared with 49 ppbv in the central and 45 ppbv in the northern regions. Since soybean foliar injury and yield suppression from O_3 tend to occur above a range of 40–50 ppbv (Morgan et al., 2006; US EPA, 2006), depending on the cultivar, weather and other factors, the integrated exposure above such concentrations is what is critical for determining how much damage is done to the crop. The slope of the regression lines in Fig. 4 is -30.3 ± 13.1 kg ha^{-1} ppbv^{-1}. The average yield over this region during these five years was 3.31×10^3 kg ha^{-1} with a range of 2.77–4.01 $\times 10^3$ kg ha^{-1} implying a yield reduction of -0.38 to -1.63% ppbv^{-1}. This value is in line with previous chamber studies (Heagle, 1989) and consistent with, but slightly lower than what was found at SoyFACE (Morgan et al., 2006). During the 2002 and 2003 growing seasons, Morgan et al. (2006) reported a value of $-1.62 \pm 0.47\%$ ppbv^{-1} (-1.15 to -2.18% ppbv^{-1}) for soybean Pioneer Hybrid 93B15, during which time the average O_3 concentration was 56 ppbv and then artificially enhanced to 69 ppbv resulting in a decline in yield of 20%.

With respect to the MLR, this finding suggests that the threshold for detecting statistically significant effects with our model may be above 49 ppbv (the average concentration in the central region), or perhaps that a larger dataset with more years of data is required to pull out a statistically significant relationship at these lower concentrations. Threshold, in this context, does not imply a definitive change point whereby there is no effect due to O_3 less than or equal to 49 ppbv; rather, it represents the concentration below which the cumulative effect of O_3 does not become clearly apparent. A more sophisticated MLR model that incorporated factors such as crop phenology and vapor pressure deficit along with seasonal- and concentration-weighted O_3 metrics might refine our ability to resolve possible yield losses due to ambient O_3.

3.2. Interpretation of MLR model using satellite measurements

The MLR model for the southern region, using TOR, temperature and PCMI as the explanatory variables is shown in Fig. 5. This model likewise produced a statistically significant result with an R-square (R^2) value of 0.79, indicating that 79% of the variability in this region could be explained by the model using these three factors. For comparison, the MLR using surface O_3 concentrations had an R^2 value of 0.81. In both models, temperature is significantly negatively correlated whereas crop moisture is significantly positively correlated. Although the impact of the O_3 is not as dominant as these other factors, its contribution is still statistically significant and produces a calculated slope using TOR of -3.30 kg ha^{-1} DU^{-1}. MLR models that use only moisture and temperature measurements do not explain as much of the variance as those that do incorporate O_3 observations, from either satellite or *in situ* measurements.

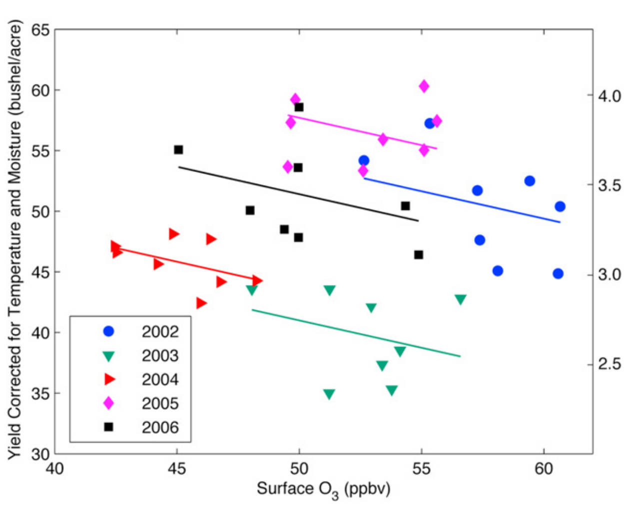

Fig. 4. Relationship between yield and surface O_3 over the southern region (37-40° N). Units for the yields on the left axis are taken directly from the USDA NASS database, which are provided in units of bushel acre^{-1}; 1 bushel acre^{-1} = 67.25 kg ha^{-1} and these units are shown on the right axis.

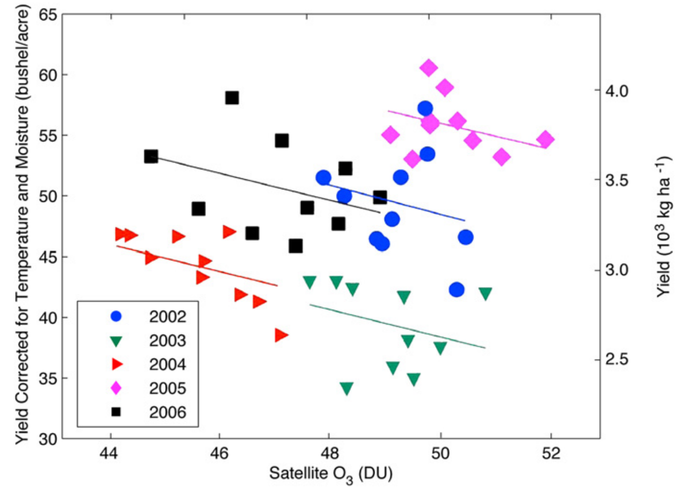

Fig. 5. Relationship between yield and satellite-derived O_3 over the southern region (37–40°N). Units for the yields on the left axis are taken directly from the USDA NASS database, which are provided in units of bushel acre^{-1}; 1 bushel acre^{-1} = 67.25 kg ha^{-1} and these units are shown on the right axis.

3.3. Utilization of satellite measurements for air quality applications

In recent years, application of satellite data for air quality purposes has primarily focused on the use of MODIS aerosol optical depth (AOD) measurements from the Moderate Imaging Spectroradiometer (MODIS) to infer information about fine particulate matter, $PM_{2.5}$ (Al-Saadi et al., 2005) at the surface. Despite the numerous studies over the past several years using this methodology, Hoff and Christopher (2009) point out that a statistically robust relationship between AOD and $PM_{2.5}$ is not uniformly present. Nonetheless, they emphasize that there are specific instances when the relationship between these quantities is sufficiently correlated that the use of the MODIS AOD measurements provided insight that could not be obtained from the existing $PM_{2.5}$ ground-based monitoring network. Analogously, we will show that the relationship between surface O_3 and its satellite-derived surrogate is not perfect, but that there is enough pertinent information in the TOR distribution that its use in this study provides insight that otherwise might not be obtained.

As stated previously, earlier studies have compared TOR amounts with ozonesonde measurements to derive the tropospheric column O_3 (TCO), which can then be directly compared with the satellite quantities (Creilson et al., 2003; Morris et al., 2006; Wozniak et al., 2005). These studies have all confirmed that the satellite data agree well with the TCO values and can be used for determining seasonal cycles and interannual variability of tropospheric O_3 with good confidence (Creilson et al., 2003;

Fishman et al., 2005; Ziemke et al., 1998, 2006). However, a comparison between surface O_3 and TOR values has never been conducted over a region with the scale resolution used in this study. Thus, although the MLR analysis supports the ability of TOR to predict crop yield with a calculated slope of -3.30 kg ha^{-1} DU^{-1}, the utility of such a finding is not obvious.

For the satellite data to be useful for assessing the impact of O_3 pollution crop yield, we need to understand the relationship between the remotely sensed information and what is actually present at the surface. Fig. 6 shows the comparison at grid cell #34, a location near Indianapolis, Indiana, where the ground-based O_3 concentration average has been determined from seven sites. It is noteworthy that the correlation coefficient ($r = 0.75$) between the TOR and the surface O_3 in this cell, which is an average value of all seven stations, is better than the correlation with measurements from any one station within the grid cell. Whereas the calculated slope in Fig. 5 is -3.30 kg ha^{-1} DU^{-1}, this finding in these units has little practical value since a Dobson Unit has little relevance with respect to air quality applications.

The linear expression that defines the relationship between the TOR and surface O_3 for all the grid cells in the southern region is given by:

$$\text{Surface } O_3 = 0.84 \times \text{TOR} + 11.70 (r = 0.64).$$

Note that the above equation has not and should not be used as a predictor equation for surface O_3, but rather is being used to help establish a non-dimensional unit (percentage) that can later be compared with a unit (ppbv) commonly used in air quality studies. Using this relationship, the calculated reduction in yield is $-1.86 \pm 0.99\%$ ppbv^{-1}, once again consistent with the SoyFACE *in situ* calculated reduction of $-1.62 \pm 0.47\%$ ppbv^{-1} and with the values that have been calculated with our own MLR that uses surface O_3 as the third explanatory variable.

4. Discussion: regional and global impact of O_3 pollution

Conservatively estimating that the elevated O_3 concentrations affected soybean production only in the southern half of the farmland in only Illinois and Indiana, where the value of the soybean crop in 2007 was ~\$6 billion, our analysis shows that the yield in these regions was diminished by 2–6%, depending on which percentage decrease above a threshold value of 49 ppbv is used. Extrapolating this loss to the average soybean yields in the southern region of this study translates to a change in revenue to the farm community on the order of \$100–300 M. If the threshold for damage were approximately 40 ppbv, then the value of the soybean crop in the entire Iowa-Illinois-Indiana region (~\$11 billion), would have been reduced by at least 10%, or by more than \$1 billion. In either scenario, the cost to farmers is substantial, and if background concentrations of surface O_3 continue to rise as predicted by 25% by 2050 (Forster et al., 2007; Meehl et al., 2007), unless more O_3-tolerant cultivars are developed, then the annual cost to U.S. farmers will certainly exceed several billion dollars, especially in light of the fact that many crops and forages such as alfalfa, barley, bean, clover, cotton, grape, oat, peanut, potato, rice, tomato, wheat and others have also been shown to be affected by elevated O_3 concentrations once a threshold concentration is reached (Booker et al., 2009; Heagle, 1989; US EPA, 2006).

Using an air quality forecast model, Tong et al. (2007) used an entirely different approach to assess the impact of current ambient O_3 concentrations on the U.S. soybean crop. The results of their calculations were based on two critical factors: the ability of the model to replicate the surface observations accurately and the response functions used in the model to calculate the relative yield loss (RYL). The RYL, in turn, is most dependent on the concentration at which damage occurs; i.e., the same uncertainty discussed previously. For the U.S., Tong et al. (2007) calculate a reduction in yield ranging between 1.7% and 14.2% for the 2005 growing season, with a concluding best estimate value of ~10%. Once again, this model-derived value is consistent with the values derived from our MLR calculations as well as with those obtained from the SoyFACE measurements.

Globally, yield losses due to O_3 (using data from 2000) have been estimated to be \$14–26 billion for rice, soybean, maize and wheat combined. In some rapidly developing regions such as South Asia, the impact of O_3 on the production of some staple crops such as wheat and rice may even present a significant threat to regional food security (Royal Society, 2008).

5. Concluding remarks

5.1. Implications from a global-change perspective and future considerations

By applying a multiple linear regression model to existing datasets, our results confirm experimental findings over recent decades that elevated ground-level O_3 concentrations decrease soybean crop yield. Fig. 7 illustrates how the findings from the

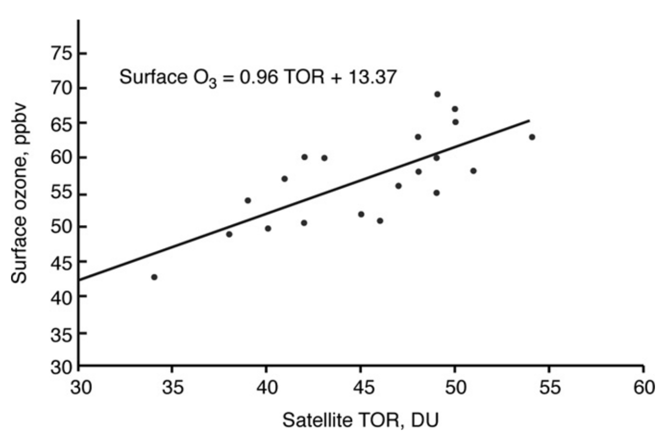

Fig. 6. Relationship between the average surface O_3 concentration derived from seven monitors and TOR over grid cell #34 (refer to Fig. 2) near Indianapolis, Indiana. Data plotted are monthly average values (June through September) for each of the five years (2002–2006).

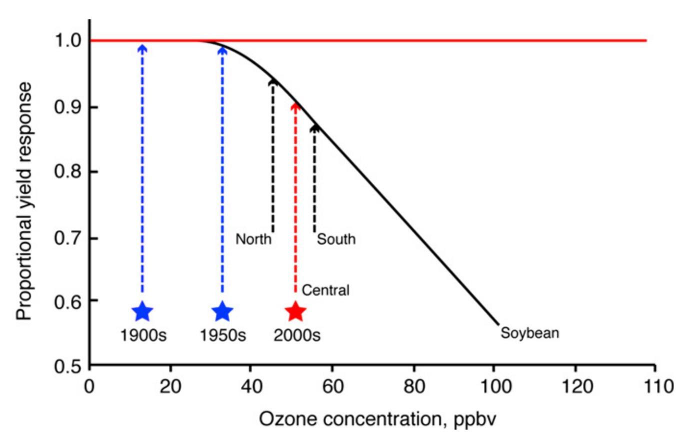

Fig. 7. Relationship between relative yield of soybean as a function of concentration (after Heagle, 1989) and measured surface O_3 concentrations over the past century (from Volz and Kley (1988) and Staehelin et al. (1994)) and in the current study over the three regions defined by "North," "Central" and "South" (see text for further details).

current study may be indicative of how increasing O_3 concentrations have become a threat to crop productivity within only past several decades. The curve on this graph is redrawn from Heagle (1989) and summarizes field-experiments that quantified the impact of increased O_3 on the relative yield of soybean. The locations of the stars indicate the approximate background O_3 concentrations over the past century (Fiore et al., 2002; Mauzerall and Wang, 2001; Staehelin et al., 1994; Volz and Kley, 1988). As can be seen from the positions of the dashed lines labeled "North", "Central" and "South," the concentrations measured during the current study are representative of today's background concentrations (e.g., Tong et al., 2007).

The answer provided by the MLR calculations is the rate of decrease of crop yield as a function of concentration, a finding that quantifies the slope of a regression line over a range of values. At which point that slope is valid is defined by the range of concentrations used in the MLR and our findings imply that such a slope is supported at a statistically significant value when the average concentration is 54 ppbv; the range of monthly concentrations used in this specific set of calculations is 42–61 ppbv. The slope found at this concentration is comparable to the Morgan et al. (2006) findings at SoyFACE where the average concentrations were similar during the years of his study (56 ppbv) to what was measured at the SoyFACE location in this study (54 ppbv).

In another aspect of our research, we have been able to show that space-based measurements of pollution provide a new tool for quantifying this impact and that the unique vantage point from space might be able to provide a global perspective that otherwise could not be achieved. Furthermore, satellite data may even be a better measure of ozone amounts outside of urban areas because of the general paucity of surface sites in predominately farmland regions. Globally, the technique described here can be used anywhere to provide an assessment of crop loss from ozone in vast regions of the world where no surface ozone network is in place.

Because the original purpose of the satellites used in this study was to observe hemispheric scale stratospheric processes, the information that we extracted to construct the TOR product with a resolution on the order of 100 km has significantly stretched the intended utility of these measurements. Nevertheless, the good agreement between the decline in crop productivity using the TOR data and previously published results, as well as their agreement with the surface O_3 data used in this study, is encouraging and suggests that these types of measurements can be used to study impacts at this resolution on monthly and seasonal time scales.

NASA is currently in the process of defining and implementing its next generation of instruments and satellites and the Agency is following the guidelines provided by the National Research Council (2007), which recommended an Earth observing program better focused on applications and societal benefits than its current program that had traditionally been focused exclusively on science. In particular, one of the NRC's recommendations is the GEO-CAPE (Geostationary Coastal and Air Pollution Events) mission. With its proposed 5- to 10-km spatial and 1-h temporal resolution, GEO-CAPE (recommended to be launched by 2016 if sufficient funding is available) will provide the time and spatial resolution required to assess the impact of O_3 on crops with better accuracy. The future use of a satellite that is designed to study tropospheric composition explicitly should provide exciting possibilities for both the air quality and agricultural communities in the forthcoming decades when the impact of air pollution on crop productivity is likely to result in significantly greater detrimental consequences as background concentrations continue to increase (Cooper et al., 2010).

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