Global Crop Yield Reductions due to Surface Ozone Exposure: 1. Year 2000 Crop Production Losses, Economic Damage, and Implications for World Hunger

Shiri Avnery a, Denise L. Mauzerall b,*, Junfeng Liu c, and Larry W. Horowitz d

a Program in Science, Technology, and Environmental Policy, Woodrow Wilson School of Public and International Affairs, 414 Robertson Hall, Princeton University, Princeton, NJ 08544, USA, savnery@princeton.edu

b Woodrow Wilson School of Public and International Affairs and Department of Civil and Environmental Engineering, 445 Robertson Hall, Princeton University, Princeton, NJ 08544, USA, mauzeral@princeton.edu

c NOAA Geophysical Fluid Dynamics Laboratory, 201 Forrestal Road, Princeton University, Princeton, NJ 08540, Larry.Horowitz@noaa.gov

d NOAA Geophysical Fluid Dynamics Laboratory, 201 Forrestal Road, Princeton University, Princeton, NJ 08540, Junfeng.Liu@noaa.gov

* Corresponding author.

Email: mauzeral@princeton.edu
Phone: +1 609-258-2498.
Fax: +1 609-258-6082
Global Crop Yield Reductions due to Surface Ozone Exposure: 1. Year 2000 Crop Production Losses, Economic Damage, and Implications for World Hunger

Abstract

Exposure to elevated concentrations of surface ozone (O₃) causes substantial reductions in the agricultural yields of many crops. As emissions of O₃ precursors rise in many parts of the world over the next few decades, yield reductions from O₃ exposure appear likely to increase the challenges of feeding a global population projected to grow from 6 to 9 billion between 2000 and 2050. This study estimates present day (year 2000) global yield reductions of three key staple crops (soybean, maize, and wheat) due to surface ozone exposure using simulated hourly O₃ concentrations by the Model for Ozone and Related Chemical Tracers version 2.4 (MOZART-2). We calculate crop losses according to two different metrics of ozone exposure—seasonal daytime (08:00-19:59) mean O₃ (M12) and accumulated O₃ above a threshold of 40 ppbv (AOT40)—and predict crop yield losses using crop-specific O₃ concentration-response functions established by field studies. We additionally calculate the economic value of crop production losses as well as the number of people who could avoid undernourishment if crop reductions due to ozone exposure were eliminated. Our results indicate that year 2000 O₃-induced global yield reductions ranged from 8.5-14% for soybean, 3.9-15% for wheat, and 2.2-5.5% for maize, depending on the metric used. Global crop production losses totaled 79-121 million metric tons, worth $11-18 billion annually (USD2000). We further calculate that the dietary energy equivalent of O₃-induced crop losses could have lifted 180-312 million people, or 21-36% of the year 2000 global undernourished population, above the undernourishment threshold as defined by the United Nations Food and Agriculture Organization. Our calculated yield reductions agree well with previous estimates, providing further evidence that yields of major crops across the globe are already being reduced by exposure to surface ozone—a risk that will grow unless O₃ precursor emissions are curbed in the future.

Keywords: ozone; ozone impacts; agriculture; crop loss; integrated assessment; food security

1. Introduction

Surface ozone (O₃) is a major component of smog, produced in the troposphere by the catalytic reactions among nitrogen oxides (NOₓ = NO + NO₂), carbon monoxide (CO), methane (CH₄), and non-methane volatile organic compounds (NMVOCs) in the presence of sunlight. In addition to having a detrimental effect on human health, field experiments demonstrate that surface ozone causes substantial damage to many plants and agricultural crops, including increased susceptibility to disease, reduced growth and reproductive capacity, increased senescence, and reductions in crop yields (Mauzerall and Wang, 2001). O₃ penetrates leaves through the stomata, where it reacts with various compounds to yield reactive oxygen species that oxidize plant tissue and results in altered...
gene expression, impaired photosynthesis, protein and chlorophyll degradation, and changes in metabolic activity (Booker et al., 2009; Fuhrer, 2009). Based on the large-scale experimental studies of the National Crop Loss Assessment Network (NCLAN) conducted in the United States in the 1980s (Heagle, 1989; Heck, 1989), the U.S. Environmental Protection Agency (EPA) estimated that the yields of about one third of U.S. crops were reduced by 10% due to ambient O₃ concentrations during this time (EPA, 1996). Results from the European Open Top Chamber Programme (EOTC) in the 1990s (Krupa et al., 1998) similarly suggest that the European Union (EU) may be losing more than 5% of their wheat yield due to O₃ exposure (Mauzerall and Wang, 2001). Although comparable large-scale studies have not been conducted in developing countries, the potential risk of ambient O₃ exposure to agricultural production has been documented through both small-scale field studies and modeling efforts in East Asia (Chameides et al., 1999, Aunan et al., 2000; Wang and Mauzerall, 2004), the Indian subcontinent (Agrawal, 2003; Wahid, 2003; Emberson et al., 2009), Egypt (Abdel-Latif, 2003), and South Africa (van Tienhoven and Scholes, 2003).

With over one billion people in the world currently estimated to be undernourished (FAO, 2009), the potential contribution of O₃ pollution to present-day and future global food insecurity deserves attention. This is especially true as both population and O₃ precursor emissions are projected to increase in most developing nations over the next few decades (Nakićenović et al., 2000; Dentener et al., 2005; Riahi et al., 2007). Rising emissions of O₃ precursors in these countries pose a risk to not only their national and regional food security but also to global food production as O₃ and some of its precursors are sufficiently long-lived to be transported between continents (Fiore et al., 2009).

To our knowledge, only one study has calculated O₃-induced crop yield reductions in the present and the near future on a global scale. Van Dingenen et al. (2009) (hereafter VD2009) use concentration:response (CR) functions derived from field studies, simulated datasets of global crop distributions, O₃ precursor emissions for the year 2000 and 2030 as projected under the optimistic “current legislation (CLE) scenario” (which assumes that presently approved air quality legislation will be fully implemented by 2030), and simulated global hourly ozone concentrations by the TM5 atmospheric
chemical transport model (CTM). VD2009 calculate that present day global crop yield losses are significant for wheat and soybean (up to 12 and 16%, respectively) but smaller for the more O3-tolerant rice and maize crops (between 3-5%), with total production losses worth $14-26 billion (USD\textsubscript{2000}) annually. VD2009 additionally find that global crop yield reductions increase only marginally under the 2030 CLE scenario, with the most significant additional losses primarily occurring in developing nations where emission regulations do not exist or are particularly lenient and/or unenforced.

The VD2009 study is an important step towards assessing O3 risk to agricultural production globally, but further work is necessary to reduce uncertainties, to verify crop yield loss estimates under both current day and potential future levels of O3, and to understand how O3-induced production losses may contribute to the problem of global food insecurity. In this first part of our two-paper series, we provide an estimate of global crop yield reductions and economic losses due to ozone exposure in the year 2000 using simulated O3 concentrations, field-based CR relationships, and crop production distributions of three key staple crops: soybean, maize, and wheat. We calculate the value of crop production losses not only in terms of pecuniary damages, but also their human toll: the number of undernourished individuals who might have been fed at minimum dietary energy requirements if not for O3-induced reductions in crop yields. In part two of the series, we compare these present-day crop yield losses and their associated costs with future estimates of O3-induced reductions in crop yields calculated with global O3 distributions simulated by the MOZART-2 model (Horowitz, 2006) using two different emission scenarios: the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) B1 and A2 storylines (Nakićenović et al., 2000). These scenarios represent optimistic and pessimistic trajectories of ozone precursor emissions in order to demonstrate the future range of possible crop losses and the importance of O3 mitigation.

We use a similar methodology to VD2009, which is modeled on the original analyses of Aunan et al. (2000) and Wang and Mauzerall (2004) (hereafter WM2004). However, our study differs from and compliments VD2009 in a number of important ways. Most significantly, we use the global chemical transport Model for Ozone and Related Chemical Tracers version 2.4 (MOZART-2) to simulate hourly O3 concentrations.
at a 2.8° x 2.8° horizontal resolution, providing higher resolution estimates of O₃ exposure and corresponding crop yield losses over some regions of the world than provided by the VD2009 analysis—namely South America, Africa, and other parts of the Southern Hemisphere where a 6° x 4° resolution was used. We also perform a detailed spatial evaluation of surface O₃ concentrations over the U.S. and Europe predicted by MOZART-2, as well as at surface observation sites in Asia, Africa, South America, Australia and New Zealand where data are available. The crop distribution maps used in this study to calculate production losses are globally-gridded, satellite datasets merged with national yield statistics (Monfreda et al., 2008; Ramankutty et al., 2008), thereby removing some of the uncertainty associated with modeling distribution maps based on crop suitability indices (as used by VD2009). Finally, our estimates of the potential for “avoided undernourishment” represent the first attempt to quantify the human cost of crop production losses due to O₃ exposure and the contribution of O₃-induced crop losses to global food insecurity.

2. Methodology

To estimate global crop yield losses due to O₃ exposure we use: (1) observation-based global crop production maps; (2) simulated surface ozone concentrations from which we calculate O₃ exposure over crop growing seasons; and (3) CR functions that relate a given level of ozone exposure to a predicted yield reduction. Here we discuss the sources of each of these datasets and the methodologies used to evaluate resulting global crop yield reductions due to O₃ exposure and their associated costs.

2.1 Distribution of selected grain crops

The global crop distribution datasets, including both crop area and yields, were compiled by Monfreda et al. (2008) and Ramankutty et al. (2008) using a data fusion technique in which two different satellite-derived products (Boston University’s MODIS-based land cover product and the GLC2000 data set obtained from the VEGETATION sensor aboard SPOT4) were merged with national-, state-, and county-level census yield statistics. The MODIS land cover product provides maps of global land cover at 1-km spatial resolution while the VEGETATION sensor has a 1-km resolution at the equator.
The satellite data is used to spatially disaggregate the census data within each administrative unit (Ramankutty et al., 2008). Using national, state, and county level census statistics with the satellite derived global maps of cropland distribution, year 2000 area harvested and yields of 175 distinct crops of the world were compiled at 5 min by 5 min latitude-longitude resolution (Monfreda et al., 2008). These crop distribution maps are regridded to match the 2.8° × 2.8° resolution of MOZART-2. Fig. 1 shows the global distributions of crop production in metric tons per grid cell of soybean, maize, and wheat used in our calculations of O₃-induced yield reductions.

2.2 Plant exposure to O₃

2.2.1 MOZART-2 model simulation

MOZART-2 (Horowitz et al., 2003) is a global chemical transport model (CTM) that contains a detailed representation of tropospheric ozone-nitrogen oxide-hydrocarbon chemistry, accounting for surface emissions, emissions from lightning and aircraft, advective and convective transport, boundary layer exchange, and wet and dry deposition. Surface emission sources include fossil fuel combustion, biomass burning, vegetation, soils, and oceans. MOZART-2 simulates the concentrations and distributions of 63 gas-phase species, 11 aerosol and aerosol precursor species (including sulfate, nitrate, ammonium, black carbon, and organic carbon), and mineral dust of 5 size bins with diameters ranging from 0.2 to 20.0 μm. The model, driven here by the National Center for Atmospheric Research (NCAR) Community Climate Model (MACCM3) (Kiehl et al., 1998), has a horizontal resolution of 2.8° latitude by 2.8° longitude with 34 hybrid sigma-pressure levels up to 4hPa, with a 20-minute time step for chemistry and transport.

The year 2000 model simulation used in this study (Horowitz, 2006) is based on the “standard” 1990 simulation from Horowitz et al. (2003) with year 1990 anthropogenic emissions (CH₄, N₂O, SOₓ, CO, NMVOC, and NOₓ) scaled by the ratio of 2000:1990 emissions in four geopolitical regions as specified by the IPCC SRES (Nakićenović et al., 2000). As these scenarios do not differ among themselves for 1990 and 2000, the scaling factors used for the year 2000 simulation are the same across scenarios (Table 1). The 1990 anthropogenic emissions are based on the Emission
Database for Global Atmospheric Research (EDGAR) version 2.0 (Olivier et al., 1996) with some modifications (Horowitz et al., 2003). Biomass burning and biogenic emission inventories for the 1990 simulation are also included, described in detail in Horowitz et al. (2003) and Horowitz (2006). The biomass burning inventory is “climatological” and thus does not vary annually to reflect actual biomass burning episodes. Two-year simulations were performed, with the first year used as spin-up and results from the second year analyzed. Simulated global distributions of O3 and its precursors for the standard 1990 scenario have been extensively evaluated against observation data, with the simulated seasonality and horizontal and vertical gradients of O3 above the surface generally in good agreement with observations (Horowitz et al., 2003). In Section 3, we carefully evaluate simulated surface O3 concentrations for the year 2000 with ground-level observation data according to the two metrics of O3 exposure used to calculate yield losses (see Section 2.2.2). We further use surface observations to bias-correct values of modeled O3 exposure in the U.S., a major agricultural production region where an extensive network of surface observations exists (Section 3.2). This is the first global spatial evaluation of surface O3 concentrations simulated by MOZART-2.

2.2.2 Metrics of O3 exposure and CR relationships

In order to assess the present and potential future impacts of O3 on agriculture, open-top chamber (OTC) field studies primarily in North America and Europe have established crop-specific CR functions that predict the yield response of a crop to a given level of ozone exposure (Heagle, 1989; Heck, 1989; Krupa et al., 1998). These CR functions require a statistical index to summarize the pattern of O3 exposure during the crop growing season. Because the response of a given crop to O3 depends on its physiology as well as surrounding environmental conditions, field studies have developed different statistical indices of varying complexity to describe seasonal O3 exposure. Such metrics include the most biologically relevant stomatal flux indices, which aim to quantify the effective flux of O3 into plant stomata after accounting for climatic conditions and plant defenses (including both stomatal closure and detoxification), to more simple cumulative and mean exposure-based metrics, which are calculated from
ambient O$_3$ concentrations during the growing season. Although stomatal flux metrics have been shown to more accurately predict the yield response of some crops, flux-based metrics are not yet suitable for large-scale impact analyses or regulatory purposes due to a lack of relevant data and the need to reduce remaining uncertainties (Musselman et al., 2006; Paoletti et al., 2008; Booker, 2009; Fuhrer, 2009). As a result, we use two exposure-based metrics, M12 and AOT40, and their CR relationships to calculate crop yield losses globally:

\[
M12 (\text{ppbv}) = \frac{1}{n} \sum_{i=1}^{n} [C_{O_3}],
\]

\[
AOT40 (\text{ppmh}) = \sum_{i=1}^{n} ([C_{O_3}]_i - 0.04) \quad \text{for} \quad C_{O_3} \geq 0.04 \text{ ppmv}
\]

where:
- $[C_{O_3}]_i$ is the hourly mean O$_3$ concentration during daylight hours (8:00 – 19:59); and
- $n$ is the number of hours in the 3-month growing season.

We define the “growing season” like VD2009 as the 3 months prior to the start of the harvest period according to crop calendar data from the United States Department of Agriculture (USDA) (USDA, 1984; 2008). While we could not obtain growing season data for every country, crop calendars for the top producing countries of each crop (representing greater than 95% of global production) were available and compiled. Global maps showing the start of the growing season (as defined here) for each crop are available in Figure 1 of the supplementary material.

Of the exposure-based metrics, cumulative indices that ascribe greater weight to higher O$_3$ concentrations are believed to be more accurate predictors of crop yield losses than mean metrics because they account for the cumulative effect of O$_3$ injury—the reduced ability of plant defense systems to combat subsequent O$_3$ exposure due to resource and energy limitations—and for the greater injury caused by elevated levels of O$_3$ (Lefohn and Runeckles, 1988). The AOT40 index is favored in Europe as the exposure-based metric that most accurately predicts the yield response of local cultivars; this metric was derived from the EOTC field experiments that found yield reductions to be highly correlated with cumulative O$_3$ exposure above a threshold of 30-40 ppbv. The AOT40 index is currently used to define air quality guidelines to protect vegetation in Europe (Fuhrer et al., 1997). We include the M12 metric (and substitute the highly
correlated M7 metric when M12 parameter values have not been defined for certain 
crops, as in VD2009) in order to facilitate intercomparisons among previous studies, and 
because this metric is the most robust in terms of replicating observed O₃ exposure values 
(see Section 3.2). The M7 metric is defined like M12 except using daylight hours from 9:00-15:59.

For each metric, CR functions have been obtained by fitting linear, quadratic, or 
Weibull functions to the yield responses of crops at different levels of O₃ exposure. The 
CR relationships for the M7 and M12 metrics have a Weibull functional form while the 
AOT40 CR relationships are linear. We use median parameter values of pooled CR 
relationships from a variety of cultivars grown in the U.S. (Heagle, 1989; Heck, 1989) 
adapted from WM2004 for the M7/M12 metrics. For the AOT40 index, we use CR 
functions based on field studies in both the U.S. and Europe from Mills et al. (2007). 
Because robust CR data are lacking for Asia, Africa, and South America, we apply the 
U.S. and European CR functions globally. Table 2 lists the CR equations used to 
calculate the relative yields (RY) of soybean, maize, and wheat as a function of each 
metric. Relative yield loss (RYL) is calculated by subtracting the RY from unity, which 
represents the theoretical yield without O₃ damage (i.e. 100% yield).

2.3  Yield reductions and associated costs

2.3.1  Integrated assessment

We follow the integrated assessment approach outlined by WM2004 and VD2009 
and combine crop distribution maps, O₃ exposure, and CR relationships to calculate 
RYL, crop production losses (CPL), and economic losses (EL). We start by calculating 
O₃ exposures using the simulated hourly O₃ concentrations over the appropriate growing 
season for soybean, maize, and wheat in each 2.8° x 2.8° grid cell, yielding global maps 
of ozone exposure during crop growing seasons. We then use these maps of O₃ exposure 
to calculate RYL using the CR functions defined in Table 2 for every grid cell and each 
crop according to both the M12 and AOT40 metrics. Using the regridded crop 
distribution maps from Ramankutty et al. (2008) and Monfreda et al. (2008) (Fig. 1), we
calculate CPL in each grid cell ($CPL_i$) from RYL and the actual crop production in the year 2000 ($CP_i$) according to:

$$CPL_i = \frac{\text{RYL}_i}{1 - \text{RYL}_i} \times CP_i$$  \hspace{1cm} (1)

We sum the crop production loss in all grid cells within each country to obtain national CPL. We then define national RYL (nRYL) as national CPL divided by the theoretical total crop production without O₃ injury (the sum of crop production loss and actual crop production in the year 2000):

$$nRYL = \frac{\sum_{i=1}^{n} CPL_i}{\sum_{i=1}^{n} ([CPL_i] + [CP_i])}$$  \hspace{1cm} (2)

Following the approach of WM2004 and VD2009, CPL is translated into economic loss by multiplying national CPL by producer prices for each crop in the year 2000 as given by the FAO Food Statistics Division (FAOSTAT, http://faostat.fao.org/), which are used as a surrogate for domestic market prices due to insufficient information on actual crop prices. Where producer prices are unavailable for minor producing countries, we apply the median crop price for the year 2000 as implemented by VD2009: $138 \text{USD}_{2000}$ per metric ton for maize, $205 \text{USD}_{2000}$ per metric ton for soybean, and $148 \text{USD}_{2000}$ per metric ton for wheat. This simple revenue approach to calculate economic loss takes the market price as given and ignores the feedbacks of reduced grain output on price, planting acreage, or farmers’ input decisions. Westenbarger and Frisvold (1995) reviewed several studies involving use of a general equilibrium model with factor feedbacks and found that economic damage estimates derived from a simple revenue approach are within 20% of those derived using a general equilibrium model.

2.3.2 Implications of CPL for world hunger

We perform a back-of-the-envelope calculation to put O₃-induced yield losses into the context of global food security: using both the M12 and AOT40 metrics, we estimate the value of crop production losses due to O₃ exposure in terms of the number of
people who could avoid undernourishment if such losses were eliminated. We use the FAO definition of undernourishment for our calculations, which establishes a food consumption threshold called the minimum dietary energy requirement (MDER) (kcal/person/day) below which individuals are classified as undernourished. Because MDER is sex- and age-specific, national MDER is computed as the weighted average of the MDERs of different age and sex groups according to each nation’s population structure (see FAOSTAT (2008) for detailed estimation procedures). We use national MDER data compiled for 2000-2002 (MDER estimates are given for three-year periods) for each country where available. We convert crop production losses computed from each index of O₃ exposure to their potential dietary energy equivalents (kcal) using the USDA National Nutrient Database (USDA, 2009). Energy-equivalents per metric ton of each crop were determined for uncooked cultivars (for crops with multiple cultivars, energy values were averaged) and then summed together by country to determine the total caloric value of crop production losses in the year 2000. These values were then divided by national MDER data (converted to kcal/person/year) to determine the number of individuals who could potentially avoid undernourishment, as defined by the FAO, in each country if crop production losses due to O₃ exposure were eliminated.

This simple calculation makes numerous assumptions. Firstly, we assume that distributional and equity issues are negligible: that is, the agricultural production that could be gained via ozone mitigation would necessarily be used to feed those who are currently undernourished within the country of production—as opposed to being exported, stored, or consumed by those already above the MDER threshold. This simplification likely produces an overestimate of the possible avoided undernourished in each country. We also consider equally those with caloric intake near the MDER threshold and those near zero consumption as an “avoided undernourished” individual, despite the fact that less food is required to avoid undernourishment in the former case than the latter. This may lead to a possible underestimation of total avoided undernourished in a given country. Due to these and other simplifications, the calculations produced here should be considered as crude, first-order estimates of the contribution of O₃ pollution to global food insecurity that are illustrative rather than definitive.
3. **Model Evaluation**

3.1 **Methodology**

Since the reliability of yield loss estimates depends on the accuracy of simulated \( \text{O}_3 \) concentrations, we evaluate the performance of MOZART-2 in predicting the two ozone exposure metrics used to calculate crop yield reductions in the year 2000 with observation data (where available) during the growing season of each crop (i.e. the time period over which metrics are calculated). This type of spatial analysis was chosen over a more typical regionally-aggregated evaluation, where 24-hour monthly averages are used to evaluate model performance over large spatial scales, due to (1) the importance understanding model performance in the specific locations of crop production at the time of greatest crop sensitivity to ozone; and (2) the need to evaluate model performance according to the agriculturally-relevant metrics of ozone exposure.

Data sources for the observation data used here are listed in Table 3. In order to be included in this analysis, each site was required to have hourly \( \text{O}_3 \) concentrations for at least 75% of the hours needed to compute the exposure metrics. Due to this requirement, data from outside the U.S. and Europe are sparse. For the U.S. observation data, metric values were computed for each three-month growing season every year within a 5-year period (1998-2002) and subsequently averaged in order to produce a 5-yr seasonal average \( \text{O}_3 \) exposure value. This was done because \( \text{O}_3 \) levels were anomalously low over some parts of the U.S. in the year 2000 and therefore may not represent “average” \( \text{O}_3 \) concentrations as simulated by MOZART-2, which is driven with the MACCM3 climatological winds rather than assimilated meteorology for 2000. Metrics were calculated only for monitoring sites with at least four years (80%) of sufficient hourly \( \text{O}_3 \) data over the 1998-2002 period. Year 2000 data was used for monitoring sites outside of the U.S. due to insufficient data over the five year period in many locations. For grid cells with more than one monitoring station, metrics were calculated at each station and subsequently averaged to determine the observed \( \text{O}_3 \) exposure value in that grid cell. We present model evaluation results for May – July for the M12 and AOT40 metrics as illustrative of crop growing seasons in the U.S. and Europe where most observation data
are located; this is also the period used to calculate AOT40 values for regulatory purposes in Europe (UN-ECE, 1994).

3.2 MOZART-2 surface O₃ evaluation

An evaluation of the ability of MOZART-2 to simulate the M12 surface O₃ exposure metric during May-July is illustrated in Figure 2. O₃ is well-simulated over Europe, with a model:observation ratio between 0.9 and 1.1 over most of the continent (with exceptions over parts of the Iberian Peninsula and Scandinavia). MOZART-2 underestimates O₃ exposure in Japan by 4-12 ppbv (modeled:observed ratio of 0.72-0.86), while O₃ is overestimated in Hong Kong, Taiwan, and Malaysia by up to 16 ppbv (1.75 modeled:observed ratio). Over the U.S., MOZART-2 systematically overestimates O₃ exposure in the central and northeastern parts of the country by 20-30 ppbv (modeled:observed ratios of 1.3-1.8), but O₃ over the West and southeastern U.S. is generally well-simulated. This type of bias is common in global models which, on average, appear to over-predict surface O₃ in the eastern US by 10-20 ppbv in summer for reasons that remain unclear (Reidmiller et al., 2009). Monitoring sites in the rest of the world are generally well-reproduced by MOZART-2 (modeled:observed ratios of 0.9-1.3) according to the M12 metric. AOT40 is less robust in terms of replicating patterns of O₃ exposure due to the sensitivity of this metric to values near the threshold of 40 ppbv (Fig. 3). This effect is particularly evident in the central and northeastern U.S. and parts of Western Europe, where MOZART-2 over-predicts AOT40 by factors of 2-4. MOZART-2 also underestimates AOT40 over much of northern and eastern Europe and Japan, where model:observation ratios vary significantly by grid cell (Fig. 3d). Difficulty in reproducing accurate AOT40 values in some regions is also seen in the VD2009 study; for example, the TM5 model by VD2009 under-predicted AOT40 by a factor of 4 and 2.25 in central Europe and the U.S. Great Lakes regions, respectively.

As evident in Figs. 2-3, the most significant overestimation of O₃ unfortunately occurs in areas of intense crop cultivation in the U.S. (i.e. central and Midwestern parts of the country) (Fig. 1). Because the U.S. is a major producer of all three crops, we use observations to bias-correct values of simulated O₃ exposure in order to constrain a major
source of uncertainty in our estimates of global and regional crop yield losses. Our corrected values are calculated by dividing the simulated value of O₃ exposure in each U.S. grid cell by the ratio of modeled:observed O₃ in the same grid cell where data exist for each crop growing season in the U.S. We use U.S. eastern and western regional averages of the modeled:observed ratio for grid cell correction factors (longitude dividing line of 90°W) where observation data do not exist, as the model reproduces O₃ in the western U.S. much more accurately than in the East. Our O₃ exposure values, relative yield loss, crop production loss, and associated cost estimates presented in the following sections are based on these bias-corrected values of O₃ exposure.

4. Results

4.1. Distribution of crop exposure to O₃

Fig. 4 illustrates the global distribution of crop exposure to O₃ according to the M12 and AOT40 metrics. The highest exposure levels generally occur in the Northern Hemisphere due to greater O₃ precursor emissions and concentrations during the growing season. M12 ranges from 10 ppbv to over 80 ppbv for all three crops while AOT40 ranges from zero to over 40 ppmh in some locations. As evident from Fig. 4, AOT40 values in many regions of the world are above the 3 ppmh “critical level” established in Europe for the protection of crops (Karenlampi and Skarby, 1996). O₃ exposure during the soybean and maize growing seasons is high in the Northern Hemisphere, as these crops’ growing seasons overlap periods of peak summer O₃ concentrations in North America and the EU; O₃ peaks during spring and fall in China and India preceding and following the annual monsoon. In the Southern Hemisphere, the high O₃ exposure levels in the Democratic Republic of the Congo (DRC) during the maize growing season and in Brazil during the wheat growing season are due to the coincidence of the relevant crop growing seasons (August – October) with the biomass burning season in each country. Both Brazil and the DRC are biomass burning hotspots in South America and Africa (Christopher et al., 1998; Roberts and Wooster, 2007) that are spatially well-simulated by MOZART-2. However, the model may overpredict O₃ during the dry season in the Amazon Basin where aircraft measurements indicate near-surface O₃ concentrations of
20-40 ppbv during July and August (Browell et al., 1988; Kirchoff, 1988), but O₃ in the cerrado region (central Brazil where crops are grown) has been found to be higher (up to 80 ppbv during biomass burning events) (Kirchoff et al., 1996). Overall, the highest levels of O₃ exposure during the soybean growing season occur in the U.S., China, South Korea, and Italy (Fig. 4a), while these nations plus the DRC also endure the highest O₃ exposures during the maize growing season (Fig. 4b). O₃ exposure during the wheat growing season is greatest in central Brazil, Bangladesh, eastern India, and the Middle East (Fig. 4c).

4.2. Relative yield loss

Fig. 5 illustrates the global distribution of national RYL due to O₃ exposure calculated for soybean, maize, and wheat according to the M12 and AOT40 metrics. Estimates of soybean and maize (wheat) yield losses are generally larger (smaller) when the M12 rather than AOT40 metric is used. On average, O₃-induced RYL of wheat is highest in Bangladesh (15-49%), Iraq (9-30%), India (9-30%), Jordan (9-27%), and Syria (8-25%). Although O₃ is elevated during the wheat growing season over much of central Brazil, most of this nation’s wheat is grown in the south where O₃ exposure is significantly lower (Figs. 1 and 4c). Soybean RYL is estimated to be greatest in Canada (27-28%), followed by Italy (24-27%), South Korea (21-25%), China (21-25%), and Turkey (16-23%). Yield losses of maize are smaller, with the highest losses occurring in the DRC (7-13%), Italy (7-12%), Canada (6-11%), South Korea (4-9%), and Turkey (4-9%).

Table 4 lists regionally and globally aggregated RYL estimates calculated using the M12 and AOT40 metrics, as well as their averages. We use some of the same regional aggregations as VD2009 to facilitate intercomparisons (i.e. North America and the EU-25), but we also add new regional groupings (see Fig. 6 for definitions). On a global scale, O₃-induced RYL according to the M12 and AOT40 metrics ranges from 3.9-15% for wheat, 8.5-14% for soybean, and 2.2-5.5% for maize. Wheat yield reductions in South Asia are calculated to be the most significant (17% according to the average of metric estimates) followed by Africa and the Middle East (13%) and East Asia (10%). Large inter-regional differences exist for soybean yield losses, with North America, the
EU-25, and East Asia calculated to suffer much larger reductions (14-26%, based on the average of metric estimates) than Latin America, India, or Africa (<8%). RYL of maize is estimated to be more evenly distributed, with the greatest losses in East Asia (5.9%) followed closely by South Asia and the EU-25 (5.7% each).

4.3. **Crop production loss (CPL) and associated economic losses (EL)**

The combined global crop production and economic losses for soybean, maize, and wheat due to O₃ exposure according to the M12 and AOT40 metrics are illustrated in Fig. 7. The distribution of CPL also accounts for production intensity, so some nations with high RYL do not have correspondingly high CPL if they are minor producers; likewise, major producers with relatively low RYL may have large CPL. The global distribution of EL is similar to the pattern of CPL, but also reflects the different producer prices for crops in each country. Table 5 lists regionally-aggregated and global CPL by crop. We estimate CPL worldwide to be between 21-93 million metric tons (Mt) of wheat, 13-32 Mt of maize, and 15-26 Mt of soybean. The range of wheat CPL is particularly large due to the fact that this crop appears to be resistant to O₃ exposure according to the M12 metric, but extremely sensitive to ozone according to the AOT40 index. This discrepancy may in turn be a consequence of the possibility that wheat is more sensitive to frequent exposure to elevated O₃ (better captured by AOT40) than to long-term exposure to moderate ozone concentrations (WM2004). On average, global CPL for all three crops totals 100 Mt (79 and 121 Mt from the M12 and AOT40 metrics, respectively). Soybean and maize CPL in North America contributes to 65% (13.2 Mt) and 43% (9.5 Mt) of the global loss of each crop, respectively (based on the average of metric estimates), while wheat CPL is more evenly spread with the highest losses occurring in South Asia (32%), East Asia (19%), and North America (11%).

Fig. 8 depicts CPL for the ten countries with the highest estimated losses for each crop individually and combined ranked according to the mean of M12 and AOT40 values, while Fig. 9 illustrates the same for economic losses. Wheat CPL is highest in India and China (6.0-26 and 3.0-19 Mt, respectively), followed by the U.S. (2.1-7.6 Mt). CPL of soybean and maize is highest in the U.S. (9.2-14 and 4.6-13 Mt, respectively), followed by China (3.7-4.6 and 4.5-9.8 Mt, respectively). The similar distribution of
soybean and maize CPL is due to the coincidence of these crops’ growing seasons with periods of elevated O₃ concentrations in high-production nations, while O₃ during the wheat growing season is highest in India, Bangladesh, and Brazil (Fig. 4). Total CPL is greatest in the U.S (21-29 Mt), followed by China (18-27 Mt) and India (8-25 Mt). We estimate that global present day crop yield losses of all three crops range from $11-18 billion (USD₂₀₀₀), with soybean accounting for $2.9-4.9 billion (27% of total losses based on the average of metric estimates), maize for $2.6-5.5 billion (15%), and wheat for $3.2-14 billion (58%). The greatest economic losses occur in the U.S ($3.1 billion USD according to the metric average), followed by China ($3.0 billion) and India ($2.5 billion) (Fig. 9)—together these three countries comprise 59% of the global economic damage (21, 21, and 17%, respectively).

4.4. Implications of O₃-induced crop loss for world hunger

We estimate the number of undernourished persons who could receive adequate caloric intake to meet minimum dietary energy requirements (MDER) if crop losses due to O₃ exposure were eliminated. We call this the “avoided undernourished” and illustrate both the number of individuals per country and the percent this number represents of each nation’s year 2000 undernourished population in Fig. 10. If O₃ induced crop losses were eliminated, potentially 180-312 million additional people globally (using M12 and AOT40 metrics, respectively), representing 21-36% of the world’s year 2000 undernourished population, would meet the MDER. Using metric average estimates, countries with greatest potential to reduce undernourishment are China (118 million individuals), India (89 million), Pakistan (15 million), and Brazil (14 million), representing 89, 40, 47, and 84% of each country’s respective undernourished populations. In some countries, the dietary energy equivalent of crop production losses is greater than that required to raise food consumption levels above the MDER threshold for the entire year 2000 undernourished population (e.g. Brazil according to CPL calculations derived from the M12 metric and China and parts of Central Asia according to the AOT40 metric). Following the geographic distribution of crop production losses, Africa (with the exception of Algeria) and the Pacific island nations generally have the smallest potential for avoiding undernourishment by reducing surface O₃ concentrations,
while the greatest potential for gains exist in Asia (including Central, South, and East) and parts of South America.

5. **Discussion**

5.1 *Comparison with previous work*

We compare our results with those of VD2009 and WM2004, two studies that follow a similar methodology to calculate RYL, CPL, and EL (Tables 6 and 7). VD2009 is a global study using the same metrics of O₃ exposure in the year 2000, while WM2004 focuses on East Asia (China, Japan, and South Korea) and the year 1990 using the M7, M12, and two cumulative metrics not implemented here to calculate crop losses. Despite the differences in agricultural datasets and model scenarios, resolution, emissions inventories, and chemistry, our estimates agree very well with the RYL results of these two studies with a few exceptions (Table 6). Our estimated RYL for crops in South Korea is lower than that of WM2004 likely due to the use cumulative metrics that ascribe more weight to O₃ concentrations above 60-65 ppbv by WM2004. Our upper boundary estimates of maize and wheat RYL in the EU-25 are larger than those of VD2009 likely due to their underestimation of AOT40 in central Europe (modeled to measured ratio of 0.25) by the TM5 model, whereas the same ratio from MOZART-2 in this region (as defined by VD2009) ranges from 0.5-2. The same is true for our higher estimate of wheat RYL in North America, as the TM5 model underestimated O₃ exposure in wheat growing regions in the U.S. by more than 50% during the growing season while we applied a simple bias-correction technique to our model results. Notwithstanding these differences, global RYL results are very similar to those of VD2009: we find RYL ranges of 9-14% for soybean, 2-6% for maize, and 4-15% for wheat, compared to the VD2009 estimates of 5-16%, 2-4%, and 7-12%, respectively (Table 6). We provide a comparison of EL in Table 1 of the supplementary material: our EL estimates for China, India, the EU-25, and North America agree very well with VD2009, as does our estimate of total global economic losses from all three crops.

5.2 *Policy implications*
As a result of growing scientific evidence about the detrimental effects of surface O₃, the EPA proposed a new rule on January 19th, 2010 to strengthen the U.S. national ambient air quality standards for ground-level ozone. The proposed rule includes the establishment of a secondary standard to protect crops and other sensitive vegetation based on a cumulative index of weighted, daytime (08:00-19:59) hourly O₃ concentrations (W126) set a level ranging from 7-15 ppmh (EPA, 2010). Our results demonstrate the need for such a secondary O₃ standard, with O₃-induced agricultural losses already estimated to cost an annual $11-18 billion globally and over $3 billion in the U.S. alone. For context, these damages are 2-3 times larger than estimated crop losses due to climate change since the 1980s ($5 billion annually) (Lobell and Field, 2007). While the selection and development of crop cultivars with O₃ resistance is therefore a worthwhile addition to efforts to increase crop resilience to climatic stresses, strategies aimed at mitigating global O₃ concentrations would provide additional cobenefits for human health and climate change (Naik et al., 2005; West et al., 2007; Fiore et al., 2008). Ozone is a noxious air pollutant in the troposphere and the third most potent greenhouse gas after carbon dioxide and methane (Forster et al., 2007).

Reductions in CH₄ in particular have been shown to decrease surface ozone concentrations globally with significant health benefits (West et al., 2007; Fiore et al., 2008) while also generating the largest net reduction in radiative forcing of all the O₃ precursor species (West et al., 2007).

Our estimate of the impact of O₃-induced crop losses on world hunger in terms of the avoided undernourished is a first attempt at quantifying the possible contribution of present-day O₃ pollution to the urgent problem of global food insecurity. We find that the potential benefits of O₃ mitigation for world hunger are considerable: the dietary energy equivalent of O₃-induced crop losses could lift almost 30% of the year 2000 undernourished population above the MDER threshold (mean estimate). Our results suggest that O₃ abatement may be one way to combat global undernutrition and feed a growing population without the negative environmental impacts associated with many farming practices aimed at improving crop yields, including increased fertilizer application, water consumption, and/or greater land cultivation. The benefits of O₃
mitigation highlighted here additionally do not account for the positive externalities associated with strengthening the agricultural sector in nations currently suffering from significant crop production losses. For example, a strong agricultural sector has been argued to be one of the pillars of economic development and poverty alleviation in the least developed countries (World Bank, 2007), as well as an economic and employment buffer during financial crises (FAO, 2009). In countries where agriculture is a major source of income and sustenance for large portions of the population and where undernourishment and O₃ pollution is widespread (e.g. Asia and parts of South America), O₃ mitigation may be an important strategy in the fight against hunger and extreme poverty—the first of the Millennium Development Goals.

5.3 Uncertainties

While extremely useful for understanding the large-scale impacts of ozone on agricultural yields, integrated assessments such as the approach used here accumulate the uncertainties of each step of the analysis (WM2004, VD2009). One of the most significant sources of uncertainty in this study is the use of a CTM with variable accuracy in predicting observed hourly surface O₃ concentrations to calculate crop losses (Section 3, Figs. 2-3). Due to the nature of the AOT40 metric, where small differences in O₃ concentrations near 40 ppbv can accumulate to a large discrepancy between modeled and observed exposure, the M12 metric is a more accurate indicator of actual O₃ exposure during the growing season. However, as cumulative indices that ascribe greater weight to elevated O₃ are considered to be better predictors of crop response to O₃ than mean indices (Lefohn and Runeckles, 1988), significant uncertainties exist when calculating crop yield losses with either metric and should be considered when interpreting results.

Our use of exposure-based indices, which do not account for climatic conditions and biological defenses that may affect crop sensitivity to O₃, introduces additional uncertainty in our results (Musselman et al., 2006). Particularly important climatic parameters include soil moisture and leaf-to-air vapor pressure deficits that moderate the flux of O₃ into the leaf stomata. Where crops are grown in arid climates without irrigation, yield losses may be less than predicted here (Fuhrer, 1997; Fiscus et al., 2005; Booker, 2009; Fuhrer, 2009). Uncertainty also arises from the uniform application of
experimentally-derived CR functions developed for Western cultivars popular in the 1980s/90s to crops across the globe today. Despite the possibility that crop cultivars currently under cultivation may have different sensitivities to O₃ than those used in the NCLAN and EOTC studies, and that experimental methods (such as the use of OTCs) may have influenced yield loss results, new research indicates that current crop sensitivity is at least as great as that found in these earlier studies. Specifically, the Free Air O₃ Concentration Enrichment (FACE) soybean experiment in Illinois found yield losses that were tantamount to or greater than losses reported in earlier chamber studies (Long et al., 2005; Morgan et al., 2006). Furthermore, in a recent comparison of North American and Asian CR relationships, Emberson et al. (2009) found that CR functions derived in North America underestimate the effects of O₃ on crop yields in Asia. Thus, our choice of CR relationships may lead to an underestimation of yield reductions resulting from O₃ exposure.

As evident from our results and observed in previous studies (Lefohn and Runeckles, 1988; Aunan et al., 2000; WM2004; VD2009), the same pattern of O₃ exposure may produce significantly different RYL estimates depending on the metric and CR relationship used. This discrepancy may be an artifact of the different statistical methods used to derive CR relationships across studies (Lesser et al., 1990), or may be due to differences in crop sensitivities to various patterns of O₃ exposure: some crops may be more sensitive to long-term exposure at modest O₃ concentrations (better captured by seasonal mean metrics), while others may be more sensitive to frequent exposure to elevated O₃ (better characterized by cumulative indices) (WM2004; VD2009). The difference in calculated RYL will be particularly large when O₃ concentrations above the threshold values of cumulative metrics are prevalent during crop growing seasons, as cumulative indices weigh elevated O₃ much more heavily than mean metrics (WM2004).

This study can be extended and improved in a number of ways. Higher resolution and improved global model simulations of surface O₃ would facilitate more accurate crop yield loss calculations. Updated CR functions derived from crop cultivars currently in use in each major agricultural region of the world would greatly enhance the present study and reduce uncertainties. The implementation of biologically-based flux metrics
would allow for inclusion of the effect of water availability and plant physiology in yield reduction calculations once such metrics become available. In addition, a study which examines the coupled effect of crop reductions due to future climate change (temperature, precipitation, and CO₂ effects) with those of surface O₃ would also be valuable to determine the combined impact of environmental change on global agricultural production. Finally, the use of an agro-economic model accounting for the feedbacks between production changes due to O₃-induced yield losses, market prices, and global demand would provide a clearer understanding of the impacts of O₃ and pave the way for a cost-benefit analysis of potential mitigation efforts.

6. Conclusions

In this study we estimated the global risk to three key staple crops (soybean, maize, and wheat) of surface ozone pollution using simulated O₃ concentrations and two metrics of O₃ exposure (M12 and AOT40), field-based CR relationships, and global maps of agricultural production compiled from satellite data and census yield statistics. We find that present day global yield losses range between 3.9-15% for wheat, 8.5-14% for soybean, and 2.2-5.5% for maize, depending on the metric used. Global crop production losses range between 79-121 Mt, worth $11-18 billion annually. The greatest economic losses occur in the U.S., India, and China—together these three nations comprise 59% of the global economic damage. Our findings agree well with previous studies, providing further evidence that O₃ already has a significant impact on global agricultural production. In addition, we show that if O₃-induced crop production losses could be eliminated, the dietary energy equivalent of improvements in the yields of the three crops examined here could lift 21-36% of the year 2000 global undernourished population, or 180-312 million people, above the MDER threshold. China, India, Pakistan, and Brazil would experience the greatest potential gains, where 171-298 million individuals could avoid undernourishment with successful O₃ mitigation. Given the significant present-day impact of O₃ on crops worldwide and the uncertainty of future mitigation efforts, our companion paper will explore the O₃-induced yield reductions and their associated costs expected under a range of policy scenarios with different levels of O₃-precursor
abatement in the future. Further work will examine the possible benefits to agriculture of methane mitigation policies with demonstrated climate change and public health benefits.

Acknowledgements

We thank N. Ramankutty and C. Monfreda for providing us with pre-publication access to their global crop area and yield datasets.
References


Figure Captions

**Fig. 1.** Global distributions of soybean, maize, and wheat in the year 2000. Data from Ramankutty et al. (2008) and Monfreda et al. (2008), regridded to MOZART-2 resolution (2.8° latitude x 2.8° longitude).

**Fig. 2.** Global distribution of O3 exposure during May-July according to the M12 metric derived from (a) simulated hourly O3 concentrations, and (b) observed hourly O3 concentrations (see Table 3 for data references). The difference of modeled minus observed M12 values is illustrated in (c), and the ratio of modeled to observed M12 is shown in (d). For grid cells with more than one observation station, M12 values for each station were computed and averaged.

**Fig. 3.** Global distribution of O3 exposure during May-July according to the AOT40 metric derived from (a) simulated hourly O3 concentrations, and (b) observed hourly O3 concentrations (see Table 3 for data references). The difference of modeled minus observed AOT40 values is illustrated in (c), and the ratio of modeled to observed AOT40 is shown in (d). For grid cells with more than one observation station, AOT40 values for each station were computed and averaged.

**Fig. 4.** Global distribution of O3 exposure according to the M12 (left panels) and AOT40 (right panels) metrics during the respective growing seasons in each country (where crop calendar data are available) of (a) soybean, (b) maize, and (c) wheat. Values in the U.S. have been corrected using observation data as described in Section 3.2.

**Fig. 5.** National relative yield loss according to the M12 (left panels) and AOT40 (right panels) metrics for (a) soybean, (b) maize, and (c) wheat.

**Fig. 6.** Definitions used to calculate relative yield and crop production losses by region (Tables 4-5).

**Fig. 7.** Total crop production loss (CPL, left panels) and economic loss (EL, right panels) for all three crops derived from (a) M12 and (b) AOT40 estimates of O3 exposure.

**Fig. 8.** Crop production loss (CPL, million metric tons) for the ten countries with highest estimated mean CPL using the M12 and AOT40 metrics for a) soybean, b) maize, c) wheat, and d) total CPL.

**Fig. 9.** Economic loss (EL, million USD\textsubscript{2000}) for the ten countries with the largest estimated EL using the M12 and AOT40 metrics for a) soybean, b) maize, c) wheat, and d) total EL.

**Fig. 10.** Potential number of undernourished individuals avoided if crop losses from O3 exposure could be eliminated (left panels), and represented as a percent of the total year 2000 undernourished population as estimated by FAO (right panels), derived from (a)
M12 and (b) AOT40 estimates of crop production losses (CPL). Dark shaded nations represent countries for which CPL was calculated but where FAO data on undernourishment do not exist.

Supplementary Material Figure Captions

SM Fig. 1. First month of growing season used for each crop. Data from USDA (1984) and (2008). Crop losses were analyzed only where growing season data are available, comprising 95% of global production.
Table Captions

Table 1. Scaling factors derived from the IPCC SRES scenarios used with the 1990 base emissions in MOZART-2 to obtain year 2000 anthropogenic emissions. The scaling factors to obtain 2000 from 1990 emissions are the same for all SRES scenarios.

Table 2. Concentration-response equations used to calculate relative yield losses of soybean, maize, and wheat. RY = relative yield as compared to theoretical yield without O₃-induced losses. See Section 2.2.2 for definitions of M7, M12 and AOT40. We calculate yield reductions for winter and spring wheat varieties separately and sum them together for our estimates of total O₃-induced wheat yield and crop production losses.

Table 3. Data sources for observed hourly O₃ concentrations used in the model evaluation (Section 3.2).

Table 4. Estimated regional relative yield loss (%) due to O₃ exposure according to the M7, M12 and AOT40 metrics and the metric average.

Table 5. Estimated regional crop production loss (million metric tons) due to O₃ exposure according to the M7, M12, and AOT40 metrics and the metric average.

Table 6. Comparison of relative yield loss (RYL) estimates derived in this study with others based on similar methodologies. The range of RYL produced from the various metrics of O₃ exposure used in each study is shown. See Section 5.1 for details about metrics used and differences among studies.