Abstract

Field studies demonstrate that exposure to elevated concentrations of surface ozone (O₃) causes substantial reductions in the yields of many crops, yet O₃ pollution is often overlooked as a potentially significant threat to current and future agricultural production. This study quantifies the global impact of O₃ on crop yields in the present (year 2000) and near future (2030) under optimistic and pessimistic scenarios of O₃ pollution, as well as associated crop production and economic losses for three key staple crops (soybean, maize, and wheat). This study additionally examines the potential of two strategies to reduce O₃-induced yield losses that supplement controls on conventional O₃ precursors: (1) O₃ mitigation via gradual reductions of methane (CH₄), an important greenhouse gas and a precursor to tropospheric background O₃ that to date has not been targeted for O₃ abatement, and (2) adapting crops to elevated O₃ by selecting cultivars with demonstrated O₃ resistance relative to median-sensitivity varieties. Finally, this work contextualizes the estimated impact of O₃ on global agricultural production with predicted climate change effects, and identifies regions of the world potentially at risk of reduced crop yields due to both O₃ and climate change over the next few decades.

Results indicate that present-day O₃-induced global crop yield reductions are substantial, ranging from 4-15% for wheat, 9-14% for soybean, and 2-6% for maize worth $11-18 billion annually (USD$_{2000}$). In the high O₃ pollution scenario, year 2030 crop yield losses could be further reduced from 2000 levels by 2-10% for wheat, 1-11% for soybean, and 2-3% for maize, worth an additional $6-17 billion in losses globally. Controls on traditional O₃ precursors in the optimistic pollution scenario appear to prevent extensive additional yield reductions in 2030, but total yield losses could remain significant, particularly for O₃ sensitive crops (up to 15-17% for wheat and soybean). We find that the supplemental policy of CH₄ control (via its additional O₃
reductions) could considerably increase year 2030 production of soybean, maize and wheat by the equivalent of ~2-8% from year 2000 levels, worth $3.5-15 billion worldwide. Choosing crop varieties with demonstrated O$_3$ resistance relative to median sensitivity cultivars may improve year 2030 production of these crops by 12% from 2000 values, worth ~$22 billion globally. This work suggests that the negative impact of O$_3$ on agriculture now and in the near future could exceed predicted climate change effects for some crops (based on climate impact estimates available in the literature), and that regions at risk of yield reductions due to both O$_3$ exposure and climate change include both significant agricultural producers (e.g. India, Russia, Brazil, and China) and net food importers (e.g. the Middle East) with possibly major implications for global food security. Efforts to reduce surface O$_3$ concentrations and adapt crops to elevated O$_3$ therefore provide an excellent opportunity to increase global agricultural production without the environmental damage associated with traditional agricultural intensification techniques or additional land cultivation.
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Chapter 1

Introduction

1. Background

For two centuries, increases in global agricultural production have defied Malthusian predictions of food shortfalls due to rapidly rising populations. Global crop production\textsuperscript{1} grew by 162\% between 1961 and 2005, from 1.8 to 4.8 billion metric tons mostly due to increasing yields on existing farmland following the dissemination of Green Revolution technologies (including fertilizers, pesticides, irrigation, and high-yielding crop varieties) (Burney et al., 2010). As a consequence of agricultural intensification, global cropland area increased by 27\% since 1961 while total crop yields grew by 135\% over this period. Recent work estimates that without the historic yield improvements of the past half century, present-day agricultural demand would have required cropland expansion of over 1,700 million hectares (\textasciitilde 183\%), an area approximately the size of Russia, with resulting emissions of up to 161 gigatons of carbon (Burney et al., 2010).

Despite the historical growth in agricultural productivity, crop yield improvement rates have been decelerating globally for key staple crops (i.e. soybean, wheat, maize, and rice): from 2.1-3.7\% per year in 1961-1970 to less than 1.5\% annually in 2001-2009,\textsuperscript{2} raising questions about the prospect of meeting future food demand primarily through agricultural intensification – particularly in regions of the world where fertilizer use is already high (e.g. China). Reduced productivity combined with population growth (as well as the rise in biofuel demand) has

\textsuperscript{1} Including cereals, fiber crops, fruit (excluding melons), oilcrops, pulses, roots and tubers, and vegetables & melons.

resulted in declining per capita cereal production for food purposes since the late 1980s, reversing a three-decade long growth trend. In the absence of continuing crop yield growth, meeting the rising food demand of the future will require an increase in farmland area – likely encroaching upon fragile natural ecosystems and leading to the loss of biodiversity and substantial emissions of carbon. Moreover, although yield improvements are generally preferable to increasing crop production area from a biodiversity and climate perspective, traditional means of agricultural intensification (e.g. through increasing water, fertilizer, and pesticide application) also cause significant environmental damage (Tilman et al., 2001; Tilman et al., 2002; Gregory et al., 2002). As such, meeting the food and biofuel demand of over 8 billion people in 2030 (U.S. Census Bureau, 2010) sustainably – i.e. without causing additional environment stress – requires new approaches beyond cropland expansion and the traditionally employed portfolio of yield improvement strategies.

A number of possible contributing factors have been cited for the slowdown in crop yield growth (Cassman et al., 1999), including degradation of farmland due to intensive agricultural practices (e.g. soil salinization and erosion), the expansion of cultivated areas into marginal lands less suitable for agricultural production (Tilman et al., 2001; Tilman et al., 2002), and the impact of climate change over the past few decades (Lobell and Field, 2007; Lobell et al., 2011). Climate change in particular has received substantial attention as a present-day and future threat to global agriculture given its potential to alter growing season temperatures, precipitation regimes, and pest and disease dynamics (see Chapter 5). However, another important – yet largely overlooked – component of global environmental change may be substantially contributing to declines in agricultural productivity: exposure to surface ozone (O₃) pollution.
O₃ is a major component of smog and a potent greenhouse gas (GHG) produced in the troposphere by photochemical reactions between nitrogen oxides (NOₓ = NO + NO₂), carbon monoxide (CO), methane (CH₄), and non-methane volatile organic compounds (NMVOCs) (Forster et al., 2007). In addition to having a detrimental effect on human health (EPA, 1996; Bell et al., 2004; Jerrett et al., 2009), surface O₃ has been found to be the air pollutant most damaging to vegetation, including crops (Heagle, 1989; Heck, 1989). Although anthropogenic sources of O₃-forming pollutants largely originate from populated metropolitan areas (see Section 1.1), O₃ and many of its precursors are sufficiently long-lived to be carried hundreds to thousands of miles downwind (with an approximate lifetime of days to months in the free troposphere) (Dentener et al., 2010), and O₃ precursor emissions in rural areas may further contribute to O₃ formation (NRC, 1991). O₃ and its precursors can also be transported across continents, such that precursor emissions in source regions may threaten agriculture in distant receptor regions despite locally implemented O₃ controls (Dentener et al., 2010). A recent review of O₃ impacts on agriculture by the Royal Society of London thus suggests that unless global O₃ precursor emissions are curbed in the future, O₃ pollution may pose as large a threat to worldwide food security as climate change by 2030 (Royal Society, 2008).

As a strong oxidant, ozone and its secondary byproducts damage vegetation by reducing photosynthesis and other important physiological functions, resulting in weaker, stunted plants, inferior crop quality, and decreased yields (Fiscus et al., 2005; Morgan et al., 2006; Booker et al., 2009; Fuhrer, 2009). O₃ enters plants through leaf stomata, where it rapidly forms oxidative products in the aqueous layer surrounding cell membranes (apoplast) that can react with many biochemical compounds in plant cells. Upon sensing O₃ and its breakdown products, plants alter gene expression in order to trigger a response to oxidative stress (Ludwikow and Sakowski,
Generally, genes involved in plant defenses are up-regulated while those related to photosynthesis, carbon assimilation, and metabolism are down-regulated due to the need to allocate energy and resources to defense systems (Li et al., 2006). Reductions in Ribulose-1,5-bisphosphate carboxylase oxygenase (Rubisco) (a key enzyme involved in photosynthesis) and carbon assimilation have been specifically associated with reduced biomass and yields (Fiscus et al., 2005; Booker et al., 2009; Singh et al., 2009).

In 1980, the U.S. Environmental Protection Agency (EPA) initiated the large-scale experimental studies of the National Crop Loss Assessment Network (NCLAN) in order to systematically examine the effects of O$_3$ on various agricultural crops under field conditions (Heagle, 1989; Heck, 1989; Adams et al, 1989). These studies demonstrated that the yields of about one third of U.S. crops were reduced by 10% due to ambient O$_3$ concentrations during this time (EPA, 1996). Results from the European Open Top Chamber Programme (EOTC) in the 1990s (Krupa et al., 1998) similarly found that the European Union (EU) may be losing more than 5% of their wheat yield due to O$_3$ exposure (Mauzerall and Wang, 2001). Although comparable large-scale studies have not been conducted in developing countries, the potential risk of ambient O$_3$ 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; Huixiang et al., 2005; Feng and Kobayashi, 2009; Zhu et al., 2011), the Indian subcontinent (Agrawal, 2003; Wahid, 2003; Emberson et al., 2009; Debaje et al., 2010), Egypt (Abdel-Latif, 2003), and South Africa (van Tienhoven and Scholes, 2003).

1.1. Surface ozone trends

Anthropogenic sources of O$_3$ precursors include vehicles, power plants, biomass burning, and other sources of combustion (e.g. industrial point sources, non-electric cook stoves, gas
appliances, and tractors and other off-road vehicles). NOx and CO emissions are estimated to have increased by at least a factor of seven and four, respectively, since preindustrial times, with major emission sources of these compounds that include on- and off-road vehicles, industry (including manufacturing and electricity production), and smaller combustion sources from the residential and commercial sectors (Horowitz et al., 2006). NMVOCs are also generated from vehicles and industry, as well as by smaller point sources (e.g. gas stations, print shops, and dry cleaners). Emissions of anthropogenic methane are estimated to have increased by a factor of 1.5 since the pre-industrial era, with sources that are significantly different from the other O3 precursors (the most important of which include rice cultivation, manure, enteric fermentation, oil and gas production, coal mines, landfills, and wastewater) (IPCC, 2007).

Over the past century, annual mean surface O3 concentrations in mid- to high latitudes (i.e. the major emitting regions of North America, Europe, and East and South Asia) have more than doubled (Hough and Derwent 1990; Marenco et al., 1994) and are now estimated at 37 ± 4 ppbv (Dentener et al., 2010). Although O3 monitoring data from tropical regions are sparse, research suggests that ozone concentrations have been increasing by ~1 ppbv per year in the Northern and Southern Hemisphere tropics since the early 1990s (Bortz et al, 2006). Surface monitoring sites and satellite imagery indicate that present-day O3 concentrations specifically over important agricultural growing regions are sufficiently high to cause at least a 5-10% reduction in annual crop yields (Feng and Kobayashi, 2009), including in the Midwestern U.S. (Fishman et al., 2010), central Europe (Mills et al., 2011a), central and northern India (Engardt et al., 2008), and the Yangtze Delta region of China (Zhu et al., 2011). Furthermore, while O3 concentrations vary significantly throughout the year, the peak “ozone season” largely coincides
with crop growing seasons, as $O_3$ production is enhanced during sunny, warmer months (Jacob, 1999).

Ozone concentrations are expected to continue to rise in developing countries over the next few decades due to increased emissions of $NO_x$ and other ozone precursors resulting from rapid industrialization (Nakićenović et al., 2000; Dentener et al., 2005; Riahi et al., 2007). Due to transport of $O_3$ pollution across national boundaries and continents (Fiore et al., 2009), rising $O_3$ precursor emissions in these nations are projected to increase hemispheric-scale background $O_3$ concentrations and hence may pose a threat to food production even in regions with increasingly stringent $O_3$ precursor controls. For example, evidence suggests that although $O_3$ mitigation efforts have reduced peak ozone levels in North America, Europe, and Japan in recent years, background levels have risen in these regions (Oltmans et al., 2006) and appear to be damaging crops and other sensitive vegetation (Mills et al., 2011a). Studies indicate that approximately half of the anthropogenic contribution to annual average surface $O_3$ concentrations in the major Northern Hemisphere regions$^3$ is due to transport of $O_3$ and its precursors from sources outside of a given region (Dentener et al., 2010).

1.2. Policy context

Current $O_3$ regulatory standards are primarily designed to protect human health. The health impact of surface $O_3$ was first acknowledged in California in the 1950s and perceived to be a local- to regional-scale problem, with control measures aimed at reducing peak $O_3$ levels that were considered to be most damaging (Royal Society, 2008). Recognition of the detrimental impact of $O_3$, along with the promulgation of policies to reduce precursor emissions, gradually took place in other parts of North America, Europe, and Japan through the 1970s; these

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$^3$ North America, Europe, East Asia, and South Asia
regulations have become increasingly stringent over time. To date, tropospheric O₃ is not regulated at the global level, although the problem of rising global background O₃ and the possible contributions of O₃ and its precursor emissions from distant sources to receptor regions has been receiving growing attention (Fiore et al., 2002; Royal Society, 2008; Fiore et al., 2009; Dentener et al., 2010). The 1979 Convention on Long-Range Transboundary Air Pollution (UNECE, 1979), now signed by 51 parties in North America, Europe, and parts of Central Asia and extended by eight protocols, includes restrictions on NOₓ and VOC emissions with the goal of reducing O₃ pollution and its transport across national boundaries.

The World Health Organization (WHO) currently sets a health guideline for O₃ not to exceed 100 μg m⁻³ (approximately 50 ppbv, 8-hour daylight mean), which was lowered in 2005 from the previous target of 60 ppbv (WHO, 2005). O₃ standards presently exist in most industrialized nations, as well as increasingly in developing countries with varying degrees of stringency and enforcement. Canada has an O₃ standard of 65 ppbv (for the 3-year average of the 4th highest daily maximum 8-hour mean), while the O₃ standard in Japan is based on a 1-hour average not to exceed 60 ppbv – one of the most stringent standards worldwide (and increasingly challenging to meet during the spring due to transport of O₃ and its precursors from China). O₃ standards in Australia include both a 1-hour metric not to exceed 100 ppbv, and a 4-hour standard with exceedance of 80 ppbv allowed only one day a year. Mexico has a daily maximum 1-hour standard of 110 ppbv country-wide, while China implements 1-hour ozone standards for residential, commercial, and industrial area classes, currently set at 120, 160, and 200 μg m⁻³ (approximately 60, 80, and 100 ppbv), respectively. India’s original air quality regulations did not include O₃ standards, but were revised in 2009 in an attempt to comply with WHO guidelines. New standards are ambitious and include a 1-hour limit of 180 μg m⁻³ (~90 ppbv)
and an 8-hour average not to exceed 100 μg m⁻³ (~50 ppbv). All of these standards are primarily designed to protect human health.

In the U.S., the Clean Air Act mandates the protection of human health and public welfare from the detrimental impact of O₃ through the setting of primary and secondary National Ambient Air Quality Standards (NAAQS), which are reviewed every five years by the U.S. EPA (CAA, 1990). Human health is protected by primary standards, while ecosystems, agriculture, and property are protected by the secondary public welfare standard. The U.S. led the world in the investigation of O₃ impacts on crops and other sensitive vegetation, which began in 1980 with the EPA-funded NCLAN – the first ever large-scale, systematic study of the ecological effects of O₃ in the world (Mauzerall and Wang, 2001). Despite decades of research into the ecological impacts of O₃, however, to date the secondary O₃ standard in the U.S. has been set equal to the primary standard. Both the primary and secondary O₃ standards have been strengthened over time: from a 1-hour standard of 0.120 ppmv in 1979 (not to be exceeded more than three times in as many years) to an 8-hour standard of 0.080 ppmv in 1997 (with the 3-year average of the fourth-highest daily maximum 8-hour mean ozone concentration required to be below this value), which was lowered to 0.075 ppmv in 2008.

In January 2010, the U.S. EPA proposed to further tighten the primary (health-based) 8-hour standard to a level within the range of 0.060-0.070 ppmv (which was the recommended range in the previous review but was not adopted by the Bush administration). In addition, the proposed rule would set a unique secondary public welfare standard to protect sensitive crops and natural ecosystems based on a biologically-relevant metric of O₃ exposure derived from NCLAN studies (W126). W126 is a cumulative, concentration-weighted metric that uses a sigmoidal function to assign greater weight to hourly O₃ concentrations believed to be most
damaging to crops, summed over the growing season (Lefohn and Runeckles, 1988; Lesser et al., 1990). Unlike a standard based on average O₃ concentrations, W126 therefore accounts for both the cumulative effect of O₃ damages throughout the growing season and the greater impact of elevated O₃ without assuming a threshold for O₃ injury (see Section 4). The proposed standard would be the three-year average of the highest three-month statistic each year set at a level within the range of 7-15 parts per million-hours (ppmh). O₃ monitoring sites across the U.S. indicate that nation-wide 5-year average W126 between 1998 and 2002 was 17.4 ppmh, with high variability between sites (standard deviation of 12.6 ppmh) such that meeting the new standard in some regions could require aggressive O₃ controls. As of September 2, 2011, the proposed revisions to the NAAQS for O₃ were withdrawn by the Obama administration under pressure from business and industry groups, who argued that meeting new requirements would be too costly – particularly given prevailing economic conditions (White House Office of the Press Secretary, 2011).

The EU is currently the only region that implements an O₃ standard to protect crops and ecosystems different than its health-based standard, which has historically been based on WHO guidelines (now set at a maximum daily 8-hour mean of 120 μg m⁻³ (~60 ppbv)). The EU adopted a “critical level” approach for the protection of vegetation, which is a threshold below which only “acceptable” levels of harm may occur due to O₃ exposure. Based on results from European field experiments, a cumulative indicator (AOT40) that sums hourly O₃ concentrations above a threshold of 40 ppbv was chosen to define the critical level for agriculture (see Section 4), which is set at 3 ppmh according to estimated crop yield losses of 5% at this level (Fuhrer et al, 1997). Currently, the AOT40 parameter exceeds 3 ppmh in most of the EU with the

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4 Author’s calculations; see Chapter 2 for details on data sources.
exception of northern regions (see Chapter 2). However, research suggests that at a given concentration, crops in northern Europe may be more susceptible to O₃ damage since the actual flux of O₃ into plant stomates is higher in moist regions than in the drier regions of the southern Mediterranean (Emberson et al., 2000). Due to the importance of accounting for climate factors (as well as inherent O₃ detoxification capacities) in determining O₃ risk to crops, the EU is moving towards an O₃ flux-based (rather than exposure-based) definition of critical levels (discussed further in Section 4 and Chapters 2 and 5) (Pleijel et al., 2004; Pleijel et al., 2007; Paoletti et al., 2008; Mills et al., 2011b).

2. Research Goals

The demonstrated phytotoxicity of O₃ and its prevalence over important agricultural regions around the world demands an assessment of the magnitude and distribution of ozone risks to global food production and food security under present-day and future O₃ concentrations. Assessments of the potential benefits to agriculture of policies that reduce O₃-induced crop losses (either through O₃ control or by adapting crops to elevated levels of O₃ exposure) additionally deserve attention, particularly as these benefits are not currently included in cost-benefit analyses of pollution mitigation strategies, nor used to inform the regulatory process of O₃ standard setting in many parts of the world. Strategies to reduce O₃-induced crop damages offer an opportunity to increase agricultural production without the negative environmental consequences of traditional intensification techniques, with possible co-benefits for human health and climate change.

At the time of commencement of this research project, estimates of current and projected future O₃-induced crop yield reductions on a global scale (and their economic value) did not exist in the literature. This dissertation aimed to fill this significant research gap by providing
the first global-scale assessment of O₃ damages to crops in the present (year 2000) and in the near future (year 2030) under different scenarios of O₃ pollution (the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES) A2 and B1 storylines (Nakićenović et al., 2000)), representing upper- and lower boundary trajectories, respectively, of ozone precursor emissions that are traditionally regulated by air quality legislation (NOₓ, CO, and NMVOCs). Through evaluating current and projected future O₃-induced crop losses according to these different paths of O₃ precursor emissions, this work quantifies a range of estimated agricultural impacts in 2030 (and global changes from 2000) and therefore the potential benefits to agriculture of O₃ pollution mitigation.

In addition to assessing the present-day and future risk of O₃ to agriculture and the benefits of reducing conventional O₃ pollutant precursors (NOₓ, CO, and NMVOCs), this dissertation examines the potential of a strategy motivated by climate change mitigation goals – methane emission controls – to lower surface O₃ concentrations and therefore O₃-induced crop production losses. CH₄ is the second most important GHG after carbon dioxide (Forster et al., 2007) and has not typically been targeted for air quality purposes despite being a long-lived O₃ precursor that contributes to global background O₃ concentrations (Fiore et al., 2002; West and Fiore, 2005). Recent work estimates that modest CH₄ controls could save 370,000-400,000 lives globally between 2010 and 2030 as a consequence of decreased O₃ concentrations (West et al., 2006; West et al., 2011), but the possible gains for agriculture have received little attention to date (West et al., 2005) despite their potential to significantly contribute to the cost-effectiveness of methane reduction policies. CH₄ abatement therefore provides an attractive “win-win” policy opportunity for both climate change and air pollution mitigation goals, as CH₄ controls would reduce radiative forcing of climate while simultaneously achieving the health and agricultural
benefits associated with surface O₃ reductions. This research examines the crop production improvements possible with a policy of methane controls relative to the “current legislation” (CLE) emissions baseline, under which existing legislation controlling the emissions of traditional air pollutants is assumed to be perfectly implemented through 2030 (Dentener et al., 2005).

Complementing the investigation of the benefits of O₃ mitigation, this work additionally explores the potential benefit to agricultural production of adapting crops to elevated levels of O₃ by choosing crop varieties with demonstrated O₃ tolerance. Although crop sensitivity to O₃ may vary significantly by crop and among cultivars of the same crop, varieties used today appear to exhibit sensitivity to ozone that is on average at least as great as that seen in earlier field studies (Long et al., 2006; Biswas et al., 2008; Emberson et al., 2009; Singh and Agrawal, 2009; Singh et al., 2010; Zhu et al., 2011), suggesting that O₃ sensitivity may be an overlooked factor in cultivar choice. To highlight this issue, we explore the possible improvements in crop production in 2030 that could be achieved by cultivating crop varieties with the greatest demonstrated O₃ resistance (from U.S. field studies) relative to “median sensitivity” cultivars. This work therefore explores two different strategies to reduce the detrimental impact of O₃ on crops that supplement reductions of traditional O₃ precursors – one based on mitigating O₃ concentrations through controls on methane emissions, and one based on adapting crops to elevated levels of O₃ exposure – in order to demonstrate the potential of two complementary methods to improve global food production without further harming the environment.

Climate change will also have a substantial impact on global agricultural production over the next few decades. Although elevated levels of CO₂ could alone benefit agriculture, associated changes in temperature and precipitation patterns may severely disrupt crop growth
and yields in many regions of the world (Easterling et al., 2007). The IPCC projects that crop yields are likely to decrease in low latitudes even for small amounts of warming (1-2°C) but that yields of some crops at mid- to high latitudes may rise with regional temperature increases of 1-3°C, with the net global effect slightly positive for temperature increases up to 3°C and negative with a further rise in temperature (Easterling et al., 2007). By contrast, the yield impact of O₃ on agriculture is always negative, and many nations at risk of yield reductions due to climate change may additionally suffer crop losses due to increased levels of O₃ exposure over the next few decades. However, little is known about the combined impact of elevated CO₂, O₃ and climate changes on crops, and most assessments of future agricultural production do not include each of these major components of global environmental change (and/or their interactive effects) in impact estimates. This work therefore reviews the current understanding of climate change and O₃ impacts on agriculture on a physiological level, highlighting known interactive effects as well as important research needs and key uncertainties. This review additionally compares quantitative estimates of crop damages due to O₃ exposure derived in earlier chapters to predicted climate change impacts globally, regionally, and nationally in order to contextualize predicted O₃ damages against an environmental problem that has received much greater academic and media attention, and to delineate regions at risk of “double exposure” to both O₃- and climate change-induced agricultural losses now and in the near future.

3. Research Questions

This dissertation aims to quantify the global impact of O₃ on crops in the present and near future under optimistic and pessimistic scenarios of O₃ pollution, and to estimate to a first order the value of associated crop production losses. This work further evaluates the potential of supplemental strategies to reduce O₃-induced agricultural losses (beyond targeting conventional
O₃ precursor pollutants), including an O₃ mitigation strategy motivated primarily by climate change abatement goals (reductions in CH₄), and an adaptive strategy focused on O₃-resistant cultivar selection. Finally, this work compares the estimated impact of O₃ on agricultural production with projected climate change effects in order to contextualize O₃ impacts, as well as to identify regions of the world potentially at risk of reduced crop yields due to both O₃ and climate change over the next few decades.

Specifically, this work seeks to answer the following questions:

1) What is the present-day impact of O₃ on global, regional, and national agricultural yields and the economic value of estimated O₃-induced crop production losses?

2) What is the projected range of future impacts of O₃ on global agriculture under optimistic and pessimistic trajectories of O₃ precursor emissions?

3) Can a methane reduction policy motivated by climate change mitigation goals generate sufficient reductions in O₃ to protect crops, increasing its desirability and cost-effectiveness?

4) In addition to policies of O₃ mitigation, how much can agricultural production be improved by adapting crops to elevated levels of O₃ exposure via choosing cultivars with demonstrated O₃-tolerance?

5) Are O₃-induced agricultural losses today larger or smaller than impacts from climate change, and what is the relative magnitude of impacts projected to be by mid-century? Is agriculture in certain regions of the world at risk of negative yield impacts from both O₃ exposure and climate change?

4. Methods Overview
To estimate global crop yield losses due to O₃ exposure under different present-day and future scenarios, we integrate: (1) observation-based global crop distribution data; (2) simulated surface ozone concentrations by the Model for Ozone and Related Chemical Tracers (MOZART-2) according to different current and future O₃ precursor emission scenarios (i.e. two present-day and three future scenarios depending on the research question, see Chapters 2-4)) from which O₃ exposure during crop growing seasons is calculated according to different policy-relevant metrics; and (3) O₃ concentration:response (CR) functions that relate a given level of ozone exposure to a predicted yield reduction.

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. Area harvested and yields of 175 distinct crops were compiled at 5 minute x 5 minute latitude-longitude resolution for the years 1997-2003 and subsequently averaged to produce a single representative value for each country circa year 2000. These crop distribution data are regridded to match the resolution of the different MOZART-2 scenarios used.

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 and 11
aerosol and aerosol precursor species (including sulfate, nitrate, ammonium, black carbon, organic carbon, and mineral dust of 5 size bins with diameters ranging from 0.2 to 20.0 µm). Global hourly surface O₃ concentrations simulated by MOZART-2 in the years 2000, 2005, and 2030 under three scenarios of future O₃ precursor emissions are used in this analysis (Horowitz et al., 2006; Fiore et al., 2008).

In order to assess the impact 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 at a given level of ozone exposure relative to the theoretical crop yield at a reference level of exposure where O₃ does not damage crops (Heagle, 1989; Heck, 1989; Krupa et al., 1998). This baseline level was determined from statistical analysis of crop:response data from the NCLAN studies, and is generally representative of natural (pre-industrial) background O₃ concentrations. A common daytime mean O₃ exposure index (M12, discussed further below) defines this threshold at 20-25 ppbv depending on the crop (Wang and Mauzerall, 2004; Feng and Kobayashi, 2009), while preindustrial O₃ concentrations in Europe are reported as approximately 10 ppbv (Marenco et al., 1994).

CR functions have been derived for different crops and individual crop cultivars, and parameterizations of CR functions that represent both median and minimum sensitivity cultivars are used in this analysis (depending on the research question). CR functions require a statistical index to summarize the pattern of O₃ exposure during the crop growing season. Because O₃ concentrations significantly vary spatially and temporally, we compile a database of crop calendar dates from the USDA (1994, 2008) to determine O₃ exposure during local growing seasons for each crop and nation. We then use three exposure-based metrics (M12, AOT40, and W126) and their CR relationships to calculate crop yield losses globally:
M12 (ppbv) = \frac{1}{n} \sum_{i=1}^{n} [Co_3]_i

AOT40 (ppmh) = \sum_{i=1}^{n} ([Co_3]_i - 0.04) \quad \text{for } Co_3 \geq 0.04 \text{ ppmv}

W126 (ppmh) = \sum_{i=1}^{n} w_i [Co_3]_i \quad \text{for } w_i = 1/\{1+4403 \exp(-126[Co_3]_i)\}

where:

- \([Co_3]_i\) is the hourly mean O3 concentration during local daylight hours (8:00 – 19:59); and
- \(n\) is the number of hours in the local 3-month growing season.

Of the two types of exposure-based metrics used here (mean and cumulative), cumulative indices (i.e. AOT40 and W126) that ascribe greater weight to higher O3 concentrations are believed to be more accurate predictors of crop yield responses than mean metrics (i.e. M12) (Lefohn and Runeckles, 1988; Lesser et al., 1990). The M12 metric is included in order to facilitate intercomparisons with earlier O3 impact studies that did not utilize cumulative metrics. The AOT40 index is favored in Europe and is currently used to define air quality guidelines to protect vegetation (Fuhrer et al., 1997). W126 was derived from U.S. field studies and uses a sigmoidal function to assign greater weight to higher levels of hourly O3 concentrations. The U.S. EPA advised that this metric be used to define the secondary standard to protect sensitive vegetation in the recently proposed revision of the ground-level O3 NAAQS (EPA, 2010), which has since been withdrawn as of September 2, 2011. Using numerous metrics and their CR relationships provides an estimate of the uncertainty range associated with the characterization of O3 impacts on crops.

We use an integrated assessment approach that combines crop distribution maps, O3 exposure, and CR relationships to calculate relative yield loss (RYL) (i.e. yield lost compared to
a theoretical yield without O$_3$ damage), crop production loss (CPL), and economic loss (EL) due to O$_3$ exposure. O$_3$ exposure for each crop (according to M12, AOT40, or W126) is calculated using simulated hourly O$_3$ concentrations over the appropriate growing season in each model grid cell, thereby creating global maps of O$_3$ exposure during local crop growing seasons under different scenarios of O$_3$ pollution. We then compute RYL (according to the different metrics and CR functions) for every grid cell and each crop, and calculate CPL from RYL and the actual crop production in the year 2000 (averaged from 1997-2003) (Monfreda et al., 2008; Ramankutty et al., 2008). Economic losses to a first order are estimated by multiplying national CPL for each crop and scenario of O$_3$ pollution by producer prices for each crop in the year 2000 as given by the Food and Agricultural Organization of the United Nations (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. This simple revenue approach to calculate economic loss (used in previous O$_3$ impact assessments (Wang and Mauzerall, 2004; Van Dingenen et al., 2009)) 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.

One of the most important sources of uncertainties in this approach is that the potential influence of climate change is not included in O$_3$-induced yield loss estimates. Through altering growing season temperature and precipitation regimes as well as atmospheric CO$_2$ concentrations, climate change will directly impact crops with an overall effect on yields that could be additive, synergistic, or antagonist with predicted O$_3$ impacts depending on the
combination of environmental stresses. For example, plants increase stomatal conductance during heat stress in order to enhance transpiration and cool their leaves, and a greater incidence of heat waves in a warmer climate could thereby exacerbate the detrimental impact of O₃ due to higher pollutant uptake. By contrast, drought and elevated CO₂ have been shown to protect against O₃ damages by reducing stomatal conductance and therefore the flux of O₃ into plant cells (Booker, 2009; Fuhrer, 2009). Currently under development are stomatal flux metrics of O₃ exposure, which attempt to quantify the effective flux of O₃ through plant stomata after accounting for possible interactions with environmental variables (including CO₂ concentrations, temperature, and water availability) and a plant’s inherent detoxification capacity. Although these metrics have been shown to more accurately predict the yield response of some crops to present-day O₃ concentrations and have been used to evaluate possible O₃ damages in a future climate (Emberson et al., 2000; Pleijel et al., 2004; Mills et al., 2011a), flux-based indices are not yet suitable for large-scale impact analysis 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). Flux metric parameterizations are furthermore only available for wheat, potato, and tomato (Mills et al., 2011b). These metrics additionally do not account for the direct impact of climate change on crop growth nor the possible effect of climate stresses on a plant’s defense capacity: because plants require energy and nutrients to respond to external pressures, they may become more vulnerable to O₃ exposure due to fewer available resources to devote to detoxification (Fuhrer et al., 2009; Mittler and Blumwald, 2010). As significant uncertainties remain and little is known about the overall impact of climate change and O₃ pollution on agriculture, Chapter 5 discusses these uncertainties in more detail and highlights the research
required to advance our understanding of crop response to the combination of these major components of global environmental change.

5. Dissertation Roadmap

This dissertation is organized as follows. Chapter 1 introduces the topic of surface ozone risks to agriculture and provides essential background, context, and a brief overview of key methods. Chapter 2 quantifies global O₃-induced agricultural losses in the present (year 2000), providing a detailed analysis of national-, regional-, and global-scale yield reductions, crop production losses, and their economic impact. Chapter 3 provides estimates of agricultural damages due to O₃ exposure in the future (year 2030) under both optimistic and pessimistic trajectories of O₃ pollution according to the IPCC SRES B1 and A2 scenarios, respectively. Chapter 4 explores the possible benefits to agricultural production of two different strategies that would reduce the detrimental impact of O₃ on crops – mitigating O₃ concentrations through controls on methane emissions, and adapting crops to elevated levels of O₃ exposure via O₃-resistant cultivar selection (and their combined effectiveness). Chapter 5 reviews the projected impacts of climate change and O₃ on agriculture as well as possible interactive effects and uncertainties. This chapter additionally compares quantitative impact estimates of O₃ exposure now and in the future with those of rising atmospheric CO₂ and global climate change in order to contextualize predicted O₃ effects, as well as to delineate regions of vulnerability to multiple environmental stressors over the next few decades. Chapter 6 summarizes major findings and discusses policy implications and future research directions.
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Chapter 2

Global Crop Yield Reductions due to Surface Ozone Exposure: 1.
Year 2000 Crop Production Losses and Economic Damage

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 year 2000 global yield reductions of three key staple crops (soybean, maize, and wheat) due to surface ozone exposure using hourly O₃ concentrations simulated by the Model for Ozone and Related Chemical Tracers version 2.4 (MOZART-2). We calculate crop losses according to two 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. Our results indicate that year 2000 O₃-induced global yield reductions ranged, depending on the

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metric used, from 8.5-14% for soybean, 3.9-15% for wheat, and 2.2-5.5% for maize. Global crop production losses totaled 79-121 million metric tons, worth $11-18 billion annually (USD2000). Our calculated yield reductions agree well with previous estimates, providing further evidence that yields of major crops across the globe are already being substantially reduced by exposure to surface ozone—a risk that will grow unless O₃ precursor emissions are curbed in the future or crop cultivars are developed and utilized that are resistant to O₃.

1. **Introduction**

Surface ozone (O₃) is a major component of smog, produced in the troposphere by the catalytic reactions of nitrogen oxides (NOₓ = NO + NO₂) with 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 in the United States, Europe, and Asia 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 odd-oxygen species that oxidize plant tissue and result 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; Huixiang et al., 2005), the Indian subcontinent (Agrawal, 2003; Wahid, 2003; Emberson et al., 2009; Debaje et al., 2010), 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 impact of O₃ pollution on present-day and future global food production 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 (USD₂₀₀₀) 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 and to verify crop yield loss estimates under both current day and potential future levels of O₃. 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 distributions of three key staple crops: soybean, maize, and wheat. In part two of the series, we compare these present-day crop yield reductions and their associated costs with future estimates of O₃-induced crop losses calculated with simulated O₃ distributions according to 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 illustrate a range of possible future crop losses and the importance of O₃ mitigation.

We use a similar methodology to VD₂₀₀₉, which is modeled on the 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. This
resolution is higher than the 6° x 4° resolution used by VD2009 over South America, Africa, and other parts of the Southern Hemisphere. We also perform a detailed spatial evaluation of MOZART-2 simulated surface O₃ concentrations over the U.S. and Europe, as well as at surface observation sites in Asia, Africa, South America, and the Pacific where data are available. Additionally, 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 crop distributions based on suitability indices (as used by VD2009).

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. Area harvested and yields of 175 distinct crops of the world were compiled at 5 minute x 5 minute latitude-longitude
resolution for the years 1997-2003 and subsequently averaged to produce a single representative value for each country circa year 2000 (see Monfreda et al. (2008) for further details). These crop distribution maps for soybean, maize, and wheat have been regridded to match the 2.8° x 2.8° resolution of MOZART-2 (Fig. 1) for 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 and 11 aerosol and aerosol precursor species (including sulfate, nitrate, ammonium, black carbon, 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 1990 simulation from Horowitz et al. (2003) with year 1990 anthropogenic emissions scaled by the ratio of 2000:1990 emissions in four geopolitical regions as specified by the IPCC SRES (Nakićenović et al., 2000). As emission changes from 1990 to 2000 are the same in all scenarios, we used the same scaling factors to obtain year 2000 B1 and A2 emissions (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.

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. We use two exposure-based metrics, M12 and AOT40, and their CR relationships to calculate crop yield losses globally:

\[
M12 \text{ (ppbv)} = \frac{1}{n} \sum_{i=1}^{n} [Co_3]_i
\]

\[
AOT40 \text{ (ppmh)} = \sum_{i=1}^{n} ([Co_3]_i - 0.04) \quad \text{for} \quad Co_3 \geq 0.04 \text{ ppmv}
\]

where:

- \([Co_3]_i\) is the hourly mean O₃ concentration during local 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 the supplementary material.

Of the two types of exposure-based metrics used here (mean and cumulative), cumulative indices (e.g. AOT40) that ascribe greater weight to higher O₃ concentrations are believed to be more accurate predictors of crop yield losses than mean metrics (e.g. M12) (Lefohn and Runeckles, 1988). The AOT40 index is favored in Europe and is currently used to define air quality guidelines to protect vegetation (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) 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). The M7 metric is defined like M12 except using daylight hours from 9:00-15:59. Although stomatal flux metrics (which aim to quantify the effective flux of O₃ into plant stomata after accounting for temperature, water availability and plant defenses) have been shown to more accurately predict the yield response of some crops, flux-based indices are not yet suitable for large-scale impact analyses 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).

Furthermore, flux metric parameterizations are currently only available for wheat and potato.

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 defined in 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.

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 relative yield lost (RYL) (i.e. yield lost compared to a theoretical yield without O3 damage), crop production losses (CPL), and economic losses (EL). We first calculate O3 exposure (according to M12 and AOT40) using the simulated hourly O3 concentrations over the appropriate growing season for soybean, maize, and wheat in each $2.8^\circ \times 2.8^\circ$ grid cell. We then calculate RYL (according to the CR functions defined in Table 2) for every grid cell and each crop. We next calculate CPL in each grid cell ($CPL_i$) from RYL and the actual crop production in the year 2000 ($CP_i$) (Monfreda et al., 2008; Ramankutty et al., 2008) according to:

$$CPL_i = \frac{RYL_i}{1 - RYL_i} \times CP_i \quad (1)$$
We sum the crop production loss in all grid cells within each country to obtain national CPL. Finally, we define national RYL 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).

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 international median crop price for the year 2000. 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.

3. Model Evaluation

We evaluate the performance of MOZART-2 in simulating regional monthly M12 (where hourly observation data are available) and M24 (24-hour average) O₃ elsewhere in Fig. 2. In Table 3, we provide regional averages of the ratio of modeled:measured M12 and AOT 40 (where data are available) and M24 elsewhere during representative crop growing seasons. Regional boundaries and sources for the observation data are listed in Table 3. Monthly simulated values are averaged over grid boxes containing the observation sites in each region and monthly observed values are averaged over all sites within every region. We provide detailed,
regionally-disaggregated maps of evaluated M12 and AOT40 during the growing season (where data are available) in the supplementary material.

In general, M12 and M24 is well-simulated by MOZART-2 in most regions of the world, reproducing seasonal trends and falling within one standard deviation of observations. O₃ is particularly well-simulated over Europe and Japan during the growing season, with a model:observed ratio for M12 (AOT40) of 0.93-1.01 (0.89-1.17) and 1.12 (1.23), respectively. However, MOZART-2 misses some of the seasonal trend in Japan, underpredicting O₃ in April by up to ~20 ppbv and overpredicting O₃ in fall by up to ~15 ppbv. The model also underestimates O₃ in central Europe by ~5-17 ppbv during the first half of the year. Based on the available data, MOZART-2 appears to perform well in China, southern India, north/central Africa, southern Africa, and South America where modeled:observed M24 ranges from 0.91-1.10 during the growing season. MOZART-2 seems to overpredict O₃ in Australia and New Zealand during the dry season (modeled:observed ratio of 1.24), but simulates observed values extremely well throughout the rest of the year. The model also appears to significantly overestimate O₃ in northern India (by ~10-18 ppbv throughout the year), a similar bias seen in TM5 CTM used by VD2009. As noted by VD2009 however, observation data in this region may not reflect regional-scale O₃ concentrations, as most monitoring sites are situated in densely-populated urban areas where local O₃ may be inhibited by NOₓ titration.

Unfortunately, MOZART-2 systematically overestimates O₃ exposure in the U.S, particularly in the north- and southeastern parts of the country by up to 22 ppbv. The bias is present to some extent throughout the year in the southeastern and western U.S., but is particularly problematic in the northeastern U.S. during the summer growing season (Table 3). This type of bias is common in global models which, on average, appear to overpredict surface
O$_3$ in the eastern U.S. by 10-20 ppbv in summer (Reidmiller et al., 2009). Although the reasons for this bias remain somewhat unclear, possible explanations include the coarse resolution of global CTMs, as well as potential issues related to heterogeneous chemistry, isoprene emissions and oxidation pathways, and the omission of elevated emission point sources (Horowitz et al., 2007; Reidmiller et al., 2009). Furthermore, as MOZART-2 returns O$_3$ concentrations from the midpoint of the surface layer (~992 hPa, approximately 175 m), surface ozone concentrations may be biased high in regions where vertical mixing in the boundary layer is suppressed. For example, Aunan et al. (2000) found that O$_3$ concentrations at the surface were $\sim$17% lower than at the 250-m layer midpoint height of the CTM used in their study of ozone impacts on crops in China. Based on a linear approximation from these results, a first order estimate of the potential ground-level bias caused by the presence of a vertical O$_3$ gradient within the surface layer of thickness $\sim$175 m is approximately $+12\%$.

Because the U.S. is a major producer of all three crops examined here, and because the most significant overestimation of O$_3$ unfortunately occurs in areas of intense crop cultivation (Figs. SM 2-3), we use observations to bias-correct values of simulated O$_3$ exposure (both M12 and AOT40) in the U.S. in order to constrain a major source of uncertainty in our estimates of U.S. crop yield losses. Our corrected values are calculated by dividing the simulated value of O$_3$ exposure in each U.S. grid cell by the ratio of modeled:observed O$_3$ in the same grid cell where data exist for each crop growing season (we use regional ratio averages where observations are unavailable). Our O$_3$ exposure values, relative yield loss, crop production loss, and economic damage estimates presented in the following sections are based on these bias-corrected values of O$_3$ exposure.

4. Results
4.1. Distribution of crop exposure to $O_3$

Fig. 3 illustrates the global distribution of crop exposure to $O_3$ according to the M12 and AOT40 metrics. The highest exposure levels generally occur in the Northern Hemisphere and Brazil due to greater $O_3$ precursor emissions and concentrations during the growing season. M12 ranges from 10 ppbv in the far north to over 80 ppbv in parts of the U.S., China and Brazil while AOT40 ranges from zero to over 40 ppmh in some locations. As evident from Fig. 3, 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). $O_3$ exposure during the soybean and maize growing seasons is high in the Northern Hemisphere, as these crops’ growing seasons overlap periods of peak summer $O_3$ in North America and the EU; $O_3$ peaks during spring and fall in China and India preceding and following the annual monsoon. In the Southern Hemisphere, the high $O_3$ 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, with observation data from Brazilian cerrado indicating that $O_3$ may reach 80 ppbv during biomass burning events (Kirchoff et al., 1996). Overall, the highest levels of $O_3$ exposure during the soybean growing season occur in the U.S., China, South Korea, and Italy (Fig. 3a), while these nations plus the DRC also endure the highest $O_3$ exposures during the maize growing season (Fig. 3b). $O_3$ exposure during the wheat growing season is greatest in central Brazil, Bangladesh, eastern India, and the Middle East (Fig. 3c).
4.2. **Relative yield loss**

Fig. 4 illustrates the global distribution of national RYL for each crop due to O$_3$ exposure. Estimates of soybean and maize (wheat) yield losses are generally larger (smaller) when the M12 rather than AOT40 metric is used. Using both metrics, O$_3$-induced RYL of wheat is highest in Bangladesh (15-49%), Iraq (9-30%), India (9-30%), Jordan (9-27%), and Syria (8-25%). Although O$_3$ is elevated during the wheat growing season over much of central Brazil, most of this nation’s wheat is grown in the south where O$_3$ exposure is significantly lower (Figs. 1 and 3c). 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 reductions 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 (see Fig. 5 for regional definitions). On a global scale, O$_3$-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 O$_3$ exposure are illustrated in Fig. 6. 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. 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, depending on the metric used. 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. Global CPL
for all three crops totals 79-121 Mt (from the M12 and AOT40 metrics, respectively). Table 2 of
the supplementary material contains regionally-averaged CPL results.

Fig. 7 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.
8 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). 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.
8)—together these three countries comprise 59% of the global economic damage (21, 21, and
17%, respectively).

We provide an in-depth comparison of our results with those of VD2009 and WM2004,
two studies that follow a similar methodology to calculate RYL, CPL, and EL, in the
supplementary material. Despite differences in the agricultural datasets and model scenarios, resolution, emissions inventories, and chemistry, our estimates agree very well with these two studies and provide further evidence that surface O₃ is already having a detrimental impact on global agricultural production.

5. **Discussion of 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 (Fig. 2, Table 3, supplementary material). The possible presence of a vertical gradient near the surface that is not resolved within the model’s bottom layer may lead to overestimated O₃ exposure at the crop canopy height in locations and at times of day when vertical mixing in the boundary layer is weak. 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 robust 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 rather than flux metrics, which 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 due to water stress resulting in the closure of stomata and hence a relative reduction in O₃ exposure (Fuhrer, 1997; Fiscus et al., 2005; Booker, 2009; Fuhrer, 2009).

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 and to their different functional form (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).

Uncertainty in our results 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 use of Western CR relationships may lead to an underestimation of yield reductions resulting from O₃ exposure.

Our choice to implement CR functions representing median cultivar ozone sensitivity for each crop and exposure metric means that our RYL and CPL calculations could be biased high or low (as predicted by each metric) depending on the relative sensitivity of the local cultivar grown. Feng and Kobayashi (2009) conduct a meta-analysis of field/experimental data that assess the impact of O₃ on crops and find that the mean yield loss of soybean and wheat was ~8 and 10%, respectively, at average O₃ levels of ~40 ppbv, but with a 95% confidence interval of ~±4% RYL depending on the cultivar. Mills et al. (2007) find that for wheat, RYL at AOT40 of ~23 ppmh could range from ~30-50% depending on the crop cultivar. Given the large intra-crop sensitivity to ozone exposure, choosing crop cultivars with O₃-resistance, or breeding new cultivars with this trait, may be an important opportunity to prevent O₃-induced agricultural losses.

Although a detailed analysis of uncertainty propagation is beyond the scope of this paper, we have the greatest confidence in our European and U.S. crop loss calculations given model performance in these regions (after a bias-correction in the U.S.), and because the CR relationships implemented here were derived from crop cultivars grown in the U.S. and Europe. We have less confidence in our results in Asia: in particular, the overprediction of O₃ by MOZART-2 in northern India may lead to an overestimate of agricultural losses in this region, especially for wheat (which is largely grown in the north, Fig. 1) and according to the threshold-
sensitive AOT40 metric. However, we are less confident about the data used to evaluate
MOZART-2 in this part of the world. Furthermore, as Asian (including Indian) cultivars may be
more sensitive to O₃ than predicted by western CR functions (Emberson et al., 2009), the
potential high bias caused by model overprediction of surface ozone may be somewhat
counteracted. Because MOZART-2 performs well in southern India during the growing season,
the use of western CR relationships may lead to an underprediction of crop losses in this region.
The same may be true in China, where O₃ is slightly underestimated by MOZART-2 and where
regional crop cultivars also exhibit greater sensitivity to O₃ exposure (Emberson et al., 2009).
By contrast, because the model appears to somewhat overestimate surface ozone in southern
Africa, agricultural losses here may be biased high. Unfortunately we do not have enough
monitoring data to evaluate model performance in South America, northern/central Africa, and
Australia/New Zealand beyond the stations used in this analysis, nor do we know the relative
sensitivity of local cultivars to O₃ in these regions compared to those of the U.S. and Europe. As
such, crop loss results in the Southern Hemisphere are considered particularly uncertain.

6. Conclusions and Policy Implications

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 year 2000
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. Our findings agree well with previous studies (see
supplementary material), providing further evidence that O₃ already has a significant impact on
global agricultural production.
The results presented here suggest that O₃ abatement may be one way to 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 U.S. EPA recently proposed a new rule (on January 19th, 2010) to strengthen the U.S. national ambient air quality standards for ground-level O₃, including the establishment of a secondary standard to protect crops and other sensitive vegetation (EPA, 2010). Our study highlights 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 global 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., 2006; Fiore et al., 2008) while also generating the largest net reduction in radiative forcing of all the O₃ precursor species (West et al., 2007).

Given the significant present-day impact of O₃ on crops worldwide and the uncertainty of future mitigation efforts, our companion paper (Chapter 3) 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 that also have demonstrated climate change and public health benefits.
References


concentrations in Asia, Africa, and South America using passive samplers. Atmospheric Environment 37, 1293–1308.


Figure 1. Global distributions of soybean, maize, and wheat in the year 2000. Data are from Ramankutty et al. (2008) and Monfreda et al. (2008), regridded to MOZART-2 resolution (2.8° latitude x 2.8° longitude).
Figure 2. Comparison of regionally averaged monthly mean surface ozone concentrations from monitoring sites (black diamonds) and MOZART-2 (grey squares). Monthly simulated values are averaged over grid boxes containing the observation sites in each region and monthly observed values are averaged over all sites within every region. Error bars on observed values indicate ±one standard deviation from the monthly mean station data in each region. Data sources for
observation sites and regional boundaries are listed in Table 3. M12 values are calculated and displayed for regions where hourly data exist that meet quality control requirements (U.S., Europe, and Japan; first 6 panels); M24 is illustrated for the rest of the world.
Figure 3. 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.
Figure 4. National relative yield loss according to the M12 (left panels) and AOT40 (right panels) metrics for (a) soybean, (b) maize, and (c) wheat.
Figure 5. Definitions used to calculate relative yield and crop production losses by region.

Figure 6. 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.
Figure 7. 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.
Figure 8. 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.
Tables

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OECD refers to countries of the Organization for Economic Cooperation and Development as of 1990, including the US, Canada, western Europe, Japan and Australia.

REF represents countries undergoing economic reform, including countries of eastern Europe and the newly independent states of the former Soviet Union.

Asia refers to all developing countries in Asia, excluding the Middle East.

ALM represents all developing countries in Africa, Latin America and the Middle East.

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>
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<th>Exposure – Relative Yield Relationship</th>
<th>Reference</th>
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<td>Soybean</td>
<td>$RY = \exp\left[-\left(\frac{M_{12}}{107}\right)^{1.58}\right]/\exp\left[-\left(\frac{20}{107}\right)^{1.58}\right]$</td>
<td>Adams et al. (1989)</td>
</tr>
<tr>
<td></td>
<td>$RY = -0.0116*\text{AOT}_{40} + 1.02$</td>
<td>Mills et al. (2007)</td>
</tr>
<tr>
<td>Maize</td>
<td>$RY = \exp\left[-\left(\frac{M_{12}}{124}\right)^{2.83}\right]/\exp\left[-\left(\frac{20}{124}\right)^{2.83}\right]$</td>
<td>Lesser et al. (1990)</td>
</tr>
<tr>
<td></td>
<td>$RY = -0.0036*\text{AOT}_{40} + 1.02$</td>
<td>Mills et al. (2007)</td>
</tr>
<tr>
<td></td>
<td>$RY = \exp\left[-\left(\frac{M_{7}}{137}\right)^{2.34}\right]/\exp\left[-\left(\frac{25}{137}\right)^{2.34}\right]$ (Winter)</td>
<td>Lesser et al. (1990)</td>
</tr>
<tr>
<td></td>
<td>$RY = \exp\left[-\left(\frac{M_{7}}{186}\right)^{3.2}\right]/\exp\left[-\left(\frac{25}{186}\right)^{3.2}\right]$ (Spring)</td>
<td>Adams et al. (1989)</td>
</tr>
<tr>
<td>Wheat</td>
<td>$RY = -0.0161*\text{AOT}_{40} + 0.99$</td>
<td>Mills et al. (2007)</td>
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Table 2. Concentration:response equations used to calculate relative yield losses of soybean, maize, and wheat. $RY = \text{relative yield as compared to theoretical yield without O}_3\text{-induced losses. Relative yield loss (RYL) is calculated by subtracting the RY from unity, which represents the theoretical yield without O}_3\text{ damage (i.e. 100% yield).}$ Adams et al. (1989) and
Lesser et al. (1990) CR functions are based on the U.S. NCLAN studies, while the relationships from Mills et al. (2007) are derived from both U.S. NCLAN data and the EOTC field experiments. 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>
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<th>Region</th>
<th>M12 (M24)</th>
<th>AOT40</th>
<th>Minimum Lon, Lat</th>
<th>Maximum Lon, Lat</th>
<th>Number of Stations</th>
<th>Data Source</th>
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<td>-64, 36</td>
<td>193</td>
<td>AQS</td>
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<td>1.69</td>
<td>-155, 18</td>
<td>-91, 63</td>
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<td>AQS</td>
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<td>1.17</td>
<td>0, 35</td>
<td>30, 45</td>
<td>8</td>
<td>European Monitoring and Evaluation Programme (EMEP), <a href="http://www.nilu.no/projects/ccc/onlineData/ozone/index.html">http://www.nilu.no/projects/ccc/onlineData/ozone/index.html</a></td>
</tr>
<tr>
<td>Central Europe</td>
<td>0.93</td>
<td>0.89</td>
<td>7, 46</td>
<td>17, 54</td>
<td>41</td>
<td>EMEP</td>
</tr>
<tr>
<td>China</td>
<td>(0.91)</td>
<td>0.67</td>
<td>74, 15</td>
<td>137, 56</td>
<td>12</td>
<td>WDCGG, Carmichael et al. (2003), Huxiang et al. (2005), Li et al. (2007)</td>
</tr>
<tr>
<td>Northern India</td>
<td>(1.43)</td>
<td>1.49</td>
<td>68, 21</td>
<td>90, 35</td>
<td>5</td>
<td>Mittal et al. (2007), Ghude et al. (2008)</td>
</tr>
<tr>
<td>Southern India</td>
<td>(1.07)</td>
<td>-</td>
<td>68, 5</td>
<td>90, 20</td>
<td>7</td>
<td>Naja and Lai (2002), Naja et al. (2003), Debaje et al. (2003), Ahammed et al. (2006), Beg et al. (2007), Mittal et al. (2007), Debaje et al. (2010)</td>
</tr>
<tr>
<td>North/Central Africa</td>
<td>(1.09)</td>
<td>-</td>
<td>19, 4</td>
<td>61, 38</td>
<td>3</td>
<td>WDCGG, Carmichael et al. (2003)</td>
</tr>
<tr>
<td>Southern Africa</td>
<td>(1.10)</td>
<td>-</td>
<td>3, 35</td>
<td>7, 54</td>
<td>9</td>
<td>Zunckel et al. (2004)</td>
</tr>
<tr>
<td>South America</td>
<td>(0.97)</td>
<td>-</td>
<td>-94, 58</td>
<td>-30, 14</td>
<td>4</td>
<td>WDCGG, Teixeira et al. (2009)</td>
</tr>
<tr>
<td>Australia and New Zealand</td>
<td>(1.24)</td>
<td>-</td>
<td>110, 50</td>
<td>180, -11</td>
<td>2</td>
<td>WDCGG</td>
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</tbody>
</table>

Table 3. Regionally-averaged ratios of modeled:observed M12, M24, and AOT40 (depending on data availability) during the representative Northern Hemisphere summer growing season (May – July) and Southern Hemisphere summer/dry season (Aug – Oct in South America and southern Africa; Dec – Feb in Australia and New Zealand). Data sources for observed O₃, regional boundaries, and the number of observation stations per region are also listed. In order for U.S. and European data to be included in the analysis of M12 and AOT40, each site was required to have hourly O₃ concentrations for at least 75% of the hours needed to compute the exposure metrics (which are then compared to 12-hr MOZART-2 metric calculations). 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 O$_3$ exposure value, as O$_3$ levels were anomalously low over some parts of the U.S. in the year 2000. Metrics were calculated only for monitoring sites with at least four years (80%) of sufficient hourly O$_3$ data over the 1998-2002 period. O$_3$ data outside of the U.S. and Europe are from the year 2000 whenever possible, but generally fall within the range of 1995-2005 according to data availability. Requirements for these data can be found in the above references. Observed AOT40 in China and northern India are from monitoring sites listed in Huixiang et al. (2005) and Ghude et al. (2008), respectively. The AOT40 comparison for China is based on April – Jun and for India Mar – May based on the available data.

<table>
<thead>
<tr>
<th></th>
<th>World</th>
<th>EU 25</th>
<th>FUSSR &amp; E. Europe</th>
<th>N. Am</th>
<th>L. Am.</th>
<th>Africa &amp; M.E.</th>
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<th>S. Asia</th>
<th>ASEAN &amp; Australia</th>
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<td><strong>Maize</strong></td>
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<tr>
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<td>1.6</td>
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<tr>
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<td>5.9</td>
<td>22.8</td>
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**Table 4.** Estimated regional relative yield loss (%) due to O$_3$ exposure according to the M7, M12 and AOT40 metrics and the metric average.
Supplementary Material

Figure SM 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.
Figure SM 2. Global distribution of \( \text{O}_3 \) exposure during May-July according to the M12 metric derived from (a) simulated hourly \( \text{O}_3 \) concentrations, and (b) observed hourly \( \text{O}_3 \) 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.
Figure SM 3. Global distribution of O$_3$ exposure during May-July according to the AOT40 metric derived from (a) simulated hourly O$_3$ concentrations, and (b) observed hourly O$_3$ 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.
<table>
<thead>
<tr>
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<th>World</th>
<th>EU 25</th>
<th>E. Europe</th>
<th>N. Am</th>
<th>L. Am.</th>
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</table>

**Table SM 1.** Estimated regional crop production loss (million metric tons) due to O$_3$ exposure according to the M7, M12, and AOT40 metrics and the metric average.
Table SM 2. 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.

We compare our results with those of VD2009 and WM2004, two studies that follow a similar methodology to calculate RYL, CPL, and EL. 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) in 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 SM 2). 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) is
0.89. 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, RYL results are very similar to those of VD2009: we
find global 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 SM 2). We provide a
comparison of EL in Table SM 3: 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.
Table SM 3. Comparison of selected economic loss (EL) estimates (billion USD$_{2000}$) derived in this study with others based on similar methodologies.

For our economic loss comparison, we convert WM2004 estimates to year 2000 USD and present the sum of economic damage due to soybean, maize, and wheat crop production losses only. We report the VD2009 EL range where available for soybean, maize, and wheat only; where the precise data were unavailable from the text, we averaged the range provided for the four crops analyzed in their study (including rice) and subtracted the average EL rice estimate provided. Our EL range for Japan agrees well with WM2004, but is lower than VD2009. This could be due to the VD2009 model overestimating O$_3$ exposure during the soybean growing season, while our model seems to underestimate O$_3$ slightly (Figs. SM 2c and 3c). Our estimate of EL is likely lower than the WM2004 in South Korea due to different metrics used (previously discussed) and because the year 2000 crop production estimates of WM2004 are over twice the values used here (Monfreda et al., 2008; Ramankutty et al., 2008), which leads to higher CPL and EL. We are confident in our South Korean crop production values, however, as they are within 3% of FAO production data (FAOSTAT, 2008). Our EL estimates for China, India, the

<table>
<thead>
<tr>
<th>Region</th>
<th>Current Study</th>
<th>VD2009</th>
<th>WM2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>2.5-3.5</td>
<td>~3.4</td>
<td>3.1-4.0</td>
</tr>
<tr>
<td>Japan</td>
<td>0.14-0.19</td>
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<td>0.13-0.2</td>
</tr>
<tr>
<td>S. Korea</td>
<td>0.07-0.08</td>
<td>~0.16</td>
<td>0.11-0.24</td>
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<tr>
<td>India</td>
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<td>1.8-4.6</td>
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</tr>
<tr>
<td>N. America</td>
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<td>1.8-3.9</td>
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</table>

<table>
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<tr>
<th>Region</th>
<th>Current Study</th>
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<th>WM2004</th>
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<td>India</td>
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<tr>
<td>N. America</td>
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Table SM 3. Comparison of selected economic loss (EL) estimates (billion USD$_{2000}$) derived in this study with others based on similar methodologies.
EU-25, and North America agree very well with VD2009, as does our estimate of total global economic losses from all three crops ($11-18 billion compared to $9.8-20 billion in VD2009).
Chapter 3

Global Crop Yield Reductions due to Surface Ozone Exposure: 2.

Year 2030 Potential Crop Production Losses and Economic Damage under Two Scenarios of O₃ Pollution

Abstract

We examine the potential global risk of increasing surface ozone (O₃) exposure to three key staple crops (soybean, maize, and wheat) in the near future (year 2030) according to two trajectories of O₃ pollution: the Intergovernmental Panel on Climate Change Special Report on Emissions Scenarios (IPCC SRES) A2 and B1 storylines, which represent upper- and lower-boundary projections, respectively, of most O₃ precursor emissions in 2030. We use simulated hourly O₃ concentrations from the Model for Ozone and Related Chemical Tracers version 2.4 (MOZART-2), satellite-derived datasets of agricultural production, and field-based concentration:response relationships to calculate crop yield reductions resulting from O₃ exposure. We then calculate the associated crop production losses and their economic value. We compare our results to the estimated impact of O₃ on global agriculture in the year 2000, which we assessed in our companion paper (Avnery et al., 2011; Chapter 2). In the A2 scenario we find global year 2030 yield loss of wheat due to O₃ exposure ranges from 5.4-26% (a further

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reduction in yield of +1.5-10% from year 2000 values), 15-19% for soybean (reduction of +0.9-11%), and 4.4-8.7% for maize (reduction of +2.1-3.2%) depending on the metric used, with total global agricultural losses worth $17-35 billion USD\textsubscript{2000} annually (an increase of +$6-17 billion in losses from 2000). Under the B1 scenario, we project less severe but still substantial reductions in yields in 2030: 4.0-17% for wheat (a further decrease in yield of +0.1-1.8% from 2000), 9.5-15% for soybean (decrease of +0.7-1.0%), and 2.5-6.0% for maize (decrease of +0.3-0.5%), with total losses worth $12-21 billion annually (an increase of +$1-3 billion in losses from 2000).

Because our analysis uses crop data from the year 2000, which likely underestimates agricultural production in 2030 due to the need to feed a population increasing from approximately 6 to 8 billion people between 2000 and 2030, our calculations of crop production and economic losses are highly conservative. Our results suggest that O\textsubscript{3} pollution poses a growing threat to global food security even under an optimistic scenario of future ozone precursor emissions. Further efforts to reduce surface O\textsubscript{3} concentrations thus provide an excellent opportunity to increase global grain yields without the environmental degradation associated with additional fertilizer application or land cultivation.

1. **Introduction**

Surface ozone (O\textsubscript{3}) is the most damaging air pollutant to crops and ecosystems (Heagle, 1989). It is produced in the troposphere by catalytic reactions among nitrogen oxides (NO\textsubscript{x} = NO + NO\textsubscript{2}), carbon monoxide (CO), methane (CH\textsubscript{4}), and non-methane volatile organic compounds (NMVOCs) in the presence of sunlight. Ozone enters leaves through plant stomata during normal gas exchange. As a strong oxidant, ozone and its secondary byproducts damage vegetation by reducing photosynthesis and other important physiological functions, resulting in
weaker, stunted plants, inferior crop quality, and decreased yields (Fiscus et al., 2005; Morgan et al., 2006; Booker et al., 2009; Fuhrer, 2009).

O3 precursors are emitted by vehicles, power plants, biomass burning, and other sources of combustion. Over the past century, annual mean surface concentrations of ozone at mid- to high latitudes have more than doubled (Hough and Derwent 1990; Marenco et al., 1994).

Although O3 mitigation efforts have reduced peak ozone levels in both rural and urban areas of North America, Europe, and Japan in recent years, background levels continue to increase (Oltmans et al., 2006). In addition, ozone concentrations are expected to rise in developing countries due to increased emissions of nitrogen oxides and other ozone precursors resulting from rapid industrialization (Nakićenović et al., 2000; Dentener et al., 2005; Riahi et al., 2007).

Due to transport of O3 pollution across national boundaries and continents (Fiore et al., 2009), rising O3 precursor emissions in these nations are projected to increase hemispheric-scale background O3 concentrations and hence may pose a threat to both local and global food security.

The demonstrated phytotoxicity of O3 and its prevalence over important agricultural regions around the world demand an assessment of the magnitude and distribution of ozone risk to global food production under present-day and future O3 concentrations. In the first of our two-part analysis (Avnery et al., 2011; Chapter 2), we calculated global yield losses of three key staple crops (soybean, maize, and wheat) and their associated costs in the year 2000 using simulated O3 concentrations by the Model for Ozone and Related Chemical Tracers version 2.4 (MOZART-2), observation-based crop production datasets, and concentration:response (CR) relationships derived from field studies. Our results indicated that year 2000 global yield reductions due to O3 exposure ranged from 8.5-14% for soybean, 3.9-15% for wheat, and 2.2-
5.5% for maize depending on the metric used, with global crop production losses (79-121 million metric tons (Mt)) worth $11-18 billion annually (USD2000). These findings agree well with the only other estimate of global O3-induced crop reductions and their economic value available in the literature (Van Dingenen et al., 2009), providing further evidence that the yields of major crops across the globe are already being significantly inhibited by exposure to surface ozone. Recent experimental- and observation-based studies support the results of model-derived estimates of regional and global crop losses (Feng and Kobayashi, 2009; Fishman et al., 2010).

Van Dingenen et al. (2009) (hereafter VD2009) additionally provide the first, and until now only, estimate of global crop yield losses due to ozone exposure in the near future (year 2030). VD2009 calculate crop losses as projected under the optimistic “current legislation (CLE) scenario”, which assumes that presently approved air quality legislation will be fully implemented by 2030. They find that global crop yield reductions increase slightly from the year 2000 (+2-6% for wheat, +1-2% for rice, and +<1% for maize and soybeans), with the most significant additional losses primarily occurring in developing nations. Unfortunately, the CLE scenario may be an overly optimistic projection of O3 precursor emissions in many parts of the world, as enforcement often lags promulgation of air pollution regulations (Dentener et al., 2006). VD2009 may have therefore significantly underestimated the future risk to agriculture from surface ozone.

Here we estimate potential future reductions in crop yields and their economic value due to O3 exposure according to two different O3 precursor emission scenarios: the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) A2 and B1 storylines (Nakićenović et al., 2000), representing upper- and lower boundary trajectories, respectively, of ozone precursor emissions. Through comparison with our year 2000
results, we identify agricultural winners and losers under each future scenario and nations where O₃ mitigation may be a particularly effective strategy to improve agricultural production without the environmental damage associated with conventional methods of increasing crop yields.

2. Methodology

2.1 Data sources

We use global crop production maps, simulated surface ozone concentrations from which we calculate O₃ exposure over crop growing seasons, and CR functions that relate a given level of ozone exposure to a predicted yield reduction to calculate global crop losses. Our first paper (Avnery et al., 2011; Chapter 2) provides an in-depth description of our data sources and methods, which we briefly summarize and supplement here.

The global crop distribution datasets for the year 2000 (which we use for our 2030 analysis) were compiled by Monfreda et al. (2008) and Ramankutty et al. (2008). They used a data fusion technique, where two 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 crop area and yield statistics at 5 minute by 5 minute latitude-longitude resolution. We regrid their data to match the 2.8° × 2.8° resolution of MOZART-2.

We use the global chemical transport model (CTM) MOZART-2 (Horowitz et al., 2003; Horowitz, 2006) to simulate O₃ exposure according to precursor emissions specified by the IPCC SRES A2 and B1 scenarios (Nakićenović et al., 2000). MOZART-2 contains a detailed representation of tropospheric ozone-nitrogen oxide-hydrocarbon chemistry, simulating the concentrations and distributions of 63 gas-phase species and 11 aerosol and aerosol precursor species. The version of MOZART-2 we use is driven by meteorological inputs every three hours.
from the National Center for Atmospheric Research (NCAR) Community Climate Model (MACC3) (Kiehl et al., 1998), and has a horizontal resolution of 2.8° latitude by 2.8° longitude, 34 hybrid sigma-pressure levels up to 4hPa, and a 20-minute time step for chemistry and transport. See Horowitz et al. (2006) for a detailed description of the simulations used here.

Anthropogenic, biogenic, and biomass burning emission inventories for the year 1990 are described in detail in Horowitz et al. (2003) and Horowitz (2006). To obtain year 2030 anthropogenic emissions, anthropogenic emissions in 1990 were scaled by the ratio of 2030:1990 total emissions in four geopolitical regions (Table 5) as specified by the A2 and B1 emissions scenarios (available from http://www.grida.no/climate/ipcc/emission/164.htm). The A2 and B1 scenarios were chosen for analysis because they represent the upper- and lower- boundary projections, respectively, of most O₃ precursor emissions in the year 2030 (the exception being NMVOC emissions, which are highest under the A1B rather than the A2 scenario). These scenarios are also opposite in terms of economic, environmental, and geopolitical driving forces, with the B1 scenario characterized by global cooperation and emphasis on environmental sustainability and the A2 scenario reflecting a more divisive world with greater importance placed on economic growth. Two-year simulations were performed with the first year used as spin-up and the second year results used for analysis.

In our first paper, we performed a detailed spatial evaluation of simulated year 2000 surface O₃ concentrations with observations according to the two metrics used to calculate O₃ exposure and yield losses (see Section 2.2 for metric definitions). We found that O₃ was fairly well-simulated over Europe and Asia, but that MOZART-2 systematically overestimated surface O₃ concentrations in the central and northeastern U.S. during the summer months, a bias commonly seen in many other global models (Reidmiller et al., 2009). Because the most
significant overestimation of O₃ unfortunately occurs in areas of intensive crop production in the U.S., and because the U.S. is a major producer of all three crops analyzed in this study, we used O₃ concentration measurements over a span of five years (1998-2002) to bias-correct values of simulated O₃ exposure. We perform the same bias-correction here for our year 2030 analysis: we divide simulated O₃ exposure in the U.S. as calculated by the metrics defined in Section 2.2 over each crop growing season by the ratio of modeled:observed O₃ in the same grid cell where measurement data exist from 1998-2002 (where multiple observation sites exist in a single grid cell, we use the average of the measurements to correct simulated values). Where measurements do not exist, we use U.S. eastern and western regional averages of the modeled:observed ratio (dividing line of 90°W), as the model reproduces O₃ in the western U.S. much more accurately than in the East. Like our first paper, O₃ exposure, relative yield loss, crop production loss, and associated cost estimates presented in the following sections for the U.S. are based on these bias-corrected values of O₃ exposure. We recognize that applying the same bias-correction factors based on surface observations from the period 1998-2002 may not be accurate in the year 2030 due to the complicated non-linear chemistry associated with ozone formation. However, we believe this is the best approach given the presence of a systematic bias over the U.S. during the summer months and our inability to use alternative correction factors based on year 2030 surface observations.

2.2. Integrated assessment

Open-top chamber (OTC) field studies that took place primarily in the U.S. and Europe during the 1980s and 1990s established crop-specific concentration:response (CR) functions that predict the yield reduction of a crop at different levels of ozone exposure (Heagle, 1989; Heck, 1989; Krupa et al., 1998). O₃ exposure can be represented in numerous ways, with different
statistical indices used to summarize the pattern of ambient O$_3$ during crop growing seasons. We implement two widely-used metrics, M12 and AOT40, and their CR relationships (Table 6) to calculate crop yield losses globally:

\[
M12 \text{ (ppbv)} = \frac{1}{n} \sum_{i=1}^{n} [Co_3]_i
\]

\[
AOT40 \text{ (ppmh)} = \sum_{i=1}^{n} ([Co_3]_i - 0.04) \text{ for } Co_3 \geq 0.04 \text{ ppmv}
\]

where:
- $[Co_3]_i$ is the hourly mean O$_3$ concentration during daylight hours (8:00 – 19:59);
- $n$ is the number of hours in the 3-month growing season.

We substitute the highly correlated M7 metric (defined like M12 except with daylight hours from 9:00-15:59) when M12 parameter values have not been defined for certain crops. Estimates of soybean and maize (wheat) yield losses are generally larger (smaller) when the M12 rather than the AOT40 metric is used. However, the AOT40 index and CR functions predict greater losses for soybean at higher levels of O$_3$ exposure than the M12 metric. See Avnery et al. (2011) for further detail about these O$_3$ exposure metrics/CR functions and their associated uncertainties.

Using hourly surface O$_3$ simulated by MOZART-2, we calculate O$_3$ exposure according to the M12 (M7) and AOT40 metrics over the appropriate growing season for soybean, maize, and wheat in each 2.8° x 2.8° grid cell. “Growing season” is here defined like in VD2009 and Avnery et al. (2011) 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); data are available for nations accounting for over 95% of global production of each crop examined here (USDA, 1984; 2008). We use our distributions of O$_3$ exposure and the CR functions defined in Table 6 to
calculate relative yield loss (RYL) in every grid cell (RYL$_i$) for each crop. Relative yield loss is defined as the reduction in crop yield from the theoretical yield that would have resulted without O$_3$-induced damages (see Table 6). Following Wang and Mauzerall (2004), we then calculate CPL in each grid cell (CPL$_i$) from RYL$_i$ and the actual crop production in the year 2000 (CP$_i$) from Ramankutty et al. (2008) and Monfreda et al. (2008) according to:

\[
CPL_i = \frac{RYL_i}{1 - RYL_i} \times CP_i
\]  

(1)

National CPL is determined by summing crop production loss in all the grid cells within each country. We define national RYL as national CPL divided by the theoretical total crop production without O$_3$ injury (the sum of crop production loss and actual crop production in the year 2000). Because this calculation uses crop data from the year 2000, which likely underestimates production in 2030 due to the projected growth in demand for food over the next few decades, our calculations of crop production losses are conservative. Finally, we implement a simple revenue approach to estimate 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/). We use FAO producer prices as a proxy for domestic market prices due to insufficient information on actual crop prices. This approach has been found to produce estimates of economic loss that are within 20% of those derived using a general equilibrium model with factor feedbacks (Westenbarger and Frisvold, 1995).

3. Results

3.1. Distribution of crop exposure to O$_3$

Figs. 9 and 10 depict the global distribution of crop exposure to O$_3$ in 2030 according to the M12 and AOT40 metrics under the A2 and B1 scenarios, respectively. Figures illustrating
the change in O$_3$ exposure from the year 2000 under each scenario are available in the Supplementary Material. O$_3$ is generally higher in the Northern Hemisphere, with exposure during the wheat growing season in Brazil and during the maize growing season in the Democratic Republic of the Congo (DRC) also elevated in both futures (Figs. 9c and 10c). As noted in our companion paper, O$_3$ exposure during the soybean and maize growing seasons is particularly elevated in the Northern Hemisphere due to the coincidence of these crops’ growing seasons with peak summer O$_3$ concentrations, while the wheat and maize growing seasons in Brazil and the DRC, respectively, coincide with these nations’ biomass burning seasons (Avnery et al., 2011; Chapter 2).

In the A2 scenario, M12 ranges from 30 ppbv to over 80 ppbv for all three crops in the Northern Hemisphere while AOT40 ranges from zero to over 40 ppmh in northern India, eastern China, and parts of the U.S. (Fig. 9). Northern Hemisphere O$_3$ exposure is considerably lower in the B1 scenario. M12 ranges from 20-60 ppbv over most continental regions with higher exposures (>70 ppbv) limited to northern India, eastern China, and parts of the southern U.S. AOT40 is most reduced compared to the A2 scenario in the U.S., Europe, and the Middle East (Fig. 10); however, AOT40 in the B1 scenario still remains largely above the 3 ppmh “critical level” established in Europe for the protection of crops (Karenlampi and Skarby, 1996), particularly during the soybean and maize growing seasons. M12 in the Southern Hemisphere ranges from 10-40 ppbv in both scenarios with the exception of Brazil during the wheat growing season and the DRC during the maize growing season, where M12 O$_3$ reaches 80 ppbv. AOT40 in the Southern Hemisphere is largely below 5 ppmh for both scenarios with the exception of the two nations listed above, as well as South Africa and parts of northern Australia (Figs. 9-10).

3.2. Relative yield loss
3.2.1. RYL Year 2030 – A2

Fig. 11 depicts the global distribution of national RYL due to O₃ exposure for each crop and metric in 2030 under the A2 scenario, while Table 7 presents regionally aggregated and global RYL results (see Avnery et al. (2011) for regional definitions). O₃-induced RYL of wheat is greatest in Bangladesh (26-80%), Iraq (14-47%), India (12-48%), Jordan (14-44%), and Saudi Arabia (13-43%), depending on the metric used. The extremely high projected RYL in Bangladesh according to the AOT40 metric is due to a predicted O₃ exposure of over 40 ppmh during the growing season. It is possible that this value is overestimated by MOZART-2; however, we are unable to evaluate our simulated concentrations in this region because no O₃ observations are available. For context, Beig et al. (2008) calculated AOT40 from observations in Pune, India between 2003-2006 and report values near 23 ppmh during the wheat growing season in India (January - March). At this location MOZART-2 predicts a value of 20 ppmh in 2000 over these months. Pune is located in western India, however, where O₃ concentrations tend to be lower than eastern India and Bangladesh during winter (the Bangladeshi wheat growing season).

Although O₃ is elevated during the wheat growing season over much of central Brazil (Fig. 9c), most of this nation’s wheat is grown in the south where O₃ exposure is significantly lower. Like the year 2000 scenario, there is a large range of RYL for wheat because 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 be a consequence of the possibility that wheat is more sensitive to frequent exposure to high O₃ concentrations (better captured by AOT40) than to long-term exposure to moderate ozone concentrations (better captured by the mean metric) (Wang and Mauzerall, 2004). Soybean RYL under the A2 scenario is estimated to
be greatest in China (35-40%), Canada (32-34%), Italy (32-33%), South Korea (31%), and Turkey (27-30%). Yield losses of maize are smaller but still substantial, with the highest losses occurring in the DRC (12-21%), Italy (10-16%), Pakistan (9.1-16%), India (8.9-16%), and Turkey (7.6-14%). Overall, global RYL totals 5.4-26% for wheat, 15-19% for soybean, and 4.4-8.7% for maize (Table 7).

Table SM 4 lists the estimated increases in regionally and globally aggregated RYL under the A2 scenario relative to year 2000 (RYL2030 - RYL2000). On a global scale, O₃-induced RYL is estimated to increase by +1.5-10% for wheat, +0.9-10% for soybean, and +2.1-3.2% for maize in 2030. South Asia is projected to suffer the greatest additional wheat RYL (+10% according to the average of metric estimates) followed by Africa and the Middle East (+9.4%), Eastern Europe (+5.8%) and East Asia (+5.0%). Increased soybean yield losses are estimated to be greatest in East Asia (+15%), South Asia (+11%), the EU25 (+7.0%), and Africa and the Middle East (+6.2%). Additional RYL of maize is projected to occur primarily in South and East Asia (+6.8 and +4.7%, respectively), but with increased losses of ~+3% also estimated for the EU25 and Eastern Europe.

3.2.2. RYL Year 2030 – B1

Fig. 12 depicts the global distribution of national RYL for each crop and metric in 2030 under the B1 scenario, while Table 8 presents regionally aggregated and global RYL results. O₃-induced RYL of wheat is greatest in Bangladesh (15-65%), India (10-37%), Iraq (10-33%), Jordan (10-30%), and Saudi Arabia (10-29%). RYL in Bangladesh is again calculated to be extremely high, as O₃ exposure is projected to be only slightly lower than under the A2 scenario (35-40 ppmh). Soybean RYL in the B1 scenario is projected to be greatest in China (31-32%), South Korea (26-28%), Canada (24-26%), Italy (20-25%), and Pakistan (18-24%). The highest
estimated yield loss of maize is expected to occur in the DRC (8.7-16%), India (6.3-12%), Pakistan (6.3-12%), China (5.8-10%), and Italy (5.1-10%). On a global scale, RYL totals 4.0-17% for wheat, 10-15% for soybean, and 2.5-6.0% for maize under the B1 scenario (Table 8).

Table SM 5 lists the projected change in regionally and globally aggregated RYL estimates for 2030 under the B1 scenario relative to 2000. Globally, O₃-induced RYL in this more optimistic future is estimated to worsen only slightly from 2000 levels with yields reduced an additional +0.1-1.8% for wheat, +0.7-1.0% for soybean, and +0.3-0.5% for maize. Regional discrepancies are apparent, however, due to differences in projected O₃ precursor emissions among industrialized versus emerging economies. Year 2030 wheat yields decrease in South Asia by +4.1% on average, with less severe additional losses (~+1-2%) predicted for other developing regions (Latin America, East Asia, and Africa and the Middle East). North America and the EU25 are projected to experience yield gains of wheat as compared to year 2000 (change in RYL of -1.7% and -0.8%, respectively). Additional yield reductions of soybean are projected to occur primarily in East and South Asia (+8.2 and +4.9%, respectively), with increased losses of ~+2% also estimated for Latin America and Africa and the Middle East. Soybean yield gains (change in RYL of -2-3%) are projected for the EU25 and North America. South and East Asia are further expected to suffer additional maize losses under the B1 scenario (+3.5% and +2.2%, respectively); maize RYL in other regions remains largely unchanged from the year 2000.

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

3.3.1. CPL and EL Year 2030 – A2

The combined year 2030 global crop production and economic losses due to O₃ exposure under the A2 scenario are illustrated in Fig. 13. Figs. 14 and 15 depict the change in CPL and EL, respectively, for the ten countries with the greatest absolute difference (2030A2 – 2000) for
each crop individually and combined. The change in regionally-aggregated and global CPL for each crop, as well as absolute year 2030 CPL, is presented in Tables SM 6 and SM 7 of the Supplementary Material. We calculate global CPL in the A2 scenario to be 29-178 Mt of wheat (a decrease in production of +9-85 Mt from the year 2000), 25-53 Mt of maize (+13-20 Mt), and 28-37 Mt of soybean (+11-13 Mt). South Asia is estimated to suffer the highest additional loss of wheat (19 Mt, average of metric estimates), while East Asia is projected to experience the greatest additional CPL of maize (6.4 Mt) and soybean (4.5 Mt) (Table SM 6). Total wheat CPL is highest in India (8.5-56 Mt) and China (3.7-33 Mt), followed by the U.S. (2.5-12 Mt). The U.S. is expected to suffer the greatest overall soybean loss (13-18 Mt), followed by China (7.7-10 Mt) and Brazil (1.8-5.7 Mt). CPL of maize is projected to be highest in China (9.7-17 Mt) and the U.S. (8.1-18 Mt), followed by India (1.0-1.9 Mt). On average, global CPL for all three crops totals 175 Mt (Table SM 7); this value represents a 75% increase over our average year 2000 CPL estimate (Avnery et al., 2011; Chapter 2). We estimate that global EL due to O3-induced yield losses totals $17-35 billion USD$_{2000}$ annually under the A2 scenario, an increase of +$6-17 billion in damages from the year 2000. Most of the economic losses, both in absolute terms and in terms of the greatest change from year 2000 values, occur in China ($5.6 billion, an increased loss of +$2.6 billion from 2000), India ($5.2 billion, +$2.7 billion), and the U.S. ($4.2 billion, +$1.1 billion) (Fig. 15). Other countries with notable losses include Iran (over $1 billion) and Brazil, Turkey, Pakistan, and Syria also each estimated to lose crop value worth $500 million annually.

3.3.2. CPL and EL Year 2030 – B1

Combined year 2030 global crop production and economic losses in the B1 scenario are illustrated in Fig. 16, while Figs. 17 and 18 depict the change in CPL and EL, respectively, for
the ten countries with the greatest absolute difference (2030B1 – 2000) for each crop individually and combined. The change in regionally-aggregated and global CPL for each crop, as well as absolute year 2030 CPL under the B1 scenario, is presented in Tables S8 and S9 of the Supplementary Material. We estimate year 2030 global CPL to be 21-106 Mt of wheat (+0.8-13 Mt from the year 2000), 14-35 Mt of maize (+1.7-2.9 Mt), and 17-27 Mt of soybean (+1.5-1.9 Mt). We calculate that South Asia will experience the greatest additional wheat CPL in this scenario, but the magnitude is greatly reduced compared to the A2 future (mean estimate of +6.4 Mt as opposed to +19 Mt). The same is true for additional maize and soybean CPL in East Asia, where increases over year 2000 estimates are projected to be +2-3 Mt for each crop (metric averages) (Table S8). Notably, production gains of 5-6 Mt of soybean, maize, and wheat are projected in North America due to reductions in O₃ precursors anticipated under the B1 scenario (Table 5). Thus, relative to 2000, developed countries experience modest yield and crop production gains in the optimistic B1 future, while developing countries suffer higher crop losses due to increased O₃ pollution (although these losses are not as severe as predicted for the A2 scenario).

As in the A2 future, wheat CPL is greatest in India (6.9-35 Mt) and China (3.0-24 Mt), followed by the U.S. (1.6-5.3 Mt). Overall soybean CPL is expected to be highest in the U.S. (7.3-12 Mt), followed by China (6.2-6.5 Mt) and Brazil (0.9-4.6 Mt). Finally, maize CPL is projected to be highest in China (6.9-13 Mt) and the U.S. (3.7-11 Mt), followed by India (0.7-1.4 Mt). Global CPL for all three crops totals 84-137 Mt (Table SM 9), approximately 10% greater than our mean year 2000 estimate (Avnery et al., 2011; Chapter 2). We estimate global EL in the B1 scenario to total $12-21 billion USD₂₀₀₀ annually, an increase in O₃-induced damages of +$1-3 billion from the year 2000. The majority of the economic losses are expected to occur in
China ($4.1 billion, an increase in losses of +$1.1 billion from the year 2000), India ($3.4 billion, +$0.9 billion), and the U.S. ($2.5 billion, -$0.6 billion). The U.S., Italy, Japan, and Canada experience monetary gains as compared to the year 2000 due to crop production improvements resulting from decreases in surface O$_3$, although gains in the U.S. are an order of magnitude greater than those of other industrialized nations (Fig. 18). It is important to highlight the fact that despite crop recovery in the U.S. under the B1 scenario, this nation is still among the top three in terms of CPL for each major crop, and is further the third greatest economic loser due to O$_3$-induced crop losses.

6. Discussion

4.1. Uncertainties

In our companion paper (Avnery et al. (2011), Chapter 2), we provided a detailed review of the most important sources of uncertainty associated with the integrated assessment approach we use for our analysis (for brevity, only new sources of uncertainty are highlighted here). A major source of uncertainty is the ability of a global CTM to accurately simulate hourly surface O$_3$ concentrations to calculate crop losses. Predicting future O$_3$ concentrations is more difficult because of: 1) uncertainty of future emissions of O$_3$ precursors; 2) inability to use surface observations to evaluate and bias-correct model simulations; and 3) potential feedbacks between climate change and O$_3$ concentrations over the next few decades that are not accounted for by CTMs. We attempt to address the first of these uncertainties by constraining potential future yield losses with optimistic and pessimistic projections of O$_3$ precursor emissions from the widely-used IPCC SRES scenarios (Nakićenović et al., 2000). Although we cannot perform a model evaluation with surface observations from the year 2030, we use as a proxy bias-correction factors derived from observations in the years 1998-2002 and the year 2000
simulation (Avnery et al., 2011; Chapter 2), as we expect similar regional biases in our future simulations. Finally, while future predictions of \(O_3\) will be complicated by the potential feedbacks between climate change and ozone, as changes in temperature, precipitation, atmospheric circulation, and other local conditions can affect ozone concentrations that can in turn impact local and regional climate (e.g. Brasseur et al., 2006; Levy et al., 2008; Wu et al., 2008, Jacob and Winner, 2009; Ming and Ramaswamy, 2009), we expect any changes in \(O_3\) concentrations and distributions due to such feedbacks to be of second order compared to those driven by anthropogenic emissions of ozone precursors.

Climate change may also influence our estimates of future crop yield reductions through altering stomatal conductance: increased temperatures and atmospheric \(CO_2\) concentrations and decreased humidity and soil water content may reduce stomatal openings and therefore the amount of \(O_3\) that enters plant leaves (Mauzerall and Wang, 2001; Fuhrer et al., 2009). In non-irrigated agricultural areas prone to water stress, this effect may be especially significant and may mitigate projected ozone damage. Additionally, climate change may directly impact crop yields through changes in temperature, precipitation patterns, and \(CO_2\) fertilization—however, little is known about the combined effect of climate change and \(O_3\) pollution on agriculture. To investigate this issue, Reilly et al. (2007) use the MIT Integrated Global Systems Model, which includes an updated version of the biogeochemical Terrestrial Ecosystem Model (TEM) that simulates the impact of both climate change and surface ozone on plant productivity. The authors find that while the effects of climate change are generally positive in mid- to high latitudes, ozone pollution may more than offset potential climate benefits. For example, yield gains of 50-100% are predicted for some regions in the year 2100 when only climate impacts are considered, but inclusion of the model’s \(O_3\) damage function produces drastic yield reductions:
combined climate and O₃ effects reduce yields by 43% in the U.S., 56% in Europe, 45% in India, 64% in China, and 80% in Japan. These results underscore the imperative for field studies that examine the combined impact on agricultural production of climate change and surface O₃ in order to evaluate model-based studies and to identify crop cultivars that are relatively robust to both O₃ and climate change.

Finally, climate change can indirectly affect our estimates of O₃-induced crop yield reductions through its impact on crop growing seasons and crop distributions, which we assume to be the same in our year 2030 analysis as the year 2000. We also do not account for potential adaptation measures farmers may embrace to maximize crop yields in the face of a changing climate or O₃ pollution, such as altering planting/harvesting dates, application of additional fertilizer/water through irrigation, or the development of new cultivars and irrigation infrastructure. Future work should account for potential adaptation through the use of a state-of-the-art agro-economic model, and should also consider feedbacks between crop yields, production areas, and commodity prices to generate a more accurate estimate of the economic cost of agricultural losses.

We compare our results with those of similar studies which calculate future RYL, CPL, and EL in the Supplementary Material. Despite differences in datasets, methodologies, model chemistry, and model simulations used among the studies, our results agree well with existing estimates of future O₃-induced crop losses and add to the literature by providing a broader range of possible future emissions of ozone precursors and their implications for global agricultural yields.

4.2. Policy Implications
Between 2000 and 2030 global population is projected to increase from approximately 6 to over 8 billion persons (US Census Bureau, 2010), with global agricultural demand expected to double due to population growth, rising demand for biofuels, and increased meat consumption particularly in developing nations (Tilman et al., 2002; Edgerton, 2009). To meet this future demand, we will need to either bring new terrain under cultivation, or increase productivity (i.e. yields) on existing agricultural land. The latter option is preferable in order to preserve remaining natural ecosystems and prevent the associated loss of biodiversity and increased greenhouse gas emissions. However, improving yields on land currently cultivated through traditional strategies—i.e., increasing agricultural inputs (water, fertilizer, pesticides)—also has detrimental environmental consequences (Tilman et al., 2001). Furthermore, research suggests that in the absence of bioengineering, the historical rate of crop yield improvements experienced since the Green Revolution is declining in many parts of the world, and that the genetic ceiling for maximal yield potential is being approached despite increasing inputs (Peng et al., 1999; Duvick et al., 1999; Tilman et al., 2002). Ozone mitigation provides a means to increase this “ceiling” and the efficiency by which crops use nitrogen, water, and land. Moreover, with mounting evidence that crop yield improvements from CO₂ fertilization may not be as great as previously expected (Long et al., 2005) and that O₃ pollution may more than offset even significant crop yield gains due to climate change in some regions (Reilly et al., 2007), surface O₃ abatement provides a critical opportunity to increase supplies of food and fuel without further environmental degradation. Because tropospheric ozone is a potent greenhouse gas in addition to a noxious air pollutant (Forster et al., 2007), O₃ reductions would also provide numerous co-benefits to climate and human health (West et al., 2007; Fiore et al., 2008, Anenberg et al. 2010). Ozone abatement measures could further benefit climate in the absence of an explicit climate
change mitigation policy, since many O$_3$ precursors are emitted by the same sources as CO$_2$ and other long-lived greenhouse gases.

5. Conclusions

In this study we estimated the global risk to three key staple crops (soybean, maize, and wheat) of surface ozone pollution in the near future (year 2030) using simulated O$_3$ concentrations under two scenarios of projected O$_3$ precursor emissions (the IPCC SRES A2 and B1 storylines), two metrics of O$_3$ 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 for the A2 scenario, global year 2030 relative yield loss of wheat ranges from 5.4-26% (a further reduction in yield of +1.5-10% from year 2000 values), 15-19% for soybean (+0.9-11%), and 4.4-8.7% for maize (+2.1-3.2%), with total crop production losses worth $17-35 USD$_{2000}$ annually (+$6-17 billion in losses). In the B1 scenario, we estimate that global relative yield loss totals 4.0-17% for wheat (a decrease in yield of +0.1-1.8% from year 2000 values), 9.5-15% for soybean (+0.7-1.0%), and 2.5-6.0% for maize (+0.3-0.5%), with total losses worth $12-21 billion annually (+$1-3 billion). Our crop production and economic loss estimates should be considered conservative given their derivation from observation-based, year 2000 crop production data that likely underestimate actual agricultural production in the year 2030.
References


**Figures**

**Figure 9.** Global distribution of O₃ exposure according to the M12 (left panels) and AOT40 (right panels) metrics under the 2030 A2 scenario during the respective growing seasons in each country (where crop calendar data are available) of (a) soybean, (b) maize, and (c) wheat. Minor producing nations not included in this analysis (where growing season data were unavailable) together account for <5% of global production of each crop. Values in the U.S. have been corrected using observation data as described in Section 2.1.
Figure 10. Global distribution of O$_3$ exposure according to the M12 (left panels) and AOT40 (right panels) metrics under the 2030 B1 scenario during the respective growing seasons in each country (where crop calendar data are available) of (a) soybean, (b) maize, and (c) wheat. Minor producing nations not included in this analysis (where growing season data were unavailable) together account for $<$5% of global production of each crop. Values in the U.S. have been corrected using observation data as described in Section 2.1.
Figure 11. National relative yield loss under the 2030 A2 scenario according to the M12 (left panels) and AOT40 (right panels) metrics for (a) soybean, (b) maize, and (c) wheat.
Figure 12. National relative yield loss under the 2030 B1 scenario according to the M12 (left panels) and AOT40 (right panels) metrics for (a) soybean, (b) maize, and (c) wheat.
Figure 13. Total crop production loss (CPL, left panels) and economic loss (EL, right panels) under the 2030 A2 scenario for all three crops derived from (a) M12 and (b) AOT40 estimates of O₃ exposure.
Figure 14. Change in crop production loss (CPL, million metric tons) for the ten countries with highest absolute difference in estimated mean CPL between 2000 and 2030 under the A2 scenario using the M12 and AOT40 metrics for (a) soybean, (b) maize, (c) wheat, and (d) total CPL.
Figure 15. Change in economic loss (EL, million USD\textsubscript{2000}) for the ten countries with highest absolute difference in estimated mean EL between 2000 and 2030 under the A2 scenario using the M12 and AOT40 metrics for (a) soybean, (b) maize, (c) wheat, and (d) total EL.
Figure 16. Total crop production loss (CPL, left panels) and economic loss (EL, right panels) under the 2030 B1 scenario for all three crops derived from (a) M12 and (b) AOT40 estimates of O₃ exposure.
Figure 17. Change in crop production loss (CPL, million metric tons) for the ten countries with highest absolute difference in estimated mean CPL between 2000 and 2030 under the B1 scenario using the M12 and AOT40 metrics for (a) soybean, (b) maize, (c) wheat, and (d) total CPL.
Figure 18. Change in economic loss (EL, million USD2000) for the ten countries with highest absolute difference in estimated mean EL between 2000 and 2030 under the B1 scenario using the M12 and AOT40 metrics for (a) soybean, (b) maize, (c) wheat, and (d) total EL.
### Tables

Table 5. Scaling factors used with the 1990 base emissions in MOZART-2 to obtain year 2030 anthropogenic emissions under the A2 and B1 scenarios (Nakićenović et al., 2000).

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Table 6. Concentration:response equations used to calculate relative yield losses of soybean, maize, and wheat. \( RY \) = relative yield as compared to theoretical yield without O\(_3\)-induced losses. Relative yield loss (RYL) is calculated as \((1 – RY)\). See Section 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 O\(_3\)-induced wheat yield and crop production losses.
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**Table 7.** Estimated year 2030 regional relative yield loss (%) due to O₃ exposure under the A2 scenario according to the M7, M12 and AOT40 metrics and the metric average.

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**Table 8.** Estimated year 2030 regional relative yield loss (%) due to O₃ exposure under the B1 scenario according to the M7, M12 and AOT40 metrics and the metric average.
Supplementary Material

Comparison with previous work

We compare our results with those of similar studies which calculate RYL, CPL, and EL in the near future. VD2009 use the M12 and AOT40 metrics of O₃ exposure in the year 2030 under the “current legislation scenario” (CLE), which assumes that all currently approved air pollution regulations will be fully implemented and enforced by 2030. Wang and Mauzerall (2004) (hereafter WM2004) use the M7, M12, and two cumulative metrics not implemented here to calculate crop losses in East Asia (China, Japan, and South Korea) in the year 2020 under the IPCC B2 scenario, which lies in between the A2 and B1 storylines in terms of Asian anthropogenic emissions of reactive trace gases (Nakićenović et al., 2000). VD2009 only report year 2030 crop loss results in terms of the change in RYL, and their optimistic CLE scenario is closest to our B1 simulation. Globally, VD2009 find an increase in RYL for wheat, soybean, and maize of +4%, +0.5%, and +0.2%, respectively, compared to our (B1) mean estimates of +1.0%, +0.8%, and +0.4%. Similar to our results, VD2009 also find that North America and the EU 25 experience stabilization or improvement of yields in 2030, with the greatest additional losses occurring in the Indian subcontinent. WM2004 project much more significant yield reductions in the near future than VD2009 (who report a yield improvement of ~2.5% for Chinese wheat and only marginally increased reductions for the other crops). According to the M7/M12 metric, WM2004 find that year 2020 wheat yield losses in China range from 2-7% depending on the growing season, soybean RYL totals 33%, and maize 16%. Our values match these extremely well (ranges represent the B1 and A2 M7/M12 values, respectively): 3-4% wheat, 31-35% soybean, and 10-13% maize. In South Korea, WM2004 find year 2020 wheat, soybean, and maize RYL to be 8%, 35%, and 4%, respectively, while our RYL estimates are 4%
for wheat, 28-31% for soybean, and 8% for maize. Finally, WM2004 estimate Japanese RYL to be 9% for wheat and 28% for soybean (maize is not a major crop in Japan), while our projections are 5-6% for wheat and 23-27% for soybean. Thus despite the differences in datasets, methodologies, model chemistry, and model simulations, our results agree very well with existing estimates of future O₃-induced crop losses and add to the literature by providing a broader range of possible future emissions of ozone precursors and their implications for global agricultural yields.
Figure SM 4. Global distribution of the change in O₃ exposure (2030 – 2000) under the A2 scenario 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. Minor producing nations not included in this analysis (where growing season data were unavailable) together account for <5% of global production of each crop. Values in the U.S. have been corrected using observation data as described in Section 2.1.
Figure SM 5. Global distribution of the change in O₃ exposure (2030 – 2000) under the B1 scenario 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. Minor producing nations not included in this analysis (where growing season data were unavailable) together account for <5% of global production of each crop. Values in the U.S. have been corrected using observation data as described in Section 2.1.
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**Table SM 4.** Estimated change in regional relative yield loss (%) (year 2030 – 2000) under the A2 scenario according to the M7, M12 and AOT40 metrics and the metric average.

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**Table SM 5.** Estimated change in regional relative yield loss (%) (year 2030 – 2000) under the B1 scenario according to the M7, M12 and AOT40 metrics and the metric average.
Table SM 6. Estimated change in regional crop production loss (million metric tons) (year 2030 – 2000) under the A2 scenario according to the M7, M12, and AOT40 metrics and the metric average.

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Table SM 7. Estimated year 2030 regional crop production loss (million metric tons) due to O₃ exposure under the A2 scenario according to the M7, M12 and AOT40 metrics and the metric average.

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Table SM 8. Estimated change in regional crop production loss (million metric tons) (year 2030 – 2000) under the B1 scenario according to the M7, M12, and AOT40 metrics and the metric average.

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Table SM 9. Estimated year 2030 regional crop production loss (million metric tons) due to O₃ exposure under the B1 scenario according to the M7, M12 and AOT40 metrics and the metric average.

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Chapter 4

Improving Global Agricultural Production by Reducing Ozone Damages to Crops via Methane Emission Controls and Ozone Resistant Cultivar Selection

Abstract

Meeting the projected 50% increase in global grain demand from 2010 to 2030 without further environmental degradation poses a major challenge for agricultural production. Because surface ozone (O₃) has a significant negative impact on crop yields, one way to increase future production is to reduce O₃-induced agricultural losses. We present two strategies whereby O₃ damage to crops may be reduced. We first examine the potential benefits of an O₃ mitigation strategy motivated primarily by climate change goals: gradual emission reductions of methane (CH₄), an important greenhouse gas and a precursor to tropospheric background O₃ that to date has not been targeted for O₃ pollution abatement. Our second strategy focuses on adapting crops to O₃ exposure: we estimate the potential benefits of selecting crop cultivars with demonstrated O₃ resistance relative to median-sensitivity varieties. We find that the CH₄ reductions considered would increase global production of soybean, maize and wheat by 23-102 Mt in 2030 – the equivalent of a ~2-8% increase in year 2000 production worth $3.5-15 billion worldwide (USD2000). Choosing crop varieties with the greatest demonstrated O₃ resistance could improve

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7 A similar version of this chapter was submitted as a research article (with Denise L. Mauzerall and Arlene M. Fiore) and is currently under review.
global agricultural production in 2030 by 143 Mt, the equivalent of a 12% increase in year 2000 production worth ~$22 billion. Combining these two strategies would yield the greatest gains to agriculture, although benefits are less than fully additive given the nature of O₃ effects on crops. Our results demonstrate the significant potential to improve global agricultural production without further environmental degradation by reducing O₃-induced crop yield losses.

1. Introduction

From 2010 to 2030 the demand for grain is expected to increase globally by 50% (1, 2) due to an increase in global population of roughly 1.4 billion people (3), a shift to a more diverse, animal protein-rich diet associated with rising living standards; and the expansion of global biofuel production. Agricultural production has historically kept pace with surging demand primarily by improving yields on existing farmland through increasing water, fertilizer, and pesticide application and employing other technologies associated with the Green Revolution (4). However, the prospects for meeting future global grain demand via agricultural intensification (i.e. yield improvements) on land already under cultivation are uncertain. The yield growth rates of some key staple crops have been stagnant or declining over the last few decades in many parts of the world, especially in South and East Asia (2, 5, 6). In the absence of yield improvements, meeting the rising global food demand of the future will likely require an increase in farmland area – leading to the loss of biodiversity and potentially tremendous emissions of carbon. For example, recent work estimates that without the historic yield increases of the past half century, present-day agricultural demand would have required cropland expansion of 1,761 million hectares (an area approximately the size of Russia), with resulting emissions of up to 161 gigatons of carbon (GtC, 1 GtC = 10⁹ metric tons) (4).
Although yield improvements are thus generally preferable to increasing crop production area from a biodiversity and a climate perspective, traditional means of agricultural intensification also have damaging environmental impacts associated with irrigation, chemical application, and other farming practices (5, 7, 8). As such, meeting the agricultural demand of over 8 billion people in 2030 without increasing environment stress requires new approaches beyond cropland expansion and the traditionally employed portfolio of yield improvement strategies.

One way to improve agricultural production without negative environmental consequences is by reducing the damage – and associated yield reductions – caused by crop exposure to surface ozone (O$_3$). O$_3$ is a major component of smog and a potent greenhouse gas (GHG) produced in the troposphere by photochemical reactions between nitrogen oxides (NO$_x$ = NO + NO$_2$), carbon monoxide (CO), methane (CH$_4$), and non-methane volatile organic compounds (NMVOCs) (9). In addition to having a detrimental effect on human health (10-12), O$_3$ has been found to be the air pollutant most damaging to vegetation (13, 14), including crops. Recent studies estimate that the global yields of key staple crops are being reduced by 2-15% due to present-day ozone exposure (15-18), and that ozone-sensitive crops could see a further 10% decline in yields by 2030 if global O$_3$ precursor emissions continue to increase (19) (see Chapters 2-3). Although O$_3$ reductions via mitigation of conventional pollutant precursors (NO$_x$, CO, and NMVOCs) would prevent significant additional future yield reductions (18, 19), even with aggressive emission controls global year 2030 losses could remain substantial – particularly for O$_3$-sensitive crops (e.g. up to 17% globally for wheat with considerable regional variability) (19). It is therefore worthwhile to explore supplemental strategies to reduce O$_3$-induced crop losses beyond the targeting of traditional short-lived O$_3$ precursors.
Here we investigate two such supplemental strategies to decrease O₃ damage to crops and thereby improve agricultural yields. Our first strategy focuses on reducing surface O₃ concentrations – and resultant crop exposure to O₃ – via methane abatement (we hereafter refer to this scenario as our “mitigation” strategy). CH₄ is the second most important GHG after carbon dioxide (9) and has not typically been targeted for air quality purposes despite being a long-lived O₃ precursor that contributes to global background O₃ concentrations (20). CH₄ abatement therefore provides an attractive “win-win” policy opportunity for both climate change and air pollution mitigation goals, as CH₄ controls would reduce radiative forcing of climate while simultaneously achieving the health and agricultural benefits associated with surface O₃ reductions. Here we quantify the crop production improvements possible with a policy of methane controls (described in Section 2.1) relative to the “current legislation” (CLE) emissions baseline. Under CLE global anthropogenic CH₄ emissions are projected to increase by 35% between 2000 and 2030 while existing legislation controlling the emissions of traditional air pollutants is assumed to be perfectly implemented (21, 22).

The second strategy we explore to reduce O₃-induced agricultural losses focuses on adapting crops to elevated levels of O₃ via cultivar selection (we hereafter refer to this as our “adaptation” policy). Large-scale, comprehensive field studies that took place primarily in the U.S. and Europe in the 1980s/90s established the existence of a wide range of crop sensitivity to ozone, both among different crops and within cultivars of the same crop (13, 14, 23). Crop varieties used today appear to exhibit sensitivity to ozone that is on average at least as great as that seen in earlier field studies (24-29), suggesting that O₃ sensitivity may be an overlooked factor in cultivar choice. To draw attention to this issue, we here estimate the amount by which crop production could potentially be improved by cultivating crop varieties with the greatest
demonstrated O₃ resistance (from large-scale U.S. field studies) relative to “median sensitivity” cultivars in 2030 CLE (i.e. a future scenario where no new climate or ozone abatement measures are implemented over the next few decades). Finally, we combine these two strategies to estimate the extent to which agricultural production could be improved by both CH₄ emission controls and careful cultivar selection. We therefore explore two different strategies to reduce the detrimental impact of O₃ on crops – one based on mitigating O₃ concentrations and corresponding agricultural damages through controls on methane emissions, and one based on adapting crops to elevated levels of O₃ exposure – and their combined effectiveness in order to demonstrate the potential of two complementary methods to improve global food production without further harming the environment.

2. Results

2.1 Reducing Crop Exposure to Surface Ozone with Methane Mitigation

We use the MOZART-2 global chemical transport model (CTM) (30) to project the response of surface O₃ to future CH₄ emissions from 2000-2030 under the CLE and the reduced CH₄ (CH₄-red) scenarios (see Methods Summary). In the CLE scenario, global anthropogenic emissions of CH₄, NOₓ, CO, and NMVOC change by +29% (+96 Mt CH₄ yr⁻¹), +19% (+5.3 Mt N yr⁻¹), -10% (-44 Mt CO yr⁻¹), and +3% (+3 Mt C yr⁻¹), respectively, from 2005 to 2030 (21, 22, 31). We utilize simulations for the CH₄-red scenario from (31), where methane controls begin in 2006 and gradually increase to 125 Mt yr⁻¹ by 2030 relative to the CLE baseline, representing a ~29% reduction in global anthropogenic year 2030 CH₄ emissions. Anthropogenic CH₄, defined as emissions originating from the agricultural and industrial sectors, contributes ~0.7 Wm⁻² to climate forcing (including O₃ forcing) and 4 ppbv to surface O₃ in year 2030 CLE (31).
We calculate the difference (CLE – CH4-red) in year 2030 crop exposure to O₃ using two metrics (AOT40 and W126) that are used by policymakers in Europe and the U.S., respectively, to set standards for the protection of sensitive vegetation (see Methods Summary). These indices (defined below) were derived from large-scale field studies and characterize the pattern of O₃ exposure during crop growing seasons:

\[
AOT40 \text{ (ppmh)} = \sum_{i=1}^{n} ([Co_3]_i - 0.04) \quad \text{for } Co_3 \geq 0.04 \text{ ppmv}
\]

\[
W126 \text{ (ppmh)} = \sum_{i=1}^{n} w_i [Co_3]_i \quad \text{for } w_i = 1/(1+4403 \exp(-126[Co_3]_i)}
\]

where:

- \([Co_3]_i\) is the hourly mean O₃ concentration during local daylight hours (8:00 – 19:59); and
- \(n\) is the number of hours in the 3-month growing season (defined in the Methods Summary).

Global land-based average and crop production-weighted AOT40 and W126 during crop growing seasons are listed in Table 9 for year 2005 (i.e. before methane reductions occur) and 2030 for the CLE and CH₄-red scenarios. For all three crops, global average land-based AOT40 is higher than the European “critical level” for the protection of agriculture (3 ppmh) (32) in 2005 and for both 2030 scenarios, with production-weighted AOT40 well-above this level (10-12.8 ppmh in 2005, rising to 11.3-15.7 ppmh in 2030). Global average W126 in 2005 is below the proposed secondary O₃ standard range in the U.S. (7-15 ppmh) for all crops (although this proposal for a unique secondary O₃ standard was recently withdrawn and will be revisited in 2013) (33). Global average soybean- and maize-season W126 is also below the proposed standard in 2030 CLE, but wheat-season W126 is within the range. However, production-
weighted W126 values are much higher, with W126 in 2030 CLE rising well-above the proposed secondary standard range (15.7-19.5 ppmh).

The spatial pattern of surface O₃ exposure changes as calculated by AOT40 and W126 is similar to the annual average tropospheric O₃ change (31), with the greatest reduction in O₃ generally occurring from 0-30°N plus the southern Mediterranean (Fig. 19). Methane controls reduce global year 2030 O₃ exposure by the greatest amount during the wheat growing season (9.1-11.9%, depending on the metric) due to the coincidence of this crop’s growing regions with locations where the O₃ response to CH₄ controls is greatest (particularly India, Pakistan, Turkey, eastern China, and parts of the U.S.) (see (31), Figs. 19 and SM 6). The response of surface O₃ to CH₄ is primarily determined by the distribution of the shorter-lived species governing O₃ production from CH₄ oxidation (e.g. OH and NOₓ) and is strongest where the local O₃ formation regime is NOₓ-saturated and where surface air mixes frequently with the free troposphere (20, 31, 34, 35). Maize-season exposure is reduced by 8.9-10.6% and soybean exposure is reduced by 7.9-9.7% under the CH₄-red scenario. The largest reductions in soybean exposure occur in the U.S., China, India, and Pakistan (up to ~2.9 and 5.2 ppmh according to AOT40 and W126, respectively) (Fig. 19), and maize exposure is reduced substantially in the above countries plus Turkey, the southern Mediterranean, and parts of the Democratic Republic of Congo (up to ~2.9 and ~6 ppmh).

2.2. Year 2030 Crop Production Gains due to Methane Mitigation

For each O₃ exposure metric and crop cultivar, concentration:response (CR) functions have been obtained by fitting linear, quadratic, or Weibull functions to the yields of crops grown under different levels of O₃ (13, 14, 23, 36). We follow previous studies (15, 18, 19, 37) and use CR functions with median parameter values pooled from a variety of cultivars grown in the U.S.
and Europe to represent the median (baseline) sensitivity of each crop to O₃, as no single CR relationship can accurately represent the response of all crop cultivars grown worldwide. Using simulated values of O₃ exposure (Fig. 19) and these CR relationships (Table SM 10), we calculate the relative yield loss (compared to a theoretical yield assuming no O₃ damage) of soybean, maize, and wheat in 2030 according to the CLE and CH₄-red scenarios. We then convert estimated yield losses (%) into crop production losses (CPL; defined in Mt) for each scenario (see Methods Summary), and calculate the improvement in year 2030 agricultural production as the difference in CPL between the CLE and CH₄-red scenarios.

We find that total (soybean, maize, and wheat) year 2030 CPL is projected to range from 224-243 Mt and 122-220 Mt under the CLE and CH₄-red scenarios, respectively, depending on the metric and CR relationship (Table 10). CPL is dominated by wheat in both scenarios, accounting for 77-85% of global losses of all three crops (Table 11). The controls on anthropogenic methane examined here would lead to a substantial change in CPL (i.e. crop production (CP) gains) of 23-102 Mt (Table 10), with over 85% of the CP improvements due to wheat yield increases. Specifically, we project relatively small gains in soybean and maize production in 2030 (~2-3 Mt each, an increase of ~1% from year 2000 values), but much larger improvements for wheat (19-97 Mt, the equivalent of a 3.7-19% increase in year 2000 production) (Table 11). The methane controls in the CH₄-red scenario could increase the combined year 2030 global production of soybean, maize and wheat by 2.0-8.3% relative to 2000 values, worth $3.5-15 billion (all economic benefits are in USD$_{2000}$). These CP gains due to CH₄ mitigation represent the prevention of 10-45% of the O₃-induced crop production losses that are otherwise projected to occur in 2030 CLE (Tables 10 and 12). CP improvements due to CH₄ mitigation represent a substantial increase from year 2000 production in many regions of the
world, particularly South Asia and parts of the Middle East (Fig. 20) where the O₃ response to CH₄ reductions is greatest (31, 38).

Economic benefits (see Methods Summary) are concentrated in regions of major production, primarily the U.S., China, and India. South Asia is projected to experience the greatest economic benefit, driven by improvements in yields of O₃-sensitive wheat: ~7-91 Mt worth ~$1.1-14 billion (Table 10). We note, however, that because 2030 CLE O₃ exposure in this region is based on significant projected growth of O₃ precursor emissions from 2005-2030 – e.g. NOₓ (~x2) and CH₄ (~x1.3) (22) – recently introduced and future emission control legislation may lead to lower O₃ levels than predicted here (18). The estimated benefit of CH₄ mitigation may therefore be overly optimistic in this region. East Asia is estimated to experience significant gains (4.6-5.3 Mt) from CH₄ mitigation due primarily to soybean production improvements worth $600-700 million in 2030. North American CP gains are driven primarily by O₃ reductions that occur during the soybean and maize growing season (Fig. 19). These gains are expected to increase CP by 3.7-4.1 Mt with a value over $400-500 million in the year 2030 (Table 10).

Previous estimates of the economic benefits of CH₄ mitigation have accounted for the value of recovered methane and the averted adverse human health effects of O₃ reductions (34, 35), but we provide an estimate of the agricultural benefits over the period of CH₄ control (2006-2030) absent from current cost-benefit analyses of methane reduction policies (see Methods Summary). Global marginal benefits for agriculture in 2030 (calculated here as the global year 2030 economic benefit (Table 10) divided by the methane reductions in 2030 (125 Mt) and discounted at 5% yr⁻¹) are estimated to be $8.20-36 per ton CH₄ reduced (depending on the metric). We find the present value of agricultural gains through 2030 to be $17-75 billion
USD$_{2000}$ (amortized to $1.2$-$5.3$ billion yr$^{-1}$), substantially increasing the cost-effectiveness of this policy of CH$_4$ mitigation.

2.3. Explaining differences in estimates of crop production improvement

The large discrepancy between global AOT40- and W126-derived estimates of potential CP improvements is driven by the different projected wheat CPL in the CH$_4$-red scenario, the majority of which occurs in the Indian subcontinent as previously highlighted (Tables 10-11). One reason for this discrepancy is the different value of the O$_3$ exposure reduction estimated by each metric. W126 accounts for hourly O$_3$ across the spectrum of concentrations rather than solely O$_3$ levels above 40 ppbv, and methane reductions decrease O$_3$ across the whole distribution of O$_3$ concentrations by a similar increment (20, 34). More important, however, are the different weights assigned to hourly O$_3$ concentrations above ~60 ppbv that are incorporated into the cumulative metric calculations (Fig. SM 7). AOT40 simply subtracts 40 ppbv from any hourly O$_3$ concentration above 40 ppbv and accumulates the total hourly exposure above this level – therefore the difference between two hourly O$_3$ concentrations and between the same two “weighted” hourly O$_3$ concentrations is always the same for concentrations above 40 ppbv. For example, the difference in accumulated weighted exposure is 20 ppbh for hourly O$_3$ concentrations of 80 and 60 ppbv or for 60 and 40 ppbv. Due to the nonlinear weighting function of W126, however, hourly O$_3$ concentrations reduced from 80 to 60 ppbv produce a much larger weighted difference than that calculated by AOT40 (47.5 rather than 20 ppbh), and the discrepancy is greatest for hourly O$_3$ changes within the range of 60-80 ppbv (i.e. along the steepest part of the W126 weighting curve) (Fig. SM 8). This occurs in the Indian subcontinent, where O$_3$ exposure as defined by W126 is reduced by 7.6 ppmh (~18%; Fig. 19) under the CH$_4$-red scenario, but AOT40 is only reduced by 1.3 ppmh (~5%). The greater change in O$_3$ exposure
projected by the W126 metric, combined with the steep slope of the W126 CR relationship for wheat at these high levels of O₃ exposure (Fig. SM 8) and the large amount of wheat grown in the Indian subcontinent (Fig. SM 6), leads to substantially greater projected crop production improvements in India when calculated by W126 rather than AOT40.

2.4.  Year 2030 Crop Production Gains due to Cultivar Selection

We use the W126 metric to quantify the potential year 2030 benefits of selecting soybean, maize, and wheat cultivars with the greatest demonstrated tolerance to ozone (i.e. minimum sensitivity varieties) relative to “median sensitivity” cultivars, which as previously described have been applied globally as an approximation of baseline crop sensitivity (15, 18, 19, 37). We refer to these two cases as CLEₘₑｄ and CLEₘᵢₙ. We analyze only W126 here because although crops grown in European field studies demonstrated variability in O₃ sensitivity, no statistically significant differences were found in the slope of the AOT40 regression lines characterizing crop response to O₃ for the individual cultivars (39, 40). Our results should be considered illustrative (rather than a definitive estimate) of the potential benefits of using crops with O₃ tolerance. However, our results are more than simply theoretical since our analysis is based on the actual range of O₃ sensitivity found in the comprehensive, large-scale US National Crop Loss Assessment Network (NCLAN) field studies (13, 14). We follow the same methods previously discussed (and detailed in the Methods Summary) to calculate CP gains, here defined as the difference between CPL in 2030 CLE derived from the two different parameterizations of the W126 CR function (CLEₘₑｄ – CLEₘᵢₙ).

We find that total (soybean, maize, and wheat) year 2030 CPL to be 81 Mt for CLEₘᵢₙ, an increase in production of 143 Mt from CLEₘₑｄ. This is the equivalent of an 11.7% improvement in year 2000 production and is projected to be worth ~$22 billion (Table 10). CP gains are once
again highest for wheat (Table 11): 122 Mt relative to \( \text{CLE}_{\text{med}} \) (an increase of ~24% from year 2000 production), representing the prevention of ~64% of the CPL otherwise projected to occur in 2030 (Table 11, columns 4 and 6). However, we project substantially greater increases in soybean and maize production when the \( \text{O}_3 \) resistant cultivar is chosen than with the policy of \( \text{CH}_4 \) control. By choosing a minimally sensitive cultivar, global soybean and maize CP would improve relative to 2000 by 8.0% and 1.6%, respectively, with total increases in these crops (~22 Mt) representing a 55-76% reduction in the losses expected to occur with a cultivar of median sensitivity in 2030 (Table 11, columns 4 and 6). For this reason, the adaptation strategy provides significantly greater benefits than methane mitigation in regions where soybean and maize are the primary sources of CPL (e.g. North America and East Asia) (Table 10, Fig. 21). CP gains are expected to be highest in the Indian subcontinent where the rise in \( \text{O}_3 \) is projected to be greatest under CLE from 2005 to 2030: \( \text{O}_3 \)-resistant crop cultivars (particularly for wheat) increase total CP by 111 Mt from \( \text{CLE}_{\text{med}} \), the equivalent of >90% of regional production in 2000 (Table 10). India and Pakistan would accrue the greatest economic benefit from \( \text{O}_3 \)-resistant cultivar selection (~$16 billion combined and ~74% of global economic benefits), followed by the U.S. ($2.5 billion) and China ($1.2 billion) (Fig. 21).

2.5. Year 2030 Crop Production Gains due to Methane Mitigation and Cultivar Selection

We follow the same approach outlined in Sections 2.2 and 2.4 to explore the benefits to agriculture of both mitigation and adaptation policies in 2030; in this case we compare W126 minimum sensitivity cultivars and the \( \text{CH}_4 \)-red scenario (hereafter \( \text{CH}_4 \)-red\(_{\text{min}} \)) with \( \text{CLE}_{\text{med}} \). Table 12 summarizes global crop production and economic benefits for each policy scenario we explore. We find that total (soybean, maize, and wheat) year 2030 CPL is projected to be 52 Mt for \( \text{CH}_4 \)-red\(_{\text{min}} \), representing an increase in global production of 172 Mt from \( \text{CLE}_{\text{med}} \). This is the
equivalent of a 14% increase in year 2000 production and is projected to be worth ~$26 billion (Table 10). Employing both mitigation and adaptation strategies would reduce ~77% of the O₃-induced CPL expected to otherwise occur in 2030 (relative to CLE_med), compared to a reduction in CPL of ~45% and 64% with mitigation and adaptation alone, respectively (Table 12). Wheat gains account for the majority of the total CP and economic improvements when both strategies are simultaneously applied (Table 11). For this reason, South Asia receives the greatest additional benefit from combining both mitigation and adaptation strategies (Table 10; Fig. SM 10). The added agricultural production arising from employing the adaptation strategy over solely CH₄ mitigation includes ~12, 8, and 51 Mt of soybean, maize, and wheat (Table 11, columns 5 and 7) worth ~$10.5 billion globally in 2030 (Table 10, column 8). Additional soybean, maize, and wheat production due to CH₄ abatement over that from cultivar selection alone is estimated to be ~0.3, 1.5, and 27 Mt, respectively, in 2030 (Table 11, columns 6 and 7) worth $4.3 billion globally (Table 10, columns 7 and 8). The benefits to agriculture of combining both strategies are less than fully additive because the benefits of adaptation are highest at elevated levels of O₃ exposure where the greatest damages to crops occur (evident from the shape of the W126 CR functions, Fig. SM 8).

3. Discussion

3.1 Major sources of Uncertainty

An important source of uncertainty in this study is the use of simulated hourly O₃ concentrations by a global CTM to predict future O₃ exposure. Although we are unable to evaluate model predictions with future surface observations, MOZART-2 and specifically the simulations used here have been extensively evaluated, with the model performing well overall
in the present (years 2000 and 2004) with few exceptions – notably a bias of >10 ppb in summer over the eastern U.S. and Japan (31, 38), a common bias in global models (38, 41).

Another major source of uncertainty stems from our reliance on CR relationships that were derived from field studies in the U.S. and Europe in the 1980s/90s, which we apply globally due to the lack of similar large-scale studies elsewhere. Crop cultivars currently used, particularly in other regions of the world, may have different sensitivities to O3 than those derived from previous studies. However, recent field research indicates that current crop sensitivity is at least as great as that found in earlier studies in the U.S. (24, 42), and that CR functions derived in North America and Europe in fact underestimate the effects of O3 on crop yields in Asia (26, 29).

Our calculation of monetized benefits for agriculture due to CH4 reductions and O3 resistant crop cultivar selection neglects future changes in commodity prices and in agricultural production. Because both will likely increase substantially over the next few decades in response to a growing population and the increasing use of biofuel, this simplification likely leads to an underestimate of O3-induced crop losses and therefore of the total agricultural and economic benefits of CH4 mitigation and cultivar selection. Furthermore, as our CH4-red simulation is not at steady state (see Methods Summary), O3 reductions due to CH4 controls would continue beyond 2030 – these benefits are not included in our analysis.

Changes in regional climate over the next few decades may affect O3 concentrations and distributions, but such changes are expected to be of second order compared to those driven by anthropogenic emissions of CH4 and other ozone precursors in most land regions (43). However, climate change may have a greater impact on O3-induced crop yield reductions through its affect on the stomatal conductance of O3 into plant cells. Increased temperatures and atmospheric CO2
concentrations and decreased humidity and soil water content in some regions may reduce stomatal openings and therefore the amount of \text{O}_3 \text{ that enters into plants and resulting damage (44, 45). As stomatal conductance is not accounted for by the O}_3 \text{ exposure metrics used here, we may overestimate O}_3 \text{-induced agricultural damages in non-irrigated, drier regions of the world (where water stress may induce stomatal closure), or those regions predicted to become drier in the next few decades (assuming no irrigation). Additionally, climate change may directly impact crop yields through changes in temperature, precipitation patterns, and CO}_2 \text{ fertilization, and little is known about the combined effect of climate change, elevated CO}_2 , \text{ and O}_3 \text{ pollution on agriculture (e.g. 24, 42, 45-47). Finally, our analysis does not account for the potential for farmer adaptation to climate change (e.g. via altering planting and harvesting dates, irrigation patterns, etc.), which may affect projections of O}_3 \text{-induced crop losses.}

3.2 \textit{Policy Implications}

In stark contrast to the gains in crop productivity made during the Green Revolution, studies suggest that growth in crop yields in many parts of the world have recently been in decline (2, 5, 6). Increasing evidence points to elevated levels of \text{O}_3 \text{ as an additional and extremely important (yet overlooked) factor in this deceleration of crop yield growth (15, 17, 18, 29, 37). Our current study follows earlier work which quantified the present and potential future (year 2030) impact of surface \text{O}_3 \text{ on the global yields of soybean, maize, and wheat given both upper- and lower-boundary projections of reactive \text{O}_3 \text{ precursor emissions (15, 19). In the latter study, (19) found substantial future yield losses globally for these crops even under a scenario of stringent \text{O}_3 \text{ control via traditional pollution mitigation measures (i.e. reductions in NO}_x , \text{ VOCs, and NMVOCs): 10-15\% for soybean, 3-9\% for maize, and 4-17\% for wheat.}}
Given the potential for significant future O₃-induced yield losses, in this study we present two additional strategies to reduce O₃ damages to crops beyond targeting traditional O₃ precursors – and thereby to increase future agricultural production without further harming the environment. Our first strategy focuses on O₃ mitigation through CH₄ control. Our second strategy centers on adaptation – in the event that O₃ concentrations remain elevated in the future, crop yields may still be increased by selecting existing (or breeding new) ozone-resistant cultivars. Although we find that the adaptation-only strategy may provide higher potential agricultural benefits than O₃ abatement through methane controls, as well as a larger share of the combined benefits of both mitigation and adaptation strategies, we do not suggest that cultivar selection is superior or that it should be pursued in lieu of O₃ mitigation. Ozone is detrimental to human health, and modest CH₄ controls could prevent over 370,000 premature mortalities via their surface ozone reductions through 2030 (35). In addition, the methane abatement policy examined here not only has cost-saving potential, but would also have major benefits for climate change by offsetting the positive net radiative forcing from CH₄ and O₃ projected to otherwise occur by 2030 (~0.16 Wm⁻²) (31). This radiative forcing measure furthermore does not account for the indirect climate benefits of CH₄ controls and corresponding O₃ reductions: the increased carbon storage potential in forests and other ecosystems that would arise from reduced O₃ exposure (48, 49). These indirect effects may have a greater effect on climate than the direct radiative forcing of tropospheric O₃ (50). O₃ mitigation via the methane reductions described here and elsewhere (31) should therefore be considered an effective strategy for long-term international air quality management with major climate change co-benefits, and should supplement local policies to reduce conventional O₃ precursors. Adaptive strategies such as cultivar selection should further supplement O₃ mitigation in order to maximize global crop
production, particularly in regions where agriculture is especially vulnerable to rapidly rising O₃ concentrations.

4. Conclusions

Elevated concentrations of surface ozone pose a significant present and potential future risk to crop production worldwide. In this paper we explore the possible benefit to agriculture of two strategies aimed at mitigating O₃-induced crop losses beyond reductions in traditional O₃ precursors: CH₄ controls and the use of O₃-resistant cultivar selection (as well as their combination) (Table 12). We find that the anthropogenic methane reductions examined here could yield global CP gains of ~2-8% in 2030 relative to year 2000 production, worth $3.5-15 billion in 2030 and $17-75 billion ($1.2-5.3 billion yr⁻¹) from 2006-2030. We further find that choosing cultivars with high O₃ resistance could increase year 2030 crop production by ~12% relative to year 2000, with an economic value of ~$22 billion. Combining both CH₄ mitigation and cultivar adaptation strategies could increase global CP by 14% from 2000, worth $26 billion worldwide (Table 12). O₃ mitigation and/or increasing ozone resistance among cultivated crop varieties therefore provide important opportunities to significantly increase future crop production without further environmental degradation. O₃ reductions via cost-effective methane controls could furthermore avert a substantial number of premature mortalities (35), as well as afford considerable co-benefits to climate by reducing the radiative forcing from CH₄ and O₃ projected to otherwise occur by 2030 (31).

5. Methods Summary

*MOZART-2 and model simulations.* We use multidecadal full-chemistry transient simulations of the MOZART-2 global CTM for the CLE and CH₄-red scenarios from 2000-2030,
with the period 2000-2004 used for spin up (31; the CH$_4$-red scenario here corresponds to their scenario B). See (31) for an evaluation of the simulations used here. Both simulations are driven by meteorological fields from the NCEP reanalysis (51) at 1.9° x 1.9° horizontal resolution with 28 vertical levels. The CLE and CH$_4$-red simulations are transient (i.e. not in steady state), such that the full benefits of the gradually increasing CH$_4$ reductions will not be realized by 2030 due to the relatively long lifetime of methane (~11 years). The “effective CH$_4$ emissions control” in year 2030, which represents the change in CH$_4$ emissions that would produce a steady state response equal to the transient response in 2030, corresponds to 76 Mt CH$_4$ yr$^{-1}$, or ~61% of the total CH$_4$ emission reductions implemented by 2030 (31).

Year 2030 Crop Production and Economic Gains. Open top chamber (OTC)-derived CR functions predict the relative yield (RY) of a crop at a given level of O$_3$ exposure (defined by AOT40 or W126) during the 3-month growing season (13, 14, 23). Following previous studies (15, 18, 19), “growing season” is defined here as the three months prior to the start of the harvest period in every country according to crop calendar data from the United States Department of Agriculture (USDA) (52, 53) where data are available (accounting for over 95% of global production). The AOT40 index is favored in Europe as the exposure-based metric that most accurately predicts the yield response of local cultivars, which is highly correlated with cumulative O$_3$ exposure above a threshold of 40 ppbv (23). W126 was derived from U.S. field studies and uses a sigmoidal function to assign greater weight to higher levels of hourly O$_3$ concentrations with an inflection point at ~65 ppbv (54). The CR relationship for the AOT40 metric is linear, while the W126 index has a Weibull form (Fig. SM 7, Table SM 10). Because robust CR data are lacking for Asia, Africa, and South America, we apply the CR functions from the U.S. and Europe globally.
Using $O_3$ exposure values in every grid cell for each metric and CR relationship (Fig. 19; Table SM 10), we calculate $RY$ and subtract this value from unity (representing a theoretical yield without $O_3$ damage) to calculate relative yield loss ($RYL$). We then use satellite-based crop distribution maps (55, 56) (Fig. SM 7), which contain mean crop production ($CP$) data per grid cell over the period 1997-2003, to convert grid cell $RYL$ (%) to $CPL$ (Mt) according to:

$$CPL_i = \frac{RYL_i}{1 - RYL_i} \times CP_i$$

We sum total $CPL$ by country and calculate the difference in $CPL$ between the two scenarios in 2030 (either $CLE_{med} - CH_4-red_{med}$, $CLE_{med} - CLE_{min}$, or $CLE_{med} - CH_4-red_{min}$, depending on the strategy examined (Table 12)) to find the gain in CP. We then multiply CP for each crop by national producer prices from the FAOSTAT database (57) (and subsequently summarize) to determine year 2030 total economic losses. This simple revenue approach has been found to produce economic damage estimates within 20% of those based on a general equilibrium model accounting for factor feedbacks between crop yields, production, and commodity prices (58).

*Economic Value of Crop Production Improvements from 2006-2030.* As methane reductions would decrease ozone gradually, we use the annual average change in global surface $O_3$ to scale year 2030 monetized benefits for agriculture over the 25-year period of $CH_4$ (and $O_3$) reductions (Fig. SM 9) (34, 35). We assume that agricultural benefits are linearly related to $O_3$ reductions – a realistic assumption for AOT40 given its linear CR relationship, and for W126 within the range of $O_3$ exposure values that generate the greatest agricultural losses (~15-60 ppmh, Fig. SM 8). Furthermore, the spatial pattern of $O_3$ reductions has been shown to be independent of the magnitude of $CH_4$ emission changes over the simulated period (31). We then calculate the present value of benefits from 2006-2030 using a 5% yr$^{-1}$ discount rate, and
amortize this sum to derive an estimate of constant annual benefits (with the same present value at the given discount rate) over the CH$_4$ reduction period (34, 35).
References


Figures

Figure 19. Global distribution of the reduction in year 2030 O₃ exposure resulting from methane mitigation (CLE – CH₄-red) according to AOT40 (left) and W126 (right) of (a) soybean, (b) maize, and (c) wheat during their respective growing seasons in each country (where crop calendar data are available). Minor producing nations not included in this analysis (where growing season data were unavailable) together account for <5% of global production of each crop (grey nations).
Figure 20. Total (soybean, maize, and wheat) year 2030 crop production (CP) gain in each nation due to CH₄ mitigation as a percent increase from year 2000 production (left panels), and the estimated economic value (EV) of CP gains (right panels) according to (a) AOT40 and (b) W126. CP improvements represent the combination of estimated changes in O₃ concentrations during specific crop growing seasons in regions where crops are grown, and the quantity of each crop produced in each nation. EV values also reflect national producer prices in addition to these factors.
Figure 21. Total (soybean, maize, and wheat) year 2030 crop production (CP) gain in each nation due to cultivating O$_3$ tolerant crops (CLE$_\text{min}$) relative to cultivars of median sensitivity (CLE$_\text{med}$), represented as a percent increase from year 2000 production (left). The estimated economic value (EV) of CP gains is also shown (right).
Table 9. Global land-based average and crop-production weighted AOT40 and W126 in 2005 and 2030 under the CLE and CH₄-red scenarios for each crop growing season, and percent change in O₃ exposure due to CH₄ mitigation in 2030 (relative to CLE). AOT40 and W126 values were calculated only for nations where growing season data were available, accounting for >95% of global production of each crop.
<table>
<thead>
<tr>
<th>Region</th>
<th>Metric/CR Relationship</th>
<th>2030 Crop Production (Mt)</th>
<th>Economic Value (Billion USD$_{2000}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>CPL$_{CLE}$</td>
<td>CPL$_{CH4-red}$</td>
</tr>
<tr>
<td>N. America</td>
<td>AOT40 - median</td>
<td>52.5</td>
<td>48.4</td>
</tr>
<tr>
<td></td>
<td>W126 - median</td>
<td>29.9</td>
<td>26.2</td>
</tr>
<tr>
<td></td>
<td>W126 - minimum</td>
<td>10.2</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
<td>8.8</td>
</tr>
<tr>
<td>S. America</td>
<td>AOT40 - median</td>
<td>1.8</td>
<td>1.6</td>
</tr>
<tr>
<td></td>
<td>W126 - median</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>W126 - minimum</td>
<td>0.1</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
<td>0.1</td>
</tr>
<tr>
<td>Europe</td>
<td>AOT40 - median</td>
<td>24.8</td>
<td>21.7</td>
</tr>
<tr>
<td></td>
<td>W126 - median</td>
<td>2.3</td>
<td>1.8</td>
</tr>
<tr>
<td></td>
<td>W126 - minimum</td>
<td>1.7</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
<td>1.2</td>
</tr>
<tr>
<td>FSU</td>
<td>AOT40 - median</td>
<td>10.5</td>
<td>9.21</td>
</tr>
<tr>
<td></td>
<td>W126 - median</td>
<td>1.2</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>W126 - minimum</td>
<td>0.9</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
<td>0.7</td>
</tr>
<tr>
<td>E. Asia</td>
<td>AOT40 - median</td>
<td>48.9</td>
<td>43.6</td>
</tr>
<tr>
<td></td>
<td>W126 - median</td>
<td>19.6</td>
<td>15.0</td>
</tr>
<tr>
<td></td>
<td>W126 - minimum</td>
<td>10.1</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
<td>7.8</td>
</tr>
<tr>
<td>S. Asia</td>
<td>AOT40 - median</td>
<td>88.5</td>
<td>81.6</td>
</tr>
<tr>
<td></td>
<td>W126 - median</td>
<td>167</td>
<td>75.9</td>
</tr>
<tr>
<td></td>
<td>W126 - minimum</td>
<td>55.8</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
<td>31.8</td>
</tr>
<tr>
<td>Africa &amp; Middle</td>
<td>AOT40 - median</td>
<td>15.8</td>
<td>13.7</td>
</tr>
<tr>
<td>East</td>
<td>W126 - median</td>
<td>3.9</td>
<td>2.6</td>
</tr>
<tr>
<td></td>
<td>W126 - minimum</td>
<td>2.2</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
<td>1.6</td>
</tr>
<tr>
<td>Australia &amp; Pacific</td>
<td>AOT40 - median</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>Pacific</td>
<td>W126 - median</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>W126 - minimum</td>
<td>0.01</td>
<td>-</td>
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<tr>
<td></td>
<td></td>
<td>-</td>
<td>0.0</td>
</tr>
<tr>
<td>World</td>
<td>AOT40 - median</td>
<td>243</td>
<td>220</td>
</tr>
<tr>
<td></td>
<td>W126 - median</td>
<td>224</td>
<td>122</td>
</tr>
<tr>
<td></td>
<td>W126 - minimum</td>
<td>81.0</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
<td>52.0</td>
</tr>
</tbody>
</table>

**Table 10.** Regionally-aggregated combined soybean, maize, and wheat crop production loss (CPL, Mt) and its economic value (EV, billion USD$_{2000}$) in 2030 under the CLE and CH$_4$-red scenarios for each O$_3$ exposure metric and concentration:response (CR) relationship examined here. The change in crop production (CP) and EV is shown, defined for AOT40-median and W126-median as the difference between CLE and CH$_4$-red CPL, and for W126-minimum (for
both CLE and CH₄-red) as the difference relative to the W126-median-derived CPL estimates in CLE. These scenarios are representative of a policy of methane mitigation, adaptation, and mitigation plus adaptation, respectively. Regional definitions are available in Fig. SM 11.

<table>
<thead>
<tr>
<th>Crop</th>
<th>CPL (Mt) - AOT40</th>
<th>CPL (Mt) - W126</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CLE_med CH₄-red_med</td>
<td>CLE_med CH₄-red_med</td>
</tr>
<tr>
<td>Soybean</td>
<td>27.9 25.9</td>
<td>16.7 15.2</td>
</tr>
<tr>
<td>Maize</td>
<td>22.8 20.7</td>
<td>16.1 13.2</td>
</tr>
<tr>
<td>Wheat</td>
<td>192 173</td>
<td>191 94.0</td>
</tr>
</tbody>
</table>

Table 11. Global year 2030 soybean, maize, and wheat crop production loss (CPL, Mt) according to each O₃ exposure metric and corresponding concentration:response (CR) relationship (i.e. median vs. minimum sensitivity) examined here for the CLE and CH₄-red scenarios.

<table>
<thead>
<tr>
<th>Policy Choice</th>
<th>Scenarios</th>
<th>Metric</th>
<th>ΔCP (Mt)</th>
<th>%ΔCPL (from CLE_med)</th>
<th>%ΔCP (from 2000)</th>
<th>Economic Benefit (Billion USD_2000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mitigation only</td>
<td>CLE_med CH₄-red_med</td>
<td>AOT40</td>
<td>23</td>
<td>10</td>
<td>2.0</td>
<td>3.5</td>
</tr>
<tr>
<td>Mitigation only</td>
<td>CLE_med CH₄-red_med</td>
<td>W126</td>
<td>102</td>
<td>45.4</td>
<td>8.3</td>
<td>15</td>
</tr>
<tr>
<td>Adaptation only</td>
<td>CLE_med CLE_min</td>
<td>W126</td>
<td>143</td>
<td>63.9</td>
<td>11.7</td>
<td>22</td>
</tr>
<tr>
<td>Mitigation and adaptation</td>
<td>CLE_med CH₄-red_min</td>
<td>W126</td>
<td>172</td>
<td>76.8</td>
<td>14.1</td>
<td>26</td>
</tr>
</tbody>
</table>

Table 12. Summary of global crop production benefits (and their economic value) in 2030 due to different policy choices: methane mitigation only, adaptation only (choice of O₃ resistant cultivars), and both mitigation and adaptation. Crop production (CP) increases in Mt are also represented as a percent reduction in O₃-induced crop production loss (CPL) relative to CLE_med in 2030, and as a percent increase from year 2000 crop production.
Figure SM 6. Global distributions of soybean, maize, and wheat crop production in the year 2000. 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. Area harvested and yields of 175 distinct crops of the world were compiled at 5 minute x 5 minute latitude-longitude resolution for the years 1997-2003 and subsequently averaged to produce a single representative
value for each country circa year 2000 (see Monfreda et al. (2008) for further details). Data have been regridded to match the 1.9° × 1.9° resolution of MOZART-2 for our calculations of O₃-induced crop losses.
Figure SM 7. Weighted hourly O₃ concentrations calculated for the cumulative AOT40 and W126 metrics as a function of actual hourly O₃ concentrations.
Figure SM 8. Concentration-response functions for wheat used in this analysis for AOT40 (solid line), median W126 (small dashes), and minimum sensitivity (representing maximum O₃ resistance) W126 (large dashes) CR functions. Equations for these functions are listed in Table SM 10.
Figure SM 9. Change in global annual surface O₃ (solid) used to scale estimated agricultural benefits in 2030 over the 25-year period of CH₄ reductions (dashed).
**Figure SM 10.** Total (soybean, maize, and wheat) year 2030 crop production (CP) gain in each nation resulting from CH$_4$ mitigation and minimum O$_3$ sensitivity cultivar choice (CLE$_{med}$–CH$_4$-red$_{min}$) relative to CLE$_{med}$, represented as a percent increase from year 2000 production (Monfreda et al., 2008; Ramankutty et al., 2008) (left). The estimated economic value (EV) of CP gains is also shown (right).

**Figure SM 11.** Regional definitions used to calculate crop production losses in Table 10.
<table>
<thead>
<tr>
<th>Crop</th>
<th>Concentration – Relative Yield Relationship</th>
<th>Relative Sensitivity</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soybean</td>
<td>$RY = -0.0116\times AOT40 + 1.02$</td>
<td>Median</td>
<td>Mills et al. (2007)</td>
</tr>
<tr>
<td></td>
<td>$RY = \exp[-(W126/110.2)^{1.359}]$</td>
<td>Median</td>
<td>Lee and Hogsett (1996)</td>
</tr>
<tr>
<td></td>
<td>$RY = \exp[-(W126/476.7)^{1.113}]$</td>
<td>Minimum</td>
<td>Lee and Hogsett (1996)</td>
</tr>
<tr>
<td>Corn</td>
<td>$RY = -0.0036\times AOT40 + 1.02$</td>
<td>Median</td>
<td>Mills et al. (2007)</td>
</tr>
<tr>
<td></td>
<td>$RY = \exp[-(W126/97.9)^{2.966}]$</td>
<td>Median</td>
<td>Lee and Hogsett (1996)</td>
</tr>
<tr>
<td></td>
<td>$RY = \exp[-(W126/94.2)^{4.167}]$</td>
<td>Minimum</td>
<td>Lee and Hogsett (1996)</td>
</tr>
<tr>
<td>Wheat</td>
<td>$RY = -0.0161\times AOT40 + 0.99$</td>
<td>Median</td>
<td>Mills et al. (2007)</td>
</tr>
<tr>
<td></td>
<td>$RY = \exp[-(W126/53.4)^{2.367}]$</td>
<td>Median</td>
<td>Lee and Hogsett (1996)</td>
</tr>
<tr>
<td></td>
<td>$RY = \exp[-(W126/76.8)^{2.031}]$</td>
<td>Minimum</td>
<td>Lee and Hogsett (1996)</td>
</tr>
</tbody>
</table>

**Table SM 10.** Concentration:response equations used to calculate relative yield loss of soybean, maize, and wheat. $RY =$ relative yield as compared to theoretical yield without O$_3$-induced injury. Relative yield loss (RYL) is calculated as $(1 – RY)$. See manuscript text for definitions of AOT40 and W126. For the AOT40 CR relationship, we use median parameter values pooled from a variety of cultivars grown in the U.S. and Europe for each crop (Mills et al., 2007). For the W126 CR function, we use median parameter values pooled from U.S. cultivars (Lee and Hogsett, 1996).
Supplementary Material References


Chapter 5

Global Agricultural Production in a High-CO₂, High-O₃, and Warmer World: Current Knowledge, Comparative Impacts, and Future Directions

1. Introduction

From 2010 to 2050 the demand for grain is expected to increase by 70% due to an increase in global population of over two billion people (~34%); the shift to a more diverse, protein- and dairy-rich diet associated with rising living standards; and an increasing demand for biofuels (FAO, 2006; FAO, 2009a). Agricultural production has historically kept pace with surging demand, but two components of global environmental change may threaten future food supplies: (1) changes in climate largely caused by rising concentrations of atmospheric carbon dioxide (CO₂), the most important anthropogenic contributor to greenhouse warming (Forster et al., 2007); and (2) increasing concentrations of surface ozone (O₃) that have adverse effects on crops and other vegetation (Heagle, 1989). Although elevated CO₂ could alone benefit agriculture, associated changes in temperatures and precipitation patterns may severely disrupt crop growth and yields in many regions of the world (Easterling et al., 2007). Recent studies estimate that the yields of maize and wheat may already be reduced by 4-6% due to climate changes since 1980 (Lobell and Field, 2007; Lobell et al., 2011), and that soybean, maize, wheat,
and rice yields may be inhibited by 2-16% due to present-day O₃ exposure (Feng and Kobayashi, 2009; Van Dingenen et al., 2009; Fishman et al., 2010; Avnery et al., 2011a).

As evidenced by the stagnant or declining yield growth rates of key staple crops in many parts of the world (Tilman et al., 2002; Bank, 2007; Dasgupta and Sirohi, 2010), the detrimental impact of environmental changes on agriculture may be beginning to outweigh the positive annual yield improvements that have characterized global agricultural production since the Green Revolution. Unless crop yields on existing farmland continue their upward trend, meeting the worldwide food demand of the future will require an increase in farmland area at the expense of natural ecosystems – leading to the loss of biodiversity and potentially tremendous emissions of carbon that will further exacerbate climate change (Burney et al., 2010). Falling yields may also have major implications for food security, particularly in developing countries where a large portion of the population is already food insecure and acutely vulnerable to decreases in crop yields given the prevalence of agriculture-based livelihood systems. Reduced productivity could additionally increase commodity prices that threaten to expose vulnerable populations to the risk of hunger, as evidenced by the recent price spike of 2008 when a combination of higher commodity prices and reduced incomes due to the global economic slowdown pushed an additional 100 million people into conditions of chronic hunger (FAO, 2009b). Rising food prices have additionally been associated with an increased incidence of anti-government demonstrations, riots, and civil conflict in low-income countries (Arezki and Bruncker, 2011): for example, during the 2008 food and fuel price spike, at least 61 countries experienced unrest as a result of price inflation, with protests in 38 countries turning violent (Von Braun, 2008).

In order to accurately assess the ability of the global food production system to meet future demand, projections of future agricultural production must account for the impact of
environmental changes on crop yields – including rising CO₂ and associated changes in
temperature and precipitation patterns, as well as surface O₃ concentrations. However, to date
major knowledge gaps exist in these areas. For example, the magnitude of possible yield
enhancements due to CO₂ fertilization and of yield declines due to O₃ exposure for various crops,
regions, and environmental and management conditions is still uncertain (e.g. Long et al, 2006;
Tubiello et al., 2007; Mills et al., 2007; Ainsworth et al., 2008a; Feng and Kobayashi, 2009;
Ainsworth and McGrath, 2010). Crop growth models that account for the impact of mean
climatic changes over the remainder of the century generally do not include the effects of extreme
weather events such as droughts, floods, and heat waves, which are projected to increase in
frequency and magnitude in a warmer world and may have a greater impact on crop production
than average changes in climate (Meehl et al., 2007; Easterling et al., 2007). Our ability to
simulate the integrated effect of multiple abiotic stressors on yields is also highly uncertain:
significant questions remain regarding the overall impact of CO₂, O₃, and climate change on
various physiological processes and therefore the direction and magnitude of crop yield
responses (Mittler, 2006; Mittler and Blumwald, 2010). Despite the demonstrated phytotoxicity
of O₃, the effect of this pollutant on crop yields has, to our knowledge, been left out of estimates
of future agricultural production that do account for CO₂ and associated climate changes (e.g.
Parry et al., 2004; Fischer et al., 2005; Nelson et al., 2009) with two exceptions in which
numerous simplifying assumptions were made (Reilly et al., 2007; Jaggard et al., 2010) (see
Section 3.2). Given these and other questions, the accuracy of current projections of future
agricultural production (as well as corresponding commodity prices and the estimated impact on
individuals at risk of hunger) is uncertain, with possibly major implications for food security,
climate change, and political stability.
We review here the current understanding of the effects of CO₂, O₃, and climate change on agriculture. We then compare and contextualize projected impacts of each of these components of global change on crop yields, and identify regions at risk of “double exposure” to both climate change and O₃-induced agricultural losses. Given the comparatively little attention that O₃ has received as a threat to global agriculture despite its demonstrated phytotoxicity and growing risk to crops (e.g. Royal Society, 2008; Feng and Kobayashi, 2009; Van Dingenen et al., 2009; Avnery et al., 2011a, Avnery et al., 2011b; Mills et al., 2011a), we additionally review several promising strategies to improve crop yields in the future by ameliorating ozone damages. Finally, we highlight the research required to better predict how crops will respond to a warmer and, in some regions, a more polluted world. In particular, we address the following questions:

1. How do CO₂, O₃, and climate change affect crops?
2. What is the magnitude of projected impacts of each of these elements of environmental change on current and future crop yields (globally and regionally), and is agriculture in certain regions of the world at risk of negative impacts from both climate change and O₃ exposure?
3. What are several promising strategies to reduce O₃-induced crop yield losses?
4. What research is required to more accurately project the future impact of global environmental change (including CO₂, O₃, and climate change) on agriculture?

2. Effects of elevated CO₂, O₃, and climate change on agriculture

We summarize here how the major components of environmental change (CO₂, O₃, mean temperature and precipitation changes, and extreme events) may affect future agricultural production. We also provide an overview of important interactive effects of these environmental changes and their combined impact on crop growth and yields.
2.1. Rising CO₂

Elevated levels of atmospheric CO₂ may directly affect the physiological processes of photosynthesis and transpiration in crops, with the overall response varying by species due to two different pathways of photosynthesis (C₃ and C₄). For crops that follow the C₃ photosynthetic pathway (most crops including wheat, soybean, and rice), CO₂ has a direct positive effect by increasing the rate of photosynthesis and dry matter production, thereby increasing crop growth and seed yield (Kimball et al., 2002; Long et al., 2004; Ainsworth and McGrath, 2010). This occurs because ribulose-1,5-bisphosphate carboxylase–oxygenase (Rubisco), the enzyme that initially fixes CO₂, is not CO₂-saturated in the present-day environment; rising CO₂ therefore increases net CO₂ uptake and consequently crop growth and yields. The yield enhancement due to CO₂ fertilization is believed to follow a nonlinear curve that asymptotically approaches a maximum yield increase of ~40-60%, which begins to level off at atmospheric CO₂ concentrations of 550-700 ppmv depending on the crop (Long et al., 2006; Tubiello et al., 2007; Ainsworth and McGrath, 2010).

Because C₄ plants (including maize, sorghum, sugarcane, and millet) concentrate CO₂ at three to six times atmospheric levels (Gornall et al., 2010), Rubisco is already saturated for these and other C₄ species – increasing CO₂ will therefore only marginally affect the growth and yields of these crops. For both C₃ and C₄ crops, however, elevated CO₂ reduces transpiration and improves water-use efficiency (WUE, the amount of dry matter produced per unit of water transpired), as plants can minimize the amount of time stomata must remain open to receive the required CO₂ for photosynthesis. This effect may lead to a yield enhancement for both types of crops, particularly under water-stressed conditions (Kimball et al., 2002; Long et al., 2004; Leakey 2009; Ainsworth and McGrath, 2010). In addition, the reduction in stomatal aperture
resulting from elevated CO₂ partially ameliorates the negative effects of plant exposure to elevated O₃ (Mauzerall and Wang, 2001; Fiscus et al., 2005; Fuhrer, 2009) (see Section 2.4). One negative impact of CO₂ fertilization is that the protein content of crops grown in elevated CO₂ may be reduced compared to crops grown at ambient levels (Ainsworth and McGrath, 2010).

In addition to photosynthetic pathway, the magnitude of yield gains due to CO₂ depends on numerous external environmental factors, such as access to direct and indirect solar radiation, water availability, nutrient abundance, and air quality. Various approaches have been used to quantify the effect of elevated CO₂ on the yields of different crops, including controlled environment chambers, open-top chambers (OTC), and free air carbon dioxide enrichment (FACE) technology where crops are grown under high CO₂ in fully open-air field conditions. Although controlled environment and OTC studies have practical advantages and have been used to develop concentration:response (CR) relationships for numerous crops grown at a range of CO₂ concentrations, they may alter the micrometeorological environment with barriers to light, precipitation, wind, and pests, and their small size may generate edge effects hence potentially influencing crop response to enhanced CO₂ (Long et al., 2006). FACE experiments are chamber-less and much larger in scale, potentially providing more realistic estimates of crop yield responses to elevated CO₂ (Long et al., 2006; Ainsworth et al., 2008b). Tubiello et al. (2007) note however that controlled-environment chamber studies and other non-FACE approaches can be used to produce reliable results and serve as a lower-cost alternative to FACE technology.

FACE studies conducted over the past two decades suggest mean yield increases in C₃ crops of 11% over ambient air in the U.S. for CO₂ concentrations of 550 ppmv (Long et al.,
(Long et al., 2006). FACE studies revealed no significant CO$_2$-fertilization effect for maize (a C$_4$ species) compared to ambient air when water supply was sufficient, but yields did increase in drought conditions due to reduced transpiration and higher WUE (Long et al., 2004). A recent statistical analysis of 50 years of historical weather and crop yield data in the U.S. supports FACE results, finding that a 73 ppmv CO$_2$ increase over the past half century generated a 9% and 14% improvement in maize and soybean yields, respectively, grown under dry conditions (McGrath and Lobell, 2010). Some researchers have raised concern that FACE studies suggest significantly smaller (by ~50%) CO$_2$-induced yield gains than found in earlier controlled environment and chamber studies (Long et al., 2006; Ainsworth et al., 2008a), while others suggest that any discrepancies are primarily due to different study methodologies and that yield increases predicted by the major crop-simulation models under unstressed conditions are consistent with earlier research results (5-20% at 550 ppmv CO$_2$) (Tubiello et al., 2007). Apart from this debate, researchers recognize that the effects of elevated CO$_2$ measured in experiments and applied in crop models may overestimate actual field and farm level responses due to local interactions with limiting factors such as nutrient and water availability, pests, weeds, and air quality that are not well understood or modeled at large scales (Easterling et al., 2007; Tubiello et al., 2007; Gornall et al., 2010).

2.2. Surface O$_3$

Surface ozone is harmful to human health, crops, and ecosystems. It is an air pollutant and potent greenhouse gas produced in the troposphere by catalytic reactions among nitrogen oxides (NO$_x$ = NO + NO$_2$), carbon monoxide (CO), methane (CH$_4$), and non-methane volatile organic compounds (NMVOCs) in the presence of sunlight. Anthropogenic O$_3$ precursors are
emitted by vehicles, power plants, biomass burning, and other sources of combustion. Annual mean surface O$_3$ concentrations at mid- to high latitudes have more than doubled over the past century (Marenco et al., 1994). Although O$_3$ mitigation efforts have reduced peak ozone levels in North America, Europe, and Japan in recent years and concentrations are expected to continue to fall (Kawase et al., 2011), background levels have been rising (Oltmans et al., 2006) due to increased emissions of O$_3$ precursors in Asia and other developing countries as a consequence of rapid industrialization and lenient air quality legislation (Dentener et al., 2005). A recent review of O$_3$ impacts on agriculture by the Royal Society of London suggests that unless global O$_3$ precursor emissions are curbed, O$_3$ pollution may pose as large a threat to worldwide food security as climate change by 2030 (Royal Society, 2008). The threat of O$_3$ is particularly alarming as mean crop sensitivity to surface O$_3$ appears higher in some regions (e.g. Europe and South Asia) than in the past (Pleijel et al., 2006; Biswas et al., 2008; Emberson et al., 2009; Rai et al., 2010; Sarkar and Agrawal, 2010), suggesting that O$_3$ tolerance may be an overlooked factor in cultivar choice and/or breeding strategies that prioritize other traits (e.g. resistance to drought or heat stress) at the expense of O$_3$ resistance.

O$_3$ diffuses into plant cells though the stomata during normal gas exchange, where it is rapidly converted into additional reactive oxygen species (ROS) that inhibit photosynthesis and reduce the rate of biomass accumulation, particularly after leaf maturation (Fiscus et al., 2005; Fuhrer, 2009). O$_3$ injury is characterized as either acute or chronic, depending on the concentration and duration of exposure. Acute damage such as unregulated and programmed cell death generally results from exposure to high O$_3$ (>120-150 ppbv) over short periods of time, while chronic injury arises from longer exposure to lower concentrations (Fiscus et al., 2005). The response of plants to acute O$_3$ injury is better understood than the biochemical reaction to
chronic damage (Gillespie et al., 2011). Although crop sensitivity to O$_3$ may vary greatly by crop and among cultivars of the same species, common physiological symptoms of chronic O$_3$ injury include: suppressed rates of photosynthesis, Rubisco damage, decreased chlorophyll content and leaf chlorosis, reduced stomatal conductance, accelerated senescence, smaller leaf area, reduced root-to-shoot biomass ratios, and decreased productivity, yields, and crop nutritive content (Ashmore, 2005; Fiscus et al., 2005; Fuhrer, 2009). The most O$_3$-sensitive crops include wheat, soybean, pulses, tomato, and some rice varieties, with potato, sugar beet, rape and maize characterized as moderately sensitive (Mills et al., 2007; Emberson et al., 2009; Feng and Kobayashi, 2009).

Large-scale OTC field studies that took place in the U.S. and Europe during the 1980s/90s, where crops were grown to maturity in chambers exposed to charcoal-filtered, ambient, or O$_3$-enriched air, established that damages to crops may occur at O$_3$ concentrations as low as 20-25 ppbv, but that the greatest yield reductions occur with O$_3$ above 40-60 ppbv (Heagle, 1989). However, a recent synthesis of published and unpublished records of O$_3$ damage to vegetation across Europe documented that 62% of injury locations (including areas with mean biomass reductions of >10%) were situated where mean hourly O$_3$ concentrations were largely below 40 ppbv during the growing season (Mills et al., 2011a), providing additional evidence that rising background O$_3$ concentrations may continue to damage crops even if peak O$_3$ levels are reduced (Royal Society, 2008). CR functions derived from OTC studies combined with model-simulated global O$_3$ concentrations have been used to estimate crop losses based on current and future O$_3$ exposure levels (Van Dingenen et al., 2009; Avnery et al., 2011a; Avnery et al., 2011b). These studies suggest that present day O$_3$ exposure may be suppressing global yields by 6-16% for soybean, 4-15% for wheat, 2-6% for maize (Van Dingenen et al., 2009;
Avnery et al., 2011a), and 3-4% for rice (Van Dingenen et al., 2009), and that O₃ could further
decrease the yields of soybean and wheat by ~10% by 2030 under a pessimistic trajectory of
future O₃ precursor emissions (Avnery et al., 2011b). These results have been supported by a
meta-analysis of 406 experimental observations of O₃ CR relationships: Feng and Kobayashi
(2009) estimate that probable present-day O₃-induced yield reductions are 5.3% for potato, 7.7%
for soybean, 8.9% for barley, 9.7% for wheat, 17.5% for rice, and 19.0% for bean. Soybean,
wheat, and rice were estimated to be at risk of a further 10% decline in yields by 2050 based on
the range of Intergovernmental Panel on Climate Change (IPCC) projections of future O₃ (Meehl
et al., 2007; Feng and Kobayashi, 2009).

On a more limited basis, the magnitude of O₃-induced crop yield losses has also been
investigated using FACE with results generally in line with CR functions derived from earlier
OTC studies (Long et al., 2005; Long et al., 2006; Morgan et al., 2006; Shi et al., 2009; Zhu et
al., 2011), as well as with independent statistical models based on historical agricultural yield
data and O₃ concentrations. Fishman et al. (2010) employ a multiple linear regression model to
estimate soybean yields over five years (2002-2006) in the U.S. Midwest as a function of
temperature, precipitation, and surface O₃ using ozone data collected from ground monitoring
sites and satellite measurements. The authors isolate the effect of O₃ from temperature and
precipitation, and found that O₃ was a statistically significant predictor of yield. The estimated
soybean yield reduction due to O₃ (0.38-1.63% ppbv⁻¹ on average, or 2-6% in total) is consistent
with results from OTC (Heagle, 1989) and FACE experiments (Morgan et al., 2006).

Predictions of future O₃ impacts are complicated by uncertainties, including the path of
future O₃ precursor emissions, the effect of climate change on O₃ concentrations (for example,
warmer temperatures and reduced cloudiness and precipitation in some regions may increase
summer peak and average ozone concentrations (Wu et al., 2008; Jacob and Winner, 2009)), the ameliorating effect of increasing carbon dioxide concentrations on ozone impacts (by reducing stomatal uptake), as well as the change in vulnerability to O₃ that climate-related stresses or elevated CO₂ may induce (Booker et al., 2009; Gillespie et al., 2011). In particular, one major caveat about the global impact studies cited above (Van Dingenen et al., 2009; Avnery et al., 2011a; Avnery et al., 2011b) is that their results are derived from exposure-based metrics that do not quantify the effective flux of O₃ into plants after accounting for environmental factors that may moderate stomatal conductance (e.g. temperature, water availability, and CO₂ concentration) or the detoxification capacity of crops (see Section 2.4). Recent research has led to the development of more biologically-relevant models of O₃ damage to crops that simulate the flux of ozone through stomates using mathematical equations to characterize the species-specific impact of temperature, photosynthetic photon flux density (PPFD), soil water potential, vapor pressure deficit (VPD) and plant growth stage on stomatal conductance (Emberson et al., 2000; Pleijel et al., 2004; Pleijel et al., 2007; Mills et al., 2011b). Such flux-based models have been developed for wheat, potato, tomato, and two tree species (beech and birch) grown in Europe, but further model specification and evaluation is required for additional crops and growing regions. Although exposure-based studies appear to be validated on a global scale by FACE experiments (Morgan et al., 2006; Shi et al., 2009; Zhu et al., 2011) and empirical studies (Feng and Kobayashi, 2009; Fishman et al., 2010), significant regional discrepancies may occur in locations where effective dose is substantially different from estimated exposure to O₃, such as drier, non-irrigated regions (lower effective dose, e.g. the Mediterranean) or wetter, cooler areas (higher effective dose, e.g. northwestern Europe) (Simpson et al., 2007). A recent review of O₃ damages to vegetation in Europe suggests that the use of an exposure-based metric in sum
underestimated O₃ damage on vegetation across the continent as compared to more biologically-relevant flux-based metrics (Hayes et al., 2007).

2.3. Climate change

2.3.1. Rising mean temperatures

Global average temperatures are predicted to rise by up to 6.4°C (with a best estimate of 1.8-4.0°C) by the end of the century (relative to 1980-1990), depending on a range of factors and pathways of human development (Meehl et al., 2007). Warming temperatures will affect agricultural productivity because most physiological processes related to crop growth and yield are highly sensitive to temperature, and crops have a specific temperature range for maximum yields. Ideal growth temperatures often correspond to optimal temperatures for net photosynthesis (gross photosynthesis minus respiration), which is a parabolic function of temperature since elevated temperature enhances both gross photosynthesis and photorespiration (which consumes photosynthates and thereby decreases net photosynthesis). However, crop response to temperature may be complex, non-linear, and exhibit threshold effects. Using regression analysis on U.S. weather and agricultural data, Schlenker and Roberts (2009) find optimal crop yield temperatures of 29°C for corn, 30°C for soybeans, and 32°C for cotton, but with the slope of the decline in yield above optimum temperatures significantly steeper than the incline below. Higher mean temperatures may benefit crop productivity in some mid- to high latitude regions by providing growth temperatures closer to optimums, increasing the length of the growing season, as well as expanding the amount of land suitable for cultivation: Fischer et al. (2005) project an increase in potential agricultural land of 40%, 16%, 64%, and 10% in North America, Europe, Russia, and East Asia, respectively, driving global potential cereal production improvements of 1.9-3.0 Gt by 2080 depending on the climate change scenario considered.
However, warming may reduce yields where crops are currently cultivated at near-optimal temperatures. Increased temperatures may additionally lead to reduced stomatal aperture as plants attempt to prevent drying due to greater evaporative demand, thereby decreasing CO₂ uptake; this may in turn further enhance rates of photorespiration and reduce net photosynthesis. Temperature also affects the rate of plant development, and even brief exposure to extreme temperatures may shorten growing periods and threaten yields if exposure occurs during important development stages such as flowering and grain filling (Wheeler et al., 2000; Wollenweber et al., 2003).

The IPCC synthesized the results of 69 global and regional integrated modeling studies at multiple simulation sites (which feed climate simulations from general circulation models into dynamic crop-growth or agro-economic models), plotting yield changes against temperature as a proxy for time and the extent of climate change (Easterling et al., 2007). Despite large uncertainties due to differences in the simulation of associated precipitation changes, the magnitude of the CO₂ fertilization effect, and other methodological discrepancies across studies, the IPCC synthesis suggests that crop yields are likely to decrease in low latitudes even for small amounts of warming (1-2°C). Yields of some crops at mid- to high latitudes may rise with regional temperature increases of 1-3°C (typical of the next few decades) by ~10% for wheat and rice (assuming no farmer adaptation as simulated by crop models⁸). Maize yields are predicted

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⁸ Agricultural adaptation can generally be characterized as either autonomous or planned (FAO, 2007). Autonomous adaptation includes individual or small-scale farmer responses to environmental changes, such as altering planting/harvesting dates or increasing water supply for crops already irrigated – actions that do not require major policy decisions, research, or economic investments, although knowledge dissemination is necessary. These kinds of “level 1” adaptation measures are often included in agro-economic projections of future climate change impacts on crops (Parry et al., 2009). Planned adaptation strategies are considered long-term, active policy decisions on the national level that aim to improve the adaptive capacity of a nation’s entire agricultural system and imply significant economic adjustments (FAO, 2007).
to decrease even at mid- to high latitudes after temperature increases of ~1.5°C, but yields will steeply decline in low latitude regions with warming above 1°C (assuming no farmer adaptation). Without adaptation, wheat yields in low latitudes may be particularly vulnerable, projected to decrease almost linearly from current levels after ~1.5°C of warming to ~20% for a temperature rise of 3°C. The IPCC predicts that the net global effect of decreased yields in lower latitudes and increased yields in mid- to high latitudes will be slightly positive for temperature increases up to 1-3°C, but negative with a further rise in temperature. Agriculture in the tropics is especially at risk from even small amounts of warming because temperatures will more rapidly exceed the optimal range for crop growth, with the greatest and most immediate detrimental yield impact projected for those regions that also have the lowest capacity to adapt to such changes (Adger et al., 2007). Mid- to high latitude regions may, by contrast, experience yield enhancements due to longer growing seasons as well as CO₂ fertilization, although the positive effects of CO₂ enrichment will not fully counterbalance negative impacts due to associated climate changes at high levels of warming. The IPCC notes that their derived estimates of crop yield responses to temperature are highly uncertain, and that changes in precipitation, evaporation, and CO₂ concentration will also shape crop responses.

Lobell and Field (2007) use a multiple linear regression model to estimate the change in yields that has occurred from 1981-2002 as a function of changes in growing season minimum and maximum temperatures and seasonal precipitation. The authors find that for most crops, temperature is the most important predictor of yield response. Wheat, maize, and barley

These are most often considered “level 2” adaptation, including major shifts in crop calendars or fertilizer application, irrigation infrastructure installation, improved pest and pathogen management, and the development and wide distribution of new crop varieties (Parry et al., 2009). Projections of future agriculture production generally incorporate level 2 adaptation measures by correlating productivity improvements with weighting factors proportional to regional economic development.
demonstrate a clear negative response to warming temperatures (~2-3% from 1981 to 2002), with losses of these crops (40 Mt) worth ~$5 billion annually. The authors note that a positive CO₂-fertilization effect may have offset a large part of the agricultural losses caused by rising temperatures, although the annual incremental CO₂ change was too small to have a measurable yield signal. Lobell et al. (2011) update this work and suggest that global maize and wheat yields have declined by 3.8 and 5.5% respectively due to rising temperatures from 1980-2008, with current losses totaling 23 Mt of maize and 33 Mt of wheat annually. Based on the CR relationships derived from FACE studies, the authors note that increased CO₂ since 1980 may have enhanced yields by 3% for the C₃ crops analyzed, such that the net effect of higher CO₂ and climate change since 1980 are slightly positive for rice and soybean (both of which showed no significant yield decline due to temperature and precipitation changes), and negative for wheat and maize.

2.3.2. Precipitation and water supply

In most tropical and equatorial regions of the world, crop yields are more limited by the amount of water available than by air temperature. The same is true for high and mid-latitude regions during summer, when growth can be inhibited if evapotranspiration exceeds rainfall (Parry, 1990). Humidity also affects rates of evapotranspiration, and dry matter production is generally an inverse function of humidity (Parry, 1990). As over 80% of global agriculture is rain-fed, changes in both rainfall and humidity could have a significant effect on crop yields (Gornall et al., 2010). However, projected impacts strongly depend on the climate model and scenario considered, since the effect of climate change on regional precipitation has strong dependencies on changes in atmospheric circulation, with models often disagreeing on both the sign and magnitude of precipitation changes. Despite such uncertainties, models generally
concur that precipitation will increase globally but with significant regional variability in both sign and intensity of individual events. The IPCC predicts that annual average precipitation is predicted to increase, especially in winter, in high-latitudes (>20% in some regions by the end of the century according to the Special Report on Emissions Scenarios (SRES)\(^9\) A1B scenario), including the northeastern U.S., Canada, northern Europe, and the Arctic. Increased precipitation is also predicted in the northern Pacific, tropical and eastern Africa, and northern Asia and Tibetan Plateau during winter. Precipitation decreases of a similar magnitude are expected in most subtropical land regions, including the Mediterranean, northern Africa, Central America, the southwestern U.S., parts of South America, and southwestern Australia (Meehl et al., 2007). Increased precipitation does not necessarily translate into improved crop yields, however, if the majority of precipitation falls during intense storms as is predicted to occur, particularly in the tropical and high latitude regions that are projected to experience an overall precipitation increase (see Section 2.3.3). Changes in the timing and frequency of precipitation may have a significant effect on crops even if the total annual precipitation quantity remains the same (Gornall et al., 2010), but large uncertainties exist in the modeling of such intra-annual precipitation variability (Meehl et al., 2007).

Because elevated temperatures will increase evaporative demand, an indirect effect of global warming is higher irrigation water requirements in many regions. Arnell (2004) projects increases in agriculture-related water stress (the ratio of irrigation withdrawals to renewable

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\(^9\) Because future emission levels are dependent on the uncertain path of human activity (which is in turn the product of a number of demographic and socioeconomic driving forces), the IPCC developed a set of scenarios to represent a range of possible futures. Forty scenarios along four distinct “storylines” (A2, A1, B2, B1) were created, each with different assumptions about the evolution of key drivers of human activity (and thereby resultant greenhouse gas and reactive pollutant emissions), including population growth, economic growth, technological change, and prioritization of environmental sustainability in each storyline.
water resources) in the Middle East and South-East Asia due to greater rates of evapotranspiration in a warmer world, but China is expected to have net decreased requirements (Tao et al., 2003) with the exception of the north- to northeast plains (Tao et al., 2010). Döll (2002) considered direct impacts of climate change on crop evaporative demand (without accounting for the CO₂ effect on WUE) and computed increases in crop irrigation requirements of +5% to +8% globally by 2070, with larger signals in some regions (e.g. +15% in South-East Asia). Under a modified SRES A2 scenario (with reduced population growth), Fischer et al. (2007) included the positive CO₂ effect on crop WUE and computed an increase in global net irrigation requirements of +20% by 2080 (395-409 Gm³), with greater impacts in developed (+36-45%) over developing (+17%) regions, due to both increased evaporative demand and longer growing seasons (necessitating irrigation for longer periods). Nelson et al. (2009) predict that internal renewable water resources may decrease in the Middle East and Africa by 4% in 2050 according to the A2 scenario, and that water stress contributes to substantial yield losses of wheat (20-34%) and rice (up to 18.5%) grown under irrigated conditions in developing regions. Iglesias et al. (2011) suggest that even under a climate stabilization scenario (at 498 ppmv and 2°C of warming), water demand will increase across most major agricultural regions worldwide including by 15% in East Asia, 20% in Africa, 10% in South America, and 15% in Central Asia.

2.3.3. Extreme events

The IPCC predicts that climate extremes like heat waves, drought, and flooding will become more severe and frequent in a warmer world, which may reduce crop yields beyond the impact of mean climate changes. However, the response of crops to extreme events is not currently included in global projections of future agricultural production (Easterling et al., 2007). Many of the greatest historical crop failures have resulted from anomalously low precipitation
The 1988 summer drought (and associated heat wave) in the U.S. depressed crop yields by 37% and cost the U.S. Congress $3 billion in bailout money to cover farmers’ crop losses (Rosenzweig et al., 2000). From an ensemble of 17 future climate scenarios simulated by variants of the HadCM3 General Circulation Model (GCM), Gornall et al. (2010) project that the amount of time global croplands endure drought conditions could increase by 11-20% by 2020 and 12-22% by 2050. Increased drought frequency may offset the benefits of higher mean temperatures and growing season length in mid- to high latitudes. Alcamo et al. (2007) use a global climate and water resource model to find that Russia would experience relatively small average changes in crop production over the next few decades, as increased productivity due to higher temperatures would be counterbalanced by decreases due to drought. However, the authors also find that although average production remained largely unchanged, incidences of food shortfalls would double in the 2020s and triple in the 2070s due to more frequent drought periods. Li et al. (2009) assess drought risk for world crop production by projecting forward the relationship between historical crop yields and meteorological drought events using ensemble results from 20 GCM simulations and 6 SRES emission scenarios. The authors find that drought-affected areas have already significantly increased, from an average of 10.76% of sown land in the period 1961-1979 to 17.10% in the present day period (1981-2006). Li et al. (2009) further find that drought affected areas could expand by an additional 15-44% globally in 2100 depending on the emissions scenario considered, with Africa and South America projected to suffer the greatest risk of drought.

Temperature extremes can also have a substantial impact on agricultural production, particularly if they coincide with critical crop development stages such as anthesis (flowering) (Wheeler et al., 2000; Wollenweber et al., 2003). Heat waves often occur simultaneously with
drought conditions and exacerbate crop losses: during the summer of 2003, for example, when European temperatures were 6°C (20-30%) above long-term means and the water balance deficit was 200-380 mm (depending on the country), crop and pasture yields were reduced by 20-36% leading to uninsured economic losses of €36 billion (Easterling et al., 2007). Heat wave frequency and severity is predicted to increase in the future, with one study estimating that the 20-year extreme temperature event over global croplands may increase in magnitude by 0.5-1.1°C by 2020 and 1.7-2.9°C by 2050 (Gornall et al., 2010). Heavy rainfall and flooding can be as detrimental to crop production as excess heat or drought, wiping out large areas of cropland and reducing soil quality (Rosenzweig et al., 2000). Excess soil moisture can cause anoxic conditions that damage crops more than direct flood damage. The flooding of the Mississippi River basin in 1993, for example, has been estimated to cost U.S. farmers $6-8 billion, 70% of which was due to saturated soils in upland areas (Rosenzweig et al., 2002), while the 2010 flooding in Pakistan destroyed almost $3 billion worth of crops and the livelihoods of over 80% of flooding victims (Dorosh et al., 2010). In addition, pest and disease outbreaks may coincide with anomalous temperature, humidity, and precipitation patterns, with warmer temperatures and higher precipitation projected to increase damages due to biotic stressors (Rosenzweig et al., 2000).

2.4. *Interactive effects of multiple environmental stressors*

Higher CO₂, O₃, and changes in temperature and precipitation patterns – as well as interactions with pest and disease dynamics and nutrient availability – may have a net effect on crops that is significantly different than the impact of any one of these factors alone (Mittler, 2006; Mittler and Blumwald, 2010). Plant response to a particular stress is generally tailored to that specific condition, and the combination of different stressors may produce either
antagonistic or synergistic reactions (Mittler, 2006). For example, plants increase stomatal conductance during heat stress in order to enhance transpiration and cool their leaves, but the addition of drought stress would suppress this response (as drought induces stomatal closure) (Mittler and Blumwald, 2010). In the absence of drought, heat stress could thereby increase the detrimental effect of salinity, heavy metals, or O₃ exposure due to increased transpiration and higher pollutant uptake. Because plants require energy and nutrients to respond to external pressures, they may become more vulnerable to additional environmental stress due to fewer available resources, with an overall response that depends on local radiation, nutrient, and water availability and that is therefore difficult to predict on large scales (Fuhrer et al., 2009; Mittler and Blumwald, 2010).

The complicated interactive effects of multiple environmental stressors have been documented in field experiments. FACE studies of wheat grown under different nitrogen (high and low) and water (wet and dry) treatments at elevated CO₂ suggest that water and nitrogen availability were more important than – and affected the magnitude of – yield enhancements due to CO₂ fertilization (Kimball et al., 1999). Elevated CO₂ may additionally inhibit nitrate assimilation, thereby leading to possibly greater nutrient requirements to realize the benefits of CO₂ fertilization (Bloom et al., 2010). Higher temperatures that occur during crop flowering can further diminish the fertilization effect of CO₂ by reducing grain number, size, and quality (Baker, 2004; Caldwell et al., 2005). Crop model simulations based on results from FACE studies predict that CO₂ benefits for wheat in the southwestern U.S. will be counterbalanced by the negative effects of temperature increases in 2050 predicted by the A2 scenario (Ko et al., 2010). Although higher levels of CO₂ reduce stomatal conductance and therefore plant transpiration, warmer temperatures may additionally counteract the benefit of higher WUE by
increasing evaporative demand. Rain-fed wheat grown in China at elevated CO2 (450 ppmv) demonstrated yield increases of 5.3% up to a temperature rise of 0.8°C (as determined by differences in mean daily temperatures due to different sowing dates), but yields declined by 5.7% when temperature rose beyond 1.5°C because of insufficient water supply at these warmer temperatures (Xiao et al., 2005). Reduced transpiration due to elevated CO2 may also increase leaf temperatures beyond optimal crop growing ranges: FACE studies on wheat and cotton indicate additional leaf warming of 0.6-1.1°C in a 550 ppmv CO2 atmosphere that would occur on top of any ambient air temperature increase (Kimball et al., 2002). The benefit of elevated CO2 may additionally be diminished by an increase in sensitivity to pests, with studies demonstrating higher soybean vulnerability to the Japanese beetle and maize vulnerability to the western corn rootworm in a high CO2 environment (Zavala et al., 2008).

O3-induced damage to crops depends on the rate of O3 absorption into plant leaves as well as the plant's inherent defense capacity. Both factors are affected by the ambient environment and will therefore be sensitive to global environmental changes. The rate of O3 absorption into leaves is determined by solar radiation, air temperature, leaf-to-air vapor pressure deficit, CO2 concentration, soil water potential, and phenological stage (Emberson et al., 2000). Reduced vapor pressure deficit and soil water potential (for example caused by climate-induced regional drying) will inhibit O3 uptake, while the opposite is true for wetter climates (Vandermeiren et al., 2009). Higher levels of CO2 also decrease stomatal conductance and therefore O3 flux into leaves, possibly mitigating O3 damages (Mauzerall and Wang, 2001; Fiscus et al., 2005; Fuhrer, 2009). The Soybean FACE experiment found that for soybean grown at 550 ppmv CO2 and elevated O3 (x1.2 ambient), the negative impact of high O3 on yields was partially offset by gains from CO2 fertilization (Dermody et al., 2008). As stomatal conductance
is a parabolic function of temperature, warmer temperatures may increase O₃ uptake in moist, temperate climates where crops currently grow in ambient air below their optimal conductance temperatures, but the opposite is true for regions where crops grow at or beyond peak temperatures for conductance (Vandermeiren et al., 2009). The oxidative defense capacity of crops can also be affected by rising air temperatures, air and soil moisture content changes, increasing CO₂, and changes in solar radiation (Fuhrer et al., 2009). Soybean grown at chronic elevated CO₂ decreased total antioxidant capacity, but the opposite was true for growth in elevated chronic O₃ (Gillespie et al., 2011). Such changes in the resistance capacity to oxidative stress will in turn affect the overall yield response of crops exposed to elevated O₃. Projecting the overall impact on crops of different elements of global environmental change would therefore benefit from the ability to predict where multiple stresses may occur on a fine scale, as well as a more robust understanding of the direction and magnitude of the effect of various stress combinations on crop yields.

3. **Comparison of estimated impacts of climate change and O₃ exposure**

Given the potential importance of both climate change and surface O₃ in affecting agricultural yields and the relatively less attention that potential O₃ impacts have received, we quantitatively compare the predicted yield response of crops to these two major components of global change using results from several important empirical and modeling studies. We focus on selected global-level studies where comparisons across countries, regions, crops, and scenarios are possible. Although robust estimates of O₃-induced crop yield losses are limited on a global scale, we choose climate change impact estimates derived using a variety of methodologies, with and without the CO₂ fertilization effect, in order to examine the range and consistency of results across studies. In addition to contextualizing predicted O₃ impacts against those of climate
change, we identify crops and regions where agriculture is at risk of yield losses due to both climate change and O3 over the next few decades.

3.1. Results

Table 13 summarizes the change in global soybean, maize, wheat, and rice yields due to climate change (with and without CO2 fertilization) over the period 1980-2008 (Lobell et al., 2011). Table 13 also lists estimated global yield reductions due to surface O3 exposure in the year 2000 (as measured from a theoretical 100% yield at a “reference” level where no O3 damages occur) (Van Dingenen et al., 2009; Avnery et al., 2011a). Table 14 provides the same comparison on a national level where data are available from these studies. Results from these analyses suggest that present-day O3 exposure is having a more detrimental effect on global crop yields than climate changes over the past three decades, although this result varies somewhat by crop and region. For example, global maize yield reductions are similar for both climate change and O3 (3.8-3.9%), but O3-induced yield losses are estimated to exceed those due to climate change by 3.4%, 4%, and 9.6% for rice, wheat, and soybean, respectively. Climate change may be having a greater negative effect than O3 in Russia, Brazil, China, and Paraguay on wheat, maize, maize, and soybean yields, respectively, but O3-induced yield reductions are estimated to be more severe for the remaining nations and crops listed. Inclusion of the CO2 fertilization effect offsets projected yield decreases due to climate change for the C3 soybean, rice, and wheat crops (assuming a 3% yield gain based on FACE results) (Lobell et al., 2011), and may more than compensate for yield losses due to changes in temperature and precipitation since 1980 for soybean and rice (with total yield gains of 2.9 and 1.3%, respectively).

The “change” in yield measured by the climate change and O3 impact studies is not defined in precisely the same terms. For climate, the difference in yield is measured relative to
that achieved in a baseline year (in this case 1980), before major shifts in temperature and precipitation patterns occurred as a consequence of anthropogenic greenhouse gas emissions. The baseline for O₃ impact studies, by contrast, is a theoretical yield at a reference level at which O₃ does not damage crops. Although the reference level of O₃ exposure varies by metric, it is generally representative of natural background O₃ concentrations. A common O₃ exposure index defines this threshold at 20-25 ppbv depending on the crop (Wang and Mauzerall, 2004; Feng and Kobayashi, 2009), while preindustrial O₃ concentrations in Europe are reported as approximately 10 ppbv (Marenco et al., 1994). Therefore despite slight definitional inconsistencies, the agricultural impacts compared here quantify the change in yield due to anthropogenic greenhouse gas or O₃ precursor emissions – in other words, the change in yield that is due to climate change or O₃ pollution resulting from human activity.

In Figs. 22-23, we plot future estimated maize and wheat crop yield changes due to climate change (with and without the CO₂ fertilization effect) (Iglesias and Rosenzweig, 2009) and O₃ exposure (Avnery et al., 2011b) according to the IPCC SRES A2 and B1 scenarios, representing pessimistic and optimistic projections, respectively, of anthropogenic greenhouse gas and pollutant emissions. These scenarios are also opposite in terms of economic, environmental, and geopolitical driving forces, with the B1 scenario characterized by global cooperation and an emphasis on environmental sustainability and the A2 scenario reflecting a more divisive world with greater importance placed on economic growth. Climate impacts on agriculture were determined by Iglesias and Rosenzweig (2009) using the HadCM3 GCM and a dynamic process crop growth model (the Decision Support System for Agrotechnology Transfer (DSSAT)) that has been specified and validated for 127 sites in major agricultural regions worldwide. Since the simulation does not account for the impact of extreme events or pests,
damages due to climate change may be underestimated – especially in tropical regions (Iglesias and Rosenzweig, 2009). While Iglesias and Rosenzweig (2009) explicitly incorporate farmer adaptation into their results, the O₃ impact estimates cited here do not include possible adaptation measures. However, recent research suggests that low-level farmer adaptation strategies (e.g. altering watering regimes or crop calendar dates) have little potential to significantly improve O₃-induced yield reductions in most regions (Teixeira et al., 2011).

Robust estimates of future global O₃-induced yield losses exist only for the year 2030, which we compare to climate impacts slightly later in the century (2050s) due to data availability and the delayed response of the climate system to greenhouse gas forcing. We note that while O₃ concentrations are predicted to have reached peak levels in 2030 in all but the most pessimistic of the new IPCC Representative Concentration Pathway (RCP) scenarios (Kawase et al., 2011) and in modified simulations of the SRES scenarios that account for air quality legislation adopted through 2006 (including CO and NOₓ controls for mobile sources in Asia and Latin America and more stringent legislation in North America and Europe) (Royal Society, 2008), climate change impacts are likely to increase well beyond 2050 given the current policy environment (see Section 3.2.1). However, even in optimistic projections of future O₃, actual emissions of O₃ precursor pollutants will depend critically on the extent of implementation and enforcement of emission control regulations. Moreover, the O₃ simulations in 2030 do not account for the possible effects of climate change on air quality, which may increase peak ozone events in continental interiors (e.g. Wu et al., 2008; Bloomer et al., 2009; Jacob and Winner, 2009) and therefore exacerbate potential O₃ impacts on crops. For example, Bloomer et al. (2009) estimated an average O₃ “climate penalty” of 3.6 ppbv per degree of warming in the
eastern U.S. before 2002 and 2.0 ppbv since this date (as substantial reductions in NO\textsubscript{x} emissions beginning in 2002 decreased the climate penalty).

Figs. 22-23 show that O\textsubscript{3} exposure is projected to reduce the global yields of maize by 4-7\% and wheat by 10-15\% in 2030 depending on the scenario, with significant regional variability (and with greater yield losses in the A2 scenario due to higher projected emissions of O\textsubscript{3} precursors). The most severe O\textsubscript{3} impacts occur in nations where crop growing seasons coincide with peak months of O\textsubscript{3} production, and where cultivated areas overlap with regions of high O\textsubscript{3} concentrations (Avnery et al., 2011b). Regions where crops are especially vulnerable to O\textsubscript{3} exposure include South and East Asia, Brazil, northern Africa, and the Middle East in both scenarios, with the U.S. and Europe also at risk in the A2 scenario. Figs. 22-23 further demonstrate that climate change in 2050 is expected to have a greater negative impact on maize than O\textsubscript{3} in 2030: global maize yields are expected to be reduced by 7-8\% with CO\textsubscript{2} fertilization and 8-11\% without CO\textsubscript{2} effects. The A2 scenario generates more severe negative yield impacts due to greater amounts of warming (combined with limited offsetting CO\textsubscript{2} fertilization projected for this C\textsubscript{4} crop), with the highest climate-induced yield losses expected to occur in Africa, the Indian subcontinent, Eastern Europe, and parts of South America on the order of 15-20\% without CO\textsubscript{2} fertilization and 10-15\% with CO\textsubscript{2} effects.

By contrast, Figs. 22-23 demonstrate that wheat yields in 2050 are projected to increase globally by 1-3\% with CO\textsubscript{2} fertilization (depending on the scenario, with the A2 scenario generating the greatest yield improvement due to higher CO\textsubscript{2} concentrations), but are expected to decline by 5-7\% when CO\textsubscript{2} is not included in results (with the A2 scenario in this case generating the more negative impact). Wheat yields are projected to decrease in Africa, parts of South America and Eastern Europe, and the Indian subcontinent in both scenarios with and
without CO₂ fertilization included in projected impact estimates (up to ~20% depending on the scenario), with many mid- to high latitude nations expected to experience yield gains with CO₂ fertilization (on the order of 5-10%) but losses without CO₂ effects. Thus unlike for surface O₃, projected global climate change impacts are not uniformly worse under the A2 scenario (if CO₂ fertilization is included in impact estimates), with the sign of the yield change dependent on the crop and region. Small wheat yield changes due to climate change (+/- 2-3%) in the B1 scenario turn into significant gains in the U.S. and other mid- to high latitude regions in the A2 scenario (up to ~10%). This is due to an enhanced CO₂-fertilization effect, longer growing seasons, warming that approaches temperature optimums without exceeding thresholds above which yields rapidly decline, and the ability of industrialized, northern-latitude nations to adapt crops to an altered environment. By contrast, yield losses of maize due to climate change are exacerbated under the A2 scenario in almost all regions, with the exception of some northern latitude nations that benefit from warmer growing season temperatures and high adaptive capacity (e.g. the U.S. and Western Europe).

In summary, this comparison suggests that O₃ exposure in 2030 could be more detrimental to wheat than climate change in 2050, but that the opposite is true for maize – which appears to be vulnerable to negative impacts from both components of environmental change on a global level. However, results vary by region and exceptions to these generalizations exist, including for maize in the A2 scenario, where the U.S. and China are expected to suffer greater yield losses due to O₃ exposure than climate change (with and without CO₂ effects), and in Eastern Europe and Brazil in the B1 scenario, where climate change impacts on wheat (without CO₂ fertilization) may outweigh negative O₃ effects.
We additionally compare projected year 2030 O$_3$-induced yield losses with predicted climate change impacts (including CO$_2$ fertilization) on potential cereal yields in 2050 according to Fischer et al. (2002) (Fig. 24). The authors use three climate models to calculate the change in maximum attainable yields on currently cultivated land under a business-as-usual scenario according to the Agro-Ecological Zones (AEZ) system, which identifies limitations on soil, climate, terrain, and other parameters relevant to agriculture to compute agronomically attainable yields and crop production. The system assumes high inputs and optimal adaptations of crop calendars and cultivars, thereby providing an optimistic view of future climate change effects on (potential) crop productivity. Because data are only available for total cereals in aggregate, we compare the climate change impact on potential cereal yields (averaged across estimates derived from the three climate models) with the average O$_3$-induced yield impacts on maize and wheat from Avnery et al. (2011b) according to the B1 and A2 scenarios.

As evident in Fig. 24, Fischer et al. (2002) predict that potential cereal yields could significantly increase for mid- to high latitude major producers, including Canada (34%), Russia (28%), parts of Central Asia (14-46%), Australia (21%), China (13%), and the U.S. (8%). Potential yields could also increase substantially in some African nations; however, these yield increases are likely due to the assumed improvements in the currently significant gap between actual present-day yields and potentially achievable yields, thereby obfuscating a negative climate-crop response signal (Fischer et al., 2005). Fischer et al. (2002) project that, due to climate change, many countries in Africa and South Asia will suffer yield losses on currently cultivated land (generally on the order of 5-15%) even with the assumption of optimal management, including countries of the Indian subcontinent, northern Africa, and the Middle East. These regions are also projected to suffer steep yield declines due to O$_3$ exposure under
both B1 and A2 scenarios. For example, India is expected to experience a 16-21% reduction in yields (depending on the scenario), Pakistan a loss of 11-15%, and Middle Eastern nations are projected to suffer yield losses ranging from 11-30% due to O3 exposure. Western European countries such as France and Spain are additionally predicted to experience potential yield declines of >15% due to climate change, with O3 exposure also a risk in these regions under the A2 scenario (where predicted yield impacts could reach 15% in some nations). In summary, results from Fischer et al. (2002) indicate that climate change may increase potential yields across much of the mid- to high latitude nations and some countries in Africa (assuming a high-input scenario), but will decrease potential yields across many low latitude regions. These regions projected to suffer potential yield reductions due to climate change may furthermore be vulnerable to even greater losses due to O3 exposure (particularly parts of South Asia and Africa).

3.1.1 Distribution of risk of double exposure

We evaluate the relative risk of crops worldwide to “double exposure” – that is, negative yield reductions due to both O3 and climate change (including the effect of CO2 fertilization) – using O3 impact data from Avnery et al. (2011b) and climate change data from Rosenzweig and Iglesias (2009)\(^\text{10}\). We asses risk on a qualitative basis by assuming O3 and climate change effects on crops are additive and dividing nations into risk categories based on their combined score. Index categories are defined as follows: Critical = >25% yield loss, High = 15-25%, Medium-high = 10-15%, Medium = 5-10%, and Low = 0-5%. Nations where the combined yield effect of O3 and climate change is predicted to be positive are also shown. This evaluation

\(^{10}\) We use this climate impact study in order to facilitate direct comparisons across the individual crops, and because this study assesses yield reductions from a baseline level (rather than the impact on potential yields).
is meant to be simply illustrative of the distribution of risk, since the joint impact on crops of O₃ and climate change is extremely complex and unlikely to be fully additive in nature. Quantitative values used for index categorization should therefore not be literally interpreted (as such, only qualitative categories are shown).

Fig. 25 demonstrates that maize has the greatest risk of double exposure in Russia, China, South Asia, and parts of Central Africa in the A2 scenario, with the later two regions also highly at risk in the B1 scenario. Maize yield losses are generally on the order of 5-12% due to each of climate change and O₃ exposure in these regions. High and critical risks for wheat productivity exist in Brazil, Mexico, South Asia, and the Middle East in both IPCC scenarios (cumulative losses could exceed 20%, mostly due to O₃ exposure), with wheat in Eastern Europe also categorized as highly at risk in the A2 scenario due to greater projected O₃ impacts. Wheat in the U.S. is classified as having medium risk to double exposure, since slight yield enhancements due to climate change (up to ~5% in the A2 scenario) could be more than offset by negative effects due to O₃ (~10% yield loss in A2 and 5% in B1). Wheat yields are also projected to improve with climate change in Western Europe (~5-10%), which counterbalances moderate O₃ impacts and renders wheat at low risk in this region. Maize in the U.S. and Western Europe is classified as moderately at risk to double exposure, as climate change (and lack of significant CO₂ fertilization) is expected to decrease yields (along with O₃). Potential net yield impacts due to climate change and O₃ may be positive in Argentina, Canada, and Australia for wheat in both scenarios (as positive climate change effects (~5-10%) could outweigh small yield losses from O₃ exposure (<5%)). The same is true for maize in Australia in the A2 scenario.

3.2. Discussion
Our analysis suggests that present-day O₃ exposure levels are having a greater impact on agriculture than climate changes over the past few decades (albeit with exceptions by region and crop). Furthermore, projected O₃-induced wheat yield reductions in 2030 could exceed those due to climate change in 2050, particularly if yield gains due to CO₂ fertilization materialize at scales predicted, while maize appears to be more vulnerable to climate change than ozone exposure (Figs. 22-23). This result is driven by the fact that maize is a C₄ crop unexpected to experience significant yield enhancements due to CO₂ fertilization, and that a substantial amount of maize is grown in low-latitude and tropical regions near temperature optimums in the present-day environment (Easterling et al., 2007). Furthermore, the C₄ photosynthetic pathway provides a measure of protection against O₃ exposure due to reduced stomatal conductance (unlike for C₃ wheat) (Mills et al., 2007).

A robust conclusion across comparisons is that crops in certain countries and regions are particularly at risk of “double exposure” to both climate change and O₃ pollution in the future, including significant agricultural producers such as India, China, parts of Europe, and possibly Brazil and Russia (Fig. 25). Major importers of grains such as Pakistan, the Middle East, and parts of Africa are also at risk of yield reductions due to both climate change and O₃ exposure, threatening already limited agricultural production in these regions that are vulnerable to food market disruptions and food insecurity. Wheat production in the tropics (especially in South Asia) appears particularly at risk of double exposure given its high sensitivity to increased warming and O₃ exposure. This could be especially threatening to food security in India, a country expected to grow by almost 300 million people by 2030 (United Nations, 2010), and where over 20% of the population was undernourished in 2005-2007 (FAO, 2009b).
Beyond effects on crop yields, climate change may additionally affect the suitability of land available for agriculture in many regions where double exposure could occur. Zhang and Cai (2011) predict that South America, Africa, and India may lose 1–21%, 1–18%, and 2–4% of its arable land area, respectively, due to reduced water availability (depending on the climate scenario considered (SRES A1B or B1)), while warmer and wetter conditions could increase cultivable land in the U.S., China, and Russia. The authors note that these figures may be an underestimate of lost arable land in the tropics given the increasing competition for land due to population growth and pressure for greater ecosystem conservation. Potential reductions in cultivable land due to climate change exacerbate the threat to food security caused by declining yields, and further underscore the necessity of raising yields on existing farmland in order to meet future food demand.

3.2.1 Timing of effects

Although we examine the distribution of agricultural risk to the major components of global environmental change, it should be noted that the timing of peak impacts due to climate change and O₃ exposure will likely not be simultaneous. The new RCP scenarios forecast that O₃ will peak over the major northern hemisphere continental regions between 2020 and 2030 (Kawase et al., 2011; Wild et al., 2011), although the assumptions underlying these new scenarios with respect to their projections of reactive pollutants have been questioned (Smith et al., 2011). Furthermore, O₃ concentrations will ultimately depend on the extent of implementation and enforcement of emissions control regulations, and NOₓ emissions in some regions (i.e. Asia) have thus far exceeded scenario predictions from 2000 to 2010 (Dentener et al., 2010).
Nevertheless, while O₃ concentrations may decline after 2030, the most severe climate change impacts will occur later in the century due to a number of factors, including the delayed response of the climate system to greenhouse forcing; the gradual leveling of CO₂ concentration:response curves (Long et al., 2006; Tubiello et al., 2007; Ainsworth and McGrath, 2010); the exceedance of growth temperature optimums during crop growing seasons in mid- and northern latitudes as warming continues (Easterling et al., 2007); and the increased disruption of the hydrological cycle expected with greater amounts of warming (Meehl et al., 2007; Gornall et al., 2010). Research indicates that CO₂ fertilization begins to level off at atmospheric CO₂ concentrations of ~550 ppmv for soybean and wheat and ~700 ppmv for rice (Long et al., 2006; Tubiello et al., 2007; Ainsworth and McGrath, 2010), with associated temperature increases that may exceed 2°C (at which point positive crop yield changes in mid- to high latitudes begin to turn negative (Easterling et al., 2007)) expected as early as the 2050s (Meehl et al., 2007). Thus the greatest negative yield impacts from climate change will occur in the 2050s and the decades that follow, depending on future climate change mitigation policies. Climate change should therefore be considered a long-term (and currently growing) threat to agriculture; by contrast, O₃ exposure may be a short-term (albeit significant) threat if concentrations are reduced over the next few decades. The immediate threat of O₃ should not be depreciated, however, given the coincidence of peak O₃ impacts with a period of rapid population and economic growth (and associated increase in food demand) (FAO, 2006; World Bank, 2007), as well as growing strains on land and water resources (Foresight, 2011; Foley et al., 2011).

3.2.2. Additional studies of double exposure
To our knowledge, only two studies have attempted to quantify the combined impact of elevated CO₂, O₃, and climatic stresses on crop yields. Reilly et al. (2007) use the MIT Integrated Global Systems Model, which includes an updated version of the biogeochemical Terrestrial Ecosystem Model (TEM) that projects the impact of both climate change and surface ozone on plant productivity. This model simulates the pathways by which ozone influences the productivity and carbon storage of terrestrial ecosystems by modifying the calculation of gross primary production (GPP) (Felzer et al., 2004). The effect of ozone is simulated to linearly reduce GPP above a threshold ozone level (represented by a cumulative O₃ exposure metric, AOT40, which sums O₃ concentrations above 40 ppb during the growing season). The authors find that while the effects of climate change (including CO₂ fertilization) are generally positive in mid- to high latitudes, ozone pollution may more than offset potential climate benefits. For example, yield gains of 50-100% are predicted for much of the northern hemisphere in the year 2100 when only climate impacts are considered in a scenario where no additional efforts are made to control greenhouse gases or O₃ precursor emissions, but inclusion of the model’s O₃ damage function produces drastic yield reductions: combined climate and O₃ impacts reduce yields by 43% in the U.S., 56% in Europe, 45% in India, 64% in China, and 80% in Japan. Although these results may be pessimistic as they do not account for new regulatory controls that cap O₃ precursors, they underscore the need for field studies that examine the combined impact on agricultural production of climate change, CO₂, and surface O₃ in order to evaluate model-based studies and to identify crop cultivars that are relatively robust to both O₃ and climate change. As the incorporation of O₃ effects in this model is fairly simple (and yield impacts appear large), this study also demonstrates the need to improve models in order to better simulate the impact of CO₂, O₃, and climate change on a process level.
Using a simple statistical supply-demand model, Jaggard et al. (2010) additionally attempt to evaluate the combined effect on agricultural yields of future CO₂, O₃, and climate change (with the inclusion of potential technology improvements) in the context of assessing whether yield increases on currently cultivated land will be enough to meet global food demand in 2050. This model makes the important simplifying assumption that the yield effects of each of these components of global change, as well as of increases in productivity due to technology, are fully additive. The authors use CO₂ fertilization data from FACE studies, regional climate change impacts from Nelson et al. (2009), and global average O₃ response data from Feng and Kobayashi (2009) applied equally to all nations. Because O₃ distributions significantly vary both temporally and spatially, this simplification may lead to both regionally under- and overestimated O₃-induced crop yield losses (depending on projected future regional O₃ concentrations). The authors find that for their conservative technology improvement scenario, crop yields will increase by ~50% globally in 2050 under the A1B scenario as technology and adaptation (and to a lesser extent CO₂ fertilization and yield enhancements due to warming in northern regions) outweigh negative effects of climate change and O₃ on yields. Although yield increases of this magnitude would meet global food demand in 2050 without requiring additional land for cultivation, the authors note that the surplus production margin is thin, and that their analysis does not account for possible alternative uses of agricultural land for biofuels, other non-food crops, conservation, or new municipal infrastructure.

4. Selected strategies to improve agricultural production in the future environment

The future crop production environment will consist of higher atmospheric CO₂, average temperatures, and regionally higher O₃; increased drought frequency and severity; and more intense precipitation events (Solomon et al., 2007; Parry et al., 2007). Aside from the CO₂
fertilization effect, these changes will likely be detrimental for crops. With many nations at risk of yield reductions due to both climate change and O₃ exposure, including major agricultural producers and net food importers, mitigation strategies should be implemented to prevent additional future warming and to reduce O₃ precursor emissions.

4.1. Mitigation of environmental changes with benefits for agriculture

Global temperatures have already risen by 0.7°C over the past 150 years, and greenhouse gas emissions currently in the atmosphere have committed the world to a further 0.6°C temperature increase (Meehl et al., 2007). Although a discussion of climate change mitigation strategies is beyond the scope of this paper, we note that preventing “dangerous anthropogenic interference with the climate system” (i.e. warming beyond 2°C globally relative to preindustrial times, or about 1.1°C above present levels) likely requires stabilizing atmospheric CO₂ concentrations below 450 ppmv (Meinshausen, 2006). Stabilizing CO₂ at this level would mean that global average temperatures would have a high probability of remaining below the 3°C threshold where crops in mid- and higher latitudes would experience yield declines. However, as crop yields are projected to decrease in the tropics even with minimal warming, strategies focusing on adapting agriculture to a warmer world are required even in the increasingly unlikely scenario that the 450 ppmv stabilization target is met. Recent work indicates that greenhouse gas concentrations will likely reach at least 550 ppmv given the current policy environment, with a related global temperature rise around 3°C by 2100 (Parry, 2010).

Our work suggests that unless O₃ precursor emissions are curbed in the future, ozone exposure could pose an even greater threat to crops over the next two decades than climate change. While climate change mitigation remains an undisputed priority, O₃ abatement may offer a politically attractive means to improve global agricultural production in the near term.
given (1) the availability of cost-saving and low-cost O_3 mitigation strategies, and (2) the potential co-benefits of O_3 reductions for human health and climate change. Recent research demonstrates that O_3 abatement via mitigation of conventional pollutant precursors (NO_x, CO, and NMVOCs) would largely prevent significant additional O_3-induced yield reductions in the future (Van Dingenen et al., 2009; Avnery et al., 2011b), yet global year 2030 agricultural losses could remain substantial – particularly for O_3-sensitive crops in high O_3 regions (e.g. up to 17% globally for wheat with considerable regional variability) (Avnery et al., 2011b). Supplemental strategies to reduce O_3-induced crop losses beyond the targeting of traditional short-lived O_3 precursors are therefore desirable.

One particularly appealing strategy is the abatement of atmospheric methane, which presents a win-win policy opportunity for both air quality and climate change mitigation goals: CH_4 reductions provide the greatest climate benefit per unit surface O_3 reduction, but have not yet been targeted by policymakers for O_3 pollution abatement (West et al., 2007). Substantial CH_4 reductions could furthermore be achieved at a net cost savings due to the value of recovered methane (EPA, 2006), while many controls on traditional pollutants are becoming increasingly expensive to implement. Avnery et al. (2011c) calculate that reducing O_3 through modest methane reductions (with a net cost savings) could improve global crop production of soybean, wheat, and maize by 23-102 Mt in 2030 – the equivalent of a ~2-8% increase in year 2000 production of these crops worth $3.5-15 billion worldwide (USD_{2000}). The methane controls considered in this study would also have major benefits for climate change by offsetting the positive net radiative forcing from CH_4 and O_3 projected to otherwise occur by 2030 (~0.16 Wm^{-2}) (Fiore et al., 2008). This radiative forcing measure does not account for the additional indirect climate benefit of increased carbon storage potential in forests and other ecosystems that would
arise from reduced O₃ exposure (Felzer et al., 2005; Felzer et al., 2007), which may have a
greater effect on climate than the direct radiative forcing of tropospheric O₃ (Sitch et al., 2007).
Moreover, modest CH₄ controls similar in scale as those examined by Avnery et al. (2011c) have
the potential to prevent over 370,000 premature mortalities globally via their surface ozone
reductions through 2030 (West et al., 2007).

While methane reductions may offer significant benefits to agriculture as well as the
greatest advantages for climate change, CH₄ controls would reduce O₃ slowly due to the long
lifetime of methane (~12 years), and benefits to health and agriculture would be spatially diffuse
compared to the largely immediate and local-to-regional scale O₃ reduction benefit of NOₓ and
NMVOC mitigation.¹¹ A coordinated policy of CH₄ reductions, particularly in sectors where
methane recovery is more challenging (e.g. enteric fermentation and rice cultivation in
agriculture), may therefore require national or international incentives. Moreover, the delayed
O₃ response suggests that CH₄ controls would best be implemented as a complement to (rather
than substitute for) local and regional NOₓ and NMVOC reduction measures (West and Fiore,
2005). NOₓ mitigation would furthermore reduce the ozone “climate penalty” – that is, the
increase in O₃ due to warming at a given emissions level – projected to occur in many
continental interiors with rising temperatures (Bloomer et al., 2009).

4.2. Adapting crops to environmental changes

Adaptation strategies should further supplement climate change and O₃ mitigation in
order to maximize global crop production, particularly in regions where agriculture is especially
vulnerable to environmental changes (e.g. the tropics). Agricultural management and adaptation

¹¹ Although the monetary benefits of methane recovery would be accrued by those investing in
such CH₄ mitigation measures.
to climate change has been discussed at length elsewhere (see Howden et al., 2007; Deryng et al., 2011; Iglesias et al., 2011; Reilly, 2011), but the potential benefits of O₃ adaptation have only recently been assessed (Teixera et al., 2011; Avnery et al., 2011c). Although Teixera et al. (2011) find limited scope for adapting to O₃ via altering planting and harvesting dates or water regimes on a global scale, one potentially promising O₃ adaptation strategy is selecting, or breeding new, cultivars with O₃ tolerance. Avnery et al. (2011c) quantify the amount by which year 2030 crop production could be improved by choosing cultivars with the greatest demonstrated resistance to O₃ based on OTC studies (as compared to median-sensitivity cultivars), and find that global soybean, maize, and wheat production could be improved by 143 Mt – the equivalent of a 12% increase in year 2000 production worth ~$22 billion (USD₂₀₀₀) globally.

We therefore highlight several promising options to improve agricultural production via conventional breeding and/or transgenic crop technology that would generate new crop varieties better adapted to higher ambient O₃. We additionally summarize work investigating the potential to improve crop yield enhancements in an elevated CO₂ environment. We focus on these two targets because despite the significant demonstrated impact of CO₂ and O₃ on crops, these compounds have received surprisingly little attention to date as potential strategies for yield improvements. For example, the major seed development companies (including Monsanto, Syngenta, and Pioneer-Du Pont) continue to promote research and investment into drought-, heat-, and cold- tolerant crops, but have yet to include targets for adaption to CO₂ and O₃ in their research and development pipelines. This is particularly striking given the 10-20 year lag time between initial seed development and its dissemination in the field (Ainsworth et al., 2008b).

4.2.1. CO₂
As CO₂ increases photosynthesis in C₃ species, and because Rubisco is frequently the rate limiting factor for photosynthesis in the present-day atmosphere, recent work has examined the potential to increase the affinity of this key enzyme for CO₂ in order to further catalyze the fixation reaction and enhance photosynthesis, in turn improving crop yields (Ainsworth et al., 2008b). However, as atmospheric CO₂ increases and/or if crops are engineered to have higher Rubisco activity, photosynthesis in C₃ crops will shift from being Rubisco-limited to being restricted by the regeneration capacity of the CO₂ acceptor (ribulose-1,5-bisphosphate, or RuBp, which is required for the initial fixation reaction) (Jaggard et al., 2010). Another potential prospect for improving crop response to CO₂ is therefore to increase the regeneration capacity of RuBp to match the stimulated Rubisco activity of an enhanced CO₂ environment (Ainsworth et al., 2008b).

Increasing the yields of C₄ crops may be more challenging, as any growth stimulation in an elevated CO₂ environment is an indirect effect of reduced stomatal conductance and increased WUE (rather than a direct fertilization effect) (Ainsworth et al., 2008b). Alternative options for yield enhancements must therefore be targeted for C₄ crops unrelated to CO₂-fertilization (these could also be C₃ breeding targets). One possibility for yield improvement focuses on increasing crops’ radiation use efficiency (RUE) (and therefore rates of photosynthesis) by manipulating canopy architecture, such that more of the canopy has access to moderate light intensity (rather than fewer leaves being light-saturated) (Long et al., 2005; Jaggard et al., 2010). This could occur through making the upper leaves of the canopy vertical to ensure minimum saturation, while the lower leaves are near horizontal so that almost all solar radiation is absorbed – this has been found to increase RUE by up to 40% in full sunlight (Long et al., 2005). Another option to increase C₄ yields is to improve crop resistance to multiple abiotic as well as biotic stressors such
as pests and pathogens (Mittler and Braggard, 2010). Because carbon supply is improved at higher CO₂ concentrations, it may be possible to partition more photosynthate into metabolites that have been associated with stress resistance. Greater tolerance to various environmental stressors could increase agricultural production by allowing crops to be grown in regions that are now considered unsuitable for cultivation, in addition to enhancing productivity in more optimal growing locations (Ainsworth et al., 2008b).

4.2.2. O₃

OTC and FACE studies have established the existence of a wide range of crop sensitivity to ozone, both among different crops and within cultivars of the same crop (Heagle, 1989; Krupa et al., 1998; Morgan et al., 2006). Crop varieties used today appear to exhibit sensitivity to ozone that is on average at least as great as that seen in earlier field studies (Long et al., 2006; Biswas et al., 2008; Emberson et al., 2009; Singh and Agrawal, 2009; Zhu et al., 2011), suggesting that O₃ sensitivity may be an overlooked factor in cultivar choice. An important note is that while conventional breeding over time would be expected to select for crop cultivars that exhibit a significant CO₂ fertilization effect given the long-lived nature of this compound and its steady increase since pre-industrial times, the same may not be true for O₃ because of the variable temporal and spatial concentrations of this short-lived pollutant – and therefore the inconsistent O₃ exposure that crops may be subjected to in a given season and location (Ainsworth et al., 2008b).

Improving crop tolerance to O₃ has largely focused on three general strategies that target the biochemical and physiological processes believed to contribute to O₃ sensitivity (Ainsworth et al., 2008b): (1) reducing O₃ entry through the stomata; (2) improving cellular detoxification capacity; and (3) altering signal transduction pathways – the process by which an extracellular
signaling molecule senses and triggers an intracellular response, including the altering of gene expression (e.g. up-regulating processes responsible for antioxidant defense while down-regulating photosynthesis and other metabolic processes). The first strategy requires decreasing stomatal conductance, but because reducing conductance also inhibits photosynthesis, this approach entails a tradeoff between O₃ protection (via lower conductance) and reduced productivity. Improving yields by increasing ROS detoxification rates has been associated with higher levels of the antioxidant ascorbate (Fiscus et al., 2005), as well as the ability of these compounds to be recycled, particularly in the apoplastic (intercellular) space where ROS forms and initial detoxification occurs (Conklin and Barth, 2004). Increasing apoplastic antioxidants like ascorbate may therefore be a useful breeding target. The engineering of sensing, signaling, and/or regulatory pathways may also be fruitful strategies to reduce O₃-induced damages by altering crop responses to oxidative damage signals (Li et al., 2006; Sarkar et al., 2010). However, this approach is complicated because the signaling pathway associated with acute O₃ damage may overlap with other signaling pathways for stress (e.g. that responsible for pathogen resistance), and may play a role in regulating major processes such as senescence. Improving crop resistance via altering signal transduction therefore requires significant additional research to ensure that modifications for O₃ tolerance do not interfere with other vital crop functions (Ainsworth et al., 2008b).

5. Research Recommendations

Numerous uncertainties remain in assessments of future agricultural production, including the magnitude of the individual and combined effects of CO₂, O₃, and climate change on crop productivity, the impact of extreme weather events, and the extent of our ability to adapt to environmental changes and improve crop yields through better management practices and new
technologies. More FACE experiments are needed to better quantify and parameterize the CO₂ fertilization effect for different crops, regions, range of CO₂ concentrations, and environmental and management conditions. The same need for FACE experiments exists to better quantify the effect of O₃ on a variety of crops in different parts of the world, particularly for local cultivars grown in major agricultural regions subject to high ambient O₃ (Van Dingenen et al., 2009; Avnery et al., 2011a). Thus far FACE technology has only been reported in three studies that examine the impact of O₃ on crops: soybean in the U.S. (Long et al., 2005; Long et al., 2006; Morgan et al., 2006) and rice and wheat in China (Shi et al., 2009; Zhu et al., 2011). As a recent comparison of local crop cultivars found that Asian varieties may be more sensitive to O₃ than those of North American and Europe (Emberson et al., 2009), and as this region is expected to experience a rise in both food demand and O₃ levels, additional ozone FACE experiments with local Asian cultivars would be highly beneficial. In the absence of FACE technology (due to prohibitive costs or other impediments), OTC studies of current cultivars of major grains, fruits and vegetables, and for additional stable crops such as cassava that are an important source of calories in tropical countries, offer a reliable and less expensive (if imperfect) alternative to FACE experiments (Tubiello et al., 2007).

In addition to experiments that investigate the individual effects of CO₂ and O₃ on agricultural yields, a critical research need are field studies that examine the combined impact on crops of multiple environmental stressors (including increased CO₂, O₃, higher temperatures, and changes in water supply). Given that the agricultural impact of severe weather events in the future may be greater than yield reductions due to mean climate changes (Easterling et al., 2007), and that this impact is currently not well-simulated by crop growth models (Soussana et al., 2010), field experiments that also examine the effect on crop yields of short-duration stress
events (e.g. peak temperatures, drought, or flood conditions) during different phenological stages of crop development are needed. Extreme weather events should be examined individually as well as in combination with additional abiotic stress conditions prevalent in the present-day and predicted future environment. Although FACE studies are highly desirable, OTC experiments may also be used to provide a first-order assessment of the impact on crops of multiple environmental stresses (e.g. heat-wave temperatures, drought, and O₃ exposure at ambient and elevated CO₂) (Tubiello et al., 2007).

Targeted model developments are needed to improve the simulation of (1) the magnitude and variability of crop yield reductions resulting from O₃ exposure for a variety of crops, cultivars and growing conditions (Van Dingenen et al., 2009; Avnery et al., 2011a); (2) the magnitude of the CO₂ fertilization effect for different crops and regions; (3) the impact of extreme weather events; (4) interactions between climate stressors (e.g. heat waves, droughts, and floods) and elevated CO₂ and O₃; (5) interactions with biotic stressors (e.g. pests and pathogens); and (6) adaptation to climate change and elevated O₃ (Challinor et al., 2009; Soussana et al., 2010). With respect to integrating O₃ and climate variables in crop impact assessments, models that calculate stomatal flux of O₃ as a function of a range of environmental factors have been developed for wheat, potato, and tomato at a regional level in Europe (Emberson et al., 2000; Pleijel et al., 2004; Pleijel et al., 2007; Mills et al., 2011b), but additional stomatal flux models for other crops and regions are needed. With few exceptions (e.g. Van Oijen et al., 2004; Reilly et al., 2007), current crop and ecosystem models do not include an O₃ damage function, and those that model direct O₃ injury do not explicitly account for possible changes in vulnerability to O₃ that may occur with climatic changes. O₃ flux models should continue to work towards incorporating plant detoxification capacities at different stages of
growth, development, and under a range of environmental conditions (including climatic stress events). These flux models could then be integrated into crop process models by simulating the impact of effective O₃ flux (i.e. cumulative O₃ dose minus detoxification) on important physiological functions (e.g. photosynthesis), which has been shown to be correlated with biomass accumulation and yield (Booker, 2009; Singh et al., 2009; Wang et al., 2009). O₃ flux, crop, and ecosystem models that aim to integrate the effects of multiple environmental stresses require experimental studies to support model development and evaluate simulated results as described above.

Integrated assessments of climate change or O₃ impacts on crops and their socioeconomic implications accumulate the uncertainties inherent in each component of the analysis (e.g. global climate/O₃ simulations, crop models, cultivar sensitivity, etc.). A careful accounting of the relative contributions of uncertainty due to the accuracy of model simulations of climate change or O₃ distributions versus crop models (or concentration:response relationships, among other factors) would help make projections of future food production more robust (Challinor et al., 2009). Perturbing parameters and ensemble approaches used in climate modeling are now being implemented for crop models coupled with climate and economic simulations (e.g. the Agricultural Model Intercomparison and Improvement Project (AgMIP)) in order to better characterize climate change impacts on crop yields, production patterns, risk of hunger, and food security (Rosenzweig, 2010). A useful complement to this work would be a similar multi-model comparison effort for O₃ impacts under present-day and projected future O₃ concentrations according to different scenarios of O₃ precursor emissions (including the new RCP scenarios) using numerous atmospheric chemistry models and O₃ concentration:response relationships. Such efforts will provide a more robust estimate of crop yield responses to climate change and
O_3 exposure, thereby reducing uncertainties associated with integrated assessments of future agricultural production under different scenarios of environmental change.

Statistical studies based on empirical data can supplement and provide an independent assessment of relationships derived from field experiments and modeling work. Using multiple linear regression and historical weather and crop productivity data, Lobell and colleagues (e.g. Lobell and Field, 2007; Lobell et al., 2011) developed statistical models of the relationship between temperature and precipitation on crop yields globally, providing empirical evidence that some crops are already being negatively affected by climate change over the past few decades. Conducting studies of this nature on a finer scale to reduce uncertainties and establish more accurate relationships between yields and climate variables by region would be beneficial – particularly for areas of the world that are predicted to be most vulnerable to immediate climate changes (e.g. the tropics). Similar empirical studies could examine crop yield responses to O_3 exposure – to our knowledge, the regional (U.S.) study of Fishman et al. (2010) (described in Section 2.2) provides the first and only independent empirical verification of O_3-induced crop losses. The authors note that their use of satellite O_3 data (which was validated by ground-level observations) facilitates the expansion of their analysis globally – and especially to regions where surface O_3 monitoring data are unavailable, which is the case for much of the developing world. This type of study for crops with high O_3 sensitivity (e.g. wheat, soybean) growing in locations where O_3 concentrations are sufficiently high to cause significant damages (e.g. India), would be beneficial to supplement model-derived estimates of O_3 damages. However, the lack of surface O_3 observations to evaluate satellite-derived estimates may be problematic, as the accuracy of this technique in reproducing O_3 concentrations in different regions of the world and under various meteorological conditions is unknown.
Empirical models have the advantage of capturing the net effect of the entire suite of variables through which climate change or O\textsubscript{3} may affect yields, including processes that are poorly understood and simulated by crop models (Lobell and Field, 2007). These models can also be applied at large scales, and they enable a quantitative evaluation of uncertainties that may be difficult for integrated modeling studies (where uncertainties are propagated and compounded). However, these studies do not include a process-based understanding of the crop-environment system, and any predictions derived from relationships between crop yields and climate/O\textsubscript{3} using present-day and historical data necessarily assume that the relationships will remain unchanged in the future. Furthermore, uncertainties may be large in statistical studies due to inherent errors from the input data sets, and results should therefore be interpreted cautiously and in conjunction with modeling and field studies.

Research priorities are therefore summarized as follows. More FACE experiments (or OTC studies) would be beneficial to inform model development, validate simulated results, and to better understand the combined impact on crops of multiple environmental stressors (particularly rising temperature, changes in water availability, CO\textsubscript{2}, and O\textsubscript{3}) on a physiological level. Field studies would be particularly useful to better quantify current crop sensitivity to O\textsubscript{3} in different parts of the world and types of crops. Modeling studies informed by field experiments would benefit from improvement in the simulation of the magnitude and variability of crop yield responses to O\textsubscript{3} exposure, CO\textsubscript{2} fertilization, extreme weather events, and combinations of these and other environmental stressors. Empirical statistical studies examining the relationship between climate change or O\textsubscript{3} exposure and agriculture could further aid in evaluating simulated results and in supporting model development. Understanding the relative
contributions of different sources of uncertainty in integrated assessments of climate change or ozone impacts on crops would make forecasts of future agricultural production more robust.

6. Conclusions

Meeting the projected 70% increase in grain demand by 2050 (FAO, 2006; FAO, 2009a) – and doing so sustainably against the backdrop of environmental changes that are expected to reduce agricultural productivity – presents a significant challenge to global food production systems. Elevated atmospheric CO2 may enhance the yields of C3 species and both C3 and C4 crops where water supply is currently or projected to be insufficient. Moreover, mean temperature increases in mid- to high latitudes may elongate growing seasons and improve the yields of crops cultivated in regions currently below optimal growth temperatures. However, agriculture in tropical nations is vulnerable to even minor warming, and crop yields worldwide are expected to decline if temperatures rise more than 3°C (Easterling et al., 2007). Changes in precipitation patterns, including an increase in the magnitude and frequency of extreme events such as droughts and floods, may disrupt crop yields more than mean climate changes. Surface O3 further threatens agricultural yields, with current crop yield reductions due to O3 exposure estimated at 2-16% globally, depending on the crop (Van Dingenen et al., 2009; Avnery et al., 2011a). O3 could further decrease the yields of soybean and wheat by ~10% by 2030 under a pessimistic trajectory of future O3 precursor emissions (Avnery et al., 2011b).

Present-day O3-induced crop yield reductions appear to exceed agricultural losses due to climate changes since 1980 for most crops and regions, and O3 impacts in 2030 could also be of similar magnitude (for maize) or possibly greater (for wheat) than those predicted due to climate change in 2050. However, this assessment strongly depends on the path of future O3 precursor emissions, the extent of CO2 fertilization, and our ability to adapt to both climate changes and O3
exposure. Many regions of the world are acutely vulnerable to double exposure from both climate changes and elevated O$_3$ – including significant agricultural producers such as India, China, Brazil, and Russia, as well as major food importers such as Pakistan, parts of Africa, and the Middle East. Tropical wheat production appears especially vulnerable to double exposure given its high sensitivity to both temperature increases and O$_3$, with yield losses on the order of 20% due to climate change without the offsetting CO$_2$ fertilization effect (up to ~5% with CO$_2$ fertilization) (Iglesias and Rosenzweig, 2009) and ~30% due to O$_3$ (Avnery et al., 2011b). However, predicted peak impacts due to O$_3$ and climate change will likely not occur simultaneously, as O$_3$ concentrations are expected to peak in most regions by 2030 while the most severe climate change impacts are expected in the 2050s and the decades that follow (depending on future climate mitigation policies) (Meehl et al., 2007; Kawase et al., 2011; Wild et al., 2011). While climate change is therefore a long-term and growing problem, the short-term threat of surface O$_3$ should not be discounted, particularly as the most severe O$_3$-induced crop yield reductions are predicted to occur at during a period of significant population growth (~1.4 billion people between 2010 and 2030 (United Nations, 2010)), rapid economic development, and corresponding increase in global food demand (FAO, 2006; World Bank, 2007).

Significant uncertainties remain in current projections of future agricultural production and the precise impact of environmental changes. The magnitude of the CO$_2$ fertilization effect and O$_3$ yield-reduction factors for different crops and cultivars requires further specification, particularly in regions of the world where FACE or large-scale OTC experiments have not taken place with current cultivars (which vary by region) under local environmental and management conditions. Major knowledge gaps exist in our understanding of crop responses to multiple environmental stressors, which may have synergistic or antagonistic effects on crop yields.

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(Mittler and Blumwald, 2010). Understanding how agriculture in regions at risk of double exposure will respond to both climate change and O3 exposure is critical, particularly in locations with presently large undernourished populations and predicted population growth (e.g. South Asia). Projections of future agricultural production would additionally be improved by better quantification of the impact of extreme weather events, vulnerability to biotic stressors such as pests and pathogens in a changing environment, and improved representations of farmer adaptation.

As environmental change will likely challenge our ability to meet growing food demand, there is a need to implement mitigation and adaptation strategies that reduce crop damages caused by climate change and O3 exposure. Climate change mitigation goals should aim to meet the 450-ppmv stabilization target that would likely prevent exceedance of the 3°C temperature threshold where crop yields worldwide would suffer significant declines (Meehl et al., 2007; Easterling et al., 2007). Reductions in surface O3 could significantly improve crop yields. O3 abatement via CH4 mitigation would additionally provide a substantial co-benefit for climate change (Avnery et al., 2011c), in turn further improving global agricultural production. Targets for biotechnology and selective crop breeding should center on exploiting traits that will maximize CO2 fertilization as well as resistance to drought, flood, above-optimal temperatures, and O3 exposure. In particular, improving crop response to CO2 and building O3 tolerance should be added to major seed companies’ research agendas. Reducing crop damages cased by climate change or O3 exposure would improve crop yields and global agricultural production sustainably – i.e. without causing further harm to the environment by exacerbating climate change or water/air pollution, or consuming increasingly scarce resources such as water, land, or energy.
References


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http://www.census.gov/ipc/www/idb/worldpopgraph.php


Figures

Figure 22. Estimated maize (left) and wheat (right) yield response (%) to (a) surface O$_3$ exposure in 2030 (Avnery et al., 2011b), (b) climate change without the CO$_2$ fertilization effect, and (c) climate change with CO$_2$ fertilization in the 2050s (Iglesias and Rosenzweig, 2009) according to the IPCC SRES A2 scenario. Iglesias and Rosenzweig (2009) use a coupled climate-crop model, while Avnery et al. (2011b) use simulated global O$_3$ exposure concentrations, concentration:response functions from field studies, and satellite-based agricultural data. Grey regions indicate nations for which crop calendar data were unavailable to calculate growing season O$_3$ exposure by Avnery et al. (2011b), which together account for <5%
of global production. The mean of two estimates of O$_3$-induced yield losses based on different O$_3$ exposure indices is presented here, as described in Table 13.
Figure 23. Estimated maize (left) and wheat (right) yield response (%) to (a) surface O₃ exposure in 2030 (Avnery et al., 2011b), (b) climate change without the CO₂ fertilization effect, and (c) climate change with CO₂ fertilization in the 2050s (Iglesias and Rosenzweig, 2009) according to the IPCC SRES B1 scenario. Iglesias and Rosenzweig (2009) use a coupled climate-crop model, while Avnery et al. (2011b) use simulated global O₃ exposure concentrations, concentration:response functions from field studies, and satellite-based agricultural data. Grey regions indicate nations for which crop calendar data were unavailable to calculate growing season O₃ exposure by Avnery et al. (2011b), which together account for <5% of global production. The mean of two estimates of O₃-induced yield losses based on different O₃ exposure indices is presented here, as described in Table 13.
Figure 24. Estimated (a) change in potential attainable cereal yields (%) on currently cultivated land due to climate change in 2050 (including the CO₂ fertilization effect and optimal agricultural management) (Fischer et al., 2002), and change in mean maize and wheat yields due to O₃ exposure in the IPCC SRES (b) B1 and (c) A2 scenarios in 2030 (Avnery et al., 2011b). Fischer et al. (2002) use three climate models to calculate the change in maximum attainable yields under a business-as-usual scenario according Agro-Ecological Zones (AEZ) system (the mean of the derived impact estimates is shown), which identifies limitations on soil, climate, terrain, and other parameters relevant to agricultural production to compute agronomically attainable yields and crop production. See Figure 22 caption for details of the O₃ impact calculations.
Figure 25. Distribution of risk of double exposure (i.e. yield reductions due to both O₃ (Avnery et al., 2011b) and climate change (including the effect of CO₂ fertilization (Iglesias and Rosenzweig, 2009)) in the SRES A2 (left) and B1 (right) scenarios for (a) maize and (b) wheat. Index categories are defined according to the potential cumulative yield loss in each nation based on the theoretical case that calculated yield impacts are fully additive: Critical = >25% yield loss, High = 15-25%, Medium-high = 10-15%, Medium = 5-10%, and Low = 0-5%. Nations where the combined yield effect of O₃ and climate change is predicted to be positive are also indicated. This index should be considered qualitative, and quantitative values used for index categorization should not be literally interpreted. See captions in Figs. 22-23 for details on the data used here. Grey regions indicate nations where O₃ yield reductions were not calculated and are therefore not included in these results.
Table 13. Global soybean, wheat, rice, and maize yield response (%) to climate change (temperature and precipitation variations) and rising CO$_2$ from 1980-2008, and yield reductions due to O$_3$ exposure in the year 2000. Climate and CO$_2$ yield changes from Lobell et al. (2011) are based on multiple linear regression results from publically available climate and crop data. O$_3$ yield reductions from Avnery et al. (2011a) for soybean, wheat, and maize, and from Van Dingenen et al. (2009) for rice, were derived using simulated global surface O$_3$ concentrations, concentration:response functions from field studies, and satellite-based agricultural data. As the O$_3$ impact studies use two indices of O$_3$ exposure to calculate yield losses, the mean of the two estimates is listed here for each crop.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Temperature</th>
<th>Precipitation</th>
<th>CO$_2$</th>
<th>Climate Only (no CO$_2$)</th>
<th>Climate &amp; CO$_2$</th>
<th>O$_3$</th>
</tr>
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<td>-3.8</td>
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<td>-5.5</td>
<td>-2.5</td>
<td>-9.5</td>
</tr>
<tr>
<td>Soybean</td>
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<td>-0.9</td>
<td>3.0</td>
<td>-1.7</td>
<td>1.3</td>
<td>-11.3</td>
</tr>
<tr>
<td></td>
<td>Maize</td>
<td>Rice</td>
<td>Wheat</td>
<td>Soybean</td>
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<td>O₃</td>
<td>CC</td>
<td>O₃</td>
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</table>

Table 14. National soybean, wheat, rice, and maize yield response (%) to climate change (CC, temperature and precipitation variations) from 1980-2008, and yield reductions due to O₃ exposure in the year 2000, where data are available for comparison. Data are taken from Lobell et al. (2011) and Avnery et al. (2011a) as described above, with the exception of rice yield response data taken from Van Dingenen et al. (2009) (we use the mean of two estimates of yield losses based on different O₃ exposure indices as described in Table 13).
Chapter 6

Conclusions, Policy Implications, and Future Research

1. Key Findings

This dissertation quantified the global, regional, and national impact of O3 on key staple crops in the present (2000) and near future (2030) under optimistic and pessimistic scenarios of O3 pollution, and estimated the value of associated crop production losses. This work further evaluated the potential of supplemental strategies (beyond targeting conventional O3 precursor pollutants) to reduce O3-induced agricultural losses, including a mitigation strategy motivated primarily by climate change abatement goals (reductions in CH4 emissions), and an adaptive strategy focused on O3-resistant cultivar selection. Finally, this work compared the estimated impact of O3 on agricultural production with projected climate change effects and identified regions of the world potentially at risk of reduced crop yields due to both O3 and climate change over the next few decades.

1.1. Present day and projected future impacts

Year 2000 global O3-induced yield losses are estimated to range from 4-15% for wheat, 9-14% for soybean, and 2-6% for maize, depending on the metric used (Chapter 2). Worldwide crop production losses (CPL) due to O3 exposure in 2000 are calculated to be 21-93 million metric tons (Mt) of wheat, 13-32 Mt of maize, and 15-26 Mt of soybean, with an economic value worth $11-18 billion (all economic values are in USD2000). Wheat comprises ~60% of global
crop production and economic losses, as this crop is both produced in large quantities
(approximately four times the production level of soybean) and is considered O₃-sensitive.

Estimated impacts vary by country and region due to a number of factors. National
relative yield losses (RYL) are a function of O₃ precursor emissions, the temporal coincidence of
elevated levels of O₃ exposure with crop growing seasons, as well as the spatial coincidence of
O₃ pollution with regions where crops are grown. The distribution of estimated CPL further
reflects crop production intensity, such that some nations with high national RYL do not have
correspondingly high CPL if they are minor producers; likewise, major producers with relatively
low RYL may have large CPL. Economic losses (EL) are additionally a function of producer
prices in each country. Thus although the U.S., China, and India do not necessarily have the
greatest estimated RYL for each crop examined here (although China and India are in the top 5
for RYL of maize and wheat, respectively), these three nations (which produced roughly 40% of
global wheat and ~60% of maize and soybean in 2000 (FAOSTAT, 2011)) incur the greatest
absolute crop production and economic losses due to O₃ exposure. Together losses in the U.S.,
China, and India comprise almost 60% of the global economic damage due to O₃-induced yield
reductions in 2000, with losses distributed roughly equally between these three nations.

If O₃ precursor emissions increase rapidly through 2030 (i.e. under the A2 scenario), we
find that global yield reductions of O₃-sensitive wheat and soybean could increase by ~10% from
2000 levels, with additional crop production losses of 40-110 Mt worth $6-17 billion (Chapter
3). China, India, and the U.S. continue to account for nearly 60% of global losses and ~55% of
additional economic damages between 2000 and 2030 in the A2 scenario, although increased
losses are a factor of ~2.5 greater in China and India than in the U.S. due to more rapid O₃
precursor emissions growth in these nations.
In the more optimistic B1 scenario (characterized by modest reductions in short-lived O₃ precursor emissions in the industrialized world and lower emissions growth in developing regions compared to the A2 scenario; Fig. 26, Table 15), we find that O₃-induced yield reductions increase only marginally (up to 2% from year 2000) on a global level (Chapter 3). Developing countries continue to see further yield declines, however, while small yield gains (due to reductions in O₃ precursors) in industrialized nations partially offset yield losses in emerging economies. Additional year 2030 global CPL in the B1 scenario (5-17 Mt) is estimated to be worth $1-3 billion, with China, India, and the U.S. projected to suffer the greatest losses in this scenario as well (with approximately 25%, 20%, and 15% of total global losses, respectively), although the U.S. experiences economic gains relative to year 2000 (worth approximately $500 million). Despite modest additional O₃-induced yield reductions in the B1 scenario, absolute O₃ impacts remain substantial (although less severe than those predicted in the pessimistic A2 scenario) given significant O₃-induced yield reductions in the baseline year (2000).

1.2. Reducing O₃ damages to crops

Reductions in traditional O₃ precursors in 2030 between the pessimistic A2 and optimistic B1 scenario (including an approximate 30% reduction in year 2030 NOₓ and NMVOCs emissions, and a ~50% reduction in CO emissions, Fig. 26) would improve crop production by 35-94 Mt, representing a 3-8% increase in the production of wheat, maize, and soybean from year 2000 levels. The largest gains in crop production would occur in India, the U.S., and China worth ~$1.5 billion each (based on the average of metric estimates) and $5-14 billion globally. Crop production improvements in India are driven by increases in wheat yields,
while the U.S. and China experience significant improvements and soybean and maize production as well.

We find that a modest methane reduction policy (beginning in 2006 and gradually increasing to ~29% of global anthropogenic year 2030 CH4 emissions) motivated by climate change mitigation goals would have significant co-benefits for agriculture via reductions in O3 exposure (Chapter 4). The greatest O3 reductions occur where the local O3 production regime is NOx-saturated (i.e. where O3 production is limited by the abundance of VOCs), and where surface air mixes frequently with the free troposphere (which increases O3 production efficiency due to a higher VOC to NOx ratio) (Jacob, 1999; Fiore et al., 2008). The most significant reductions in global O3 exposure occur during the wheat growing season, with the Indian subcontinent projected to experience the greatest surface O3 decrease due to CH4 abatement as a consequence of elevated NOx emissions and strong vertical mixing in this region.

The controls on anthropogenic methane examined in this study would lead to a substantial change in CPL (i.e. crop production (CP) gains) of 23-102 Mt, with over 85% of the CP improvements due to wheat yield increases. This is the equivalent of a 2-8% increase in the combined year 2030 global production of soybean, maize and wheat, worth $3.5-15 billion. Economic benefits are concentrated in regions of major agricultural production where the O3 response to CH4 reductions is greatest, primarily in South Asia, East Asia, and North America. Over the 25-year period of methane controls (2006-2030), the present value of agricultural gains due to reduced O3 exposure are estimated to be $17-75 billion USD2000 (amortized to $1.2-5.3 billion yr⁻¹), substantially increasing the cost-effectiveness of the policy of CH4 mitigation considered in this study.
Adapting crops to elevated levels of O$_3$ exposure by choosing cultivars with demonstrated O$_3$ resistance could additionally improve global agricultural production. We find that cultivating crop varieties with the greatest O$_3$ tolerance (from cultivars examined in U.S. field studies) instead of median-sensitivity varieties could increase global crop production by 143 Mt in 2030, the equivalent of a 12% increase in year 2000 production worth ~$22 billion (Chapter 4). CP gains are once again largest for wheat given its high baseline O$_3$ sensitivity, although crop production improvements are higher for soybean and maize in this adaptation scenario than the methane mitigation scenario. India and Pakistan would accrue the greatest economic benefit from O$_3$-resistant cultivar selection (~74% of global economic benefits) due to high levels of O$_3$ predicted in 2030, followed by the U.S. ($2.5 billion) and China ($1.2 billion). Combining the methane mitigation and cultivar selection strategies would yield the greatest gains for agriculture (worth ~$24 billion globally), although benefits are less than fully additive given the nature of O$_3$ effects on crops (with the highest damages occurring at elevated levels of O$_3$ exposure).

1.3. Risk of double exposure to O$_3$ and climate change

Comparisons of climate change impact studies with the estimated agricultural impacts of O$_3$ derived here suggest that present-day O$_3$ exposure is having a more detrimental effect on global crop yields than climate changes since 1980 (Lobell and Field, 2007; Lobell et al., 2011). Climate change impacts in 2050 (both with and without inclusion of the CO$_2$ fertilization effect) are projected to be greater on maize than O$_3$-induced yield reductions in 2030 in both the IPCC B1 and A2 scenarios, but the opposite appears true for wheat (Chapter 5). This results from the fact that maize is a C$_4$ species that is not expected to experience a significant yield enhancement due to rising CO$_2$ concentrations, and because a significant amount of maize is grown in low
latitude regions where small amounts of warming will push growing season temperatures above optimal thresholds (Easterling et al., 2007). By contrast, C3 wheat is expected to experience a substantial CO2 fertilization effect, and large quantities of wheat are produced in mid- to high latitude regions that may benefit from warming due to longer growing seasons. Additionally, O3 impacts are projected to be more detrimental to wheat than to maize, as reduced stomatal conductance associated with C4 species affords maize a degree of protection from O3 exposure compared to C3 wheat (Mills et al., 2007).

Many regions of the world are acutely vulnerable to negative yield impacts due to both climate changes and elevated O3 exposure – including significant agricultural producers such as India, China, Brazil, and Russia, as well as major grain importers such as Pakistan, parts of Africa, and the Middle East. Tropical wheat production appears especially at risk of double exposure given its high sensitivity to both temperature increases and O3, with yield losses on the order of 20% due to climate change in 2050 without the offsetting CO2 fertilization effect (~5% with CO2 fertilization) (Iglesias and Rosenzweig, 2009) and ~30% due to O3 exposure in 2030 (Avnery et al., 2011b; Chapter 5).

However, predicted peak impacts due to climate change and O3 exposure will likely not occur simultaneously. As income levels rise in developing nations, policymakers are expected to face increasing pressure to impose clean air polices (Smith et al., 2011). Many of the new IPCC Representative Concentration Pathway (RCP) scenarios project substantially lower NOx emissions growth than the IPCC SRES and CLE scenarios through 2030 (Kawase et al., 2011; Wild et al., 2011), suggesting that future O3-induced yield losses may be less than predicted here. In particular, year 2030 NOx emissions are predicted to be up to 25% lower in the RCP scenarios than the IPCC B1 scenario, but range from 18% lower to 7% higher than the CLE scenario (Fig.
However, the RCP scenarios are primarily designed to project the path of long-lived greenhouse gases in order to meet different radiative forcing targets, and the accuracy of their assumptions and predictions for the evolution of reactive pollutants is questionable (Smith et al., 2011). Future O$_3$ concentrations are therefore highly uncertain, and it should be noted that even for optimistic projections of O$_3$ precursor pollutants, actual emission levels depend critically on the extent of implementation and enforcement of emissions control regulations. NO$_x$ emissions in Asia, for example, have exceeded scenario predictions between 2000 and 2010 despite more optimistic assessments of pollutant emissions (Dentener et al., 2010).

While peak O$_3$ impacts may thus occur over the next two decades, the most severe climate change impacts are projected in the 2050s and beyond (depending on future climate change mitigation policies) when temperatures begin to exceed 2-3°C and crop yields globally start to decline (Meehl et al., 2007), and when the rate of increase in CO$_2$ fertilization begins to decelerate. Climate change should therefore be considered a long-term and a growing threat to agriculture given the current policy environment, while O$_3$ exposure is a shorter-term yet significant concern – particularly as peak O$_3$ impacts are projected during a time of rapid population and economic growth (World Bank, 2007), rising food demand (FAO, 2009), and increasing natural resource strains (Foresight, 2011).

1.4. Summary

The results presented here suggest that O$_3$ abatement may be one way to 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. As present-day O$_3$-induced yield reductions are substantial and could remain so in the future even with abatement of conventional pollutant precursors (NO$_x$, ...
CO, and NMVOCs), supplemental strategies are needed to reduce O₃-induced crop losses beyond targeting traditional short-lived O₃ precursors. CH₄ abatement provides an attractive “win-win” policy opportunity for both climate change and air pollution mitigation goals, as CH₄ controls would reduce radiative forcing of climate while simultaneously achieving the health and agricultural benefits associated with surface O₃ reductions (West et al., 2006; Fiore et al., 2008; West et al., 2011). Adaptive strategies such as cultivar selection should further supplement O₃ mitigation policies in order to maximize global crop production, particularly in regions where agriculture is especially vulnerable to rapidly rising O₃ concentrations. While climate change is a comparatively longer-term threat to global agriculture, the impacts of surface O₃ exposure should not be depreciated, particularly as the most severe O₃-induced crop yield reductions are predicted to coincide with a period of rapid growth in global food demand and natural resource and environmental strains (FAO, 2009; Foresight, 2011; Foley et al., 2011). Reducing O₃-induced crop yield losses would thus help improve global agricultural production sustainably – i.e. without causing further harm to the environment by exacerbating climate change, air/water pollution, or consuming increasingly scarce resources such as water, land, and energy.

2. Policy Implications

The results presented have direct implications for policymakers concerned with improving domestic agricultural production. The U.S., India, and China, which together produce over 50% of global wheat, maize, and soybean (FAOSTAT, 2011), may be particularly be motivated to reduce O₃ damages to crops given the significant O₃ impacts projected in these three nations. Although adapting crops to elevated levels of O₃ exposure (by selecting existing or breeding new cultivars with O₃ tolerance) would benefit global agricultural production, reducing O₃ concentrations would have numerous co-benefits for human health as well as
climate change (if CH₄ is targeted as an O₃ abatement strategy). Reducing O₃ concentrations across the globe should therefore be a priority, while adaptive strategies such as cultivar selection should further supplement O₃ mitigation. This section discusses strategies to reduce O₃ precursors with benefits for agriculture, as well as possible policy frameworks to encourage global O₃ precursor emissions reductions.

2.1. Reductions in conventional O₃ precursor emissions

Policymakers face increasing pressure to impose clean air polices – including O₃ reduction strategies – as income levels rise (Smith et al., 2011). Reductions in O₃ precursors have historically been motivated by domestic concerns for public health, but benefits to agriculture may provide additional incentive to reduce these pollutants in many parts of the world – especially for nations concerned about food security where agricultural benefits have significance beyond their economic value. In particular, India is projected to experience rapid population and economic growth (World Bank, 2007) as well as increasing strains on arable land and water resources (Foresight, 2011), and agriculture in this nation is highly at risk of negative yield impacts due to both O₃ exposure and climate change (Chapter 5). India may therefore be especially motivated to make more rapid and stringent reductions in O₃ precursor emissions as a food security strategy to help meet the challenge of feeding its growing and increasingly wealthy population.

Measures to reduce O₃ concentrations generally target the short-lived O₃ precursors, in particular NOₓ and CO. NOₓ emission controls have been found to generate the greatest decrease in surface O₃ concentrations (in populated continental regions) of all the O₃ precursors (West et al., 2007), and NOₓ reductions effectively lower peak O₃ levels believed to be most damaging to human health, crops, and ecosystems (West and Fiore, 2005). NOₓ and CO can be
substantially reduced from motor vehicles and large point sources (e.g. power plants) using relatively low-cost, currently available technologies (i.e. selective catalytic and non-catalytic converters and low NOx boilers) (Molina et al., 2009). The U.S. has made significant progress in reducing the emissions of these short-lived O3 precursors primarily through targeting vehicle emissions and power plants, including a 52% and 82% decrease in NOx and CO, respectively, from 1980 to 2008, with a corresponding reduction in the fourth highest daily mean (8-hour) O3 concentration of 28% over this time (EPA, 2010a).

While O3 precursors have been declining in the U.S. and other industrialized nations, emissions of these compounds are currently rising in developing countries due to rapid economic industrialization and lenient air quality regulation. However, new emission standards for vehicles have recently been introduced in Latin America, Russia, India, and China, which are expected to curb rapid O3 precursor emissions growth in the future (Dentener et al., 2005; Cofala et al., 2005). It should be noted, however, that NOx emissions from vehicles account for only a small portion of total present-day emissions in India and China (11% and 8%, respectively), while the energy sector (heat production and public electricity generation) currently contributes to ~50% of anthropogenic NOx emissions in these two nations (European Commission, 2010). Reducing O3 precursor emissions from power plants would therefore help to further reduce O3 levels in India and China in the near term, while motor vehicle emission standards will become increasingly important in reducing emissions growth in the future due to the exponential increase in vehicle ownership projected in developing nations (Dentener et al., 2010).

2.1.1. International cooperation

Given the potential for transport of O3 and its precursors across continents – and for corresponding O3-induced health and agricultural impacts in receptor regions that would be
incurred despite domestic emission controls – interest has been growing in forming an international air quality agreement to encourage further reductions in global O₃ (Holloway et al., 2003). One suggested possibility would be to expand the 1979 Convention on Long-Range Transboundary Air Pollution (UNECE, 1979), now signed by 51 parties in North America, Europe, and parts of Central Asia, to a hemispheric-scale treaty that would include China, India, and other nations of Asia. In the 28th Executive Body Session of LRTAP, the co-chairs of the Task Force on Hemispheric Transport of Air Pollution (HTAP) noted that intercontinental transport of air pollution was a growing problem that would make meeting air quality standards increasingly difficult for signatory parties, and that members should work to strengthen air quality management in other regions of the world (HTAP, 2010). The co-chairs suggested that a hemispheric or global framework for air quality management may be merited, which could take the form of an expanded LRTAP, or through forming partnerships between LRTAP and other regional air quality treaties (for example the Association of Southeast Asian Nations (ASEAN) Agreement on Transboundary Haze Pollution (ASEAN, 2002)), creating linkages to regional and global institutions (such as development banks), and/or through direct provision of support for emissions reductions in developing countries (HTAP, 2010).

LRTAP has had modest success in reducing transboundary air pollution in Europe and the U.S., but has also been recognized for a number of indirect achievements: the treaty raised awareness of an important environmental problem in signatory countries; augmented national scientific and technical capacities for addressing environmental issues; formed a dense scientific network that linked researchers of member states; and provided a forum for ongoing regional negotiations that encouraged more stringent national emission reduction policies (Levy, 1993; Levy, 1995; Holloway et al., 2003). Expansion of LRTAP to include countries of South and East
Asia (and especially India and China) may therefore benefit global air quality by catalyzing more rapid O₃ precursor emissions reductions in these nations than would otherwise occur. However, since India and China benefit from LRTAP without being signatory parties given their downwind location to North America and Europe (Fiore et al., 2009), these nations have little motivation to participate in an international treaty unless offered financial, technological, or other incentives from upwind parties. Because the U.S. and Canada would be the primary beneficiaries of O₃ precursor emissions abatement implemented in China, these two nations may be motivated to provide such incentives to encourage Chinese emission reductions. South Asian emissions of O₃ precursors have been demonstrated to have a more local effect, however, due to regional meteorology and monsoonal dynamics (Fiore et al., 2009; Dentener et al., 2010). Reductions in conventional O₃ precursors in India would therefore likely require domestic motivation, as other regions have little incentive to support control measures in this country given limited potential for intercontinental pollutant transport.

2.2. Reductions in methane

Methane abatement may present a more practical opportunity for international cooperation on reducing global O₃ concentrations. Unlike for reductions in shorter-lived O₃ precursors (e.g. NOₓ, CO, and NMVOCs), the spatial pattern of O₃ reductions due to methane controls is independent of the location and timing of CH₄ emissions abatement due to the ~12-year lifetime of this compound. This suggests that the lowest-cost methane emission controls can be targeted in order to achieve the same global benefit. For nations that have already undertaken aggressive NOₓ, CO, and NMVOC mitigation measures, and therefore where additional abatement of these shorter-lived O₃ precursors is expected to be increasingly expensive (e.g. the U.S. and Europe), CH₄ mitigation may offer a more inexpensive alternative to
further reduce surface O₃ and meet increasingly stringent regulatory standards (West and Fiore, 2005). Furthermore, the top three nations that would accrue the greatest agricultural benefits (India, China, and the U.S.) due to CH₄ reductions via decreased O₃ concentrations are also the top three methane emitters, which collectively contribute to ~30% of global anthropogenic CH₄ emissions (World Resources Institute, 2007).

CH₄ controls additionally have a clear co-benefit for climate change, while reductions in NOₓ have a net effect on global climate that varies by region due to the competing effect of decreasing O₃ forcing but increasing CH₄ forcing (as NOₓ reductions decrease OH, the primary methane sink, and thereby increase the lifetime and atmospheric concentrations of CH₄) (Fuglestvedt et al., 1999; Naik et al., 2005; West et al., 2007). However as previously noted, the benefits of CH₄ emission reductions are realized gradually over its lifetime, rather than within hours to weeks as for the shorter-lived O₃ precursors, suggesting that CH₄ controls would best be implemented as a complement to (rather than substitute for) local and regional NOₓ, CO, and NMVOC reduction measures (West and Fiore, 2005). CH₄ abatement also produces ozone reduction benefits that are spatially diffuse, while the effects of reductions in the shorter-lived O₃ precursors are primarily local or regional in scale – the nation undertaking the cost of the emission reductions receives the greatest benefit.¹² A coordinated policy of CH₄ reductions, particularly in sectors where methane recovery is more challenging (e.g. enteric fermentation and rice cultivation), may therefore require national or international incentives.

While the Kyoto Protocol to the United Nations Framework Convention on Climate Change is still in effect (UNFCCC, 1998), this multilateral agreement offers international mechanisms designed to support national efforts to reduce methane emissions. These include the

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¹² Although as previously noted, the monetary benefits of methane recovery would be accrued by those investing in such CH₄ mitigation measures.
Clean Development Mechanism (CDM) and Joint Implementation (JI), which permit developed countries to fund projects in developing nations (where emission controls may be cheaper) and receive credit towards their emissions reduction commitments as delineated by Kyoto. Methane abatement projects represent approximately 15% of all CDM projects, but a current backlog of registered projects exists in the CDM due to a lack of financing and uncertain future given the impending expiration of the Kyoto Protocol in 2012 (Molina et al., 2009). Currently implemented CDM projects additionally account for only ~4% of global anthropogenic methane emissions (Molina et al., 2009).

The recently proposed Prototype Methane Financing Facility (PMFF), a partnership between national governments, private foundations, and the private sector, aims to promote additional CH$_4$ abatement by serving as a stable, financial guarantee mechanism for methane reduction projects through providing initial start-up funding and a price floor on carbon credits generated from methane mitigation projects (Molina et al., 2009). Initially funded projects would be those currently registered in the CDM (but possibly extended to local and regional carbon markets), with the goal of reducing approximately half of the methane emissions that can be mitigated at a cost of less than $40/ton CO$_2$-equivalent by 2020 (which are projected to comprise ~25% of year 2020 methane emissions) (EPA, 2006; Molina et al., 2009). The PMFF is estimated to have an initial cost of ~$100 million annually, but aims to become self-financing by receiving a portion of the certified emission reductions generated by funded projects. This cost represents a small fraction of the estimated benefits to agriculture ($3.5-15$ billion in 2030) that a modest CH$_4$ control policy would provide (Chapter 4), and India, China, and the U.S. have particular incentive to support the PMFF given that they would accrue the greatest benefits of CH$_4$ reductions facilitated by this mechanism.
A similar public-private fund is the Global Methane Initiative (GMI), which builds on the Methane to Markets Partnership between national governments, international development banks, and the private sector. The GMI also aims to promote cost-effective CH$_4$ emission reductions primarily via methane recovery projects in coal mines, oil and gas systems, and more recently agriculture and landfills through facilitating project investment, technology transfer, and providing training and assistance with regulatory and legal issues (GMI, 2009). While achieving modest success, the scale of GMI projects has thus far been limited: the GMI garnered financial commitments of only $84 million from partner nations between 2004 and 2009, with supported projects generating reductions of 63 Mt CO$_2$-equivalent annually (GMI, 2009) – approximately 1% of global anthropogenic methane emissions in 2010 (GMI, 2010).

Voluntary programs such as the PMFF and GMI may represent the most feasible short-term means to encourage further CH$_4$ emission reductions across the globe, particularly in the absence of an international agreement on climate change (or O$_3$) mitigation. However, these programs require additional funding from partner nations and institutions in order to catalyze large-scale CH$_4$ abatement. While the U.S. has pledged $50 million to the GMI from 2007 through 2011 (EPA, 2007), this pledge represents only ~10% of the estimated year 2030 benefits to agriculture that the U.S. would accrue due to the modest methane reductions examined in Chapter 4. Benefits to agriculture in India and China could additionally be on the order of billions of dollars as a consequence of methane controls. Given the potential for substantial benefits to crops (as well as human health (West et al. 2006; West et al., 2011)) that could be achieved in the U.S., China, and India by global CH$_4$ reductions, and given that the most inexpensive emission reduction measures are located in developing countries (and are especially prevalent in India and China) (EPA, 2006), these three nations have significant incentive to
cooperate on mitigating CH₄ – and in particular, to lend additional support to the PMFF, GMI, and other efforts that facilitate cost-effective reductions in methane emissions.

3. Potential Future Research Directions

This work can be enhanced and augmented in a number of different ways in order to reduce major uncertainties, as well as to extend research into related fields that would further illuminate the benefits of reducing O₃ damages to crops. Several suggestions for future work are described below.

3.1. Benefits for agriculture of new O₃ standards

This dissertation suggests that O₃ exposure is currently contributing to declining agricultural productivity, and demonstrates the need to strengthen global O₃ standards – and more importantly, to reduce the emissions of O₃ precursors – in order to avoid substantially increased damages to crops in the future. The methods used in this research could inform the process of O₃ standard setting by providing a first-order estimate of the economic benefits associated with crop production gains due to O₃ mitigation policies and meeting proposed regulatory standards in different regions of the world.

For example, we calculated the potential benefits of implementing the proposed – and recently withdrawn – secondary O₃ standard in the U.S, and submitted comments in support of the proposed rule to the U.S. Environmental Protection Agency (EPA) based on results presented here. As described in Chapter 1, the EPA (in January 2010) proposed to tighten the current primary (health-based) 8-hour O₃ standard from 0.075 ppmv to a level within the range of 0.060-0.070 ppmv (EPA, 2010b). In addition, the proposed rule would create a unique secondary public welfare standard to protect sensitive crops and natural ecosystems based on the
biologically-relevant W126 metric of O₃ exposure set at range between 7 and 15 ppmh. However, the proposed rule was not adopted by the Obama administration under pressure from business and industry groups, who argued that meeting new requirements would be too costly (White House Office of the Press Secretary, 2011).

We used both simulated and observed surface O₃ concentrations across the U.S. (according to the technique outlined in Chapter 2) to calculate year 2000 O₃ exposure according to the W126 metric, as well as corresponding crop (soybean, maize, and wheat) yield, production, and economic losses at current levels of O₃ exposure (i.e. a no-policy scenario). In order to assess the benefits of different levels of the proposed secondary standard, we artificially reduced W126 values in grid cells that were above the proposed standard to the level of the standard (assuming 2-ppmh intervals, i.e. 7, 9, 11, 13, and 15 ppmh), and calculated crop losses at each standard level. By finding the difference between crop losses associated with each interval of the standard and those of the no policy scenario, we were able to calculate the marginal benefits of meeting the secondary O₃ standard at various levels. We found that the largest marginal benefits would be accrued by an initial setting of the standard at 15 ppmh (~$340 million annually), with additional gains in crop production worth ~$100 million for each 2-ppmh incremental strengthening. Setting the secondary standard at a level of 7 ppmh would improve agricultural production worth ~$770 million annually. It should be noted that among the widely-used O₃ exposure metrics and their corresponding CR relationships, the W126 index chosen by the EPA generates estimates of present-day yield losses in the U.S. at the low end of the range of variability for the three crops examined here, and therefore benefits to crops could be substantially greater.

3.2. Optimal O₃ mitigation strategies
O₃ abatement represents an attractive means to increase global food production with numerous co-benefits for human health and climate change, and without the negative environmental impacts associated with many agricultural practices aimed at improving crop yields. However, identifying the most effective O₃ mitigation policies is difficult because of the highly complex processes of ozone formation and destruction. O₃ production is limited by the availability of volatile organic compounds (VOCs) in regions of high NOₓ emissions such as cities and power plant plumes (NOₓ-saturated regime), but limited by the availability of NOₓ in high VOC environments such as rural regions where biogenic hydrocarbon emissions are abundant (NOₓ-limited regime). Furthermore, O₃ sensitivities may not be static over time due to the temporal variability of precursor emissions (e.g. NOₓ from power plants or lightning) and of atmospheric conditions (e.g. temperature, water vapor concentrations, mixing height, etc.) that also affect O₃ formation. The potential transport of tropospheric O₃ (as well as some of its precursors) across state and national boundaries may additionally confound the efficacy of local O₃ mitigation measures. Understanding O₃ sensitivities to precursor emissions in different regions of the world where crops are currently and projected to be adversely affected by O₃ is therefore vital to establishing effective policies to reduce ozone in order to protect global agricultural production.

A useful extension of this work would therefore be to help policymakers identify the best O₃ mitigation policies in regions where ozone-induced crop yield reductions are substantial. One approach would be to use adjoint analysis to quantify O₃ sensitivity to precursor emissions (including species, source type (anthropogenic vs. natural), geographic origin, and timing of emissions) in locations where significant crop losses are expected to occur. In adjoint analysis, a perturbation in a receptor-based metric (e.g., concentration at a receptor, or an observation-based
cost function) is propagated backward in time, facilitating the calculation of its sensitivities with respect to different inputs. Adjoint sensitivity analysis is a computationally more efficient technique compared to traditional forward analysis when calculating sensitivities of a limited number of scalar outputs with respect to a large number of inputs. This technique has been used to quantify O₃ sensitivity according to air quality metrics used for public health standards (including for O₃ and particulate matter, e.g. Hakami et al., 2006; Henze et al., 2009), but studies based on agriculturally-relevant metrics (e.g. AOT40 and W126) have not been implemented to date and could help regions comply with secondary O₃ standards and protect domestic agricultural production.

3.3. Additional co-benefits for climate change

As previously discussed, O₃ mitigation would have substantial co-benefits for human health and climate change in addition to agriculture. Climate change benefits would be gained through the direct benefit of reduced radiative forcing of O₃ (and CH₄ if methane control was the chosen O₃ mitigation strategy), as well as the indirect benefit of greater carbon storage potential in forests and other ecosystems as a consequence of reduced O₃ damages. These co-benefits of O₃ have previously been investigated and quantified (West et al., 2006; West et al., 2007; Sitch et al., 2007; Fiore et al., 2008; West et al., 2011). An extension of this work, however, would be to estimate the climate change (and/or air quality) benefits of “avoided” fertilizer use (and correspondingly, avoided greenhouse gas and air pollutant precursor emissions¹³) resulting from O₃ mitigation, as yield increases due to decreased O₃ exposure could reduce the fertilizer required to achieve a given level of output or yield improvement. Nitrous oxide (N₂O) is a potent GHG with a 100-year global warming potential of 298 (Forster et al., 2007), and

¹³ These could include avoided emissions of N₂O, NOₓ, and NH₃.
emissions resulting from the use of nitrogen fertilizers account for almost 40% of GHG emissions from the agricultural sector (which in turn contributes to 10-12% of global anthropogenic GHG emissions) (Metz et al., 2007). Such a study would be complicated by (1) the complex, non-linear relationship between fertilizer application and crop yields (which follows the law of diminishing returns\textsuperscript{14}), as well as (2) between N\textsubscript{2}O emissions and nitrogen fertilizer application (which strongly varies by local management practices, fertilizer types, and climatic and soil conditions). However, a first-order estimate of the former relationship could possibly be obtained from crop simulation models, or could be based on historical relationships between fertilizer use and yields in different regions of the world. N\textsubscript{2}O emissions from fertilizer application could be roughly evaluated by scaling estimates from local studies based on a careful accounting of fertilizer type and environmental conditions, or by using a range of emission factors currently utilized in global emission inventories and scenarios (e.g. the IPCC SRES, which assumes an N-N\textsubscript{2}O/N-fertilizer loss rate of 1.25% (0.25-2.25% depending on conditions) (Nakicenovic et al., 2000)).

3.4. Contribution of O\textsubscript{3} exposure to global yield gaps

Meeting the projected 50% increase in global grain demand from 2010 to 2030 (FAO, 2006; World Bank, 2007) without further environmental degradation poses a major challenge for agricultural production. Foley et al. (2011) recently reviewed strategies to meet the world’s future food demand while simultaneously reducing the environmental footprint of agriculture, and highlighted the need to halt agricultural expansion and close crop yield gaps globally (i.e. the difference between realized crop yields and potential yields at a given location). In particular, Foley et al. (2011) and others (Licker et al., 2010; Neumann et al., 2010) quantified crop yield

\textsuperscript{14} A decrease in the marginal output per unit of additional input.
gaps in different regions of the world, demonstrating that the difference between actual and potential yields is especially high in the central U.S., Eastern Europe, northern India, eastern China, and southern Brazil. These studies additionally modeled the contribution of different limiting factors to global yield gaps, including nutrient availability, adequate water supply, and the genetic yield ceiling (Licker et al., 2010; Foley et al., 2011). However, notably absent from this group of possibly limiting variables is O3 exposure, which is elevated during crop growing seasons in many of these regions where yield gaps are substantial (Fig. 3). An empirical analysis similar to that of Licker et al. (2010) and Foley et al. (2011), but that includes O3 exposure as an additional explanatory variable, would therefore be highly informative in identifying the potential contribution of O3 to present-day crop yield gaps. Such a study would further provide an independent empirical assessment of the effects of O3 on crop yields globally and would be a useful supplement the model-derived O3 impact estimates presented here.

3.5. Agro-economic impacts

As previously noted, greater attention is being allocated to the potential threat of climate change to crops than that of O3 pollution despite its demonstrated detrimental impact on agricultural yields globally. Chapter 5 contextualized the magnitude of O3-induced crop losses against those predicted due to climate change in part to draw attention to significant risk that O3 poses against a better-known environmental problem. However, this comparison focused only on the direct effects of O3 on crops (i.e. changes in yields and production), while an assessment of the economic and food security impact of O3 using advanced agro-economic simulations has yet to be undertaken – and has been increasingly called for in recent studies investigating the future of agriculture (Royal Society, 2008; Royal Society, 2009; Foresight, 2011; Harmens et al., 2011). A more sophisticated analysis of the food security consequences of O3 pollution would
therefore be desirable, including the projected impacts of O₃-induced yield losses on crop production (accounting for factors other than changes in yields, e.g., feedbacks between reduced output on price, planting acreage, and farmers’ input decisions), global commodity prices, international trade, and risk of hunger.

One approach could be to use an agro-economic model such as the International Food Policy Research Institute’s International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) to simulate the agro-economic consequences of changes in crop yields due to O₃ exposure. This model accounts for crop area elasticities with respect to crop prices, crop yield elasticities with respect to various inputs, as well as changes in population, income, and diets projected in the future (Rosegrant et al., 2008). Another model that could be utilized is the partial general equilibrium model developed by the Organization for Economic Cooperation and Development (OECD) and the Food and Agriculture Organization (FAO) AGLINK Commodity Simulation Model (COSMO) (OECD, 2006), which is used to produce the annual OECD-FAO agricultural outlook reports (e.g., OECD-FAO, 2011). The FAO is additionally developing an integrated model (FAO Modelling System for Agricultural Impacts of Climate Change (MOZAICC)) to examine the effect of climate change on agriculture and world trade, which links climate scenarios with crop simulation models to determine yield impacts, and then feeds these yield projections into a general equilibrium model to simulate resultant agro-economic consequences of climate change (FAO, 2011).

The O₃-induced relative yield loss estimates calculated for each crop and nation (under different scenarios of O₃ pollution) could be used as either primary or intermediary inputs into one of these agro-economic models, which would then project resultant changes in regional production, fluctuations in global commodity prices and regional trade patterns, as well as the
corresponding impact on the total number of people considered at risk of hunger worldwide. This type of study would build on the results presented here by providing a more robust analysis of the agro-economic and food security implications of yield reductions due to O₃ exposure, as well as facilitate further grounds for comparison with predicted climate change effects. Given the focus on food security, such a study could additionally help raise awareness among policymakers about the risk to agriculture posed by O₃ and further highlight the need to mitigate and adapt crops to O₃ exposure in addition to climate change.

3.6. Multi-model intercomparison of O₃ impacts

Finally, the substantial projected impacts of O₃ exposure on global agriculture presented here demand a multi-model intercomparison in order to more robustly quantify O₃ effects on crop yields, and, if used as input into an agro-economic model, corresponding effects on crop production, trade patterns, and risk of hunger. The Agricultural Model Intercomparison and Improvement Project (AgMIP) is currently underway to accomplish this goal for projected climate change impacts on agriculture (including crop yields, production, trade, and food security) (Rosenzweig, 2010). A useful complement to this work would be a similar multi-model comparison effort for O₃ impacts, which could examine different model simulations of present-day (and future) O₃ concentrations under various scenarios of O₃ pollution (including the new RCP scenarios), as well the corresponding range of projected impacts as a result of variance in simulated growing season O₃ exposures. This comparison could additionally examine the impact of using different metrics of O₃ exposure and concentration:response relationships on O₃-induced yield loss estimates. A multi-model intercomparison of the projected agricultural impacts due to both major components of global change (i.e. O₃ exposure and climate change) would assist in reducing uncertainties in integrated assessments of future agricultural production,
thereby helping policymakers better prepare for and respond to the dual threat of O₃ exposure and climate change.
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http://www.census.gov/ipc/www/idb/worldpopgraph.php


Figure 26. Growth in O₃ precursor emissions from 2000 to 2030 as predicted by IPCC SRES A2, B1 (Nakicenovic et al., 2000), RCP (Van Vuuren et al., 2011; IIASA RCP Database, 2011), and IIASA CLE scenario emission inventories (Cofala et al., 2005; Dentener et al., 2005).
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<sup>a</sup> ‘OECD’ refers to countries of the Organization for Economic Cooperation and Development as of 1990, including the US, Canada, western Europe, Japan and Australia.

<sup>b</sup> ‘REF’ represents countries undergoing economic reform, including countries of eastern European and the newly independent states of the former Soviet Union.

<sup>c</sup> ‘Asia’ refers to all developing countries in Asia, excluding the Middle East.

<sup>d</sup> ‘ALM’ represents all developing countries in Africa, Latin America and the Middle East.

**Table 15.** Growth in O₃ precursor emissions from 2000 to 2030, represented as a percent change from 2000 as predicted by IPCC SRES A2, B1 (Nakicenovic et al., 2000), RCP (Van Vuuren et al., 2011; IIASA RCP Database, 2011), and IIASA CLE scenario emission inventories (Cofala et al., 2005; Dentener et al., 2005).