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### **Key Points:**

- The 2008 economic recession significantly affected air quality over the United States
- It is feasible to combine computer models and ground/space observations to quantify the air quality effect of economic recessions
- Timely updates of emission inventories become increasingly important during major socioeconomic events for air quality management

### **Supporting Information:**

Supporting Information S1

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# Impact of the 2008 Global Recession on air quality over the United States: Implications for surface ozone levels from changes in NO<sub>x</sub> emissions

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**Abstract** Satellite and ground observations detected large variability in nitrogen oxides (NO<sub>x</sub>) during the 2008 economic recession, but the impact of the recession on air quality has not been quantified. This study combines observed NO<sub>x</sub> trends and a regional chemical transport model to quantify the impact of the recession on surface ozone (O<sub>3</sub>) levels over the continental United States. The impact is quantified by simulating O<sub>3</sub> concentrations under two emission scenarios: business-as-usual (BAU) and recession. In the BAU case, the emission projection from the Cross-State Air Pollution Rule is used to estimate the "would-be" NO<sub>x</sub> emission level in 2011. In the recession case, the actual NO<sub>2</sub> trends observed from Air Quality System ground monitors and the Ozone Monitoring Instrument on the Aura satellite are used to obtain "realistic" changes in NO<sub>x</sub> emissions. The model prediction with the recession effect agrees better with ground O<sub>3</sub> observations over time and space than the prediction with the BAU emission. The results show that the recession caused a 1–2 ppbv decrease in surface O<sub>3</sub> concentration over the eastern United States, a slight increase (0.5–1 ppbv) over the Rocky Mountain region, and mixed changes in the Pacific West. The gain in air quality benefits during the recession, however, could be quickly offset by the much slower emission reduction rate during the post-recession period.

# 1. Introduction

Air pollution, including smog and haze, is caused in part by economic activities that emit reactive gases and particles into the air. Hence, air quality can be affected by the changes in the level of economic activity. An economic downturn (recession) generally sees less energy demand, lower traveled mileage, and less industrial activities for manufacture and services [*Goodman and Mance*, 2011], resulting in decreased emissions of air pollutants from power plants, vehicles, and industries [*Vrekoussis et al.*, 2013]. Simultaneously, economic recession can severely depress automobile sales, increasing the age of a vehicle fleet. Tunnel measurements of on-road vehicle exhaust in three United States cities showed that the 2008–2010 economic recession has caused 40%, 38%, and 35% reduction in the fleet fractions of the 2009 model year vehicles in Denver, Los Angeles, and Tulsa, respectively [*Bishop and Stedman*, 2014]. Consequently, emissions from the 2013 fleet increased by 17–29% for carbon monoxide (CO), 9–14% for volatile organic compounds (VOCs), 27–30% for nitric oxide (NO), and 7–16% for ammonia (NH<sub>3</sub>) in relation to historical fleet turnover rates. The overall impact of the recession on air quality is determined by these competing factors controlling emissions of air pollutants.

This study attempts to quantify the effect of the 2008 economic recession on surface ozone (O<sub>3</sub>) concentrations over the continental United States. The 2008 global recession, also known as the Great Recession, is one the longest and deepest recessions since World War II. Fueled by widespread economic troubles, most notably the housing bubble and subprime financial crisis, the United States economy officially entered a recession in December 2007. At its lowest point, employment had declined by 8.8 million from the pre-recession level, and the Producer Price Index fell by 16% from July 2008 to July 2009—the steepest 12 month decline since 1931 [Goodman and Mance, 2011].

©2016. American Geophysical Union. All Rights Reserved. The widespread socioeconomic slowdown caused noticeable emission reduction detected by satellite measurements [*Castellanos and Boersma*, 2012; *Russell et al.*, 2012], which found that the decreases in urban NO<sub>2</sub> column densities in the United States accelerated during the recession, changing from -6%/yr beforehand to -8%/yr during the financial crisis and then slowing to -3%/yr thereafter [*Russell et al.*, 2012]. A recent study using both satellite and ground observations confirmed that distinct rates of emission change were observed from both space and surface data over eight large cities [*Tong et al.*, 2015], yet the impact of the emission changes caused by the 2008 recession on air quality has not been well quantified. This study combines observed emission changes and a regional chemical transport model to quantify the effect of the 2008 economic recession on O<sub>3</sub> levels over the continental United States. Here O<sub>3</sub> is used as an indicator of air quality change because of its well-established health impacts and the fact that more than one third of the United States population live in areas that do not meet the health-based National Ambient Air Quality Standards for O<sub>3</sub> [*U.S. Environmental Protection Agency (U.S. EPA*), 2016].

# 2. Methodology

The impact of the recession on air quality is quantified by simulating  $O_3$  concentrations under two scenarios: business-as-usual (BAU) and recession. In the BAU case, the rate of emission change from the Cross-State Air Pollution Rule (CSAPR) is used to adjust emission inventories from the pre-recession year (2005) to postrecession year (2011) [*Pan et al.*, 2014; *Tong et al.*, 2015]. In the recession case, the actual NO<sub>2</sub> trends observed from the Air Quality System (AQS), a ground monitoring network, and the Ozone Monitoring Instrument (OMI) on the Aura satellite are used to obtain "realistic" or observed emission changes. The CSAPR and observed emission data are then used to drive the chemical transport model, called the Community Multiscale Air Quality (CMAQ) model [*Byun and Schere*, 2006], in order to calculate surface  $O_3$  levels under each scenario. The difference between the predicted  $O_3$  concentrations in these cases is attributed to the impact of the recession.

A major challenge in quantifying the impact is to determine the magnitude in emission changes caused by the recession. While the CSAPR projection has considered possible emission changes caused by existing and predicted emission control regulations, there is no emission data set available that is designed to capture the impact of the economic recession on the emission changes. For instance, the 2011 National Emission Inventories (NEI) prepared by the United States Environmental Protection Agency (EPA) used a different emission model for vehicle emissions, making the NEI data unsuitable to study the temporal trend of nitrogen oxide (NO<sub>x</sub>) emissions during the study period (2005–2011). The MOBILE6 model was used to estimate vehicle emissions in NEI2005, while another mobile source emission model, Motor Vehicle Emission Simulator (MOVES), was used to estimate emissions for NEI2011. The two emission models are very different, with MOVES giving much higher NO<sub>x</sub> emission rates than MOBILE6. As a result, the NO<sub>x</sub> emissions in NEI2011 are actually higher than in NEI2005, in contrast to the observed downward trend [Tong et al., 2015]. Tong et al. [2015] demonstrated that the consistent long-term trends observed by satellite and ground monitors make it feasible to detect accurately the changes of NO<sub>x</sub> emissions over a long time span. Here we have developed a new method to use space and ground observations to determine the emission changes in the recession scenario. This approach consists of three steps. First, monthly NO<sub>2</sub> changing emission rates are derived from ground and satellite observations. For ground measurements (AQS), morning rush hour means are calculated from quality-controlled hourly  $NO_x$  values for the hours 0600, 0700, and 0800 local time, following the observed temporal patterns of NO<sub>x</sub> variations presented by Godowitch et al. [2010]. These morning hours are associated with the highest NO<sub>x</sub> concentrations contributed by both typical commuter traffic peaks and the shallow planetary boundary layer, making them an ideal indicator for assessing local emission conditions [Tong et al., 2015]. Besides ground data, the OMI standard product (version 2.1, collection 3) described by Bucsela et al. [2013] is used to derive the satellite-based emission trends using the data-filtering approach described in Tong et al. [2015]. In the normal global operational mode, the OMI ground pixel at nadir is 13 km  $\times$  24 km, with a local equator-crossing time of 13:45 h in ascending node. The OMI NO<sub>2</sub> data are filtered using quality flags, cloudiness, and row anomaly (an anomaly caused by an obstruction in part of OMI's aperture) [Bucsela et al., 2013]. Additionally, we apply a cutoff value  $(0.7 \times 10^{15} \text{ molecules cm}^{-2})$  to the OMI data as low-value pixels are less responsive to local emission density but more influenced by regional background and retrieval noise.

Table 1. Simulations Designed to Represent Different Emission Scenarios									
Scenario	Meteorology	Emission	Chemical Transport Model						
Base Case Business-as-usual Recession	July 2011 July 2011 July 2011	2005 National Emission Inventories (NEIs) NEI 2005 with NO <sub>x</sub> emissions adjusted by CSAPR Projection NEI 2005 with NO <sub>x</sub> emissions adjusted by OMI and AQS observations	CMAQv4.7.1-based NAQFC CMAQv4.7.1-based NAQFC CMAQv4.7.1-based NAQFC						

Next, a weighting function is used to combine the AQS-based and OMI-based rates of change to obtain merged state-level projection factors. To take advantage of both data sets, we adopt the following fusing function to construct the merged emission adjustment factor (AF) for each state:

$$\mathsf{AF} = \frac{\Delta S \times N_{\mathsf{S}} \times f_{\mathsf{S}} + \Delta G \times N_{\mathsf{G}} \times f_{\mathsf{G}}}{N_{\mathsf{S}} \times f_{\mathsf{S}} + N_{\mathsf{G}} \times f_{\mathsf{G}}} \tag{1}$$

where  $\Delta S$  and  $N_S$  are the rate of change and the number of satellite data (OMI), respectively,  $\Delta G$  and  $N_G$  are the rate of change and the number of ground data (AQS), respectively, and  $f_{\rm S}$  and  $f_{\rm G}$  are two weighting factors applied to the satellite and ground data, respectively. In this study, the value of  $f_{\rm S}$  is set to be 1 and  $f_{\rm G}$  to be 100 to avoid dominance by either data source. Finally, the projection factor AF derived from the fused data for each state is used to adjust the 2005 base NEIs to those of 2011 to represent the recession emission scenario.

The effect of the emission changes on surface O<sub>3</sub> concentration is estimated using a CMAQ version tailored for the NOAA National Air Quality Forecast Capability (NAQFC) system [Pan et al., 2014; Tong et al., 2015]. This version of CMAQ is configured with the Carbon Bond 2005 chemical mechanism [Yarwood et al., 2005] and AERO5 aerosol module [Carlton et al., 2010]. The lateral boundary conditions used in the simulation are monthly averaged profiles extracted from the 2006 simulation with Harvard University's GEOS-Chem model [Zhang et al., 2011]. We conducted three model runs using the 2005 NEIs, the CSAPR projected inventories, and the observation-adjusted inventories (Table 1). These cases represent the pre-recession, BAU, and recession scenarios, respectively. The model domain covers the continental United States with a 12 km horizontal grid spacing. All simulations use the same meteorology for July 2011, generated by the Weather Research and Forecasting Nonhydrostatic Mesoscale Model (WRF-NMM) [Janjic, 2003], to exclude the effect of varying weather conditions on surface  $O_3$ . The performance of this modeling system to predict  $O_3$  and its key precursors has been extensively evaluated with ground and field campaign data [Chai et al., 2013; Pan et al., 2014; Tong et al., 2015]. This study will evaluate model predictions under each emission scenario using surface O<sub>3</sub> observations from the EPA AQS network following the protocols established by Tong and Mauzerall [2008].

# 3. Results

# 3.1. NO<sub>x</sub> Emission Changes

Changes of NO<sub>x</sub> emissions under the BAU and recession scenarios are compared first. Large reductions in NO<sub>x</sub> emissions are seen in both cases, but there is a noticeable difference in the rates of change for most states. Figure 1 shows the differences in NO<sub>x</sub> emissions between the base, BAU, and recession cases in July 2011. From 2005 to 2011, the BAU projection estimated that national NO<sub>x</sub> emissions have been reduced by 21% (Figure 1a), with the majority of the reduction seen over urban areas and along major highways. NO<sub>x</sub> emission increases are shown at isolated locations within the United States, which are due to changes in point source emissions that are treated separately from the state-level projections of mobile and area sources. Considerable changes are also seen in the Canadian and Mexican parts of the domain due to different versions of inventories used in these scenarios. Figure 1b depicts the AF or rate of change in  $NO_x$  emissions (%) derived from fused OMI and AQS observations (equation (1)). The emission trend data are aggregated at the state level to be consistent with the CSAPR projection. Similar to the BAU projection, the observed trend shows large reduction (-20% to -50%) in most states, but smaller decreases and even slight increases are seen in several states (Figure 2b). The recession emissions differ from the BAU emissions over space and time (Figure 1c), which further complicates the estimated  $O_3$  impact given the importance of regional  $O_3$ transport [Tong and Mauzerall, 2008; Fiore et al., 2009] and the nonlinearity of O<sub>3</sub> photochemistry [Cohan et al., 2005]. Compared with the BAU, the recession emissions are lower in much of the east, lower midwest, and the Pacific west but slightly higher in the southeast and the Rocky Mountains (Figure 1c).



**Figure 1.** Changes of NO<sub>x</sub> emissions under the BAU and recession scenarios and their differences: (a) changes based on the CSAPR projection; (b) observed changes from OMI and AQS; (c) differences between BAU and recession.





The regional difference is controlled by several factors that include the assumptions made in the CSAPR projection and departures from these assumptions caused by socioeconomic events. The CSAPR approaches used to project future-year emissions vary from sector to sector, but these approaches consider only rules and settlements finalized by early 2009 [*U.S. EPA*, 2016]. Additionally, some local control programs were not included due to technical difficulty or being designed later to address new nonattainment problems. Besides these known issues, the emission trend was perturbed by several unexpected factors according to recent observations. Intensive oil and gas operations also took place during the study period [*Kemball-Cook et al.*, 2010; *Edwards et al.*, 2014]. Since the new oil and gas emissions are not included in the base emission inventories until NEI 2011, which cannot be directly used here for the reason mentioned earlier, the temporal adjustment cannot accurately account for the spatial pattern of the new or increased emissions within the state boundaries.

# 3.2. Ozone Impacts

Figure 2 shows the predicted changes in surface daily maximum 8 h  $O_3$  concentrations from the 2005 level under the BAU and recession emission scenarios and the difference between the two. Without considering the recession impact, the model simulation shows a widespread decrease in surface  $O_3$  concentration across the continental United States (Figure 2a), with the exception of a few areas downwind of large metropolitan areas where  $O_3$  concentration increases as a result of diminished titration by freshly emitted  $NO_x$  [*Tong et al.*, 2006]. Figures 2b and 2c indicate that the recession has caused considerable changes in surface  $O_3$  concentrations. Under the recession scenario, the largest decrease is found in the central eastern United States and central and northern California, where surface  $O_3$  concentration decreases by over 5 ppbv from the pre-recession level. Between the BAU and recession scenarios, there are distinct patterns in the  $O_3$  changes, with large decreases in much of the eastern United States, a slight increase or no change in the central United States, and mixed changes in the western United States (Figure 2c).

The spatial pattern of the  $O_3$  variations reflects a combination of local  $O_3$  production and regional transport of tropospheric  $O_3$  in response to  $NO_x$  emission changes. The large decrease in the east is attributed to the significantly lower emissions in this region, especially in the states along and west of the Mississippi River extending from Texas to Wisconsin, and those with favorable O<sub>3</sub> production conditions, where abundant VOCs are available to be mixed with NO<sub>x</sub> to produce O<sub>3</sub>. During the summertime, atmospheric circulation and regional O<sub>3</sub> transport in the eastern United States are largely controlled by the Bermuda high-pressure system [Tong et al., 2009], developing an "O<sub>3</sub> River" flowing from the south to the northeast [Wolff and Lioy, 1980]. There is little change in surface  $O_3$  concentration over Texas upwind of the transport corridor, where a noticeable decrease in NO<sub>x</sub> emission was not transferred into O<sub>3</sub> benefits due to low O<sub>3</sub> production efficiency in the absence of sufficient reactive VOCs. The maximum reduction occurs in and around Illinois, where a slight increase in NO<sub>x</sub> emissions was found. As the O<sub>3</sub> River further proceeds into the Ohio Valley, the decrease becomes smaller as a result of diminished  $O_3$  transport and offset by increased local  $O_3$  production due to a positive change in NO<sub>x</sub> emissions. Across the eastern United States, however, the effect of large  $NO_x$  decreases in the upstream states dominates the  $O_3$  changes in the downstream states. The  $O_3$  changes in the Pacific west states display a similar pattern to that observed in the eastern states. The largest NO<sub>x</sub> changes are seen in California, which influences O<sub>3</sub> concentrations in the nearby states, most significantly over the Central Valley and southern California, as well as in several downwind states.

The  $O_3$  responses over the Rocky Mountain region are more controlled by local emission changes than by regional transport [*Tong and Mauzerall*, 2008]. The western and central states are generally large in size and associated with complex topography and low emission density, which collectively leads to less cross-state transport than in the eastern states [*Tong and Mauzerall*, 2008]. Over the Rocky Mountain region, the smaller decrease in surface  $O_3$  concentration in the Recession case is caused by the observed lower  $NO_x$  decrease than projected in the BAU case. The  $O_3$  increase ranges from 0.5 ppbv to 1.5 ppbv over Colorado, Nebraska, and the Dakotas.

Comparison of the  $O_3$  prediction against AQS observations shows that the model run with the recession emissions has captured the temporal and spatial variability in surface  $O_3$  with higher accuracy than that with the BAU emissions. Inclusion of the recession impact reduces model bias by 0.4 ppbv for hourly  $O_3$  concentration and 0.2 ppbv for the daily maximum (8 h)  $O_3$  concentration, respectively (Table 2). Other statistical

	Mean Bias (MB) (ppbv)		Normalized Mean Bias (NMB) (%)		Root-Mean-Square Error (RMSE) (ppbv)	
	Hourly	Max8	Hourly	Max8	Hourly	Max8
BAU Recession	11.9 11.5	9.9 9.7	29.7 28.7	20.3 20.1	23.1 22.7	21.5 21.4

**Table 2.** Comparison of Model O<sub>3</sub> Prediction Using the Emissions Under the Business-as-Usual (BAU) and Recession Scenarios Against Ground Observations from the US EPA Air Quality System (AQS) Network

metrics show a similar improvement from the recession simulation (for more details on regional comparisons, see Table S1 in the supporting information). The values of biases are generally within the ranges acceptable for air quality models [*Russell and Dennis*, 2000]. A closer look at the model performance shows that much of the bias is contributed by low  $O_3$  concentrations during hours when  $O_3$  photochemical production is not active [*Chai et al.*, 2013; *Pan et al.*, 2014]. The model tends to perform better during high- $O_3$  periods. There are several factors affecting the model sensitivity to predict  $O_3$  response to  $NO_x$  emission changes, including VOC/NO<sub>x</sub> ratio, VOC reactivity, photochemical aging, and rates of meteorological dispersion [*Sillman*, 1999]. By keeping other factors constant, this study quantifies the  $O_3$  response to changes in  $NO_x$  emissions from BAU to recession. Since the difference between BAU and recession is not large enough to change the chemical regimes in most cases, we expect limited influence of the uncertainties in these factors on model sensitivity to quantify the induced  $O_3$  changes.

Several factors may contribute to the uncertainties in our estimation of the recession impact, which is estimated based on the difference between a BAU emission projection scenario and the observed trend. Therefore, the uncertainty associated with the emission projection will affect the final impact. Tong et al. [2015] have compared the CSAPR projection against satellite and ground observations of NO<sub>2</sub> over eight large cities around the recession period. The CSAPR projection estimated approximately -4%/yr changing rate, which is lower than the observed rates before and during the economic recession (-6%)/yr to -7%/yr from AQS and OMI). The CSAPR rate, however, is higher than the observed rate (-3%/yr from both OMI and AQS) during the post-recession period, and therefore, the bias in the CSAPR projection is likely to be reduced as the emission reduction proceeds into the post-recession period. The inclusion of two postrecession years in this study is likely to result in a lower estimation of the recession impact on O<sub>3</sub> concentration. Second, this study considers the effect of the recession on NO<sub>x</sub>, but not the VOCs, which are another key  $O_3$  precursor that may also be affected by the recession. Compared to NO<sub>2</sub>, it is more difficult to quantify the recession effect on VOC emissions reliably, due to the dearth of VOC measurements and the complexity of the VOC composition and reactivity. The effect of changed VOC emissions is expected to be relatively small in the eastern states where biogenic VOCs are abundant and more reactive than anthropogenic VOCs, as shown in the long-term variations of VOC species in Atlanta, Georgia (Figure S4b). This may be an issue in the less forested western United States. For instance, anthropogenic VOC species and total hydrocarbons concentrations saw a steep reduction (over 50%) during the recession in Houston, Texas (Figure S4a). There are, however, few observations of VOCs from both ground monitors and satellites, limiting our capability to obtain reliable emission trends on a continental scale. Third, we used a single satellite sensor (OMI on the Aura satellite) to represent space observations, and there are other NO<sub>2</sub> products, such as other OMI products and GOME2, that can be used to examine the long-term trends. Fourth, this study does not consider the effect of changing  $O_3$  background, which could affect the quantification of  $O_3$  changes induced by domestic emission reduction. Satellite NO<sub>2</sub> observations from OMI and other sensors show detectable decreasing trends in NO<sub>2</sub> VCD during the recession (data not shown here). Earlier observations and model simulations [Zhang et al., 2008; Lin and McElroy, 2011; Zhang et al., 2011] have shown that Asian pollution outflow contribute a significant portion of background ozone in western North America. For instance, Zhang et al. [2011] estimated that intercontinental pollution (by all emissions outside the United States) and anthropogenic methane enhance background O<sub>3</sub> by 9 ppbv at low-altitude sites and 13 ppbv at high-altitude sites. This study focuses on quantifying the effect of change in domestic emissions, and we expect that the O<sub>3</sub> background change during the study period is not significant enough to change the chemical regime and hence the O<sub>3</sub> production efficiency from NO<sub>x</sub> emissions. However, future studies are needed to understand the overall impact of the recession on air quality in North America by including the effects of decreased Asian emissions and hence O<sub>3</sub> background. Finally, we choose a simple weighing factor approach to fuse the ground and space data, which need to be explored further in order to identify an optimized method to use these data sets better (more on this matter can be found in the supporting information). This estimation can benefit from further development of more robust data fusion techniques. Nevertheless, we have demonstrated a method that can be used to assess the effect of major socioeconomic events on air quality. Our results show that the inclusion of these events in the emission data can noticeably improve the  $O_3$ prediction over time and space.

# 4. Conclusions and Discussion

The 2008 economic recession has exerted noticeable effects on air quality over the United States, with widespread O<sub>3</sub> decrease in the east and Pacific west and a slight increase in the central United States. The increase over the central region, although small, indicates the heterogeneous nature of the effects economic activities have on air emissions. The model prediction shows that the recession has caused 1–2 ppbv decrease in much of the eastern United States, with 3–5 ppbv in a large area west of the Ohio Valley. There is a smaller decrease by 1 ppbv in surface O<sub>3</sub> in central United States in the recession compared to the BAU.

The information on the impact of a quantified recession has broad implications for air quality management in the United States. The recession has caused a decrease in surface O<sub>3</sub> concentration from 0.2 ppbv (for peak 8 h concentration) to 0.4 ppbv (for 24 h concentration) across the nation (averaged over all grids within the United States), resulting in significant health benefits from reduced population exposure to ambient O<sub>3</sub> [e.g., Bell et al., 2006]. The largest  $O_3$  decrease is found over the region where soybeans are planted [Tong et al., 2007], since among all the major crops in the United States, the soybean is the most sensitive to  $O_3$ damages [Lefohn and Foley, 1992; Morgan et al., 2003]. Therefore, the collocation of peak O<sub>3</sub> decrease and soybean planting is expected to result in sizable benefits from avoided soybean yield loss. Meanwhile, the difference in the O<sub>3</sub> impact between the recession and BAU scenarios suggests that the cost and benefit analysis that does not consider the recession impact is likely to underestimate health and welfare benefits from improved air quality. Finally, our results suggest further challenges for some regions to attain the new National Ambient Air Quality Standards (NAAQS) for  $O_3$  under a changing climate [*Lin et al.*, 2015]. The U.S. Environmental Protection Agency (U.S. EPA) has recently tightened the NAAQS for  $O_3$ , putting more areas into nonattainment under the new standards. The model results presented here show that the projected O<sub>3</sub> decrease has been partially offset by emerging emission sources and there is also the wintertime high-O<sub>3</sub> problem stemming from these sources [Pinto, 2009; Edwards et al., 2014]. Timely updates and accurate accounting of emission inventories caused by the changing economy hence become increasingly important when addressing these critical air quality issues.

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