Impacts of control strategies, the Great Recession and weekday variations on NO2 columns above North American cities

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ABSTRACT

The Ozone Monitoring Instrument (OMI) has been estimating NO2 columns from space for over 10 years, and these have been used to estimate emissions and emission trends for point and area sources all over the world. In this study we evaluate the trends in NO2 columns over 54 cities in the USA and Canada to identify the long term trends due to air quality policies, the impact of the Great Recession, and the weekday-weekend effect. A multiple linear regression model is used to fit annual, seasonal and weekly factors for individual swath retrievals along with the impact of temperature, wind speed and pixel size. For most cities, the correlation coefficients of the model fit ranges from 0.47 to 0.76. There have been strong reductions in NO2 columns, with annual decreases of up to 7% per year in most cities. During the years of the Great Recession, NO2 columns were as much as 30% lower than they would have been had they followed the linear annual trend. The analysis yielded insights into the timing of the reductions, with some cities in the northwest and in the east experiencing reductions in 2008 already, and most areas back to where they would have been based on the uniform trend by 2011. The analysis also finds that reductions in columns during the weekend vary significantly from city to city, with a range in reductions of 10%–30% on Saturdays, and 20%–50% on Sundays.

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1. Introduction

Estimation of air pollutant emissions from space (Streets et al., 2013) is making significant contributions to air quality management (Duncan et al., 2014) thanks to the presence of numerous and diverse instruments in orbit (Martin, 2008; Hoff and Christopher, 2009). In particular, the Ozone Monitoring Instrument (OMI, Levelt et al. (2006)) has enabled extensive analyses of nitrogen dioxide (NO2). Earlier trend analysis of nitrogen oxides (NOx) found different annual patterns over megacities mainly in Europe using the SCIAMACHY and GOME retrievals (Konovalov et al., 2010).
and using SCIAMACHY over the whole globe (Schneider and van der A, 2012; Schneider et al., 2015). These results are in agreement with Hilboll et al. (2013) who merged SCIAMACHY and GOME data with the OMI retrievals to obtain long term trends over megacities all over the world. In the developed world, trends were negative with decreases as strong as 6% per year in Los Angeles. In contrast, megacities in Asia and the Middle East experienced increases of 5–10% per year. Duncan et al. (2016) and Krotkov et al. (2016) have further described the different trends in NO₂ columns around the world, including recent decreases in China due to new regulations, but continued growth in India and in the Middle East.

Curier et al. (2014) reported decreasing trends over Europe using OMI data, and used a grid model to separate the trends according to the dominant NO₂ source for each area in order to improve emission inventories. By using spectral analysis, Castellanos and Boersma (2012) reported that NO₂ trends depend on the complex interplay between environmental policy and economic activity: a general decreasing trend due to longer-term reductions in emissions was combined with faster reductions due to the Great Recession. Zhou et al. (2012) enhanced their trend analysis with meteorological and temporal factors in order to get a clearer estimate of emission reductions in, for example, northern Spain and central England. Lelieveld et al. (2015) showed that in certain cases, longer-term trends are drastically altered as a result of political upheaval in the Middle East, with impacts on the NO₂ columns that can be clearly seen in annual averages of column retrievals.

For the United States of America, Lamsal et al. (2015) took account of non-linear effects of the seasons to obtain more accurate trend estimates. Comparisons with in-situ surface measurements suggested that the OMI retrievals are sufficiently robust to be used for improving emission inventories. They found larger annual decreases in NO₂ columns from 2005 to 2008 than from 2010 to 2013, in agreement with the earlier study of the impact of the recession by Russell et al. (2012). Decreasing trends were also reported for Texas (Cho and Souri, 2015) who further analyze the ozone sensitivity to NOₓ in different urban areas. Tong et al. (2015) found good agreement in the downward trends of OMI NO₂ columns with surface data, and suggested that national emission inventories could be updated more frequently using this data. This is corroborated by Lu et al. (2015) who found that accurate estimates of NO₂ emissions in urban areas can be made directly from the OMI retrievals. Furthermore, they confirm very significant reductions in NO₂ concentrations in the USA of between 40 and 50% from 2005 to 2014 due to successful control of emissions from the power and transportation sectors. Furthermore, Russell et al. (2012) highlight the role of the Clean Air Interstate Rule (CAIR), which came into force in the eastern states starting in 2009, as well as the Tier II Tailpipe NO₂ Emissions Standard which led to emission reductions of 77–86% in vehicles produced in the USA between 2004 and 2009. Emission trends of mobile sources have been well documented (Dallmann and Harley, 2010; McDonald et al., 2012; Bishop and Stedman, 2015) and have led to strong reductions in NO₂ despite growth in vehicle miles traveled.

There has been extensive analyses of the weekend effect on NOₓ emissions with in situ data, see for example Harley et al. (2005), but comparatively few studies with satellite retrievals. Beirle et al. (2003) reported that NO₂ columns are lower by 25–50% on Sundays in Europe and the USA based on GOME retrievals. Russell et al. (2010) found similar values for California using OMI retrievals. By using oversampling, they were able to distinguish different strengths of the weekend effect within areas of the Los Angeles air basin. Valin et al. (2014) found that these were not represented in chemical grid models, and that satellite retrievals can provide further constraints on the varying chemical regimes in large urban areas.

In this paper we analyze OMI NO₂ vertical column data for 54 cities over a 10 year period from 2005 to 2014 inclusive. Most prior work cited above has relied on a combination of averaging of OMI pixels to larger grids and/or to longer time periods as these are required to perform accurate emissions estimates using OMI data (see for example de Foy et al. (2014, 2015)). Oversampling has been used to extract higher resolution pollution maps (de Foy et al., 2009; Russell et al., 2010), but this requires longer time periods and usually does not account for varying pixel resolution. In this study, we perform the analysis directly on the individual OMI pixel data available, such that there is neither spatial nor temporal averaging of the data. We use a multiple linear regression analysis to evaluate the impact of annual, seasonal, and weekly variations as well as the contribution of meteorology and pixel resolution to the NO₂ columns over the urban areas. The study is closest to Zhou et al. (2012) who used a general additive model to account for the impact of meteorology and seasonal variations in their analysis.

2. Methods

2.1. OMI retrievals

The Ozone Monitoring Instrument (OMI) was launched on NASA’s Aura satellite in July 2004 and has been providing measurements of ultraviolet and visible radiation down to a resolution of 13 km by 24 km (Levett et al., 2006). This paper uses the Vertical Column Density (VCD) of tropospheric NO₂ from the DOMINO v2.0 product (Boersma et al., 2007, 2011) which is publicly available from the European Space Agency’s Tropospheric Emission Monitoring Internet Service (http://www.temis.nl/airpollution/no2.html).

We selected 51 cities in the USA and 3 in Canada, as shown in Table 1 and Fig. 1. We selected the largest cities and the ones with distinct signatures in the NO₂ columns as reported in Russell et al. (2012) and Lu et al. (2015). In addition, we added smaller cities for better geographical coverage. Lu et al. (2015) rejected some cities because they needed a distinct plume signature for the exponentially-modified Gaussian method. In our case, we are just looking at the vertical columns above a city, and so we can include cities such as San Francisco that have large neighboring urban areas. For the same reason, the method is not sensitive to the size of the area from which pixels are selected. Prior testing with areas ranging from 0.25° to 1° radii found that the results were robust. For each city selected, we therefore retrieve all level 2 swath pixels within a 0.5° radius of the urban center.

OMI has suffered from a partial blockage of its field of view leading to row anomalies. In order to have a consistent record, we limit the analysis to rows 10 to 27 for the years from 2005 to 2014 inclusive. (Note that similar results have subsequently been obtained when limiting the analysis to rows 11 to 23.) Only pixels with a Quality Assurance flag of 0 were retained which excludes all pixels with a cloud radiance fraction greater than 50%. Furthermore, pixels with a surface albedo exceeding 30% were excluded, as were pixels with a solar zenith angle greater than 70°. Overall, we therefore have between 4000 and 13,000 OMI data points from individual OMI pixels for each of the 54 cities selected over the 10 year period being analyzed.

2.2. Multiple linear regression model

We use a multiple linear regression model to quantify the variations in the signal which is similar to the ones used by Lamsal et al. (2015) and Hilboll et al. (2013). We do not average the level 2 pixel data either spatially or temporally. This means that we can
augment the linear regression model to include variations at the submonthly scale as was done by Zhou et al. (2012). Because we do not spatially average the data, we can include the effect of pixel size in the regression model. A least squares solver is used for the multiple linear regression as described in de Foy and Schauer (2015).

The overall model for the NO$_2$ columns includes variations at the annual, seasonal and weekly timescales, as well as variations due to meteorology and pixel resolution as shown in Eq. (1):

$$\log(C) = c_{\text{int}} + \sum_{yr=2008}^{2011} c_{yr} \cdot \text{yr} + \sum_{wd=\text{Mon}} \text{SUN} c_{wd} \cdot \text{wd} + f(\text{other}) + \epsilon$$

(1)

where $C$ is the series of NO$_2$ columns; the coefficients $c$ are determined by the Iteratively Reweighted Least Squares procedure; the time vectors ($t_{yr}, t_{wd}$) represent the annual and weekly variation; and $\epsilon$ is the residual between the model and the retrievals. $f(\text{other})$ is made up of the following components:

$$f(\text{seasons}) = \sum_{j=1}^{2} c_{j} \sin \left(\frac{2 \pi j t_{yr}}{365.25}\right) + c_{j} \cos \left(\frac{2 \pi j t_{yr}}{365.25}\right)$$

(2)

$$f(\text{meteorology}) = c_{\text{temp}}(\log(\text{WS} + 3)) + c_{T^2} + c_{u_{10}} U'_{10} + c_{v_{10}} V'_{10}$$

(3)

$$f(\text{resolution}) = c_{\text{amin}} D'_{\text{min}} + c_{\text{max}} D'_{\text{max}}$$

(4)
The inputs to the meteorology and resolution function are normalized variables $(T = (T - \mu(T))/\sigma(T))$: WS is the 10 m wind speed; $T_2$ is the 2 m temperature; $U_{10}$ and $V_{10}$ are the zonal and meridional 10 m wind speeds. $D_{\text{min}}$ is the distance of the nearest pixel corner to the center point of the urban area, and is negative if the urban area is inside the pixel. $D_{\text{max}}$ is the distance of the farthest pixel corner from the center of the urban area. Table 2 shows a summary of the factors included in the regression model.

We use two different approaches to estimate the annual trend in the columns. The period from 2008 to 2011 was influenced by the recession. The first method uses a linear function that covers 2005 to 2007 and 2012 to 2014. In practice, this is a linear time series ranging from 0 to 2007 and 2012 to 2014. In practice, this is a linear time series retrieval and 1 Jan 2010, with zero values for the years in between. We assume that the columns have been if they had followed the linear annual trend during this time period.

The second method used separate factors for each year instead of using a combination of a linear trend and individual factors for the years influenced by the recession. This method does not make any assumptions about the temporal evolution of the columns.

Because OMI NO2 columns over polluted areas are log-normally distributed, we take the log of the data. This means that the model for the NO2 columns is multiplicative rather than additive; the columns are represented by a series of scaling factors multiplied by each other, rather than a series of subcomponents added to each other as in Lamsal et al. (2015). The linear trend factor therefore corresponds to a fixed percentage annual increase or decrease in the columns. The regression factors for the annual trend and the individual years can be converted to percentages using the following equation:

$$ p_i = (e^{c_i} - 1) \times 100\% $$

where $p$ is the factor in % corresponding to the output $c$ of the multiple linear regression algorithm, for all components $i$ of the regression which includes $c_{\text{lin}}, c_{\text{zn}},$ and $c_{\text{wf}}$.

We represent the seasonal signal in the column data using a cosine and a sine function with a time period of 1 year and 1/2 year. In practice, these mainly account for the impact of the varying lifetime of NO2 from long lifetimes in winter to shorter ones in the summer.

The weekly variation is represented by a factor for each day: a time series of ones on that particular weekday, and zero otherwise. In the same way as the annual factors, the weekday factors are converted to percentages. In this case the percentages are calculated compared to the average NO2 columns from Tuesday to Thursday. In this way, the values reported for Saturday and Sunday can be interpreted as reduction factors compared to the midweek levels. One advantage of using factors like this, instead of harmonic functions, is that we can treat holidays separately. There are not enough of them to create a robust separate category, so instead we chose to include them as Sundays as this was found to improve the fit of the regression. The holidays we selected include New Year, Good Friday, Memorial Day, July 4th, Labor Day, Thanksgiving Day, Black Friday, Christmas Eve and Christmas Day.

For meteorology, we use data from ERA-Interim at 1° and 6 h resolution (Dee et al., 2011) which are available from the European Center for Medium-Range Weather Forecasts (http://apps.ecmwf.int/datasets/). The grid point closest to the urban center was selected for the time series and this was interpolated to the time of the OMI pixel measurement. In the analysis we include the 10 m wind speed and the 2 m temperature. We further include the 10 m zonal and meridional component of the wind ($u$ and $v$) to represent wind direction effects. To obtain a normal distribution of the wind speed parameter we added 3 m/s to the wind speed and then took the logarithm. We use ERA-Interim surface data because testing with different sources of meteorological data as well as different heights of wind data found that this gave the best estimates of emissions (de Foy et al., 2015). Although that study was for power plants, it should be even more applicable for urban areas which have mostly surface emissions.

OMI retrievals have varying pixel resolution depending on the position of the pixel within the swath. To account for this effect, we include the distance of the closest and farthest pixel corner to the

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**Table 2**

Factors included in the multiple linear regression analysis of the NO2 columns.

<table>
<thead>
<tr>
<th>Annual</th>
<th>Seasonal</th>
<th>Weekly</th>
<th>Meteorology</th>
<th>Pixel resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Trend</td>
<td>Sin 1yr</td>
<td>Monday</td>
<td>Wind Speed</td>
<td>Min Pixel Distance</td>
</tr>
<tr>
<td>2008</td>
<td>Cos 1 yr</td>
<td>Tuesday</td>
<td>Zonal Wind</td>
<td>Max Pixel Distance</td>
</tr>
<tr>
<td>2009</td>
<td>Sin 6 mo</td>
<td>Wednesday</td>
<td>Meridional Wind</td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>Cos 6 mo</td>
<td>Thursday</td>
<td>Temperature</td>
<td></td>
</tr>
<tr>
<td>2011</td>
<td></td>
<td>Friday</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Saturday</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sunday</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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**Fig. 1.** Map showing the average OMI NO2 tropospheric Vertical Column Density and the 54 urban areas in this study. OMI pixels were selected within the circles shown for each urban area.
urban center point. This serves as a proxy for both the size of the pixel and the distance of the pixel from the urban center. Testing with the multiple linear regression model suggested that these two variables led to models that were as good as or better than alternatives such as including the pixel area and the distance between the pixel center and the urban area.

Note that there are negative column density values in the retrievals. To preserve a uniform treatment for all urban areas and keep the data approximately normally distributed, we reset all values smaller than $1 \times 10^{15}$ molec/cm$^2$ to $1 \times 10^{15}$ molec/cm$^2$. Because we are not applying spatial or temporal averaging, and because we have limited rows of OMI data, it was not possible to obtain an accurate estimate of the background column value for each pixel. This is an inherent limitation of the analysis, although it affects the eastern urban areas which have a higher background more than the western ones which have relatively clean background air.

Least squares estimates are sensitive to outliers, and so we use an Iteratively Reweighted Least Squares (IRLS) procedure to increase the robustness of the results: all points with a residual greater than 2 times the standard deviation of all the residuals are excluded from the analysis.

Fig. 2. Left: Distribution of NO$_2$ tropospheric Vertical Column Density above Atlanta with the best fit log-normal distribution (dashed line). Middle: Distribution of log(NO$_2$) showing the best fit normal distribution (dashed line). Right: Distribution of residuals of the multiple linear regression model without outliers, showing approximate normal distribution (dashed line).

Fig. 3. Multiple linear regression analysis for Atlanta, GA showing the time series of NO$_2$ OMI retrievals of tropospheric Vertical Column Density and the multiple linear regression model fit (top), the annual and seasonal scale factors (middle) and the residual (bottom). Outliers rejected by IRLS are shown by open circles in the top panel.
2.3. Uncertainty analysis

We use the bootstrapping algorithm to estimate the uncertainties in the results. Instrument errors are assumed to be uncorrelated, and model errors are unlikely to be correlated beyond a couple of days. Randomly selecting the data included in the analysis can therefore yield an estimate of the impact of both measurement errors and model errors. We perform 100 realizations of the model with random selection of the data included, with replacement. In order to account for correlation in synoptic meteorological conditions from one day to the next, we also tested block-bootstrapping with a 7 day interval, where weeks of data are randomly selected for inclusion in the model. Both methods gave similar estimates of the uncertainty, and so we will only report results from regular bootstrapping.

3. Results & discussion

3.1. Atlanta case study

We present the results for Atlanta as an example of the method and include the detailed results for all areas in the Supplementary Information. Fig. 2 shows that the OMI NO2 columns over Atlanta are log-normally distributed, and that the residuals from the regression are normally distributed.

Fig. 3 shows the time series of the OMI columns along with the Multiple Linear Regression fit, the seasonal factor, the annual factors and the residual (see Fig. S13 for the actual values). There are 8525 data points in the time series, with an average NO2 column of $5.27 \times 10^{15}$ molec/cm$^2$. 462 points were excluded by the Iteratively Reweighted Least Squares procedure, with a resulting correlation...
coeficient \( r \) of 0.74. Atlanta has a downward linear trend of 5.5% and a drop in the columns of 16% in 2009 and 11% in 2010.

Fig. 4 show the median, interquartile range, data extent and outliers for the entire time series of OMI NO2 columns by weekday and by year. The bottom panels shows the corresponding results from the Multiple Linear Regression model with the uncertainty determined by bootstrapping. This shows that the results of the regression model are in agreement with the averages of the original data but that by accounting for all the different factors in the model, the method determines factors with much narrower uncertainty ranges. Furthermore, features of the temporal variation such as the weekend effect and the drop during the recession become much more clearly visible.

3.2. North American cities

Table 1 shows the average OMI NO2 column, the number of observations and the Pearson correlation coeficient for each urban area in the analysis. The 10-year average annual trend is shown along with the impact of the recession from 2008 to 2011. Also shown are the impact of Saturdays and Sundays on total column amounts. The time series for each urban area along with tables containing all the multiple linear regression factors are in the Supplementary Information (Figs. S12–S65). In addition, maps of the meteorological and pixel resolution factors are shown in Figs. S5–S10.

Uncertainty analysis using bootstrapping shows that the results are robust with respect to data selection. Table S1 shows the standard deviation of the results. The uncertainty in the annual trend ranges between 0.2 and 0.4% depending on the city, the annual factors have uncertainties of around 2–3% and the weekend factors have uncertainties of around 1–2%.

Areas with larger average NO2 columns have higher correlation coefficients of the regression model as can be seen in Table 1 and Fig. 5. The columns vary from \( 1.37 \times 10^{15} \) molec/cm\(^2\) for Boise to \( 14.6 \times 10^{15} \) molec/cm\(^2\) for Los Angeles, and the correlation coefficients vary from 0.47 for Boise to 0.76 for Philadelphia. Note that these are high correlation coefficients given that there are between 4000 and 13,000 data points in the time series. The positive association between column loadings and model fit is expected as larger loadings lead to stronger signal to noise ratios in the data. Los Angeles, New York and Chicago have the largest average NO2 columns, but the correlation coefficients are not as high as Philadelphia. We speculate that this is related to issues of urban morphology and meteorological impacts due to the presence of complex geography. As discussed later, future satellite missions with improved spatial resolutions will give better constraints on these factors.

There are 22 factors included in the multiple linear regression analysis (see Table 2). By taking the sum of the square of these, we can estimate the contribution of each factor to the variability in the model fit. In practice, we take the sum of the square of the individual coefficients multiplied by the corresponding time series, and we do this with the transformed variables used in the model. We then combine the contribution to the overall variance into 5 groups: Meteorology, Pixel Resolution, Weekday effects, Seasonal variation and Annual trends. Fig. 5 shows a pie chart of the contributions for each urban area. We find that coastal urban areas are
more influenced by meteorology, mainly because the wind direction has a large impact on column values as expected when considering the impact of on-shore and off-shore winds. Pixel resolution has a larger effect in the West. Fig. 1 shows that background levels are lower in the west and the urban areas more distinct, which could account for this. The seasonal variation is the largest component for many urban areas, especially in the Midwest and the interior of the US. This is related to the longer lifetimes of NO\textsubscript{2} in winter which leads to significantly higher column values.

The weekday impacts contribute between 5 and 30\% of the variability in the analysis. The annual impacts contribute between 2 and 25\% of the variability. For the annual impacts, the contributions...
3. Long term trends and reductions during the Great Recession

Fig. 6 shows the annual factors for all the urban areas by geographical group based on the simulation with individual factors for each year of the analysis. From this, it can be seen that a linear model with a drop between 2008 and 2011 is an accurate representation of the trend for most cities (note that a linear model in log space translates to an exponential curve in this figure). For some areas, especially in the south and west, the temporal profile looks more like a sudden drop in 2009 followed by stable levels since then. Nevertheless, even for these cities the time series can be approximated as a linear trend, so that the drop in 2009 and 2010 can be compared across all urban areas.

The annual trend in NO2 columns was calculated using the years from 2005 to 2007 and 2012 to 2014, as shown in Fig. 7 and Table 1. The urban areas in the eastern US have the strongest reductions with annual decreases in NO2 columns ranging between 6 and 7%. Urban areas on the West Coast and in the Midwest typically have annual decreases between 3 and 6%. Urban areas along the southern border and in the central West have decreases ranging from 4 to 0%.

Fig. 7 also shows the trends for 2005 to 2014 in the Gross Domestic Product of the metropolitan areas in real US dollars based on estimates from the United States Bureau of Economic Analysis and the annualized population trends based on estimates from the United States Census Bureau. Overall, there is a correlation between the trends in NO2 columns and population, but there is little correlation between the trends in NO2 columns and real Gross Domestic Product (GDP). Urban areas with faster population growth experienced the smallest reductions in NO2 columns (eg. San Antonio, Houston, Salt Lake City), whereas the urban areas with decreasing populations experienced larger decreases in NO2 columns (eg. Cleveland and Detroit). Of particular interest in these diagrams is the fact that economic growth in these diagrams is decoupled from pollution trends.

As shown in Table 1, the years from 2008 to 2011 have lower NO2 columns than would be expected from linear trends. This is especially true for 2009 and 2010, which are shown in Fig. 8. These reductions can also be seen in the annual factors shown in Fig. 6. In 2008, the columns of most urban areas are not significantly different than what would be suggested by the trend. However, there are a group of urban areas in the Midwest, in the eastern US,
and along the Pacific coast that already show a decrease in columns of 10–20%. By 2009, the drop in NO₂ columns are clearly visible across the country with reductions of up to 30%. There are just a handful of areas that do not experience these large reductions including Houston, San Antonio, Philadelphia, Tulsa and Little Rock. Some of these areas do not have a strong decadal downward trend in columns either. By 2010, most urban areas experienced decreases of between 10 and 20%. The West Coast however is still significantly lower than the rest of the nation with decreases between 20 and 30%. In 2011 most urban areas are back to where they would have been had they followed the linear annual trend. There are a few outliers, although these may be in part because the annual

Fig. 9. Top: Percentage drop in GDP in real US Dollars in 2009 and 2010 compared with 2007 and 2008. Middle: Percentage drop for GDP related to Transportation and Utilities. Bottom: Percentage drop for GDP related to Trade. Data from the US Bureau of Economic Analysis. In black and white figure circles show positive values, diamonds show negative values.
trends shown in Fig. 6 did not show as clear a pattern as most of the other urban areas. For example, Fig. 6 shows that several Californian urban areas along with Minneapolis and some other cities experienced a sharp decline in NO$_2$ columns during the recession, which was followed by stabilization at the new level. This is a distinct pattern from those cities, especially in the Northeast, where the recession caused a short term departure from a strong, long term downward trend.

As discussed in Russell et al. (2012), there were changes in pollution levels due to air quality policies at the same time as changes in economic activity due to the recession. Fig. 9 shows the percentage drop in real GDP for the average of 2009 and 2010 compared with the average of 2007 and 2008. The figure has panels for GDP from all sectors; from transportation and utilities alone; and from trade. Note that not all metropolitan areas have complete data, and consequently there are missing values for transportation and utilities as well as for trade. For overall GDP, there is a range from $-16\%$ for Reno, NV to $8\%$ for Portland, OR. For transportation and utilities, the range is from $-18\%$ for San Antonio, TX to $6\%$ for Boise, ID. For trade, the range is from $-16\%$ for Tulsa, OK to $-5\%$ for Pittsburgh, PA.

The reductions in GDP values for 2009 and 2010 are larger for transportation, utilities and trade than they are for overall GDP. As these sectors are significant contributors to NO$_x$ emissions, it is reasonable to expect that part of the reductions in NO$_2$ columns observed in 2009 and 2010 are due to the recession. In addition to reduced activity levels, there have been reductions in the turnover of the vehicle fleet associated with the recession (Bishop and Stedman, 2014). This could be a confounding factor, as it leads to an increase in emissions. Overall it is therefore not possible to ascribe exactly which changes are caused by which factors. Roughly speaking, the columns are reduced by as much as 30% and the sectoral GDP values are reduced by as much as 15%. This suggests that potentially half of the reductions are due to the recession whereas the other half are due to other longer term policies.

3.4. Weekend impacts

The multiple linear regression analysis revealed a strong weekly variation in NO$_2$ columns all over the US. Fig. 10 shows maps of the reductions in OMI NO$_2$ columns on Saturdays and Sundays. The columns are mostly similar throughout the week and have reductions of 10–35% on Saturday and 20–55% on Sunday. Some of the largest Sunday effects are seen in the urban areas in the Northeast, and in the largest urban areas. Smaller urban areas in the central US have comparatively weak Sunday effects.

Overall, there is a strong association between the size of the weekend effect and the population of the urban area, the vehicle
miles traveled, and the mean NO2 column, as shown in Fig. S11
based on Schrank et al. (2015). There is very little correlation of
the weekend effect with the average length of the commute but a
stronger association with the average delay per person as can also
be seen in Fig. S11.

Furthermore, there is an association between the weekend ef-
fect and the magnitude of the long term trends. It is not possible to
deconvolve the causation chains in the current analysis, but it
would be interesting to relate these changes to varying emissions
profiles across the US. Russell et al. (2012) suggested that the
recession had different impacts on the weekday and weekend
emissions, however we did not find a clear signal of this in our
analysis.

Fig. S4 displays the weekly variation for all sites which shows
that columns are also lower on Mondays but flat otherwise. Some
cities do experience a gradual increase throughout the week
reaching a maximum on Friday. From this analysis it is not possible
to distinguish the impact of day-to-day carry over from that of
varying emissions. This would most likely require air quality sim-
ulations with 3D grid models.

4. Summary
We have used a multiple linear regression model and the OMI
NO2 columns at the original pixel resolution above 54 cities in
the USA and Canada to identify the linear annual trends in the data,
along with reductions at the time of the Great Recession and
weekend-weekday effects. The model included the impact of
meteorology, pixel resolution and seasonal variation in order to
obtain a better fit in the model for the NO2 columns and hence a
more robust estimate of the trends.

The analysis confirmed that there have been significant down-
ward trends of NO2 columns in selected North American cities with
decreases of up to 7% per year in the Northeast despite the fact that
most cities have experienced population and economic growth.
This highlights the successful impacts of emissions control of both
the power sector and the transportation sector.

During the recession, NO2 columns decreased by up to 30% in
2009. The most affected cities were in the Midwest and in Cali-
ifornia. Some cities experienced decreases starting in 2008. By 2010,
most areas were recovering and by 2011 they returned to the level
that they would have had if they had followed a linear annual trend.
Note however that some cities on the West coast experienced a
sharper drop, and then stabilization at the new level. This is in
contrast to cities on the East coast that have followed steeper linear
trajectories and had a comparatively smaller impact from the
recession. These differences are in agreement with regional dif-
fferences in economic impacts of the recession as described in
Connaughton and Madsen (2012). By comparing the NO2 columns
with data from the US Bureau of Economic Analysis, the results
suggest that undesirable drops in activity levels can lead to sig-
nificant reductions in emissions. Over the long term however, re-
ductions in emissions due to control strategies and improved
technology have a larger impact on achieving cleaner air.

Weekday-weekend effects were found across the country, with
reductions varying quite widely from 10% to 30% on Saturdays, and
from 20% to 50% on Sundays. Large, congested urban areas appear
to have stronger weekend reductions, whereas smaller, central
cities have a much weaker weekend effect. Satellite remote sensing
provides an effective way of estimating the geographic variation in
the emissions and hence of improving the emission inventories
used in different regions.

By creating a model to represent NO2 columns at the original
pixel resolution that includes variability due to different time scales
and different factors, this analysis shows that concurrent estimates
can be made of very different input variables. This can be used to
improve existing emission inventories which may not currently
account for different recession and day-of-week effects across the
urban areas considered in this study. Future satellite missions will
greatly expand the ability to refine emission inventories and to
identify temporal and spatial patterns in local pollution levels
(Veekind et al., 2012; Chance et al., 2013).

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Appendix A. Supplementary data
Supplementary data related to this article can be found at http://
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