Evaluating ΔCO:ΔNOx in a near-road environment using ambient data from Las Vegas

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Heather Simon[1], R. Chris Owen[1], Richard Baldauf[2,3], Pat Dolwick[1], Kristen Foley[4], Barron Henderson[1], Sue Kimbrough[3], Norm Possiel[1], Lukas Valin[4]

[1]Office of Air Quality Planning & Standards, US EPA, RTP, NC; [2]Office of Transportation and Air Quality, US EPA, Ann Arbor, MI; [3]National Risk Management Research Laboratory, US EPA, RTP, NC; [4]National Exposure Research Laboratory, US EPA, RTP, NC

Heather Simon l Simon.Heather@epa.gov l 919-541-1803

Motivation

- Many previous studies have used CO and NOx linear regressions to evaluate onroad mobile source inventories[1-8]
  - Mobile sources were isolated using near-road or morning rush-hour observations.
  - The regression slope was interpreted as the ratio of emitted CO to emitted NOx from onroad sources
- To our knowledge, no previous research tested the assumption that linear regression slopes from near-road data accurately reflect CO:NOx emitted ratios (ERs)

Overview

- Combined upwind and downwind measurements made during a recent EPA-FHWA near-road study in Las Vegas provides a unique opportunity to measure onroad mobile source contributions of CO (ΔCO) and NOx (ΔNOx)
- We use onroad source contributions to validate ΔCO:ΔNOx derived from linear regressions
- Traffic data collected during this campaign can also be used as inputs into EPAs MOtor Vehicle Emissions Simulator (MOVES) model to compare modeled CO:NOx ERs with ambient measurements

Evaluation of regression-based ΔCO:ΔNOx ratios for estimating onroad emissions

Figure 3. Boxplots summarizing the distribution of ΔCO:ΔNOx from cross-road gradient and all three regression methodologies at each of the downwind monitor locations. Regressions slopes with p-values > 0.05 are not included in the boxplots.

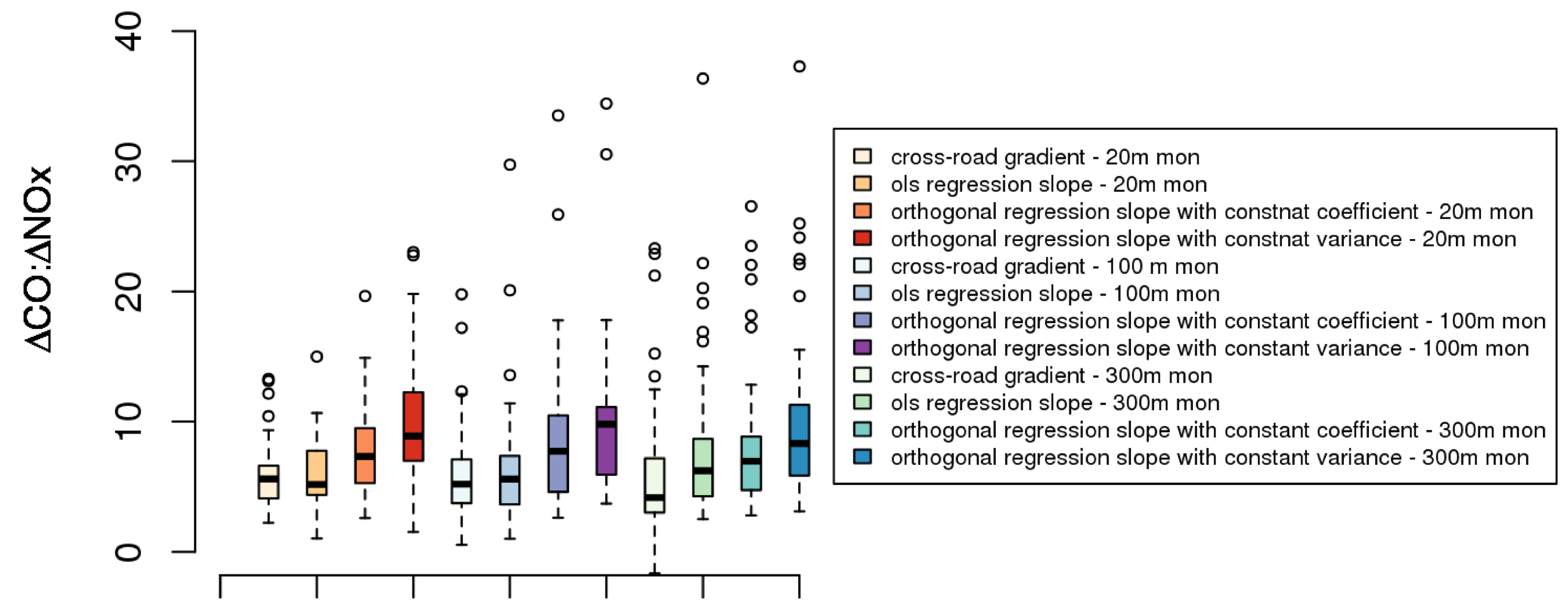


Figure 4 Comparison of ΔCO:ΔNOx derived using all 3 regression methodologies versus the ΔCO:ΔNOx derived from the cross-road gradient for the 100m downwind monitor. Regressions slopes that with p-values > 0.05 are not shown.

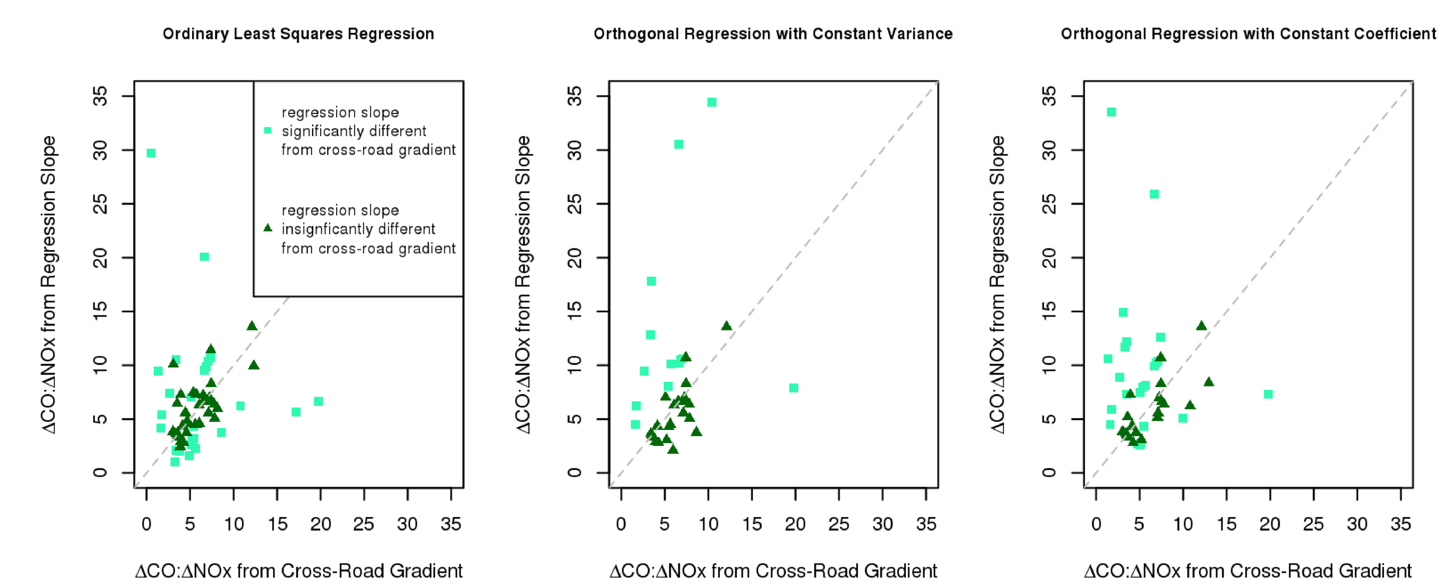


Table 1. ΔCO:ΔNOx values and performance information for the all regression methods.

	DW Monitor Distance (m)	% of regressions with a significant slope	Mean ΔCO:ΔNOx*	cross-road gradient not within 95% CI of regression slope* (% of regressions)	ΔCO:ΔNOx Difference from cross-road gradient*	
					mean	Welch t-test p-value
Cross-road gradient	20	N/A	5.8	N/A	N/A	N/A
	100	N/A	5.8-6.2**	N/A	N/A	N/A
	300	N/A	6.4-6.7**	N/A	N/A	N/A
Ordinary Least Squares	20	25%	6.1	32%	0.3	0.60
	100	35%	6.4	43%	0.6	0.43
	300	38%	8.4	52%	2.0	0.15
Orthogonal with Constant Coefficient	20	23%	8.1	21%	2.3	<0.01
	100	25%	8.8	52%	3.0	<0.01
	300	27%	9.5	38%	2.9	0.12
Orthogonal with Constant Variance	20	21%	10.0	19%	4.1	<0.01
	100	21%	10.4	36%	2.9	<0.01
	300	31%	11.2	49%	4.5	<0.01

*These values are only calculated using results from regressions with statistically significant slopes ($p < 0.05$).
**Mean ΔCO:ΔNOx differs for each regression method comparison due to different sets of hours with valid regressions

Methods

Las Vegas near-road measurements

- CO and NOx were measured between December 2008 and February 2010
- Measurements were made at one upwind site (nominal distance of 100m) and three downwind sites (nominal distances of 20m, 100m, 300m) near a section of I-15 on the south side of Las Vegas
- Data selection criteria:
  - Cross-road flow (230-300° wind direction) at ≥ 1 m/s
  - Data completeness (5 valid, 5-min average measurements in each hour)

Using upwind monitor to determine

- Ratio of cross-road gradient of CO and NOx at each of the 3 downwind monitors (at distance x) and hourly resolution is calculated as follows:

$$\frac{\Delta CO^x}{\Delta NOx^x} = \frac{[CO]_{1h}^{x} - [CO]_{1h}^{-100m}}{[NOx]_{1h}^{x} - [NOx]_{1h}^{-100m}}$$

Using linear regressions to determine roadway ΔCO:ΔNOx

- Figure 2 provides an example linear regression of CO vs NOx
- 1 regression per hour using 5-minute average measurements
- Three different linear regression methods
  - Ordinary Least Squares (OLS) – minimizes **vertical** distance between points and the line-of-best-fit. Assumes no uncertainty in the independent variable
  - Orthogonal – minimizes **perpendicular** distance between points and the line-of-best-fit. Assumes uncertainty in both variables.
    - Constant coefficient: treats uncertainty as % of measured value for both variables
    - Constant variance: treats uncertainty as constant value for both variables

$$[CO]_{5min}^{x} = \frac{\Delta CO^x}{\Delta NOx^x}[NOx]_{5min}^{x} + b$$

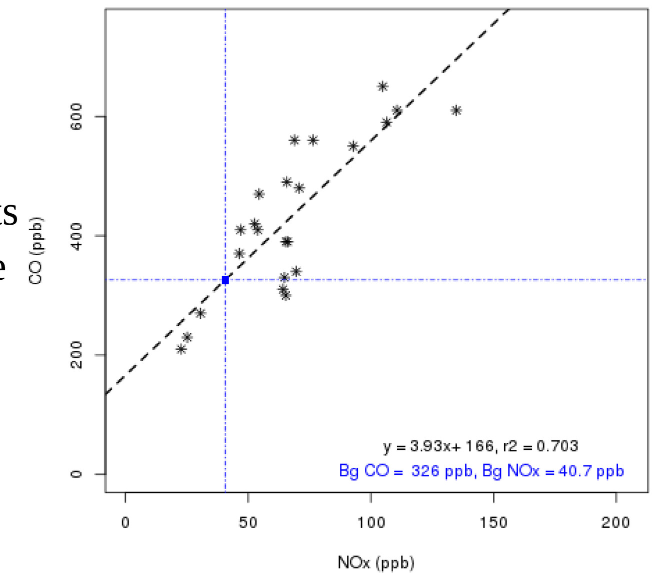


Figure 2. Example of ΔCO:ΔNOx regression

Using MOVES to simulate roadway ΔCO:ΔNOx

- MOVES 2014a used generate emissions for range of speed, temperature, and RH with county-level defaults
- On-site traffic and meteorology used to generate hourly emissions for each lane
- Emissions were summed across all lanes for comparison with cross-road gradient ΔCO:ΔNOx
- Suspected issues with traffic data in DJF may be reflected in poor ER and ΔCO:ΔNOx agreement

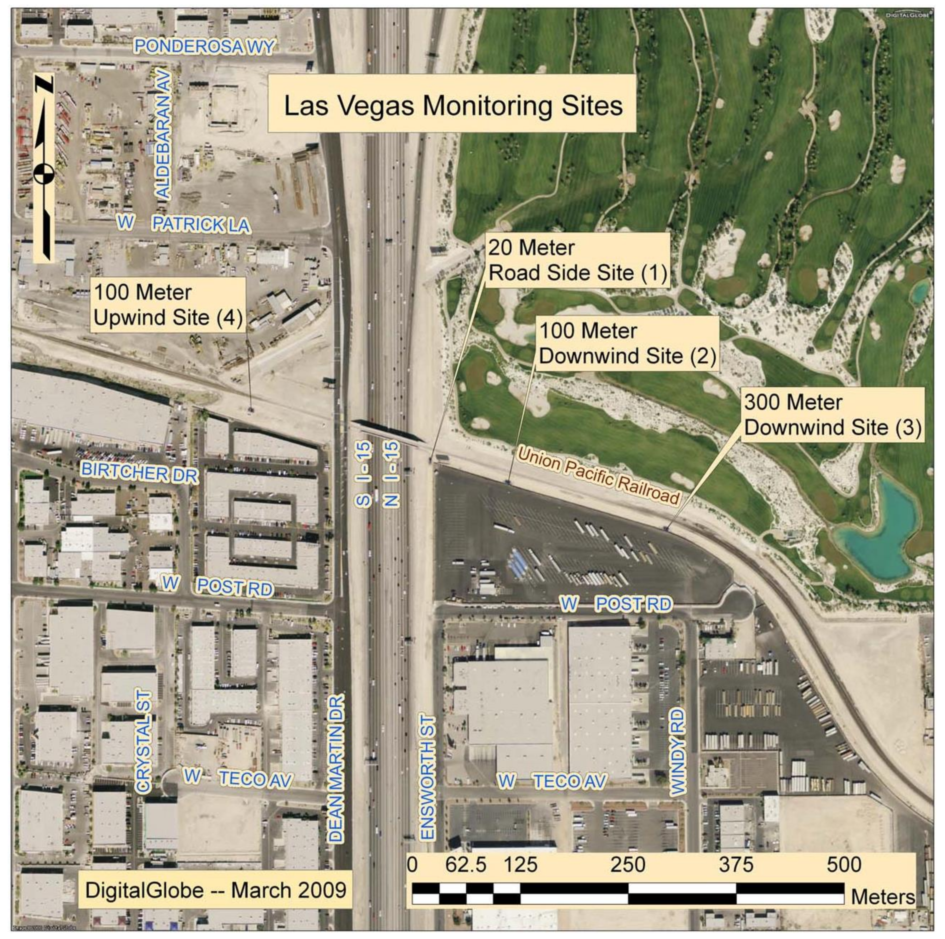


Figure 1. Las Vegas Study Sites

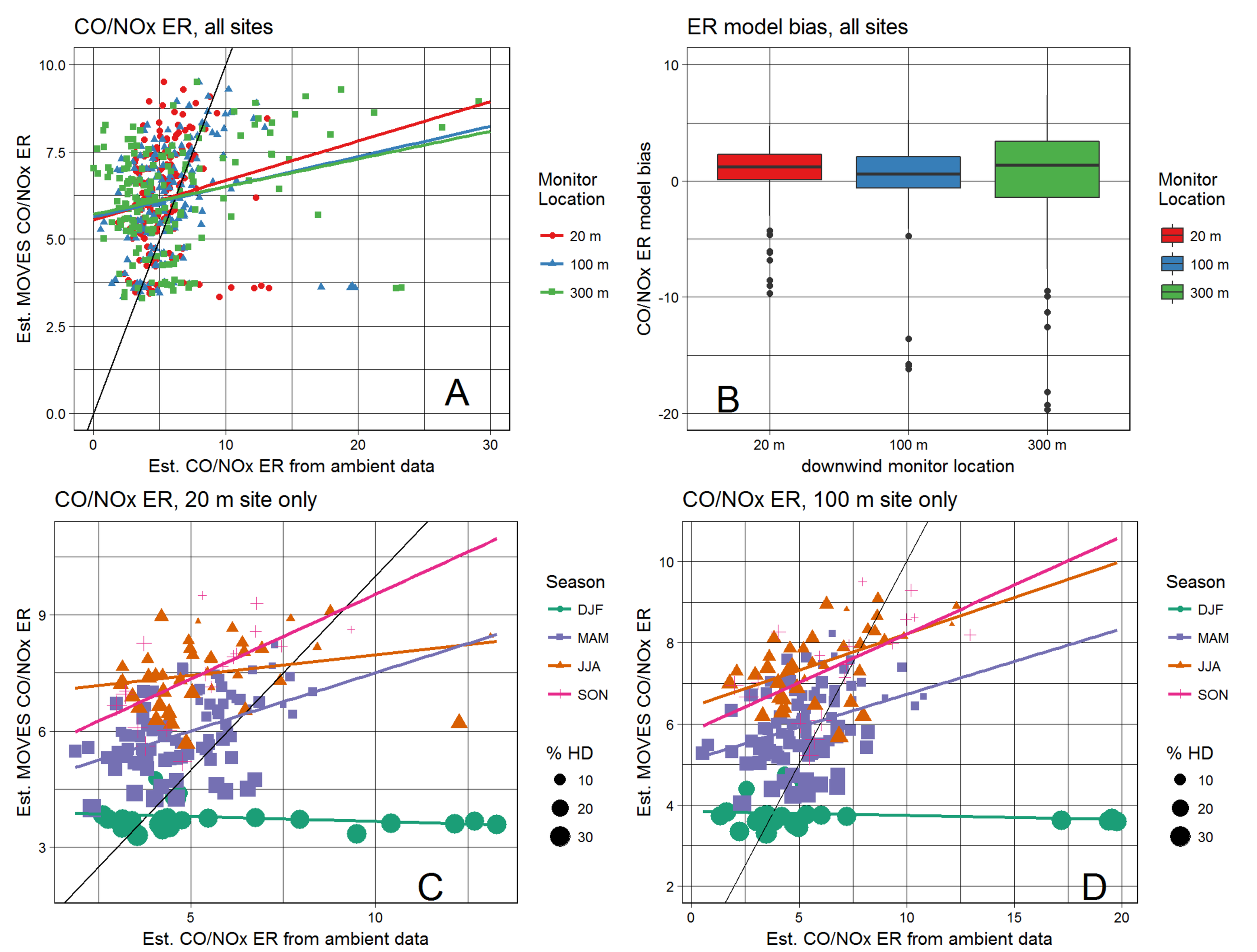
Comparison of cross-road gradient ΔCO:ΔNOx to MOVES ERs

Figure 5.

(A) comparison of cross-road gradient ΔCO:ΔNOx against the MOVES generated ER

(B) Distribution of ER bias based on estimates from each downwind monitor

(C&D) comparison of ΔCO:ΔNOx ER broken down by Season and Heavy Duty fraction for 20m and 100m downwind sites



Conclusions

- The regression method that performed the best was the OLS regression at the 20m and 100m downwind sites.
  - Performance was mixed for comparisons between regression-based ΔCO:ΔNOx and cross-road gradient ΔCO:ΔNOx for individual hours
  - OLS may be a reliable method for characterizing the ratio of CO to NOx emissions coming from vehicles on that roadway over a large number of hours
- The orthogonal regressions, in most cases, had distributions that were significantly different from the cross-road gradient ($p < 0.01$) on average by 2.3-4.5
- Despite the large range of variability, cross-road gradient ΔCO:ΔNOx and MOVES ER have good average agreement with potentially small over-predictions. Over-predictions of the ER could mean that estimated CO emissions are too high or or that NOx emissions are too low.

[1] Harley et al., 1997; [2] Kourtidis et al., 1999; [3] Marr et al., 2002; [4] Ariaga-Colina et al., 2004; [5] Parish et al., 2006; [6] Vivanco et al., 2006; [7] Luke et al., 2010; [8] Wallace et al., 2012