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To cite this article: Nam P Nguyen and Julian D Marshall 2018 *Environ. Res. Lett.* **13** 024002

Environmental Research Letters

LETTER

OPEN ACCESS

RECEIVED
5 October 2017

REVISED
20 November 2017

ACCEPTED FOR PUBLICATION
23 November 2017

PUBLISHED
24 January 2018

Impact, efficiency, inequality, and injustice of urban air pollution: variability by emission location

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Keywords: environmental justice, environmental equality, air pollution, diesel, particulate matter

Supplementary material for this article is available online

Abstract

Reducing exposure to air pollution is an important goal for many local and national governments. Disparities in air pollution exposure by race, ethnicity, and socioeconomic class are well documented; reducing these disparities is another important policy target. Meeting both goals requires tools to evaluate how emission reduction options affect average exposures and exposure disparities. Here, we consider the role of emission location in implementing control strategies, and investigate the effect of two practical, space-based approaches—low-emission zones and truck rerouting—on diesel particle levels in Southern California. We employ Eulerian grid modeling to explore the impact that emission location has on four outcomes important to policymakers: total pollution exposure, exposure efficiency (i.e. exposure impact per unit emission), exposure inequality (i.e. deviations from exposure being equally distributed across the population; unequal exposure among individuals), and exposure injustice (i.e. associations between exposure and demographic attributes such as race or ethnicity; unequal exposure among groups). Our results highlight potential trade-offs (e.g. an increase in equality but reduction in justice for interventions in some locations) as well as opportunities for 'win-win' solutions (locations for which emission reductions would reduce all four target outcomes). We find that a simple, straightforward approach—reducing emissions in neighborhoods with a high proportion of minority residents—may or may not yield the strongest benefits to environmental justice; the reason is that the straightforward approach fails to account for meteorology and where pollution travels after being emitted. In short, we demonstrate an approach that can be used to identify areas in which emissions reductions would have high efficiency and would also result in disproportionately large reductions to average exposure, exposure inequality, and exposure injustice. The approach presented here could be used to design and prioritize local or national emission reduction efforts.

1. Introduction

In the United States, ambient fine particulate matter ($PM_{2.5}$) causes approximately twice as many deaths per year as are caused by traffic accidents ($PM_{2.5}$: ~88 000 deaths/year); globally, $PM_{2.5}$ causes ~4.2 million deaths per year, a rate that exceeds the combined total of traffic accidents, malaria, HIV/AIDS, and tuberculosis [1]. Regulations to reduce air pollution exposures include the US Clean Air Act. Passed in 1970 and amended in 1990, this act provides the greatest monetized benefits of any federal legislation [2], with benefits estimated to be more than 30 times greater than costs [3]. The act obliges the federal government to set national standards for outdoor concentrations; states are responsible for meeting the standards. Since 1970, consumption and GDP have increased, yet air quality in the United States has improved dramatically

[4]. Even so, disparities persist, both for exposures (which are generally higher-than-average for minority, lower-income, and lower-education individuals [5]) and health. For example, relative to whites, Blacks' levels of exposure are ~50% higher for industrial air pollution [6] and ~30% higher for transportation-related air pollution [7, 8]. For conditions in 2006, reducing minorities' NO_2 concentrations to levels experienced by whites would reduce ischemic heart disease mortality by ~7000 deaths per year [7]; that health benefit is equivalent to 25 million people increasing their physical activity level from 'insufficiently active' (<2.5 hours/week of physical activity) to 'sufficiently active' (>2.5 hours/week of physical activity), or 3 million fewer adults beginning to smoke [7]. Although more widely documented and researched in the US, disparities also exist globally [9, 10]. Disparities in the burden that racial or other groups bear from environmental risks are described by the term 'environmental injustice.'

Much of the existing scientific research on environmental justice focuses on documenting disparities in exposure or risk. Limited research identifies quantifiable strategies and opportunities to address these disparities, and even fewer articles consider multiple health- and equity-based outcomes [5]. The few publications on this topic support the idea that quantifying environmental justice and health-based outcomes can help identify scenarios that maximize both goals. Levy *et al* evaluated potential emission reductions for power plants in terms of reductions in premature mortalities and improvement in equity (i.e. Atkinson Index); they reported that scenarios with the largest improvements in health-based outcomes also had the largest improvements in equity [11]. The authors also identify potential tradeoffs (e.g. greater or lesser improvement of one goal relative to the other) and that the results may vary by pollutant, spatial distribution of the population, and existing pollutant levels. A separate article on mobile sources reported similar findings: control scenarios with greater improvements in equity also exhibited greater improvements in health-based outcomes [12]. A study of specific source categories in Southern California (on-road, off-road [e.g. construction equipment], trains, ships, and stationary [e.g. generators]) reported 'win-win' opportunities and potential tradeoffs between equity- and efficiency-based goals [5]. An analysis of large greenhouse gas emitters in California found that the majority of the total air pollution exposure disparity by ethnic/racial group can be attributed to a select few facilities located near minority communities. Therefore, implementing climate change and GHG control strategies (e.g. market-based, unrestricted cap-and-trade) that do not distinguish these facilities from others could exacerbate pollution exposure disparities [13]. Conversely, opportunities are present to improve both climate change and equity. Collins *et al* reported similar findings with industrial toxic pollutants: a few facilities contribute to a majority of disproportionate minority human health risk. Therefore, they report that targeted regulation on the worst environmental polluters could have a larger impact on equity than broad-based regulations [14].

The present paper expands on the limited prior research by investigating how spatially targeted emission-reductions can reduce environmental injustice while also meeting multiple other air quality management goals. We highlight how spatial targeting can be incorporated into practical strategies such as low-emission zones (LEZs) and truck re-routing that are already in use in many major cities. Since air quality management involves multiple goals, we consider multiple outcomes important to policymakers. We use Eulerian reactive grid modeling for Southern California to calculate how reducing emissions of a known carcinogen, $PM_{2.5}$ from diesel engines (DPM) [15–17], would affect (1) total exposure, (2) exposure efficiency (i.e. human inhalation of pollution, per amount emitted), (3) exposure inequality (i.e. deviations from a scenario in which exposure is equally distributed across the population), and (4) exposure injustice (i.e. associations between exposure and demographic attributes such as race or ethnicity). All four outcomes are important for air quality management: total exposure is a proxy for total health impact, efficiency is an indicator of the proportion of emissions that are actually inhaled (e.g. which emissions are near people), inequality reflects differential individual exposures, and injustice reflects differential group/subpopulation exposures. We demonstrate that the spatial targeting approach presented here can be used to identify areas in which emission reductions would have high efficiency and would also result in disproportionately large reductions to average exposure, exposure inequality, and exposure injustice.

2. Methods

We modeled DPM in Southern California using the Comprehensive Air Quality Model with extensions (CAMx), an Eulerian reactive air dispersion model. By using meteorological, deposition, emission, and chemical inputs, CAMx temporally and spatially represents the transport, removal, and chemical reactions of pollutants in a three-dimensional grid [18]. Model inputs were from the Multiple Air Toxics Emission Study III (MATES III) [16]. The modeling domain (total size: 240 km × 150 km; grid size: 2 km × 2 km grids; total population = 15.9 M) included areas within the South Coast Air Basin in Southern California and encompassed the Los Angeles metropolitan area, the Long Beach and Los Angeles ports, and nearby shipping lanes in the Pacific Ocean. Simulations employed 1-hour time steps to quantify annual average concentrations for the year 2005 (see supplementary data, figure S2 available at stacks.iop.org/ERL/13/024002/mmedia). One reason for choosing this model is that it has been reviewed, validated, and used by technical experts, including members of the California Air Resources Board. For MATES III, the average predictive accuracy (percentage difference between monitored and modeled concentrations) for fine elemental carbon particulate matter—a major component of DPM—is 17%, which is within the Environmental Protection Agency's predictive accuracy goal of 30% for particulate matter modeling [16].

We evaluated and prioritized spatial reduction scenarios for air pollution, based on four goals: *intervention* impact, efficiency, equality, and justice. To measure progress toward these goals, we measured the *emissions*' impact, efficiency, inequality, and injustice.

1. Impact was measured using total inhalation intake (units: mass per time) by the population; this metric provides a proxy for the total health burden of a pollutant. An impact of 464 g d^{-1} would mean that 464 g are cumulatively inhaled by the population each day.
2. Efficiency was measured as intake fraction: the mass of pollutant inhaled per mass emitted. Intake fraction is generally reported in ppm (parts per million); an intake fraction of 1 ppm would mean that 1 μg is inhaled per 1 g emitted.
3. Inequality was measured with the Dissimilarity Index, a 0-to-1 representation of the deviation from a scenario in which pollutant exposure is distributed equally among all individuals. The Dissimilarity Index is commonly used in public health and sociology research, simple to calculate, and intuitive [19, 20], and values for the Dissimilarity Index correlate with other popular inequality metrics (see supplementary data, figure S3). A Dissimilarity Index of 0.20 would mean that 20% of the total pollution would need to be redistributed to achieve a hypothetical scenario in which all people are exposed to the same concentration. This measure contains no information about which groups are more or less exposed, instead focusing on differences in *individual* exposure.
4. Injustice was measured using the difference in average air pollution exposures for 'minority' ($n = 9.8$ million) and white non-Hispanics ('white'; $n = 6.1$ million). This metric reflects differences between *groups/subpopulations.* (In this paper, 'white' refers to white non-Hispanic individuals, and 'minority' refers to everyone else [i.e. all non- (white non-Hispanic) individuals]. For the study location, white individuals comprise <50% of the total population.)

First, we determined the impacts of spatial emission reductions via 385 sensitivity analyses. In each sensitivity analysis, emissions within one 2 km × 2 km grid were zeroed, and the results of the revised model and baseline model were compared to determine the approximate impact of pollution sources within the selected grid. This multi-simulation ('brute force') approach is advantageous because of its simplicity, wide use in air dispersion modeling, and applicability to the development of emission reduction scenarios [21, 22].

For all metrics, we assumed at-home emission exposures equal to outdoor concentrations (no indoor sources), with no microenvironments (e.g. travel inside of a car), and a time-invariant breathing rate (14.5 m^3 d^{-1} $person^{-1}$). Demographic data (e.g. population size, racial information, economic information) was derived using year-2000 US Census block groups (see supplementary data, figures S4 and S5). Prior research suggests that the simplified census-based analysis employed here yields results that are consistent with more refined models incorporating time-varying breathing rates and microenvironments [5].

For computational efficiency, we selected, modeled, and analyzed a representative sample of grid cells. Grid cells were selected based on a population-weighted random sample. We then interpolated the remaining grids using Ordinary Kriging in ArcGIS (see supplementary data for further analysis and supplementary data figure S7 for selected grid locations). Finally, as detailed in the Results section, we used linear regression and then linear regression with spatial lag to explore associations between the demographics in a grid cell and the changes to domain-wide environmental inequality and injustice that resulted from reducing emissions in that cell.

3. Results and discussion

First, we evaluated population exposure to DPM based on the year-2005 emissions inventory for California's South Coast Air Basin. As highlighted above, model validation steps have previously been conducted. Our baseline results for our four outcome metrics, each measuring progress toward a different goal, are shown in table 1: reduction in population intake of DPM is used as a proxy for intervention impact; intake fraction (also called 'exposure efficiency'; defined as the proportion of pollution inhaled by people) is used as a proxy for intervention efficiency; reduction of the Dissimilarity Index, or the proportion of emissions that would need to be redistributed to achieve equal exposure across the population, is used as a proxy for intervention equality; and reduction in the difference between mean exposures for minorities vs. whites is used as a proxy for intervention justice. Baseline exposures were consistent with prior research [5, 23–33]. The intake fraction was 18 ppm, meaning 18 grams of DPM were inhaled per million grams emitted [5, 23–26]. The Dissimilarity Index was 0.20, meaning that achieving equality would require redistributing 20% of exposures [5]. Mean DPM exposures were 0.62 $\mu g\ m^{-3}$ (38%) higher for minorities (2.25 $\mu g\ m^{-3}$) than for whites (1.63 $\mu g\ m^{-3}$) [5, 27–33]. (The proportion of individuals with exposures higher than the arithmetic mean

Table 1. Emission reduction goals.

Goal	Metric	Equation[a]	Baseline value[b]
Impact	Population intake	$\text{intake} = \sum_{i=1}^{n} C_i * Q_i$	$464\ \text{g d}^{-1}$
Efficiency	Intake fraction[c]	$iF = \frac{1}{E} * \sum_{i=1}^{n} C_i * Q_i$	18 ppm
Reduce Inequality	Dissimilarity Index[d]	$D = 0.5 * \sum_{i=1}^{n} \left\lvert \frac{C_i}{\sum_{j=1}^{n} C_j} - \frac{1}{n} \right\rvert$	0.20
Reduce Injustice	Difference between mean exposures for whites versus minorities[e]	$\text{Difference} = \mu_{\text{minority}} - \mu_{\text{white}}$	$0.62\ \mu\text{g m}^{-3}$

[a] Variables: C_i, concentration (μg m^{-3}) for person *i*; Q_i, breathing rate (here, 14.5 m^3 d^{-1}) for person *i*; *E*, total emissions (g d^{-1}); *n*, number of people (~16M); μ_{minority}, μ_{white}, mean exposures for minorities and whites, respectively.

[b] Results here are year-2005 estimates.

[c] An intake fraction (*iF*) of 18 parts per million (ppm) means that 18 μg diesel $PM_{2.5}$ are inhaled per g emitted.

[d] A Dissimilarity Index (*D*) of 0.20 means that reaching total equality would require redistributing 20% of total diesel exposure.

[e] A difference of 0.62 μg m^{-3} represents the disparity between mean exposures for minorities and whites. That value is ~31% of the overall population average exposure, 2.01 μg m^{-3}.

[2.01 μg m^{-3} d^{-1}] was approximately double for minorities than whites [62% vs 32%].) As context for the 0.62 μg m^{-3} greater DPM exposure value for minorities, we note that Pope *et al* [34] reported a 0.61-year increase in life expectancy per 10 μg m^{-3} decrease in $PM_{2.5}$ exposure. A 'back-of-the-envelop' calculation suggests that the 0.62-μg m^{-3} greater level of exposure for minorities would correspond to ~14 days of life lost per individual (i.e. 0.61 years * (0.62/10) = ~0.04 years per individual), or collectively, an estimated ~370 000 years of lost life expectancy in total for the 9.8 million minority individuals in the study area.

Next, we modeled how the location of an emission reduction strategy could affect the impact, efficiency, inequality, and injustice of an intervention (figure 1). Figure 1(*a*) shows that eliminating all emissions from a single grid cell in downtown Los Angeles would reduce total population inhalation of DPM in the region (i.e. pollution impact) by more than 414 000 μg d^{-1}; by contrast, when emissions were eliminated from certain parts of Newport Beach, the reduction in inhalation would be less than 46 800 μg d^{-1}. The results in figure 1(*a*) reflect a combination of two factors: total emissions per grid cell and the fraction of emissions inhaled. Both aspects are important, and both are generally higher for downtown Los Angeles than for Newport Beach. The former factor (emissions) is displayed in the supplementary data, figure S1; the latter factor (intake fraction) is displayed in figure 1(*b*). Figures 1(*c*) and (*d*) show how shifts in the inequality and injustice metrics vary depending on where an emission reduction occurs. Values represent the positive or negative impacts to the inequality or injustice metrics of a 1 t d^{-1} emission increase in a grid cell. For example, a 1 t d^{-1} decrease in a single grid cell in downtown Los Angeles would reduce total inequality (Dissimilarity Index) by more than 0.010. Overall, the results highlight locations, such as downtown Los Angeles, where reducing DPM emissions would have high efficiency and would yield marked reductions in total pollution impact, inequality, and injustice.

The maps in figure 1 differ from each other, which illustrates how the choice of metric can have important implications for exactly which areas are targeted for emission reduction—and why considering multiple metrics can be beneficial. Both the port region and downtown Los Angeles exhibit high amounts of population intake (i.e. pollution impact), downtown Los Angeles owing to its high population density and major transportation corridors, and the port region owing to shipping-related emissions (e.g. ships, tractor trailers). However, the pollution in downtown Los Angeles has a greater intake fraction (so that targeting this area translates into higher intervention efficiency), making this location the better choice for maximizing both impact and efficiency. Another example illustrates the tension that can occur when seeking to maximize multiple outcomes. To reduce the inequality metric (figure 1(*c*)), which is blind to which groups experience higher levels of exposure, one would likely focus on metropolitan Los Angeles, extending to the ports of Los Angeles and Long Beach. By contrast, to reduce the injustice metric, which considers racial makeup, one would target emission reductions in some of the same areas (downtown Los Angeles and the area immediately east of the LA Port) but some different areas as well (e.g. LAX and immediately south; Sylmar and the Van Nuys area). Targeting emission reductions to the area east of the Los Angeles/Orange County line would reduce inequality (figure 1(*c*)) but increase injustice (figure 1(*d*)). (People inhaling the emissions from that area have higher-than-average exposures, and a greater-than-average proportion of them are white; thus, emission reductions in that area would reduce exposures for more-exposed individuals while also widening the gap in average exposures between whites and minorities.) Evaluating the ethics of tradeoffs among the four goals is important but is not considered here.

Next, we explored how modeling could be used to target two types of emission reduction strategies currently in use: LEZs and truck re-routing. First, via a spatial overlay of the results in figure 1, we sought locations for which all four metrics were in the top quartile (figure 2). Figure 2 also shows the largest contiguous area identified from that overlay. We then modeled the result of implementing an LEZ there, an air quality strategy used in hundreds of cities worldwide.

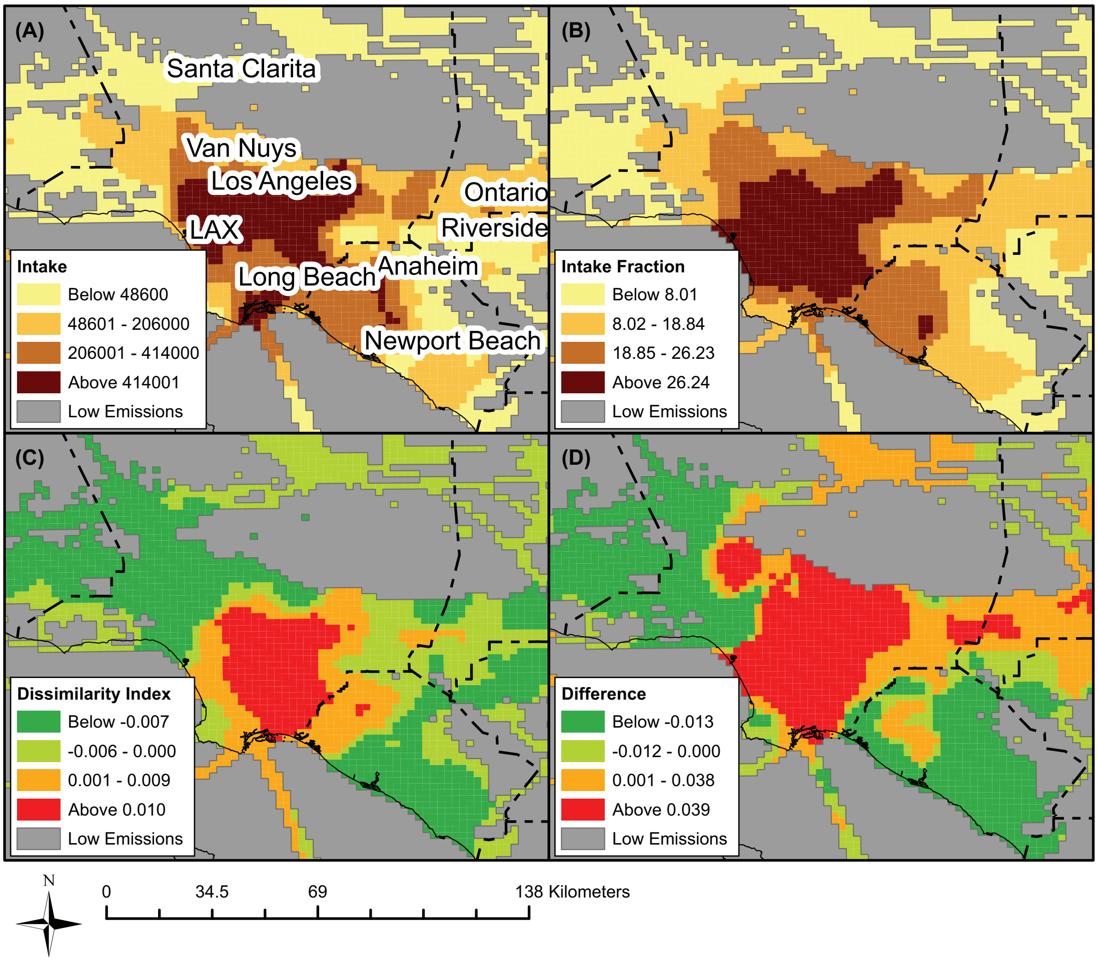

Figure 1. Changes in the four area-wide outcome metrics for pollution, as a function of where diesel $PM_{2.5}$ emission reductions occur. In each map, a cell's color is determined by the result of reducing that cell's emissions to zero, while leaving emission levels in the other cells intact. (*a*) Impact: population intake (μg d^{-1}) attributable to emissions in that cell. (*b*) Efficiency: intake fraction (ppm) for emissions in that cell. Results for (*c*) inequality [Dissimilarity Index] and (*d*) injustice [difference in basin-wide average exposures for minorities and whites (μg m^{-3})] reflect the impact of a 1 t d^{-1} emissions reduction. Colors in plots (*a*) and (*b*) were assigned by emissions quartile (i.e. each color contains 25% of total emissions; not necessarily proportional to land area). Values for plots (*c*) and (*d*) were first divided into positive vs. negative values, and then each subset was subdivided at the emissions-based median for that subset (i.e. red and orange each contain half of the emissions with a positive-value metric; light and dark green each contain half of the emissions with a negative-value metric). Grey regions reflect low-emission regions (59% of total area; 1% of total emissions).

LEZs often reduce or eliminate the entry of high-emitting vehicles (e.g. older, more-polluting diesel trucks) into a designated zone via rules and/or tolls, although they can also target non-vehicle emissions. Here, the LEZ was 588 km^2 (1.6% of basin-wide area) and represented ~2.7 tonnes-per-day of emissions (~10% of the basin-wide total), with an areal-average intake fraction of 36 ppm (approximately double the basin-wide average). We simulated the results of a 25% emission reduction inside the LEZ, with no emission changes outside the LEZ (i.e. a 2.6% [~0.7 t d^{-1}] reduction in domain-wide emissions). The magnitude of this emission reduction is comparable to that observed for other LEZs worldwide [35–38]. Our results (table 2) indicate that this emission reduction would reduce pollution impact by 5%, inequality by 18%, and injustice by 6%. Therefore, targeting emission reductions to certain locations can yield disproportionately large advantages for impact, efficiency, equity, and justice: win-win-win-win situations.

We next examined the broader effects of an LEZ by considering truck re-routing; rules or tolls would lead vehicles to circumvent the LEZ. We performed simulations for trucks starting in the port region and needing to travel either north (figure 3(*a*)) or east (figure 3(*b*)) to reach popular cargo destinations. In each case, two paired routes started and ended at the same place; however, one route passed through the LEZ while the other avoided it as much as possible. For this exploratory analysis, we did not consider the effects of differential traffic congestion. For all four routes, the emissions resulted in 'unjust' population exposures (higher exposure for minorities than whites; see tables 2 and S3). However, the non-LEZ routes were 67% (figure 3(*a*)) and 34% (figure 3(*b*)) less unjust than the respective LEZ routes. In addition, intake fractions (i.e. exposure efficiency) indicated that total pollution inhaled per gram emitted was 14%–17% lower for the non-LEZ route than for the LEZ route. These results reinforce how spatially targeted reductions can reduce

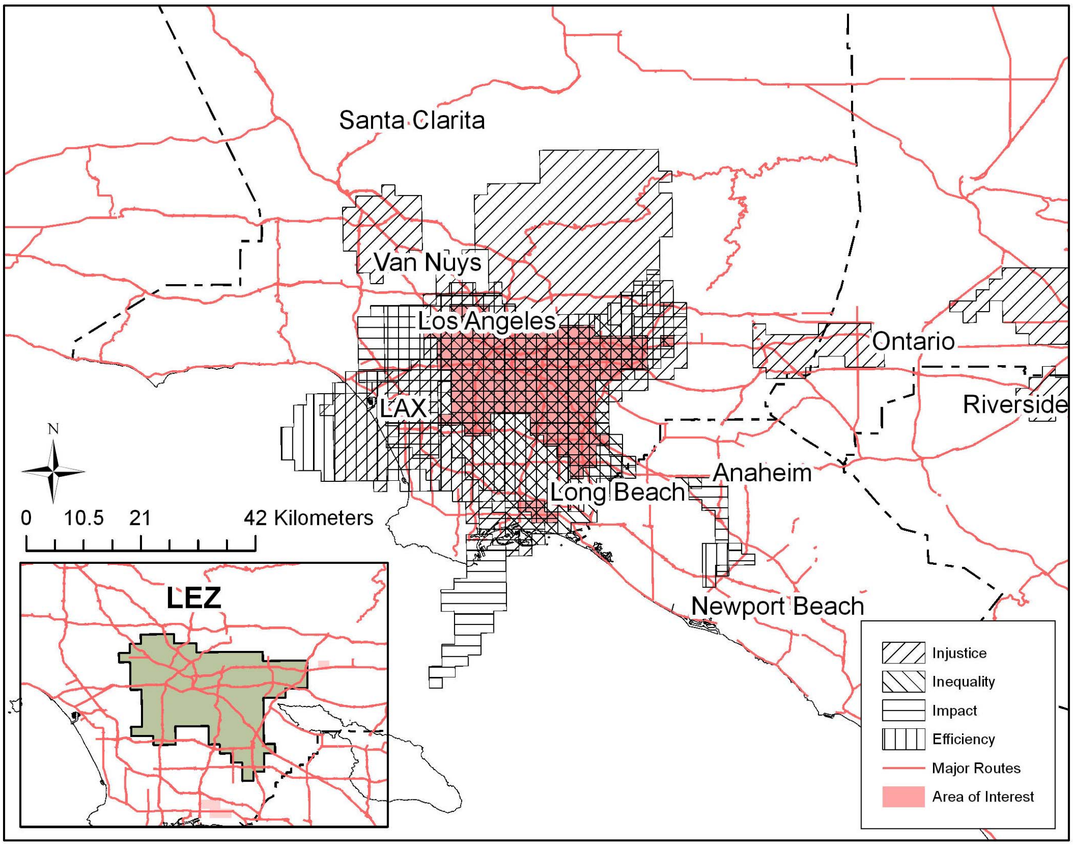

Figure 2. The area of interest represents the area in which reducing emissions would have the highest intake fraction ('efficiency'; top quartile) as well as the greatest reductions for impact, inequality, and injustice (top quartile). The hypothetical low-emission zone (LEZ: inset map) is based on the largest contiguous area within the area of interest.

Table 2. Results of two emission reduction strategies.

	Intake[a] ($g\,d^{-1}$)	Intake fraction (ppm)	Dissimilarity index	White-vs-minorities exposure difference ($\mu g\,m^{-3}$)
Low-emission zone				
Baseline	464	–[c]	0.197	0.62
25% emissions reduction[b]	439	–[c]	0.186	0.51
Reduction	25.0 (5%)	–[c]	0.011 (6%)	0.11 (18%)
Truck re-routing[d]				
Route 1	–	28.1	–0.012	0.04
Route 2	–	33.7	0.003	0.13
Reduction		5.6 (17%)	0.015 (500%)	0.09 (69%)
Route 3	–	28.7	0.013	0.10
Route 4	–	33.3	0.015	0.15
Reduction		4.6 (14%)	0.002 (13%)	0.05 (33%)

[a] Basin-wide intake from basin-wide emissions. For example, the basin-wide total intake of all emissions is 464 $g\,d^{-1}$ before implementing the LEZ or truck re-routing. For the illustrative calculations shown here, we do not estimate emission-reductions from truck re-routing.

[b] Scenario represents a 25% reduction in all emissions within the low-emission zone (2.6% reduction overall).

[c] For a primary pollutant like diesel $PM_{2.5}$, emission reduction would not change the intake fraction (i.e. fraction of DPM emissions inhaled does not depend on amount emitted). Intake fraction values are 17.8 ppm overall and 35.9 ppm for emissions in the low-emission zone.

[d] See figure 3(*a*) and (*b*) for routes. 'Reduction' represents the change that occurs after converting from the heavily-LEZ route to the non-/reduced-LEZ route (switching from route 2 to route 1; switching from route 4 to route 3).

multiple exposure metrics (here, exposure efficiency and injustice) [9].

Importantly, we found that our predictions could not be replicated with simple linear regression models. Values for the injustice metric were only moderately correlated with income ($R^2 = 0.18$) and with proportion of the population that is minority ($R^2 = 0.37$); in simple regression models for the injustice metric (tables S1 and S2), the normalized regression coefficient is −0.098 for income and 0.32 for proportion of the population that is minority (i.e. on average, holding other variables constant, a 1-standard-deviation change in the proportion of the population that is minority corresponds to a 0.32-standard-deviation change in the

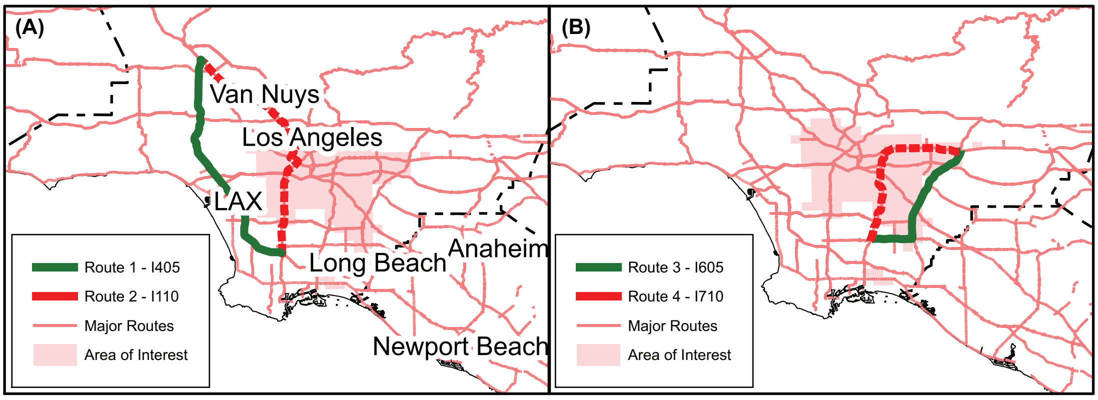

Figure 3. Alternative routes (A) and (B) represent two hypothetical truck re-routing scenarios to avoid or reduce travel in the LEZ.

injustice metric). These simple regression models only consider demographics in the same grid cell as the injustice metric and therefore ignore domain-wide patterns in meteorological and demographic variables, as well as potential spatial autocorrelation in the dependent variables (e.g. the injustice metric) and in regression model residuals. (For an example of the importance of these domain-wide patterns, consider that our spatial simulations showed that reducing emissions in white and higher-income areas along the coastline south of LAX would reduce injustice and inequality. One reason for that finding is the proximity of those grid cells to minority and low-income neighborhoods directly adjacent and downwind; see figures 1(*c*) and (*d*).) Ignoring spatial autocorrelation generally inflates regression coefficients: the normalized regression coefficients—the values –0.098 and 0.32 given above—are ~20%–60% smaller in regression models that account for spatial autocorrelation (basis: queen order of contiguity 1, 2, and 3; see supplementary data). Overall, those findings highlight that simply identifying areas with high proportions of low-income or minority residents may or may not be an effective means of targeting emission reduction interventions; the demographics of other areas, as well as patterns of pollution dispersion, are also important considerations.

4. Conclusion

Results and methodologies presented here represent a new lens with which to approach and quantify environmental inequities; 'win-win' opportunities exist in which multiple pollution reduction goals can be accomplished. These methods can be applied to other pollutants, years, or locations for which spatially detailed fate and transport models have been developed. Fortunately, fate and transport models have been developed for many locations throughout the world. The resulting information may have applications in various well-known contexts, including issuing new emission permits; targeting enforcement of existing permits; crafting zoning rules for pollution sources; low-emission zones; and developing pollution reduction strategies, including education and other outreach activities.

Understanding the spatial patterns of exposure will allow us to prioritize emission control strategies that maximize intervention impact, efficiency, equality, and justice, thus bringing us closer to meeting local and national goals to reduce exposure to pollution and address health disparities. Local and national policymakers could use our approach to consider impact, efficiency, environmental inequality, and environmental injustice when evaluating emission reduction opportunities.

Acknowledgments

This research was supported by funding from the US Environmental Protection Agency (STAR grant #RD-83362401-0, ACE grant #RD83587301). The research has not been subjected to EPA review and therefore does not necessarily reflect the views of the Agency; no official endorsement should be inferred. The authors thank Matthew Bechle, Lara Clark, Dr. Kristin Harper, Katie Swor, Dr. Chris Tessum, and Dr. Kristina Wagstrom for fruitful discussions and other contributions. We gratefully acknowledge helpful feedback from anonymous peer reviewers.

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