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Traffic, Air Pollution, and Distributional Impacts in Dar es Salaam

A Spatial Analysis with New Satellite Data

Susmita Dasgupta
Somik Lall
David Wheeler

WORLD BANK GROUP
Development Economics
Development Research Group
&
Urban, Disaster Risk Management, Resilience and Land Global Practice
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Abstract

Air pollution from vehicular traffic is a major source of health damage in urban areas. The problems of urban traffic and pollution are essentially geographic, because their incidence and impacts depend on the spatial distribution of economic activities, households, and transport links. This paper uses satellite images to investigate the spatial dynamics of vehicle traffic, air pollution, and exposure of vulnerable residents in the Dar es Salaam metro region of Tanzania. The results highlight significant impacts of seasonal weather (temperature, humidity, and wind-speed factors) on the spatial distribution and intensity of air pollution from vehicle emissions. These effects on the metro region's air quality vary highly by area. During seasons when weather factors maximize pollution, the worst exposure occurs in areas along the wind path of high-traffic roadways. The research identifies core areas where congestion reduction would yield the greatest exposure reduction for children and the elderly in poor households.

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Traffic, Air Pollution, and Distributional Impacts in Dar es Salaam: A Spatial Analysis with New Satellite Data

Susmita Dasgupta[1], Somik Lall and David Wheeler

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[1] Authors' names are in alphabetical order. The authors are respectively Lead Environmental Economist, World Bank; Lead Urban Economist, World Bank; and Senior Fellow, World Resources Institute.

1. Introduction

Air pollution from urban traffic is a major source of health damage in developing countries. In a global study, Dora et al. (2011) find that urban road transport often accounts for more than 50% of dangerous air pollutants (e.g., fine particulates, nitrogen oxides, carbon monoxide, ozone, sulfur dioxide). The World Health Organization (2016) attributes about 3.3 million annual premature deaths to outdoor air pollution in low- and middle-income countries: 72% from heart disease and strokes, 14% from chronic obstructive pulmonary disease, and 14% from lung cancer. The World Bank (2016) estimates welfare losses from ambient fine particulate and ozone pollution at 4.8% of GDP equivalent in East Asia, 3.5% in South Asia, 2.1% in the Middle East and North Africa, 1.6% in Latin America and 1.5% in Sub-Saharan Africa.

Urban traffic and pollution problems are essentially geographic, because their incidence and impacts depend on the spatial distributions of economic activities, households, and transport links. Although urban planners, researchers and policy makers are sensitive to this spatial component, incomplete information has hindered their attempts to identify and implement cost-effective strategies. Local traffic and pollution are often poorly measured because monitoring systems are sparse, costly and difficult to maintain. Since this problem is pervasive in developing countries, rigorous empirical analyses of alternative strategies are rare. As a consequence, urban planners and policy makers have little guidance on appropriate spatial measurement techniques, spatially-oriented methodologies for benefit-cost assessment of policy alternatives, and transferable empirical models from other urban areas. In practice, they have frequently been forced to estimate city-wide traffic volume from observations on a few traffic arteries, and air pollution from aggregate fuel consumption data, coupled with air pollutant emission factors for gasoline and diesel vehicles that may have been generated from small samples in other places. As a result, educated guesswork has often guided the placement of subway lines, road corridor improvements and other spatially-targeted interventions for reducing traffic and pollution.

Recent developments in satellite monitoring offer a potential escape from this information trap. High-resolution imagery now permits frequently-updated observations of polluting aerosols and traffic in multiple zones within urban areas. Appropriately mobilized and interpreted, data from these new sources can elevate the state of the art in urban traffic/pollution research, policy analysis and implementation for developing countries.

Satellite coverage is global, so the new approach can enable cities in all regions to benefit from the rigorous analyses that have traditionally been limited to well-endowed cities in developed countries. This paper is a pilot exercise for Dar es Salaam that incorporates spatially and temporally non-uniform distributions of vehicle traffic and air pollution into an investigation of impacts on vulnerable households. We highlight potential health damage in areas of Dar es Salaam with high poverty incidence and large numbers of vulnerable children and elderly adults.

The remainder of the paper is organized as follows. Section 2 reviews prior research on the health impacts of NO2 pollution, the links between traffic and air pollution, and the socioeconomic dimensions of air pollution impact. In Section 3, we introduce the new data sources for our analysis. Section 4 uses econometric modeling to investigate the spatial dynamics of NO2 pollution in the metro region, with a particular focus on critical weather factors that drive the locus of pollution from motor vehicle emissions. Section 5 explores the implications for the distributional impact of air pollution, while Section 6 extends the analysis to identification of areas where reduction of traffic congestion would have the greatest distributional benefits. Section 7 summarizes and concludes the paper.

2. Prior Research

2.1 Air Pollutants and Health

This paper uses data from the European Space Agency's Sentinel-5P platform that have been published since July 2018. Sentinel-5P measures four air pollutants that are generated by vehicular emissions: nitrogen dioxide (NO2), ozone (O3), carbon monoxide (CO) and sulfur dioxide (SO2) Extensive research has analyzed their significance as sources of health damage, with particular attention to respiratory problems for children and cardio/pulmonary problems for the elderly. For this pilot exercise, we focus on NO2, which prior research has assigned the greatest impact among the four. NO2 impacts have been extensively studied, both singly and in combination with other air pollutants (Brauer et al. 2002, 2007; Cesaroni et al. 2008; Chen et al. 2012a; Gauderman et al. 2005; Gehring et al. 2002, 2006; Hoeck et al. 2002; Morgenstern et al. 2007; Naess et al. 2007; Nafstad et al. 2004; Sunyer et al. 2006). NO2 emissions also have significance as a source of particulate matter less than 2.5 micrometers in diameter (Hodan and Barnard 2004), which is strongly associated with health problems but not measured by Sentinel-5P.

2.2 Modeling Traffic and Air Pollution

Empirical research on spatial relationships between traffic and air pollution falls into three broad categories. In the first category, metropolitan-scale assessments of traffic and pollution employ engineering models calibrated for developing-country cities with plentiful information about the spatial distributions of vehicle traffic, emissions, and atmospheric conditions (Jerrett et al. 2005). For urban researchers and planners in developing countries who use these imported models, the scarcity of supporting information often requires extensive spatial and temporal interpolation to cover gaps in local data.

In the second category, local measurements of traffic and air pollution along road corridors are used to estimate vehicular emissions intensities, the local effects of meteorological variables, and the attenuation of pollution with distance from roads (Brauer et al. 2003; Gualtieri et al. 1998; Walker et al. 1999). These studies provide useful information for local zoning in developed countries. In developing-country cities, where regulatory enforcement is often difficult, they have played a useful role in promoting awareness of vehicle-based air pollution as a serious health hazard for young children and elderly adults. However, the limited scope of road corridor studies makes it difficult to extrapolate their empirical results to metropolitan scale.

The third research category has grown rapidly with the development of Geographic Information System (GIS) technology. It uses georeferenced data to assess relationships between the spatial distributions of vehicle traffic and air pollution (Briggs et al. 2010). Until recently, the spatial coverage and resolution of these studies have been greater for developed-country cities with more plentiful spatial information on vehicle traffic and air pollution. Recently, however, higherresolution satellite monitoring has begun to close the gap for developing-country cities. The most advanced example is provided by Heger et. al. (2018), whose research combines extensive air monitoring data for Cairo with vehicle counts obtained from ultra-high-resolution satellite imagery using a machine learning algorithm. Even for this study, significant problems remain: Spatial panels of vehicle counts must be pieced together from overlapping but non-identical satellite image frames; vehicle counts are sensitive to the technical characteristics of different satellite platforms; and pollution measures are limited to incomplete panels of particulate pollution at PM10 scale or low-resolution satellite measures of aerosol optical depth whose ability to measure particulate pollution remains controversial.

Differences in technical and institutional resources have produced bifurcated approaches to air pollution modeling in developed and developing countries. Some air quality modelers in developed countries have produced sophisticated atmospheric pollution transport models that link detailed emissions inventories from geo-located ground sources (Dommen et al. 2003) to pollution levels in three-dimensional atmospheric grids (Baertsch-Ritter et al. 2003; Keller et al. 2002; Khalid and Samson 1996; Jane et al. 1995). These exercises draw on scientifically-grounded models of atmospheric flow dynamics and photochemistry (Baertsch-Ritter et al. 2004; Russel and Dennis 2000; Gery et al. 1989). They also permit explicit incorporation of detailed meteorological data (Khalid and Samson 1996; Sillman and Samson 1995).

These models require so much data that their application is not widespread, even in high-income metropolitan regions. Where they are applied, they are not statistically fitted to local data because the available degrees of freedom (total observations minus the number of model parameters) are insufficient for robust nonlinear estimation. Even the most recent and sophisticated applications (e.g., Kim et al. 2018) are confined to verifying that predictions from imported atmospheric transport models are spatially correlated with gridded observations on local pollution.

Urban air quality modelers in developing countries have generally adopted more modest approaches tailored to limitations in data availability, technical resources and institutional constraints. Some of the more sophisticated statistical exercises in this domain have been applied in Nepal (Giri et al. 2008); Egypt (Elminir 2005); China (Zhang et al. 2015); Mexico (Csavina et al. 2014); Turkey (Ocak and Turalioglu 2008); Vietnam (Hien et al. 2002); the Islamic Republic of Iran (Hosseinibalam and Azadeh 2012); and India (Punithavathy et al. 2015). These studies relate air pollution near ground monitoring stations to actual and estimated emissions from nearby sources, with meteorological controls drawn from available measures of temperature, pressure, precipitation, wind speed and wind direction. However, air pollution data are typically drawn from a few ground monitoring stations that are located where pollution is expected to be highest. In addition, technical problems often create random, lengthy gaps in observations from individual monitoring stations. Appropriate spatial econometric panel estimators are difficult or impossible to apply under these conditions. In addition, the concentration of ground monitors in areas where pollution is expected to be high creates a severely-truncated sample of citywide air pollution.

2.3 Socioeconomic Dimensions of Pollution Impact

An extensive empirical literature has considered the interrelationships between air pollution, the demographic and socioeconomic characteristics of impacted neighborhoods, and health outcomes for their inhabitants. Some studies feature impacts on the elderly (Morris et al. 2005; Naess et al. 2007; Martins et al. 2004) or children (Brauer et al. 2002; Ciccone et al. 1998; Gauderman et al. 2004, 2005, 2007; Gehring et al. 2002; McConnell et al. 2002, 2003, 2006; Morgenstern et al. 2007; Pandey et al. 2005; Pikhart et al. 2001; van Vliet et al. 1997). Many other studies feature impacts on poor households (Hejat et al. 2015; Evans and Kantrowitz 2002; Laurent et al. 2007; Molitor et al. 2011; Rooney et al. 2012; Fan et al. 2012; Havard et al. 2009; Fann et al. 2011; Dionisio et al. 2010; Forastiere et al. 2007; Næss et al. 2007).

Studies that consider these groups serve one of two policy objectives, at least implicitly. First, highlighting their vulnerability can help promote measures for general reduction of traffic and pollution. Examples include stricter pollution controls for motor vehicles and fuel price increases to reduce motor fuel use. A second approach features targeted intervention to reduce pollution in areas where vulnerable groups are concentrated. In this context, many associational studies have linked proximity to heavily-traveled urban roads to respiratory and cardio-pulmonary problems associated with vehicular emissions (Ciccone et al. 1998; Gauderman et al. 2007; McConnell et al. 2006; van Vliet et al. 1997). Frequently-adopted measures include reserved bus lanes, new subway lines, and improved peripheral roads to divert traffic from congested areas. Extensive research has assessed the impact of mass transit measures on traffic and pollution (Adler et al. 2016; Anderson 2014; Basagaña et al. 2018; Gendron-Carrier et al. 2018; Goel and Gupta 2015; Tabatabaiee and Rahman 2011; Yang et al. 2017). Although magnitudes vary considerably, these studies all find significant traffic and/or pollution impacts.

2.4 Traffic Congestion and Air Pollution in Dar es Salaam

Limited research has documented the rapid growth of motor vehicle traffic in Dar es Salaam, and its consequences for traffic congestion. Kiunsi (2013) draws on Tanzania Revenue Authority records to report that a total of 1,010,732 cars registered between 2003 and 2011, with Dar es Salaam accounting for 60% to 70% of the total. Similarly, Elinaza (2012) reports that Dar es Salaam absorbed most of the 245,180 motorcycles and 7,408 motorized tricycles registered in 2010 and 2011.

One major consequence of rapid growth in motor vehicle use has been severe traffic congestion. A 2007 JAICA study finds major slowdowns on primary traffic arteries under peak morning and evening conditions (Kiunsi, 2013). Congestion has in turn generated significant economic losses. Katala (2019) estimates a total loss of T Sh 655 billion per year from congestion-related delays and extra fuel use. Elinaza (2010) cites a Confederation of Tanzania Industries study which finds that traffic congestion reduces business profits by about 20 percent. Othman (2010) and Lupala (2010) identify congestion as a major source of air pollution in the city. Recent years have witnessed major investments to address these problems in Dar es Salaam, particularly an extensive bus rapid transit (BRT) system. Chengula and Kombe (2017) report that the BRT has provided significant benefits in time-saving, convenience and comfort. Nevertheless, serious congestion has persisted in Dar es Salaam as the number of motor vehicles has continued to grow. Aside from occasional exercises like the previously-cited JAICA study, the city has no ongoing capacity for detailed monitoring of traffic flows.

Previous research on vehicle-based air pollution in Dar es Salaam has been limited to small roadside monitoring exercises In 2012 and 2015, Hamdun and Arakak (2015) measured NOx, NO2, and NO levels in Dar es Salaam for brief periods at three urban sites (Mapipa, Ubungo, and Posta) and two suburban sites (Kunduchi and Vijibweni). They found NO2 concentrations at some sites as high as 231 ug/m^3, as compared with the WHO (2005) reference standard of 40 ug/m^3. In a similar vein, Njee et al. (2016) report results from five spatially-varied monitoring locations in July and August 2006. They find average NO2 concentrations ranging from 8 to 109 μg/m3, with a particularly strong role for emissions from road traffic. Having found such high concentrations at some sites, both studies recommend adoption of continuous air quality monitoring and effective air pollution control measures for Dar es Salaam.

3. New Satellite Data

Budgetary and technical constraints have prevented adoption of extensive traffic and air pollution monitoring systems in Dar es Salaam. Thus, the spatial distributions, intensities and impacts of NO2 and other air pollutants have remained matters for speculation. Fortunately, the advent of high-resolution satellite-based pollution monitoring promises will help close this information gap. On October 13, 2017, the European Space Agency (ESA) launched the Sentinel-5P platform, which provides daily high-resolution coverage of NO2, ozone (O3), carbon monoxide (CO), and sulfur dioxide (SO2). The ESA has provided full open-source access to the Sentinel-5P database since July 2018, and the entire database is now available on Google Earth Engine (GEE) for rapid extraction of daily imagery for specific locations. We have used GEE to extract daily NO2 readings for the Dar es Salaam metro region, as well as the surrounding area (Fig. 1).

Figure 1: Study coverage area for Sentinel-5P NO2 data

In a similar vein, the traffic information problem can now be addressed using Google Maps, which provides real-time traffic reports for the Dar es Salaam metro region. Although desktop monitors do not show this, Google Traffic continuously produces a map large enough to cover the entire metro region at 100 m resolution. However, Google provides no facility for georeferenced downloads. To mobilize this huge information resource, one of the authors has developed an algorithm that maps region-scale Google Traffic displays into a panel database of traffic measures for a reference grid with arbitrary cell size.

Google Traffic provides a four-color measure of vehicle speed along each 100-meter road link, with separate speed measures for traffic flows in two directions on primary roads. For this study, we match information from Google Traffic with time-compatible NO2 imagery within a grid of spatial cells with a resolution of .01 decimal degrees (approximately 1.1 km). Since Google Traffic data are available continuously, we also construct a database of traffic measures by day and hour for the period March 20 - May 23, 2019. We convert these files to geoTIFF format for grid-based spatial computations. Using the Dar es Salaam region shapefile provided by OpenStreetMaps (OSM), we divide roads into two classes, primary (OSM classes primary and trunk) and secondary (all other OSM classes). Then we overlay Google Traffic's color-coded pixels on the OSM map and estimate vehicle speeds by road class and color code using trip routings for a sample of real-time Google Traffic information. Table 1 reports our results for two road classes and four color codes.

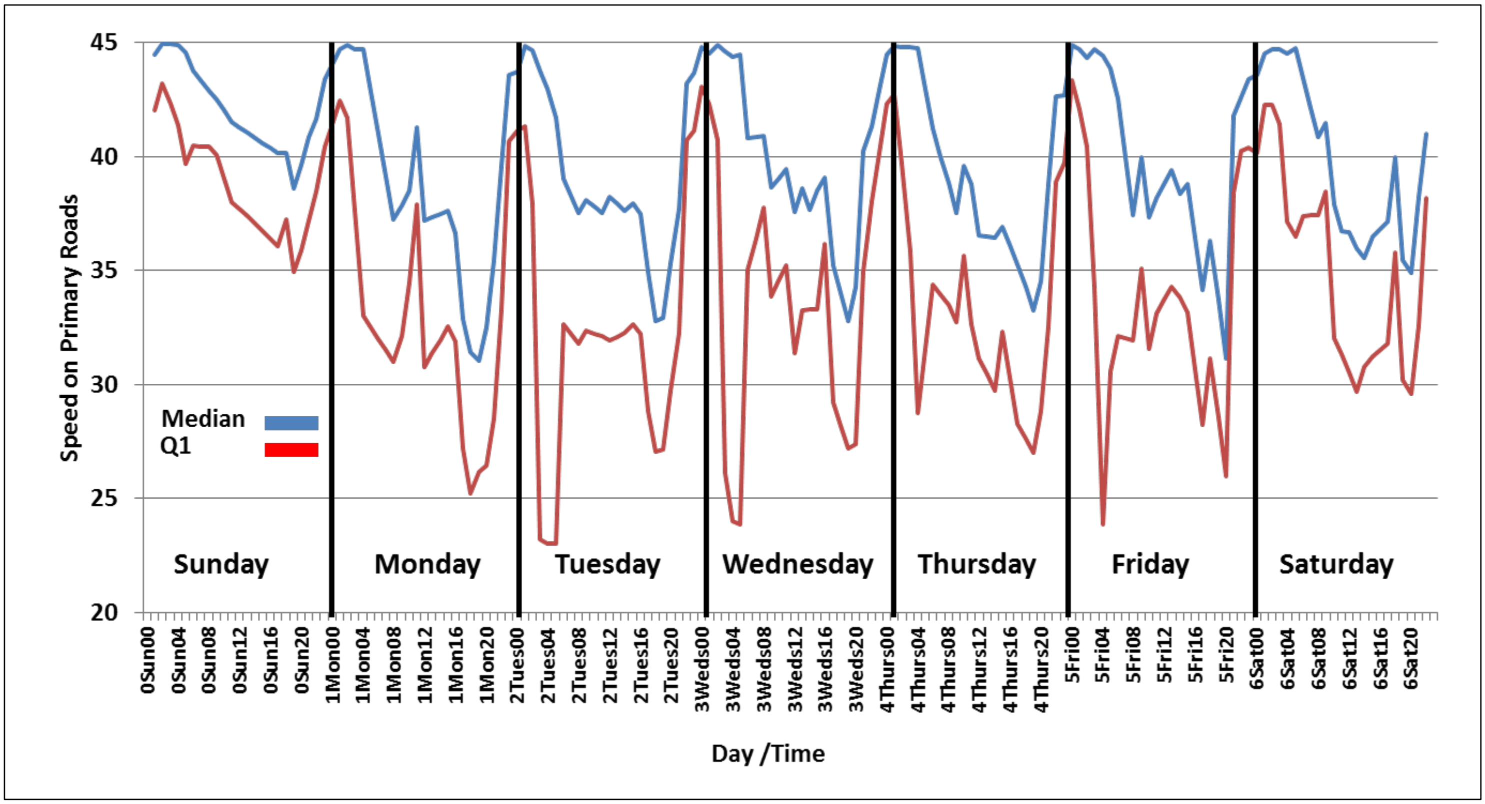
Table 1: Google Traffic indicators and speeds (km/hr) in Dar es Salaam

Color Indicator	OpenStreetMaps Road Type	
	Primary	Secondary
Green	45	24
Orange	23	16
Red	11	7
Purple	7	4

Source: Google Traffic

Figure 2 provides a composite summary of traffic data for the metro region. Since the database is formatted at grid scale, it could also produce the same display for each grid cell. Figure 2 displays regional hourly median and 1st-quartile traffic speeds on primary roads. Several features of the display are particularly evident. First, driving on primary roads is much faster on Sunday, the least congested day, and somewhat faster on Saturday Second, on weekdays traffic speed declines steadily from its midnight peak to around 8 AM; remains roughly in the same range until mid-afternoon; declines rapidly through 6-7 PM; and then increases rapidly until midnight. Third, the path of Q1 shows that the worst traffic conditions display more volatility than median conditions. On weekdays, Q1 speed falls twice daily from about 43 km/hr near midnight to 25-30 km/hr during the morning and evening peak traffic hours.

Figure 2: Dar es Salaam: Hourly median and Q1 primary road speeds (km/hr)



Source: Google Traffic

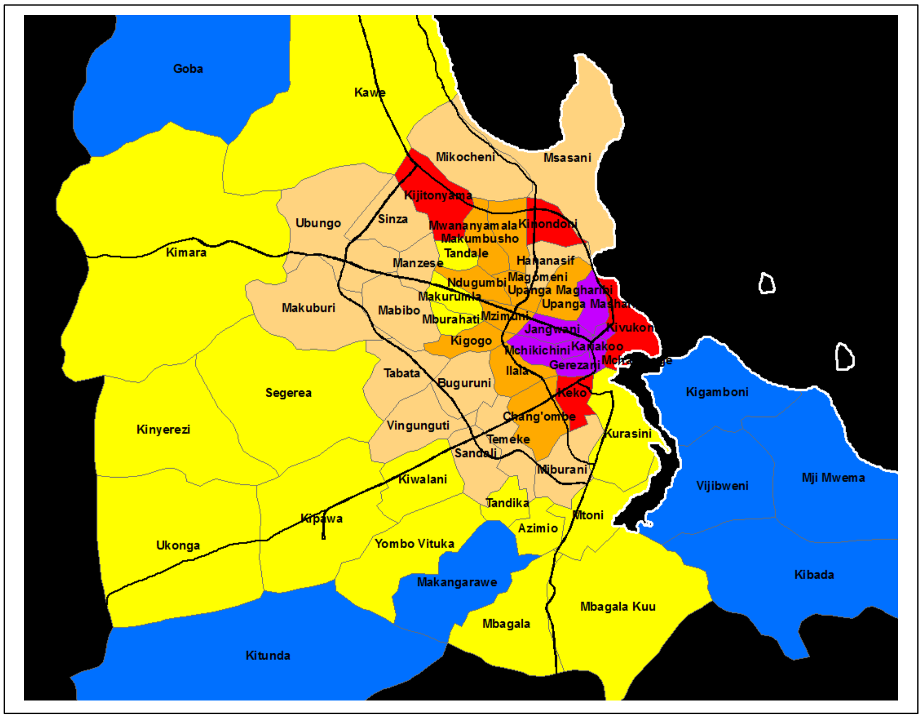
Figure 2 summarizes much more evidence about Dar es Salaam traffic than was available before the advent of Google Traffic. And, although the introduction of bus rapid transit service has undoubtedly speeded traffic on some arteries, Figure 2 shows that the metro region remains subject to intense, twice-daily bouts of serious congestion.

4. Annual Weather Variations and NO2 Pollution

Until recently, even sophisticated analyses of metro-area air pollution in developed countries were limited by the geographic coverage of the available monitoring systems. Equipment is costly to acquire and maintain, so monitors have been primarily located in areas thought to have particularly serious pollution problems. With the advent of Sentinel-5P, it has become possible to extend assessments of NO2 pollution to broader regions. While the contrast with the previous state of the art is striking in developed-country cities, it is much more so in developing-country cities like Dar es Salaam. Sentinel-5P represents a fortuitous “leveling of the field”, because it provides the same coverage for all cities.

In this section, we use daily measurements by Sentinel-5P over 10 months to investigate the pattern of NO2 pollution in the region of Dar es Salaam. We begin with the spatial distribution of vehicular air pollution sources, drawn from our Google Traffic data. As the previously-cited studies have found, vehicle traffic is a major contributor to NO2 pollution in the city.

Figure 3: Dar es Salaam: Composite traffic volume indicator by administrative division
Indicator scaling from lowest to highest:



Source: Google Traffic

We created Figure 3 in three steps. First, for each grid cell and observation period, we separately normalize primary and secondary road speeds to the range 0-100. Then we create a weighted average of the two normalized speed measures, with the weights provided by Google Traffic pixel counts for the two road classes in each grid cell. To create an overall traffic volume indicator, we divide the total Google Traffic pixel count by the weighted average of the normalized primary and secondary speed measures. This indicator increases with the pixel count and decreases with weighted average speed (the latter effect also reflects vehicle crowding on roads in the grid cell). We assign grid cells to the administrative divisions displayed in Figure 3. Then we compute the mean traffic volume indicator across all available periods for each administrative division and normalize the result to the range 0 - 100 for ease of interpretation. The results show a roughly-concentric spatial ordering of traffic volume, with the highest intensities in Upanga Mashariki, Kisutu, Mchafukoge, Gerezani, Kariakoo, Jangwani and Mchikichini. NO2 emissions are proportional to traffic volume, so the area centered in these seven divisions is the dominant source of vehicular NO2 emissions in the metro area.

We investigate the spatial dynamics of this NO2 pollution using maps from Sentinel-5P for the metro region and the surrounding area. We compute monthly mean NO2 concentration and display the results in Figure 4. We superpose the system of primary roads for spatial reference.

Three patterns are evident in Figure 4. First, for the afternoon period observed by Sentinel-5P (2 PM - 3 PM) the NO2 cloud produced by vehicles centered in the core area of Dar (Figure 3) is consistently displaced to neighboring areas. Second, the displaced cloud seems to follow an annual cycle, from northwest of the city in August-September 2018, to due west in October 2018, then shifting progressively southwestward through March 2019, and finally shifting to the area north of the city during April - May 2019. The third evident pattern is variation in the intensity of the pollution cloud. Particularly notable are the light NO2 concentrations in January, April and May 2019.

Our traffic volume data from Google Traffic are limited to the period from late March to late May, so we cannot test whether longer-term fluctuation in traffic volume is a significant contributing factor in this context. However, we have complete daily weather data for the study period.[2] Table 2 reports results from a linear regression fitted to Sentinel-5P data for 288 daily observations from August 2018 to May 2019. The dependent variable is mean daily NO2. We have excluded rainfall from the estimation because prior experimentation revealed that is insignificant when included with the other factors. We find that temperature, wind speed and humidity all have negative impacts on NO2 concentration with high levels of statistical significance. We have also included cloud cover, on the expectation that Sentinel-5P NO2 measurement would be reduced on cloudier days. Our result for cloud cover is highly significant and consistent with this expectation.

Figure 5 aggregates daily NO2 predictions from the regression model into monthly means. The figure illustrates the striking seasonal effects of the weather variables: Weather-predicted NO2 drops sharply from December 2018 to January 2019, increases through March 2019, and then drops even more sharply in April and May 2019. Inspection of Figure 4 reveals the strength of this seasonal pattern at regional scale, with a notably smaller, weaker NO2 cloud in January 2019 and virtual disappearance of the cloud in April and May 2019.

We also consider the effect of prevailing winds on spatial NO2 dynamics. First, we calculate the mean wind direction angle for each month. Then, for each grid cell, we construct monthly one-kilometer-wide elongated rectangular strips aligned with the wind direction that extend upwind to cover all cells where traffic volume has been measured. We calculate mean traffic volumes for the strips, as well as weighted mean distances of strip cells to the downwind cell where pollution is measured by Sentinel-5P. We use distance weights that are proportional to traffic volumes.

[2] We obtained daily weather data from World Weather Online (https://www.worldweatheronline.com).

Figure 4: Dar es Salaam region: Monthly mean NO2 concentration

Indicator scaling from lowest to highest:

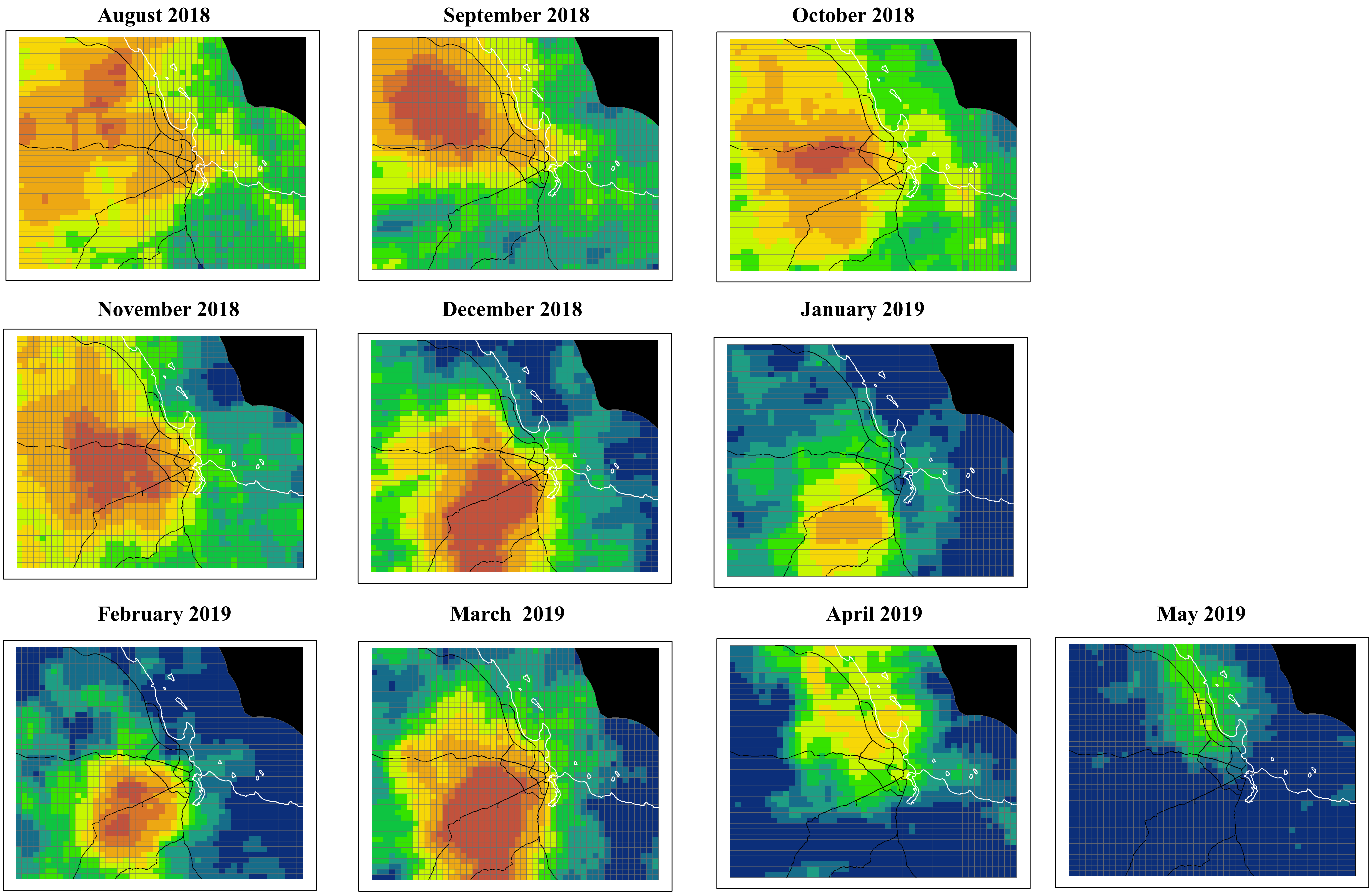
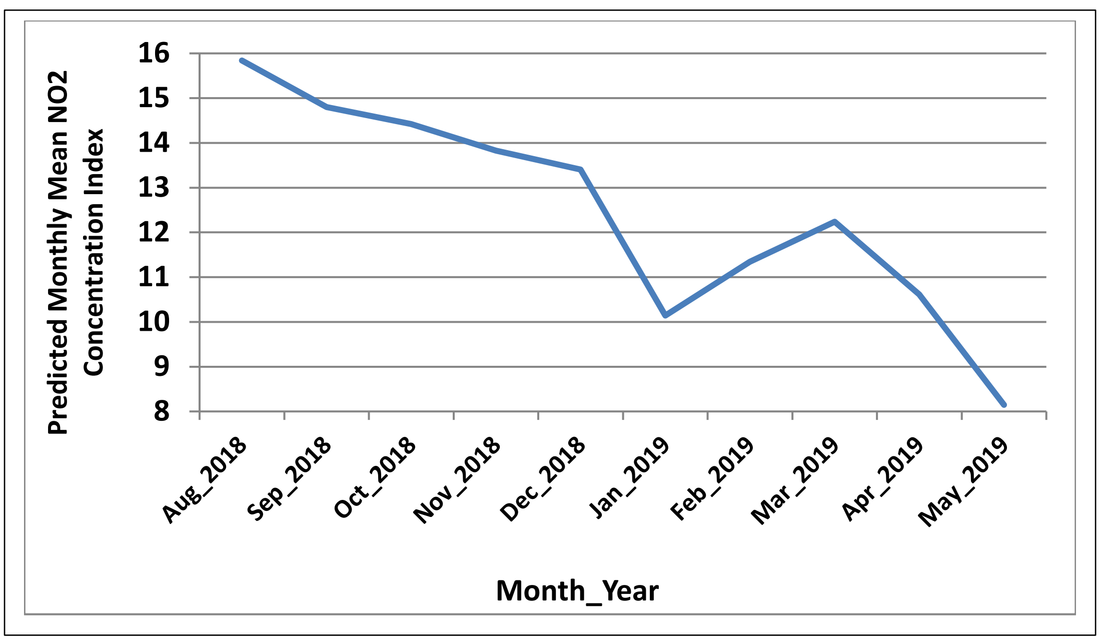


Table 2: Regression Results: Dar es Salaam Weather Factors in Mean NO2 Concentration

Temperature (C)	**-0.512**
	(2.77)**
Wind Speed (km/hr)	**-0.254**
	(2.66)**
Humidity (%)	**-0.257**
	(3.06)**
Cloud Cover (%)	**-0.072**
	(3.00)**
Constant	**51.847**
	(5.75)**
Observations	**288**
R-squared	**0.25**

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

Figure 5: Predicted monthly mean NO2 concentration from weather factors and cloud cover



For each month, we fit a regression that incorporates a dynamic model of wind impacts on NO2 from the points of emission. In this model, an emitted pollution particle is subject to both displacement by the wind and atmospheric decay with elapsed time from emission. For a destination grid cell and accompanying strip aligned with the prevailing wind direction, we posit a non-linear relationship linking mean NO2 in the destination cell to mean traffic volume and weighted mean distance from vehicular emissions sources in the strip.

(1) $N_{it} = \alpha_0 + (\alpha_1 + \alpha_2 d_{it} + \alpha_3 d_{it}^2 + \alpha_3 d_{it}^3)V + \varepsilon_{it}$

Expected signs: $\alpha_1 > 0$; $\alpha_2 < 0$; $\alpha_3 > 0$

where

N_{it} = Mean NO2 in destination cell for wind-aligned strip i, month t
d_{it} = Traffic-volume-weighted distance from the destination cell for strip i, month t
V_{it} = Mean traffic volume indicator for strip i, month t

Tables 3 and 4 tabulate our regression results for the 10 months from August 2018 to May 2019. They can be interpreted as tests of the hypothesis that the spatial displacement of NO2 concentrations observed in Figure 4 is primarily due to wind direction effects. In all cases except April 2019, we find very strong confirmation of the hypothesis, with high levels of statistical significance and the expected signs for regression parameters.

We investigate the long-term stability of wind-direction effects in Figure 6, which summarizes 10 years of annual data in box plots of wind angle by month. The figure shows highly stable wind directions for almost all months and a smooth pattern of annual wind direction change. March (month 3) is a notable exception, and November (month 11) also exhibits more variation than the other months. By implication, the pollution cloud displacements in Figure 4 represent seasonal wind patterns that recur each year.

Figure 6: Dar es Salaam: Monthly variation in wind direction, 2009-2018

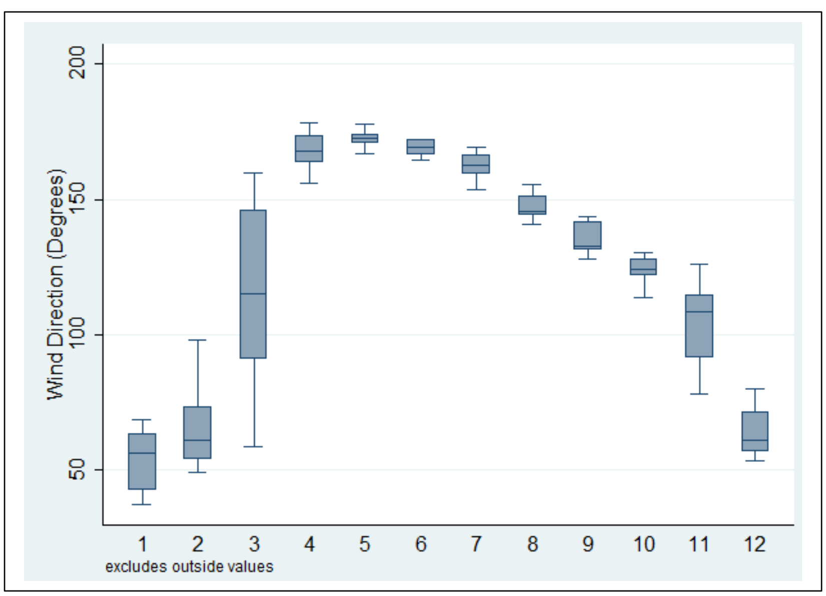


Table 3: NO2 pollution vs. source traffic volume and distance, 2018

	Aug_2018	Sep_2018	Oct_2018	Nov_2018	Dec_2018
α_1	-0.068	-0.211	-0.196	-0.143	-0.165
	(4.89)**	(9.54)**	(10.44)**	(5.50)**	(7.03)**
α_2	0.066	0.060	0.077	0.094	0.147
	(19.73)**	(11.79)**	(18.02)**	(13.73)**	(24.63)**
α_3	-0.003	-0.002	-0.005	-0.006	-0.010
	(12.45)**	(5.89)**	(16.45)**	(11.10)**	(21.22)**
α_4	.00004	.000019	.00008	.0001	0.00016
	(8.08)**	(2.65)**	(14.53)**	(8.74)**	(16.97)**
α_0	15.396	16.440	17.654	16.029	12.651
	(127.07)**	(81.96)**	(103.46)**	(70.20)**	(53.84)**
Observations	745	780	797	822	907
R-squared	0.75	0.54	0.33	0.34	0.58

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

Table 4: NO2 pollution vs. source traffic volume and distance, 2019

	Jan_2019	Feb_2019	Mar_2019	Apr_2019	May_2019
α_1	-0.050	-0.058	-0.062	0.151	-0.072
	(2.71)**	(2.99)**	(2.23)*	(5.95)**	(3.65)**
α_2	0.082	0.133	0.210	-0.003	0.066
	(17.24)**	(26.44)**	(29.37)**	(0.38)	(11.82)**
α_3	-0.006	-0.009	-0.014	0.000	-0.002
	(15.76)**	(23.16)**	(26.66)**	(0.64)	(4.50)**
α_4	0.0001	0.0001	0.0002	-0.000	0.0003
	(12.97)**	(18.78)**	(21.82)**	(0.52)	(2.17)*
α_0	10.132	7.788	10.974	11.100	6.744
	(54.00)**	(40.07)**	(38.29)**	(62.07)**	(48.68)**
Observations	906	909	907	485	464
R-squared	0.45	0.65	0.72	0.23	0.82

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

5. Distributional Impact of NO2 Pollution

5.1 Pollution-Vulnerable Residents of Dar es Salaam

To assess the impact of vehicular NO2 pollution, we focus on two vulnerable populations: children (0-5 years) and elderly adults (65+ years). We incorporate poverty in a composite vulnerability index for each grid cell by multiplying population in the groups [0-5,65+] by the estimated proportions of cell residents living in MPI-defined poverty, below $1.25/day, and below $2.00/day. For each variable, we use raster databases from the previously-cited WorldPop program at 1 km resolution.

Figure 7 displays the vulnerability index for the three poverty definitions. In each case, high-vulnerability areas form roughly concentric rings around the city center. Nevertheless, there are evident differences in the pattern across poverty definitions. For MPI-defined poverty, the vulnerability index is greatest in Azimio, Mbagala and Makangarwe divisions. For a poverty line of $1.25/day these divisions remain in the most critical group, but they are joined by Tandika division in the south and a cluster of divisions northwest of the city center that includes Kigogo, Mzimuni, Mburahati, Makurumla, Ndugumbi and Magomeni. For a poverty line of $2.00/day the southern cluster disappears but five of six divisions in the northwest cluster remain.

5.2 Pollution Exposure Paths

Figure 7 displays areas where potential vulnerability is high, but actual vulnerability will vary with exposure. To assess this component, we produce pollution exposure paths for each month by tracing pollution measured by Sentinel-5P in each grid cell back along the wind vector to its traffic sources. Figure 4 indicates the general direction of these effects as the wind direction changes: Exposure paths shift toward the northwest in August and September; toward the west in October, November and December; and toward the southwest in February and March. The winds shift the paths toward the north in April and May, but weather-related factors lead to minimal pollution during that period.

We estimate the effects of these trends by assigning pollution in the destination cell of each vector strip (from our previously-explained methodology) to the cells that the strip intersects back to its origin at the most distant cell where traffic is measured. For each destination cell, we sum the assigned pollution values of all intersecting strips. We multiply by our three vulnerability measures (for MPI, $1.25/day and $2.00/day) and normalize to the range [0-100] to obtain indicators that incorporate both pollution vulnerability and actual pollution exposure.

Figure 8 displays the results for the three poverty criteria. In each case, high-vulnerability areas surround the core area where traffic volume is highest. However, the geography of vulnerability differs by poverty definition. For MPI-defined poverty, vulnerability is greatest in five divisions southwest of the city center: Tandika, Azimio, Yombo Vituka, Makangarawe and Mbagala. This area is also high-vulnerability if $1.25/day is used as the poverty line, but it is joined by a group of divisions northwest of the city center: Ndugumbi, Makurumla, Mzimuni, Kigogo, Mabibo and Mburahati. The locus shifts again for the poverty line of $2.00/day; the most critical northwest cluster for $1.25/day remains but the southern cluster is reduced to two divisions.

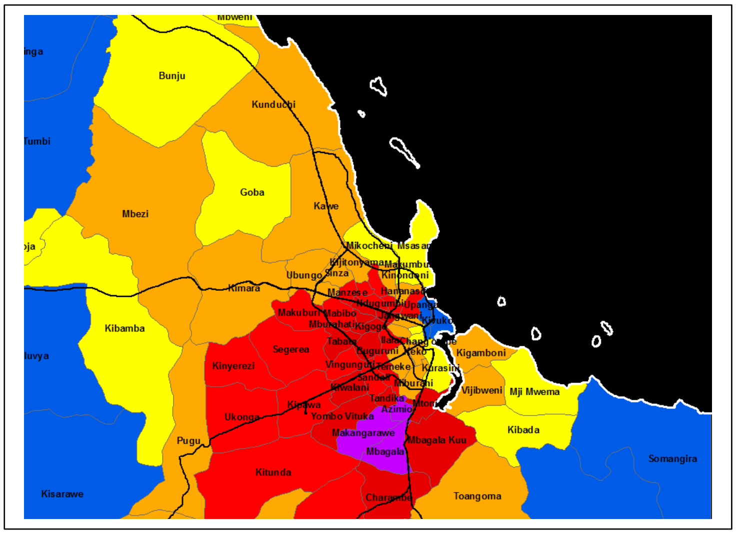
6. Distribution-Related Priorities for Reducing Traffic Congestion

Our results also have implications for priorities assigned to congestion-relieving measures in different parts of the metro area. The intuition here is straightforward: Each grid cell is the origin of NO2 pollution that is proportional to its traffic volume. This pollution in turn affects residents in other cells, in proportion to their demographic vulnerability. Distance matters as well: Other things equal, the impact of emissions from a cell on another cell will decline with the distance between them. To produce a summary indictor, we identify each grid cell as a pollution origin cell and use its traffic as the NO2 emissions indicator. We quantify its impact on another cell by multiplying its emissions indicator by the pollution vulnerability of the other cell and dividing by the distance between them. For each origin cell, we add the quantified impacts across all affected cells, normalize to the range [0-100], and display the result as a priority indicator for traffic congestion relief. The top-ranking cell in this ordering is the cell whose current traffic volume has the most effect on vulnerable populations in other cells, taking into account their degrees of vulnerability and their distances from the top-ranking cell. Similarly for all other cells in the grid.

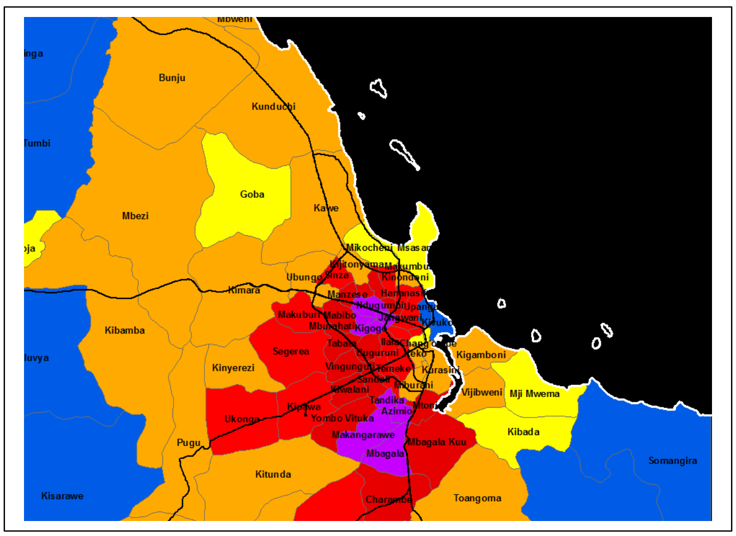
We display the results of these calculations in Figure 9. They exhibit more geographic stability than the vulnerability indicators, although some variations remain. For all three indicators, the most critical areas for congestion relief are six central-city divisions: Kisutu, Jangwani, Kariakoo, Mchafukogi, Gerezani and Mchikichini. In the second rank, there are also divisions to the west, east and north that recur for each poverty measure. Nevertheless, some second-rank divisions remain unique to each poverty measure.

Figure 7: Dar es Salaam resident vulnerable to NO2 pollution
Indicator scaling from lowest to highest:

Vulnerable residents, MPI-defined poverty



Vulnerable residents: Poverty line $1.25/day



Vulnerable residents: Poverty line $2.00/day

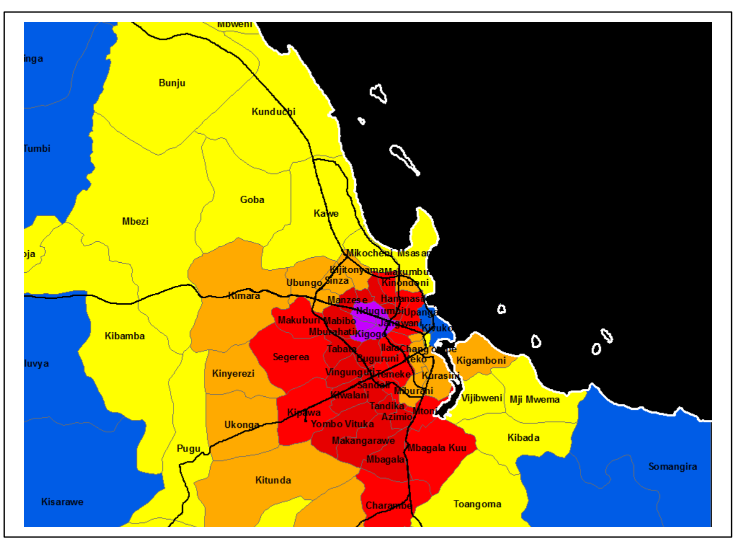
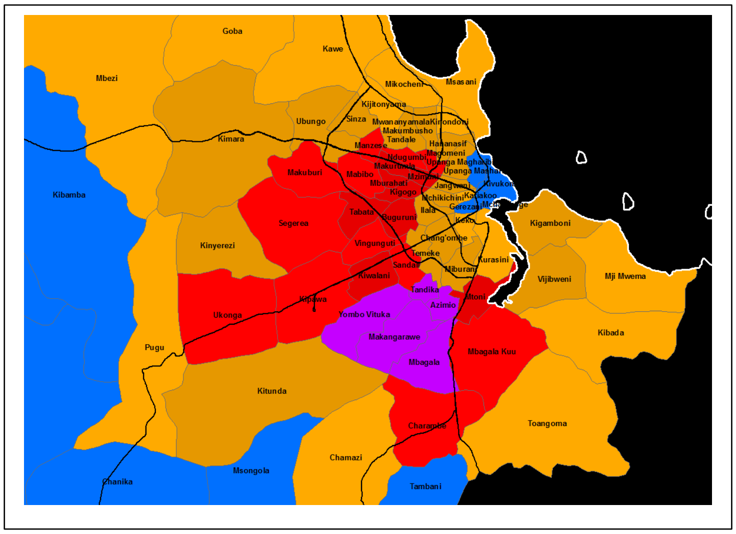
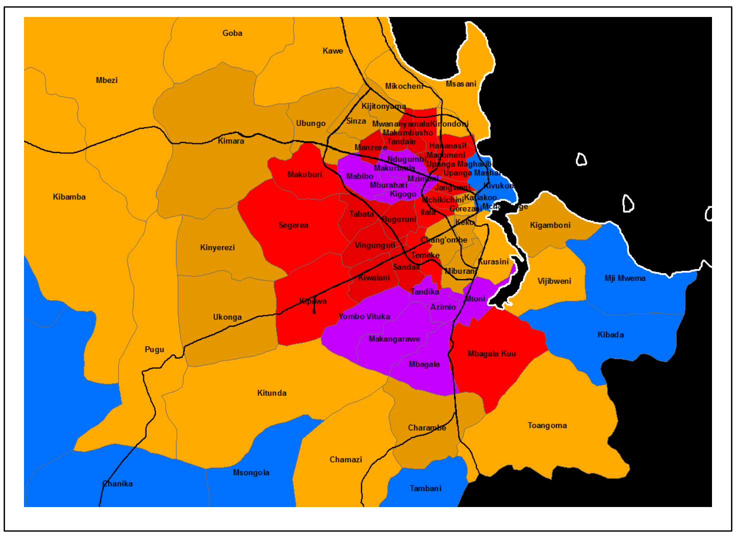


Figure 8: Composite vulnerability for residents of Dar es Salaam
Indicator scaling from lowest to highest:

Vulnerability, MPI-defined poverty



Vulnerability: Poverty line $1.25/day



Vulnerability: Poverty line $2.00/day

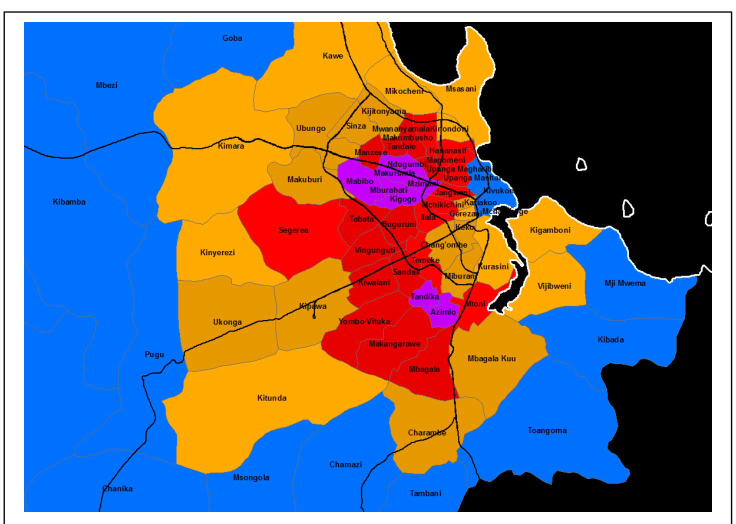
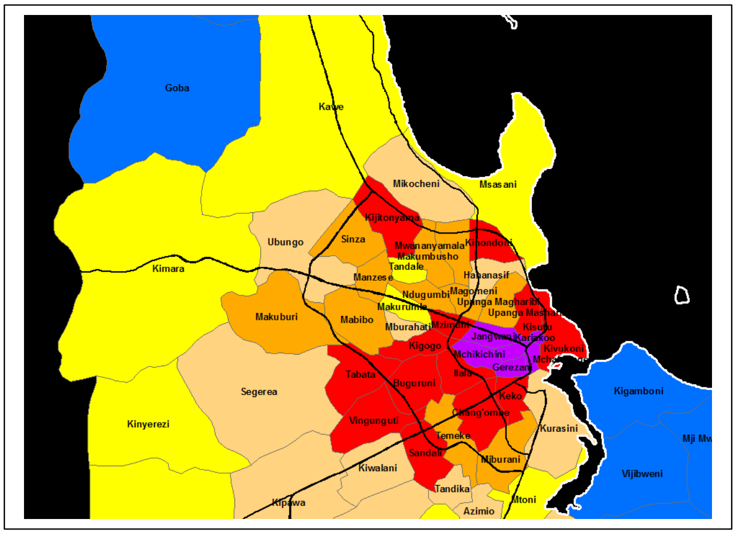
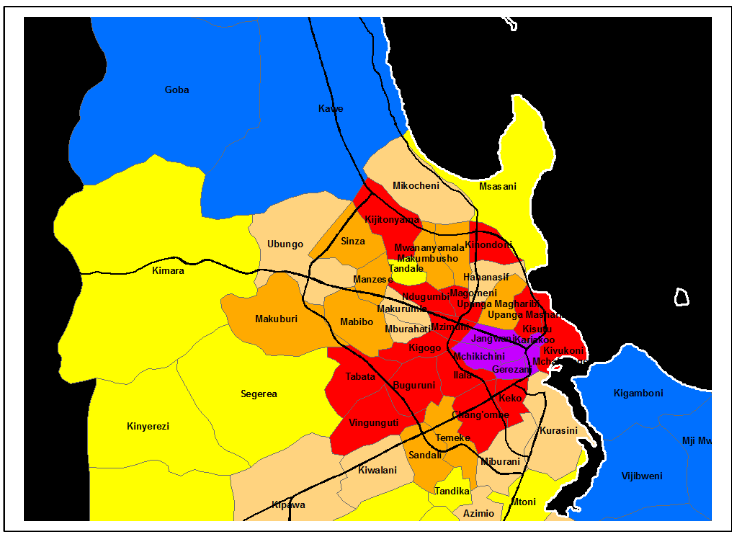


Figure 9: Dar es Salaam traffic cells by congestion relief priority
Indicator scaling from lowest to highest:

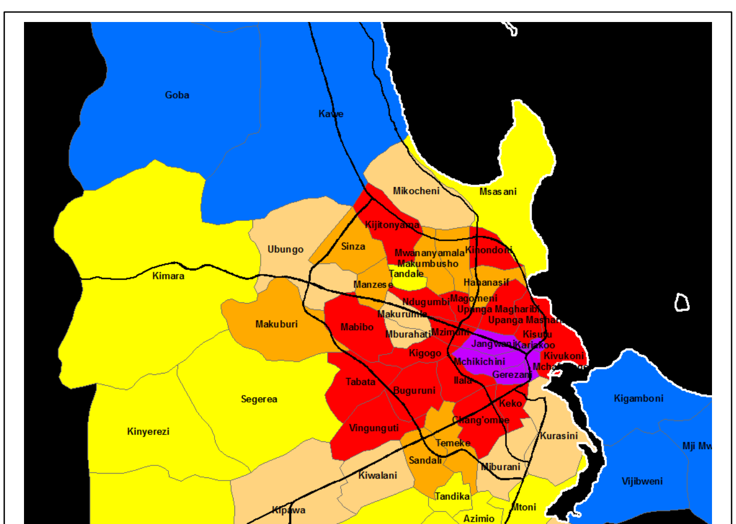
For affected vulnerable residents, MPI-defined poverty



For affected vulnerable residents: Poverty line $1.25/day



For affected vulnerable residents: Poverty line $2.00/day



7. Summary and Conclusions

In this paper, we have used new databases for the Dar es Salaam metro region to investigate the spatial dynamics of traffic congestion, regional air pollution, and impacts on vulnerable residents. We use Google Traffic to develop high-resolution traffic measures, which provide the first temporally- and spatially-comprehensive view of congestion in the metro area. We assess the spatial dynamics of air pollution using high-resolution nitrogen dioxide (NO2) measures from the European Space Agency's new Sentinel-5P satellite platform. Our information on the spatial distribution of vulnerable residents uses demographic and poverty maps assembled from numerous sources by the WorldPop project of the School of Geography and Environmental Sciences, University of Southampton. We combine these information sources in a spatial grid with 1-km cells for the metro region.

Our empirical modeling highlights the impact of weather factors on the spatial distribution and intensity of NO2 pollution from the emissions of motor vehicles in the region. We identify critical weather dimensions in two econometric analyses. The first uses daily NO2 measures from Sentinel-5P and weather data from World Weather Online to measure the effects of temperature, rainfall, humidity and wind speed on air pollution, as well as the effect of cloudiness on measurement by Sentinel-5P. We aggregate regression-based NO2 predictions by month and find a strong seasonal pattern of weather impacts on pollution. In the second econometric exercise, we estimate a model that relates spatial displacement of NO2 pollution from its traffic source locations to the locations observed by Sentinel-5P. Our analysis clearly identifies wind direction as the critical driving variable and, like the other weather factors, wind direction is strongly seasonal. Taken together, these weather variables account for a major portion of spatial pollution dynamics in the Dar es Salaam region. We confirm the strong seasonality of wind direction in a 10-year analysis for the region.

In the second part of the paper, we explore the distributional implications of our findings. Using our methodology for analysis of spatial pollution displacement, we quantify NO2 pollution exposure for residents in the displacement path. To index relative vulnerability, we use WorldPop digital maps to estimate the number of children (0-5 years) and elderly adults (65+) in poor households in each grid cell. We develop separate indicators for three measures of poverty incidence based on the global multi-dimensional poverty index (MPI); a poverty line of $US 1.25/day; and a poverty line of $US 2.00/day.

We combine our pollution exposure and pollution vulnerability measures to produce a composite pollution impact measure for each grid cell. We aggregate our measures for level-3 administrative divisions and map the results to assess the implications. We find three elements of primary significance. First, areas of the city have highly-varied "environmental endowments" driven by strongly-seasonal weather effects on the spatial distribution and intensity of NO2 pollution. Pollution exposure is worst for areas that are in the wind path from high-traffic areas in seasons when pollution is maximized by weather factors. The second critical element is the spatial juxtaposition of environmental endowments and vulnerability. Some highly-vulnerable areas have poor environmental endowments while others do not, with potentially-critical significance for pollution impact analysis. The third element relates to the definition of poverty. Vulnerability maps of the region differ significantly for the three poverty definitions that we have employed for this exercise. By extension, our pollution impact maps also vary by poverty indicator.

Using our integrated spatial database, we also consider the implications for targeted measures to reduce traffic congestion in Dar es Salaam. For each grid cell, we calculate a composite traffic impact indicator from three elements: traffic volume in the focal cell, the vulnerability of all other cells, and the distance of the focal cell to each of those cells. Then we map the results for each poverty indicator. We find more spatial stability here than in the distribution of pollution impacts: The maps for all three poverty indicators identify the same core areas where congestion reduction would yield the greatest estimated reductions in impact.

To conclude, we should stress that our assessment for Dar es Salaam is inevitably a pilot exercise because, to our knowledge, these high-resolution information sources have not previously been combined for an integrated regional assessment of any city. As more cases are studied, we will undoubtedly gain further insight into the key factors that link traffic, air pollution and distributional impacts in metropolitan regions. In closing, we should note one particularly beneficial side of this new direction for research: It depends only on free global information sources, so it can be undertaken as readily in developing-country cities like Dar es Salaam as in developed-country cities where such research has traditionally been conducted. And even those cities will benefit from the new information sources, because their pollution and distributional impact issues can be revisited with data that simultaneously offer more granularity and broader spatial coverage than has previously been available.

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