

Modelling the Spatio-Temporal Distribution of Ambient Nitrogen Dioxide and Investigating the Effects of Public Transit Policies on Population Exposure

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Abstract

Estimating the future state of air quality associated with transport policies and infrastructure investments is key to the development of meaningful transportation and planning decisions. This paper describes the design of an integrated transportation and air quality modelling framework capable of simulating traffic emissions and air pollution at a refined spatio-temporal scale. For this purpose, emissions of Nitrogen Oxides (NO_x) were estimated in the Greater Montreal Region at the level of individual trips and vehicles. In turn, hourly Nitrogen Dioxide (NO_2) concentrations were simulated across different seasons and validated against observations. Our validation results reveal a reasonable performance of the modelling chain. The modelling system was used to evaluate the impact of an extensive regional transit improvement strategy revealing reductions in NO_2 concentrations across the territory by about 3.6% compared to the base case in addition to a decrease in the frequency and severity of NO_2 hot spots. This is associated with a reduction in total NO_x emissions of 1.9% compared to the base case; some roads experienced reductions by more than half. Finally, a methodology for assessing individuals' daily exposure is developed (by tracking activity locations and trajectories) and we observed a reduction of 20.8% in daily exposures compared to the base case. The large difference between reductions in the mean NO_2 concentration across the study domain and the mean NO_2 exposure across the sample population results from the fact that NO_2 concentrations dropped largely in the areas which attract the most individuals. This exercise illustrates that evaluating the air quality impacts of transportation scenarios by solely quantifying reductions in air pollution concentrations across the study domain would lead to an underestimation of the potential health gains.

Keywords: Air quality; Dispersion modelling; Traffic emissions; Nitrogen dioxide (NO_2); CALMET; CALPUFF; Public Transit; Policy Scenario

Highlights:

- ▶ An integrated transportation, emissions, air quality modelling chain is developed
- ▶ Our modelling framework is able to account for the spatio-temporal distribution of NO₂
- ▶ The modelling framework was used to test the effect of transit investments
- ▶ Increased transit service was associated with reductions in population exposure to NO₂

Information on funding sources supporting the work

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1. Introduction

Heavily trafficked urban streets are major sources of Nitrogen Oxide (NO_x) emissions and exposure to nitrogen dioxide (NO₂) has been associated with a range of health effects (Clark et al., 2012; Crouse et al., 2010; Parent et al., 2013). In metropolitan areas around the world, urban air pollution modelling has been conducted for a variety of road and network configurations (Batterman et al., 2010; Hatzopoulou and Miller, 2010) using a range of methods such as, dispersion models (Cheng and Li, 2010; Den Boeft et al., 1996; Hertel et al., 1989; Vardoulakis et al., 2007), box and Neural Networks models (Shekarzifard et al., 2012), and Land use regression models (LUR) (Johnson et al. 2010; Crouse et al. 2009; Hoek et al. 2008). Among these methods, dispersion models have the advantage of capturing the influence of many factors such as the topology of the street and local wind turbulence.

Modelling traffic-related air pollution using an integrated approach, starting from travel demand, captures the interactions between individual mobility, on-road traffic, meteorology, emissions, atmospheric transport, and chemical transformations. Furthermore, this integration between traffic, emission, and dispersion modelling enables the investigation of the effects of transportation plans and policies on air pollution and public health thus adding an important dimension to decision-making in transportation.

A number of interdisciplinary research initiatives have developed modelling frameworks that account for vehicle emissions whereby activity-based models were used to calculate person- and trip-level emissions for varieties of pollutants such as PM₁₀ (McCreddin et al., 2015) and NO_x (Int Panis et al., 2011). Among these, most analyses of exposure took into account variations of the emission source, but assumed fixed receptor conditions (Bae et al., 2007). Based on this approach, individuals are considered to remain at home and, therefore, only exposed to air pollution at their home address. The attempts at dynamic exposure assessments are uncommon and often focus on long time scales (De Ridder et al., 2008).

Several recent studies have addressed the impacts of transport policies on health and well-being (Hosking et al., 2011; Grabow et al., 2012; Dhondt et al., 2013; Braubach et al., 2015; Perez et al., 2015). Among the early studies that show the importance of dynamic population modelling over the traditional static modelling, we note the work of Dons et al. (2011) and Beckx et al. (2009). These studies demonstrated significant exposure differences (ranging from 12% to 20% depending on pollutant) between the static approach where people are assumed to

be at a fixed residential location and dynamic micro-simulation approach. Hatzopoulou and Miller (2010) and Hao et al. (2010) also developed integrated modelling frameworks to estimate exposures in Canada. Dhondt et al. (2012) applied an integrated modelling framework consisting of an activity based model and dispersion models and found a large difference between static and dynamic approaches (12%). Lefebvre et al. (2013) incorporated a land use modelling component to the integrated modeling framework to account for regional concentration patterns. Additionally, Vallamsundar et al. (2016) developed an integrated modelling framework to estimate the population exposure of PM_{2.5} in Arizona. Rowangould (2015) calculated exposure levels across Los Angeles County, California using a multi-modal platform combining concentration data from trip-based regional travel demand models with population information from census.

A variety of other studies demonstrated how these model capabilities are useful for planning applications, and how they can be used to evaluate the effects of various transport policy scenarios on air pollution and exposure. Nieuwenhuijsen et al. (2016) observed that policies that emphasize changes in travel behaviour, including the increased use of public transit, are essential in reducing transport emissions and the adverse health effects of traffic-related air pollution. Recently, a number of studies have attempted to quantify the overall health co-benefits of replacing car travel with alternative transport modes (Woodcock et al. 2009; Maizlish et al., 2013; Macmillan et al., 2014; Xia et al. 2015; Tobollik et al. 2016; Gariazzo et al., 2016). Woodcock et al. (2009) quantified the environmental and health benefits of various alternative transport scenarios for 2030 in London. The authors estimated that over 500 premature deaths could be saved under alternative transport scenarios. Tobollik et al. (2016) estimated the greenhouse gas reduction potential of various policies in Rotterdam using a base year of 2010 and projecting to 2020. The authors estimated reductions in PM_{2.5} and elemental carbon of around 40% and 60% respectively.

This paper describes the development and validation of an integrated transportation, emission, and dispersion model system for the Montreal metropolitan area taking into account population mobility. The developed framework has the ability to estimate population exposures during travel and at activity locations, an element that has not been emphasized in the literature. One of the novel aspects of this model is its ability to identify the contribution of travelling/commuting to daily exposure, in addition to its capability for predicting travel demand

and the travel mode, analyzing vehicle movements, estimating traffic emissions, and modelling the dispersion of air pollutants. This means that, in addition to being policy sensitive, our model system is refined in terms of spatio-temporal variability in air pollution levels thus making it relevant for exposure analysis. Beyond the description of our modelling system, we present an evaluation of proposed transit expansions in Montreal in terms of their effects on urban air quality and population exposure. Our scenario analysis demonstrates the strength of our modelling system in terms of its ability to unveil a different dimension to policy performance. Rather than simply analyzing policies based on their effects on ambient air quality, we also quantify their effects on exposure, illustrating a different angle.

Beyond this introduction, the paper is divided into four sections: Section 2.1 explains the general overview of modelling system and the components of the integrated model for the study area. Then in section 2.2 and 2.3 integrated model components are described in detail. Following model development, validation efforts are described in section 2.4. A scenario is introduced in section 2.5 and the method of finding population exposure to traffic related pollution is defined in section 2.6. Section 3 discusses the results and section 4 concludes the paper.

2. Model development

2.1 General overview

Our modelling system consists of two main components: 1) the travel demand and emission module and 2) the atmospheric dispersion module that simulates air quality based on road segment emissions. Fig. 1 presents the components of the integrated model. The output of the transportation and emission model includes spatially refined emissions of NO_x generated at the level of every road segment and varying by time of day. The dispersion model is driven by a meteorological processor and is capable of dispersing emissions of every individual road segment in our modelling domain (127,217 road segments).

Our study is set in Montreal, Canada and includes the city of Montreal as well as the larger metropolitan region. The Montreal Metropolitan area with a surface of 4258 km² and population of 4.1 million is the second largest city in Canada and located in south west of the province Quebec. The city of Montreal covers most of the island of Montreal at the confluence of the St. Lawrence and Ottawa river. The island is crossed north-south and east-west by major highways causing high congestion during rush hours. The city center is relatively dense with busy arterials

and tall buildings. The west of the island also known as the “West Island Region” is composed of relatively affluent suburbs while the east of the island includes a large number of industries. A high-activity port is located near the city center on the St. Lawrence River.

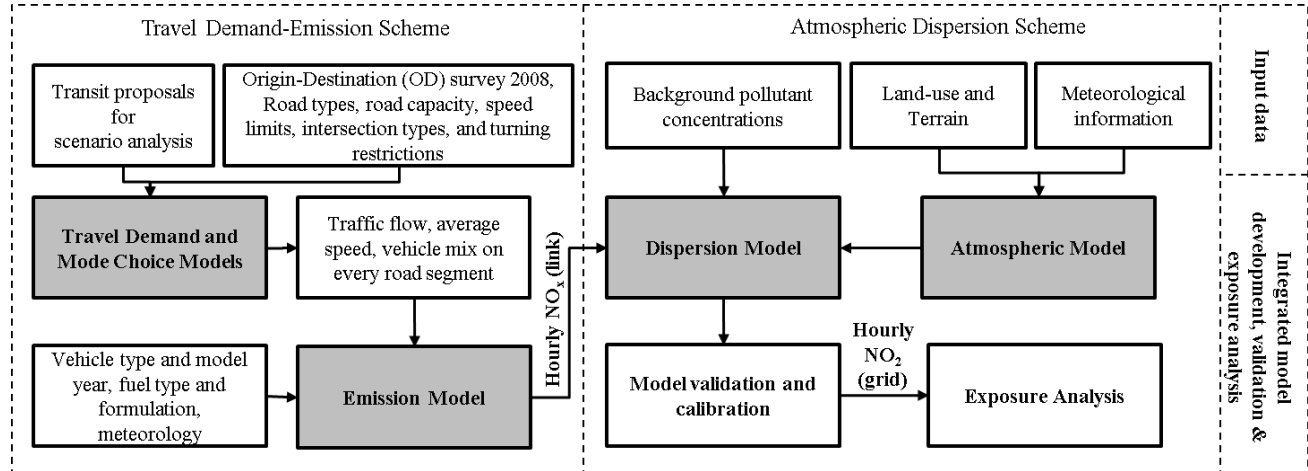


Fig. 1. Schematic flowchart of the integrated transportation-emission-dispersion model system.

2.2 Travel demand and emissions model

Our travel demand model is intended to generate trips including their respective modes as a response to various changes in population patterns, demographics, the built environment, and transportation. For example, new transit infrastructure would improve the travel times of individuals previously driving and potentially induce mode shift towards public transit. Briefly, we used 2008 origin-destination survey data for the Montreal metropolitan area to develop trip level mode choice models (Eluru et al., 2012). The 2008 origin-destination data includes information for a 5% sample of the Montreal population, encompassing a total of 66,000 households and approximately 157,000 individuals conducting a total of 355,000 daily trips across the metropolitan region. We categorized trips based on their origin and purpose into four groups: home-based-work (origin is home, purpose is work), home-based-other (origin is home and purpose is non-work), work-based (origin is work and purpose is any) and non-home based (origin is any location other than trip maker’s home, purpose is any). For each category, we estimated a mode choice model separately. Our mode choice models consider various travel modes including drive, passenger, transit, walk, bike, and combinations of these modes. The models were calibrated on a 7.5% sample of the origin-destination data. The drive mode trips

obtained from our mode choice models and scaled up to the total population were used as input to generate traffic flows on the network using a traffic assignment model.

A regional traffic assignment model was developed for the Montreal metropolitan area. The traffic assignment model allocates vehicle flows on the road network using the road types ranging from expressways to local roads. The model includes road capacities, speed limits, number of lanes, type and length of roads, intersection types, and turning restrictions. Output of the traffic assignment model includes traffic volume, average speed, and vehicle mix on every road segment in the region. Our regional network consists of 127,217 road segments and 90,467 nodes associated with 1,552 traffic analysis zones (TAZs). The trips made by driving were aggregated into 24 hourly origin-destination (OD) matrices based on trip departure times. The OD matrices were generated at the TAZ level. In order to get the total number of trips (expand to the total population), we applied weighting factors available in the 2008 OD survey. The simulated traffic was assigned to the network employing the Stochastic User Equilibrium approach (SUE) using the VISUM platform (developed by PTV Group, PTV Vision, 2009). This ensures a probabilistic distribution of path choices between any OD pair. It is important to note that we only simulated household travel and therefore truck movements were not included in our model. This is a limitation that we fully recognize considering that diesel trucks are significant emitters of NO_x. In Montreal, on average the proportion of heavy and medium trucks on the road is 4% responsible for about 30% of the emissions. Through ongoing research, we are extending our model to incorporate truck movements.

Using the model output, emissions of NO_x (in gram) at the level of every individual vehicle were estimated based on its type, age, speed, and type of road. Emissions were based on emission factors that we generated using the Mobile Vehicle Emissions Simulator (MOVES) platform developed by the United States Environmental Protection Agency (USEPA) and calibrated with Montreal-specific data. To estimate emissions, MOVES requires various inputs such as link information; vehicle type and composition; vehicle model year; fuel type and formulation; and meteorology. Data on vehicle ownership were purchased from the vehicle registry database for Montreal, provided by the Societe de l'Assurance Automobile du Quebec (SAAQ). The SAAQ database includes vehicle ownership information for the Montreal region at the level of the Forward Sorting Area (FSA), indicated by the first three characters of the postal code. Within each FSA, the total number of vehicles by type (e.g. passenger car, sports utility vehicle,

minivan, small truck, large truck) and model year was provided. Hourly emissions of NO_x were estimated for each road by summing the contributions of all vehicles on every segment. Details on the development of the transportation and emission model are presented in Sider et al. (2013). The resulting segment-level NO_x emission rates (in grams/km) are presented in Fig. 2 which illustrates total daily NO_x for each road link in the Montreal metropolitan area (Fig. 2a) and the frequency distribution of NO_x across the 127,217 road links (Fig. 2b). It is important to note that we do estimate traffic and emissions for each hour of the day but we only simulate a single day which is considered to be representative of an average weekday in terms of travel patterns. This is a limitation of the origin-destination survey which covers a single day in the travel patterns of each household.

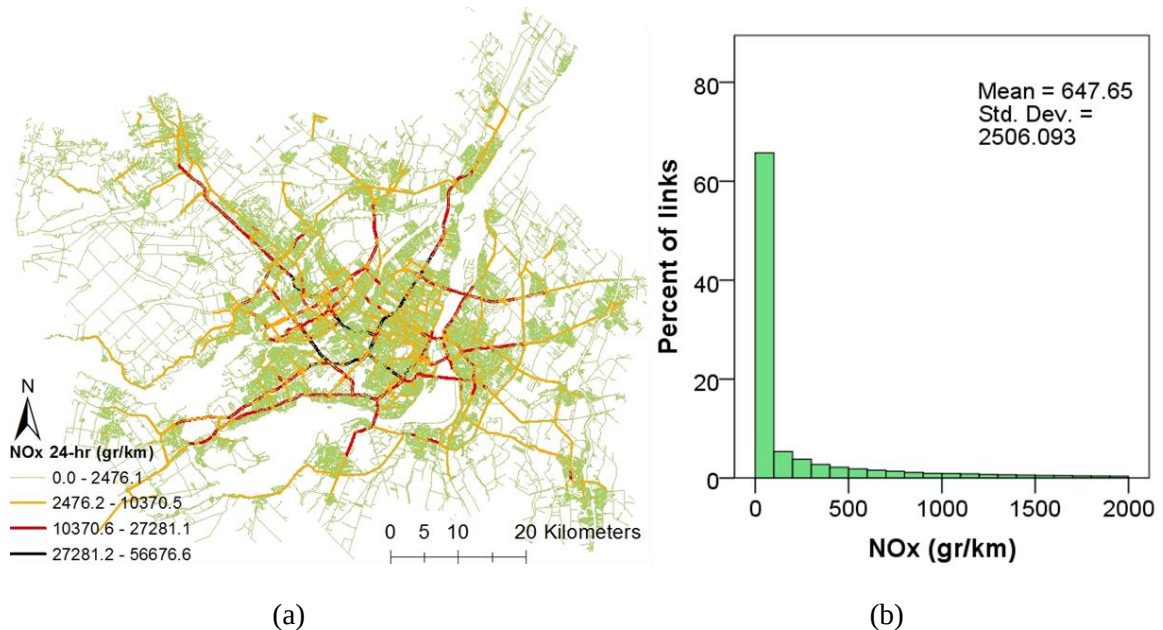


Fig. 2. Total daily NO_x emissions for each road link in the Montreal metropolitan area (a) and frequency distribution of NO_x across the 127,217 road links (b).

2.3 Dispersion model

In recent years, various dispersion models that address a variety of source emissions (road, point and area) have been developed. Among these, the multi-layer, multi-species non-steady state model CALPUFF is becoming more commonly applied for the dispersion of traffic emissions because of its capability for handling complex terrain and land use interaction effects (Scire et al., 2000a; Cohen et al., 2005). Several researchers who used such advanced tools reported appropriate simulation performance (Carper and Ottersburg, 2003; Radonjic et al.,

2013). In this study, NO₂ concentrations were modeled using the CALMET/CALPUFF modelling system (Scire et al., 2000a; Scire et al., 2000b).

CALMET is a meteorological pre-processor to CALPUFF and it was used to interpolate winds and temperatures using higher-resolution terrain elevation and land-use data and create detailed hourly meteorological fields as well as predict boundary layer parameters such as mixing height. Since the data interpolation process accounts for land slopes, blocking effects of terrain, and preserves the air-mass continuity, it must be driven either by observations or by three-dimensional data from prognostic models (e.g. MM5, WRF, RAMS). We obtained land use and land-cover data from the Montréal DMTI Spatial Inc. database 2009. The resolution of the data is 1 x 1 Km; using a land-use processor, we computed the fractional land-use/land cover for each grid cell in the modelling domain. Terrain elevation data was obtained from the Shuttle Radar Topography Mission (SRTM) conducted by the National Aeronautics and Space Administration (NASA) and the National Geospatial-Intelligence Agency (NGA). The data for the modelling domain is in SRTM3 (spacing for individual data points is 3 arc-seconds), which corresponds to 90 meters in resolution. SRTM3 data were allocated to the modelling grid. Fig. 3 presents land-use and topography for the entire modelling domain. Note that our modelling domain is significantly larger than our study area, which is the Montreal metropolitan area. This is done in order to ensure that the meteorology and dispersion account for the full land-use and topography effects. Three dimensional hourly wind speed and direction for the 1 x 1 Km resolution were obtained from the Pennsylvania State University/National Center for Atmospheric Research (PSU/NCAR) mesoscale model MM5 (Grell et al., 1994). Surface meteorological data were obtained from the National Oceanic and Atmospheric Administration (NOAA) database, 2008 (NOAA, 2012). In total, data for 12 surface stations were used in model development.

The development of accurate wind speeds and directions across the modelling domain is crucial for dispersion modelling. We first used the meteorological model to produce initial guess wind fields by adjusting MM5 winds for terrain effects. In a next step, these adjusted values were refined through the introduction and processing of surface observations. In order to force the simulated winds to follow the wind vectors at each surface station included in the model and to account for terrain effects using MM5 data, weights were assigned to surface stations. A high weight given to a surface station would force winds to follow the wind vector recorded at the

station thereby wiping out terrain effects. In this study, 10 different combinations of weights and terrain effects were tested. The resulting wind fields were validated against observed values at two monitoring stations, which were not included in the model. We conducted this exercise for different months of the year (January, April, March and July) in order to find the weights that would achieve the best fit across all seasons. The meteorological data were simulated at a resolution of 1 x 1 Km which were then used to drive the dispersion model.

CALPUFF is based on the Lagrangian puff equation, which estimates the growth diffusion and transport of released puffs in the modelling domain. Besides inputting spatially resolved meteorology, emissions from each of the 127,217 road links in Greater Montreal were input. The road links were broken down into smaller segments (less than 0.5 km) of one-directional links to increase the accuracy of road source modelling (in total 370,000 segments); in turn, the corresponding coordinates of start and end points of each link were generated using ArcGIS v10.2. Then, the base elevation for each point was found using the SRTM maps in order to account for road elevation. In CALPUFF, each link is treated as a road source separately whether it is a one-way link or one half of a two-way link. The road input file for simulation must include the start and end coordinates, initial vertical and horizontal dispersion coefficients; sigma z (σ_z) and sigma y (σ_y), base elevation, and emissions in gram/sec.meter. Values of 3.5 and 3 meters were considered (iterations) for sigma z and sigma y, therefore representing traffic-induced mixing near the roadway.

Background NO_2 concentrations were also included in the simulation using data observed at station 99, located west of the Montreal Island. CALPUFF incorporates a set of chemical and physical processes. During the chemical reactions, NO_x transforms to NO_2 . Chemical reactions reduce NO_x concentrations in the presence of O_3 , solar radiation UV, and VOCs. There is a non-linear relation in the response of O_3 concentrations to reductions in NO_x and VOC (Wu et al., 2009). Since the conversion rate of NO_x to NO_2 is a non-linear function of O_3 , solar radiation, and NO_x concentrations, and since solar radiation and O_3 vary between different seasons, the simulated concentrations for each season are expected to be different. We used O_3 as an input to model chemistry of NO_x to NO_3 and HNO_3 . A RIVAD chemistry scheme in CALPUFF was used. In this scheme, NO_x was transformed to NO_3 and HNO_3 . However since part of NO_x is transferred to smog using VOC, we have to account for the transformation of NO_2 in the presence of hydrocarbons producing PAN, aldehyde, smog, etc. This means we have to account

for further reactions that vary with the NO_2/NO_x ratio which is not always constant. As a result, the NO_2/NO_x ratio curve/equation is an additional input to the model. For this purpose, we used data for observed NO_2 and NO_x values to estimate and validate the regression parameters. Data were extracted from 9 stations across the city of Montreal to account for spatial variability. We put together all 69,400 data available from all stations to account for both temporal and spatial variability and estimated the regression parameters. Then, simulated NO_x emissions were transformed to NO_2 concentrations using a regression relation between NO_x (dependent variable) and NO_2/NO_x ratio (independent variable) in CALPUFF.

The simulation started at 4:00 LST on the 7th and ended at 4:00 LST on the 14th of the following 4 months: January, April, August and October 2008. CALMET and CALPUFF share the same modelling domain. The domain is divided into 200 grid cells in the X direction (Easting) and 140 grid cells in the Y direction (Northing) centered around the Montreal Island; the size of every grid cell is 1 x 1 Km. In terms of vertical model resolution, the domain consists of 10 levels (the elevations of level 1 to level 10 are: 20m, 40m, 80m, 160m, 320m, 700m, 1300m, 1700m, 2300m, and 3000m).

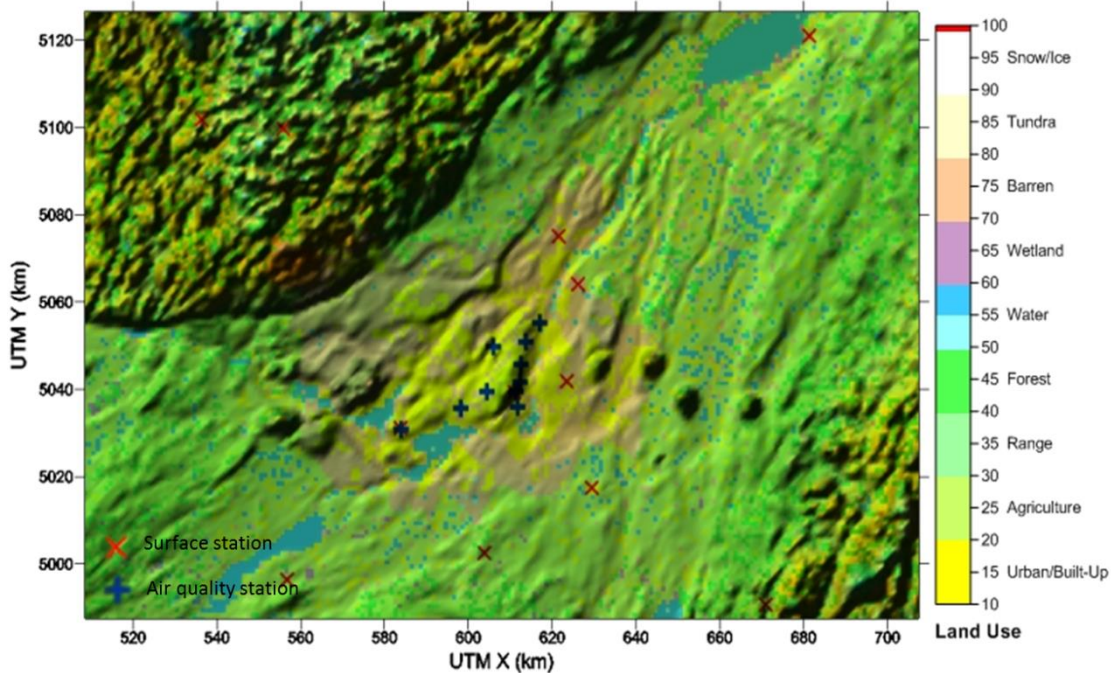


Fig. 3. Land-use and topography across the study domain. The locations of meteorological surface stations (x) and air quality stations (+) are presented on the map. The air quality stations were used for model validation.

2.4 Validation of meteorology and dispersion model

Comparison of model predictions with data measured at monitoring stations is a core element of dispersion model evaluation. Examining wind roses generated from the available meteorological data provides a better understanding of the complex wind flows within the modelling domain. To calibrate our meteorological model, as mentioned in section 2.3, different weights were assigned to surface stations to force winds to follow the wind vector recorded at the station and accounting for terrain effects using MM5 data. The resulting wind speeds and directions were validated against observations. We generated and compared daily, monthly, and seasonal wind roses from CALMET with observed data at two airport stations (Mirabel and Dorval stations). We also estimated the correlation between observed and predicted wind speeds and wind directions.

To validate the dispersion model, the predicted NO₂ concentrations were validated against NO₂ data collected at a total of 9 fixed-site air quality monitoring stations managed and operated by the City of Montreal through the Réseau de Surveillance de la Qualité de l’Air (RSQA). These monitors are located on the Montreal Island. After pairing simulated and measured NO₂ concentrations in both space and time, we used a number of performance measures proposed by Chang and Hanna (2004) as presented in Table 1.

Table 1. Performance measures for urban dispersion model validation
(adapted from (Chang and Hanna, 2004).

Performance measures	Equation	Ideal Value	Acceptable Value
Normalized absolute difference (<i>NAD</i>)	$NAD = \frac{ \overline{C_0} - \overline{C_P} }{\overline{C_0} + \overline{C_P}}$	0	<0.5
Fractional mean bias (<i>FB</i>)	$FB = \frac{2(\overline{C_0} - \overline{C_P})}{\overline{C_0} + \overline{C_P}}$	0	-0.67 to 0.67
Normalized mean-square error (<i>NMSE</i>)	$NMSE = \frac{\overline{(C_0 - C_P)^2}}{\overline{C_0} * \overline{C_P}}$	0	<6

C_0 and C_P represent the observed and predicted concentrations, respectively.

The overbar represents the average over the hourly values.

2.5 Scenario analysis

The need for air quality prediction associated with transportation policies is important for health impact assessment (Bhalla et al., 2014; De Nazelle et al., 2011). We estimated the current NO₂ concentrations linked to driving trips using travel data for the year 2008 as the base year. Then, a transit scenario was introduced which evaluates the effects of major public transit

expansions throughout the region. We assumed that all of these expansions would occur in 2008 without projecting a future business as usual scenario. The reason for assessing a policy scenario in the current base year rather than in a future year is to control for all other factors such as population growth as well changes in land-use and socio-demographics. Since the thrust of this paper is to test the robustness of our modelling tool rather than to explore feasible policies and timelines, we are interested in an extreme scenario that helps us assess the response of the model. For this purpose, we have obtained information on all of the public transit projects that are currently planned or are under construction. These include subway extensions, light rail, and regional rail proposals included within Montreal region's land-use and sustainable transportation plan for 2031. The plan is entitled Plan Métropolitain d'Aménagement et de Développement (PMAD) and includes three main dimensions: transportation, land-use, and environmental protection.

Using the travel demand and mode choice models, we re-estimated trip decisions and modes. With the new transit proposals, our transit travel times for the trips originating or with destinations in areas within 1km of new stations were reduced by about 60 to 100% of the original transit travel times. This reduction in travel time by transit is expected to lead to an increased ridership.

2.6 Evaluating population exposure to air pollution

Traditional epidemiologic studies often rely on average air pollutant concentrations at the residential location as a potential predictor for the odds of air pollution-related health effects. In this study, we estimated a daily NO₂ exposure based on individuals' trajectories and activity locations. To demonstrate our methodology, we used data from the origin-destination survey. We extracted all 29,272 individuals who underwent single mode trips which started and ended at home as drivers or passengers (90,000 trips). Based on the traffic assignment model, we assigned a path to each trip. Then, hourly NO₂ surfaces were used to assign NO₂ to the path. The NO₂ exposure over a selected path was calculated as the weighted average NO₂ concentration at every individual road segment throughout the trip. Concentrations of NO₂ were also extracted for each activity location based on the duration of the individual's activity at each location and the NO₂ concentration at each time period. Then, for every individual, daily exposure was calculated as

the average NO₂ concentration resulting from the NO₂ concentrations at all activity locations and trips (Eq. 1).

$$C_{NO_2}^i = \frac{\sum_{t=1}^n \left(\sum_{k=1}^m \left[C_{NO_2-t}^k \times t_{trip}^k(t) + C_{NO_2-s}^k \times t_{stop}^k(t) \right] \right)_t}{N} \quad (1)$$

i is individual,

n is the total number of time steps per day (for hourly time steps *n*=24),

t is indicator for time step,

m is the total number of locations per individual trip,

k is indicator for location number,

N is the sum of trip and stop durations (*N*=24 since the exposure is computed for the entire day),

$t_{trip}^k(t)$ is the time an individual spent in every trip,

$t_{stop}^k(t)$ is the time an individual spent at every stop or activity location,

$C_{NO_2-s}^k(t)$ is the NO₂ concentration during the stop at the end of trip *k* at time *t*,

$C_{NO_2-t}^k(t)$ is the NO₂ concentration for part of trip *k* at time *t*.

3. Results and discussion

3.1 Meteorology

The CALMET simulated wind fields were compared with observed data at Mirabel airport. Fig. 4 presents side-by-side, two windroses plotted based on CALMET output and observed data for one week in April. In general, CALMET captures reasonably well the most frequent winds observed at the station (spearman correlations for wind speed and wind direction are 0.64 and 0.82 respectively). Northwestern winds were somehow under-represented by the model. Moreover, CALMET predicted lower wind speeds. Similar results were reported in other studies whereby overall wind directions and speeds were well captured by the model but the frequency of high wind speeds is lower in simulated data (Hatzopoulou and Miller, 2010; Klausmann A.M, 2005).

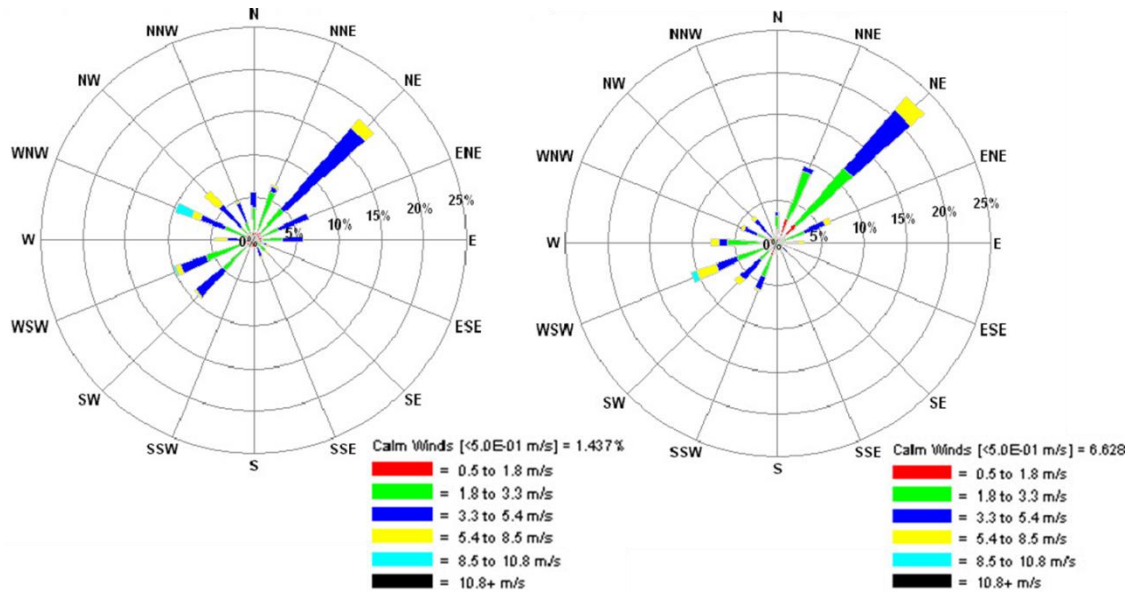


Fig. 4. Simulated winds using CALMET (left) and observed winds at Mirabel airport (right) for April 7-14, 2008.

3.2. Dispersion

Fig. 5 presents the simulated NO_2 concentrations over 24 hours. The hourly data in this map represent the average NO_2 in each hour across the four weeks of simulation (in January, April, August, and October). This represents a long-term average concentration in each hour.

The simulated weekly averages for NO_2 in January, April, August, and October are presented in Fig 6. NO_2 concentrations for January, April, August and October range between 6.5-23.0 ppb, 4.4-25.1 ppb, 1.06-29.6 ppb and 3.7-31.7 ppb, respectively. The minimum value for NO_2 is higher in January and April while the maximum value is higher in August and October. Also, Fig. 6 illustrates that the four-week average NO_2 concentration for the study region ranges between 4 ppb and 17 ppb. Note that these concentrations reflect the contribution of traffic only, without the contribution of other sources (industrial, residential). In addition, the contribution of traffic does not include truck movements.

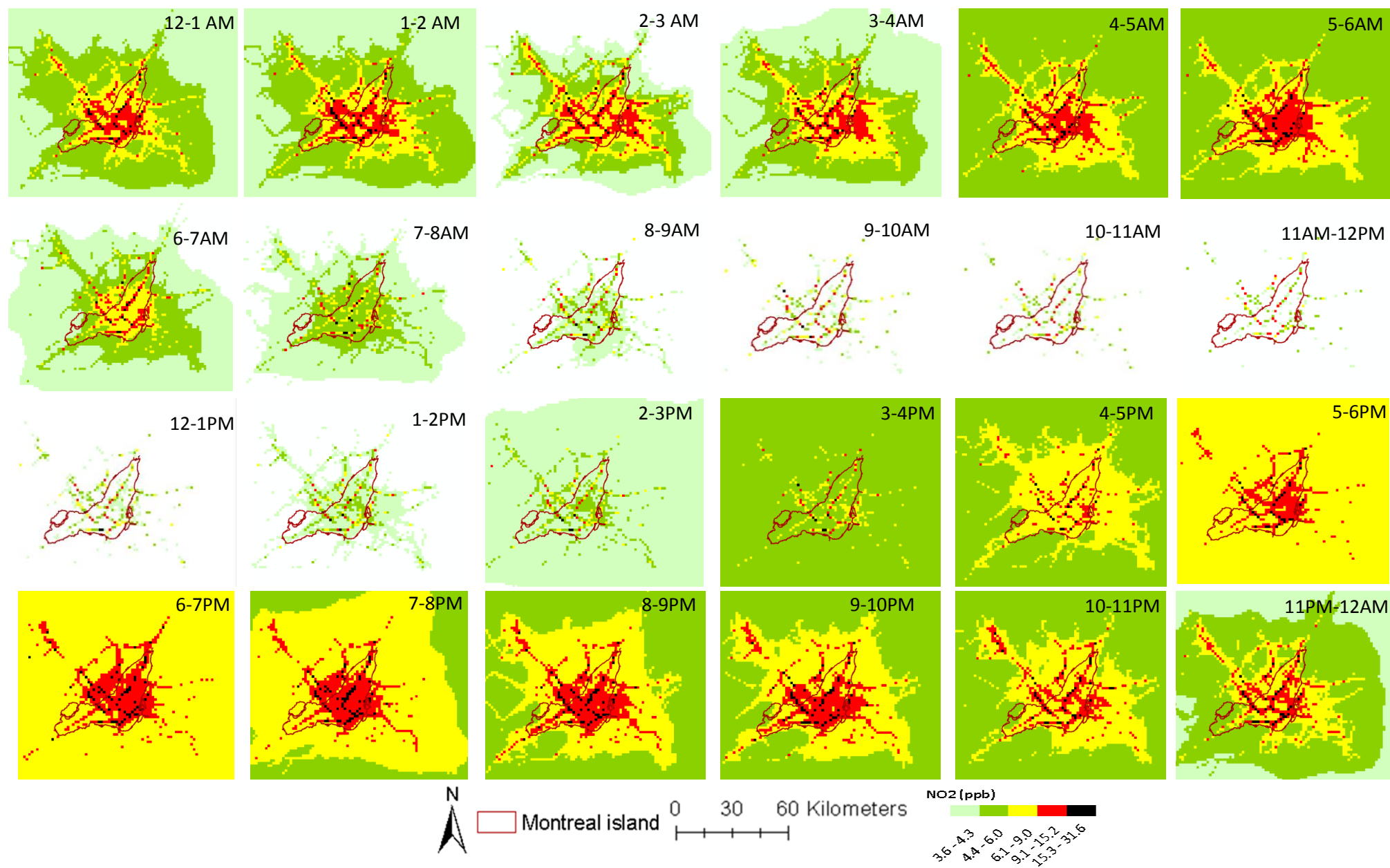


Fig. 5. Hourly simulated NO₂ concentrations (ppb), starts form 12 am (top left image) to 11 pm (downright image). The red and green areas show the highest and lowest concentrations, respectively.

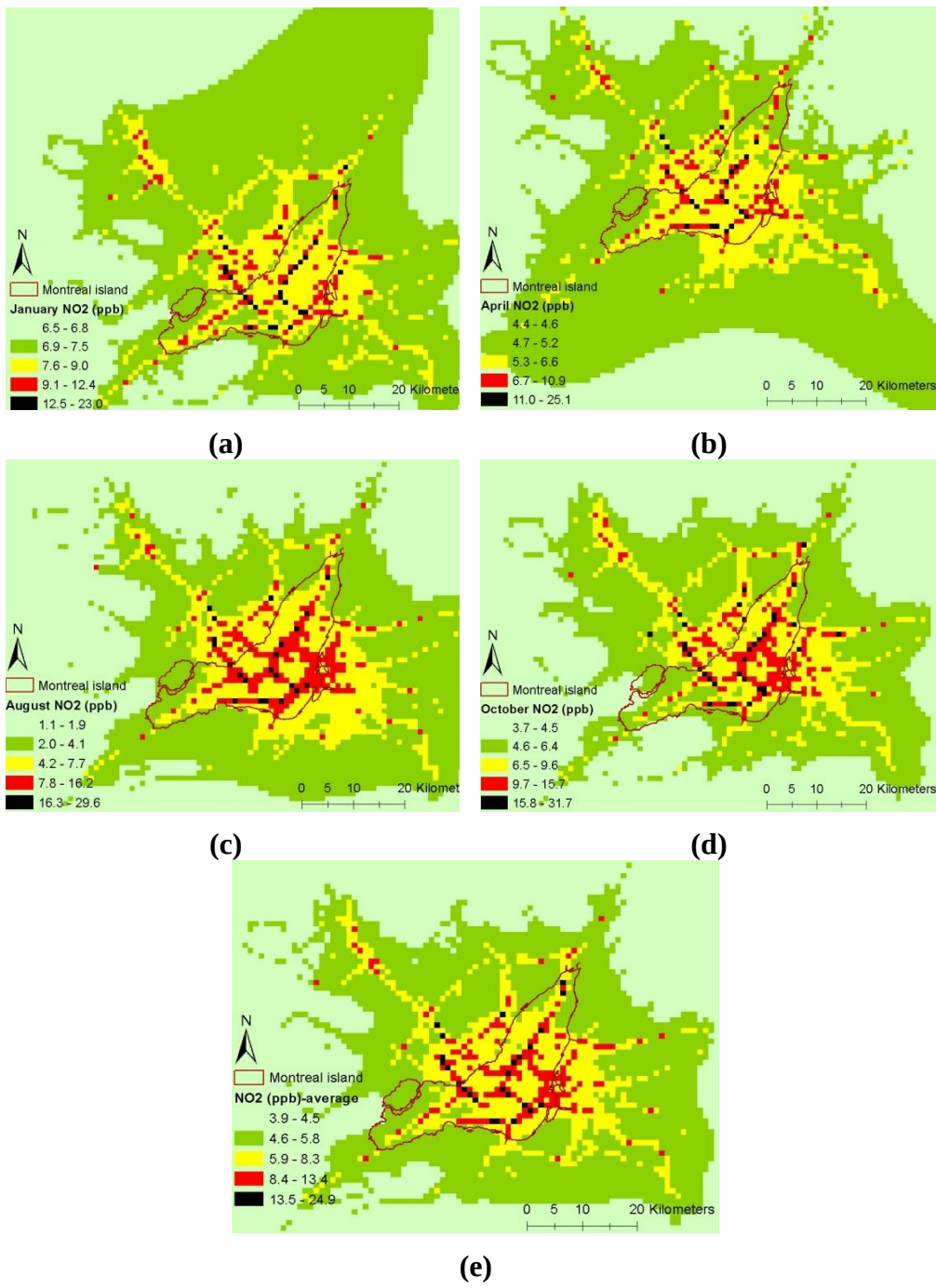


Fig. 6. Weekly (a, b, c, d) and long-term (four-weeks, e) average simulated NO_2 concentrations.

The validation of simulated concentrations was conducted along various dimensions. Our validation against observed concentrations entailed matching our simulated concentrations against data from nine fixed monitoring stations in Montreal for 168 hours of each week in January, April, August and October. We then calculated the Spearman correlations between the hourly observed and simulated NO₂ concentrations at the 9 stations. As presented in Table 2, the correlations vary among weeks and stations: Spearman correlation coefficients range from 0.55 - 0.78 for January, 0.45 - 0.83 for April, 0.02 - 0.70 for August, and 0.24 - 0.69 for October. The lower correlations noted in the month of August are predominantly due to the meteorology and generally lower wind speeds observed during this period, with days of extremely low wind speeds. Tables I to IV in the supplementary material present frequency distributions of observed and simulated concentrations. We also estimated correlations for each station based on pooled data for the four weeks and observed a range of correlations between 0.39 and 0.74. Finally, we computed the correlation between the averages for the four weeks of simulation with the averages of the measured concentrations at each station. This leads to 10 simulated vs 10 measured values, we obtain a spearman correlation coefficient of 0.78, significant at the 0.05 level (2-tailed), picking up the robustness of our model at capturing the spatial variability in ambient NO₂.

In addition, a set of performance measures were estimated for all selected stations as shown in Table 3. The fractional mean bias (*FB*) indicates that the model performance is acceptable for the selected simulation periods (less than 0.65). We also observe a high variability in *FB* across the seasons and stations, ranging from a minimum of -0.38 (which indicates an overprediction at a single station in October) to a maximum of 1.13 (which indicates underprediction at a single station in April). The *FB* measures the mean relative bias and indicates only systematic errors. In contrast, *NMSE* and *NAD* are measures of mean relative scatter and reflect both systematic and random errors. If a model systematically overpredicts or underpredicts, but still has the same scatter as the observations, the values for *NMSE* and *NAD* would equal 0, an ideal result. As indicated in Table 1, the model performance is also acceptable in terms of the Normalised Mean-Square Error (*NMSE*<6) and Normalized Absolute Difference (*NAD*<0.5).

Finally, we compared our simulated NO₂ surface (for the four weeks in 2008) with two land-use regression (LUR) surfaces developed previously for Montreal (Crouse et al., 2009; Deville-Cavellin et al., 2015). The surface developed by Crouse et al. (2009) reflects an annual mean for 2005/2006 while the surface developed by Deville-Cavellin et al. (2015) reflects an

annual mean for 2014. Between 2005 and 2015, Montreal did not witness significant changes in land-use therefore it is expected that the spatial variability in NO₂ remains relatively stable. The correlation between our dispersion surface and the LUR developed by Crouse et al. (2009) is 0.78 while that with the LUR developed by Deville-Cavellin et al. (2015) is 0.76, indicating reasonably strong correlation between the three surfaces.

Table 2. Correlations between simulated and observed NO₂ concentrations at air quality stations in Montreal.

Spearman Correlation	Station Number								
	1	3	7	12	28	29	61	66	68
January	0.71	0.55	na	0.78	0.65	0.78	0.71	0.76	0.66
April	0.55	0.55	0.53	na	0.45	0.59	0.59	0.83	0.70
August	0.70	0.56	0.63	0.48	0.02	0.46	0.10	na	0.37
October	0.63	0.56	0.53	na	0.24	0.69	0.30	0.43	0.56
Pooled data	0.62	0.55	0.62	0.65	0.40	0.74	0.39	0.65	0.47

NA indicates that no observations were recorded by The City of Montreal for that pollutant

Table 3. Model performance across the four seasons.

Performance measures	January	April	October	August
Normalized absolute difference (<i>NAD</i>)	0.39	0.34	0.28	0.40
Fractional mean bias (<i>FB</i>)	0.23	0.67	0.46	0.56
Normalized mean-square error (<i>NMSE</i>)	1.23	1.45	1.01	6.92

3.3 Scenario analysis

We observed a modal shift towards transit especially for the trips that are affected by the new public transit alternatives (this increase is 1.86% for the total population and 16.65% for the population with high access to the new transit stations). Subsequently, we observed a decrease in traffic volumes on the road network and increases in speed. The 2008 transit scenario resulted in a reduction in total NO_x emissions of 1.9% compared to the base case; some roads experienced reductions by more than half. Recall that by applying the transit policies in 2008 rather than in a future year, we do not face the confounding effects of lower emissions due to improved vehicle technology. Fig. 7 illustrates the difference in hourly NO_x emission rates between the 2008 scenario and the base scenario, highlighting that the larger reductions occur during peak periods where traffic congestion is highest.

Fig. 8 compares the simulated NO₂ concentrations for 2008 base case and transit scenario. These maps represent the average NO₂ concentrations across the four weeks of simulation (in January, April, August and October). Beyond the overall decrease in NO₂ concentrations, we observe that people living near major roads enjoy the highest decrease. The mean NO₂ concentration was reduced by 3.6%. This decrease is more than twice the reduction in mean NO_x emissions (1.9% compared to the base case) illustrating the importance of dispersion modelling when evaluating the air quality effects of various policies.

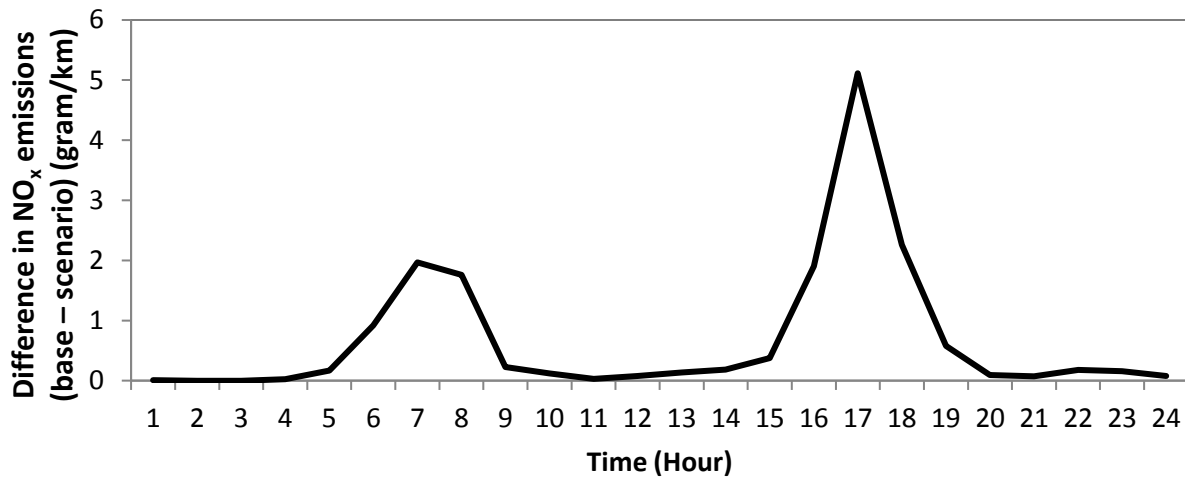


Fig. 7. Hourly difference between baseline and scenario NO_x emissions in gram per unit of length (g/km) for Montreal.

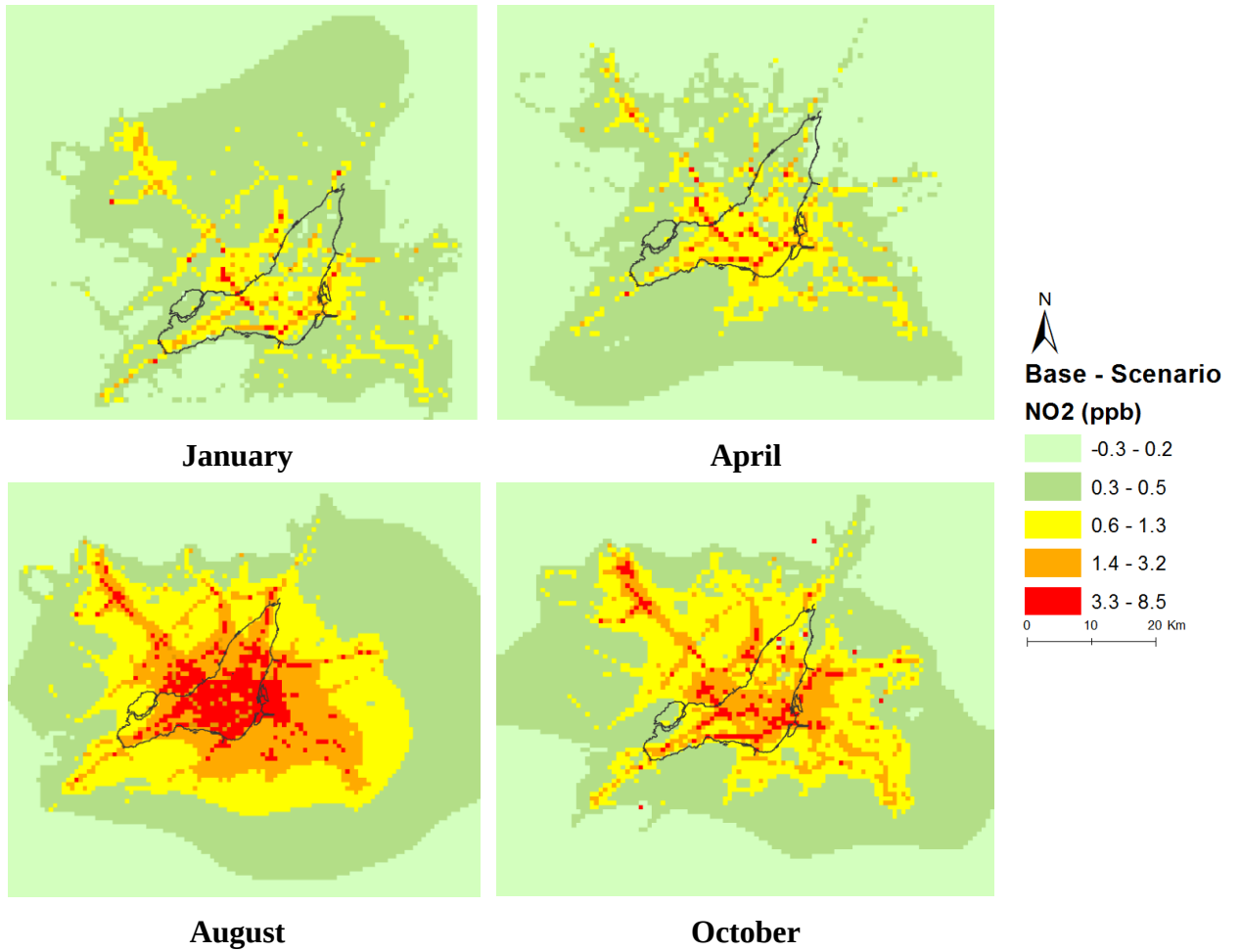


Fig. 8. Difference between base case and transit scenario for weekly average simulated NO₂ concentrations

3.4 Exposure analysis

After simulating NO₂ concentrations across the study domain, we estimated a 24-hour average exposure for a sample of the population based on individual trajectories and daily activities. Individual exposures were estimated in the base and transit scenarios. Fig. 9 illustrates the frequency distributions of individual exposures under the base case and the transit scenario for the average of four weeks. Compared to the baseline, the transit scenario resulted in substantially lower daily NO₂ exposures. For example, in the base case, the percentage of individuals with a daily exposure exceeding 8ppb is 14% while this percentage decreases to 1.7% in the transit scenario. In the base case, around half of the sample (53%) is exposed to NO₂ concentrations above 6 ppb while this percentage drops to less than 13% in the transit scenario. Fig. 10 presents the frequency distributions of NO₂ concentrations at the home locations of individuals in our sample under the base case and the transit scenario. Compared to the base case,

the transit scenario resulted in a mean reduction of 26.4% in NO₂ concentrations at the home locations of individuals in the sample.

In summary, we observe that the percentage reduction in NO_x emissions (1.9%) across the road segments and NO₂ concentrations across the grid-cells in the study domain (3.6%) are far from proportional to the decrease in average NO₂ concentrations at the home locations of participants (26.4%), or to the decrease in daily exposures based on mobility patterns (20.8%). We also observe a difference in the daily exposures based on trips and activity locations compared to the daily mean concentration at the home location indicating that the latter slightly overestimate the improvements associated with transit investments. The difference between the expected decreases in NO₂ concentrations and daily NO₂ exposures illustrates the power of our integrated emission dispersion and exposure model in policy analysis. This is particularly true when these models are further used for health impact assessments therefore translating exposures to health effects. The large discrepancy between NO₂ daily concentrations across the study area and NO₂ daily exposures clearly indicates that the evaluation of the effects of transportation policies on air quality should include an analysis of population exposure.

In order to better understand the spatial variability in ambient NO₂ reductions as a result of the transit scenario and compare them with reductions in NO₂ exposures across individuals' home locations, we developed two maps illustrated in Fig. 11. Fig. 11a presents the reductions in NO₂ exposures computed as $(\text{NO}_2 \text{ exposure in Base} - \text{NO}_2 \text{ exposure in Scenario}) / \text{NO}_2 \text{ exposure in Base}$. Fig. 11b presents the reductions in ambient NO₂ concentrations computed as $(\text{NO}_2 \text{ in Base} - \text{NO}_2 \text{ in Scenario}) / \text{NO}_2 \text{ in Base}$. Starting with Fig. 11b, we clearly observe higher reductions in NO₂ concentrations in downtown areas due to the presence of transit and active transportation facilities affecting mode choice. However, reductions in exposure (Fig. 11a) turned out to be higher for individuals living in peripheral areas in light of their mobility patterns, visiting the areas with highest reductions in NO₂ concentrations and therefore significantly reducing their daily exposure. In fact, Fig. 11a illustrates what we have already quantified at a region-level, that reductions in exposures are higher than reductions in ambient air quality. Reductions in exposures are also more expansive as seen by the large area in the warmer colours (Fig. 11a).

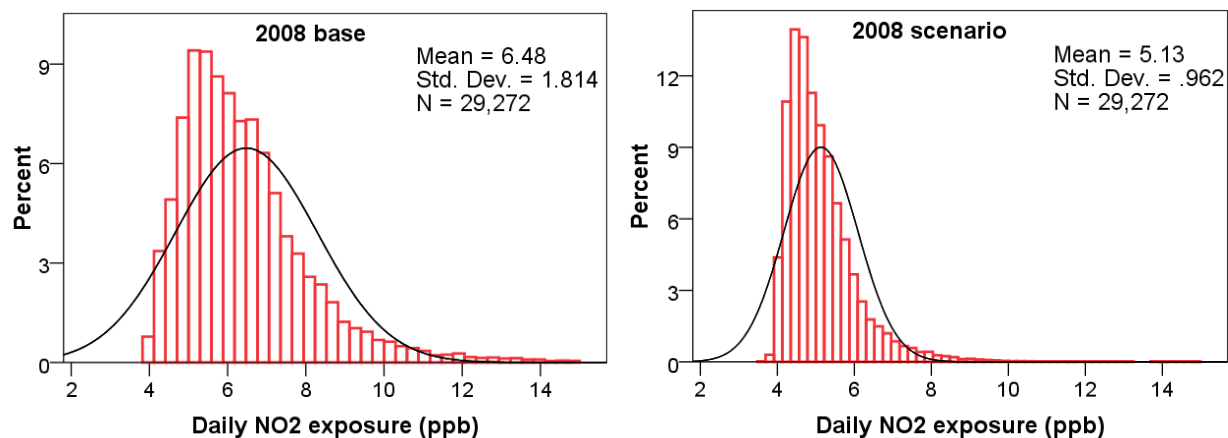


Fig. 9. Frequency distributions for daily NO₂ exposures for 2008 base (left) and scenario (right).

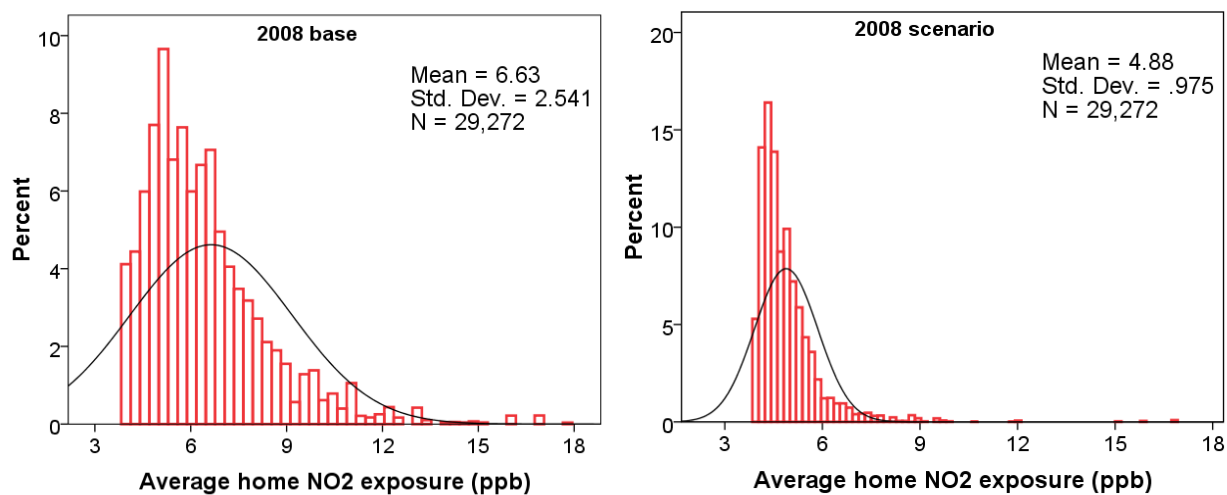


Fig. 10. Frequency distributions for daily NO₂ concentrations at home locations of individuals in the sample for 2008 base (left) and scenario (right).

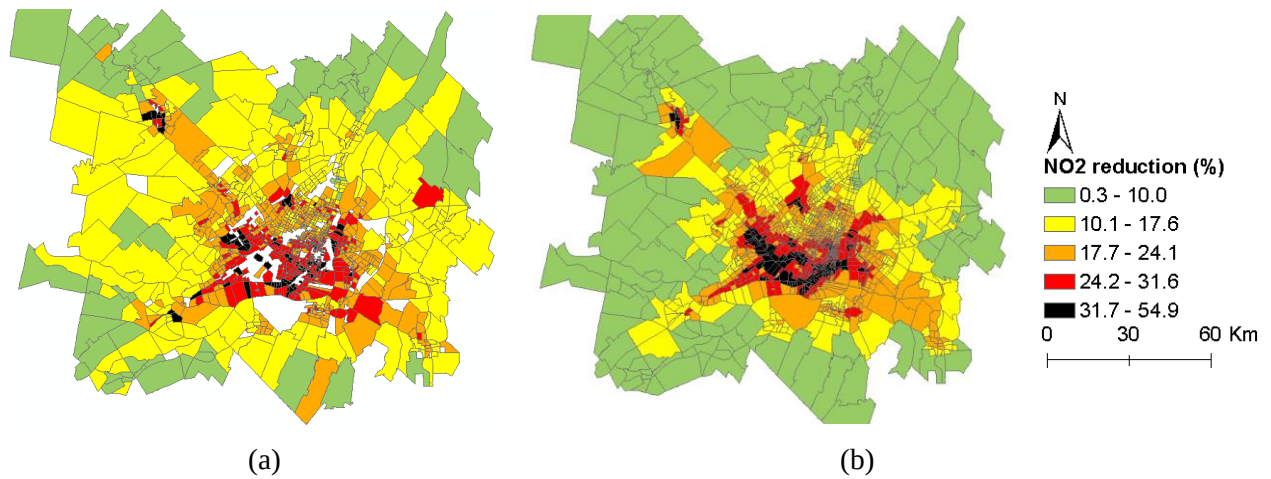


Fig. 11. Reduction in NO₂ concentrations (b) and daily NO₂ exposure (a) mapped across traffic analysis zones (the white zones represent the places with no individuals in our sample). Traffic analysis zones were chosen for better visualisation

4. Conclusion

This paper describes the development and validation of a travel demand, emission, and dispersion model for the Montreal Metropolitan Area. The simulated meteorological variables and NO₂ concentrations were compared with the corresponding observed values at different stations within the study area. In general, the meteorological model captures reasonably well the most frequent winds observed at the meteorological stations. This study also showed that simulated concentrations can be reasonably correlated with the observed data when detailed meteorological and dispersion characteristics are accounted for. However, the model underestimates observed concentrations mainly due to the fact that the emissions of trucks and residential/commercial point sources were not accounted for.

The modelling system was used to evaluate the impact of an extensive regional transit improvement strategy revealing reductions in NO₂ concentrations by about 3.6% compared to the base case across the territory in addition to a decrease in the frequency and severity of NO₂ hot spots. Finally, a methodology for assessing individuals' daily exposure is developed and we observed a reduction of about 21% in daily exposures of individuals compared to the base case. The difference between reductions in the mean NO₂ concentration across the study domain and the mean NO₂ exposure across the sample population results from the fact that NO₂ concentrations dropped largely in the areas which attract the most individuals and where most people live.

The strength of our modelling system is that it allows us to investigate the impacts of various policies on travel, emissions, air pollution, and exposure therefore illustrating the non-

linearity of these effects. Evaluating policies solely based on their emission reduction potential may overestimate or underestimate their effect on air quality. Similarly, simulating air quality as a result of various policies does not allow us to infer the full effects on population exposure. Air quality improvements may occur in the least or the most populated and/or visited areas, spatial variability matters. Our model system is primarily geared towards policy appraisal of transport plans, allowing policy evaluation to move beyond traditional performance measures putting a greater emphasis on health.

A number of limitations are associated with this study, some of which are the objective of future model developments. First, we only simulate a single day for travel. This limitation is an inherent downside of most travel surveys since they capture the daily travels of a single day at the household level. Despite this limitation, we conducted dispersion over various days and seasons in order to capture the very important effect of meteorology. Under the same travel and traffic patterns, meteorological conditions may lead to largely different ground-level concentrations. Another limitation is associated with the lack of commercial vehicle movements therefore our model includes household travel only. This limitation is partially overcome by the fact that our model will be mostly used to investigate the effects of scenarios affecting household travel. Finally, our dispersion model incorporates basic NO₂ chemistry at the expense of an improved dispersion algorithm. Proper accounting for all transformations affecting NO₂ can only be done with a chemical transport model.

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Supplementary Materials

I- Descriptive statistics for observed and predicted NO₂ concentrations (ppb) at 9 air quality stations (April).

Statistical index	Stations																	
	66		68		28		61		1		29		7		3		12	
	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs
N	167	92	167	164	167	167	167	168	167	168	167	168	167	168	167	168	167	-
Mean	5.29	15.25	10.97	15.84	17.23	19.00	6.78	23.86	5.31	12.97	5.47	15.72	5.36	11.76	4.73	9.53	8.78	-
Std. Error of Mean	0.64	1.54	0.85	1.07	1.09	0.89	0.67	0.88	0.61	0.82	0.62	0.85	0.58	0.73	0.58	0.51	0.60	-
Median	1.18	8.81	7.02	11.15	15.21	15.87	3.30	20.57	1.40	9.34	1.57	13.07	1.70	8.41	0.92	7.57	6.38	-
Std. Deviation	8.25	14.79	10.95	13.74	14.07	11.45	8.62	11.44	7.93	10.67	7.99	10.97	7.56	9.46	7.44	6.56	7.73	-
Variance	68.01	218.77	119.92	188.89	197.88	131.01	74.23	130.83	62.92	113.91	63.80	120.29	57.11	89.41	55.37	43.06	59.76	-
Minimum	0.04	2.09	0.13	1.68	0.07	4.87	0.36	7.05	0.12	2.65	0.05	3.03	0.04	1.55	0.02	2.02	0.24	-
Maximum	47.93	51.13	61.32	59.10	74.11	55.01	52.08	62.96	47.97	52.63	47.35	50.16	50.19	46.15	47.60	35.64	30.61	-

- Missing data

II- Descriptive statistics for observed and predicted NO₂ concentrations (ppb) at 9 air quality stations (August).

Statistical index	Stations																	
	66		68		28		61		1		29		7		3		12	
	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs
N	167	-	167	167	167	53	167	167	167	163	167	168	167	168	167	164	167	167
Mean	4.92	-	18.43	13.25	28.10	13.45	9.22	15.76	6.18	9.41	5.00	11.15	6.45	9.22	3.25	8.41	8.24	12.59
Std. Error of Mean	0.56	-	1.09	0.48	1.51	0.77	0.82	0.45	0.62	0.40	0.49	0.42	0.58	0.42	0.29	0.38	0.83	0.41
Median	1.34	-	13.80	12.44	26.46	12.46	5.65	16.56	2.90	8.36	2.39	10.65	3.59	8.22	1.75	7.27	3.86	12.06
Std. Deviation	7.30	-	14.06	6.14	19.52	5.63	10.58	5.82	8.08	5.13	6.29	5.51	7.50	5.50	3.74	4.91	10.71	5.35
Variance	53.29	-	197.74	37.72	381.18	31.73	111.93	33.87	65.22	26.34	39.56	30.32	56.26	30.20	13.96	24.13	114.65	28.63
Minimum	0.05	-	1.03	2.52	0.13	5.96	0.36	4.32	0.27	1.20	0.10	1.84	0.10	0.53	0.03	1.74	0.57	3.35
Maximum	35.52	-	61.94	27.63	63.13	31.99	58.97	28.65	40.05	23.06	36.25	25.79	39.48	25.90	16.84	22.52	57.76	28.11

- Missing data

III- Descriptive statistics for observed and predicted NO₂ concentrations (ppb) at 9 air quality stations (January).

Statistical index	Stations																	
	66		68		28		61		1		29		7		3		12	
	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs
N	164	167	167	167	165	167	168	167	168	167	168	167	167	-	167	167	169	169
Mean	7.16	17.20	11.39	19.62	22.45	18.28	10.12	20.15	7.80	16.50	7.70	17.74	7.98	-	7.16	10.11	8.78	17.52
Std. Error of Mean	0.55	0.88	0.63	0.92	1.45	0.69	0.65	0.65	0.56	0.82	0.59	0.89	0.60	-	0.56	0.57	0.60	0.70
Median	4.63	15.75	11.06	19.51	16.65	17.43	6.50	20.08	5.08	15.38	4.81	14.93	4.91	-	4.21	8.62	6.38	17.13
Std. Deviation	7.07	11.23	8.10	11.95	18.72	8.83	8.45	8.41	7.26	10.58	7.65	11.57	7.71	-	7.24	7.33	7.73	9.08
Variance	49.96	126.13	65.64	142.69	350.44	78.03	71.48	70.79	52.73	111.92	58.45	133.92	59.44	-	52.44	53.77	59.76	82.53
Minimum	0.03	2.09	0.08	2.99	0.23	4.62	0.46	5.38	0.17	2.08	0.05	2.00	0.32	-	0.10	0.48	0.24	3.83
Maximum	24.16	48.56	42.44	85.68	72.10	39.22	35.38	40.46	25.64	36.74	29.04	41.88	31.81	-	25.67	23.62	30.61	34.36

- Missing data

IV- Descriptive statistics for observed and predicted NO₂ concentrations (ppb) at 9 air quality stations (October).

Statistical index	Stations																	
	66		68		28		61		1		29		7		3		12	
	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs
N	168	163	168	168	168	188	168	167	168	167	168	188	168	168	168	166	-	-
Mean	5.47	12.72	15.25	16.53	13.16	17.82	31.65	16.37	7.83	15.19	6.59	14.02	9.11	11.72	5.57	11.72	10.57	-
Std. Error of Mean	0.45	0.53	1.12	0.64	1.15	0.47	1.69	0.50	0.73	0.59	0.51	0.65	0.77	0.46	0.46	0.46	0.96	-
Median	3.67	11.94	9.77	15.12	7.13	16.91	26.46	15.47	4.96	13.65	4.22	11.44	5.12	10.44	3.63	10.44	6.07	-
Std. Deviation	5.80	6.83	14.48	8.23	14.87	6.00	21.82	6.47	9.38	7.57	6.55	8.41	9.96	5.89	5.92	5.89	12.41	-
Variance	33.68	46.62	209.67	67.77	221.21	36.06	476.07	41.91	88.05	57.26	42.94	70.70	99.11	34.72	35.04	34.72	153.91	-
Minimum	0.03	1.10	0.43	3.86	0.33	7.14	0.83	4.82	0.14	2.73	0.06	2.35	0.25	1.86	0.08	1.86	0.36	-
Maximum	23.21	37.69	59.32	40.90	66.86	36.26	76.63	35.27	60.20	39.04	27.83	43.21	56.68	27.08	24.09	27.08	66.79	-

- Missing data