Journal of Environmental Management 168 (2016) 133–141

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Mapping real-time air pollution health risk for environmental management: Combining mobile and stationary air pollution monitoring with neural network models

Matthew D. Adams*, Pavlos S. Kanaroglou

School of Geography and Earth Science, McMaster University, Main St. West, Hamilton, ON, 1280, Canada

ARTICLE INFO

Article history:
Received 30 April 2015
Received in revised form
7 December 2015
Accepted 10 December 2015
Available online 17 December 2015

Keywords:
Risk mapping
Air pollution modelling
Particulate matter
Nitrogen dioxide
Neural networks
Land use regression

ABSTRACT

Air pollution poses health concerns at the global scale. The challenge of managing air pollution is significant because of the many air pollutants, insufficient funds for monitoring and abatement programs, and political and social challenges in defining policy to limit emissions. Some governments provide citizens with air pollution health risk information to allow them to limit their exposure. However, many regions still have insufficient air pollution monitoring networks to provide real-time mapping. Where available, these risk mapping systems either provide absolute concentration data or the concentrations are used to derive an Air Quality Index, which provides the air pollution risk for a mix of air pollutants with a single value. When risk information is presented as a single value for an entire region it does not inform on the spatial variation within the region. Without an understanding of the local variation residents can only make a partially informed decision when choosing daily activities. The single value is typically provided because of a limited number of active monitoring units in the area. In our work, we overcome this issue by leveraging mobile air pollution monitoring techniques, meteorological information and land use information to map real-time air pollution health risks. We propose an approach that can provide improved health risk information to the public by applying neural network models within a framework that is inspired by land use regression. Mobile air pollution monitoring campaigns were conducted across Hamilton from 2005 to 2013. These mobile air pollution data were modelled with a number of predictor variables that included information on the surrounding land use characteristics, the meteorological conditions, air pollution concentrations from fixed location monitors, and traffic information during the time of collection. Fine particulate matter and nitrogen dioxide were both modelled. During the model fitting process we reserved twenty percent of the data to validate the predictions. The models' performances were measured with a coefficient of determination at 0.78 and 0.34 for $PM_{2.5}$ and NO_2, respectively. We apply a relative importance measure to identify the importance of each variable in the neural network to partially overcome the black box issues of neural network models.

1. Introduction

The management of air pollution is challenging due to the complexity of sources, insufficient resources for monitoring and enforcement, and issues in defining policy (Krupnick, 2008). These problems, along with rapid economic growth in many countries, have led to air pollution exposure as a global environmental management concern (Evans et al., 2013; Van Donkelaar et al., 2010). Global management issues cannot be easily remediated and many steps must be taken to minimize impacts. Strategies for reducing air pollution exposure can include capping or limiting air pollution emitters (Wolff, 2014), improvements to technology to reduce or eliminate emissions (Oltra and Saint Jean, 2009), and providing awareness of health risks to citizens to potentially allow them to change their behaviour to limit exposure (Plaia and Ruggieri, 2010). Improvements to technology, and policies to limit or cap air pollution emitters can be slow to implement or they may not be aligned to the values of the state. For example, capping emissions or requiring industries to implement new technologies

* Corresponding author.
E-mail address: adamsmd@mcmaster.ca (M.D. Adams).

http://dx.doi.org/10.1016/j.jenvman.2015.12.012
0301-4797/

may reduce economic output. Providing air pollution health risk information is a practical first step for management that does not require any change to current emissions and if implemented effectively, should provide health benefits.

Globally, cities are rapidly expanding. Many cities are developing with increased density in the core, while others are expanding into the surrounding landscape (suburbs) (Schneider and Woodcock, 2008), which changes the density and location of emissions within the city. As well, these urban centres have land use policies that often isolate pockets of industrial and commercial activities. The combined variations in land uses and meteorological conditions can result in local space-time variation in urban air pollution concentrations (Johnson et al., 2010; Tang et al., 2013). Modellers expend significant effort in designing techniques for the identification of these factors. Geographic Information System (GIS) tools play a prominent role for enhancing efforts in space-time modelling (Briggs, 2006). Data for the modelling is commonly provided through a network of monitoring instruments that are installed within the region and record concentrations over a time-interval that is defined by the operator. Optimal location theory can be applied when siting the instruments to ensure spatial variability is observed (Ainslie et al., 2009). Epidemiological studies identify that space-time variation must be accounted for to elicit accurate estimates (Ozkaynak et al., 2013). Long-term exposure is often estimated with land use regression models, opposed to traditional interpolation techniques (e.g. kriging and inverse distance weighted interpolation) because of insufficient monitor density to capture the spatial variability. These models incorporate land use information to provide additional knowledge about emission source potential to improve modelling the spatial variation.

To help citizens manage their air pollution exposure and resulting health risks, some nations across the world have established programs to inform citizens to the risks of air pollution in their region. This risk information is either provided as the concentrations of the pollutants or as an index of air quality, which at the most basic definition translates a cocktail of air pollutants onto a scale that can be interpreted by the public. These air quality indexes (AQI) vary in their approach for translating pollutant concentrations onto the scale, because the scales are determined by regional policies (Plaia and Ruggieri, 2010). For example, Canada, has developed and adopted an Air Quality Health Index (AQHI), which is an 11-point scale that is a non-linear combination of particulate matter 2.5 microns or smaller in aerodynamic diameter ($PM_{2.5}$), nitrogen dioxide (NO_2), and ozone (O_3) (Steib et al., 2008). AQHI values in Canada are presented to the public through the national and local news outlets and allow citizens to make informed decisions about their activity level for the day based on their personal health risk. Users in the high-risk category, such as the elderly, may rely on this information to plan their activity for the day. The information the public is presented with are single representative values for the entire city where they reside. Unfortunately, these representative values do not account for any spatial variation that may occur within the city.

Real-time systems that map air pollution are limited and have yet to incorporate land use information in their models. Information that has been demonstrated as critical to modelling long-term air pollution exposure (Hoek et al., 2008). In this paper, we present two models for real-time air pollution mapping, which can be utilized to map air quality heath indices. The technique leverages approaches from land use regression modelling within neural network models for the spatial prediction of air pollutants across Hamilton, Ontario, Canada. The prediction of air pollution concentrations across space is based on a number of data including mobile and stationary air pollution monitoring data, meteorological data, land use characteristics, and traffic information. The value in these models is they require few fixed location stationary monitoring units, which are expensive to operated, while providing improved the health risk information to the general public in a region beyond an individual representative value.

2. Methods

2.1. Study area

The City of Hamilton, Ontario, Canada is located at the western tip of Lake Ontario, which is a body of water that bridges Canada and the United States of America. Hamilton is Canada's 9th and Ontario's 3rd largest city with a population of 520,000 (Statistics Canada 2012). Between the census years of 2006 and 2011 Hamilton's population increased by 3%. The city is divided into an upper and lower city by a 90 m escarpment. Hamilton's economic prosperity relied on its steel industry, which began in the early 20th century. Access to Lake Ontario benefitted the industry from low-cost transportation and the use of water as cooling medium. World War II brought an economic boom to Hamilton's steel sector; however, the jolt to the economy resulted in air, water and soil contamination. During steel production air pollution is a result of the processing of steel that begins with creation of pig iron, which consists of iron ore, coke (residue after the distillation of bituminous coal), and limestone. This processing releases criteria air contaminates including Nitrogen Oxides, Carbon Monoxide, Sulphur Dioxide, Particulate Matter, and Volatile Organic Compounds, which are monitored in Canada under the National Pollutant Release Inventory. Air pollution issues are still prevalent in Hamilton, but are now due to a diverse set of sources (Adams et al., 2012).

Air pollution concerns have led to multiple air pollution studies in Hamilton (Adams et al., 2012; Jerrett et al., 2001; Kanaroglou et al., 2013; Wallace and Kanaroglou, 2008; Wallace et al., 2009). Two air quality monitoring networks operate in Hamilton. The first has four monitors near and within Hamilton and is operated by the provincial ministry of the environment; the second network has 14 monitors and is operated in partnership with the local industries, focussing to the northern portion of the city. In Fig. 1, we present a map of industrial lands within Hamilton along with the fixed monitors of the provincial network, which record the pollutants used in the AQHI. Hamilton was chosen for this study due to the variation identified across the city by mobile air pollution monitoring (Adams et al., 2012).

2.2. Modelling

Air pollution health risk is typically presented to the public as individual values for a city or region, excluding any spatial variation. In Fig. S1 in the supplemental material of this paper, we present two air quality health index maps for Alberta and British Columbia in Canada, both of which present air quality health risk at single geographical points. This approach provides a general overview of the air pollution, but it can be more informative if the spatial variation within the cities became available. The challenge for many locations is the limited number of monitoring sites that renders spatial interpolation inappropriate. For example, Hamilton has four monitoring stations that could be used to determine the AQHI.

Mobile air pollution monitoring technologies allow for a greater spatial coverage of a city compared to traditional fixed stations. Their limitation is that the monitoring data do not provide a continuous time-series of observations. These discontinuous time-series data can become useful with the use of appropriate modelling techniques.