Science of the Total Environment 598 (2017) 168–178

Contents lists available at ScienceDirect

Science of the Total Environment

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

Modelling drivers and distribution of lead and zinc concentrations in soils of an urban catchment (Sydney estuary, Australia)

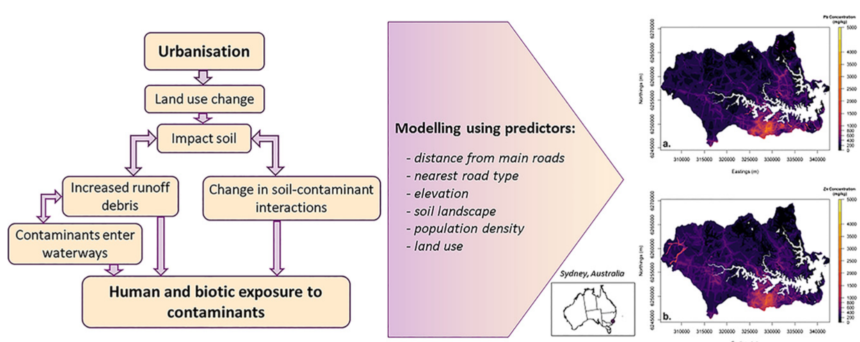
L.E. Johnson [a,*], T.F.A. Bishop [a], G.F. Birch [b]

[a] School of Life and Environmental Sciences, The University of Sydney, Australia
[b] School of Geosciences, The University of Sydney, Australia

HIGHLIGHTS

- Mapping soil contamination with known uncertainty improves key management decisions.
- Soil data and covariates were used in linear mixed models to predict lead and zinc distribution.
- Distributions were driven by traffic, soil landscape, elevation, land use (Zn), population (Pb).
- Highest proportions of observed lead concentrations existed in residential areas.
- Predicted lead exceeded the set guide value across the catchment whereas predicted zinc did not.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 6 February 2017
Received in revised form 4 April 2017
Accepted 5 April 2017
Available online xxxx

Editor: F.M. Tack

Keywords:
Soil contamination
Mapping
Linear mixed models
Uncertainty
Covariates

ABSTRACT

The human population is increasing globally and land use is changing to accommodate for this growth. Soils within urban areas require closer attention as the higher population density increases the chance of human exposure to urban contaminants. One such example of an urban area undergoing an increase in population density is Sydney, Australia. The city also possesses a notable history of intense industrial activity. By integrating multiple soil surveys and covariates into a linear mixed model, it was possible to determine the main drivers and map the distribution of lead and zinc concentrations within the Sydney estuary catchment. The main drivers as derived from the model included elevation, distance to main roads, main road type, soil landscape, population density (lead only) and land use (zinc only). Lead concentrations predicted using the model exceeded the established guideline value of 300 mg kg^{-1} over a large portion of the study area with concentrations exceeding 1000 mg kg^{-1} in the south of the catchment. Predicted zinc did not exceed the established guideline value of 7400 mg kg^{-1}; however concentrations were higher to the south and west of the study area. Unlike many other studies we considered the prediction uncertainty when assessing the contamination risk. Although the predictions indicate contamination over a large area, the broadness of the prediction intervals suggests that in many of these areas we cannot be sure that the site is contaminated. More samples are required to determine the contaminant distribution with greater precision, especially in residential areas where contamination was highest. Managing sources and addressing areas of elevated lead and zinc concentrations in urban areas has the potential to reduce the impact of past human activities and improve the urban environment of the future.

* Corresponding author.
E-mail address: liana.pozza@sydney.edu.au (L.E. Johnson).

http://dx.doi.org/10.1016/j.scitotenv.2017.04.033

1. Introduction

The human population is rapidly increasing around the world and majority of people reside within urban areas (United Nations, 2015). To accommodate for this increase, population density in cities is growing and outer urban areas are sprawling, often involving land use change from rural or industrial to urban land and loss of greenspace (Pauleit et al., 2005). Land use change can disturb the soil profile and alter soil properties, while resulting in increased areas of hard, impermeable surfaces such as asphalt and concrete. Soil disturbance and increased impermeable surfacing amplifies water runoff within a hydrological catchment, increasing the chances of pollution, sedimentation and greater turbidity in waterways (Jartun et al., 2008; Shi et al., 2007).

Chances of human exposure to soil contaminants are increasing as more people either choose, or are forced to reside in areas that have a history of industrial activity, or near areas of high atmospheric deposition of contaminants (e. g. near busy roads). Effects of contaminants vary depending on the type and concentration. If absorbed to large enough concentrations within a body, the contaminant may be toxic, resulting in cancer, developmental problems, abnormalities or death of those affected (Aelion et al., 2008; Laidlaw and Taylor, 2011; UWE, 2013). It is therefore important to plan urban growth and development in order to decrease risk of human exposure to contaminants and risk of contaminants entering the natural environment. Many countries, for example, Canada, Australia and the Netherlands, have legislative requirement that if a site contains contaminants over agreed guideline values, the site must be managed and remediated (BC MoE, 2014; NEPM, 1999; VROM, 2000).

Previous studies have investigated contaminant distributions within a city through sampling and interpolation of chemical data (Birch et al., 2011; Bourennane et al., 2006; Cattle et al., 2002; Lark and Scheib, 2013; Manta et al., 2002). Most investigations have observed heavy metals as they are able to remain in the soil for extended periods and so present a greater risk in urban areas years after the source has ceased (Wang et al., 2005). Once soil chemical concentrations are quantified, the contaminants can be mapped, analysed using spatial statistics and interpolated to determine areas of elevated concentrations. Current interpolation methods are effective in reducing the number of samples required, however due to the cost of site assessment, hazardous nature of laboratory analytical methods and large cost of remediation, there is potential for improvement in the precision of mapping of contaminants, both site- and city-wide (Horta et al., 2015).

Precision could be improved by integrating spatially dense covariates into the spatial model, forming a linear mixed model (LMM). Covariates are potential predictors which may be related to natural factors, such as soil texture, or anthropogenic factors, such as proximity to roads and land use. Use of spatially dense covariates allows finer scale predictions, rather than estimating mean metal concentration, or interpolating over a broader area. Integrating covariates into a model helps determine drivers of contaminant distribution, which may enable investigators to improve source management, thus reducing further contaminant input and exposure (Lacarce et al., 2012; Maas et al., 2010).

It is also important to understand the uncertainty of the predicted distributions. Past studies that have assessed contaminant distribution in cities include those by Lark and Scheib (2013), Birch et al. (2011) and Manta et al. (2002). These, like many other studies have presented maps of distribution, which is a point estimate, but have not addressed uncertainty of these predictions in terms of an interval estimate or prediction interval and the likelihood of exceeding threshold values. It is critical that maps include both a prediction and an associated prediction interval as it gives end users an understanding of the reliability of the predictions, which may help improve management decisions to address contamination. With such a high and ever-increasing risk of exposure to contaminants in urban areas, it is essential to use the most precise and up-to-date methods for mapping contamination in cities with high population growth.

Sydney, Australia, similar to many other cities around the world, has a rapidly increasing population and a long history of industrial activity, resulting in considerable land use change over the past two hundred years. Colonised by Europeans in 1788, urbanisation and industrialisation slowly spread along the city's main arterial river - the Parramatta River. As time progressed, areas in Sydney that were historically used for industry were replaced by housing and greenspace for the growing population (Birch et al., 2015a, 2015b). A wide variety of industries, such as chemical factories, abattoirs, gas works and munitions have adversely affected catchment soil and aquatic sediments (Birch et al., 2000; Birch and Taylor, 1999, 2002; Danis et al., 2014; McCready et al., 2006, 2004; McLoughlin, 2000).

It is essential for local governments to prevent risk of exposure of residents to historical soil contaminants. Two ways to aid this include mapping areas that have potentially elevated heavy metal concentration and determining the drivers of metal distribution.

With these ideas in mind, the current study aimed to: 1. Combine a number of datasets that have assessed soil Pb and Zn content in Sydney, Australia; 2. Develop a spatial prediction model using covariates to investigate the drivers of Pb and Zn distribution in Sydney; 3. Use this model to predict Pb and Zn distribution onto a grid, providing both a point estimate and interval estimate, to identify areas where contaminant concentrations exceed guideline values. The information provided by this study will provide a starting point for investigation and management of contaminant sources in urban areas.

2. Methods

2.1. Study area

The Sydney estuary catchment (approximately 500 km^2), has a mean population density of 2000 people per square km and a total population (as of the 2011 census) of 1.42 million people (ABS, 2011). Land uses include residential (50%), greenspace (24%), industrial (7%) and other uses, such as commercial and recreational land (19%) (NSW Department of Planning and Environment, 2016). Soils in the catchment are predominantly comprised of Technosols, Podzols, Arenosols, Cambisols and Lixosols (Bannerman and Hazelton, 1990; Chapman and Murphy, 1989; Isbell et al., 1997; IUSS Working Group WRB, 2015). The region's geology consists of Hawkesbury Sandstone, alluvial sediments and Wianamatta Group shale and sandstone, with igneous rocks occurring in a small portion in the south-west of the study area (Bannerman and Hazelton, 1990; Chapman and Murphy, 1989).

2.2. Data compilation

2.2.1. Soil data

The soil data were compiled from six surveys (Table 1). Samples were taken from the topsoil, ranging from 2 to 10 cm in depth, and chemically analysed by aqua regia digestion using ICP-OES (USEPA Method 200.8 modified) spectrometry. Quality Assurance and Quality Control (QA/QC) methods are described in detail in the references for each of the studies in Table 1. The studies quantified a range of metals, with Pb and Zn being consistently recorded in all studies, hence this study will focus on these elements.

Sampling density varied due to differing objectives of each study. The data used in Birch et al. (2011) covered the entire catchment and used a coarser semi-grid sampling scheme, whereas the other studies used more intensive sampling over smaller study areas (Fig. 1). By combining these spatially varied datasets, small-scale clustering became evident. Furthermore, the majority of samples were taken from the southern side of the catchment, resulting in larger-scale clustering. This clustering, along with variation of point and diffuse contamination can present as peaks in a variogram model which may in turn prevent development of a model that is applicable on a