Air Pollution Land-Use Regression Modelling – US Model Adopted

In this project, we adopt the US-wide LUR model developed by Bechle et al. (2015) to estimate the annual 2000 and 2010 NO2 concentrations at the centroid location of the census block. The census block is the smallest geographical entity publicly available for census data collection. NO2 is a good predictor for traffic related air pollution sources, and studies have associated NO2 pollution with multiple adverse health outcomes including asthma and asthma exacerbations (Anderson et al 2011, Anderson et al 2013, Khreis et al 2017). A brief description of the model developed by Bechle et al. (2015) is given below. The results of the model are discussed in the section after.

Bechle et al (2015) developed an improved NO2 LUR model for the Contiguous United States, mainly using Satellite and EPA monitor based measurements of NO2. In this work, we are interested in their models for years 2000 and 2010, as these years have complete decennial census data that we link the exposure data to. The LUR models developed in their work are an expansion of previously developed LUR model in the year 2006, for ground level NO2 for the Contiguous United States.

The model building was divided into two parts, building the “Spatial” model which included spatial covariates and adding on the “Temporal” component which included temporal scaling of the spatial model. The land-use covariates that were included to build the base model were six and are shown in Table 2 below, and the final base “Spatial” model is shown in Table 3 below. The validation of the spatial model was satisfactory achieving an R2 = (0.50-0.81) in hold-out cross-validation, as shown in Table 4 below. The spatial model had an excellent spatial resolution typical for urban-scale LURs (∼100 m scale) and covered 100% of US Census blocks.

The temporal component added on the spatial model was used to derive other year’s exposure surfaces including 2000 and 2010. The scaling to the other years was done using temporal scaling factors established from NO2 monthly mean concentrations from EPA monitors in the contiguous US, for the respective years. For each monitor to be used, it should have had at least 75% of the hourly values. Adding temporal scalability to the spatial model enhanced the models in terms of accuracy (R2 = 0.63-0.82), as shown in Table 5 below. Models were evaluated using R2 and Adjusted R2, mean error and absolute error, mean bias and absolute bias. Results for the final model are shown in Tables 4 and 5. Sensitivity analysis was done using a Monte Carlo random sampling approach to explore the model stability as a function of the number of training locations used for model building. This was done by using random subsets of monitoring data and for each subset running 500 iterations (Figure 2).

The R2 of Bechle’s LUR model which we adopt here is consistent with other continental-scale NO2 models. For example, Novotny et al. (2011) reported on a US National NO2 LUR model with an R2 = 0.78, Haystaf et al. (2011) reported on a Canadian National NO2 LUR model with an R2 = 72%, Beelen et al, (2009) reported on an EU NO2 LUR model with an R2 = 61%, and Vienneau et al. (2013) reported on a Western European NO2 LUR model with an adjusted R2 = 58%.

Using land use regression model for exposure assessment has several limitations. The exposure model assumes that NO2 exposure is from ambient outdoor air pollution but does not take into account indoor air pollution, for example how much of the personal exposure is from indoor NO2 concentrations. It also assigns that NO2 exposure at one single location and does not take into account time-activity patterns, for example how much of the exposure happens at school or at the playground. Another limitation is exposure misclassification error, the precision of the LUR model varies within urban areas although it has spatiotemporal predictive pattern of (R2 = 0.61-0.79), leading to misclassification of exposure in either direction depending the direction of error of the NO2 prediction, for example if the model is over predicting this will lead to overexposure classification but if the model is under predicting the opposite might be true.