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# Defra urban model evaluation analysis – Phase 1

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## Executive summary

This report provides a summary of the evaluation of models used for the assessment of urban air quality. Specifically, this report considers the prediction of annual mean concentrations of $NO_x$, $NO_2$, $O_3$, $PM_{10}$ and $PM_{2.5}$ for a large sample of measurements sites in London. In addition, the evaluation of hourly predictions is considered for a subset of models and receptor locations. The report focuses on a range of quantitative metrics commonly used for model evaluation together with a series of graphical comparisons that aim to reveal some of the characteristics of each model. While the comparisons are not exhaustive, they are presented in such a way as to easily allow further analysis by each modelling group. The principal aim of this report is to provide information to the *Air Quality Modelling Review Steering Group* to assist their deliberations concerning the future use of air quality models by Defra.

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# 1 Introduction

## 1.1 Document history

This document has had the following updates.

**12th January 2011** Changed model name "BRUTO" to "BRUTAL".

**8th February 2011** Fixed scatter plots to ensure same scaling.

Added total number of data points 'n' to the summary statistics; useful to gauge whether sample sizes are large enough to draw meaningful inferences from.

Changed names used in hourly modelling to make it clearer what is modelled/measured.

Confirmed CERC-queue results were used correctly.

**23rd February 2011** Added new section on conditional quantiles — subsection 4.5.

**24th February 2011** Added analysis on how well model performance compares with Directive requirements (subsubsection 3.1.1 and subsubsection 3.3.1)

**15th April 2011** Changed name of models run by CERC, plus other mostly minor edits.

## 1.2 Background

This document will summarise the evaluation of air pollution models as part of Defra's model evaluation exercise. Model evaluation can be a complex and time consuming task. The results presented in this report are focused on providing some input to the Defra Model Evaluation exercise. The performance statistics used here have mostly been guided by Derwent et al. (2010). Dennis et al. (2010) provide useful and more general framework for model evaluation. They distinguish between several types of evaluation:

**Operational evaluation** in which model predictions are compared with data in an overall sense using a variety of statistical measures;

**Diagnostic Evaluation** in which the relative interplay of chemical and physical processes captured by the model are analysed to assess if the overall operation of the model is correct;

**Dynamic Evaluation** in which the ability of the modelling system to capture observed changes in emissions or meteorology is analysed; and,

**Probabilistic Evaluation** in which various statistical techniques are used to capture joint uncertainty in model predictions and observations.

On this basis, the evaluation carried out here forms a small part of *operational evaluation* and to a lesser extent *diagnostic evaluation*. By the same token, considerably more in-depth analysis would be possible and perhaps desirable but that is currently beyond the scope of the Defra work.

## 1.3 Methods used

This document blends text with code in that the whole document must be 'run' to produce it. Each time a version of this documentation is produced, all the code is run at the same time to generate all the various outputs e.g. plots and tables. This process is described in Leisch (2002). There are several reasons for adopting this approach:

- It provides a good way of presenting and distilling a large amount of information; hopefully an advantage to the modelling steering group.

- Every plot, table or statistic is entirely reproducible by anyone. An up to date version of R and R package called **openair** is all that is required. The commands shown can be pasted into R and all the workings are shown in a logical sequence.
- The approach makes it much easier to deal with revised results from models. For example, if modelling groups discover a problem with their results, a new set of results can be analysed very quickly and all the plots, tables etc. updated accordingly. Account can be taken of such changes at the last minute.
- It is clear that this document can only show a limited amount of information given the number of modelling groups, receptor points and the wide range of analyses that could potentially be undertaken. However, by showing the commands used to carry out the analysis, the modelling groups can choose to undertake further more detailed analysis should they wish to.
- Finally, this approach is fully transparent. All the code and methods used in the analysis are open to scrutiny by anyone.

All the code used in this document is based on R and use is also made of existing functions in **openair** to help with the evaluation. Several new functions have also been written related to model performance statistics.

Where possible we have tried to use files and file names as directly supplied by the modelling groups, as this ought to make it easier for each group on understand exactly the data used in the evaluation. In some cases minor editing of these files was necessary e.g. to change column names. Where more major manipulation was necessary, this is shown in the document.

This document was produced using R version 2.13.0 and **openair** version 0.4-16.

## 2 Data preparation

Modelling includes $NO_x$, $NO_2$, $O_3$, $PM_{10}$ $PM_{2.5}$. All predictions should be in µg m$^{-3}$ for annual means (for $NO_x$ the results should be in µg m$^{-3}$ as $NO_2$). For the particle metrics it is assumed that gravimetric-equivalent predictions will be made. All the analyses in this report relate to 2008 i.e. emissions inventory and ambient measurements.

Details of the receptors etc can be found in Appendix A. Note that for $PM_{10}$ and $PM_{2.5}$ the measured concentrations are expressed gravimetrically using the Volatile Correction Model.

Note that once all the model results are available they will be compiled into a consistent data set and imported in a straightforward way. It is expected that all the data would be imported using a couple of lines of code.

First it is necessary to load **openair** and some additional functions to help with the evaluation, including ensuring that the times are displayed in GMT:

```
library(openair)
source("~/Projects/modelEvaluation/modStats.R")
## make sure all times are displayed in GMT
Sys.setenv(TZ = "GMT")
## set file paths
setwd("~/Projects/modelEvaluation/urban")
```

Next we import the measured data from a pre-prepared file.

```
urban.meas <- read.csv("urban_template_complete.csv", header = TRUE)
```

KCL have provided two sets of results. The first set uses their urban model for London using fixed assumptions about background concentrations external to London i.e. the *ERG Toolkit*. The second set uses the CMAQ model, which explicitly models all UK and European sources and thus does not rely on assumed background concentrations. The latter model results only include $NO_x$, $NO_2$ and $O_3$. The ERG Toolkit is referred to as 'KCLurban' and the CMAQ-based modelling as 'KCLurbanCMAQ'.

Import the KCL data and merge with measurements:

```
KCLurban <- read.csv("urbanTemplate_KCL_final_Year2008.csv", header = TRUE)
KCLurban <- merge(KCLurban, urban.meas, by = c("id", "site.code", "easting", "northing", "site.type"))
## add model group name
KCLurban$group <- "KCLurban"
```

The KCL-CMAQ results:

```
KCLurbanCMAQ <- read.csv("urbanTemplate_KCLCMAQ_final_Year2008.csv", header = TRUE)
KCLurbanCMAQ <- merge(KCLurbanCMAQ, urban.meas, by = c("id", "site.code", "easting", "northing",
                                               "site.type"))
## add model group name
KCLurbanCMAQ$group <- "KCLurbanCMAQ"
```

And the BRUTAL results:

```
BRUTAL <- read.csv("urbanTemplateV1.3_UKIAMBRUTAL_Data4MIP_01Dec10.csv", header = TRUE)
BRUTAL <- merge(BRUTAL, urban.meas, by = c("id", "site.code", "easting", "northing", "site.type"))
BRUTAL$group <- "BRUTAL"
```

The AEA pollution climate mapping (PCM) results:

```
PCM <- read.csv("pcm_urbanTemplateV1 3.csv", header = TRUE, na.strings = "N/A")
PCM <- merge(PCM, urban.meas, by = c("id", "site.code", "easting", "northing", "site.type"))
PCM$group <- "PCM"
```

The CERC results are imported as follows. Note that CERC producd two sets: the first where all hours of the year were modelled and the second where only hours where there were valid monitored values were available.

Note that there are some difficulties comparing the hourly models (CERC and KCL) with annual models. The annual models essentially assume that data capture rates are 100% because they cannot take account of partial years. Conversely, the hourly models can predict concentrations consistent with the measurements e.g. they could take account of missing hours in the wintertime. It is not possible therefore to ensure complete consistency in the comparisons. However, by choosing a relatively high data capture rate of 75% these issues are mitigated somewhat. The hourly models would however be expected to provide more representative predictions that allow a consistent comparison with the measurements.

```
ADMSUrban <- read.csv("urbanTemplateV13CERC(valid monitoring hours only).csv", header = TRUE)
ADMSUrban <- merge(ADMSUrban, urban.meas, by = c("id", "site.code", "easting", "northing", "site.type"))
ADMSUrban$group <- "ADMSUrban"
```

CERC (17 December 2010) have provided an additional set of results that aims to treat vehicle queuing. We refer to these results as ADMSUrban.queue.

```
ADMSUrban.queue <- read.csv("urbanTemplateV13(valid monitoring hours only)16Dec.csv", header = TRUE,
                      na.strings = c("x", "n/a"))
ADMSUrban.queue <- merge(ADMSUrban.queue, urban.meas, by = c("id", "site.code", "easting", "northing",
                                                     "site.type"))
ADMSUrban.queue$group <- "ADMSUrban.queue"
```

Now we can combine all the model results:

```
all.results <- rbind.fill(KCLurban, BRUTAL, PCM, ADMSUrban, KCLurbanCMAQ, ADMSUrban.queue)
```

# 3 Analysis examples

## 3.1 Annual mean $NO_x$ and $NO_2$ concentrations

First we will extract the $NO_x$ and $NO_2$ data and apply a data capture threshold.

Not every group predicted at every receptor, which could therefore introduce an inconsistency into the analysis. The code below therefore extracts receptors where all groups made a prediction.

```
nox.results <- subset(all.results, nox.count > 0.75 * 8784)
## extract only those results where all groups made a prediction
## sites where this is true
fullSites <- with(nox.results, tapply(NOx, site.code, function (x) length(na.omit(x))))
fullSites <- fullSites[fullSites == length(unique(nox.results$group))]
nox.results <- subset(nox.results, site.code %in% names(fullSites))
```

Model evaluation statistics can be estimated using the `modStats` function. Note that these statistics will be defined and explained later. These numerical summaries can easily be added to e.g. to provide means, 95th percentile values etc. In using the function below, it is supplied with the data (`nox.results`), the analysis type (statistics by site i.e. `type = "site"`), the modelled results column is called `"NOx"` and the observations column in this case is `"nox.meas"`.

```
noxStats <- modStats(nox.results, type = c("site.type", "group"), obs = "nox.meas", mod = "NOx")
```

**Table 1:** Summary model evaluation statistics for annual mean $NO_x$.

| site.type | group | n | FAC2 | MB | MGE | NMB | NMGE | RMSE | r |
|---|---|---|---|---|---|---|---|---|---|
| kerbside | ADMSUrban | 7 | 0.71 | -73.70 | 80.76 | -0.32 | 0.35 | 113.55 | 0.77 |
| kerbside | ADMSUrban.queue | 7 | 0.86 | -53.63 | 60.69 | -0.23 | 0.26 | 82.04 | 0.89 |
| kerbside | BRUTAL | 7 | 0.43 | -129.15 | 129.96 | -0.56 | 0.57 | 184.49 | 0.21 |
| kerbside | KCLurban | 7 | 0.86 | -60.23 | 79.39 | -0.26 | 0.35 | 106.88 | 0.75 |
| kerbside | KCLurbanCMAQ | 7 | 0.57 | -57.86 | 72.36 | -0.25 | 0.32 | 79.85 | 0.95 |
| kerbside | PCM | 7 | 0.86 | -74.53 | 81.72 | -0.32 | 0.36 | 119.02 | 0.77 |
| roadside | ADMSUrban | 30 | 1.00 | -22.78 | 23.64 | -0.17 | 0.18 | 27.94 | 0.94 |
| roadside | ADMSUrban.queue | 30 | 1.00 | -14.29 | 18.89 | -0.11 | 0.14 | 21.77 | 0.93 |
| roadside | BRUTAL | 30 | 1.00 | -35.26 | 38.33 | -0.27 | 0.29 | 46.10 | 0.79 |
| roadside | KCLurban | 30 | 0.93 | -14.35 | 28.00 | -0.11 | 0.21 | 41.47 | 0.61 |
| roadside | KCLurbanCMAQ | 30 | 0.87 | -31.89 | 46.58 | -0.24 | 0.35 | 59.96 | 0.63 |
| roadside | PCM | 30 | 0.97 | 16.20 | 41.68 | 0.12 | 0.32 | 50.06 | 0.42 |
| suburban | ADMSUrban | 11 | 1.00 | -4.51 | 8.23 | -0.09 | 0.16 | 9.20 | 0.45 |
| suburban | ADMSUrban.queue | 11 | 1.00 | -4.51 | 8.23 | -0.09 | 0.16 | 9.20 | 0.45 |
| suburban | BRUTAL | 11 | 1.00 | -7.48 | 8.73 | -0.15 | 0.17 | 9.87 | 0.62 |
| suburban | KCLurban | 11 | 1.00 | -4.26 | 7.09 | -0.08 | 0.14 | 8.18 | 0.52 |
| suburban | KCLurbanCMAQ | 11 | 1.00 | -15.37 | 15.37 | -0.30 | 0.30 | 17.23 | 0.36 |
| suburban | PCM | 11 | 1.00 | -6.14 | 7.56 | -0.12 | 0.15 | 9.17 | 0.59 |
| urban background | ADMSUrban | 29 | 1.00 | 5.62 | 14.64 | 0.08 | 0.21 | 18.14 | 0.79 |
| urban background | ADMSUrban.queue | 29 | 1.00 | 5.62 | 14.64 | 0.08 | 0.21 | 18.14 | 0.79 |
| urban background | BRUTAL | 29 | 0.93 | -2.71 | 18.15 | -0.04 | 0.25 | 25.35 | 0.33 |
| urban background | KCLurban | 29 | 1.00 | 1.43 | 10.66 | 0.02 | 0.15 | 13.70 | 0.80 |
| urban background | KCLurbanCMAQ | 29 | 0.97 | -11.02 | 17.21 | -0.15 | 0.24 | 22.91 | 0.66 |
| urban background | PCM | 29 | 0.97 | -4.67 | 12.13 | -0.07 | 0.17 | 17.73 | 0.65 |

```
scatterPlot(nox.results, x = "nox.meas", y = "NOx", type = "group", mod.line = TRUE,
            pch = 16, smooth = FALSE, group = "site.type", xlim = c(0, 550), ylim = c(0, 550))
```

```
scatterPlot(noxStats, x = "group", y = "FAC2", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

```
scatterPlot(noxStats, x = "group", y = "MB", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

```
scatterPlot(noxStats, x = "group", y = "RMSE", type = "site.type", key = FALSE, pch = 16, cex = 1.5,
            ref.y = 0)
```

```
scatterPlot(noxStats, x = "group", y = "r", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

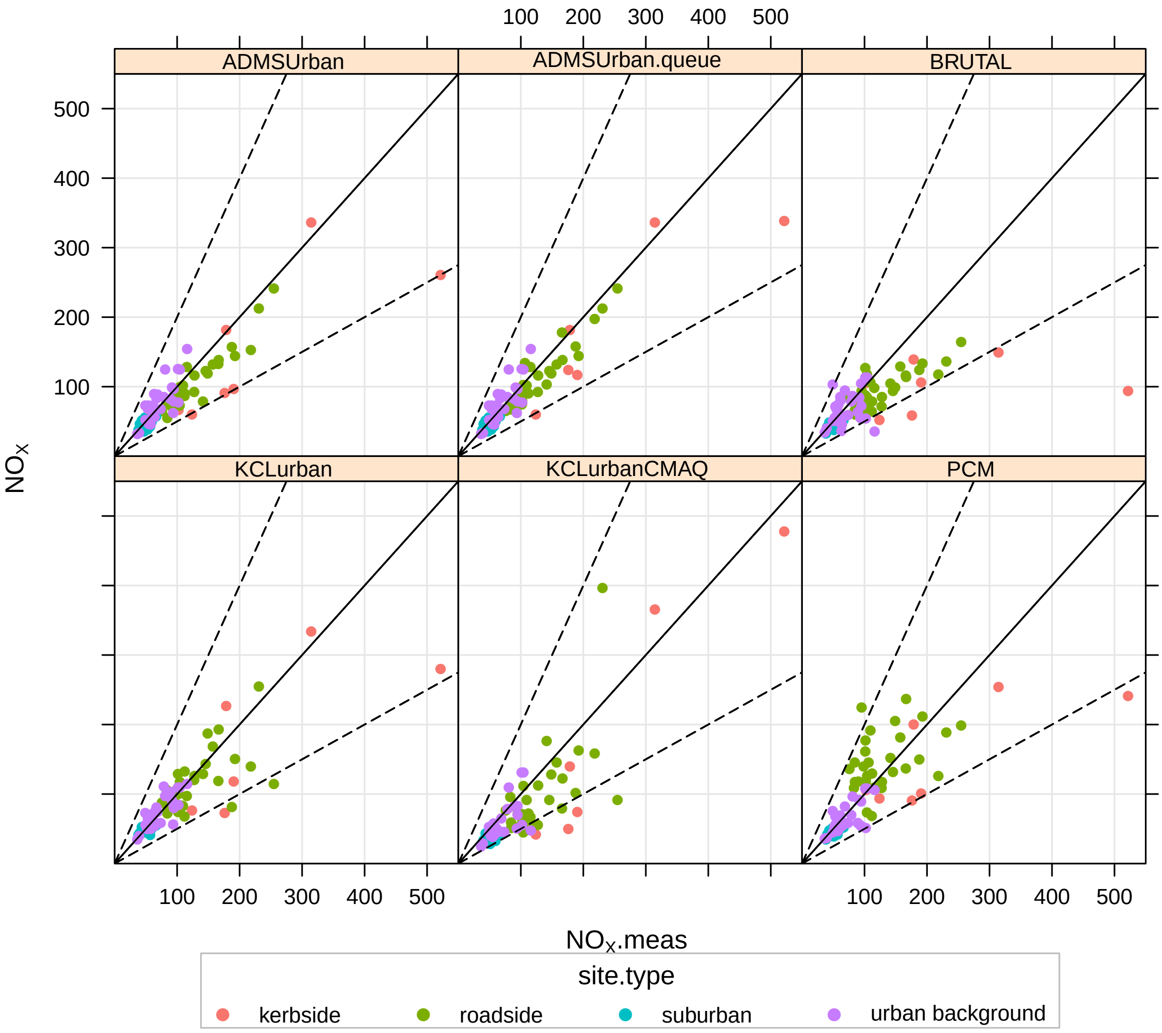


**Figure 1:** Scatter plot of measured versus predicted annual mean $NO_x$ concentrations.

```
modStats(nox.results, type = c("site.type", "group"), obs = "no2.meas", mod = "NO2")
```

```
scatterPlot(nox.results, x = "no2.meas", y = "NO2", type = "group", mod.line = TRUE,
            pch = 16, smooth = FALSE, group = "site.type", xlim = c(0, 250), ylim = c(0, 250))
```

```
no2Stats <- modStats(nox.results, type = c("site.type", "group"), obs = "no2.meas", mod = "NO2")
```

```
scatterPlot(no2Stats, x = "group", y = "FAC2", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

```
scatterPlot(no2Stats, x = "group", y = "MB", type = "site.type", key = FALSE, pch = 16, cex = 1.5,
            ref.y = 0)
```

```
scatterPlot(no2Stats, x = "group", y = "RMSE", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

```
scatterPlot(no2Stats, x = "group", y = "r", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

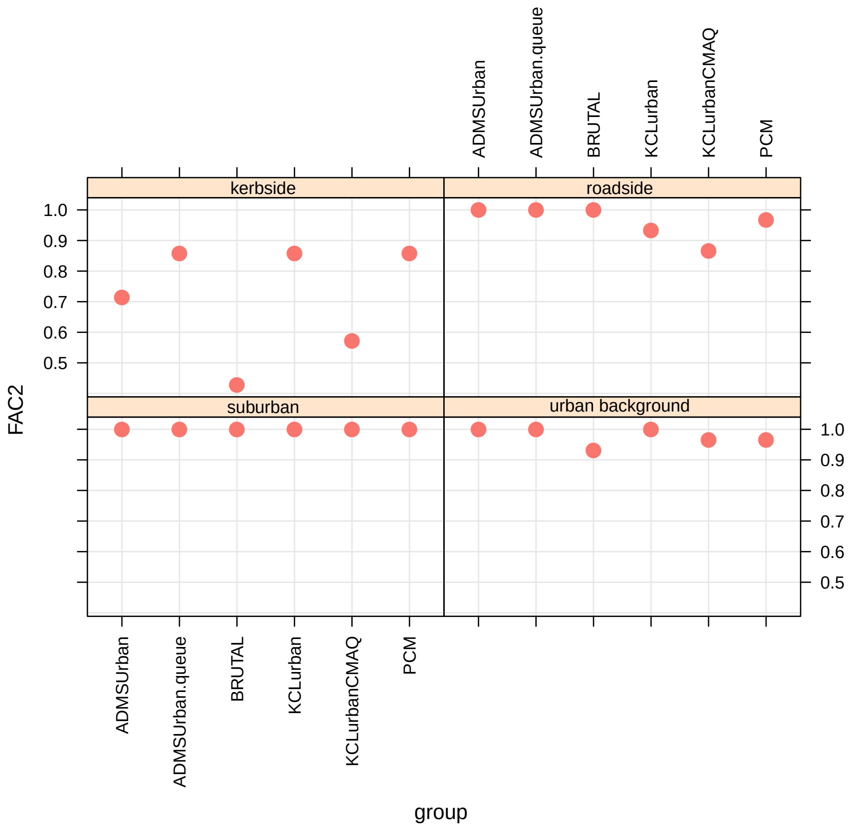


**Figure 2:** Graphical summary of FAC for each model by site type for $NO_x$.

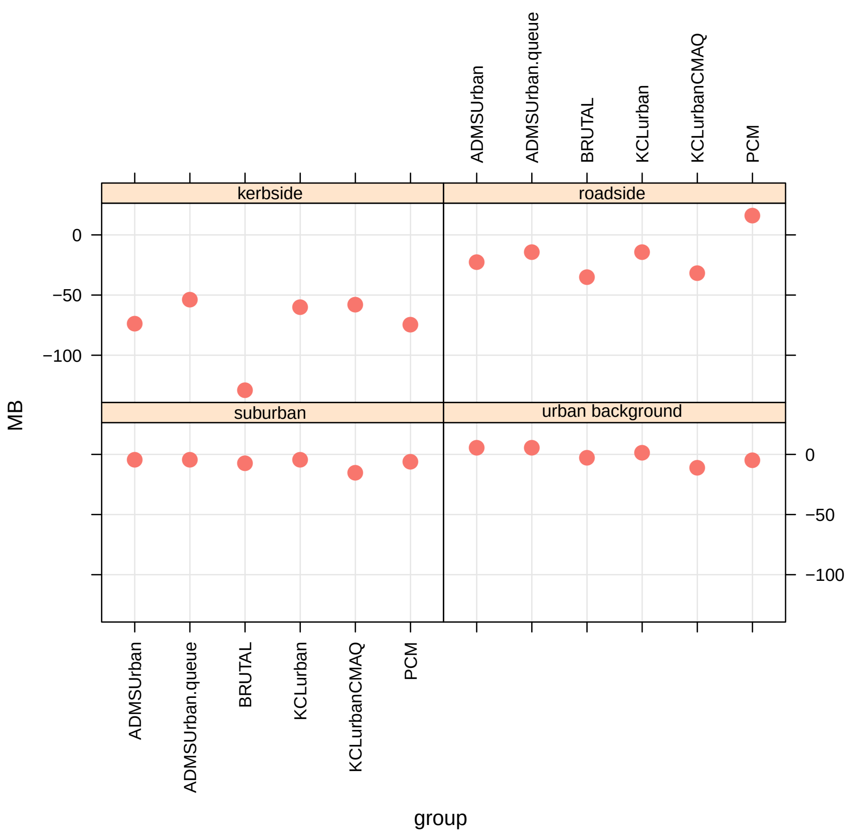


**Figure 3:** Graphical summary of mean bias for each model by site type for $NO_x$.

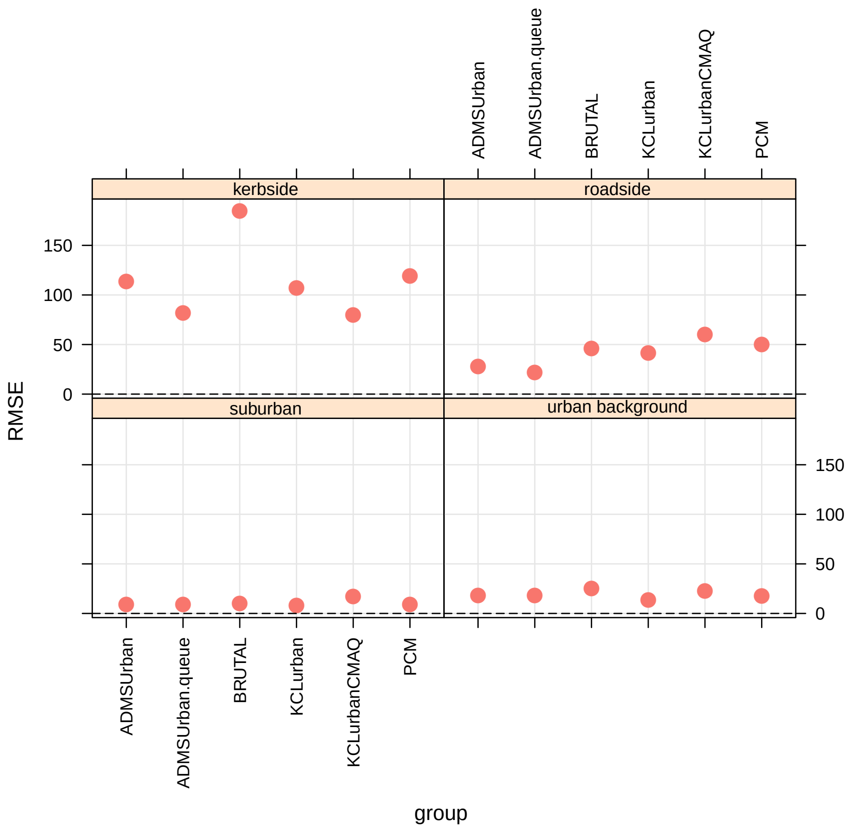


**Figure 4:** Graphical summary of RMSE for each model by site type for $NO_x$.

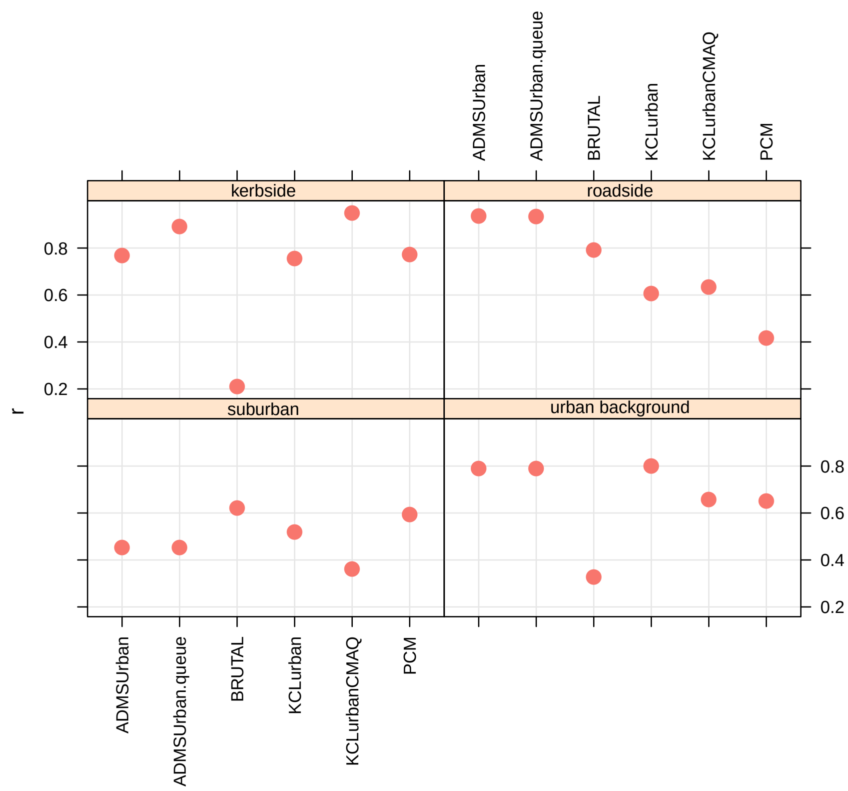


**Figure 5:** Graphical summary of the correlation coefficient, $r$, for each model by site type for $NO_x$.

**Table 2:** Summary model evaluation statistics for annual mean $NO_2$.

| site.type | group | n | FAC2 | MB | MGE | NMB | NMGE | RMSE | r |
|---|---|---|---|---|---|---|---|---|---|
| kerbside | ADMSUrban | 7 | 0.86 | -29.00 | 30.48 | -0.31 | 0.32 | 47.54 | 0.73 |
| kerbside | ADMSUrban.queue | 7 | 1.00 | -22.59 | 24.07 | -0.24 | 0.26 | 37.53 | 0.86 |
| kerbside | BRUTAL | 7 | 0.71 | -39.61 | 42.24 | -0.42 | 0.45 | 67.09 | 0.15 |
| kerbside | KCLurban | 7 | 0.86 | -25.84 | 28.77 | -0.27 | 0.31 | 45.59 | 0.75 |
| kerbside | KCLurbanCMAQ | 7 | 0.86 | -21.94 | 24.26 | -0.23 | 0.26 | 29.39 | 0.93 |
| kerbside | PCM | 7 | 1.00 | -25.53 | 27.26 | -0.27 | 0.29 | 43.15 | 0.81 |
| roadside | ADMSUrban | 30 | 1.00 | -6.12 | 7.70 | -0.11 | 0.14 | 9.94 | 0.86 |
| roadside | ADMSUrban.queue | 30 | 1.00 | -3.42 | 6.00 | -0.06 | 0.11 | 7.75 | 0.89 |
| roadside | BRUTAL | 30 | 1.00 | -3.02 | 9.30 | -0.05 | 0.16 | 11.67 | 0.69 |
| roadside | KCLurban | 30 | 1.00 | -2.19 | 8.44 | -0.04 | 0.15 | 11.12 | 0.72 |
| roadside | KCLurbanCMAQ | 30 | 1.00 | -4.22 | 10.32 | -0.07 | 0.18 | 14.22 | 0.76 |
| roadside | PCM | 30 | 1.00 | 7.93 | 16.02 | 0.14 | 0.28 | 19.69 | 0.38 |
| suburban | ADMSUrban | 11 | 1.00 | -1.26 | 3.34 | -0.04 | 0.11 | 3.89 | 0.39 |
| suburban | ADMSUrban.queue | 11 | 1.00 | -1.26 | 3.34 | -0.04 | 0.11 | 3.89 | 0.39 |
| suburban | BRUTAL | 11 | 1.00 | -2.15 | 4.07 | -0.07 | 0.13 | 4.29 | 0.40 |
| suburban | KCLurban | 11 | 1.00 | 0.10 | 2.65 | 0.00 | 0.09 | 3.23 | 0.38 |
| suburban | KCLurbanCMAQ | 11 | 1.00 | -2.02 | 3.82 | -0.07 | 0.12 | 4.41 | 0.27 |
| suburban | PCM | 11 | 1.00 | -3.00 | 3.97 | -0.10 | 0.13 | 4.85 | 0.33 |
| urban background | ADMSUrban | 29 | 1.00 | 0.77 | 4.42 | 0.02 | 0.11 | 5.47 | 0.85 |
| urban background | ADMSUrban.queue | 29 | 1.00 | 0.77 | 4.42 | 0.02 | 0.11 | 5.47 | 0.85 |
| urban background | BRUTAL | 29 | 0.97 | -3.13 | 7.12 | -0.08 | 0.17 | 9.76 | 0.56 |
| urban background | KCLurban | 29 | 1.00 | 0.42 | 3.67 | 0.01 | 0.09 | 4.97 | 0.87 |
| urban background | KCLurbanCMAQ | 29 | 1.00 | -0.20 | 4.34 | -0.00 | 0.11 | 6.15 | 0.84 |
| urban background | PCM | 29 | 1.00 | -3.34 | 4.82 | -0.08 | 0.12 | 7.23 | 0.77 |

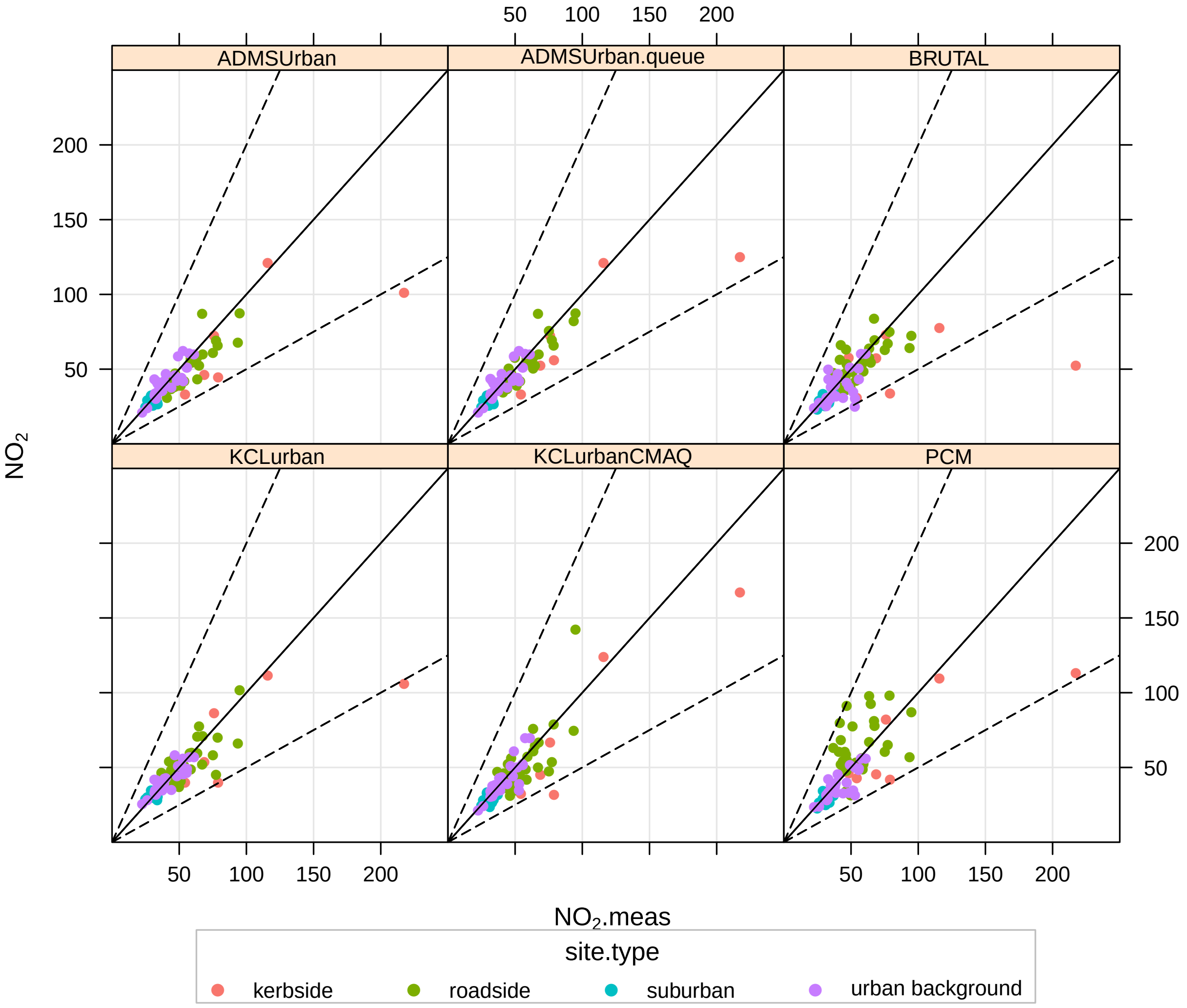


**Figure 6:** Scatter plot of measured versus predicted annual mean $NO_2$ concentrations.

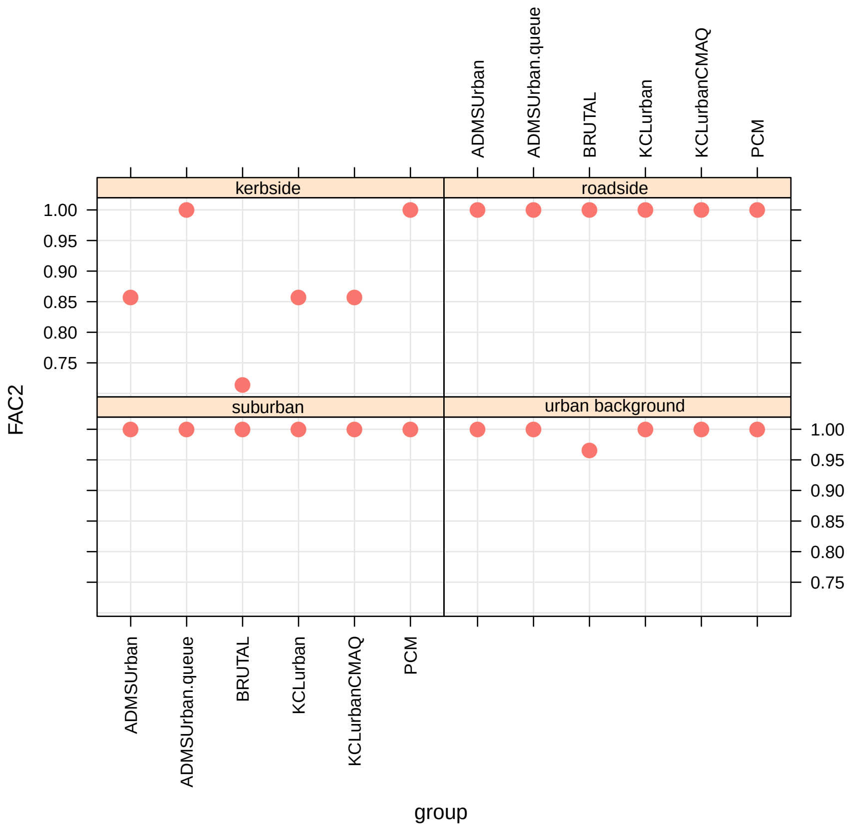


**Figure 7:** Graphical summary of the FAC2 for each model by site type for $NO_2$.

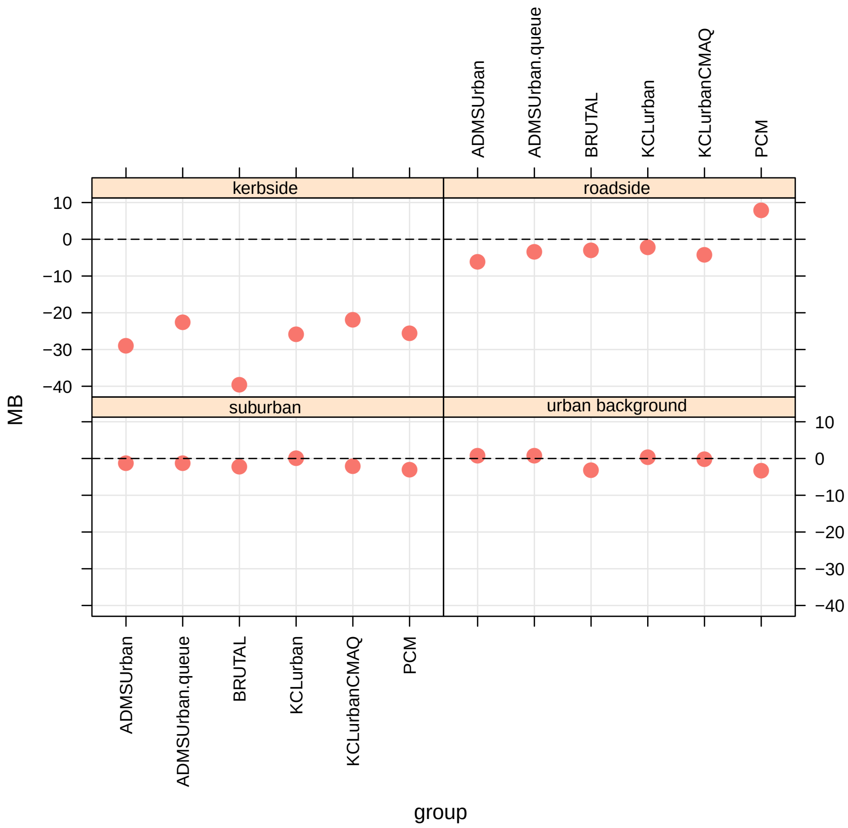


**Figure 8:** Graphical summary of the mean bias for each model by site type for $NO_2$.

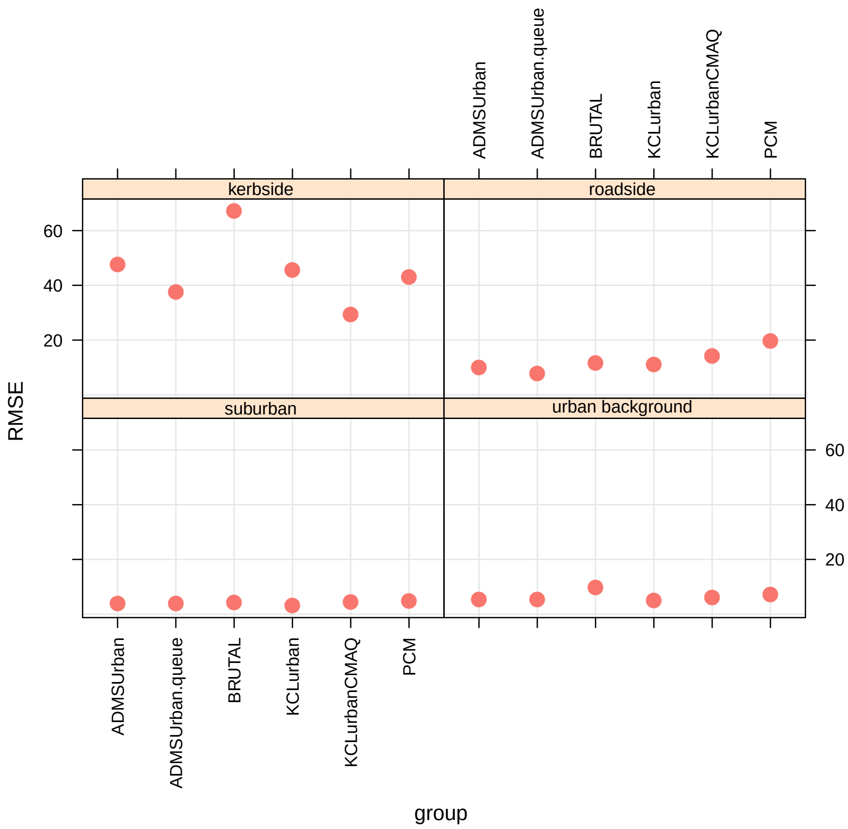


**Figure 9:** Graphical summary of the RMSE for each model by site type for $NO_2$.

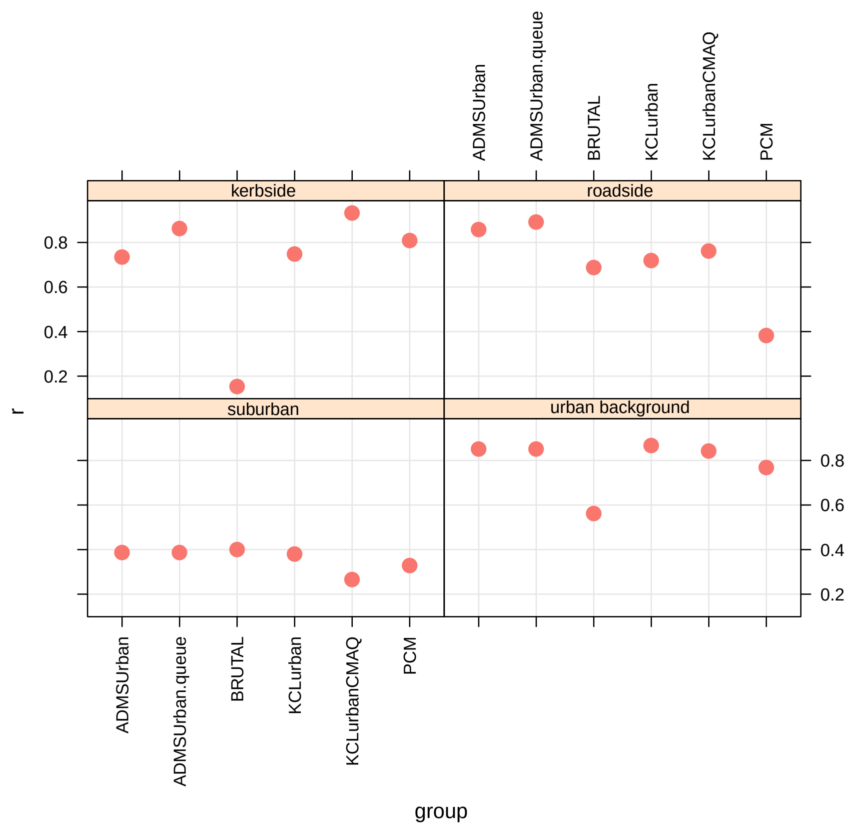


**Figure 10:** Graphical summary of the correlation coefficient, $r$, for each model by site type for $NO_2$.

### 3.1.1 Relative Directive Error, *RDE*

We have also considered how the predictive performance of the models compare with the Directive requirements. It seems that the Directive requirements for model performance are ambiguous.[1] The FAIRMODE report attempts to provide some clarification in this respect by defining *Relative Directive Error (RDE)*:

$$RDE = \frac{|O_{LV} - M_{LV}|}{LV} \tag{1}$$

where $O_{LV}$ is the closest observed concentration to the limit value concentration (LV) and $M_{LV}$ is the correspondingly ranked modelled concentration. The RDE is expressed as a percentage. The maximum of this value found at 90% of the available stations is then the *Maximum Relative Directive Error, (MRDE)*.

For the $PM_{10}$ daily LV the daily means are ranked and closets observed concentration to 50 $\mu$g m$^{-3}$ recorded. The corresponding ranked modelled value is then calculated. These two values are then input into Equation 1.

For annual means Equation 1 is used directly without any ranking. This slightly bizarre procedure allows models to be judged against Directive requirements. The $PM_{10}$ procedure will be applied in subsection 3.3.

The RDE for $NO_2$ is calculated as follows:

```
nox.results$RDE.NO2 <- 100 * abs((nox.results$no2.meas - nox.results$NO2)) / 40
```

The RDE results for $NO_2$ are plotted in Figure 11. The RDE is then interpreted as the 90th perrcentile value i.e. there is some allowance for outliers. However, the FAIRMODE report is rather tentative about the interpretation of 90% suggesting it should not be taken literally e.g. no allowance for outliers if there are fewer than 10 sites in a conurbation. However, there are easily sufficent sites in London for this statistic to be calculated in a direct way.

```
scatterPlot(nox.results, x = "group", y = "RDE.NO2")
```

The 90th percentile values are shown in Table 3. The Directive specifies that the models should have a value $< 30\%$ at an overall comparison across the territory of a member state. This intercomparison exercise only focuses on London as subset of the UK so is therefore not suitable for the application of the RDE statistic. The RDE will in effect penalise conurbations with higher concentrations of $NO_2$ such as London, because there are a lot of sites with annual means >40 $\mu$g m$^{-3}$. The value will always be higher in areas such as London where concentrations are high, and lower in areas where the limit value is not exceeded. Furthermore, the absolute error in annual mean predictions tends to increase with increasing concentration and Equation 1 will tend to penalise these sites because the denominator is fixed at 40 $\mu$g m$^{-3}$. These results therefore show the model performance for a subset of data and as such is not comparable with the scenario at which the FAIRMODE guidance is aimed. Unsurprisingly then, none of the models are within 30% — although the CERC and KCLurban models are close to this value.

```
RDE.NO2 <- with(nox.results, tapply(RDE.NO2, group, function (x) quantile(x, prob = 0.9, na.rm = T)))
```

**Table 3:** Summary of the Maximum Relative Directive Error for annual mean $NO_2$ by group (%).

| ADMSUrban | ADMSUrban.queue | BRUTAL | KCLurban | KCLurbanCMAQ | PCM |
|---|---|---|---|---|---|
| 33.76 | 30.53 | 56.51 | 33.78 | 46.27 | 66.05 |

[1]Guidance on the use of models for the European Air Quality Directive A working document of the Forum for Air Quality Modelling in Europe, FAIRMODE ETC/ACC report Version 6.1.

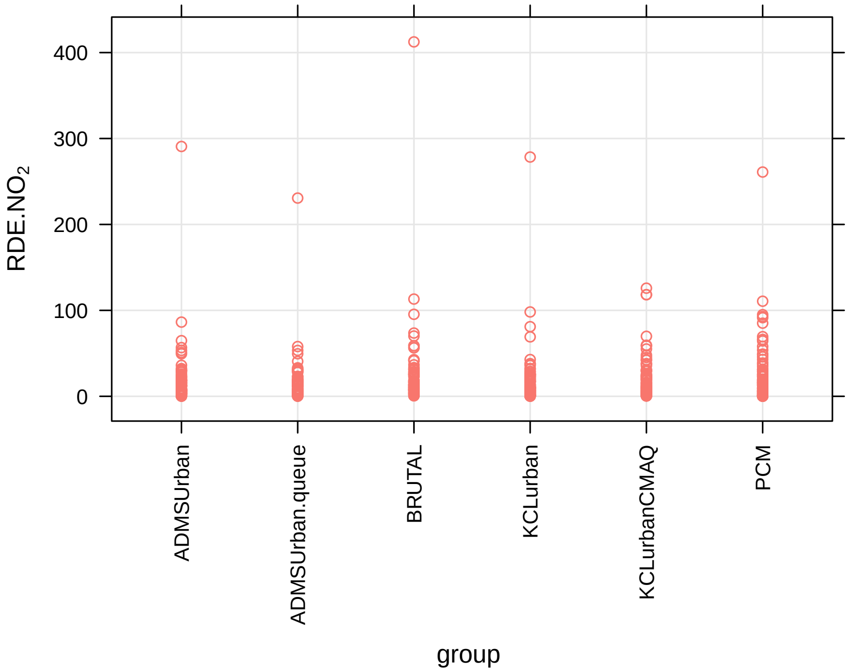


**Figure 11:** The RDE for annual mean $NO_2$ concentrations by group.

## 3.2 Annual mean $O_3$

Ozone data measurements with a data capture of >75% are first extracted and the BRUTAL/PCM model results omitted.

```
o3.results <- subset(all.results, o3.count > 0.75 * 8784 & group != BRUTAL & group != PCM)
```

And the model evaluation statistics are:

```
o3Stats <- modStats(o3.results, type = c("site.type", "group"), obs = "o3.meas", mod = "O3")
```

**Table 4:** Summary model evaluation statistics for annual mean $O_3$.

| site.type | group | n | FAC2 | MB | MGE | NMB | NMGE | RMSE | r |
|---|---|---|---|---|---|---|---|---|---|
| airport | ADMSUrban | 1 | 1.00 | 0.28 | 0.28 | 0.01 | 0.01 | 0.28 | |
| airport | ADMSUrban.queue | 1 | 1.00 | 0.28 | 0.28 | 0.01 | 0.01 | 0.28 | |
| airport | KCLurban | 1 | 1.00 | 3.99 | 3.99 | 0.11 | 0.11 | 3.99 | |
| airport | KCLurbanCMAQ | 0 | | | | | | | |
| kerbside | ADMSUrban | 1 | 1.00 | 2.43 | 2.43 | 0.16 | 0.16 | 2.43 | |
| kerbside | ADMSUrban.queue | 1 | 1.00 | 2.43 | 2.43 | 0.16 | 0.16 | 2.43 | |
| kerbside | KCLurban | 1 | 1.00 | 2.82 | 2.82 | 0.18 | 0.18 | 2.82 | |
| kerbside | KCLurbanCMAQ | 1 | 1.00 | 3.69 | 3.69 | 0.24 | 0.24 | 3.69 | |
| roadside | ADMSUrban | 9 | 1.00 | 4.81 | 4.81 | 0.16 | 0.16 | 5.81 | 0.85 |
| roadside | ADMSUrban.queue | 9 | 1.00 | 4.80 | 4.80 | 0.16 | 0.16 | 5.81 | 0.85 |
| roadside | KCLurban | 11 | 1.00 | 2.27 | 3.63 | 0.07 | 0.12 | 4.83 | 0.74 |
| roadside | KCLurbanCMAQ | 11 | 1.00 | 8.04 | 9.57 | 0.26 | 0.31 | 10.28 | 0.60 |
| suburban | ADMSUrban | 8 | 1.00 | -0.08 | 1.65 | -0.00 | 0.04 | 2.10 | 0.92 |
| suburban | ADMSUrban.queue | 8 | 1.00 | -0.08 | 1.65 | -0.00 | 0.04 | 2.10 | 0.92 |
| suburban | KCLurban | 9 | 1.00 | 1.85 | 3.15 | 0.05 | 0.08 | 3.50 | 0.74 |
| suburban | KCLurbanCMAQ | 7 | 1.00 | 10.30 | 10.30 | 0.25 | 0.25 | 10.76 | 0.41 |
| urban background | ADMSUrban | 14 | 1.00 | 0.32 | 2.90 | 0.01 | 0.08 | 3.84 | 0.65 |
| urban background | ADMSUrban.queue | 14 | 1.00 | 0.32 | 2.90 | 0.01 | 0.08 | 3.84 | 0.65 |
| urban background | KCLurban | 15 | 1.00 | 2.93 | 3.79 | 0.08 | 0.11 | 4.97 | 0.63 |
| urban background | KCLurbanCMAQ | 14 | 1.00 | 8.42 | 8.63 | 0.24 | 0.24 | 9.95 | 0.58 |

```
scatterPlot(o3.results, x = "o3.meas", y = "O3", type = "group", mod.line = TRUE,
            pch = 16, smooth = FALSE, group = "site.type", cex = 1.5,
            xlim = c(0, 60), ylim = c(0, 60))
```

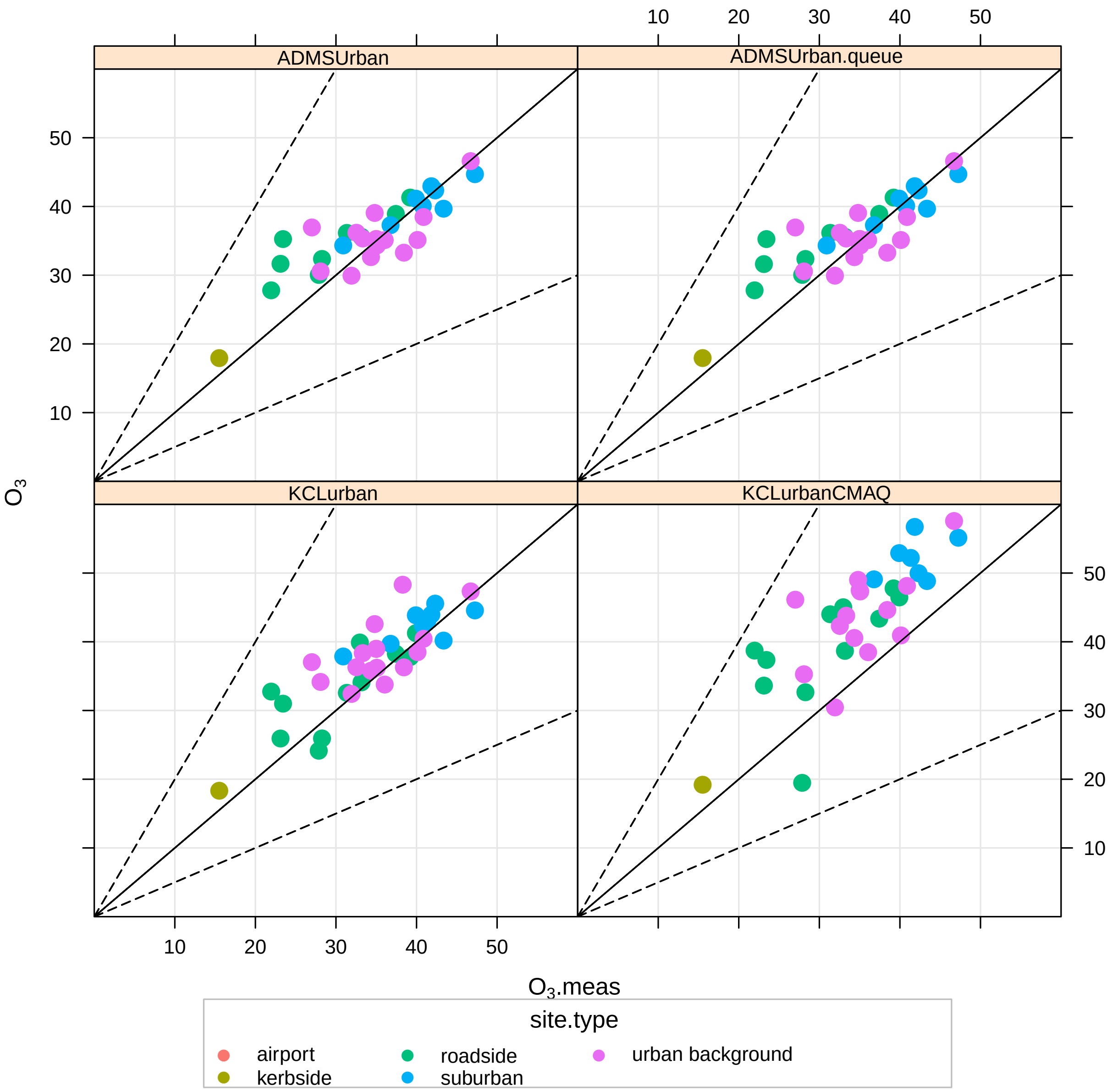


**Figure 12:** Measured vs. modelled annual mean $O_3$ concentrations for each model.

### 3.3 Annual mean $PM_{10}$

```
pm10.results <- subset(all.results, pm10.count > 0.75 * 8784 & group != "KCLurbanCMAQ")
## extract only those results where all groups made a prediction
## sites where this is true
fullSites <- with(pm10.results, tapply(PM10, site.code, function (x) length(na.omit(x))))
fullSites <- fullSites[fullSites == length(unique(pm10.results$group))]
pm10.results <- subset(pm10.results, site.code %in% names(fullSites))
```

And the model evaluation statistics are:

```
pm10Stats <- modStats(pm10.results, type = c("site.type", "group"), obs = "pm10.meas", mod = "PM10")
```

**Table 5:** Summary model evaluation statistics for annual mean $PM_{10}$.

| site.type | group | n | FAC2 | MB | MGE | NMB | NMGE | RMSE | r |
|---|---|---|---|---|---|---|---|---|---|
| kerbside | ADMSUrban | 6 | 1.00 | -4.80 | 4.80 | -0.15 | 0.15 | 6.04 | 0.76 |
| kerbside | ADMSUrban.queue | 6 | 1.00 | -3.81 | 3.81 | -0.12 | 0.12 | 5.08 | 0.81 |
| kerbside | BRUTAL | 6 | 1.00 | -4.73 | 5.30 | -0.15 | 0.17 | 6.63 | 0.57 |
| kerbside | KCLurban | 6 | 1.00 | -7.14 | 7.14 | -0.23 | 0.23 | 8.31 | 0.67 |
| kerbside | PCM | 6 | 1.00 | -4.22 | 4.47 | -0.13 | 0.14 | 5.33 | 0.84 |
| roadside | ADMSUrban | 17 | 1.00 | -1.24 | 2.06 | -0.05 | 0.08 | 3.11 | 0.66 |
| roadside | ADMSUrban.queue | 17 | 1.00 | -0.63 | 1.91 | -0.02 | 0.07 | 2.92 | 0.66 |
| roadside | BRUTAL | 17 | 1.00 | -0.69 | 2.87 | -0.03 | 0.11 | 3.84 | 0.35 |
| roadside | KCLurban | 17 | 1.00 | -4.57 | 4.57 | -0.18 | 0.18 | 5.53 | 0.57 |
| roadside | PCM | 17 | 1.00 | -0.02 | 2.55 | -0.00 | 0.10 | 3.18 | 0.57 |
| suburban | ADMSUrban | 8 | 1.00 | 1.81 | 1.81 | 0.09 | 0.09 | 2.08 | 0.39 |
| suburban | ADMSUrban.queue | 8 | 1.00 | 1.81 | 1.81 | 0.09 | 0.09 | 2.08 | 0.39 |
| suburban | BRUTAL | 8 | 1.00 | 1.05 | 1.63 | 0.05 | 0.08 | 1.97 | 0.08 |
| suburban | KCLurban | 8 | 1.00 | -1.69 | 1.72 | -0.09 | 0.09 | 2.03 | 0.05 |
| suburban | PCM | 8 | 1.00 | 0.52 | 1.20 | 0.03 | 0.06 | 1.39 | 0.27 |
| urban background | ADMSUrban | 19 | 1.00 | 1.00 | 1.50 | 0.05 | 0.07 | 1.84 | 0.63 |
| urban background | ADMSUrban.queue | 19 | 1.00 | 1.00 | 1.50 | 0.05 | 0.07 | 1.84 | 0.63 |
| urban background | BRUTAL | 19 | 1.00 | 1.43 | 1.86 | 0.07 | 0.09 | 2.11 | 0.72 |
| urban background | KCLurban | 19 | 1.00 | -2.50 | 2.52 | -0.12 | 0.12 | 2.93 | 0.72 |
| urban background | PCM | 19 | 1.00 | 0.21 | 1.21 | 0.01 | 0.06 | 1.45 | 0.70 |

```
scatterPlot(pm10.results, x = "pm10.meas", y = "PM10", type = "group", mod.line = TRUE,
            pch = 16, smooth = FALSE, group = "site.type", xlim = c(0, 40), ylim = c(0, 40))
```

```
scatterPlot(pm10Stats, x = "group", y = "FAC2", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

```
scatterPlot(pm10Stats, x = "group", y = "MB", type = "site.type", key = FALSE, pch = 16, cex = 1.5,
            ref.y = 0)
```

```
scatterPlot(pm10Stats, x = "group", y = "RMSE", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

```
scatterPlot(pm10Stats, x = "group", y = "r", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

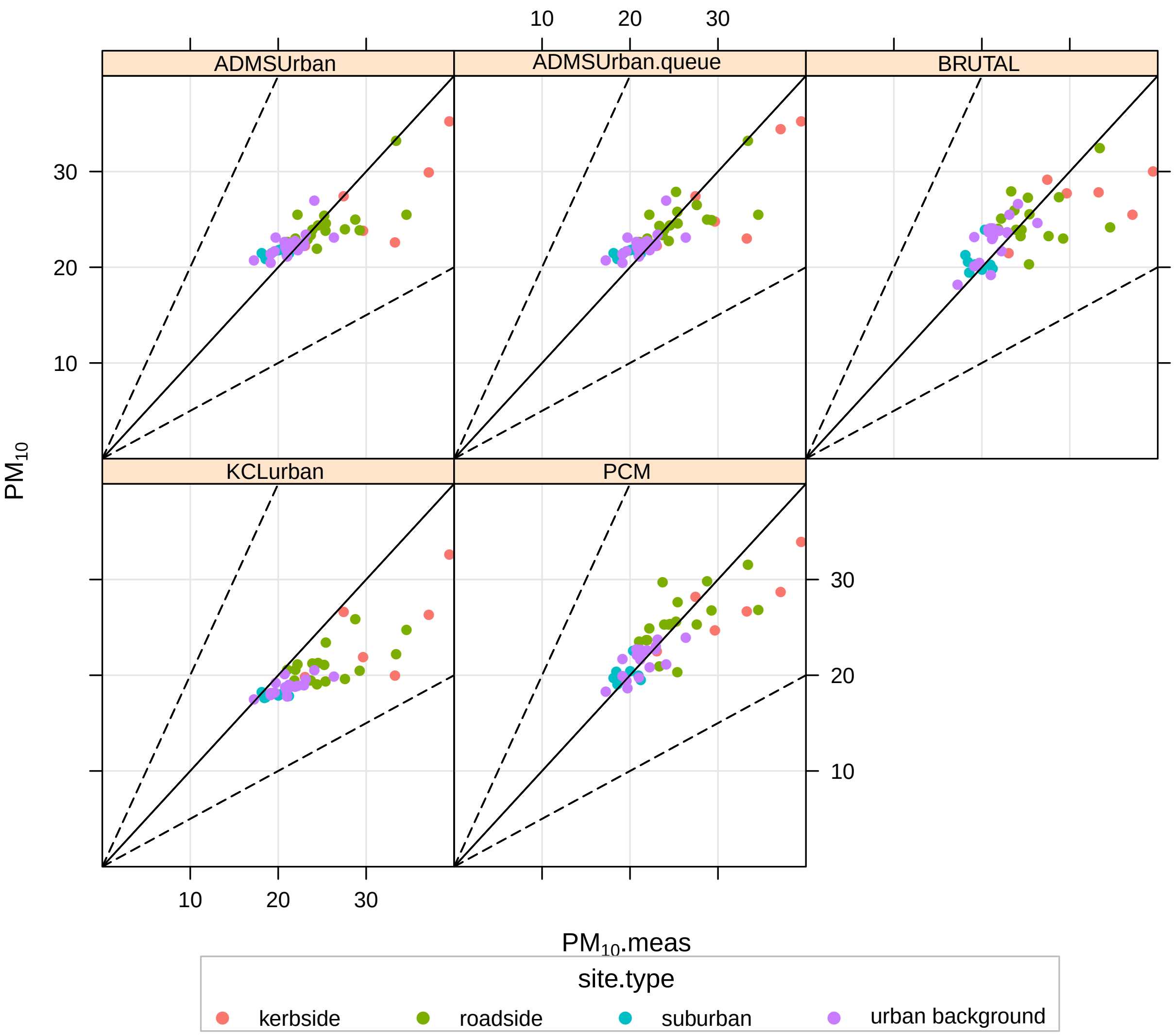


**Figure 13:** Measured vs. modelled annual mean $PM_{10}$ concentrations for each model.

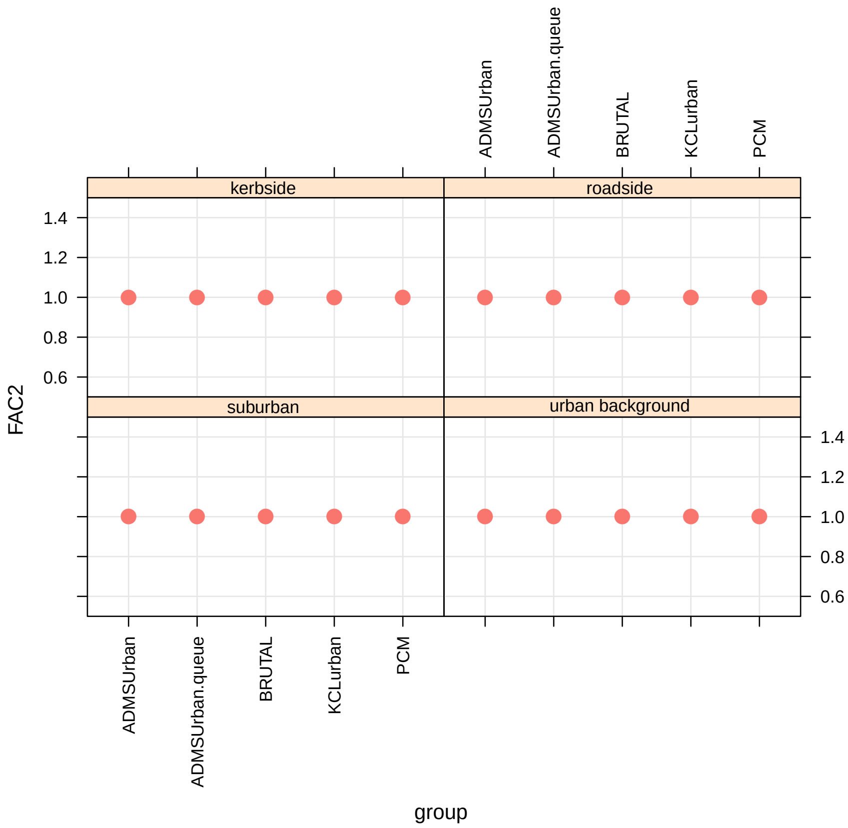


**Figure 14:** Graphical summary of FAC for each model by site type for $PM_{10}$.

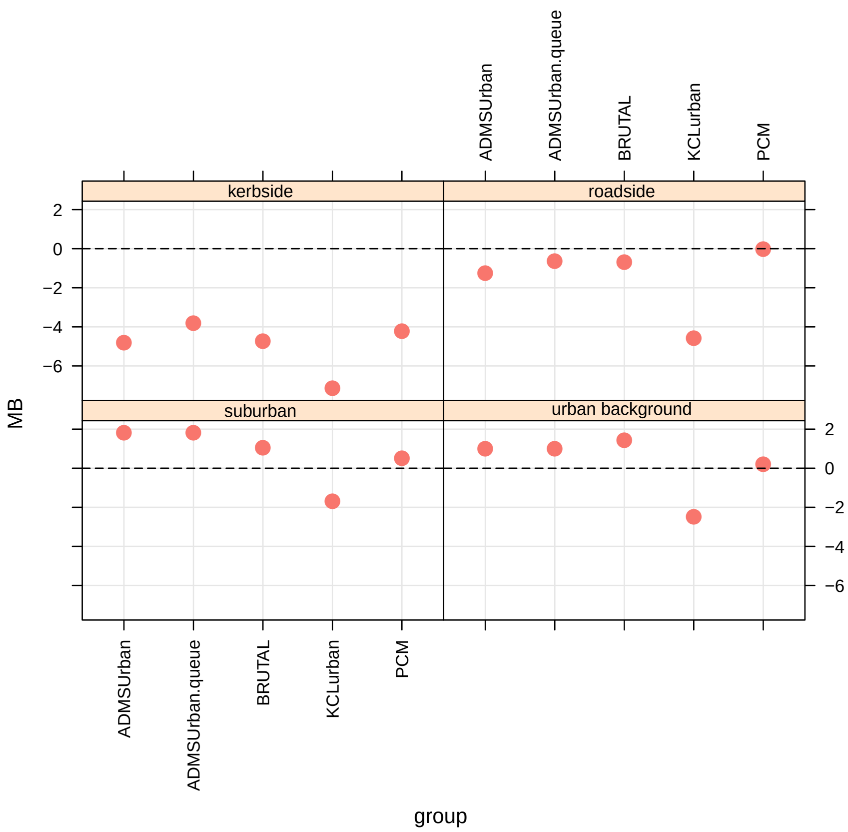


**Figure 15:** Graphical summary of mean bias for each model by site type for $PM_{10}$.

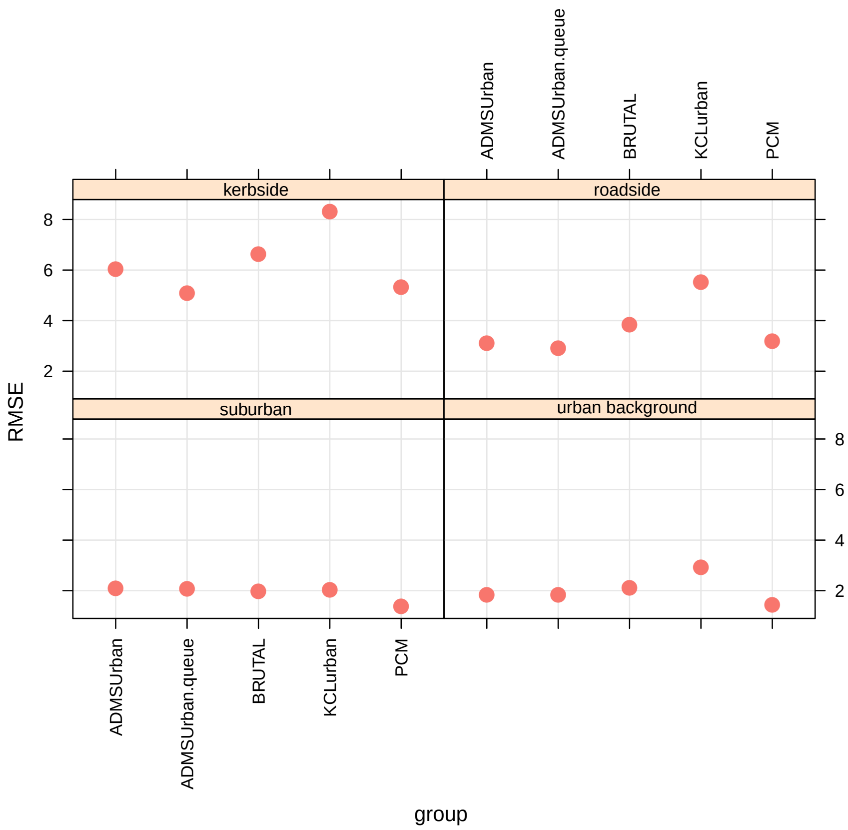


**Figure 16:** Graphical summary of RMSE for each model by site type for $PM_{10}$.

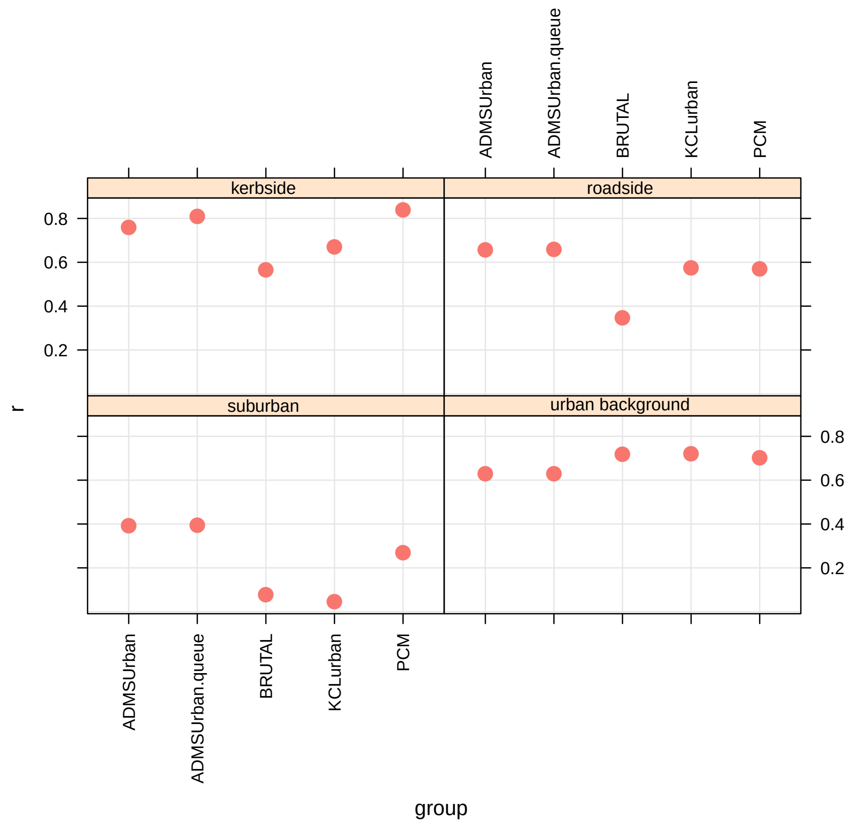


**Figure 17:** Graphical summary of the correlation coefficient, $r$, for each model by site type for $PM_{10}$.

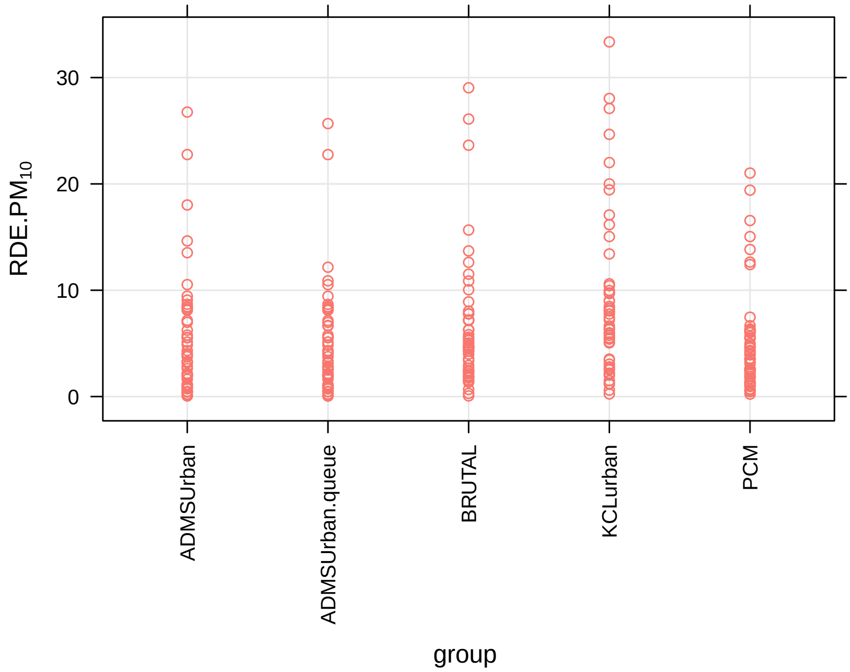


**Figure 18:** The RDE for annual mean $PM_{10}$ concentrations by group.

### 3.3.1 Relative Directive Error, *RDE*

```
pm10.results$RDE.PM10 <- 100 * abs((pm10.results$pm10.meas - pm10.results$PM10)) / 40
```

The RDE results for $PM_{10}$ are plotted in Figure 18. The RDE is calculated in the same way as for $NO_2$ shown in subsubsection 3.1.1. It should be noted, as in the case of $NO_2$, that the RDE would be applied to national scale data and not London in isolation. These results therefore show the model performance for a subset of data and as such is not comparable with Directive requirements.

```
scatterPlot(pm10.results, x = "group", y = "RDE.PM10")
```

The 90th percentile values are shown in Table 6. The Directive specifies that the models should have a value $< 50\%$, which all models meet comfortably. The reason why the models meet the uncertainty requirement for $PM_{10}$ so easily compared with $NO_2$ is because the $PM_{10}$ concentrations are much lower than $NO_2$.

```
RDE.PM10 <- with(pm10.results, tapply(RDE.PM10, group, function (x) quantile(x, prob = 0.9, na.rm = T)))
```

**Table 6:** Summary of the Maximum Relative Directive Error for annual mean $PM_{10}$ by group (%).

| ADMSUrban | ADMSUrban.queue | BRUTAL | KCLurban | PCM |
|---|---|---|---|---|
| 10.83 | 9.55 | 12.73 | 20.20 | 12.77 |

## 3.4 Annual mean $PM_{2.5}$

```
pm25.results <- subset(all.results, pm25.count > 0.75 * 8784 & group != "KCLurbanCMAQ" & group != "BRUTAL")
## extract only those results where all groups made a prediction
## sites where this is true
fullSites <- with(pm25.results, tapply(PM2.5, site.code, function (x) length(na.omit(x))))
fullSites <- fullSites[fullSites == length(unique(pm25.results$group))]
pm25.results <- subset(pm25.results, site.code %in% names(fullSites))
```

And the model evaluation statistics are:

```
pm25Stats <- modStats(pm25.results, type = c("site.type", "group"), obs = "pm25.meas", mod = "PM2.5")
```

**Table 7:** Summary model evaluation statistics for annual mean $PM_{2.5}$.

| site.type | group | n | FAC2 | MB | MGE | NMB | NMGE | RMSE | r |
|---|---|---|---|---|---|---|---|---|---|
| kerbside | ADMSUrban | 1 | 1.00 | 2.86 | 2.86 | 0.14 | 0.14 | 2.86 | |
| kerbside | ADMSUrban.queue | 1 | 1.00 | 2.86 | 2.86 | 0.14 | 0.14 | 2.86 | |
| kerbside | KCLurban | 1 | 1.00 | 1.81 | 1.81 | 0.09 | 0.09 | 1.81 | |
| kerbside | PCM | 1 | 1.00 | 0.95 | 0.95 | 0.05 | 0.05 | 0.95 | |
| roadside | ADMSUrban | 9 | 1.00 | -1.88 | 2.74 | -0.13 | 0.18 | 3.37 | 0.21 |
| roadside | ADMSUrban.queue | 9 | 1.00 | -1.59 | 2.90 | -0.11 | 0.19 | 3.43 | 0.06 |
| roadside | KCLurban | 9 | 1.00 | -1.16 | 1.79 | -0.08 | 0.12 | 2.16 | 0.68 |
| roadside | PCM | 9 | 1.00 | 3.00 | 3.16 | 0.20 | 0.21 | 3.49 | 0.70 |
| suburban | ADMSUrban | 1 | 1.00 | -0.62 | 0.62 | -0.06 | 0.06 | 0.62 | |
| suburban | ADMSUrban.queue | 1 | 1.00 | -0.61 | 0.61 | -0.06 | 0.06 | 0.61 | |
| suburban | KCLurban | 1 | 1.00 | 0.22 | 0.22 | 0.02 | 0.02 | 0.22 | |
| suburban | PCM | 1 | 1.00 | 2.83 | 2.83 | 0.26 | 0.26 | 2.83 | |
| urban background | ADMSUrban | 2 | 1.00 | -2.07 | 2.07 | -0.14 | 0.14 | 2.59 | -1.00 |
| urban background | ADMSUrban.queue | 2 | 1.00 | -2.07 | 2.07 | -0.14 | 0.14 | 2.59 | -1.00 |
| urban background | KCLurban | 2 | 1.00 | -1.85 | 1.85 | -0.13 | 0.13 | 2.18 | -1.00 |
| urban background | PCM | 2 | 1.00 | 1.94 | 1.94 | 0.14 | 0.14 | 2.54 | -1.00 |

Save all the statistics for external processing if necessary.

```
save(noxStats, no2Stats, o3Stats, pm10Stats, pm25Stats, file = "urbanStats.RData")
```

```
scatterPlot(pm25.results, x = "pm25.meas", y = "PM2.5", type = "group", mod.line = TRUE,
            pch = 16, smooth = FALSE, group = "site.type",
            cex = 1.5, xlim = c(0, 21), ylim = c(0, 21))
```

```
scatterPlot(pm25Stats, x = "group", y = "FAC2", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

```
scatterPlot(pm25Stats, x = "group", y = "MB", type = "site.type", key = FALSE, pch = 16, cex = 1.5,
            ref.y = 0)
```

```
scatterPlot(pm25Stats, x = "group", y = "RMSE", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

```
scatterPlot(pm25Stats, x = "group", y = "r", type = "site.type", key = FALSE, pch = 16, cex = 1.5)
```

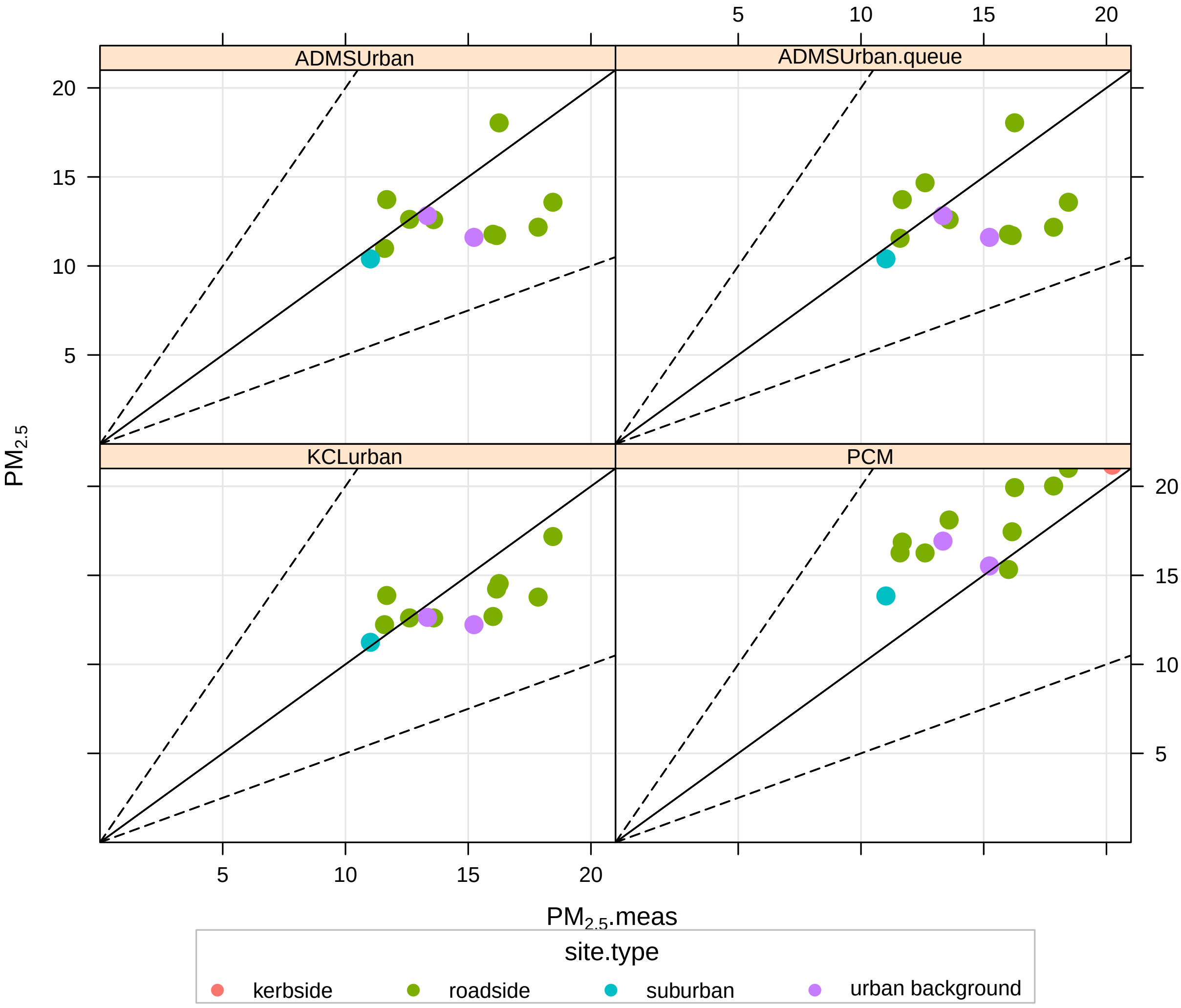


**Figure 19:** Measured vs. modelled annual mean $PM_{2.5}$ concentrations for each model.

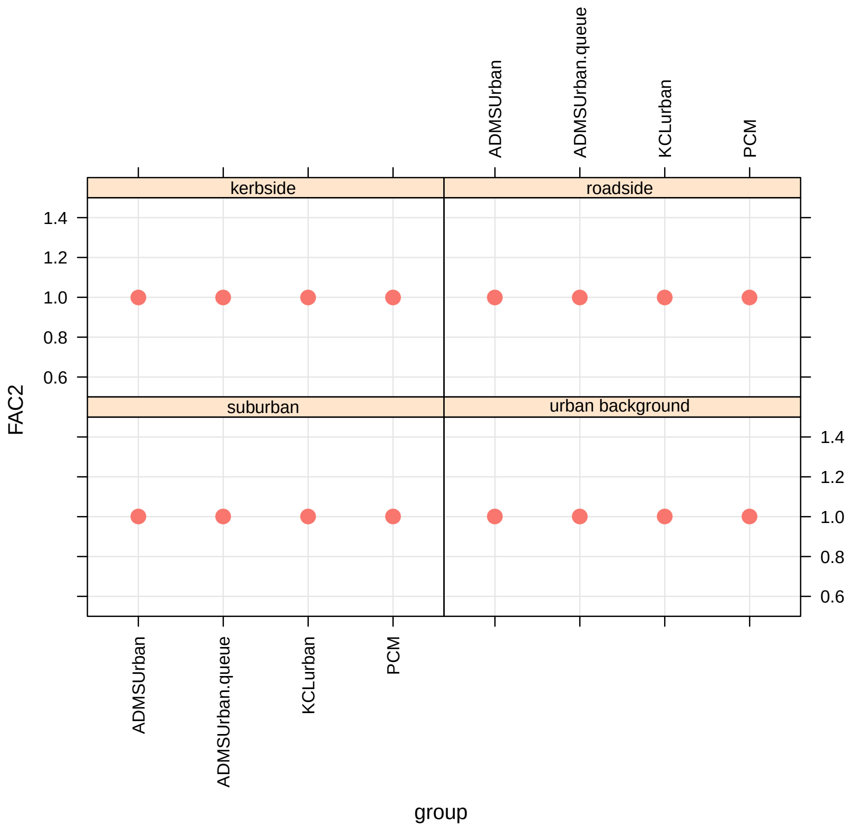


**Figure 20:** Graphical summary of FAC for each model by site type for $PM_{2.5}$.

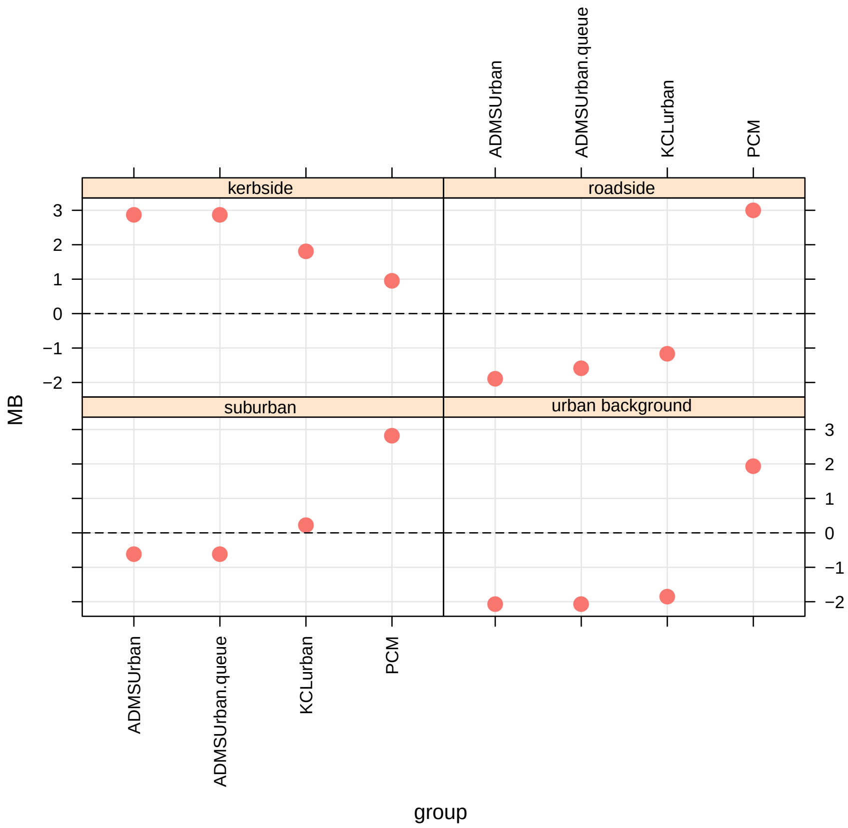


**Figure 21:** Graphical summary of mean bias for each model by site type for $PM_{2.5}$.

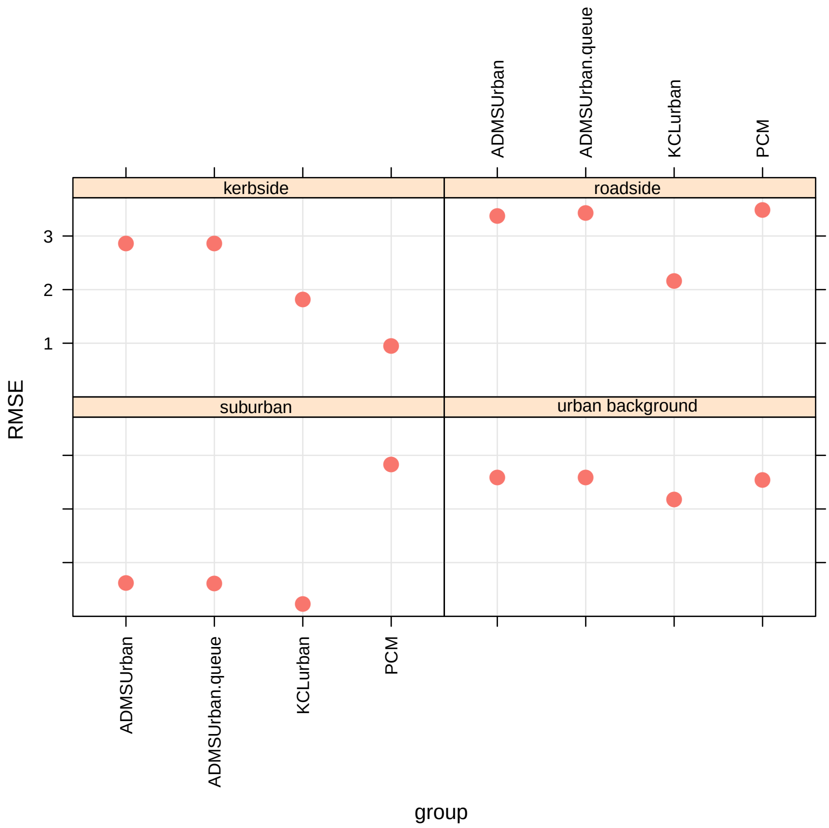


**Figure 22:** Graphical summary of RMSE for each model by site type for $PM_{2.5}$.

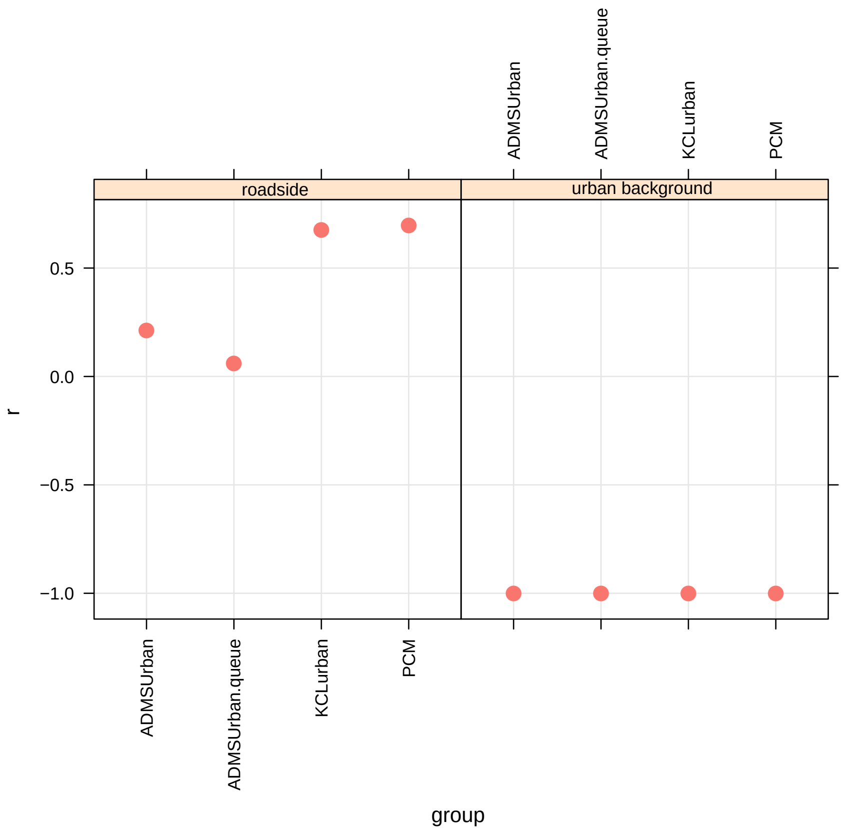


**Figure 23:** Graphical summary of the correlation coefficient, $r$, for each model by site type for $PM_{2.5}$.

# 4 Hourly analysis

## 4.1 Data preparation

This sections considers the hourly predictions from the KCL and CERC models. Neither BRUTAL nor the PCM models provide hourly outputs.

The KCL data are imported as follows.

```
## note different data order here
KCL.hourly <- import("KCLRoadsideNOxO3Hourly.csv")
```

```
    date1      date2      month       day      hour site.code site.name site.type
"POSIXct"  "POSIXt" "integer" "integer" "integer"  "factor"  "factor"  "factor"
      NOx        NO2         O3
"numeric" "numeric" "numeric"
```

```
KCL.hourly$group <- "KCLurbanCMAQ"
```

The CERC data are in several files and need some pre-processing. Missing data are shown as `-999`.

```
## data are sites by column; need to stack and combine
nox <- import("HourlyNOxCERC.csv", na.strings = "-999")
```

```
     date1      date2        BL0        BX1        CD3        CR4        EA1        EA2
 "POSIXct"   "POSIXt"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"
       EN1        GR4        HG1        KC1        LB4        LW2        TD0        TH1
 "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"
       TH2
 "numeric"
```

```
## stack data
nox <- melt(nox, id.vars = "date")
names(nox) <- c("date", "site.code", "NOx")
## NO2
no2 <- import("HourlyNO2CERC.csv", na.strings = "-999")
```

```
     date1      date2        BL0        BX1        CD3        CR4        EA1        EA2
 "POSIXct"   "POSIXt"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"
       EN1        GR4        HG1        KC1        LB4        LW2        TD0        TH1
 "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"
       TH2
 "numeric"
```

```
## stack data
no2 <- melt(no2, id.vars = "date")
names(no2) <- c("date", "site.code", "NO2")
## O3
o3 <- import("HourlyO3CERC.csv", na.strings = "-999")
```

```
     date1      date2        BL0        BX1        EA1        EA2        GR4        KC1
 "POSIXct"   "POSIXt"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"
       TD0        TH1
 "numeric"  "numeric"
```

```
## stack data
o3 <- melt(o3, id.vars = "date")
names(o3) <- c("date", "site.code", "O3")
## PM10
pm10 <- import("HourlyPM10CERC.csv", na.strings = "-999")
```

```
     date1      date2        BL0        BX1        CD3        CR4        EA2        GR4
 "POSIXct"   "POSIXt"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"
       HG1        KC1        LB4        LW2        TH1
 "numeric"  "numeric"  "numeric"  "numeric"  "numeric"
```

```
## stack data
pm10 <- melt(pm10, id.vars = "date")
names(pm10) <- c("date", "site.code", "PM10")
## PM2.5
pm25 <- import("HourlyPM25CERC.csv", na.strings = "-999")
```

```
     date1      date2        BL0        BX1        EA2        GR4        KC1        TD0
 "POSIXct"   "POSIXt"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"
```

```
## stack data
pm25 <- melt(pm25, id.vars = "date")
names(pm25) <- c("date", "site.code", "PM2.5")
```

Now the data can be combined:

```
ADMSUrban.hourly <- rbind.fill(nox, no2, o3, pm10, pm25)
ADMSUrban.hourly$group <- "ADMSurban"
```

Note also that CERC produced an alternative set of predictions that aimed to take better account of vehicle queuing. These data are imported as follows.

```
## data are sites by column; need to stack and commbine
nox <- import("HourlyNOx(16Dec).csv", na.strings = "-999")
```

```
    date1      date2       BL0       BX1       CD3       CR4       EA1       EA2
"POSIXct"  "POSIXt" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
      EN1        GR4       HG1       KC1       LB4       LW2       TD0       TH1
"numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
      TH2
"numeric"
```

```
## stack data
nox <- melt(nox, id.vars = "date")
names(nox) <- c("date", "site.code", "NOx")
## NO2
no2 <- import("HourlyNO2(16Dec).csv", na.strings = "-999")
```

```
    date1      date2       BL0       BX1       CD3       CR4       EA1       EA2
"POSIXct"  "POSIXt" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
      EN1        GR4       HG1       KC1       LB4       LW2       TD0       TH1
"numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
      TH2
"numeric"
```

```
## stack data
no2 <- melt(no2, id.vars = "date")
names(no2) <- c("date", "site.code", "NO2")
## O3
o3 <- import("HourlyO3(16Dec).csv", na.strings = "-999")
```

```
    date1      date2       BL0       BX1       EA1       EA2       GR4       KC1
"POSIXct"  "POSIXt" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
      TD0        TH1
"numeric" "numeric"
```

```
## stack data
o3 <- melt(o3, id.vars = "date")
names(o3) <- c("date", "site.code", "O3")
## PM10
pm10 <- import("HourlyPM10(16Dec).csv", na.strings = "-999")
```

```
    date1      date2       BL0       BX1       CD3       CR4       EA2       GR4
"POSIXct"  "POSIXt" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
      HG1        KC1       LB4       LW2       TH1
"numeric" "numeric" "numeric" "numeric" "numeric"
```

```
## stack data
pm10 <- melt(pm10, id.vars = "date")
names(pm10) <- c("date", "site.code", "PM10")
## PM2.5
pm25 <- import("HourlyPM25(16Dec).csv", na.strings = "-999")
```

```
    date1      date2       BL0       BX1       EA2       GR4       KC1       TD0
"POSIXct"  "POSIXt" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
```

```
## stack data
pm25 <- melt(pm25, id.vars = "date")
names(pm25) <- c("date", "site.code", "PM2.5")
## combine and name
ADMSUrban.hourly.queue <- rbind.fill(nox, no2, o3, pm10, pm25)
ADMSUrban.hourly.queue$group <- "ADMSurbanQueue"
```

The CERC and the KCL data can now be combined:

```
urban.hourly <- rbind.fill(ADMSUrban.hourly, KCL.hourly, ADMSUrban.hourly.queue)
```

These results need to be combined with measurements. These can be downloaded using the importKCL function as shown below. However, for the sake of speed, these data are imported from a pre-prepared file.

```
## to imprt using importKCL
urban.meas <- importKCL(site = c("BL0", "BX1", "CD3", "CR4", "EA1", "EA2", "EN1", "GR4", "HG1", "KC1", "LB4",
                       "LW2", "TD0", "TH1", "TH2"), year = 2008)
```

And to import pre-prepared values:

```
## this loads a data frame called urban.meas
load("urbanMeas.RData")
## rename some fields
urban.meas <- rename(urban.meas, c(nox = "nox.meas", no2 = "no2.meas", o3 = "o3.meas",
                                  pm10 = "pm10.meas", pm25 = "pm25.meas", code = "site.code"))
```

Finally, all these data can be combined, ready for processing.

```
urban.hourly <- merge(urban.hourly, urban.meas, by = c("date", "site.code"), all = TRUE)
## rename to make axes clearer
urban.hourly <- rename(urban.hourly, c(NOx = "nox.mod", NO2 = "no2.mod", O3 = "o3.mod",
                                  PM10 = "pm10.mod", PM2.5 = "pm25.mod"))
```

## 4.2 Evaluation metrics

First we consider the evaluation statistics by group and by site.

```
NOx.stats <- modStats(urban.hourly, type = c("group", "site"), obs = "nox.meas", mod = "nox.mod")
```

```
NO2.stats <- modStats(urban.hourly, type = c("group", "site"), obs = "no2.meas", mod = "no2.mod")
```

```
O3.stats <- modStats(urban.hourly, type = c("group", "site"), obs = "no2.meas", mod = "o3.mod")
```

```
PM10.stats <- modStats(urban.hourly, type = c("group", "site"), obs = "pm10.meas", mod = "pm10.mod")
```

**Table 8:** Summary model evaluation statistics for hourly mean $NO_x$.

| group | site | n | FAC2 | MB | MGE | NMB | NMGE | RMSE | r |
|---|---|---|---|---|---|---|---|---|---|
| ADMSurban | Camden - Bloomsbury | 8316 | 0.84 | 4.50 | 39.29 | 0.05 | 0.43 | 62.75 | 0.65 |
| ADMSurban | Bexley - Slade Green | 8175 | 0.75 | -12.41 | 27.17 | -0.23 | 0.50 | 54.58 | 0.60 |
| ADMSurban | Camden - Shaftesbury Avenue | 8250 | 0.74 | -17.24 | 71.57 | -0.10 | 0.43 | 101.05 | 0.55 |
| ADMSurban | Croydon - George Street | 8192 | 0.83 | 30.18 | 42.99 | 0.32 | 0.45 | 72.06 | 0.75 |
| ADMSurban | Ealing - Ealing Town Hall | 8291 | 0.75 | 18.67 | 36.99 | 0.29 | 0.58 | 64.18 | 0.67 |
| ADMSurban | Ealing - Acton Town Hall | 7307 | 0.80 | -7.61 | 51.44 | -0.06 | 0.42 | 81.90 | 0.66 |
| ADMSurban | Enfield 1 - Bushhill Park | 6782 | 0.77 | -11.13 | 21.49 | -0.24 | 0.46 | 44.13 | 0.60 |
| ADMSurban | Greenwich - Eltham | 8020 | 0.73 | 7.77 | 21.35 | 0.20 | 0.55 | 43.97 | 0.67 |
| ADMSurban | Haringey - Haringey Town Hall | 8326 | 0.83 | -8.08 | 29.93 | -0.11 | 0.41 | 59.06 | 0.68 |
| ADMSurban | Kensington and Chelsea - North Ken | 7592 | 0.63 | 24.12 | 34.55 | 0.50 | 0.71 | 55.59 | 0.64 |
| ADMSurban | Lambeth - Brixton Road | 7413 | 0.51 | -259.34 | 275.59 | -0.50 | 0.53 | 358.24 | 0.63 |
| ADMSurban | Lewisham - New Cross | 7914 | 0.70 | -27.36 | 66.40 | -0.19 | 0.45 | 99.31 | 0.64 |
| ADMSurban | Richmond - National Physical Laboratory | 8131 | 0.77 | 1.56 | 19.42 | 0.04 | 0.54 | 41.44 | 0.65 |
| ADMSurban | Tower Hamlets - Poplar | 8317 | 0.79 | 15.37 | 27.87 | 0.28 | 0.51 | 49.54 | 0.68 |
| ADMSurban | Tower Hamlets - Mile End Road | 8182 | 0.60 | -60.36 | 69.61 | -0.43 | 0.50 | 99.40 | 0.62 |
| ADMSurban | | 0 | | | | | | | |
| ADMSurbanQueue | Camden - Bloomsbury | 8316 | 0.84 | 4.50 | 39.29 | 0.05 | 0.43 | 62.75 | 0.65 |
| ADMSurbanQueue | Bexley - Slade Green | 8175 | 0.75 | -12.41 | 27.17 | -0.23 | 0.50 | 54.58 | 0.60 |
| ADMSurbanQueue | Camden - Shaftesbury Avenue | 8250 | 0.74 | -17.24 | 71.57 | -0.10 | 0.43 | 101.05 | 0.55 |
| ADMSurbanQueue | Croydon - George Street | 8192 | 0.83 | 30.18 | 42.99 | 0.32 | 0.45 | 72.06 | 0.75 |
| ADMSurbanQueue | Ealing - Ealing Town Hall | 8291 | 0.75 | 18.67 | 36.99 | 0.29 | 0.58 | 64.18 | 0.67 |
| ADMSurbanQueue | Ealing - Acton Town Hall | 7307 | 0.80 | -7.61 | 51.44 | -0.06 | 0.42 | 81.90 | 0.66 |
| ADMSurbanQueue | Enfield 1 - Bushhill Park | 6782 | 0.77 | -11.13 | 21.49 | -0.24 | 0.46 | 44.13 | 0.60 |
| ADMSurbanQueue | Greenwich - Eltham | 8020 | 0.73 | 7.77 | 21.35 | 0.20 | 0.55 | 43.97 | 0.67 |
| ADMSurbanQueue | Haringey - Haringey Town Hall | 8326 | 0.83 | -8.08 | 29.93 | -0.11 | 0.41 | 59.06 | 0.68 |
| ADMSurbanQueue | Kensington and Chelsea - North Ken | 7592 | 0.63 | 24.12 | 34.55 | 0.50 | 0.71 | 55.59 | 0.64 |
| ADMSurbanQueue | Lambeth - Brixton Road | 7413 | 0.62 | -181.51 | 237.07 | -0.35 | 0.46 | 313.80 | 0.60 |
| ADMSurbanQueue | Lewisham - New Cross | 7914 | 0.70 | -27.36 | 66.40 | -0.19 | 0.45 | 99.31 | 0.64 |
| ADMSurbanQueue | Richmond - National Physical Laboratory | 8131 | 0.77 | 1.56 | 19.42 | 0.04 | 0.54 | 41.44 | 0.65 |
| ADMSurbanQueue | Tower Hamlets - Poplar | 8317 | 0.79 | 15.37 | 27.87 | 0.28 | 0.51 | 49.54 | 0.68 |
| ADMSurbanQueue | Tower Hamlets - Mile End Road | 8182 | 0.63 | -35.59 | 68.99 | -0.26 | 0.50 | 97.86 | 0.53 |
| ADMSurbanQueue | | 0 | | | | | | | |
| KCLurbanCMAQ | Camden - Bloomsbury | 8175 | 0.78 | -10.85 | 40.45 | -0.12 | 0.43 | 62.79 | 0.60 |
| KCLurbanCMAQ | Bexley - Slade Green | 8027 | 0.70 | -17.26 | 29.94 | -0.31 | 0.54 | 59.47 | 0.56 |
| KCLurbanCMAQ | Camden - Shaftesbury Avenue | 8101 | 0.78 | 26.70 | 82.19 | 0.16 | 0.48 | 125.35 | 0.57 |
| KCLurbanCMAQ | Croydon - George Street | 8048 | 0.60 | -40.86 | 48.03 | -0.44 | 0.51 | 76.40 | 0.51 |
| KCLurbanCMAQ | Ealing - Ealing Town Hall | 8150 | 0.75 | -19.63 | 32.32 | -0.30 | 0.49 | 68.69 | 0.57 |
| KCLurbanCMAQ | Ealing - Acton Town Hall | 7454 | 0.70 | -14.69 | 64.35 | -0.11 | 0.50 | 104.40 | 0.53 |
| KCLurbanCMAQ | Enfield 1 - Bushhill Park | 6512 | 0.66 | -13.09 | 25.20 | -0.28 | 0.54 | 50.17 | 0.52 |
| KCLurbanCMAQ | Greenwich - Eltham | 7943 | 0.72 | -6.23 | 21.39 | -0.15 | 0.53 | 46.37 | 0.53 |
| KCLurbanCMAQ | Haringey - Haringey Town Hall | 8182 | 0.75 | 0.73 | 37.13 | 0.01 | 0.49 | 69.97 | 0.60 |
| KCLurbanCMAQ | Kensington and Chelsea - North Ken | 7365 | 0.72 | 1.18 | 26.04 | 0.02 | 0.54 | 47.46 | 0.49 |
| KCLurbanCMAQ | Lambeth - Brixton Road | 7234 | 0.75 | -34.76 | 225.78 | -0.07 | 0.43 | 325.74 | 0.61 |
| KCLurbanCMAQ | Lewisham - New Cross | 7789 | 0.64 | -17.98 | 72.17 | -0.12 | 0.49 | 105.95 | 0.60 |
| KCLurbanCMAQ | Richmond - National Physical Laboratory | 7992 | 0.73 | -8.08 | 20.70 | -0.22 | 0.56 | 46.55 | 0.49 |
| KCLurbanCMAQ | Tower Hamlets - Poplar | 8182 | 0.75 | 2.12 | 28.50 | 0.04 | 0.51 | 51.36 | 0.54 |
| KCLurbanCMAQ | Tower Hamlets - Mile End Road | 8036 | 0.72 | 38.20 | 77.52 | 0.28 | 0.56 | 113.70 | 0.58 |
| KCLurbanCMAQ | | 0 | | | | | | | |

**Table 9:** Summary model evaluation statistics for hourly mean $NO_2$.

| group | site | n | FAC2 | MB | MGE | NMB | NMGE | RMSE | r |
|---|---|---|---|---|---|---|---|---|---|
| ADMSurban | Camden - Bloomsbury | 8316 | 0.91 | -4.04 | 15.76 | -0.07 | 0.29 | 21.05 | 0.66 |
| ADMSurban | Bexley - Slade Green | 8175 | 0.80 | -5.52 | 12.53 | -0.17 | 0.38 | 18.03 | 0.68 |
| ADMSurban | Camden - Shaftesbury Avenue | 8250 | 0.82 | -12.86 | 27.02 | -0.16 | 0.34 | 34.63 | 0.49 |
| ADMSurban | Croydon - George Street | 8192 | 0.93 | 4.83 | 15.50 | 0.10 | 0.31 | 23.87 | 0.74 |
| ADMSurban | Ealing - Ealing Town Hall | 8268 | 0.89 | 3.52 | 12.79 | 0.09 | 0.33 | 18.14 | 0.73 |
| ADMSurban | Ealing - Acton Town Hall | 7301 | 0.90 | -3.74 | 18.21 | -0.06 | 0.31 | 26.07 | 0.68 |
| ADMSurban | Enfield 1 - Bushhill Park | 6782 | 0.82 | -4.84 | 11.06 | -0.16 | 0.36 | 15.61 | 0.68 |
| ADMSurban | Greenwich - Eltham | 8019 | 0.80 | 3.61 | 10.57 | 0.14 | 0.41 | 16.45 | 0.71 |
| ADMSurban | Haringey - Haringey Town Hall | 8326 | 0.88 | 1.63 | 12.13 | 0.04 | 0.33 | 16.79 | 0.70 |
| ADMSurban | Kensington and Chelsea - North Ken | 7592 | 0.80 | 9.07 | 14.38 | 0.28 | 0.44 | 19.91 | 0.71 |
| ADMSurban | Lambeth - Brixton Road | 7412 | 0.48 | -115.95 | 119.19 | -0.53 | 0.55 | 151.02 | 0.53 |
| ADMSurban | Lewisham - New Cross | 7914 | 0.77 | -11.65 | 25.05 | -0.18 | 0.39 | 33.81 | 0.62 |
| ADMSurban | Richmond - National Physical Laboratory | 8131 | 0.79 | 0.60 | 10.11 | 0.02 | 0.42 | 16.24 | 0.72 |
| ADMSurban | Tower Hamlets - Poplar | 8317 | 0.91 | 3.42 | 11.85 | 0.09 | 0.32 | 16.94 | 0.73 |
| ADMSurban | Tower Hamlets - Mile End Road | 8182 | 0.76 | -19.81 | 23.83 | -0.31 | 0.38 | 30.77 | 0.61 |
| ADMSurban | | 0 | | | | | | | |
| ADMSurbanQueue | Camden - Bloomsbury | 8316 | 0.91 | -4.04 | 15.76 | -0.07 | 0.29 | 21.05 | 0.66 |
| ADMSurbanQueue | Bexley - Slade Green | 8175 | 0.80 | -5.52 | 12.53 | -0.17 | 0.38 | 18.03 | 0.68 |
| ADMSurbanQueue | Camden - Shaftesbury Avenue | 8250 | 0.82 | -12.86 | 27.02 | -0.16 | 0.34 | 34.63 | 0.49 |
| ADMSurbanQueue | Croydon - George Street | 8192 | 0.93 | 4.83 | 15.50 | 0.10 | 0.31 | 23.87 | 0.74 |
| ADMSurbanQueue | Ealing - Ealing Town Hall | 8268 | 0.89 | 3.52 | 12.79 | 0.09 | 0.33 | 18.14 | 0.73 |
| ADMSurbanQueue | Ealing - Acton Town Hall | 7301 | 0.90 | -3.74 | 18.21 | -0.06 | 0.31 | 26.07 | 0.68 |
| ADMSurbanQueue | Enfield 1 - Bushhill Park | 6782 | 0.82 | -4.84 | 11.06 | -0.16 | 0.36 | 15.61 | 0.68 |
| ADMSurbanQueue | Greenwich - Eltham | 8019 | 0.80 | 3.61 | 10.57 | 0.14 | 0.41 | 16.45 | 0.71 |
| ADMSurbanQueue | Haringey - Haringey Town Hall | 8326 | 0.88 | 1.63 | 12.13 | 0.04 | 0.33 | 16.79 | 0.70 |
| ADMSurbanQueue | Kensington and Chelsea - North Ken | 7592 | 0.80 | 9.07 | 14.38 | 0.28 | 0.44 | 19.91 | 0.71 |
| ADMSurbanQueue | Lambeth - Brixton Road | 7412 | 0.61 | -91.93 | 102.88 | -0.42 | 0.47 | 133.35 | 0.53 |
| ADMSurbanQueue | Lewisham - New Cross | 7914 | 0.77 | -11.65 | 25.05 | -0.18 | 0.39 | 33.81 | 0.62 |
| ADMSurbanQueue | Richmond - National Physical Laboratory | 8131 | 0.79 | 0.60 | 10.11 | 0.02 | 0.42 | 16.24 | 0.72 |
| ADMSurbanQueue | Tower Hamlets - Poplar | 8317 | 0.91 | 3.42 | 11.85 | 0.09 | 0.32 | 16.94 | 0.73 |
| ADMSurbanQueue | Tower Hamlets - Mile End Road | 8182 | 0.79 | -12.66 | 22.90 | -0.20 | 0.36 | 30.19 | 0.55 |
| ADMSurbanQueue | | 0 | | | | | | | |
| KCLurbanCMAQ | Camden - Bloomsbury | 8175 | 0.90 | -2.83 | 16.52 | -0.05 | 0.30 | 21.85 | 0.60 |
| KCLurbanCMAQ | Bexley - Slade Green | 8027 | 0.80 | -1.93 | 12.83 | -0.06 | 0.39 | 17.67 | 0.63 |
| KCLurbanCMAQ | Camden - Shaftesbury Avenue | 8101 | 0.93 | 0.69 | 24.18 | 0.01 | 0.30 | 31.97 | 0.48 |
| KCLurbanCMAQ | Croydon - George Street | 8048 | 0.76 | -14.14 | 18.95 | -0.28 | 0.38 | 25.10 | 0.62 |
| KCLurbanCMAQ | Ealing - Ealing Town Hall | 8127 | 0.85 | -3.75 | 13.03 | -0.10 | 0.34 | 18.27 | 0.67 |
| KCLurbanCMAQ | Ealing - Acton Town Hall | 7448 | 0.84 | -1.16 | 22.15 | -0.02 | 0.37 | 31.25 | 0.56 |
| KCLurbanCMAQ | Enfield 1 - Bushhill Park | 6512 | 0.73 | -2.87 | 12.94 | -0.10 | 0.43 | 17.49 | 0.59 |
| KCLurbanCMAQ | Greenwich - Eltham | 7942 | 0.77 | 2.03 | 11.12 | 0.08 | 0.43 | 15.90 | 0.65 |
| KCLurbanCMAQ | Haringey - Haringey Town Hall | 8182 | 0.79 | 10.60 | 16.68 | 0.29 | 0.46 | 21.97 | 0.67 |
| KCLurbanCMAQ | Kensington and Chelsea - North Ken | 7365 | 0.79 | 3.93 | 13.75 | 0.12 | 0.42 | 18.84 | 0.61 |
| KCLurbanCMAQ | Lambeth - Brixton Road | 7233 | 0.78 | -48.26 | 85.50 | -0.22 | 0.39 | 113.90 | 0.55 |
| KCLurbanCMAQ | Lewisham - New Cross | 7789 | 0.77 | 1.01 | 25.78 | 0.02 | 0.41 | 35.07 | 0.55 |
| KCLurbanCMAQ | Richmond - National Physical Laboratory | 7992 | 0.74 | 0.03 | 11.32 | 0.00 | 0.47 | 17.17 | 0.62 |
| KCLurbanCMAQ | Tower Hamlets - Poplar | 8182 | 0.86 | 5.27 | 13.83 | 0.14 | 0.37 | 18.34 | 0.64 |
| KCLurbanCMAQ | Tower Hamlets - Mile End Road | 8036 | 0.88 | 13.35 | 22.07 | 0.21 | 0.35 | 28.31 | 0.67 |
| KCLurbanCMAQ | | 0 | | | | | | | |

**Table 10:** Summary model evaluation statistics for hourly mean $O_3$.

| group | site | n | FAC2 | MB | MGE | NMB | NMGE | RMSE | r |
|---|---|---|---|---|---|---|---|---|---|
| ADMSurban | Camden - Bloomsbury | 8246 | 0.66 | 2.10 | 11.02 | 0.07 | 0.39 | 14.75 | 0.78 |
| ADMSurban | Bexley - Slade Green | 8097 | 0.76 | -0.45 | 11.69 | -0.01 | 0.27 | 16.21 | 0.82 |
| ADMSurban | Camden - Shaftesbury Avenue | 0 | | | | | | | |
| ADMSurban | Croydon - George Street | 0 | | | | | | | |
| ADMSurban | Ealing - Ealing Town Hall | 8277 | 0.70 | -1.34 | 11.06 | -0.04 | 0.31 | 15.49 | 0.80 |
| ADMSurban | Ealing - Acton Town Hall | 8046 | 0.57 | 10.80 | 14.10 | 0.46 | 0.60 | 18.20 | 0.77 |
| ADMSurban | Enfield 1 - Bushhill Park | 0 | | | | | | | |
| ADMSurban | Greenwich - Eltham | 8086 | 0.76 | 0.74 | 10.73 | 0.02 | 0.27 | 14.85 | 0.83 |
| ADMSurban | Haringey - Haringey Town Hall | 0 | | | | | | | |
| ADMSurban | Kensington and Chelsea - North Ken | 8281 | 0.69 | -5.69 | 12.07 | -0.15 | 0.31 | 17.38 | 0.80 |
| ADMSurban | Lambeth - Brixton Road | 0 | | | | | | | |
| ADMSurban | Lewisham - New Cross | 0 | | | | | | | |
| ADMSurban | Richmond - National Physical Laboratory | 8247 | 0.79 | -3.14 | 11.66 | -0.07 | 0.24 | 16.60 | 0.82 |
| ADMSurban | Tower Hamlets - Poplar | 8306 | 0.69 | -5.90 | 12.46 | -0.14 | 0.31 | 17.48 | 0.81 |
| ADMSurban | Tower Hamlets - Mile End Road | 0 | | | | | | | |
| ADMSurban | | 0 | | | | | | | |
| ADMSurbanQueue | Camden - Bloomsbury | 8246 | 0.66 | 2.10 | 11.02 | 0.07 | 0.39 | 14.75 | 0.78 |
| ADMSurbanQueue | Bexley - Slade Green | 8097 | 0.76 | -0.45 | 11.69 | -0.01 | 0.27 | 16.21 | 0.82 |
| ADMSurbanQueue | Camden - Shaftesbury Avenue | 0 | | | | | | | |
| ADMSurbanQueue | Croydon - George Street | 0 | | | | | | | |
| ADMSurbanQueue | Ealing - Ealing Town Hall | 8277 | 0.70 | -1.34 | 11.06 | -0.04 | 0.31 | 15.49 | 0.80 |
| ADMSurbanQueue | Ealing - Acton Town Hall | 8046 | 0.57 | 10.80 | 14.10 | 0.46 | 0.60 | 18.20 | 0.77 |
| ADMSurbanQueue | Enfield 1 - Bushhill Park | 0 | | | | | | | |
| ADMSurbanQueue | Greenwich - Eltham | 8086 | 0.76 | 0.74 | 10.73 | 0.02 | 0.27 | 14.85 | 0.83 |
| ADMSurbanQueue | Haringey - Haringey Town Hall | 0 | | | | | | | |
| ADMSurbanQueue | Kensington and Chelsea - North Ken | 8281 | 0.69 | -5.69 | 12.07 | -0.15 | 0.31 | 17.38 | 0.80 |
| ADMSurbanQueue | Lambeth - Brixton Road | 0 | | | | | | | |
| ADMSurbanQueue | Lewisham - New Cross | 0 | | | | | | | |
| ADMSurbanQueue | Richmond - National Physical Laboratory | 8247 | 0.79 | -3.14 | 11.66 | -0.07 | 0.24 | 16.60 | 0.82 |
| ADMSurbanQueue | Tower Hamlets - Poplar | 8306 | 0.69 | -5.90 | 12.46 | -0.14 | 0.31 | 17.48 | 0.81 |
| ADMSurbanQueue | Tower Hamlets - Mile End Road | 0 | | | | | | | |
| ADMSurbanQueue | | 0 | | | | | | | |
| KCLurbanCMAQ | Camden - Bloomsbury | 8104 | 0.58 | 7.14 | 16.17 | 0.25 | 0.57 | 20.84 | 0.58 |
| KCLurbanCMAQ | Bexley - Slade Green | 7947 | 0.67 | 6.95 | 19.36 | 0.16 | 0.45 | 24.90 | 0.55 |
| KCLurbanCMAQ | Camden - Shaftesbury Avenue | 0 | | | | | | | |
| KCLurbanCMAQ | Croydon - George Street | 0 | | | | | | | |
| KCLurbanCMAQ | Ealing - Ealing Town Hall | 8129 | 0.63 | 12.04 | 19.03 | 0.34 | 0.54 | 24.03 | 0.61 |
| KCLurbanCMAQ | Ealing - Acton Town Hall | 7813 | 0.51 | 14.63 | 18.20 | 0.62 | 0.77 | 22.30 | 0.62 |
| KCLurbanCMAQ | Enfield 1 - Bushhill Park | 0 | | | | | | | |
| KCLurbanCMAQ | Greenwich - Eltham | 7941 | 0.67 | 12.38 | 20.69 | 0.31 | 0.52 | 25.95 | 0.53 |
| KCLurbanCMAQ | Haringey - Haringey Town Hall | 0 | | | | | | | |
| KCLurbanCMAQ | Kensington and Chelsea - North Ken | 8140 | 0.64 | 6.05 | 18.39 | 0.16 | 0.48 | 23.89 | 0.58 |
| KCLurbanCMAQ | Lambeth - Brixton Road | 0 | | | | | | | |
| KCLurbanCMAQ | Lewisham - New Cross | 0 | | | | | | | |
| KCLurbanCMAQ | Richmond - National Physical Laboratory | 8106 | 0.74 | 7.57 | 19.11 | 0.16 | 0.40 | 24.69 | 0.56 |
| KCLurbanCMAQ | Tower Hamlets - Poplar | 8171 | 0.64 | 0.58 | 18.18 | 0.01 | 0.45 | 23.81 | 0.55 |
| KCLurbanCMAQ | Tower Hamlets - Mile End Road | 0 | | | | | | | |
| KCLurbanCMAQ | | 0 | | | | | | | |

**Table 11:** Summary model evaluation statistics for hourly mean $PM_{10}$.

| group | site | n | FAC2 | MB | MGE | NMB | NMGE | RMSE | r |
|---|---|---|---|---|---|---|---|---|---|
| ADMSurban | Camden - Bloomsbury | 6734 | 0.90 | 0.76 | 7.21 | 0.03 | 0.32 | 10.63 | 0.68 |
| ADMSurban | Bexley - Slade Green | 8099 | 0.83 | 3.11 | 7.15 | 0.17 | 0.39 | 10.21 | 0.65 |
| ADMSurban | Camden - Shaftesbury Avenue | 8291 | 0.86 | -4.06 | 10.00 | -0.14 | 0.34 | 15.09 | 0.53 |
| ADMSurban | Croydon - George Street | 8296 | 0.88 | 2.69 | 7.41 | 0.12 | 0.33 | 10.74 | 0.67 |
| ADMSurban | Ealing - Ealing Town Hall | 0 | | | | | | | |
| ADMSurban | Ealing - Acton Town Hall | 8300 | 0.91 | 0.33 | 7.38 | 0.01 | 0.31 | 11.17 | 0.69 |
| ADMSurban | Enfield 1 - Bushhill Park | 0 | | | | | | | |
| ADMSurban | Greenwich - Eltham | 7848 | 0.89 | 0.56 | 6.96 | 0.03 | 0.33 | 10.70 | 0.63 |
| ADMSurban | Haringey - Haringey Town Hall | 5436 | 0.87 | 2.69 | 7.60 | 0.13 | 0.36 | 10.98 | 0.66 |
| ADMSurban | Kensington and Chelsea - North Ken | 8213 | 0.88 | 1.68 | 6.92 | 0.08 | 0.33 | 10.25 | 0.68 |
| ADMSurban | Lambeth - Brixton Road | 6345 | 0.90 | -6.75 | 11.75 | -0.18 | 0.32 | 22.90 | 0.43 |
| ADMSurban | Lewisham - New Cross | 7879 | 0.90 | -0.42 | 7.73 | -0.02 | 0.31 | 11.52 | 0.66 |
| ADMSurban | Richmond - National Physical Laboratory | 0 | | | | | | | |
| ADMSurban | Tower Hamlets - Poplar | 8321 | 0.90 | -0.00 | 7.06 | -0.00 | 0.31 | 10.72 | 0.67 |
| ADMSurban | Tower Hamlets - Mile End Road | 0 | | | | | | | |
| ADMSurban | | 0 | | | | | | | |
| ADMSurbanQueue | Camden - Bloomsbury | 6734 | 0.90 | 0.76 | 7.21 | 0.03 | 0.32 | 10.63 | 0.68 |
| ADMSurbanQueue | Bexley - Slade Green | 8099 | 0.83 | 3.11 | 7.15 | 0.17 | 0.39 | 10.21 | 0.65 |
| ADMSurbanQueue | Camden - Shaftesbury Avenue | 8291 | 0.86 | -4.06 | 10.00 | -0.14 | 0.34 | 15.09 | 0.53 |
| ADMSurbanQueue | Croydon - George Street | 8296 | 0.88 | 2.69 | 7.41 | 0.12 | 0.33 | 10.74 | 0.67 |
| ADMSurbanQueue | Ealing - Ealing Town Hall | 0 | | | | | | | |
| ADMSurbanQueue | Ealing - Acton Town Hall | 8300 | 0.91 | 0.33 | 7.38 | 0.01 | 0.31 | 11.17 | 0.69 |
| ADMSurbanQueue | Enfield 1 - Bushhill Park | 0 | | | | | | | |
| ADMSurbanQueue | Greenwich - Eltham | 7848 | 0.89 | 0.56 | 6.96 | 0.03 | 0.33 | 10.70 | 0.63 |
| ADMSurbanQueue | Haringey - Haringey Town Hall | 5436 | 0.87 | 2.69 | 7.60 | 0.13 | 0.36 | 10.98 | 0.66 |
| ADMSurbanQueue | Kensington and Chelsea - North Ken | 8213 | 0.88 | 1.68 | 6.92 | 0.08 | 0.33 | 10.25 | 0.68 |
| ADMSurbanQueue | Lambeth - Brixton Road | 6345 | 0.88 | -2.22 | 13.03 | -0.06 | 0.36 | 23.47 | 0.38 |
| ADMSurbanQueue | Lewisham - New Cross | 7879 | 0.90 | -0.42 | 7.73 | -0.02 | 0.31 | 11.52 | 0.66 |
| ADMSurbanQueue | Richmond - National Physical Laboratory | 0 | | | | | | | |
| ADMSurbanQueue | Tower Hamlets - Poplar | 8321 | 0.90 | -0.00 | 7.06 | -0.00 | 0.31 | 10.72 | 0.67 |
| ADMSurbanQueue | Tower Hamlets - Mile End Road | 0 | | | | | | | |
| ADMSurbanQueue | | 0 | | | | | | | |
| KCLurbanCMAQ | Camden - Bloomsbury | 0 | | | | | | | |
| KCLurbanCMAQ | Bexley - Slade Green | 0 | | | | | | | |
| KCLurbanCMAQ | Camden - Shaftesbury Avenue | 0 | | | | | | | |
| KCLurbanCMAQ | Croydon - George Street | 0 | | | | | | | |
| KCLurbanCMAQ | Ealing - Ealing Town Hall | 0 | | | | | | | |
| KCLurbanCMAQ | Ealing - Acton Town Hall | 0 | | | | | | | |
| KCLurbanCMAQ | Enfield 1 - Bushhill Park | 0 | | | | | | | |
| KCLurbanCMAQ | Greenwich - Eltham | 0 | | | | | | | |
| KCLurbanCMAQ | Haringey - Haringey Town Hall | 0 | | | | | | | |
| KCLurbanCMAQ | Kensington and Chelsea - North Ken | 0 | | | | | | | |
| KCLurbanCMAQ | Lambeth - Brixton Road | 0 | | | | | | | |
| KCLurbanCMAQ | Lewisham - New Cross | 0 | | | | | | | |
| KCLurbanCMAQ | Richmond - National Physical Laboratory | 0 | | | | | | | |
| KCLurbanCMAQ | Tower Hamlets - Poplar | 0 | | | | | | | |
| KCLurbanCMAQ | Tower Hamlets - Mile End Road | 0 | | | | | | | |
| KCLurbanCMAQ | | 0 | | | | | | | |

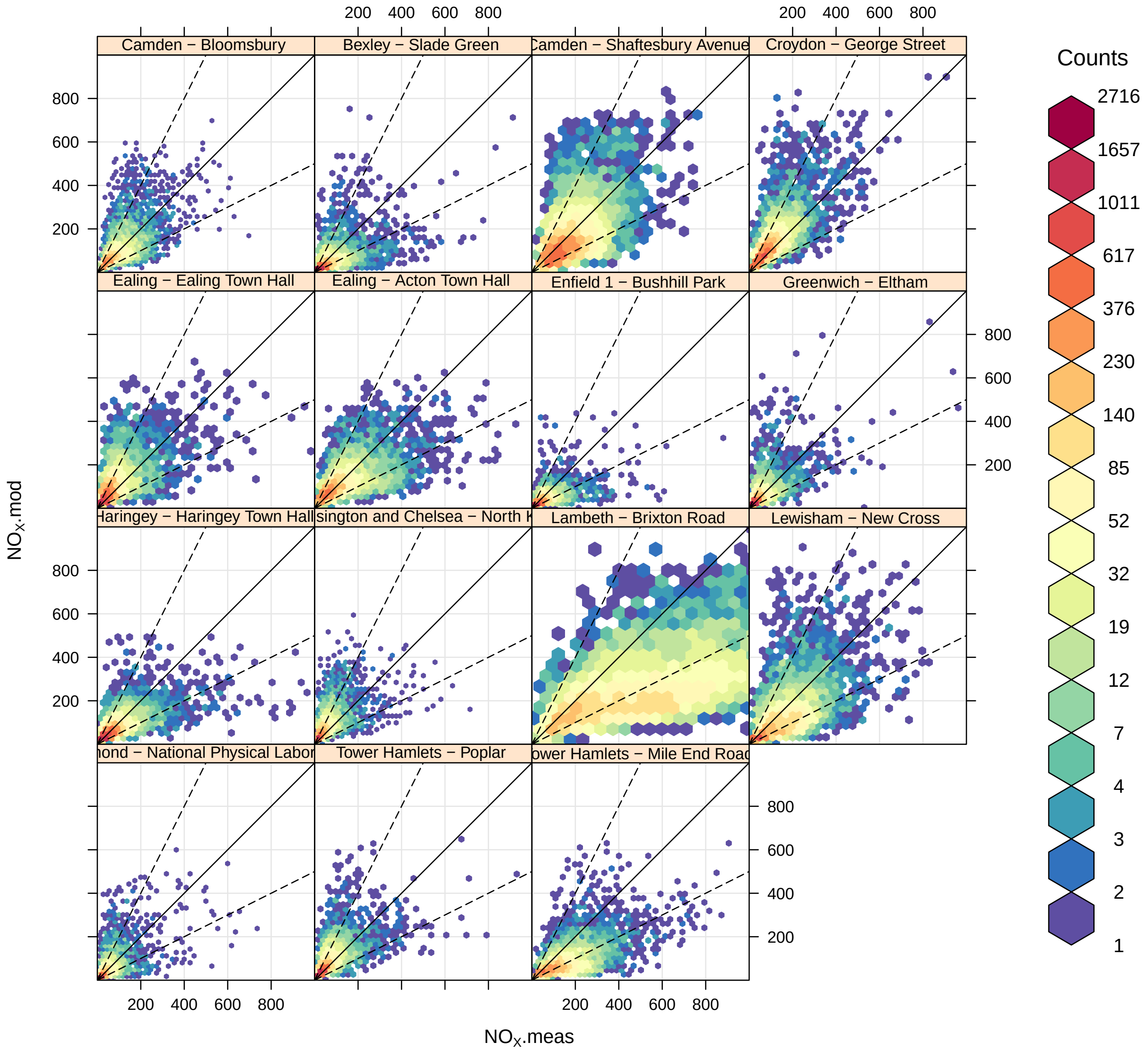


**Figure 24:** Scatter plot of measured vs. modelled $NO_x$ concentrations using the CERC model.

## 4.3 Scatter plots

```
scatterPlot(subset(urban.hourly, group == "ADMSurban"), x = "nox.meas", y = "nox.mod", mod.line = TRUE,
            type = "site", method = "hexbin", xlim = c(0, 1000), ylim = c(0, 1000))
```

```
scatterPlot(subset(urban.hourly, group == "ADMSurbanQueue"), x = "nox.meas", y = "nox.mod", mod.line = TRUE,
            type = "site", method = "hexbin", xlim = c(0, 1000), ylim = c(0, 1000))
```

```
scatterPlot(subset(urban.hourly, group == "KCLurbanCMAQ"), x = "nox.meas", y = "nox.mod", mod.line = TRUE,
            type = "site", method = "hexbin", xlim = c(0, 1000), ylim = c(0, 1000))
```

```
scatterPlot(subset(urban.hourly, group == "ADMSurban"), x = "no2.meas", y = "no2.mod", mod.line = TRUE,
            type = "site", method = "hexbin", xlim = c(0, 600), ylim = c(0, 600))
```

```
scatterPlot(subset(urban.hourly, group == "KCLurbanCMAQ"), x = "no2.meas", y = "no2.mod", mod.line = TRUE,
            type = "site", method = "hexbin", xlim = c(0, 600), ylim = c(0, 600))
```

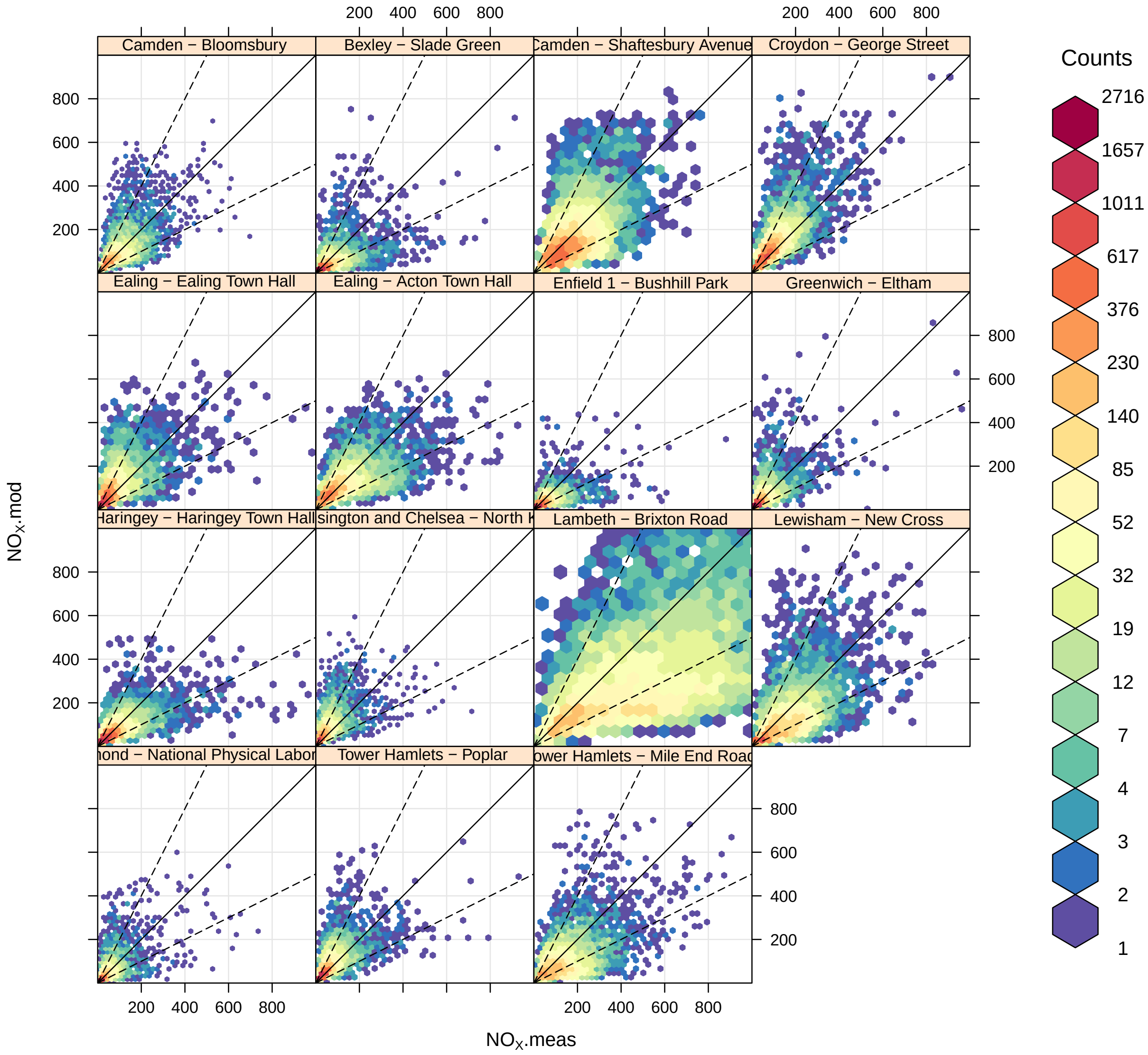


**Figure 25:** Scatter plot of measured vs. modelled $NO_x$ concentrations using the CERC queue model.

```
scatterPlot(subset(urban.hourly, group == "ADMSurban"), x = "o3.meas", y = "o3.mod", mod.line = TRUE,
           type = "site", method = "hexbin", xlim = c(0, 180), ylim = c(0, 180))
```

```
scatterPlot(subset(urban.hourly, group == "KCLurbanCMAQ"), x = "o3.meas", y = "o3.mod", mod.line = TRUE,
           type = "site", method = "hexbin", xlim = c(0, 180), ylim = c(0, 180))
```

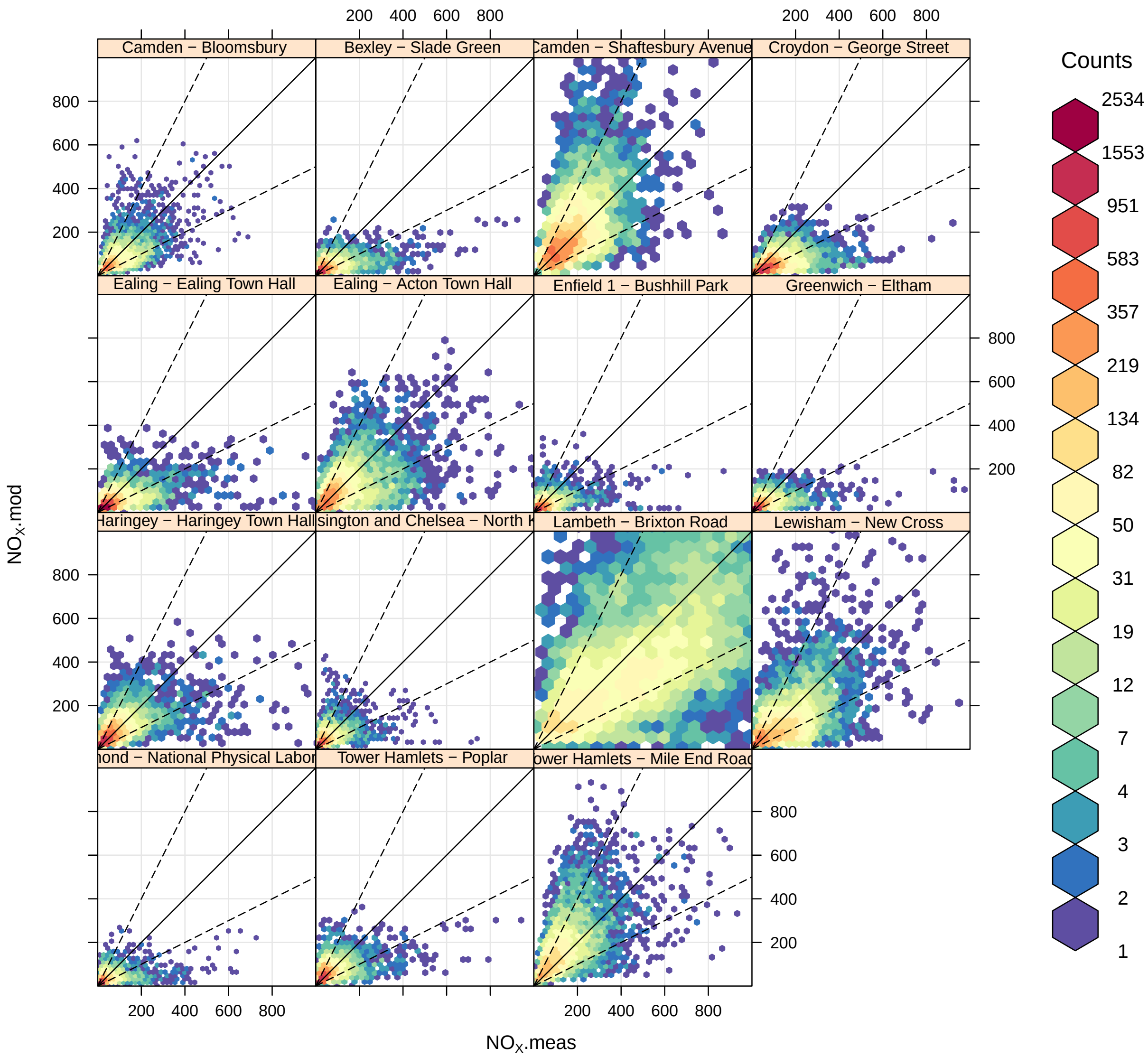


**Figure 26:** Scatter plot of measured vs. modelled $NO_x$ concentrations using the KCL model.

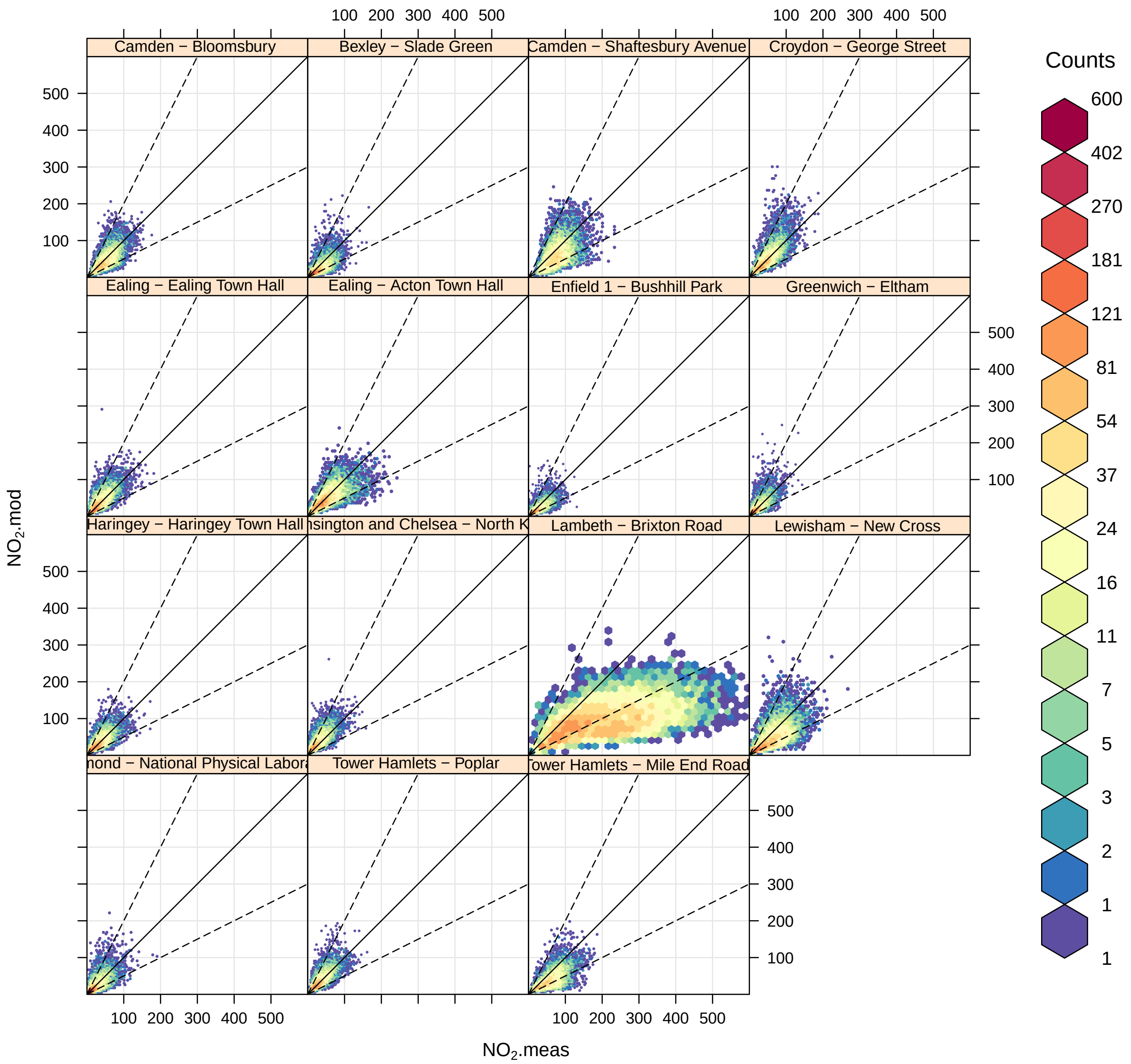


**Figure 27:** Scatter plot of measured vs. modelled $NO_2$ concentrations using the CERC model.

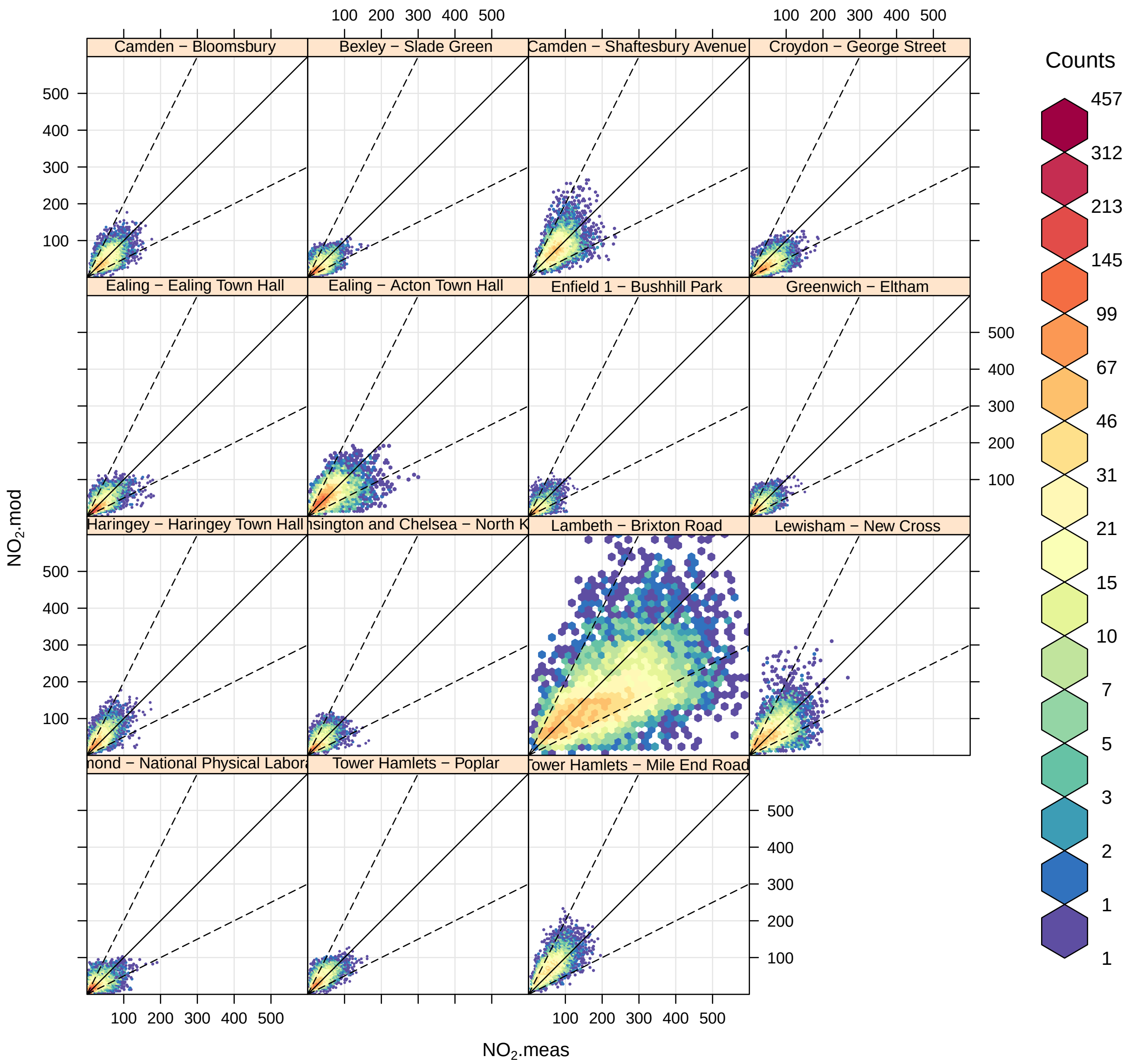


**Figure 28:** Scatter plot of measured vs. modelled $NO_2$ concentrations using the KCL model.

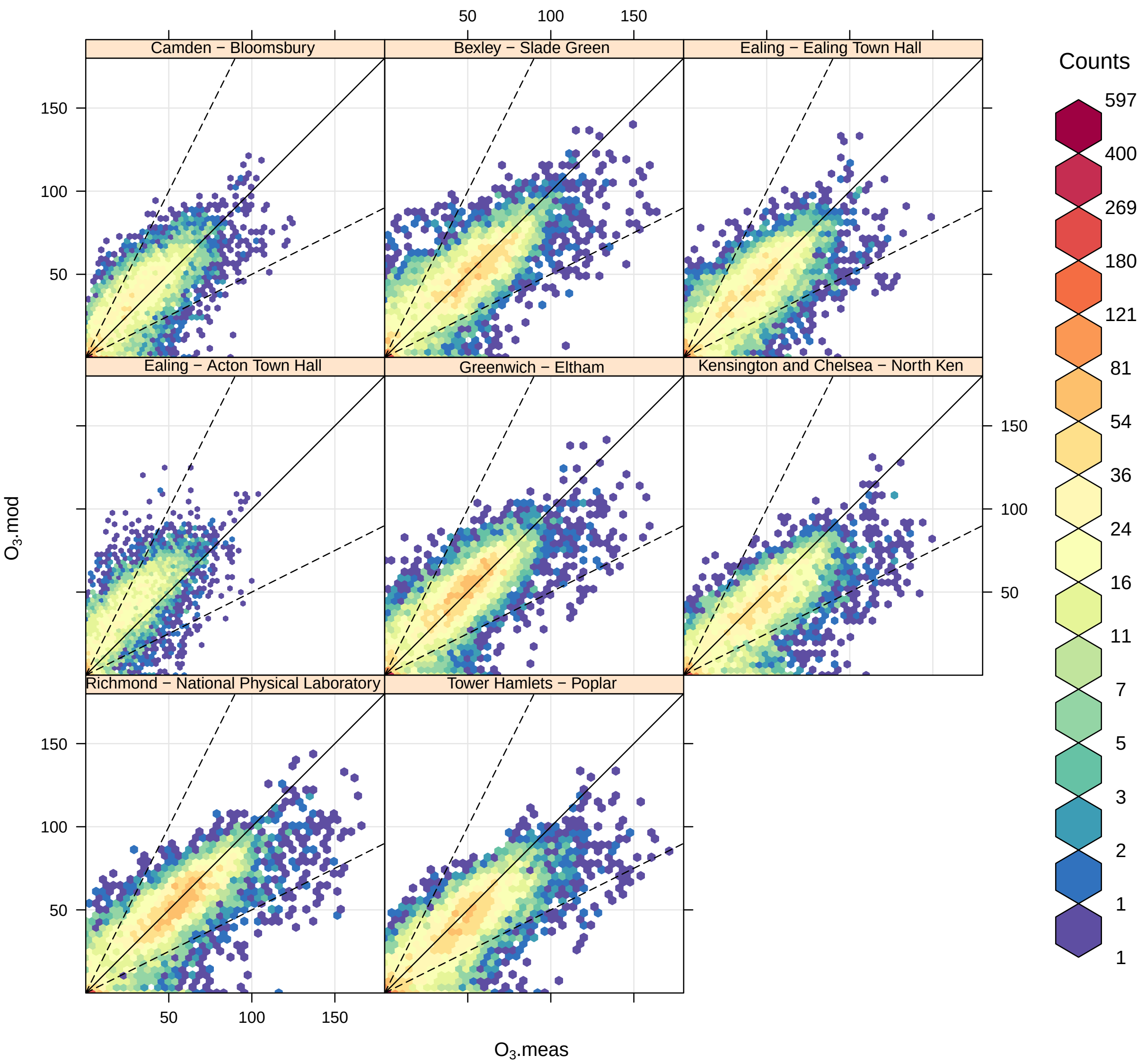


**Figure 29:** Scatter plot of measured vs. modelled $O_3$ concentrations using the CERC model.

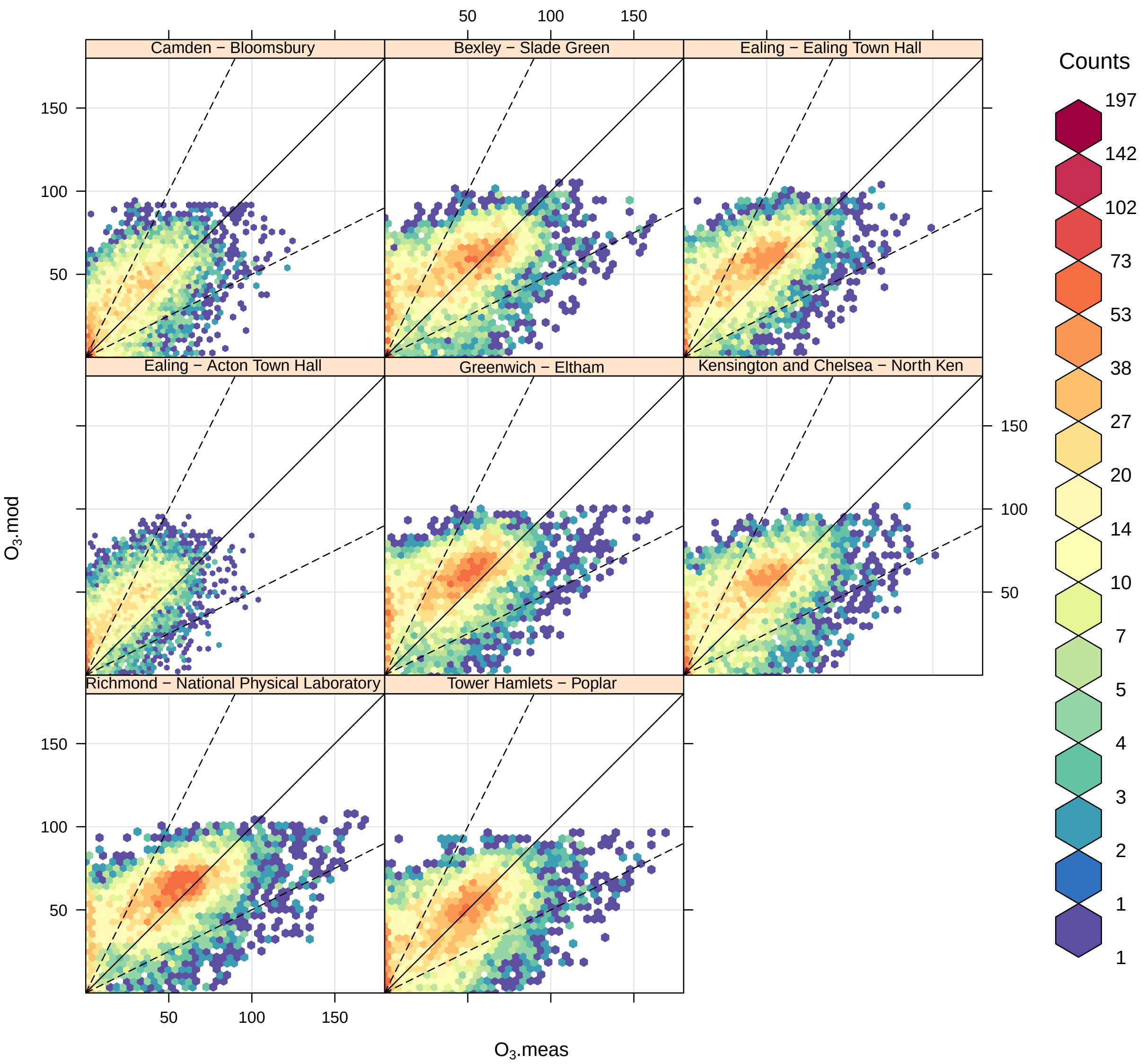


**Figure 30:** Scatter plot of measured vs. modelled $O_3$ concentrations using the KCL model.

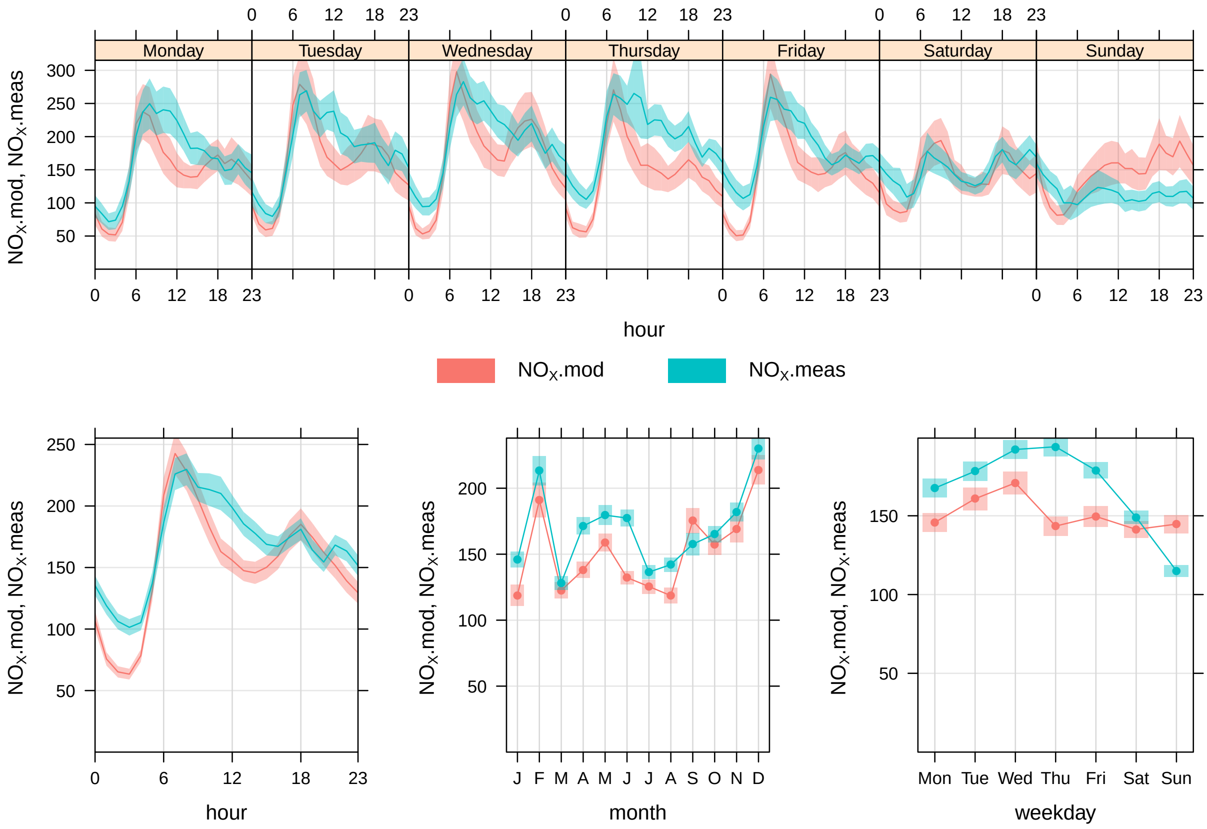


**Figure 31:** Temporal variations in $NO_x$ at the Shaftesbury Avenue site using the CERC model.

## 4.4 Temporal variations

With so many sites to consider, only two have been chosen for plotting here: the Ealing Town Hall site (EA1, urban background) and the Camden Shaftesbury Avenue site (CD3, roadside).

```
timeVariation(subset(urban.hourly, site.code  == "CD3" & group == "ADMSurban"),
              pollutant = c("nox.mod", "nox.meas"), ylim = c(0, NA))
```

```
timeVariation(subset(urban.hourly, site.code  == "CD3" & group == "KCLurbanCMAQ"),
              pollutant = c("nox.mod", "nox.meas"), ylim = c(0, NA))
```

```
timeVariation(subset(urban.hourly, site.code  == "GR4" & group == "ADMSurban"),
              pollutant = c("nox.mod", "nox.meas"), ylim = c(0, NA))
```

```
timeVariation(subset(urban.hourly, site.code  == "GR4" & group == "KCLurbanCMAQ"),
              pollutant = c("nox.mod", "nox.meas"), ylim = c(0, NA))
```

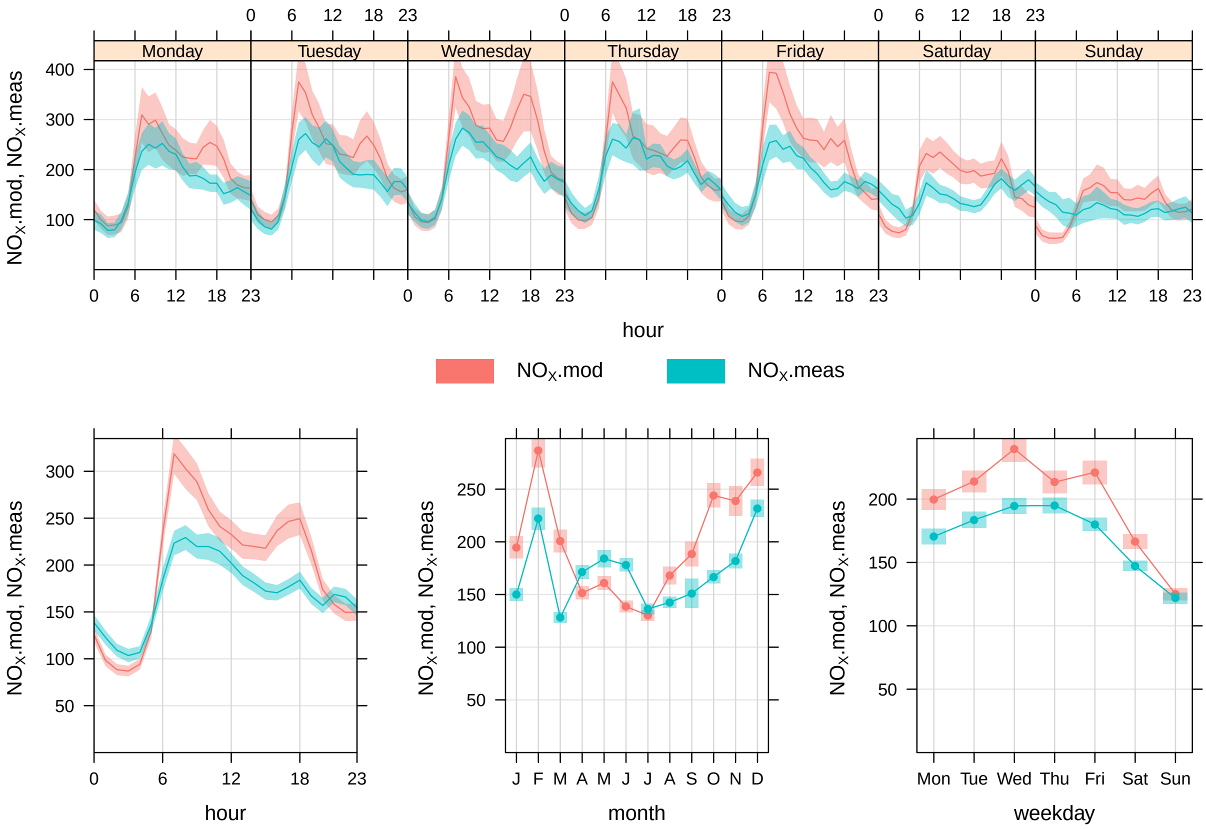


**Figure 32:** Temporal variations in $NO_x$ at the Shaftesbury Avenue site using the KCL-CMAQ model.

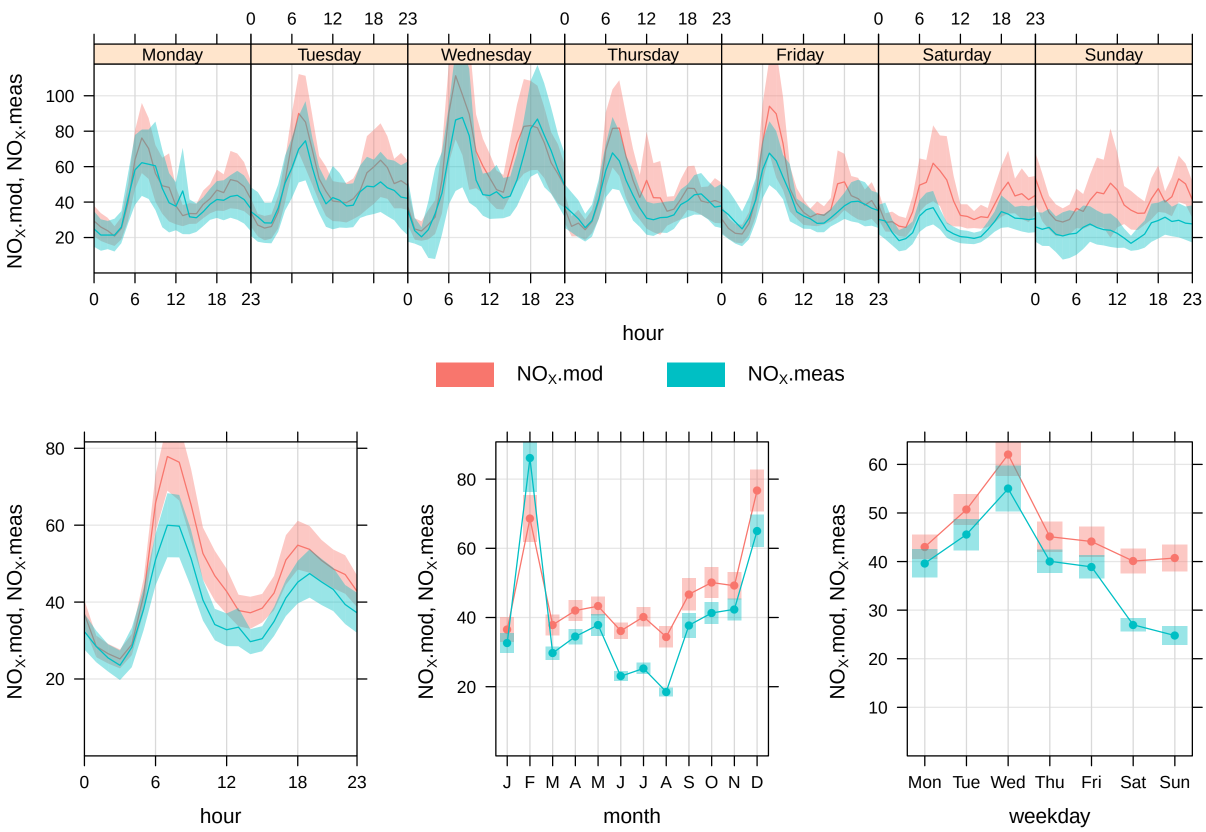


**Figure 33:** Temporal variations in $NO_x$ at the Greenwich Eltham site using the CERC model.

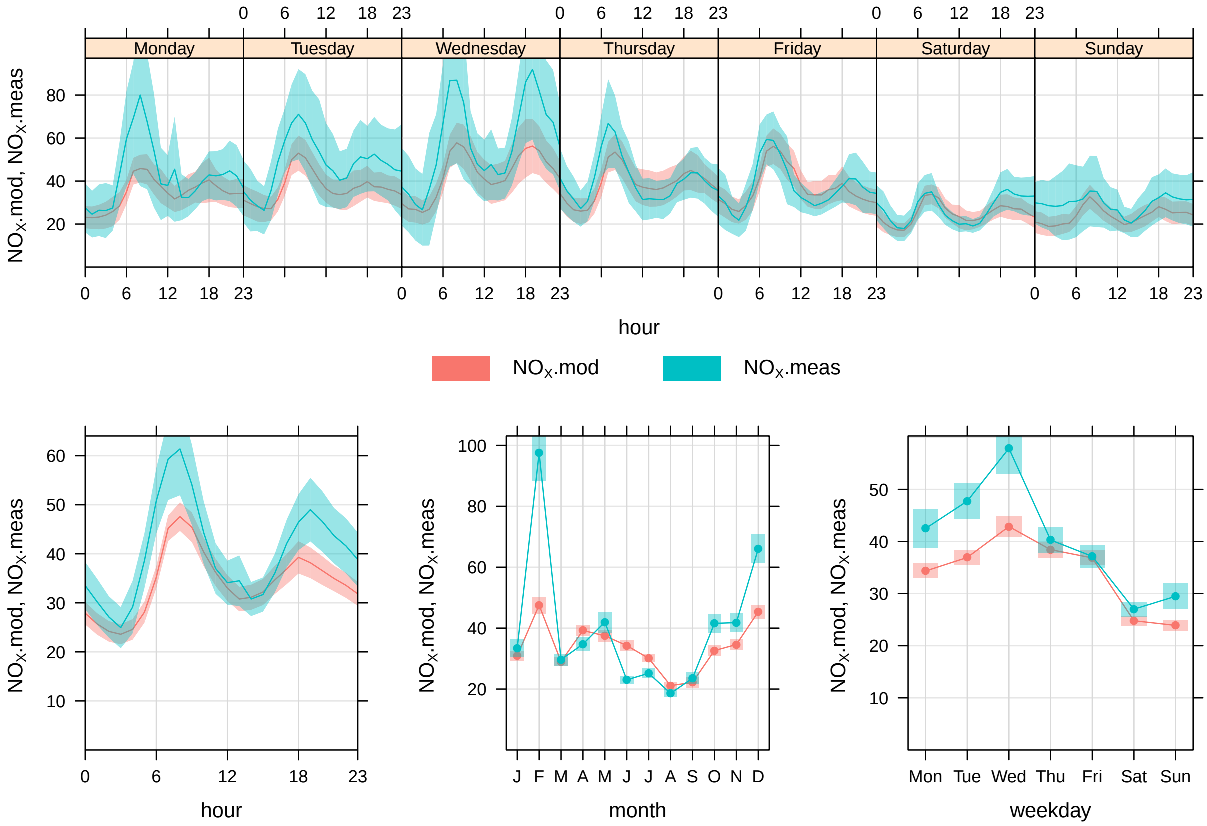


**Figure 34:** Temporal variations in $NO_x$ at the Greenwich Eltham site using the KCL-CMAQ model.

### 4.5 Conditional quantiles

Conditional quantiles are a very useful way of considering model performance against observations for continuous measurements Wilks (2005). The conditional quantile plot splits the data into evenly spaced bins. For each predicted value bin e.g. from 0 to 10 μg $m^{-3}$ the *corresponding* values of the observations are identified and the median, 25/75th and 10/90 percentile (quantile) calculated for that bin. The data are plotted to show how these values vary across all bins. For a time series of observations and predictions that agree precisely the median value of the predictions will equal that for the observations for each bin.

The conditional quantile plot differs from the quantile-quantile plot (Q-Q plot) that is often used to compare observations and predictions. A Q-Q plot separately considers the distributions of observations and predictions, whereas the conditional quantile uses the corresponding observations for a particular interval in the predictions. Take as an example two time series, the first a series of real observations and the second a lagged time series of the same observations representing the predictions. These two time series will have identical (or very nearly identical) distributions (e.g. same median, minimum and maximum). A Q-Q plot would show a straight line showing perfect agreement, whereas the conditional quantile will not. This is because in any interval of the predictions the corresponding observations now have different values.

Plotting the data in this way shows how well predictions agree with observations and can help reveal many useful characteristics of how well model predictions agree with observations — across the full distribution of values. A single plot can therefore convey a considerable amount of information concerning model performance. The `conditionalQuantile` function in **openair** allows conditional quantiles to be considered in a flexible way e.g. by considering how they vary by season. We first demonstrate the usage with some sample data before applying it to the urban data.

First, the data are extracted and then plotted as shown in Figure 35. In addition to the text in the caption, these results show that there is a tendency for the model to over estimate $NO_x$ concentrations as the concentrations increase (as seen by the divergence of the red line from the blue line for increasingly high $NO_x$). The other point to note in Figure 35 is that the percentile shading shows that the predictions become increasingly worse as the concentration of $NO_x$ increases, as shown by their broadening.

A comprehensive analysis would consider each site separately for each pollutant. However, given the time available we only consider results across all receptors split by model used.

In the following plots (Figure 36 to Figure 40) the following points can be made.

**$NO_x$— Figure 36** The ADMS Urban queue model does a better job of capturing higher concentrations than the base ADMS Urban model. There is a tendency for higher $NO_x$ concentrations in the KCLurbanCMAQ model to be under estimated.

**$NO_2$— Figure 37** Again the ADMS Urban queue model captures the higher concentrations better than the base model.

**$O_3$— Figure 38** These results show that the ADMS Urban models do well in capturing $O_3$ concentrations across the full range of observed values. This is shown by how close the median line is to the blue (perfect model) line. The KCLurbanCMAQ are not as good as they have broader percentile distributions and the higher concentrations are not captured as well as the ADMS Urban models.

**$PM_{10}$— Figure 39** Hourly $PM_{10}$ concentrations seem to be difficult to capture as these plots show that the higher concentrations are not predicted well and the percentile ranges are broad.

**$PM_{2.5}$— Figure 40** The results for $PM_{2.5}$ are better than for $PM_{10}$, although again the higher concentrations are not as well predicted.

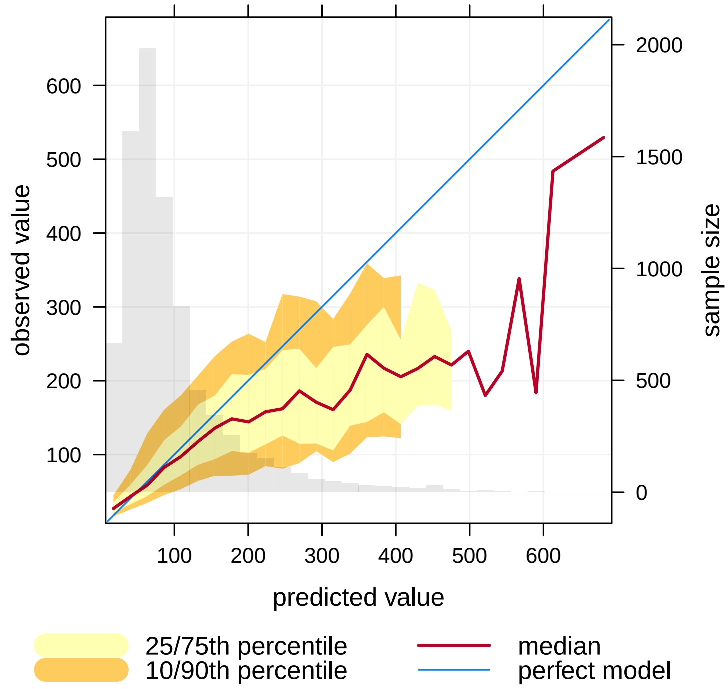


**Figure 35:** Example of the use of conditional quantiles applied to the ADMS Urban model at London Bloomsbury for hourly $NO_x$ concentrations. The blue line shows the results for a perfect model. In this case the observations cover a range from 0 to 700 $\mu g\ m^{-3}$. The red line shows the median value of the predictions. The maximum predicted value is close to 700 $\mu g\ m^{-3}$, which shows the range of predictions from the model is similar to that of the observations. The shading shows the predicted quantile intervals i.e. the 25/75th and the 10/90th. A perfect model would lie on the blue line and have a very narrow spread. There is still some spread because even for a perfect model a specific quantile interval will contain a range of values. However, for the number of bins used in this plot the spread will be very narrow. Finally, the histogram shows the counts of predicted values.

Note that much more interpretation would be possible with other analysis e.g. by site, by day of the week and so on, that might help better understand the conditions under which model performance is poor.

```
conditionalQuantile(subset(urban.hourly, site.code == "BL0" & group == "ADMSurban"),
                    obs = "nox.meas", mod = "nox.mod")
```

```
conditionalQuantile(urban.hourly, obs = "nox.meas", mod = "nox.mod", type = "group")
```

```
conditionalQuantile(urban.hourly, obs = "no2.meas", mod = "no2.mod", type = "group")
```

```
conditionalQuantile(urban.hourly, obs = "o3.meas", mod = "o3.mod", type = "group")
```

```
conditionalQuantile(urban.hourly, obs = "pm10.meas", mod = "pm10.mod", type = "group")
```

```
conditionalQuantile(urban.hourly, obs = "pm25.meas", mod = "pm25.mod", type = "group")
```

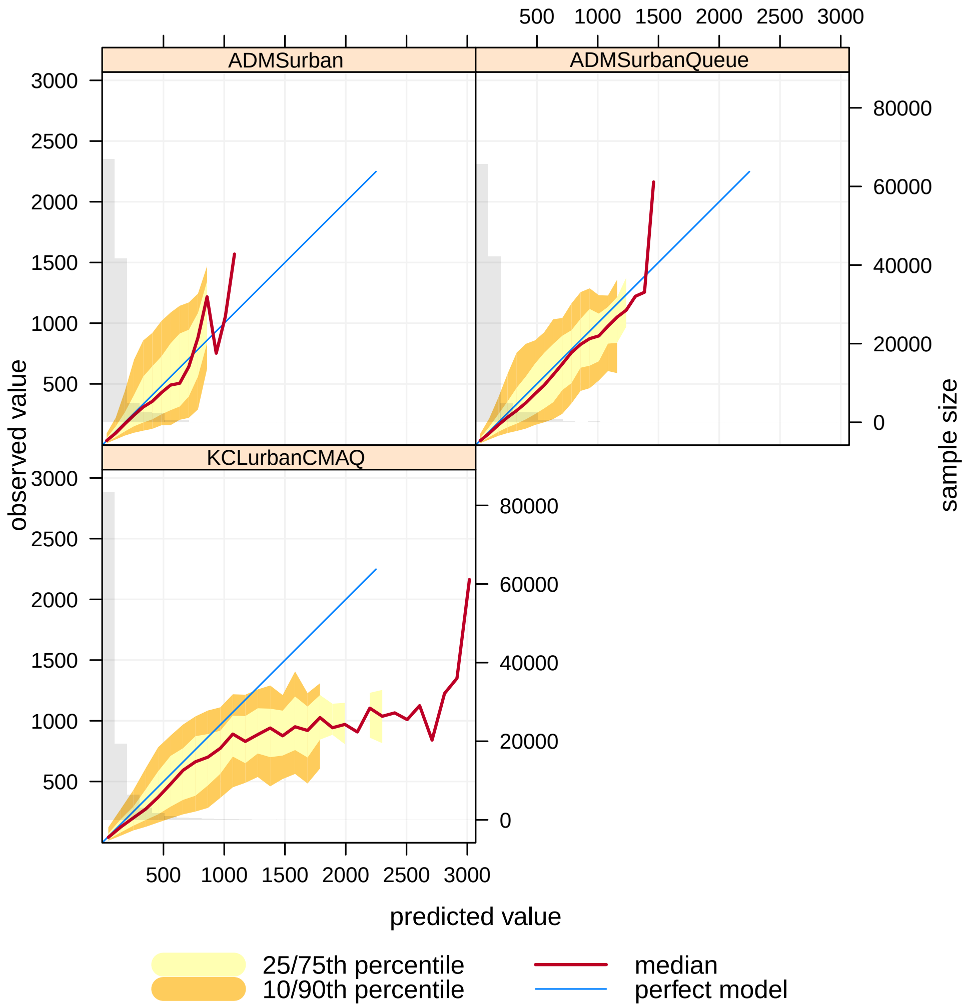


**Figure 36:** Conditional quantile plot for hourly $NO_x$ concentrations across all sites.

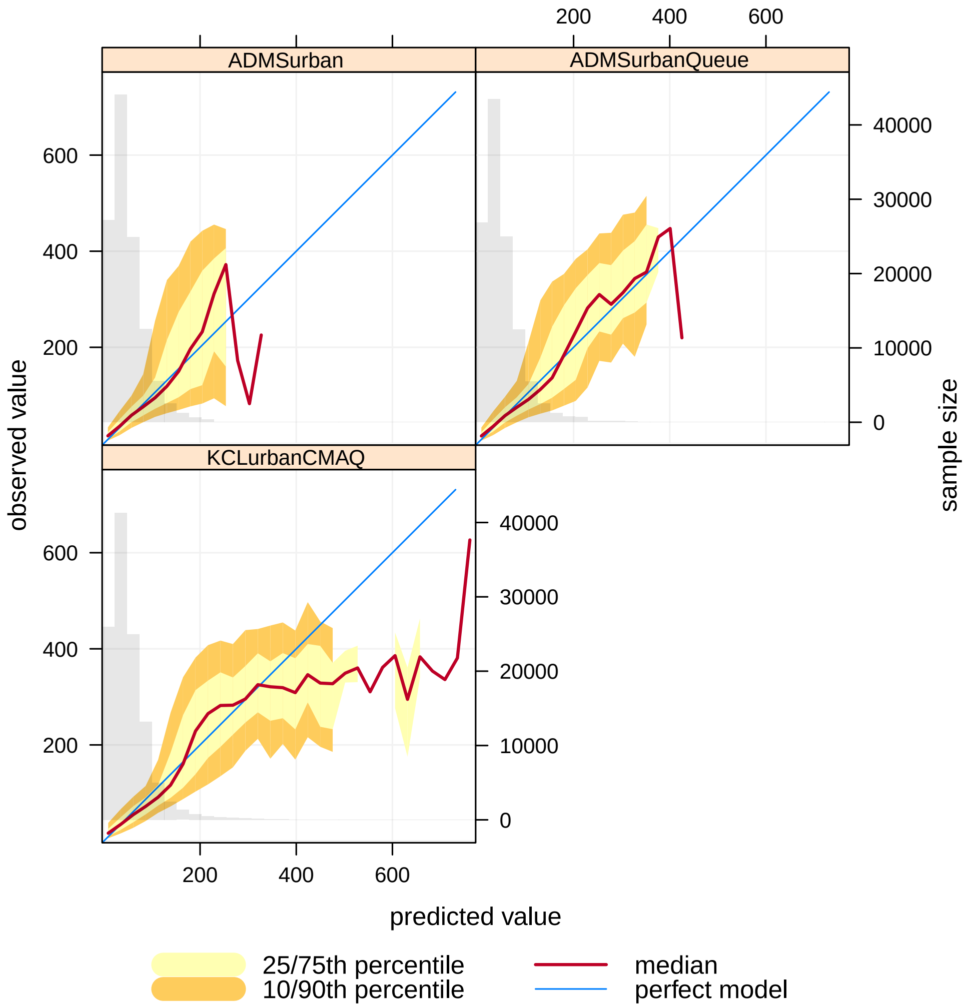


**Figure 37:** Conditional quantile plot for hourly $NO_2$ concentrations across all sites.

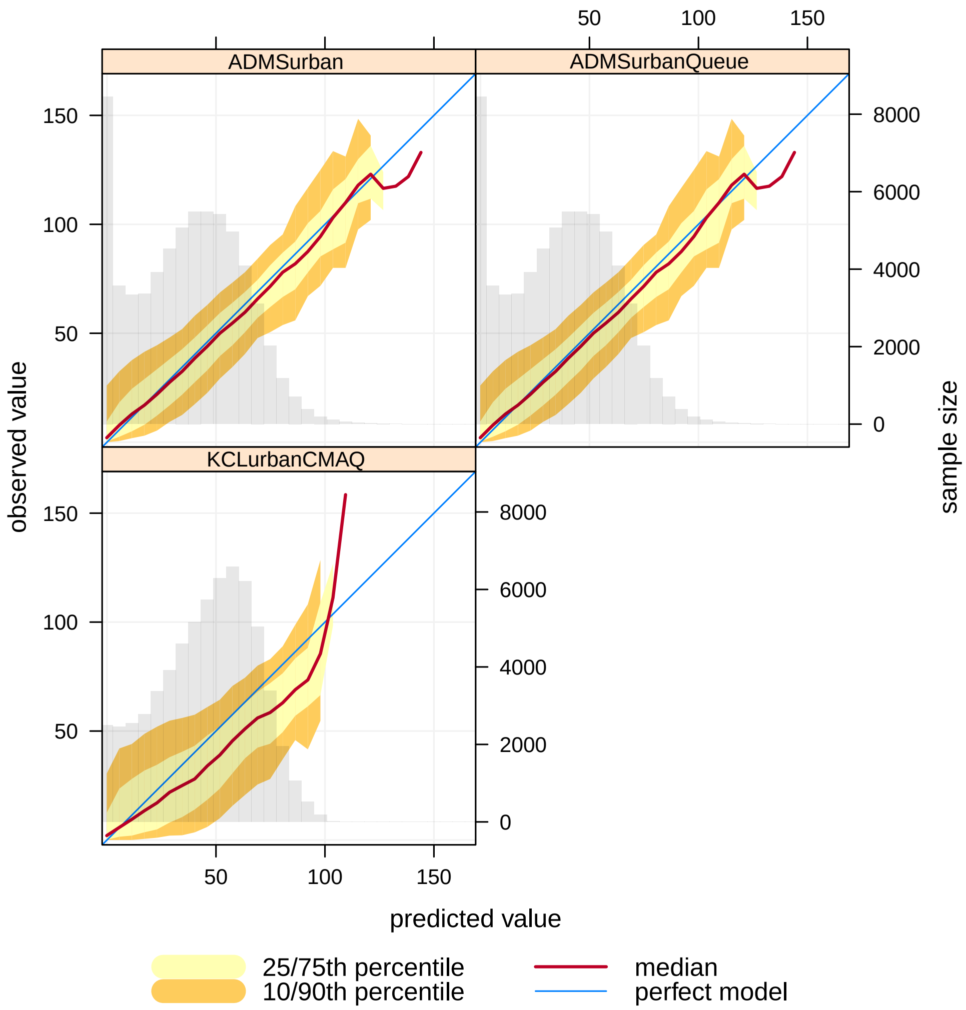


**Figure 38:** Conditional quantile plot for hourly $NO_2$ concentrations across all sites.

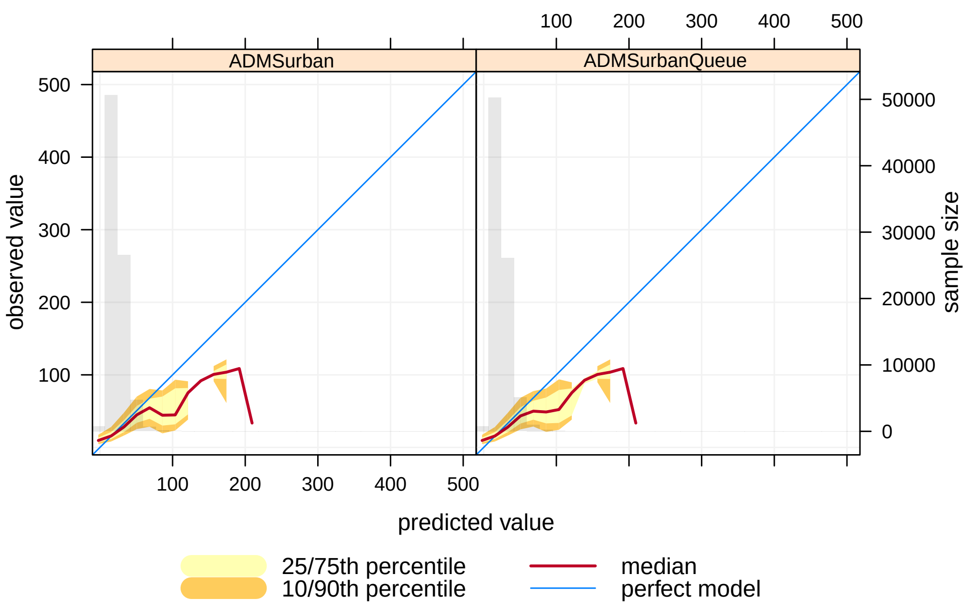


**Figure 39:** Conditional quantile plot for hourly $PM_{10}$ concentrations across all sites.

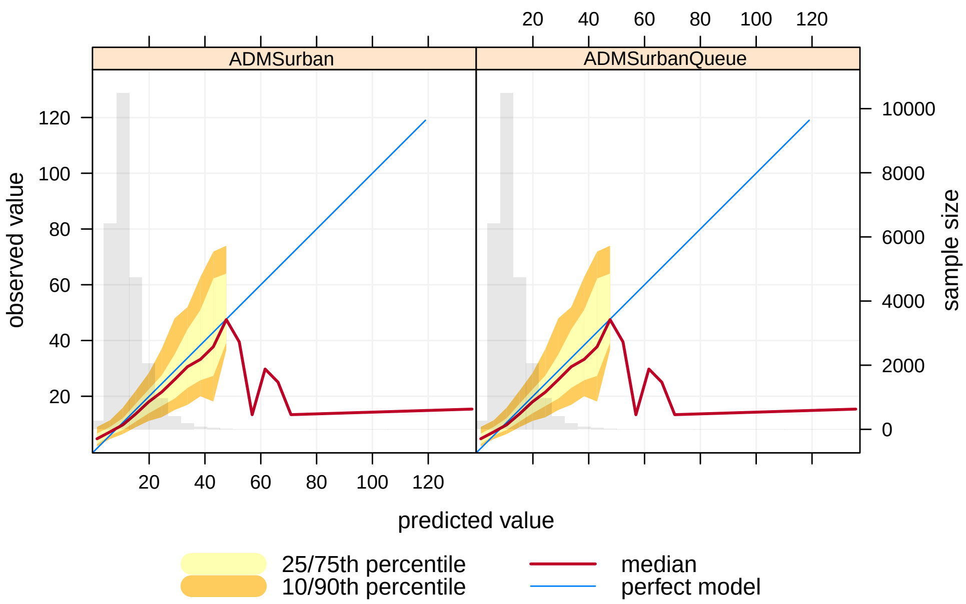


**Figure 40:** Conditional quantile plot for hourly $PM_{2.5}$ concentrations across all sites.

## Acknowledgements

We appreciate the contributions made by the following organisations to the evaluation exercises: Imperial College London, University of Hertfordshire, AEA, Cambridge Environmental Research Consultants, The Joint Environment Programme (JEP), King's College London, University of York, Norwegian Meteorological Institute, CEH, University of Nottingham, The Met Office, RdScientific, the University of Edinburgh, Nicholson Environmental, The Environment Agency , NCAS and the University of Birmingham. We would like to thank the Met Office for providing the meteorological data used in this study and to the data providers including the AURN, the London Air Quality Network (LAQN) and he UK Eutrophying and Acidifying atmospheric Pollutants (UKEAP) network.

## References

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URL http://www.stat.uni-muenchen.de/~leisch/Sweave 6

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## A Model performance evaluation statistics

There are a very wide range of evaluation statistics that can be used to assess model performance. There is, however, no single statistic that encapsulates all aspects of interest. For this reason it is useful to consider several performance statistics and also to understand the sort of information or insight they might provide. The performance statistics used here have mostly been guided by Derwent et al. (2010).

In the following definitions, $O_i$ represents the $i$th observed value and $M_i$ represents the $i$th modelled value for a total of $n$ observations.

### Fraction of predictions within a factor or two, $FAC2$

The fraction of modelled values within a factor of two of the observed values are the fraction of model predictions that satisfy:

$$0.5 \leq \frac{M_i}{O_i} \leq 2.0 \quad (2)$$

### Mean bias, $MB$

The mean bias provides a good indication of the mean over or under estimate of predictions. Mean bias in the same units as the quantities being considered.

$$MB = \frac{1}{n} \sum_{i=1}^{N} M_i - O_i \quad (3)$$

### Mean Gross Error, $MGE$

The mean gross error provides a good indication of the mean error regardless of whether it is an over or under estimate. Mean gross error is in the same units as the quantities being considered.

$$MGE = \frac{1}{n} \sum_{i=1}^{N} |M_i - O_i| \quad (4)$$

### Normalised mean bias, $NMB$

The normalised mean bias is useful for comparing pollutants that cover different concentration scales and the mean bias is normalised by dividing by the observed concentration.

$$NMB = \frac{\sum_{i=1}^{n} M_i - O_i}{\sum_{i=1}^{n} O_i} \quad (5)$$

### Normalised mean gross error, $NMGE$

The normalised mean gross error further ignores whether a prediction is an over or under estimate.

$$NMGE = \frac{\sum_{i=1}^{n} |M_i - O_i|}{\sum_{i=1}^{n} O_i} \quad (6)$$

### Root mean squared error, $RMSE$

The RMSE is a commonly used statistic that provides a good overall measure of how close modelled values are to predicted values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(M_i - O_i)^2}{n}} \tag{7}$$

### Correlation coefficient, $r$

The (Pearson) correlation coefficient is a measure of the strength of the linear relationship between two variables. If there is perfect linear relationship with positive slope between the two variables, $r = 1$. If there is a perfect linear relationship with negative slope between the two variables $r = -1$. A correlation coefficient of 0 means that there is no linear relationship between the variables.

$$r = \frac{1}{(n-1)} \sum_{i=1}^{n} \left( \frac{M_i - \overline{M}}{\sigma_M} \right) \left( \frac{O_i - \overline{O}}{\sigma_O} \right) \tag{8}$$

# A Urban modelling receptor information

**Table 12:** Site/receptor details relevant to the urban modelling groups.

| | site.code | easting | northing | site.name | site.type | hourly? | $PM_{10}$ technique | $PM_{2.5}$ technique | $NO_x$ & $NO_2$ | $PM_{10}$ | $PM_{2.5}$ | $O_3$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | BG1 | 551053 | 187233 | Barking and Dagenham - Rush Green | suburban | | | | x | | | |
| 2 | BG2 | 548043 | 183320 | Barking and Dagenham - Scrattons Farm | suburban | | TEOM | | x | x | | |
| 3 | BG3 | 543955 | 184432 | Barking and Dagenham - North Street | kerbside | | BAM | | x | x | | |
| 4 | BL0 | 530123 | 182014 | Camden - Bloomsbury | urban background | x | TEOM | FDMS | x | x | x | x |
| 5 | BN1 | 526342 | 192223 | Barnet - Tally Ho Corner | kerbside | | TEOM | | x | x | | |
| 6 | BN2 | 524370 | 189640 | Barnet - Finchley | urban background | | TEOM | | x | x | | |
| 7 | BT1 | 519560 | 189271 | Brent - Kingsbury | suburban | | TEOM | | x | x | x | |
| 8 | BT4 | 520866 | 185169 | Brent - Ikea | roadside | | TEOM | TEOM | x | x | x | x |
| 9 | BT6 | 521619 | 183554 | Brent - John Keble Primary School | roadside | | TEOM | | x | x | | |
| 10 | BT7 | 525173 | 183297 | Brent - St Marys Primary School | urban background | | TEOM | | x | x | | |
| 11 | BX1 | 551860 | 176376 | Bexley - Slade Green | suburban | x | TEOM | TEOM | x | x | x | x |
| 12 | BX2 | 549975 | 179064 | Bexley - Belvedere | suburban | | TEOM | TEOM | x | x | | |
| 13 | BX7 | 552615 | 175416 | Bexley - Thames Road North | roadside | | TEOM | TEOM | x | x | x | |
| 14 | BX8 | 552566 | 175384 | Bexley - Thames Road South | roadside | | TEOM | TEOM | x | x | x | |
| 15 | BY7 | 540518 | 169324 | Bromley - Harwood Avenue | roadside | | BAM | | x | x | | |
| 16 | CD1 | 526629 | 184391 | Camden - Swiss Cottage | kerbside | | TEOM | | x | x | | |
| 17 | CD3 | 530057 | 181285 | Camden - Shaftesbury Avenue | roadside | x | TEOM | | x | x | | |
| 18 | CD4 | 530511 | 181665 | Camden - St Martins College (NOX 1) | urban background | | | | x | | | |
| 19 | CD5 | 530511 | 181665 | Camden - St Martins College (NOX 2) | urban background | | | | x | | | |
| 20 | CR2 | 531123 | 164299 | Croydon - Purley Way | roadside | | | | x | | | |
| 21 | CR4 | 532583 | 165636 | Croydon - George Street | roadside | x | TEOM | | x | x | | |
| 22 | CR5 | 530626 | 169707 | Croydon - Norbury | kerbside | | | | x | | | |
| 23 | CR6 | 531369 | 166096 | Croydon - Euston Road | suburban | | | | x | | | |
| 24 | CRD2 | 526530 | 178975 | London Cromwell Rd2 | roadside | | | | x | | | |
| 25 | CT1 | 532235 | 180892 | City of London - Senator House | urban background | | | | x | | | x |
| 26 | CT3 | 533480 | 181186 | City of London - Sir John Cass School | urban background | | BAM | | x | x | | |
| 27 | CT6 | 532527 | 180789 | City of London - Walbrook Wharf | roadside | | | | x | | | x |
| 28 | CY1 | 533901 | 171290 | Crystal Palace - Crystal Palace Parade | roadside | | TEOM | | x | x | | |
| 29 | EA1 | 517541 | 180738 | Ealing - Ealing Town Hall | urban background | x | | | x | | | x |
| 30 | EA2 | 520304 | 180054 | Ealing - Acton Town Hall | roadside | x | TEOM | TEOM | x | x | x | x |
| 31 | EA6 | 518537 | 182708 | Ealing - Hanger Lane Gyratory | roadside | | | | x | | | |
| 32 | EA7 | 511677 | 180071 | Ealing - Southall | urban background | | TEOM | | x | x | | |
| 33 | EL1 | 511403 | 164915 | Elmbridge - Bell Farm Hersham | urban background | | TEOM | | x | x | | x |
| 34 | EL2 | 514024 | 164792 | Elmbridge - Esher High Street | roadside | | | | x | | | |
| 35 | EN1 | 533900 | 195800 | Enfield - Bushhill Park | suburban | x | | | x | | | |
| 36 | EN3 | 535440 | 195000 | Enfield - Salisbury School | urban background | | BAM | | x | x | | x |
| 37 | EN4 | 535025 | 192449 | Enfield - Derby Road | roadside | | BAM | | x | x | | |
| 38 | EN5 | 529894 | 192223 | Enfield - Bowes Primary School | roadside | | TEOM | | x | x | | |
| 39 | GB6 | 544997 | 175098 | Greenwich and Bexley - Falconwood | roadside | | TEOM | TEOM | x | x | x | x |
| 40 | GN0 | 544084 | 178881 | Greenwich - A206 Burrage Grove | roadside | | TEOM | FDMS | x | x | x | |
| 41 | GN2 | 540169 | 178999 | Greenwich - Millennium Village | urban background | | | FDMS | x | | x | |
| 42 | GN3 | 545560 | 178526 | Greenwich - Plumstead High Street | roadside | | | FDMS | x | | x | x |
| 43 | GR4 | 543978 | 174655 | Greenwich - Eltham | suburban | x | TEOM | FDMS | x | x | x | x |
| 44 | GR5 | 538960 | 177954 | Greenwich - Trafalgar Road | roadside | | TEOM | | x | x | | |
| 45 | GR7 | 538141 | 176710 | Greenwich - Blackheath | roadside | | TEOM | | x | x | | |
| 46 | GR8 | 540200 | 178367 | Greenwich - Woolwich Flyover | roadside | | TEOM | TEOM | x | x | x | x |
| 47 | GR9 | 541879 | 175016 | Greenwich - Westhorne Avenue | roadside | | | FDMS | x | | x | x |
| 48 | HF1 | 523420 | 178590 | Hammersmith and Fulham - Broadway | roadside | | | | x | | | |
| 49 | HF2 | 523625 | 179010 | Hammersmith and Fulham - Brook Green | urban background | | TEOM | | x | x | | |
| 50 | HG1 | 533891 | 190707 | Haringey - Haringey Town Hall | roadside | x | TEOM | | x | x | | |
| 51 | HG2 | 529894 | 189125 | Haringey - Priory Park | urban background | | BAM | | x | x | | x |
| 52 | HI0 | 506945 | 178609 | Hillingdon - Sipson Road | suburban | | | | x | | | x |
| 53 | HI1 | 510835 | 184916 | Hillingdon - South Ruislip | roadside | | TEOM | | x | x | | |
| 54 | HI2 | 506990 | 181925 | Hillingdon - Hillingdon Hospital | roadside | | TEOM | | x | x | | |
| 55 | HI3 | 509551 | 176974 | Hillingdon - Oxford Avenue | roadside | | TEOM | | x | x | | |
| 56 | HK4 | 534830 | 186234 | Hackney - Clapton | urban background | | | TEOM | x | | x | x |
| 57 | HK6 | 532947 | 182575 | Hackney - Old Street | roadside | | TEOM | TEOM | x | x | x | x |
| 58 | HR1 | 517877 | 192314 | Harrow - Stanmore | urban background | | TEOM | FDMS | x | x | x | |
| 59 | HR2 | 513504 | 188998 | Harrow - Pinner Road | roadside | | TEOM | | x | x | | |

**Table 12:** Site/receptor details relevant to the urban modelling groups.

| | site.code | easting | northing | site.name | site.type | hourly? | $PM_{10}$ technique | $PM_{2.5}$ technique | $NO_x$ & $NO_2$ | $PM_{10}$ | $PM_{2.5}$ | $O_3$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 60 | HRL | 508299 | 177809 | London Harlington | airport | | | | x | | | x |
| 61 | HS2 | 510371 | 177198 | Hounslow - Cranford | suburban | | TEOM | | x | x | | x |
| 62 | HS4 | 521083 | 178501 | Hounslow - Chiswick High Road | roadside | | TEOM | | x | x | | |
| 63 | HS5 | 517423 | 178070 | Hounslow - Brentford | roadside | | TEOM | | x | x | | |
| 64 | HS6 | 513653 | 176842 | Hounslow - Heston Road | roadside | | TEOM | | x | x | | |
| 65 | HS7 | 509332 | 174997 | Hounslow - Hatton Cross | urban background | | TEOM | | x | x | | |
| 66 | HV1 | 553110 | 182516 | Havering - Rainham | roadside | | | | x | | | |
| 67 | HV3 | 551105 | 188261 | Havering - Romford | roadside | | TEOM | | x | x | | |
| 68 | IS2 | 530698 | 185735 | Islington - Holloway Road | roadside | | TEOM | | x | x | | |
| 69 | IS6 | 531325 | 186032 | Islington - Arsenal | urban background | | TEOM | | x | x | | |
| 70 | KC1 | 524046 | 181750 | Kensington and Chelsea - North Ken | urban background | x | TEOM | FDMS | x | x | x | x |
| 71 | KC2 | 526527 | 179646 | Kensington and Chelsea - Cromwell Road | roadside | | TEOM | | x | x | | |
| 72 | KC3 | 527551 | 180020 | Kensington and Chelsea - Knightsbridge | roadside | | | | x | | | |
| 73 | KC4 | 527264 | 178727 | Kensington and Chelsea - Kings Road | roadside | | | | x | | | |
| 74 | KC5 | 525671 | 179080 | Kensington and Chelsea - Earls Court Rd | kerbside | | | | x | | | |
| 75 | LB1 | 530628 | 173368 | Lambeth - Christchurch Road | roadside | | BAM | | x | x | | |
| 76 | LB3 | 532137 | 175701 | Lambeth - Loughborough Junct | urban background | | BAM | | x | x | | |
| 77 | LB4 | 531070 | 175593 | Lambeth - Brixton Road | kerbside | x | BAM | | x | x | | |
| 78 | LB5 | 530317 | 177952 | Lambeth - Bondway Interchange | roadside | | BAM | | x | x | | |
| 79 | LH0 | 508300 | 177800 | Hillingdon - Harlington | urban background | | TEOM | FDMS | x | x | x | x |
| 80 | LH2 | 508393 | 176742 | Heathrow Airport | urban background | | TEOM | | x | x | | x |
| 81 | LW1 | 537675 | 173689 | Lewisham - Catford | urban background | | | | x | | | x |
| 82 | LW2 | 536241 | 176932 | Lewisham - New Cross | roadside | x | TEOM | | x | x | | |
| 83 | MY1 | 528125 | 182016 | Westminster - Marylebone Road | kerbside | | TEOM | TEOM | x | x | x | x |
| 84 | RB1 | 544377 | 187647 | Redbridge - Perth Terrace | urban background | | BAM | | x | x | | x |
| 85 | RB3 | 544555 | 190402 | Redbridge - Fullwell Cross | kerbside | | BAM | BAM | x | x | x | |
| 86 | RB4 | 540823 | 188369 | Redbridge - Gardner Close | roadside | | BAM | BAM | x | x | x | |
| 87 | RB5 | 540017 | 190488 | Redbridge - South Woodford | roadside | | BAM | | x | x | | |
| 88 | RI1 | 522498 | 177165 | Richmond - Castelnau | roadside | | TEOM | | x | x | | |
| 89 | RI2 | 522989 | 176729 | Richmond - Barnes Wetlands | suburban | | TEOM | | x | x | | x |
| 90 | SK1 | 532240 | 178561 | Southwark - Larcom Street | urban background | | TEOM | | x | x | | x |
| 91 | ST3 | 527776 | 164513 | Sutton - Carshalton | suburban | | | | x | | | x |
| 92 | ST4 | 528925 | 163804 | Sutton - Wallington | kerbside | | | | x | | | |
| 93 | ST6 | 522557 | 165787 | Sutton - Worcester Park | kerbside | | | | x | | | |
| 94 | TD0 | 515600 | 170600 | Richmond - National Physical Laboratory | suburban | x | | FDMS | x | | x | x |
| 95 | TH1 | 537509 | 180867 | Tower Hamlets - Poplar | urban background | x | TEOM | | x | x | | x |
| 96 | TH2 | 535927 | 182221 | Tower Hamlets - Mile End Road | roadside | x | | | x | | | |
| 97 | TH3 | 535100 | 182664 | Tower Hamlets - Bethnal Green | urban background | | TEOM | | x | x | | |
| 98 | TH4 | 538290 | 181452 | Tower Hamlets - Blackwall | roadside | | | FDMS | x | | x | x |
| 99 | TK1 | 560900 | 177700 | Thurrock - London Road (Grays) | urban background | | TEOM | | x | x | | x |
| 100 | TK2 | 556738 | 177928 | Thurrock - Purfleet | roadside | | BAM | | x | x | | |
| 101 | TK3 | 569356 | 182736 | Thurrock - Stanford-le-Hope | roadside | | TEOM | | x | x | | |
| 102 | TK8 | 556698 | 177937 | Thurrock - London Road (Purfleet) | roadside | | BAM | | x | x | | |
| 103 | WA2 | 525774 | 174660 | Wandsworth - Town Hall | urban background | | | | x | | | x |
| 104 | WA6 | 527712 | 171184 | Wandsworth - Tooting | roadside | | TEOM | | x | x | | |
| 105 | WL1 | 538389 | 186723 | Waltham Forest - Dawlish Road | urban background | | TEOM | | x | x | | |
| 106 | WL4 | 537466 | 191071 | Waltham Forest - Crooked Billet | kerbside | | TEOM | | x | x | | |
| 107 | WL5 | 537802 | 186021 | Waltham Forest - Leyton | urban background | | | | x | | | |
| 108 | WM0 | 529802 | 178962 | Westminster - Horseferry Road | urban background | | | | x | | | x |
| 109 | WM4 | 529992 | 180691 | Westminster - Charing Cross Library | roadside | | | | x | | | |
| 110 | CR3 | 532336 | 168934 | Croydon - Thornton Heath | suburban | | TEOM | | | x | | x |
| 111 | CT8 | 532829 | 180694 | City of London - Upper Thames Street | roadside | | TEOM | | | x | | |
| 112 | EI0 | 514323 | 184070 | Ealing - Greenford | urban background | | TEOM | | | x | | |
| 113 | FB1 | 485063 | 156969 | Rushmoor - Medway Drive | roadside | | TEOM | | | x | | |
| 114 | MV3 | 517033 | 149806 | Mole Valley - Dorking | urban background | | TEOM | | | x | | |
| 115 | NM2 | 538661 | 183969 | Newham - Cam Road | roadside | | TEOM | | | x | | x |
| 116 | NM3 | 539889 | 181469 | Newham - Wren Close | urban background | | TEOM | | | x | | x |
| 117 | BX3 | 547323 | 181231 | Bexley - Thamesmead | suburban | | | TEOM | | | x | |
| 118 | BX9 | 551860 | 176376 | Bexley - Slade Green FDMS | suburban | | | FDMS | | | x | |