A regression approach to assessing urban NO_2 from passive monitoring

Application to the Waterview Connection

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Executive summary

In 2009 NIWA were commissioned to prepare material for the Air Quality Technical Report as part of the Assessment of Environmental Effects for the SH20 Waterview Connection project, including an analysis of baseline levels of nitrogen dioxide (NO_2). NO_2 is a significant pollutant for road project assessment because it is the subject of a National Environmental Standard (as well as other non-statutory Guidelines) and road vehicle emissions are its dominant source. NO_2 concentrations are known to be strongly elevated within tens of metres of major roads.

It is common to assume that NO_2 data from a conventional continuous monitoring site can be considered representative of a wide area only if a significant degree of conservatism is applied when analysing the data. The 'margin of error' applied can be highly arbitrary and applied inconsistently. An alternative approach is to employ low-cost low-resolution passive monitoring, although the data this provides cannot directly be used for comparison with the Air Quality National Environmental Standard or Air Quality Guideline for NO_2.

The SH20 Waterview Connection is a large road project for which a substantial network of passive NO_2 monitors were deployed across the project area, supplementing the NZTA NO_2 Network (at the time of writing, there are 152 sites across Auckland). This network provided an opportunity to develop a more sophisticated approach to baseline analysis for NO_2 to improve the accuracy in the assessment of current air quality and in particular the fine-scale spatial variation across the project area.

In brief the approach consists of three components:

- **Seasonal adjustment factors** to permit annual mean concentrations of NO_2 to be estimated from less than a year's worth of monthly passive monitoring data.
- A **spatial correlation model** (also known as a land-use regression model) which predicts annual mean concentrations of NO_2 at a given location as a function of local spatial traffic data, initialised using passive monitoring data.
- **Empirical NO_2-NO_x relationships** to predict short-term concentrations from annual mean concentrations, for use in Cumulative impact analyses and comparison with air quality Standards and Guidelines.

Analysis showed that for most sites, 6 months of data were sufficient to provide a confident prediction of the annual mean. On average, 3 months of data were required to keep average errors below 1 $\mu g\ m^{-3}$. The seasonal adjustment factors were validated by successfully predicting annual means from monthly mean data gathered at 11 ARC continuous monitoring sites.

Empirical relationships between short-term peak NO_2 (and NO_x) and long-term NO_2 concentrations were derived from ARC (and NZTA) continuous monitoring data (12 sites in total) from 1987 – 2008 inclusive:

$$99.9^{th} \text{ percentile 1-hr } NO_2 = (2.31 \times \text{mean } NO_2) + 28$$

$$\text{maximum 24-hr } NO_2 = (0.694 \times 99.9^{th} \text{ percentile 1-hr } NO_2) - 2.5$$

$$99.9^{th} \text{ percentile 1-hr } NO_2 = (0.055 \times 99.9^{th} \text{ percentile 1-hr } NO_x) + 37$$

We developed a spatial regression model to permit the information derived from passive monitoring sites to be translated in space to nearby alternative sites (or receptors) within the same general spatial domain. The resulting model is:

Annual mean NO_2 (μg m^{-3}) = 0.00077(***traffic proximity factor)*** + 10.4

Where ***traffic proximity factor*** = $\sum_{0}^{20}\left(AADT \bullet distance^{-0.65}\right)$

'Distance' is the shortest distance from the location of interest to a given road, and AADT is the annual average daily traffic on that link. The traffic proximity factor is the sum of the expression given for the 20 nearest road links. The power 0.65 is derived from NIWA's Roadside Corridor Model (Longley *et al.*, 2010) and is representative of the long-term average general rate of dilution of pollutants from a line source under Auckland meteorology.

The 10.4 represents the 'urban background' concentration, i.e. the concentration arising from sources beyond the 20th nearest road link. Our analysis indicated that this value varied little (if at all) across the area where most sites are located (principally around the SH16 Upgrade, SH20 Waterview and SH20 Mt Roskill projects). More passive data from Auckland's periphery and CBD might confirm whether the background concentration reduces at the urban edge, and/or increases in the CBD, and at what rate.

The general applicability of the model is dependent upon the existence of passive monitoring data. Strictly the model derived can only be applied with confidence to areas around SH16 and SH20. The model's performance in north, east and south Auckland, for instance, cannot be specified due to the relative absence of monitoring sites in those areas. However, the approaches demonstrated should apply generally to any urban area.

The regression model was used to predict annual mean NO_2 at the 103 Waterview Connection project assessment receptors. Predictions were compared with predictions of 99.9th percentile 1-hour NO_x concentrations from dispersion modelling (conducted within the Waterview project assessment). A strong correlation was observed (r^2 = 0.87), especially once an empirical correction factor was applied to account for differences in NO_2/NO_x ratio with respect to distance from dominant roads. It was concluded that the regression model and the dispersion model were in general agreement and are mutually supportive.

To apply the regression model elsewhere, passive monitoring sites must encompass a wide range of AADT and distances to major roads, and more generally a wide range of traffic intensities. For example, we recommend a variety of sites adjacent to minor roads, feeder roads, major roads and arterial roads, plus a combination of areas of generally higher and lower traffic density. To deploy a single urban background and single roadside site will not give sufficient coverage to extend the model to a new area. For the purposes of project assessment we recommend that urban background sites are especially useful. These are sites which are fully embedded in the urban fabric (not at the urban periphery), but far from major roads.

We suggest that the methods developed could also be used for other applications, such as

- Health risk assessment
- Emission trends assessment

- Management and rationalisation of the NO_2 Network
- Roadside corridor definition for mitigation and reverse sensitivity.

1 Introduction

1.1 Background

In 2009 NIWA were commissioned to prepare material for the Air Quality Technical Report as part of the Assessment of Environmental Effects for the SH20 Waterview Connection project. Broadly NIWA's contribution consisted of three components:

- Baseline analysis (i.e. assessment of current pre-project air quality),
- Dispersion modelling (predicting the change in air quality attributable to the project),
- Cumulative analysis (the combined impact of the project and non-project contributions to future air quality).

Baseline analysis conventionally relies on monitoring data from one, or a few sites which may or may not be located for the purpose of project assessment, and which may or may not be in locations representative of the impact of the project. NO_2 is a significant pollutant for road project assessment because it is the subject of a National Environmental Standard (as well as other non-statutory Guidelines) and road vehicle emissions are its dominant source. NO_2 is mostly a 'secondary' pollutant which forms in the atmosphere through chemical reaction of the primary pollutant nitric oxide (NO). This reaction is rapid but strongly influenced by several factors including meteorological conditions. One consequence is that NO_2 concentrations are known to be strongly elevated within tens of metres of major roads.

The implication of all of these factors is that there is always significant uncertainty as to whether any given monitor can represent concentrations of NO_2 at other nearby locations. Consequently, it is common to assume that data from a monitoring site can be considered representative of a wide area only if a significant degree of conservatism is applied when analysing the data. The 'margin of error' applied can be highly arbitrary and applied inconsistently.

An alternative approach is to employ passive monitoring. Because of their low cost, passive monitors can be deployed in dense networks across areas of interest. Their main limitation, however, is that they report only a single concentration per deployment (usually 2 weeks or a month). They also have a relatively low accuracy. This means that, although they can provide an insight into spatial variation, they cannot be used for comparison with the AQNES or AAQG (which are 1-hour and 24-hour average concentrations respectively). They can be used to draw comparisons with the World Health Organisations' annual guideline, but a whole year's worth of data is required. Even then, whether or not any given year is typical or not is open to challenge. These factors have previously limited the use of passive monitoring.

Finally, the prediction of cumulative impacts requires the combination of the effect of project-related emissions (usually expressed as oxides of nitrogen, or NO_x – the sum of NO and NO_2) with the baseline (usually expressed as NO_2 only) .The complex chemistry of NO_x means that NO_x from emissions cannot simply be summed with baseline NO_2. It is advantageous if the baseline is also expressed in terms of NO_x with the cumulative NO_x impact re-apportioned between NO_2 and NO. Although all of this can, in principle, be achieved with complex chemical-transport modelling, this approach is dependent upon (and sensitive to) substantial amounts of data which are rarely available and is usually considered too complex and uncertain for the purposes of a regulatory air quality assessment.

The SH20 Waterview Connection is a large, high-value and complex project. Before NIWA began its assessment a substantial network of passive NO_2 monitors were deployed by NZTA across the project area, supplementing the then rapidly growing NZTA NO_2 Network. NIWA believed that this network provided an opportunity to develop a more sophisticated approach to baseline analysis for NO_2 which would help to overcome the problems discussed above. The aim was to improve the accuracy in the assessment of current air quality and in particular its fine-scale spatial variation across the area affected by the project.

In brief the approach consists of three components:

- **Seasonal adjustment factors** to permit annual mean concentrations of NO_2 to be estimated from less than a year's worth of monthly passive monitoring data.
- A **spatial correlation model** (also known as a land-use regression model) which predicts annual mean concentrations of NO_2 at a given location as a function of local spatial traffic data, initialised using passive monitoring data.
- **Empirical NO_2-NO_x relationships** to predict short-term concentrations from annual mean concentrations, for use in Cumulative impact analyses and comparison with air quality Standards and Guidelines.

In the process of developing this new approach, further information and tools of more general value has been derived regarding the influence of road traffic emissions on urban air quality.

1.2 Scope of the report

This report documents the approach taken to develop NO_2 baseline data for the Waterview project. It also briefly indicates other applications of the information and tools derived during the development of the approach. These further applications could be developed more fully in the future.

More specifically, it covers

- The development of seasonal adjustment factors to estimate annual mean NO_2 concentrations from monthly mean data.
- A prototype empirical regression model which generalises the long-term spatial distribution of air quality impacts from roads, as described by the NZTA NO_2 network (currently Auckland only)
- The use of this model to provide baseline NO_2 (and NO_x) data for the Waterview project
- Recommendations for how these approaches can be generalised (and combined with other approaches) for other locations and other projects

It is important to note that this project is based on passive monitoring data as its main input. The project scope did not include quality assurance or control of this data. It has been assumed throughout that the data we have received from NZTA had already been through a full QA/QC process.

It is our long-term intention that the approaches, methods and tools described in this report are applicable nationwide. However, at present, the analysis is based solely on data from the Auckland Region, and principally from areas around SH20 and SH16. The applicability of results to other locations cannot, as yet, be assured.

2 Data used

2.1 Data sources

NZTA operate a nationwide monitoring network for NO_2 using passive samplers. At the time the analysis in this report was conducted (early 2010) there had been 152 sites established at some time within the Auckland Region. Approximately 37 of these sites had been in operation since 2007 and 34 further sites were added in April 2009. Further sites were added in specific areas from July to October 2009: 16 sites around Te Atatu (July), 31 sites around Waterview (September) and 25 sites around Massey (October). The locations of the sites are shown in Appendix One.

Data from all Auckland sites from January 2007 to February 2010 were provided by NZTA.

2.2 Validity of data from passive monitoring

Passive samplers have been repeatedly deployed at several locations around Auckland where NO_2 is also monitored continuously using chemi-luminescence analysers (the method required for monitoring compliance with the National Environmental Standards). One of those sites is the MfE/ARC monitoring station at Gavin Street in Penrose, where passive sampler tubes have been regularly installed in triplicate. Figure 2-1 shows the monthly average NO_2 from the continuous monitor compared to the monthly averages obtained from the three passive samplers up to December 2009. Both methods follow the same trend over time, with peak NO_2 in June and low NO_2 in December. A regression plot for the data indicates that while there is considerable scatter in the data, there is a 1 to 1 relationship between the two methods (slope of 0.9996). The passive samplers appear to measure 1 - 2 $\mu g\ m^{-3}$ higher than the continuous monitor.

This verification could not be repeated for other monitoring sites as passive samplers have been installed only recently at most sites and there is a short temporal overlap.

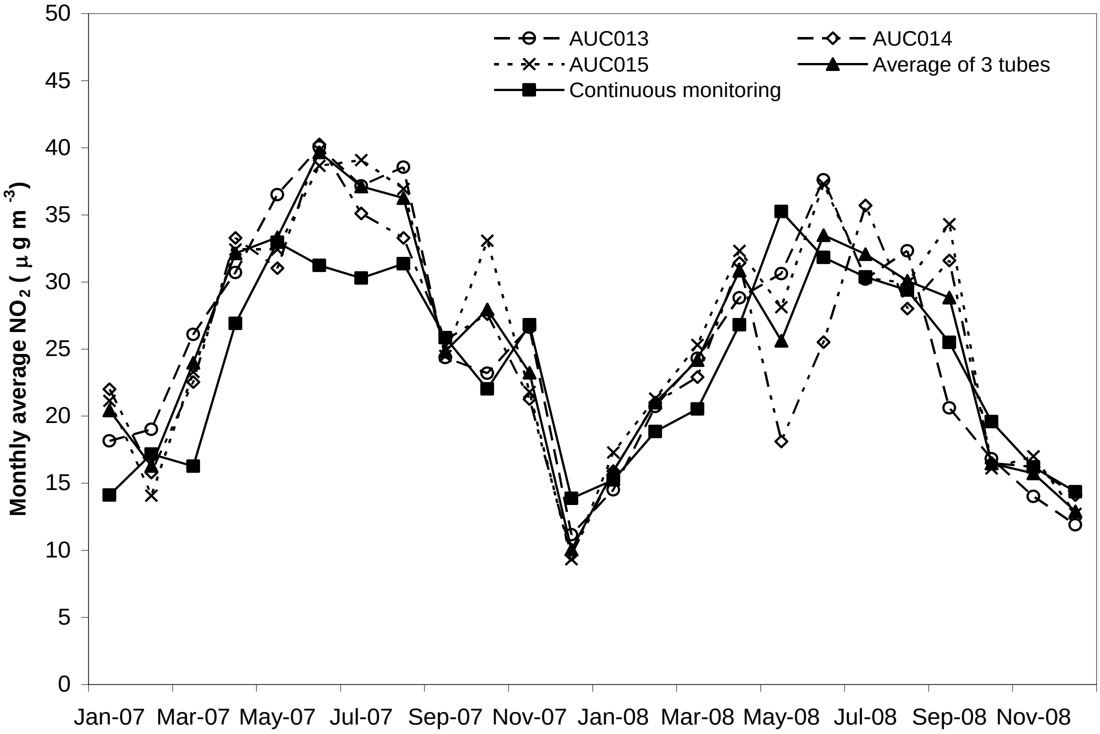

Figure 2-1: Comparison of data from passive monitoring NO_2 tubes with continuous monitoring (chemi-luminescence analyser) data from the MfE Gavin Street site.

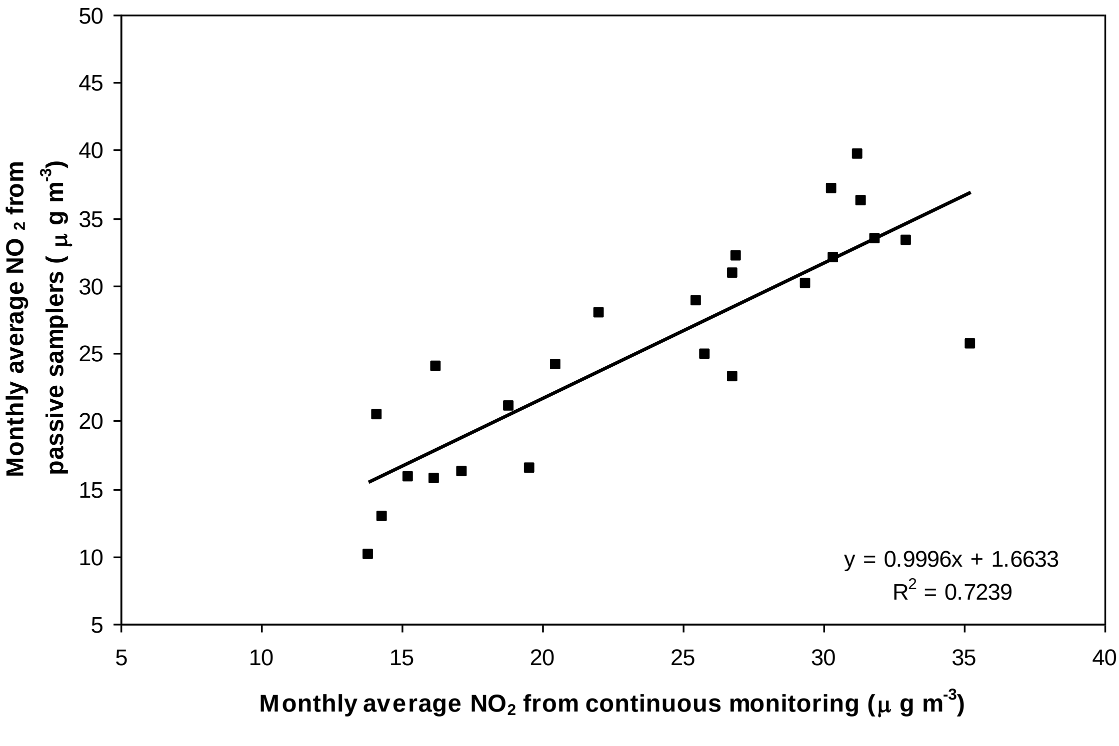

Figure 2-2: Comparison of data from passive monitoring NO_2 tubes with continuous monitoring data from the MfE Gavin Street site.

3 Seasonal adjustment of monthly data

3.1 Seasonal patterns from long-term tube sites

Continuous monitoring of NO_2, and previous analysis of passive monitoring of NO_2 (ARC, 2007; Watercare, 2008, 2010) have shown that there is a strong and consistent seasonal variation in concentrations in Auckland, with relatively elevated concentrations in winter.

3.2 Monthly adjustment factors

We sought to derive seasonal (monthly) adjustment factors for deriving estimates of annual means from monthly means by investigating the relationship between monthly mean and annual mean concentrations across the passive monitoring sites in Auckland with more than 12 months of data. Data from 41 sites (with an average of 31 months of data per site) were used to produce a seasonal regression relationship for each month. For example, values for January 2010 for each site were plotted against the rolling mean of data from the previous 12 months (February 2009 – January 2010) for that site. For the month of January, there were up to four years of data for each site (2007-2010). Each of the 41 sites was plotted and a linear regression was fitted with the intercept fixed to the origin (Figure 3-1). This was repeated for each month, to provide 12 regression plots (Figures 3-2 and 3-3).

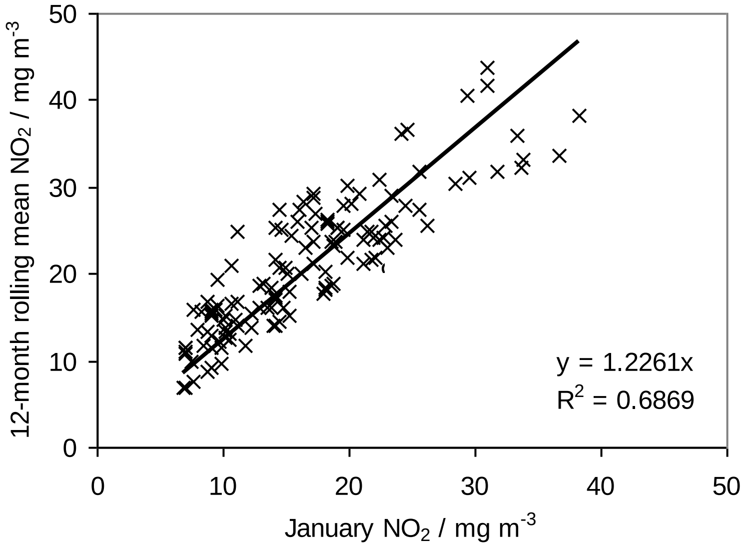

Figure 3-1: Regression plot of monthly January data versus 12-month rolling mean data for each site.

Data were segregated data into highly- and less-trafficked sites to investigate whether this influenced the resulting regression slopes. Based on the range of sites available for this analysis, ‘High traffic’ was defined as annual average daily traffic >60,000. Highly-trafficked sites were further segregated into ‘roadside’ (site < 30 m from the road) and ‘setback’ (site 60 – 120 m from the road). Figure 3-4 shows that these ‘High traffic’ sites exhibited approximately the same seasonal relationship between monthly and annual means (only January is shown for simplicity). Figure 3-5 also shows the time series of monthly mean of all sites in each class. Winter peaks can be clearly seen, along with inter-annual variation (such as the clear dip in concentrations in May 2008 compared to May 2007 and May 2009). However, the average difference between roadside and setback sites (despite some random variation) is approximately constant (average 6 μg m^{-3}), exhibiting no significant seasonal variation. We interpret these results to mean that the seasonal adjustment factors are equally applicable at low-traffic, high-traffic, roadside and setback sites.

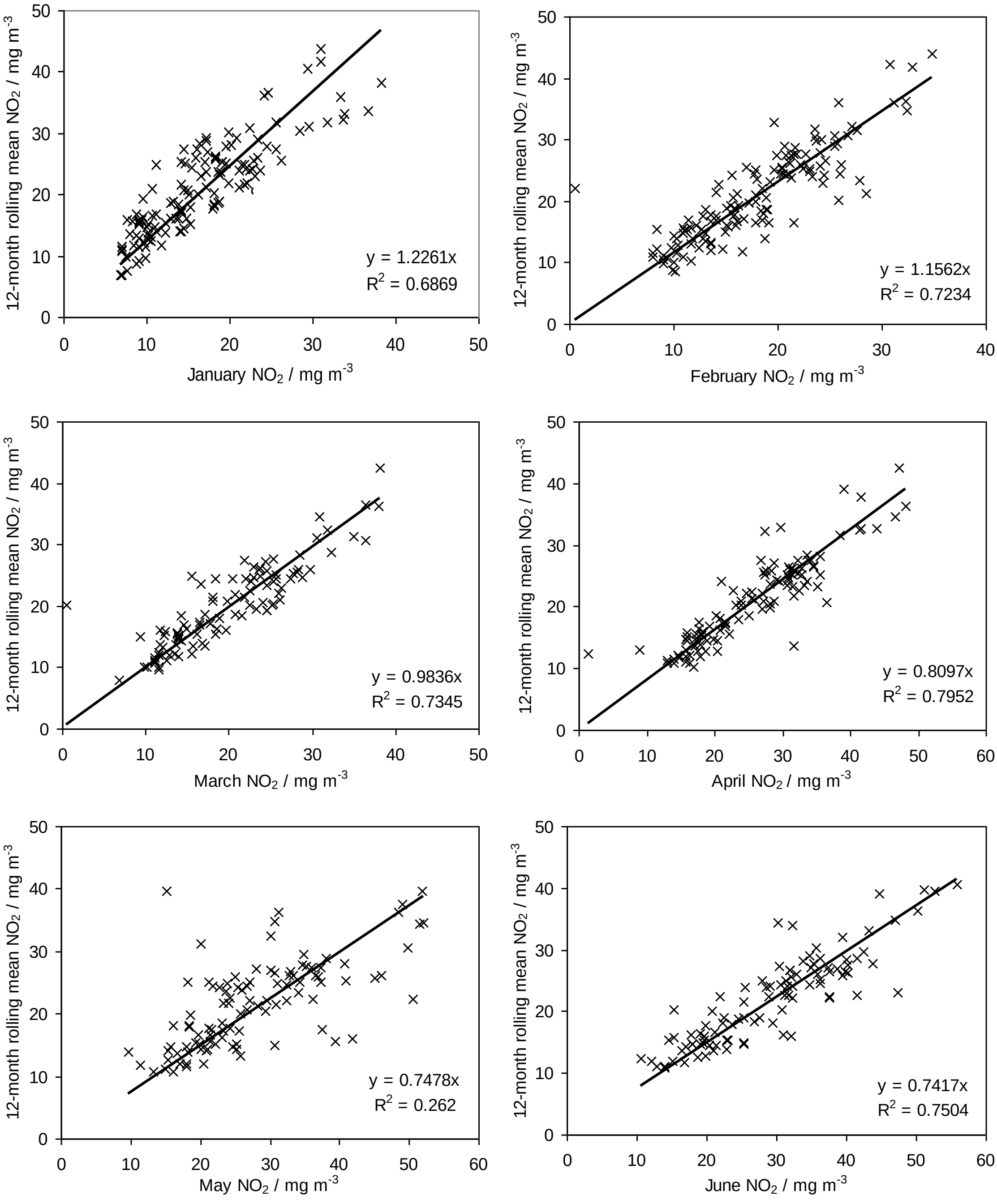

Figure 3-2: Regression plot of data versus 12-month rolling mean data for January to June.

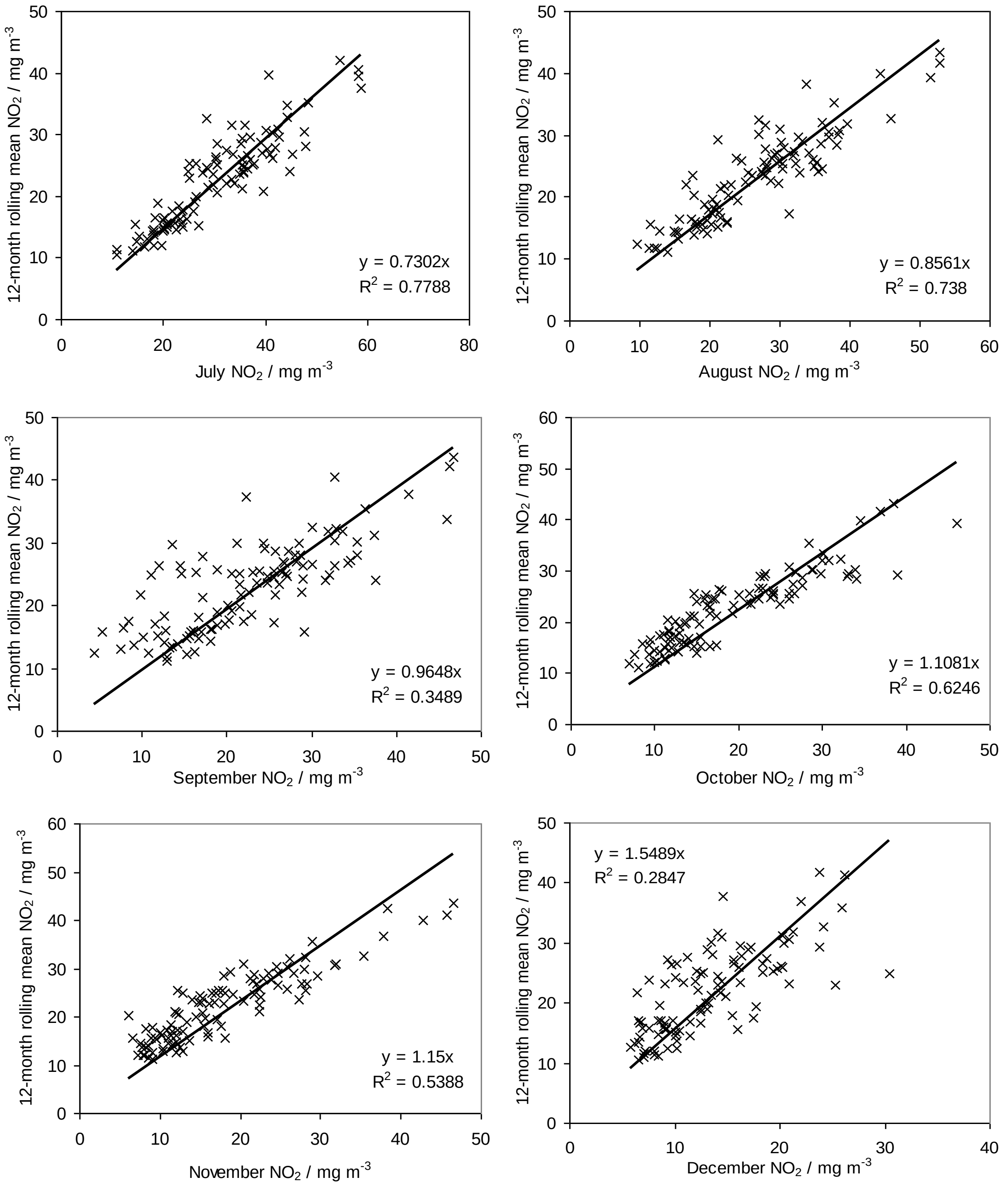

Figure 3-3: Regression plot of monthly data versus 12-month rolling mean data for July to December.

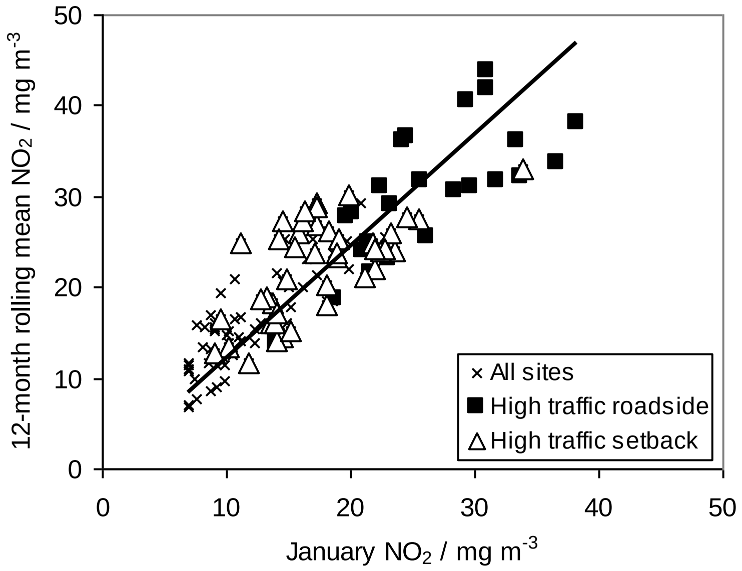

Figure 3-4: Regression plot for January including data for highly trafficked sites.

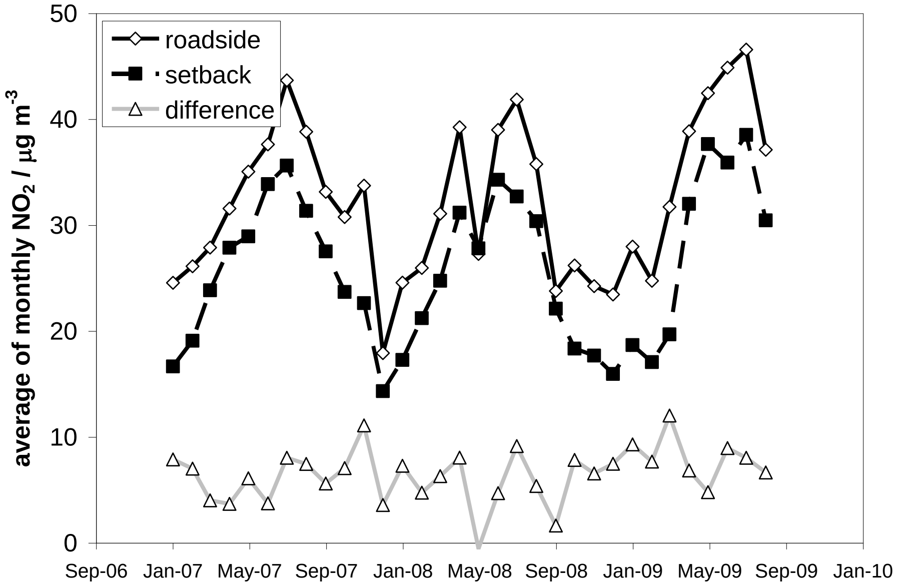

Figure 3-5: Time series of monthly mean of all highly trafficked roadside and setback sites, and the difference between them.

The resulting regression slopes, or seasonal adjustment factors, are listed in Table 3-1. In the absence of any evidence to the contrary we suggest that these factors apply at all sites in Auckland.

Table 3-1: Adjustment factors used to estimate annual mean concentrations based on monthly means.

Month	Slope Factor
January	1.226
February	1.156
March	0.984
April	0.810
May	0.748
June	0.742
July	0.730
August	0.856
September	0.965
October	1.108
November	1.150
December	1.549

These factors were applied to all of the data used in this analysis to seasonally de-trend the data. The results are shown in Figure 3-6. From this analysis the deviation of individual months from the "norm" (from which the seasonal adjustment factors are derived) stand out more clearly. For instance, the abnormally low concentrations in May 2008 are clear. A similar dip occurred in December 2007. Whether these deviations are representative of general meteorology (affecting all sites) or more local phenomena (which may still be meteorological phenomena, or atypical emissions or instrumental/analytical errors) would require more detailed exploration.

With more lengthy time series it is plausible that seasonal de-trending could be used to reveal long-term trends or step-changes (due to sudden changes such as implementation of a traffic management scheme or opening of a new road).

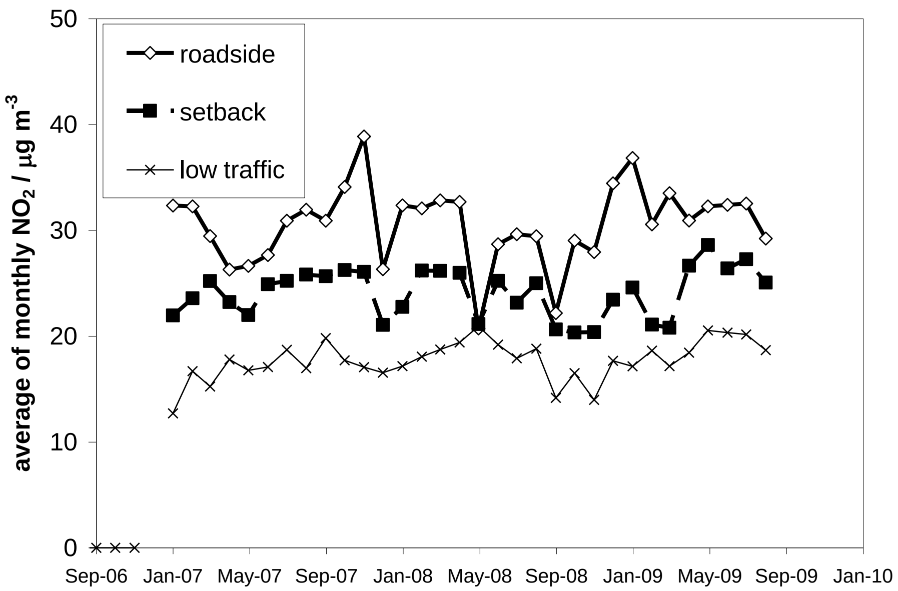

Figure 3-6: Time series of seasonally de-trended monthly mean of all highly trafficked roadside and setback sites, and low-traffic sites.

3.3 How many months of data are required for a stable prediction of annual mean?

We analysed those sites with a long-term record (32 sites used with 29 – 37 months of data each). Annual values were estimated using the seasonal adjustment factors in Table 3-1 for each month. Cumulative averages were then calculated for each additional month of data. For example, if a site started reporting data in July, we estimated the annual mean based on July data only, then the average of estimates based on July and August, then July, August and September, etc.

The change in the estimated annual mean by adding each additional month of data is illustrated in Figure 3-7. In this figure a random selection of sites is shown covering the range from low (urban background) to high (highly trafficked) concentrations. This shows that for most sites, 6 months of data are sufficient to provide a clear indication of the annual mean. At all sites all but one the estimated annual means based on 6 months of data were within 5 $\mu g\ m^{-3}$ of the estimate based on 12 months of data. Figure 3-8 shows the average absolute error (deviation from an annual mean based on 12 months of data) arising from having less than 12 months of monthly data. It shows that, on average, 3 months of data are required to keep average errors below 1 $\mu g\ m^{-3}$.

After 12 months of data has been included there is very little further change in the estimate of annual mean. Some perturbations can be seen and the estimates never fully converge. This is because random deviations from the norm (atypical monthly concentrations) can occur at any time due to atypical meteorological conditions, and may also reflect long-term trends in concentrations. Thus the error inherent in this technique cannot be reduced by collecting additional data.

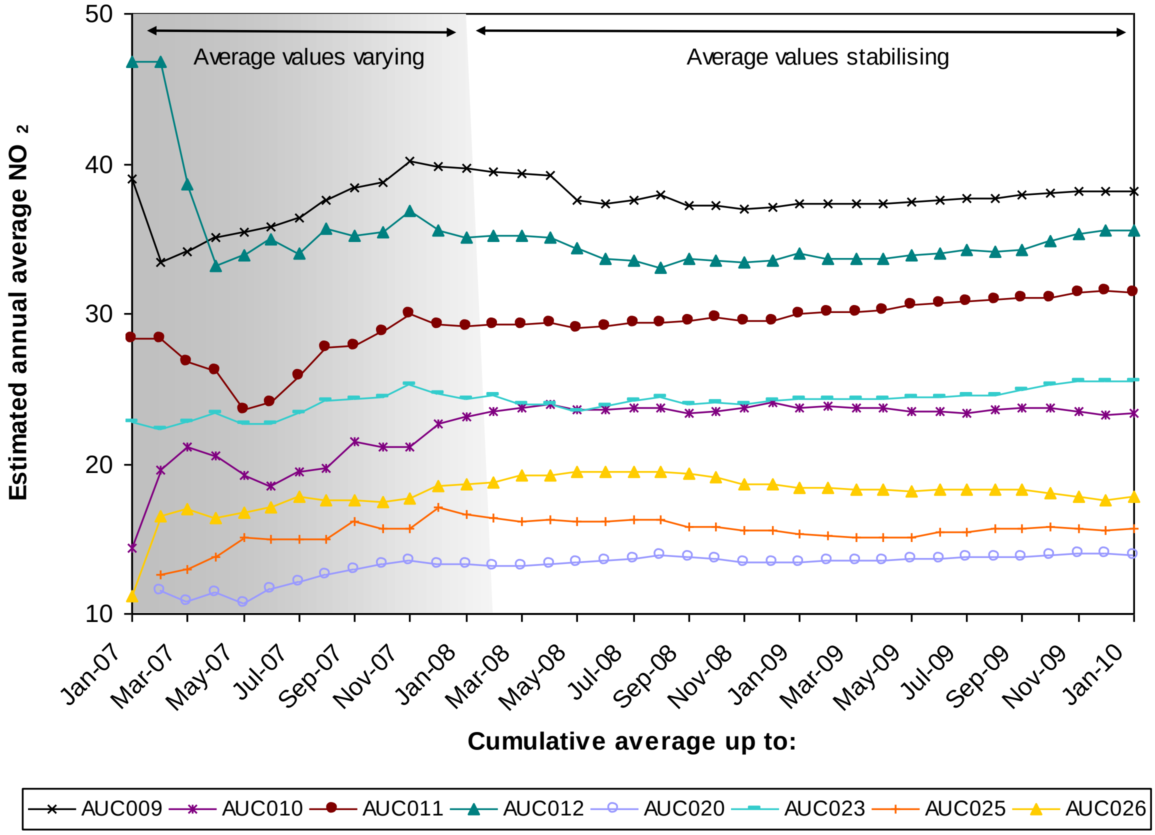

Figure 3-7: Annual averages based on 1 to 37 annual values calculated from monthly data.

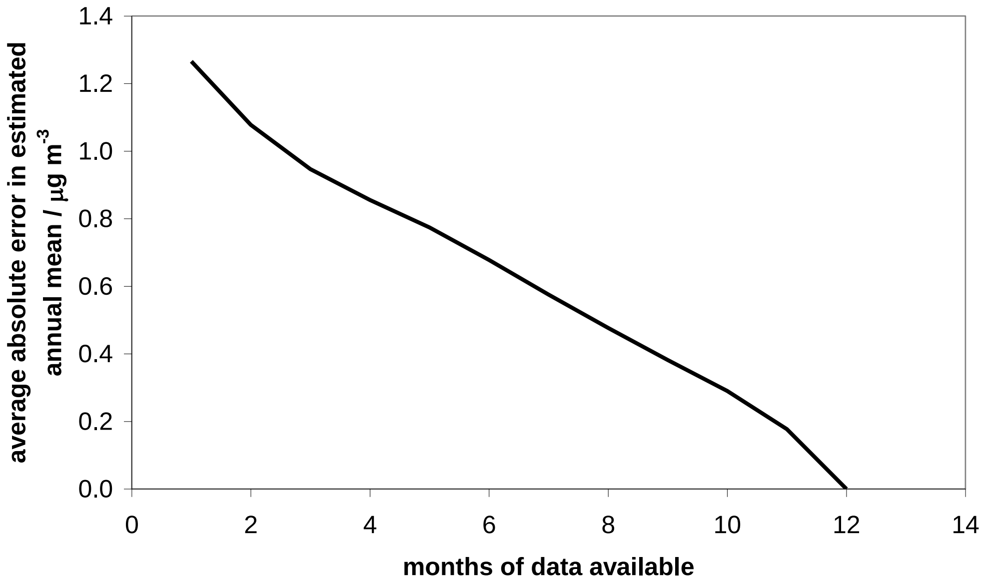

Figure 3-8: Relationship between number of months of data upon which an estimated annual mean is based and the average absolute error in that estimate.

3.4 Validation against continuous data

To verify the seasonal factor adjustment, we used the seasonal factors to predict annual mean NO_2 for data from ARC's continuous monitoring data. 24 hour average NO_2 concentrations were used to calculate monthly means, which were then adjusted using the seasonal factors derived above to provide annual estimates. The mean of these annual estimates was calculated for three individual years of monitoring (2006, 2007, 2008) and compared to the annual mean for those years calculated directly from the 24 hour data.

This showed a clear correlation between the annual means based on seasonally adjusted monthly means and those based on raw data (Figure 3-9).

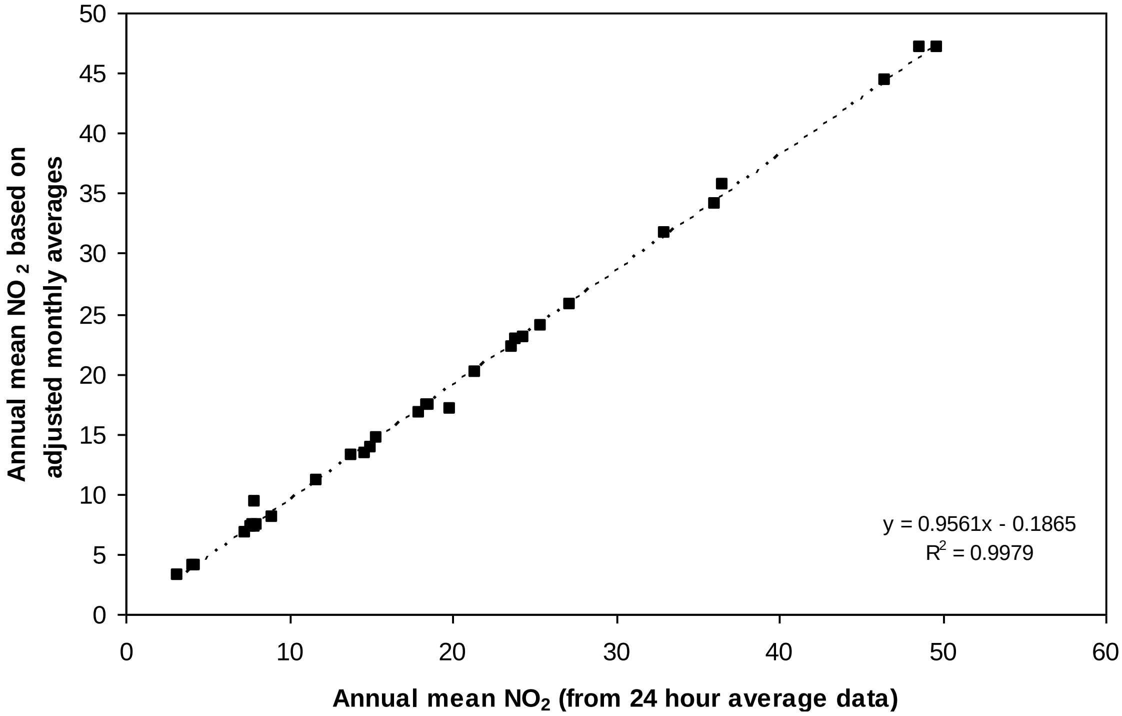

Figure 3-9: Comparison of annual averages calculated from 24 hour averages, compared with annual averages calculated from adjusted monthly averages.

3.5 Results of seasonal adjustment for NZTA Network sites in Auckland

We applied the seasonal adjustment factors to all of the NZTA passive NO_2 data provided to us from Sep 2009 – Feb 2010 inclusive. The results are plotted on maps in Appendix One.

4 Empirical prediction of short-term impacts based on annual means

4.1 Relationship between short and long-term impacts using ARC data

The chemical reactivity of nitrogen dioxide, and the complexity of the factors influencing its short-term ambient concentration, means that concentrations are highly variable. Prediction of NO_2 concentrations is technically very demanding and inherently uncertain. On the other hand, locations which are prone to high long-term concentrations (i.e. chronically highly traffic-influenced locations) are also likely to be locations most likely to experience elevated short-term concentrations due to the dominant role of local traffic emissions in ambient NO_2 levels.

The approach to baseline analysis for NO_2 is based on using passive monitoring data reporting monthly mean concentrations, seasonally adjusted to estimate annual mean concentrations. However, comparison with the AQNES and AAQG requires prediction of peak 1-hour and 24-hour concentrations respectively. Strictly, peak (i.e. maximum) 1–hour NO_2 concentrations have been observed to be highly random short-lived events that are unlikely to be generally representative of a site. Consequently, the convention is to assess the 99.9th percentile as opposed to the true maximum, as representing the typical, repeatable and representative peak NO_2 concentration. This concept is also embedded in the National Environmental Standard for NO_2, which permits 9 exceedences per year – this equates to the 10th highest hourly concentration (approximately the 99.9th percentile) constituting a breach of the Standard.

We compiled data from the Auckland Regional Council network of continuous NO_2 monitors to derive an empirical relationship between actual observed annual 99.9th percentile 1-hour concentrations and the annual mean concentration for the same site for the same year. Data has been incorporated from 1987 to 2008 inclusive. Data from 4 sites have been excluded because the sites are thought to not be generally representative. Queen Street II is in a deep CBD street canyon, whilst Khyber Pass Road is alongside a busy intersection with the monitor inlet very close to a building façade. Both sites are subject to complex local air flows such as recirculation which biases the data in certain wind conditions. Data from the Penrose and Penrose IIA sites has also been excluded. These sites were deliberately placed in industrial locations. Many industrial processes can emit large quantities of volatile organic compounds which can locally promote the formation of NO_2 in the atmosphere. Finally we have also excluded data points in which a site reported less than 90 % data that year.

The resulting relationships are shown in Figure 4-1 and Figure 4-2. We have applied a least-squares linear fit (three outliers seen in Figure 4-2 (circled) were not included in the regression):

$$99.9^{th} \text{ percentile 1-hr } NO_2 = (2.31 \times \text{mean } NO_2) + 28$$

$$\text{maximum 24-hr } NO_2 = (0.694 \times 99.9^{th} \text{ percentile 1-hr } NO_2) - 2.5$$

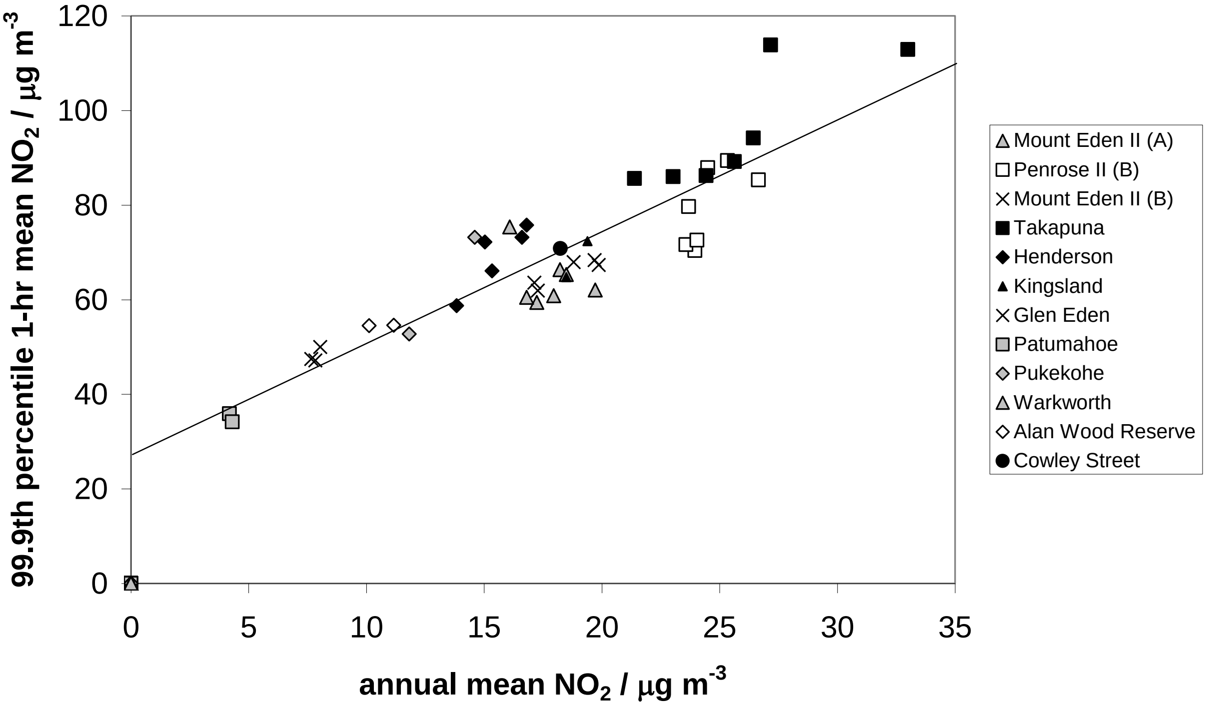

Figure 4-1: Empirical relationship between 99.9th percentile 1-hr NO_2 concentrations and annual mean NO_2 concentrations. AC and NZTA sites reporting > 90% coverage per year.

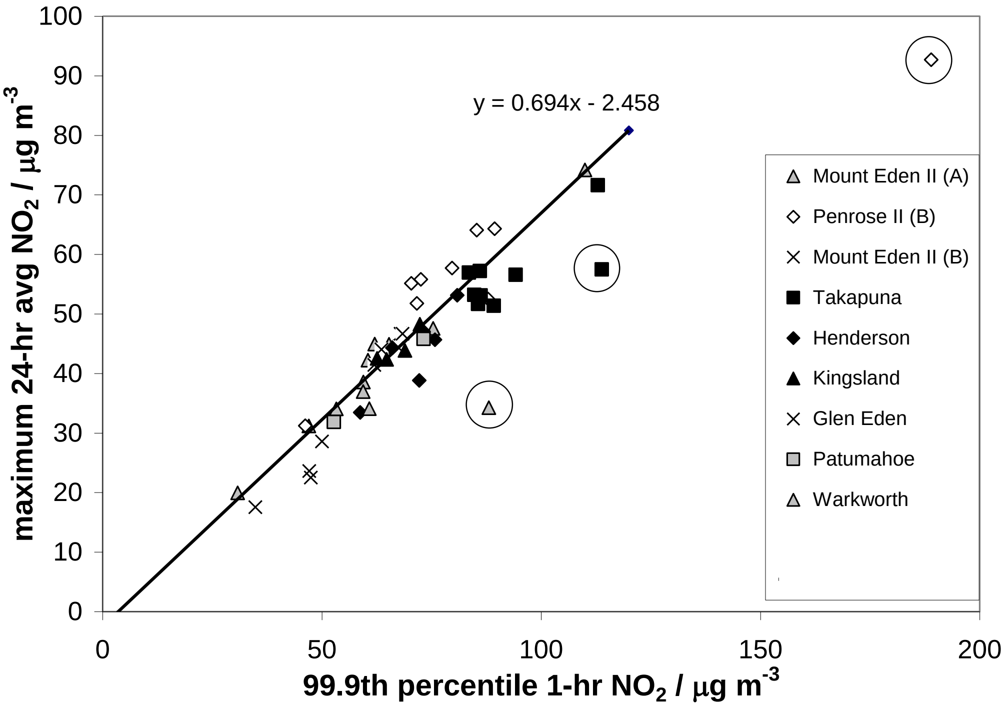

Figure 4-2: Empirical relationship between maximum 24-hr average NO_2 concentrations and 99.9th percentile 1-hr NO_2 concentrations. AC and NZTA sites reporting >90 % coverage per year.

4.2 Providing upper percentile NO_x data for calculation of cumulative effects

Following the empirical analysis above we also empirically derived the relationship between 99.9th percentile NO_2 concentrations and 99.9th percentile NO_x concentrations, as it is NO_x concentrations which are required for summing to dispersion modelling predictions to make predictions of cumulative impacts. The cumulative 99.9th percentile NO_x concentration can then be used to predict 99.9th percentile NO_2 concentrations for comparison with the AQNES. Our analysis considered the same database as illustrated in Figure 4-1 and 4-2 above, and is shown in Figure 4-3. The resulting relationship is

$$99.9^{th} \text{ percentile 1-hr } NO_2 = (0.055 \times 99.9^{th} \text{ percentile 1-hr } NO_x) + 37$$

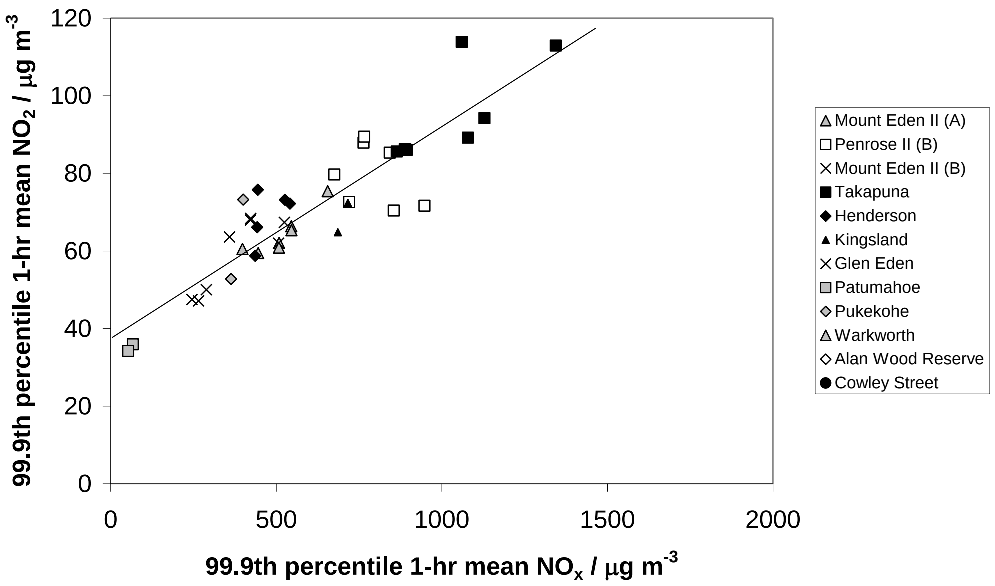

Figure 4-3: Empirical relationship between 99.9th percentile 1-hr NO_2 and NO_x concentrations at ARC sites reporting >90% data coverage in any given year.

5 The Spatial regression model

5.1 Aims, approach and assumptions

5.1.1 The need for the model

It has been described in the preceding chapters how monthly mean concentrations derived from passive monitoring can be used to predict annual means and peak short-term means (1-hour and 24-hour averages) by applying empirically derived formulae. However, in the case of project assessment it is quite likely that passive monitoring sites do not cover all of the project assessment receptors, nor are co-located with them. This was certainly the case in the Waterview Connection project. Whereas small spatial deviations in location between monitoring and receptor are commonly accepted, and may be acceptable for PM_{10}, the sharp spatial gradients in NO_2 around roads means that relatively small displacements could lead to large errors in predicted NO_2 concentrations.

5.1.2 The purpose of the model

We chose to develop a spatial regression model to permit the information derived from passive monitoring sites to be translated in space to nearby alternative sites (or receptors) within the same general spatial domain. Specifically, the model empirically relates annual mean NO_2 (derived from passive monitoring either directly or by seasonal adjustment of monthly means) to geographical variables relating to the passive monitoring site. The resulting regression model will then predict annual NO_2 for another site using that site's variable values. The approach is equivalent to land-use regression models, which have been widely used elsewhere, particularly for population exposure assessment for health-effects studies (Hoek *et al.,* 2008). However, we have chosen not to use the term 'land-use' as our model does not rely on what is generally considered to be 'land-use' data, but instead relies on roads and traffic data (see below).

5.1.3 Anticipated explanatory variables

Land-use regression models have been developed for many cities around the world, incorporating a range of explanatory variables (see the review by Hoek *et al.,* 2008.). Our aim was to keep the number of variables to a minimum. It was also our intention to permit for the future transferability of the model to other parts of Auckland and to other cities in New Zealand. This implies a need to minimise the number of explanatory variables. It was also a requirement that the variables chosen should be easily obtainable from readily available data sources.

Our initial choice was to include three factors:

- annual average daily traffic on nearby roads
- distance to nearby roads
- background factors.

The background component represents sources beyond the nearby roads. It could also represent urban density (as a proxy for traffic density on a ~km^2 scale or larger). The background component might be expected to reduce at the urban periphery and in low/no emission locations such as the harbours, parks, etc.

5.2 Model derivation

5.2.1 Model formulation

A trial version of the model was developed based on the assumption:

NO_2 = *f*(background, AADT on nearest major road, 1/√distance to nearest major road).

The trial version gave encouraging results, but highlighted the need to deal with the AADT and distance to multiple roads in urban settings.

After the trial version, all further model development was conducted using ArcGIS to generate independent variables as input to the model. We firstly used GIS functionality to systematically extend the search for nearby traffic data to the nearest 20 road links. In doing so we potentially captured some of the background component also.

The first version of the model was formulated as follows:

$$NO_2 = \textbf{\textit{traffic proximity factor}} + \text{residual}$$

$$\text{Where } \textbf{\textit{traffic proximity factor}} = \sum_0^{20}\left(AADT \bullet distance^{-0.65}\right)$$

The distance is the shortest distance to the road link. The power 0.65 is derived from NIWA's Roadside Corridor Model (Longley *et al*., 2010) and is representative of the long-term average general rate of dilution of pollutants from a line source under Auckland meteorology. A sensitivity analysis confirmed that this value gave a better performing model than one based on the powers 0.33, 0.5 and 1 (cube root, square root and linear-inverse, respectively). The nature of the residual was left unspecified until the first (traffic) term had been evaluated.

5.2.2 Traffic/road data

The road link and traffic data used for the derivation of the spatial regression model was provided to NIWA for the purposes of the Waterview Connection assessment. The data was provided as a single shape file and represented the project's 2006 scenario. The traffic data was derived from the ART3 model and contained AADT for both directions (each direction constituting one road link).

This data was not ideal for the purposes of constructing the regression model for the following reasons:

- Being representative of 2006, the file did not include the SH20 Mt Roskill Extension or the Albany-Greenhithe section of the SH18 Upper Harbour Highway. Both roads were recently opened and some of the passive monitoring data comes from sites next to these two roads. We would therefore not expect this data to be correlated with traffic on roads that do not exist in the traffic file.
- The original purpose of the shape file was for traffic modelling. One implication was that the location of the road links was indicative rather than geographically accurate, leading to some errors in alignment.
- Some minor roads were missing.

In May 2010, Beca Infrastructure was able to supply NIWA with geographically-accurate replacement shape file data for a 1 km corridor surrounding SH16 from Te Atatu to the Central Motorway Junction.

5.2.3 GIS analysis

A script was written for use in ArcGIS to evaluate the traffic proximity factor for a given list of co-ordinates. The script conducted a search for the 20 nearest road links to the given co-ordinates evaluated by the shortest direct distance.

The co-ordinates of the NZTA NO_2 Network sites in Auckland were provided as input. The traffic proximity factor for each site was calculated using Microsoft Excel.

5.2.4 Implications of searching for 20 nearest links

By specifying that the analysis should seek the 20 nearest links we found that the search extended 214 m on average, up to a maximum of 511 m (with one exception – site AUC040 located in Greenhithe, from which the 20th nearest link was nearly 1 km away).

We compared the implications of searching for 20 links rather than 10. For 84 % of the tube sites, including the 10 more distant links increase the *traffic proximity factor* by less than 20 %, and for half of the sites the increase was less than 7 %. Thus decreasing the links from 20 to 10 would have a relatively minor effect in most cases. However, for the remaining 16 % of sites, the extra 10 links increase the *traffic proximity factor* by 20 – 50 %. There was no clear common characteristic to these more-affected sites, although 5 were clearly in more peripheral locations (Glen Eden, Westgate, Albany) than most sites.

Although further research is justified in considering the implications of the number of links chosen for the search process, we chose to proceed with 20 as this involved no significant further processing time compared to 10.

5.3 Model results

Figure 5-1 shows the initial results of annual mean NO_2 concentration for all of the NZTA NO_2 Network sites (data based on seasonal adjustment of data from September 2009 to February 2010 inclusive) plotted against the traffic proximity factor (based on 20 nearest links). The sites have been allocated to several groups as follows:

- Several sites alongside the busiest sections of SH1 (from Sulphur Beach Rd, north of the Harbour Bridge to Gavin Street in Penrose) were found to exhibit slightly lower NO_2 per traffic proximity factor than other sites
- Several sites alongside SH16 (near the Pt Chevalier/Great North Road and Te Atatu Road interchanges) were found to exhibit slightly lower NO_2 per traffic proximity factor than other sites
- Those sites in very close proximity to intersections exhibited significant scatter.
- Several sites were affected by alignment or missing link errors in the traffic shape file and many of these sites were outliers in Figure 5-1.
- Sites around SH16 in Massey were subject to shape file alignment errors and missing links.

- Data near SH20 Mt Roskill have been segregated due to the motorway not appearing in the 2006 traffic data leading to an under-estimate of traffic proximity factor.
- A few other sites were segregated due to other recent traffic changes (construction work on Manukau Harbour Crossing, opening of Upper Harbour Highway), complex terrain or roadway/site elevation (which introduces error in calculating distance).
- Three further sites were removed due to NO_2 values that did not appear to be credible (too high or low for their respective sites).

For all 45 remaining sites a best fit linear regression ($r^2 = 0.84$) was found:

Annual mean NO_2 = (0.00077 x traffic proximity factor) + 10.4

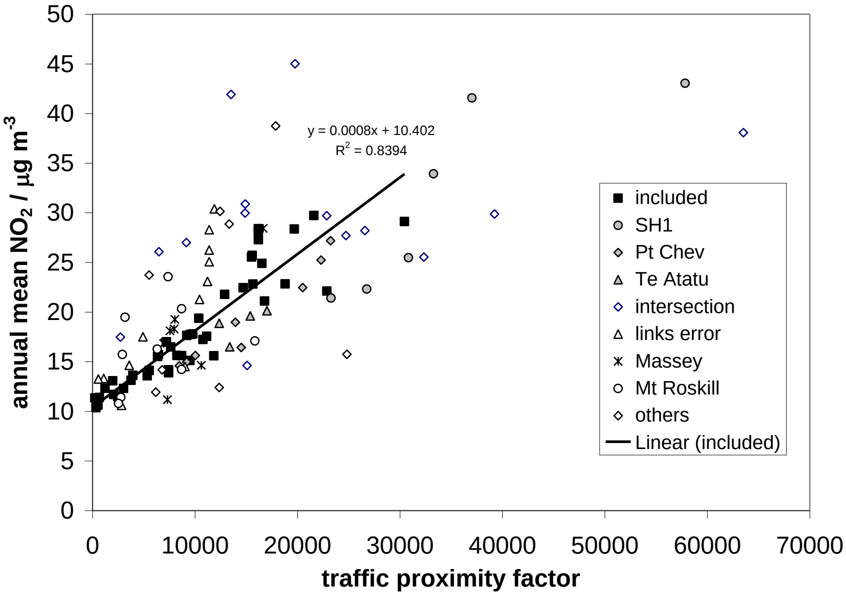

Figure 5-1: Initial results of plotting estimate annual mean NO_2 at Auckland NZTA diffusion tube sites against traffic proximity factor. White = sites excluded from regression model, grey = motorway sites, black = all other sites.

Until the shape file errors can be resolved, and current traffic data provided for the SH20 Mt Roskill Extension, we have discarded sites from Massey, Mt Roskill, and others with links errors. Furthermore we have discarded intersection sites at the expense of limiting the model to not be applicable at intersections. This was appropriate in the case of the Waterview project as no receptors were located at intersections. Furthermore, we have clustered the SH1 and SH16 (Te Atatu and Pt Chevalier) sites together to form a cluster of ‘motorway’ sites. However, it must be noted that, at this time, the ‘motorway’ cluster does not include motorway sites at other locations (e.g. SH1 Northern Motorway, other than Sulphur Beach Road, and SH1 Southern Motorway south of Penrose, or SH16 west of Te Atatu and east of Pt Chevalier). Further research is justified into whether a separate ‘motorway’ cluster is necessary and what physical explanation might justify it.

The resulting regression is displayed in Figure 5-2. The regression for the motorway sites (of which there are 18) is

$$\text{Annual mean } NO_2 = (0.00064 \text{ x traffic proximity factor}) + 9.3$$

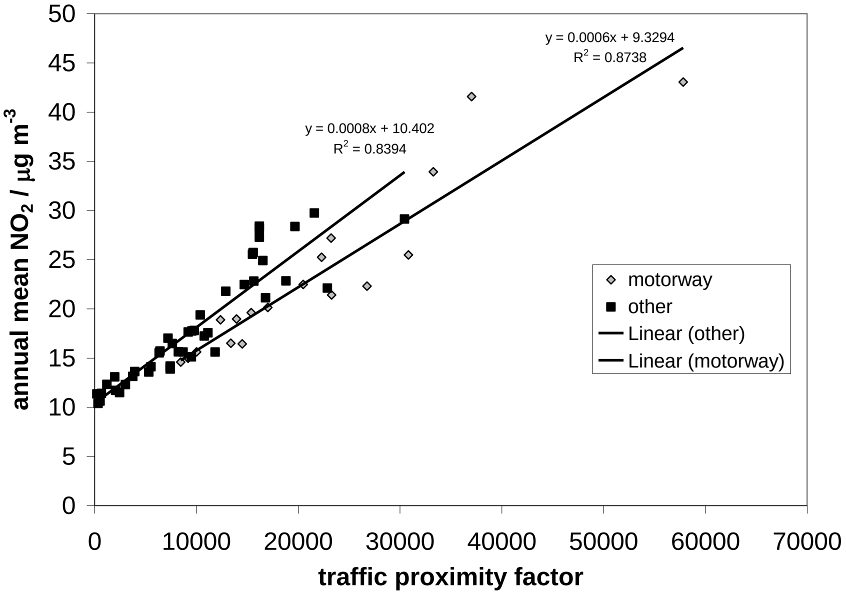

Figure 5-2: Regression curves for 'motorway' and other sites.

5.4 Evaluating urban background using the regression model

It was noted above that we developed a model of the form

$$NO_2 = \textbf{\textit{traffic proximity factor}} + \text{residual}$$

With an assumption that the residual would likely represent the 'background', i.e. concentrations due to sources other than the nearby roads, and that this background may or may not possess a degree of spatial variation. It can be seen from Figures 5-1 and 5-2 that the model indicated a residual of approximately 10 $\mu g\ m^{-3}$ (the y-axis intercept). As this value is well-defined we conclude that there is no discernible spatial variation in the residual (and hence background) in this dataset.

It must be borne in mind that the ability of the model to detect a variation in the background is in part dependent upon the monitoring sites actually encompassing locations which would reveal such a variation. Not shown in Figures 5-1 and 5-2 are data from the passive monitors co-located with ARC's Glen Eden monitoring station. This site is towards the urban periphery and far from any major roads. The estimated annual mean NO_2 at these sites is 7 – 8 $\mu g\ m^{-3}$. More passive data from the urban periphery might confirm whether the background concentration does indeed reduce at the urban edge, and at what rate. However, for the purposes of the Waterview project, this analysis strongly supports the assumption that urban background NO_2 is 10.4 $\mu g\ m^{-3}$ across the project area.

5.5 Improving the regression model

The next step in developing the regression model is to re-evaluate the model with fully geographically accurate road/traffic shape files. Small improvements should be gained from incorporating road/traffic data for new links opened since 2006 (such as SH20 Mt Roskill Extension).

The general applicability of the model is dependent upon the passive monitoring sites from which input data is available. The model's performance in east Auckland, for instance, cannot be specified due to the general absence of sites in that area.

6 Application of Regression Model to Waterview Project receptors

6.1 Aims

We used the regression model developed in chapter 5 (non-motorway formulation) to predict annual mean NO_2 at the 103 Waterview Connection project assessment receptors (the receptor locations are shown in Figure 6-1). This involved running the GIS script to search for the 20 nearest links to the receptors to calculate the traffic intensity factor for each. The same 2006 traffic shape file was used as described above.

During the dispersion modelling for the Waterview Connection, the co-ordinates of the assessment receptors had been adjusted to account for alignment errors in the traffic shape file. We used the same adjusted co-ordinates in this exercise.

6.2 Results

The full set of predictions of annual NO_2 concentrations at the project receptors is provided in Appendix Two. They are also plotted on a map in Figure 6-2.

N.B: It is important to note that the spatial regression model was based on 2006 traffic data, and does NOT therefore, include the SH20 Mt Roskill Extension. Hence predictions close to that motorway are likely to be under-predictions of concentrations relative to those measured in the area by passive monitoring which was installed after the motorway opened.

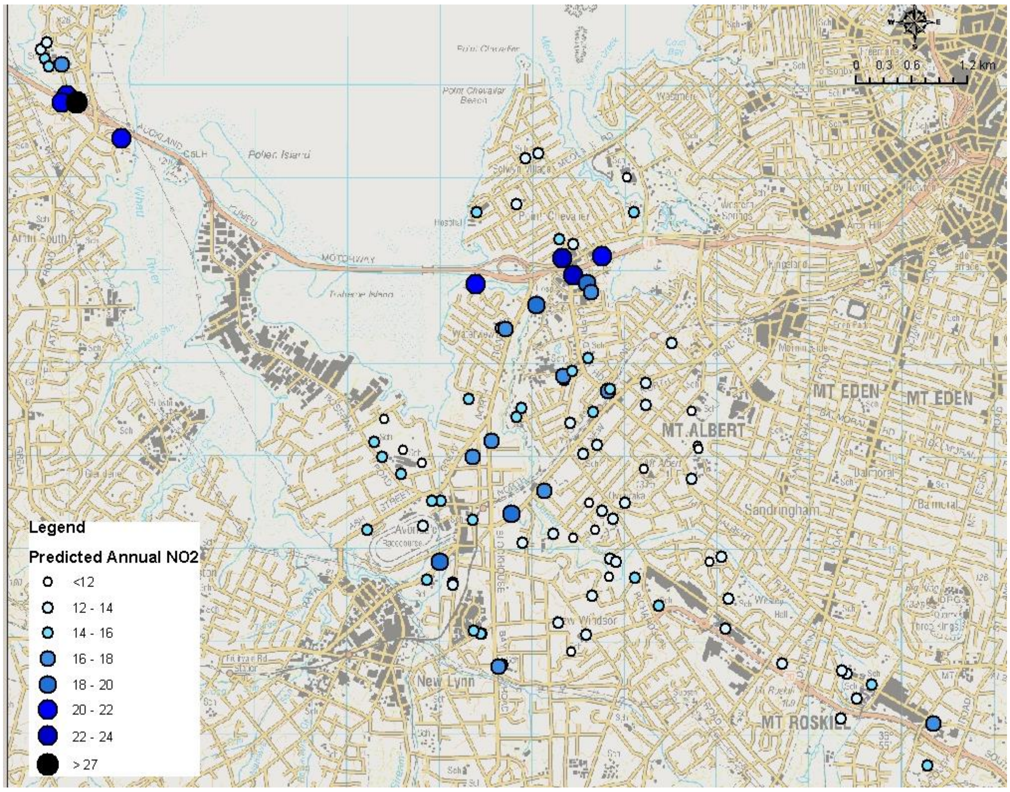

Figure 6-1: Annual Mean NO_2 concentrations ($\mu g\ m^{-3}$) at Waterview project assessment receptors, as predicted by the spatial regression model.

6.3 Cross-validation against dispersion modelling

A degree of confidence in the results of the spatial regression model can be gained by comparing the results with those from the Waterview project dispersion modelling. That dispersion modelling predicted the 99.9th percentile 1-hour NO_x concentration (for the assessment year of 2007) arising from vehicle emissions on local roads only. The roads modelled are shown in Figure 6-2. The regression model seeks to do a very similar thing, i.e. assess the contribution from local roads only (the nearest 20, i.e. up to 214 m away on average). Although the dispersion model predicts NO_x and the regression model NO_2, we might expect them to give reasonably correlated results given that, in the long-term, NO_x and NO_2 are reasonably well correlated (see Figures 4-1 and 4-3). The correlation might break down towards the edge of the emission modelling domain (i.e. the roads whose emissions were explicitly modelled).

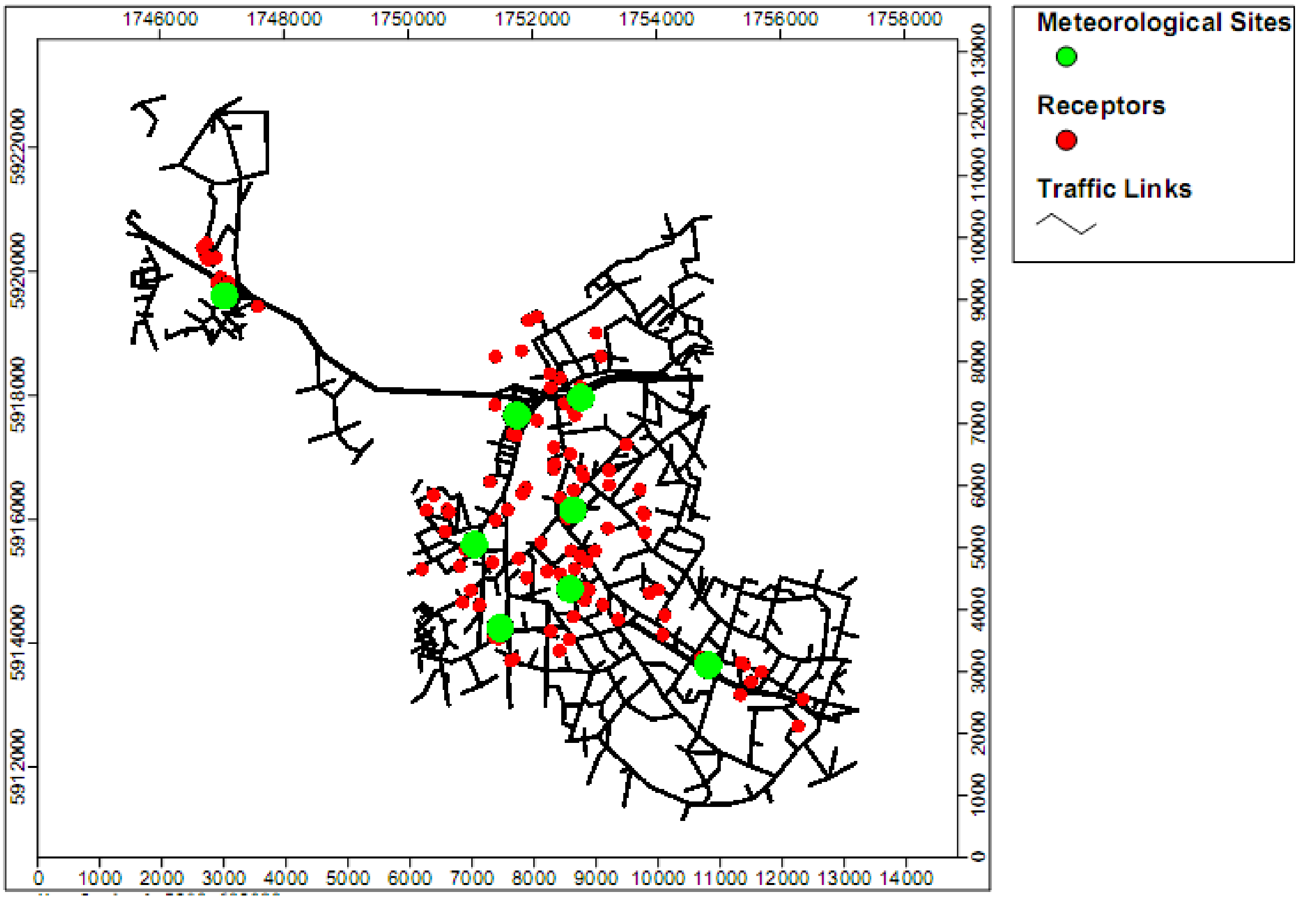

Figure 6-2: The road links explicitly modelled in the Waterview project dispersion modelling task, with the project assessment receptors shown in red.

Figure 6-3 shows the result of the regression model predictions plotted against the dispersion model predictions. There appears to be a reasonable linear relationship ($r^2 = 0.68$).

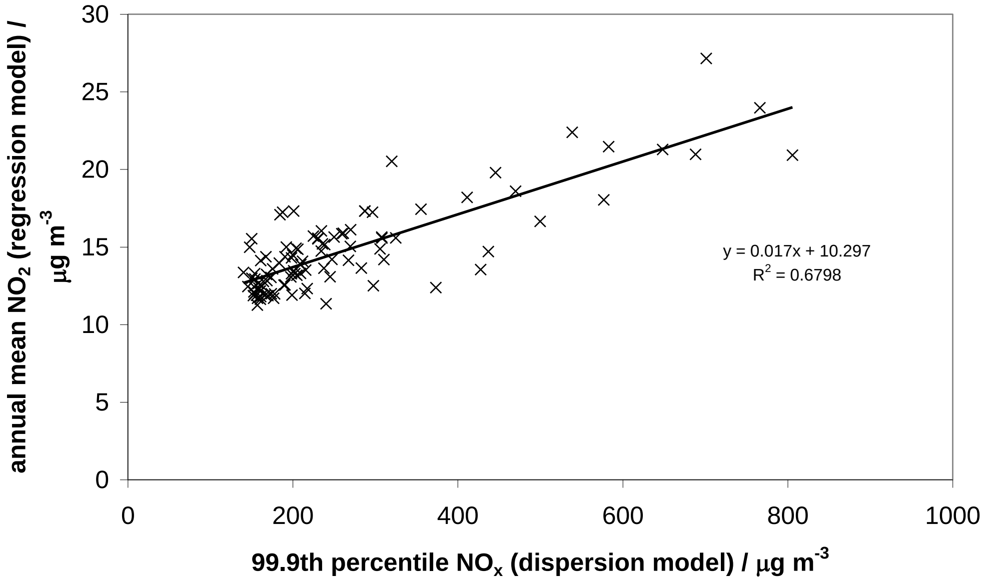

Figure 6-3: Comparison between regression model and dispersion model (annual NO_2 and 99.9th percentile 1 hour NO_x respectively) for project assessment receptors.

We applied a least-squares linear fit and calculated the residual. There appeared to be a relationship between the residual and the distance of the receptor to the 'dominant' local road (Figure 6-4). The 'dominant' local road was defined as the road link making the largest contribution to the traffic proximity factor (i.e. the link with the largest value of AADT x distance$^{-0.65}$). There may be some error in identifying this link, and the links chosen have not been independently verified. This may account for the outliers seen in Figure 6-4.

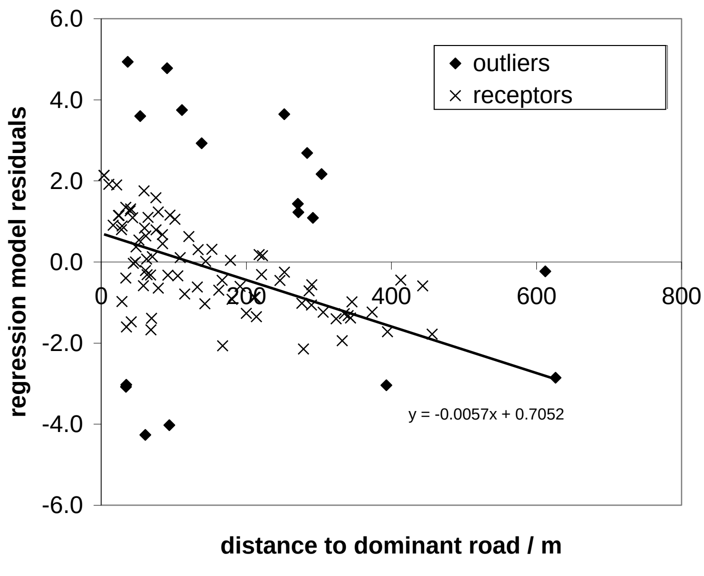

Figure 6-4: Residual in the NO_2 (regression) – NO_x (dispersion) correlation as a function of distance of each receptor from its dominant road.

We derived a correction to account for this relationship:

Correction to annual NO_2 = (-0.0057 x distance to dominant road) +0.71

The 'corrected' NO_2 values are re-plotted against dispersion model NO_x in Figure 6-5. A strong correlation is seen with $r^2 = 0.87$. Thus, we can conclude that the regression model and the dispersion model are in general agreement and are mutually supportive.

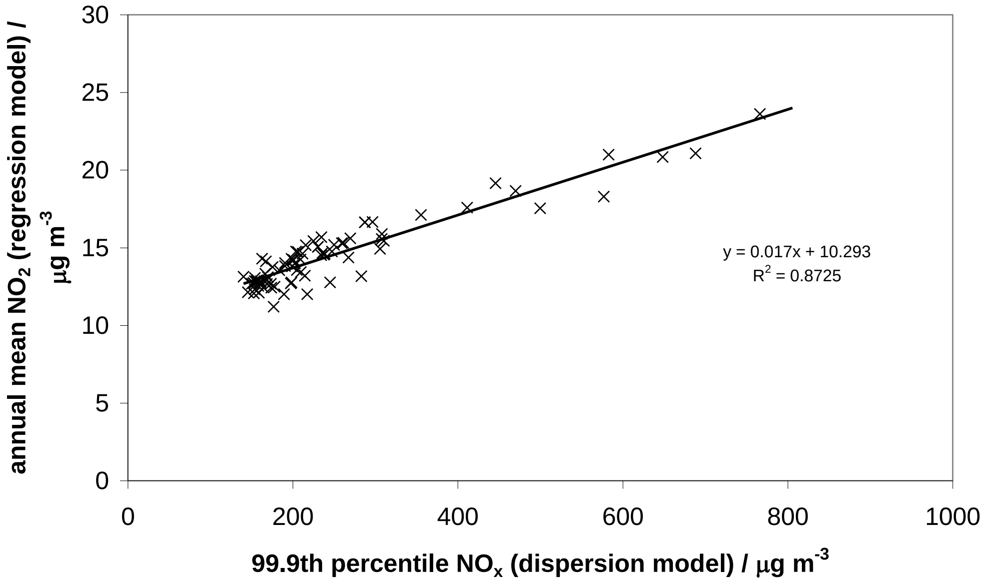

Figure 6-5: Improved relationship between annual mean NO_2 (predicted by regression model) and peak NO_x (predicted by dispersion model).

It is beyond the scope of this research at present to explain or provide a physical interpretation of the distance-related correction derived above. However, it is generally known that the NO_2/NO_x ratio is related to distance to emission source in the long-term. We believe that further research is justified to investigate the cause and nature of these relationships.

7 Recommendations for use in future assessments and feedback to management of the NO_2 Network

7.1 Scope of application

The three components of our approach to baseline NO_2 assessment:

- seasonal adjustment,
- empirical relationships between short- and long-term measures and NO_2 and NO_x,
- the spatial regression model

are all empirical models based on analysis of location-specific data. In this case the specific location is the urbanised parts of the Auckland Region, and specifically those areas with a dense network of passive monitoring, i.e. areas around SH20 and SH16 in Auckland City and Waitakere City. Strictly the methods can only be applied with confidence to these areas. However, the approaches demonstrated should apply generally to any urban area.

Given the sites available to us in Auckland we were unable to detect a gradient in background concentrations at the urban periphery. Consequently, it is plausible that the spatial regression model would over-estimate concentrations in the urban periphery. Further deployment of passive monitoring sites intended to cover variation in the urban background would assist in further determining if an urban background term is required in the model.

7.2 Management of the NO_2 Network

The validity of the methods developed, and the confidence in the assessment they provide, should increase if the number of passive monitoring sites increases. During the course of our analysis we have found that some passive monitoring sites were very useful for the purpose of model development, whereas others were problematic, and others were discarded from our analysis.

In general, the spatial regression model quantifies whatever variation exists between sites. The general principle of custom-built land-use regression models is that they are based on monitoring sites which are chosen to represent variation in an explanatory variable. In the case of our model, the explanatory variables are AADT, distance to road and (possibly) 'background' (although what the background variable consists of or whether it is needed requires review). To enable this, sites must encompass a wide range of AADT and distances to major roads, and more generally a wide range of traffic intensities. For example, if the model is required to apply to a new area we recommend a variety of sites adjacent to minor roads, feeder roads, major roads and arterial roads, plus a combination of areas of generally higher and lower traffic density (e.g. from 'quiet' low-density suburbs to busy 'high streets"). To deploy a single urban background and single roadside site will not give sufficient coverage to extend the model to a new area.

For the purposes of project assessment we recommend that urban background sites are especially useful. These are sites which are fully embedded in the urban fabric (not at the urban periphery), but far from major roads.

At present we are unable to incorporate intersection sites into our model. This is probably because NO_2 levels are highly unpredictable at such sites as they are highly sensitive to the precise layout of the roads and buildings, plus the complexities of accelerating and congested traffic emissions. Although intersections may provide peak concentrations, these concentrations exist over a highly limited spatial area and true exposure may be minimal (in terms of either small populations exposed, or exposures being exceedingly brief). We found that the data from intersections was uninformative and unnecessary to gain a detailed understanding of the spatial variation in NO_2 across a large section of Auckland.

In the case of Auckland reference to Figures A-1 to A-4 (in Appendix One) shows that, at the time of writing, there is an absence of any sites in the centre of the Auckland isthmus (between SH1, SH20 and SH16), there are almost no sites east of SH1 and few sites in Waitakere City away from SH16. There are few (if any) urban background or low-traffic sites in North Shore or Manukau. At present this limits the model from being applied with confidence in any of these areas.

Figure 5-2 shows that the NZTA NO_2 Network sites which were incorporated into the model covered a wide range of traffic proximity factor up to 30 000. Sites above 30 000 were relatively few. However, this is understandable as this translates to very high traffic sites which are limited to close proximity to the busiest section of SH1.

Apart from the sites excluded due to shape file errors or changes in traffic described above, the sites which were excluded from the regression model are listed in Table 7-1.

Table 7-1: NZTA NO_2 Network sites excluded from the spatial regression model.

ID	Location	comment
AUC023	Whitaker Place (CMJ)	Complex terrain
AUC036	Gaunt Street (VPT)	Elevated motorway
AUC037	Hepburn Street (VPT)	Elevated motorway
AUC030	Fairlands Avenue, Waterview	Outlier – cause unknown
AUC108	Ivanhoe Rd, St Lukes (SH16)	Outlier – cause unknown
AUC113	Kotuku Street, Te Atatu	Outlier – cause unknown

We have not included land-use variables into our model. If it was considered that factors such as industrial areas, open space and water bodies were likely to be important explanatory variables, then it would be necessary to establish passive monitoring sites representing variability in those land-uses.

7.3 Potential other uses of the model and approach

The methods developed in this report, especially the spatial regression model, have potentially many more applications than baseline analysis for air quality project assessment. Possibilities include:

- Exposure and health risk assessment.

- Emission trends assessment (through seasonally de-tending long-term passive monitoring datasets).
- Rationalising the NO_2 Network. Further analysis could investigate the sensitivity of the regression model to the removal of various sites.
- Roadside corridor definition for mitigation and reverse sensitivity. In the case of urban Auckland the regression model clearly shows that no **single** road is likely to lead to the exceedence of any NO_2 guideline or Standard. However, when the influence of other surrounding roads is considered then it should be possible to relate the probability of any given concentration occurring to the traffic volume of the nearest major road and distance to it. This can then be used to define the width of a corridor within which a given concentration is likely to be exceeded.

8 Acknowledgements

The passive monitoring data analysed in this report was collected by Watercare Services Ltd on behalf of the New Zealand Transport Agency. NZTA made the data available to NIWA for the purposes of this analysis. Continuous monitoring data from Cowley Street and Alan Wood Reserve was provided to NIWA by NZTA. Other monitoring data was made available by Auckland Regional Council. Road link and traffic data was provided by Beca Infrastructure.

9 Glossary of abbreviations and terms

AADT	annual average daily traffic
AAQG	Ambient Air Quality Guideline
AQNES	Air Quality National Environmental Standard
ARC	Auckland Regional Council
MfE	Ministry for the Environment
NO2	nitrogen dioxide
NOx	oxides of nitrogen
SH16	State Highway 16
SH20	State Highway 20

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Watercare, 2010. New Zealand Transport Agency Quarterly Report of Ambient Passive Nitrogen Dioxide Monitoring Winter 2009. Prepared for New Zealand Transport Agency (NZTA) By Watercare Laboratory Services - Air Quality Group. March 2010. AQ8028-01.

Appendix A Estimated annual mean NO_2 at passive monitoring sites in Auckland

The following figures indicate the locations of sites from which data was used in this report. The size and colour of each site symbol represents the annual mean NO_2 concentration, estimated on the basis of monthly mean data from September 2009 to February 2010 inclusive, adjusted using the seasonal adjustment factors described in chapter 3.

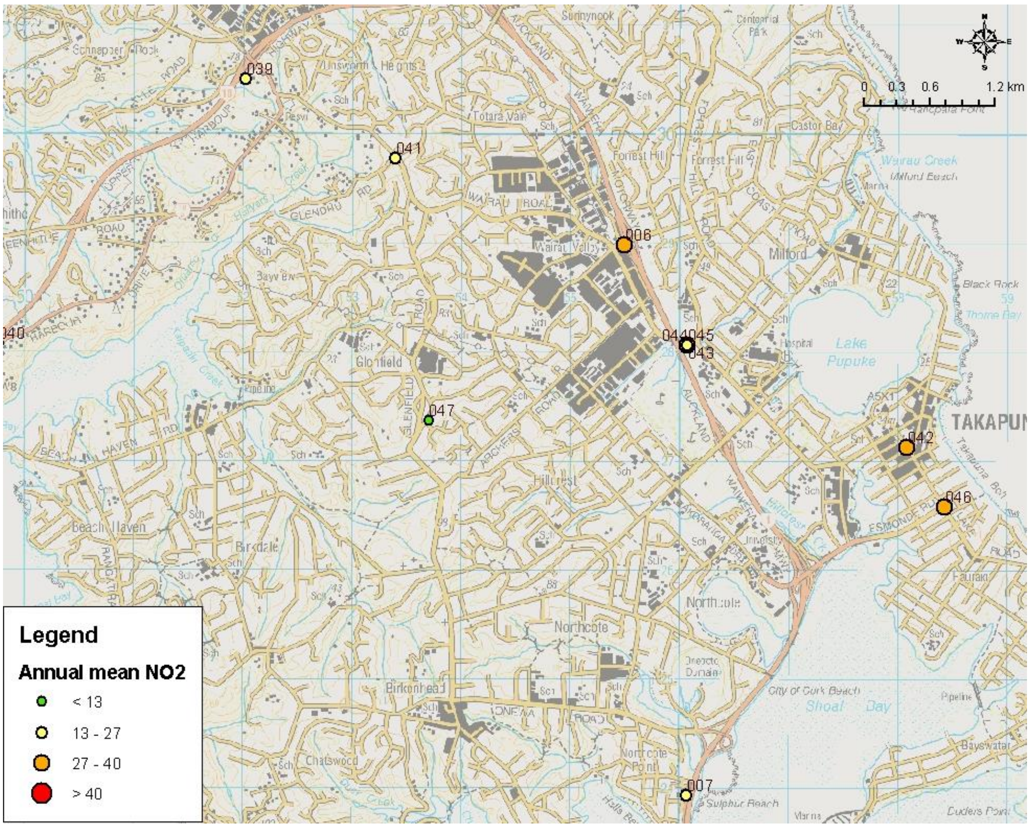

Figure A-1: Annual mean NO_2 based on passive monitoring data in the north of Auckland.

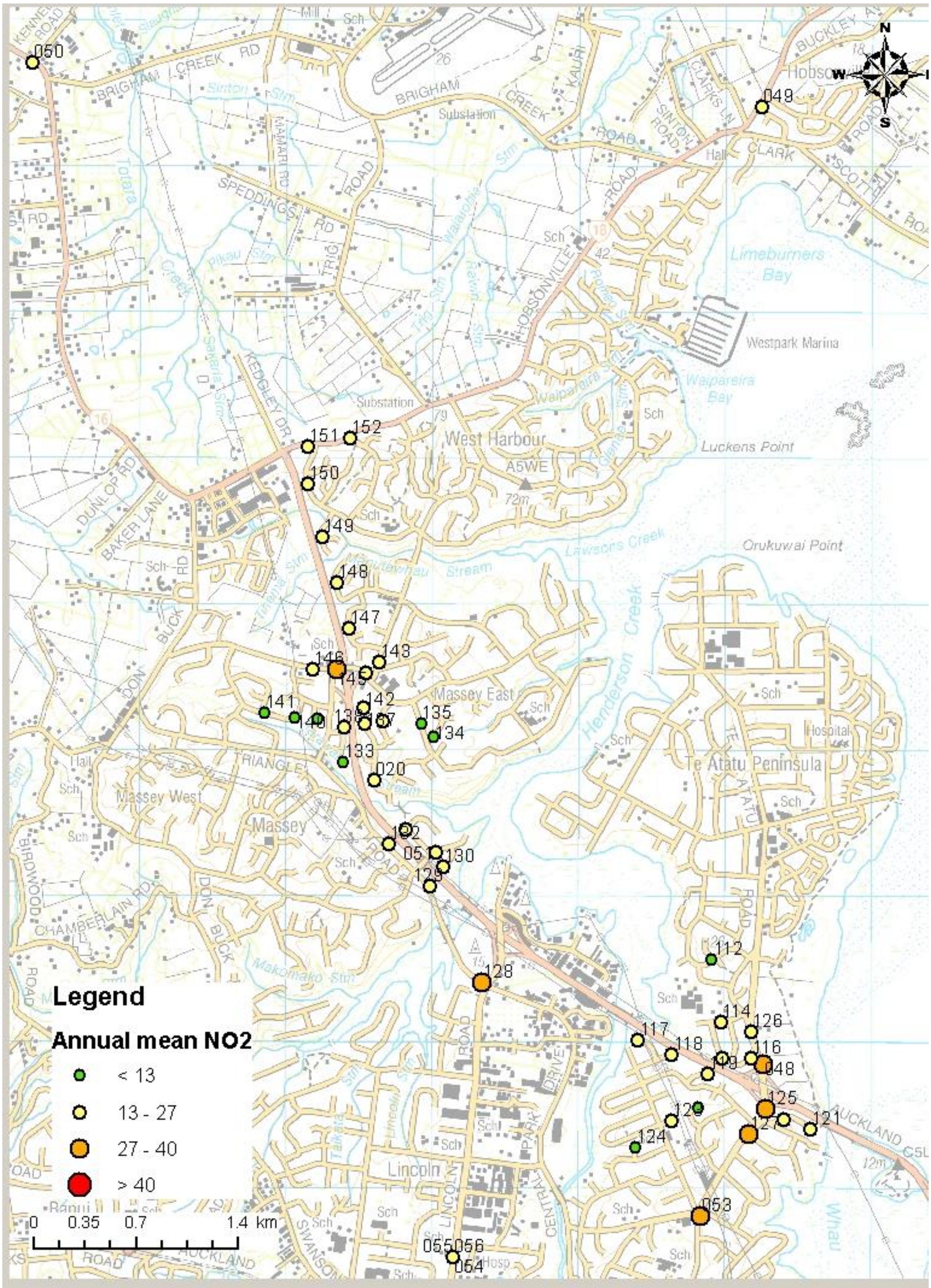

Figure A-2: Annual mean NO_2 based on passive monitoring data in the north west of Auckland.

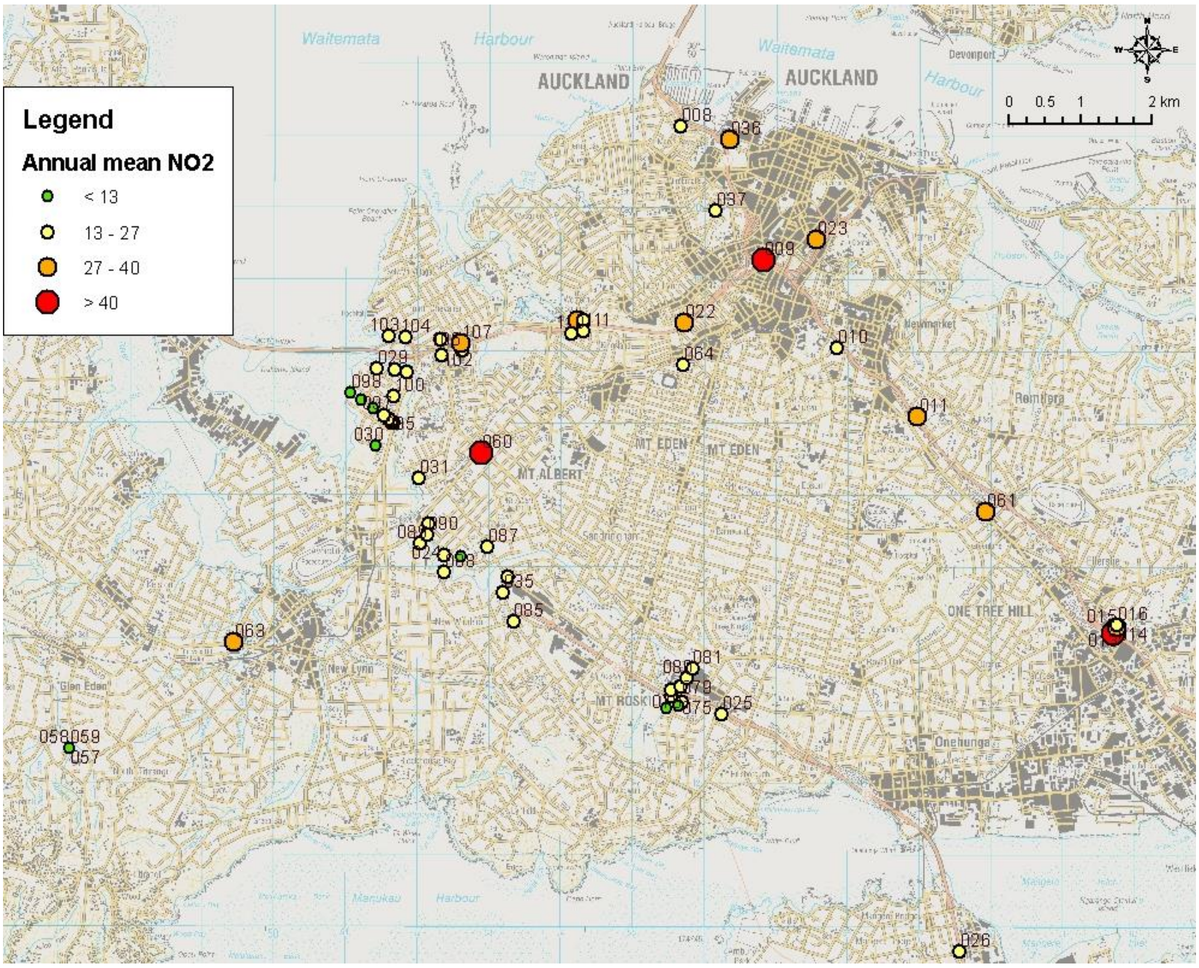

Figure A-3: Annual mean NO_2 based on passive monitoring data in the central isthmus of Auckland.

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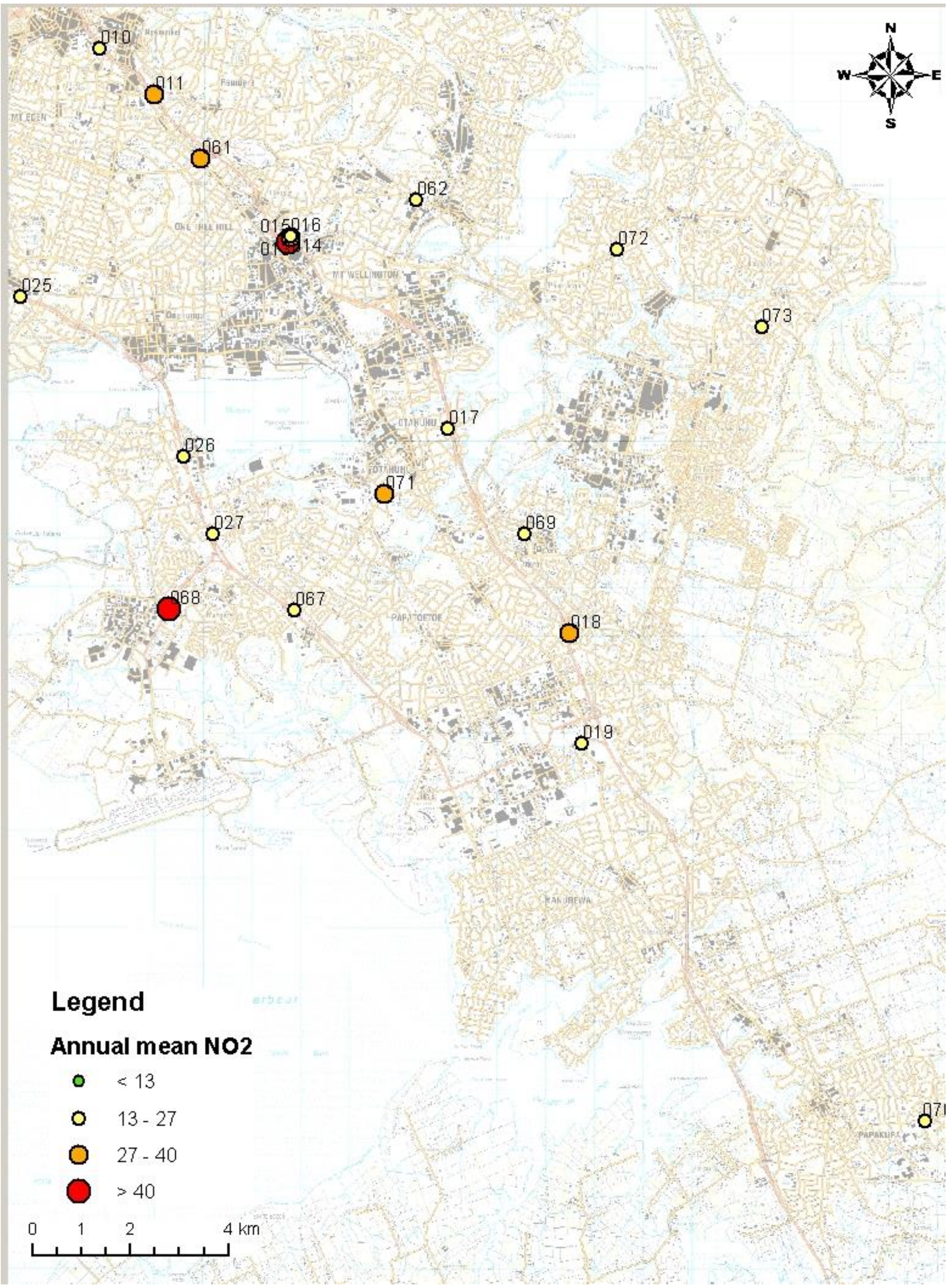

Figure A-4: Annual mean NO_2 based on passive monitoring data in the southeast of Auckland.

Appendix B Predicted baseline NO_2 at the Waterview Connection project assessment receptors

The table below lists the annual mean NO_2 concentration (in $\mu g\ m^{-3}$) predicted by the regression model described in this report. It should be noted that these values are lower than those in the projects' technical assessment report. This is because the regression model was developed after the technical report was completed. Values in the technical report were derived from an early trial version of the regression model and incorporated some conservative assumptions no longer required in the current model version.

Table B-1: Annual NO_2 concentrations predicted for the Waterview Project assessment receptors using the spatial regression model.

ID	Receptor	Name	annual NO2
1	59 Victor Street	Avondale College	11.7
2	12 Holly Street	Avondale Intermediate	11.6
3	4 Crayford Street West	Avondale Primary School	14.2
4	288 Richardson Road	Christ The King School	14.4
5	8 Seaview Terrace	Gladstone School	15.7
6	340 Blockhouse Bay Road	Glenavon School	13.3
7	1 McLean Street	Hebron Christian College	13.6
8	63 St Georges Road	Immanuel Christian School	13.3
9	30-36 Alberton Avenue	Mt Albert Grammar School	11.9
10	185 New Windsor Road	New Windsor School	13.1
11	56 Bollard Avenue	Odyssey House School Auckland	12.6
12	113-115 Richardson Road	Owairaka District School	13.0
13	Moray Place	Pasadena Intermediate	14.2
14	7-31 Te Ra Road	Pt Chevalier School	12.0
15	217 Rosebank Road	Rosebank School	11.9
16	16-20 Kotuku Street	Rutherford College	15.0
17	2 Kotuku Street	Rutherford School	16.1
18	2-20 Montrose Street	St Francis School	22.4
19	140 Haverstock Road	Te Kura Kaupapa Maori o Nga Maungarongo	12.0
20	16-20 Kotuku Street	Te Kura Kaupapa Maori o Te Kotuku	13.6
21	19 Oakley Avenue	Waterview School	14.9
22	776 Sandringham Road	Wesley Intermediate	12.4
23	24 Potter Avenue	Wesley School	11.9
24	100-102 Motions Road	Western Springs College	11.3
25	24A Fairlands Avenue	ABC Waterview	15.0
26	63 St Georges Road	Avondale Christian Kindergarten	13.3
27	59 Victor Street	Avondale College Early Childhood Centre	14.5
28	99 Rosebank Road	Avondale Community Pre-School	15.9
29	195 Rosebank Road	Avondale Kindergarten	15.9
30	32 Wairere Avenue	Bright Beginnings ECEC Ltd.	12.4
31	28 Carrington Road	Collectively Kids Limited	24.0
32	64 A Stoddard Road	Edukids Stoddard Road Centre	12.4
33	830 New North Road	Ferndale Kindergarten	13.6
34	340 Blockhouse Bay Road	Glenavon Early Childhood Centre	17.3
35	22B Willcott Street	Jump Start Kids Centre	14.7

ID	Receptor	Name	annual NO2
36	2 Sandy Lane	Kids World	15.6
37	4 Ennismore Road	Kidz Unlimited Learning Centre	17.3
38	18 Wolverton Street	Kiwicare Preschool Avondale	15.2
39	20 Wolverton Street	Kiwicare Preschool West	15.2
40	25 Wolverton Street	Kiwicare Wolverton 3	15.6
41	20 Huia Road	Learning at the Point Kindergarten	13.5
42	14 Stewart Road	Little Dudes Childcare Centre	12.0
43	6 D Carr Road	Little Scholars Early Learning Centre	16.0
44	222 Carrington Road	Little Scholars ELC - Mt Albert	17.2
45	122 Mt Albert Road	Minimarc Childcare Centre	13.1
46	24 Mark Road	Mt Albert Kindergarten	13.5
47	25 Phyllis Street	Mt Albert Playcentre	15.0
48	88 Mt Royal Avenue	Mt Royal Early Learning Centre	12.9
49	64 Peter Buck Road	New Windsor Playcentre	11.8
50	6 A Dunkirk Terrace	Owairaka Kindergarten	12.1
51	30 Walford Road	Pt Chevalier Kindergarten	12.3
52	36 Blockhouse Road	Rocket Kids Early Learning Centre	17.1
53	217 Rosebank Road	Rosebank Early Childhood Centre	14.4
54	16-20 Kotuku Street	Rutherford Preschool	15.6
55	2140 Great North Road	St Marys Preschool Avondale	15.5
56	90 Point Chevalier Road	Stylee Kids Ahead Early Learning Centre Limited	14.7
57	36 Titoki Street	Te Puna Reo O Manawanui	21.3
58	140 Haverstock Road	Te Puna Reo Maori O Nga Maungarongo	12.0
59	Gate 4 Unitec	Te Puna Reo o Wairaka	17.3
60	16-20 Kotuku Street	Te Kotuku Kohanga Reo	13.5
61	1217 New North Road	Treasure Hunt Montessori Preschool	18.2
62	Building 57 Unitec Carrington Road	Unitec Early Learning Centre	14.1
63	Carrington Road	UNITEC Early Learning CentrePukeko Whare	14.1
64	10 Herdman Street	Waterview Kindergarten	17.4
65	26 A O'Donnell Avenue	Wesley Kindergarten	12.5
66	54 Carrington Road	WDHB Addiction Unit	18.0
67	Carrington Road	Mason Clinic	18.6
68	54 Carrington Road	Rehab Plus	16.6
69	19 Woodward Road	Aranui Hospital	14.0
70	2095 Great North Rd	Avon Rest home	19.8
71	92 Rosebank Rd	Avondale Rest Home & Hospital	15.6
72	39 Batkin Road	Bettina Residential Care Home	12.2
73	63 Allendale Road	Everill Orr Village	12.2
74	23 Roberton Road	Rosaria Rest Home	17.2
75	20 Shaftsbury Avenue	Selwyn Village	15.6
76	103 Tiverton Road	Tiverton House Rest Home	13.9
77	45 Lloyd Ave	Warrengate Private Hospital	13.2
78	46 Bollard Avenue	Morwood Motorcamp	12.5
79	89 Hendon Avenue	89 Hendon Avenue	11.7
80	5 Barrymore Street	5 Barrymore Street	12.8

ID	Receptor	Name	annual NO2
81	9 Valonia Street	9 Valonia Street	14.9
82	204 Methuen	204 Methuen	11.2
83	1102G Great North Road	Res5	21.5
84	77 Herdman Road	Res6	21.0
85	21 Alwyn Avenue	21 Alwyn Avenue	20.5
86	17 Milich Terrace	Res8	20.9
87	20 Titoki Street	Res9	27.2
88	7-51 Walker Road	Walker Park	12.5
89	22a Phyllis Street	Phyllis Reserve	15.5
90	117 Richardson Road	Murray Halberg Park	11.9
91	27 Summit Drive	Mt Albert-Owairaka Domain	11.9
92	2-48 Ash Street	Avondale Race Course	13.3
93	63 Hendon Avenue	Alan Wood Reserve	12.8
94	Denbigh Avenue	Mt Roskill Intermediate	12.6
95	Frost Road	Mt Roskill Grammar	13.4
96	Frost Road	Mt Roskill Primary School	14.3
97	21 Currie Avenue	Hillsborough Playcentre	14.1
98	1 Prospero Terrace	Little Scholars Baby Cottage	14.9
99	Somerset Road	Mt Roskill Early Childhood Centre	13.0
100	68 Mt Roskill Rd	Gracedale Hospital	13.2
101	660 Richardson Road	Keith Hay Park	12.4