Aspects of Statistical Design for Monitoring Waters of Port Curtis, Queensland

Coastal CRC Project Name & Code:
Statistical Design of a Baseline Monitoring Program (PC3)

By

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Executive Summary

This report focuses on two key design questions for the Port Curtis Integrated Monitoring Program, which relies on regular sampling of the macrobenthos. The two aspects are

- The optimal number of macrobenthos grabs needed at each sampling time, and
- The most effective spatial configuration of sampling stations within the constraints imposed by the available resources.

Macrobenthos samples can be highly variable and it is not immediately clear to us if such sampling is necessarily the best way to conduct a Port monitoring program, but investigating the optimal number of grabs is important both for providing information on this key question and for making the sampling program efficient and effective should it proceed.

The primary method we have used for this exercise relies on the spatial interpolation of water quality parameters and contaminant distributions, and the maps of these interpolations form an important output of the research in their own right. The spatial interpolation maps that accompany this report come in two forms. Firstly a map of the parameter itself provides a graphic indication of where the values are, on average, high or low. Secondly the coefficient of variation map that accompanies it gives some indication of the places where the parameter is either highly variable or uncertain because of insufficient sampling. Both of these possibilities would suggest that in such areas the sampling effort might be increased, even if this is not the sole criterion. (The coefficient of variation is a measure of variability relative to the mean.)

Optimal number of grabs
The choice of the number of grab samples depends on two aspects of the situation: the inherent variability in such samples and the size of any change that the sampling scheme needs to be able to detect, and with what confidence, for the objectives of the monitoring program to be effective. Both of these – the size of the change that needs to be detectible and the confidence with which it should be – clearly need to be very carefully established within the monitoring program before sampling begins.

The variability in the historical macrobenthos data suggests that a sample of 10 grabs enables detection of a 60% difference in abundance at a conventional level of confidence. In general, of course, the larger the percentage difference needed to trigger some action by the program, the smaller the number of grabs that may be needed, hence the need to set the protocols carefully. Conversely if the program needs to detect very subtle changes in the macrobenthos to be effective and this in turn requires very intensive sampling to achieve, it casts doubt on the strategy of sampling macrobenthos as the sole monitoring program strategy.

Spatial interpolation of water quality and contaminants
Sediment predictions within the port were generally found to be more variable than predictions for the water quality parameters. Hence more sampling points within the port would be required to reduce the sediment prediction uncertainty to the range currently attained by the water quality parameters. Increasing the intensity of sampling stations in the eastern section of the port may be initially warranted as higher coefficient of variation values were generally found in this section of the port.

Spatial modelling techniques have been used to investigate a range of water quality parameters and the information gained is primarily used for spatial power analysis, which gives the optimal spatial configuration of sampling stations. In this context 'optimal' means minimizing the level of variability associated with different sampling intensities.

A full discussion of spatial power analysis is beyond the scope of this report, however the results given here should provide stakeholders with the level of confidence a monitoring design could achieve for detecting change across a given set of monitoring parameters. The best way of realising this would be for stakeholders to interact with modellers and analysts with a view to establishing the best use of available monitoring resources to achieve agreed goals. We suggest this happen as soon as possible.

Temporal frequency of sampling
The historical data does not contain sufficient temporal information for this report sensibly to address questions of optimal temporal sampling frequency. With only biannual samples it is impossible to assess whether any finer temporal sampling is needed. To address this for sampling macrobenthos, water quality parameters or contaminants, the necessary strategy is at least clear. Firstly an intensive sampling program at, say, the monthly level is required as a pilot. These finer scale data can then be considered at various coarser scales of temporal frequency and the appropriate one selected.

In addition, monitoring data collected for all relevant parameters over a series of years is necessary for understanding the level of natural longer time-scale variability in the system. Knowledge of the natural variability can then enable confident inferences to be made about other the impact of other known or unknown sources of variation in the system, in particular anthropogenic impacts.

Other considerations
The aspects of monitoring design considered here have been based on historical macrobenthos data and spatial surveys of water chemistry and contaminants that were not originally designed to answer spatial design questions. In particular, the spatial coverage of the historic macrobenthos sampling stations was limited and thus only represented a subset of habitats and intertidal locations within the Port environment. While total abundance has been considered in this report, there is also scope to consider other macrobenthos indicator variables, such as species richness, diversity measures and/or functional groupings of species. These indicators may prove to be more or less sensitive to environmental change than total abundance.

Nonetheless, the statistical analysis of these data has provided valuable insights to inform a pilot whole-of-Port sampling strategy.

1. Introduction

This report provides design input for an ecosystem health monitoring program that displays and highlights change in the ecological health of Port Curtis. Here, ecological health is defined in terms of the spatial distribution of processes, habitats and anthropogenic impact zones. Ecological health monitoring therefore requires a combined analysis of spatial extent and temporal persistence, with the latter used to detect trends and assess the condition of the port over time.

After investigation of four data sets made available for statistical analysis, two main design aspects have been considered, 1) the optimal number of grabs for macrobenthos sampling and 2) spatial configuration of sampling stations via inference gained through interpolation of water quality parameters and contaminants throughout the port.

Investigation of the optimal number of grabs is an important aspect for a) determining if the inherent variability in macrobenthos samples is conducive for inclusion in a port monitoring program, and b) ascertaining via statistical power analysis the number of grab samples required for detection of various percentage difference levels. Of course, the appropriate percentage difference required for detection by the sampling scheme needs to be considered in relation to the overall objectives of the monitoring program.

Spatial interpolation of water quality parameters and contaminants provide two main sets of information as input for revising sampling schemes throughout the Port. Firstly, prediction maps and the variability associated with these maps (a direct result of the sampling scheme employed) are produced providing knowledge about the distribution of these parameters throughout Port Curtis, potentially identifying areas of impact or non-impact. Secondly, the variability maps provide and indication of where sampling effort should be intensified and hence decrease the level of variability in the spatial predictions modelled.

Section 2 of this report outlines the historical data analysed and the statistical methodology and results associated with investigating the optimal number of grabs for macrobenthos sampling. A comment on the implications of these results for monitoring macrobenthos in Port Curtis is also provided.

Section 3 outlines the statistical methods, grid data analysed and the resulting spatial prediction and variability maps for the water quality parameters and contaminants considered.

Section 4 provides recommendations for monitoring throughout Port Curtis based on the overall results of the statistical analyses reported in Sections 2 and 3.

2. Optimal Number of Grabs for Macrobenthos Sampling

2.1 *Data Available for Analysis*

The historical macrobenthos data available came from 30 stations at which 10 replicate samples were made at each of 11 dates from November 1995 to November 2000 (Refer to Appendix A for details). Not all stations were sampled at each time point. Counts of individual species were made but in the following we will consider the total benthos count as the measure of benthic community status. It was beyond the scope of this report to consider other measures of benthic community status such as species richness, diversity measures and/or functional groups of species.

It must also be noted that the historic macrobenthos data represent

- a subset of habitat and intertidal ranges within the Port, with stations mostly located in the industrialised inner harbour
- a specific 5-year period with evidence of macrobenthos decline and recovery during this timeframe.

(David Currie, *pers. comm.*, Central Qld University, Gladstone)

2.2 *Determining Mean-Variance Relationship Amongst Replicates*

To develop a sampling strategy that accounts for the testing of differences in total benthos magnitude from one occasion to another, it is necessary to determine if the variability of abundance over replicates changes with the mean abundance. Table 1 highlights how the mean abundance for each station varies with time. Refer to Appendix B for individual station plots representing these time series.

The variance and mean of total abundance are plotted for various transformations of abundance in Figure 1. From Figure 1, we see that with the untransformed (Figure 1a), square root transformed (Figure 1b) and fourth root transformed abundances (Figure 1c) there is a strong relation between the variance and mean over replicates. Ignoring this relationship between the variance and mean would produce biased results from subsequent statistical power analyses. With the log transformed abundances the variance of replicates does not appear to have a systematic relation to the mean abundance (Figure 1d). Hence the variance of the difference between any two mean log abundances will be constant, no matter what the magnitudes of the two means. Importantly, this ensures no biases in subsequent power analyses will be likely.

Table 1 Mean total abundance of 10 replicates for station by date combinations. 'NA' refers to information that was 'Not Available'. Refer to Appendix A for latitude and longitude values for each station.

Station	Date										
	Nov 95	Apr 96	Nov 96	Apr 97	Nov 97	Apr 98	Nov 98	Apr 99	Nov 99	Apr 00	Nov 00
1	25.0	6.4	5.70	5.78	7.44	2.56	6.78	4.17	6.20	5.90	40.50
2	14.5	7.8	11.20	4.40	7.90	2.80	8.50	3.22	2.10	23.00	9.00
3	8.0	14.1	14.30	6.10	6.00	2.75	11.50	8.70	1.67	8.40	12.90
4	18.7	11.0	15.30	7.89	14.00	5.11	13.70	11.50	5.90	7.00	10.40
5	23.5	9.8	13.10	5.56	13.10	3.00	4.60	3.90	2.00	10.40	10.60
6	21.5	33.0	22.10	13.00	16.60	7.30	6.90	4.80	6.44	14.10	106.60
7	21.8	12.4	13.20	6.40	12.30	11.67	4.33	4.00	4.38	10.60	6.67
8	23.9	13.8	19.70	14.10	14.80	6.80	9.80	7.89	3.90	6.80	42.90
9	42.0	24.5	35.40	4.10	14.10	6.70	5.30	7.60	4.00	13.90	50.20
10	23.9	20.1	14.10	4.11	13.20	6.30	11.70	3.89	11.40	11.70	20.50
11	15.0	53.0	20.70	23.40	30.80	5.80	8.11	2.14	7.33	21.10	10.60
12	43.2	54.7	34.20	19.50	35.20	21.50	22.40	24.10	20.40	23.11	55.20
13	39.0	7.7	11.10	11.70	27.80	14.90	8.20	6.20	11.00	4.89	10.30
14	26.2	18.7	11.30	6.10	22.90	9.20	4.11	5.30	7.40	7.30	12.10
15	29.2	9.3	12.80	12.67	25.30	11.00	3.11	8.60	8.30	13.00	44.10
16	16.5	37.1	7.78	13.00	14.20	8.00	3.90	17.50	7.30	19.25	30.00
17	14.5	10.8	10.20	7.70	10.70	2.33	4.30	4.30	3.00	NA	8.56
18	19.9	11.0	9.40	7.20	7.30	3.13	5.44	1.67	3.75	NA	9.90
19	38.2	30.3	23.90	20.80	16.80	3.30	10.90	11.40	3.43	NA	10.20

Station	Date										
	Nov 95	**Apr 96**	**Nov 96**	**Apr 97**	**Nov 97**	**Apr 98**	**Nov 98**	**Apr 99**	**Nov 99**	**Apr 00**	**Nov 00**
20	20.5	13.7	12.40	5.60	10.50	2.67	7.40	2.67	7.50	NA	9.20
21	NA	NA	NA	14.60	13.22	7.30	2.60	1.57	4.50	NA	5.80
22	NA	NA	NA	10.90	4.50	2.86	9.60	2.00	3.89	NA	3.33
23	NA	NA	NA	3.63	4.56	1.25	8.40	3.40	2.67	NA	9.70
24	NA	NA	NA	16.40	6.20	2.00	16.50	2.38	21.70	NA	16.50
25	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	12.20
26	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	10.20
27	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	54.30
28	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	16.30
29	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	8.20
30	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	24.10

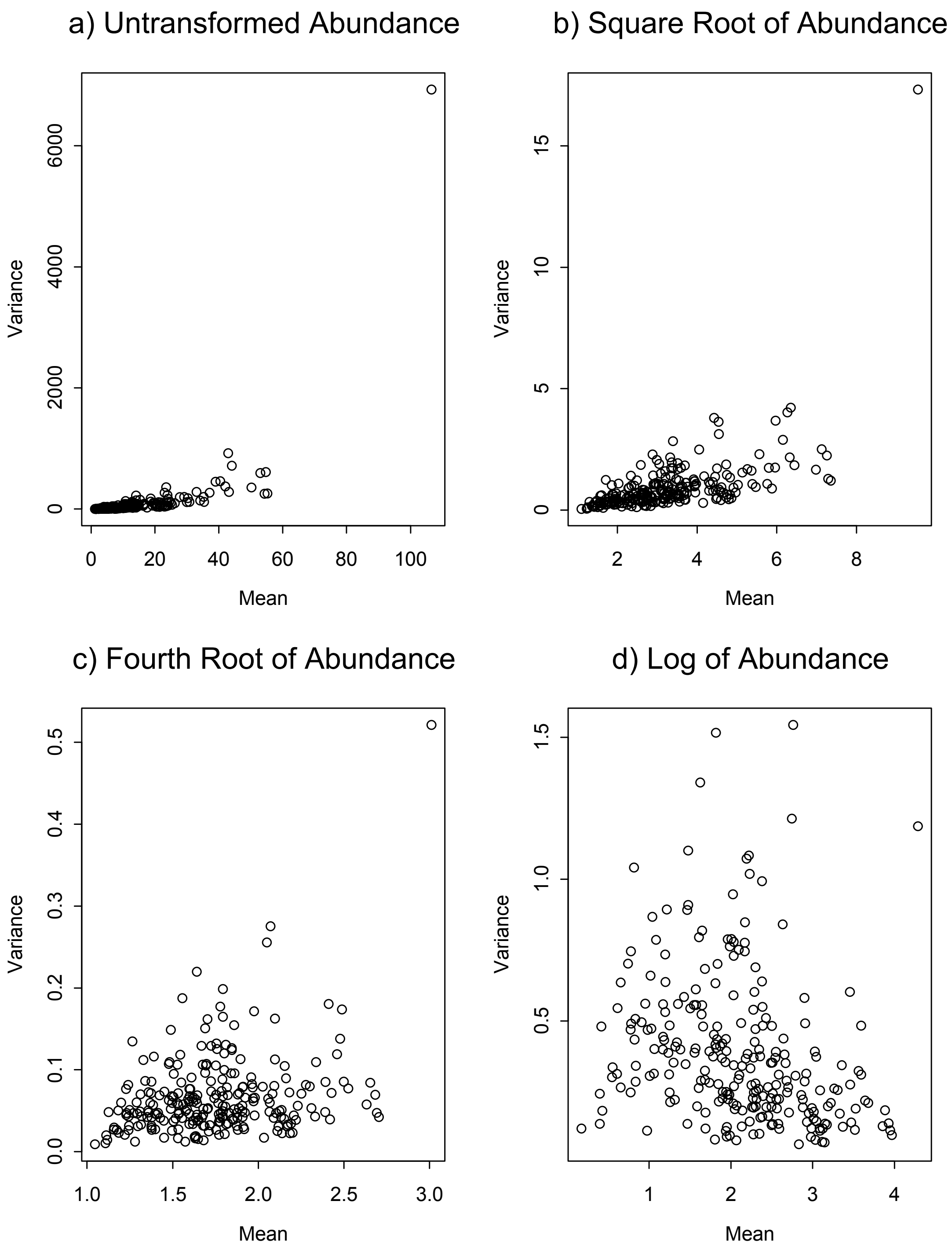

Figure 1 The variance and mean of macrobenthos total abundance plotted for a) untransformed, b) square root, c) fourth root and d) log of abundance.

2.3 *Determining Optimal Number of Grabs*

To investigate the optimal number of grabs for macrobenthos sampling, we are interested in testing for proportional reductions in mean abundance. This involves going from mean μ to mean pμ, where p is between 0 and 1. Consequently, the difference in logs of these two means becomes simply [–log(p)]. For simplicity, the term "percentage difference" [100(1-p)] will be used throughout the text, rather than the terms "percentage reduction" or "proportional reduction".

We have analysed the replicate data that made up Table 1 using a linear model with normal errors for the log of abundance. [We have already shown that on this scale the assumption of constant variance applies (Figure 1d).] The results from this analysis provide an estimate of the residual variance (σ^2), which is one of the parameters required to compute sample sizes (*n*) in Equation (1). With the linear model accounting for the main effects of station and time and their interaction, we estimate the residual variance (σ^2) for the log of abundance to be 0.39.

To compute sample sizes (*n*) for the difference in two means, we can use the sample size formula of Snedecor and Cochran (1989)

$$n = 2(z_\alpha + z_\beta)^2 \sigma^2 / \delta^2 \qquad (1)$$

where α is the significance level required for the test, β=2(1-P), where P is the power of the test, and the residual variance of log abundance σ^2 is estimated to be 0.39. The mean difference δ is [–log(p)], as calculated above for the difference in mean log abundance. The z_α and z_β terms are normal distribution percentage points corresponding to the probabilities α and β, respectively. The term $(z_\alpha + z_\beta)^2$ is calculated to be 10.5 for α=0.05 and P=0.9.

For testing that the percentage difference between mean abundance at any two times is 60%, we would need at least 10 grab samples. If we needed to know that a percentage difference of 67% had occurred, we would only require 7 grab samples on each occasion. For differences of 75% and 90% in mean abundance as our measures of benthic community change, we would only need 5 and 2 grab samples, respectively. Figure 2 shows the relationship between percentage difference and number of grabs.

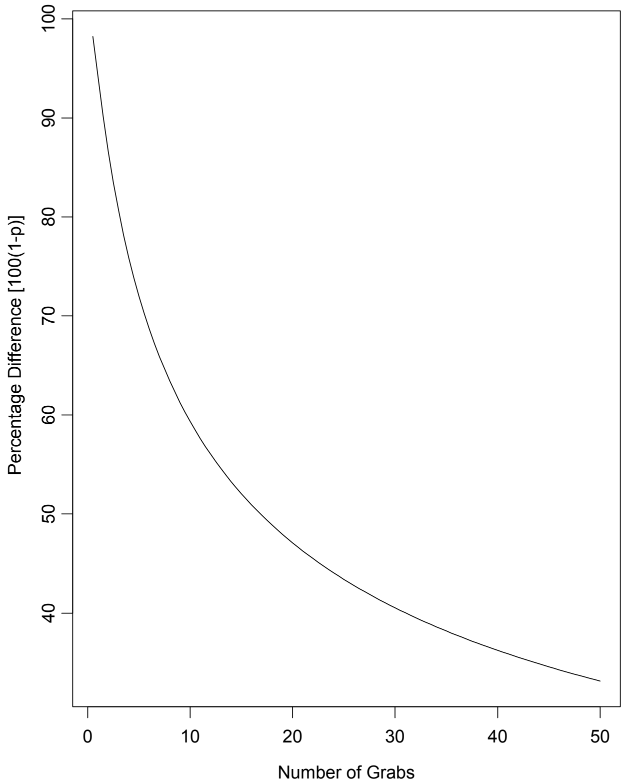

Figure 2 Percentage difference [100(1-p)] in mean abundance related to number of grabs. Calculations based on $\alpha = 0.05$ and $\mathrm{P}=0.9$.

2.4 *Implications for Monitoring Macrobenthos*

The results outlined above highlight that the choice of the number of grab samples to take during the sampling of macrobenthos depends on how great a percentage difference we want to use as a measure of benthic community change. As can be seen from Table 1, 90% differences in mean abundance occur in Port Curtis and these may be due to natural variation. More subtle differences may occur as a result of specific human intervention, and the ability to detect these will depend on what the key percentage difference in abundance is that you wish to be able to detect as significant.

The histogram in Figure 3 shows the distribution of percentage differences, when comparing the greater of two successive means to the lesser, taken over all the pairs of successive occasions for the first 24 stations. The individual station histograms can be seen in Appendix C. The full range of percentage difference values in the macrobenthos data for Port Curtis (depicted in Figure 3 and Appendix C) suggest that a monitoring program including macrobenthos may need to take a conservative approach in setting the level of detection possible through such a sampling program. That is, the smaller percentage difference values (0 to 60% - implying subtle differences between sampling events) may require accommodation and hence at least 10, preferably more, grab samples of macrobenthos are required for each sampling station.

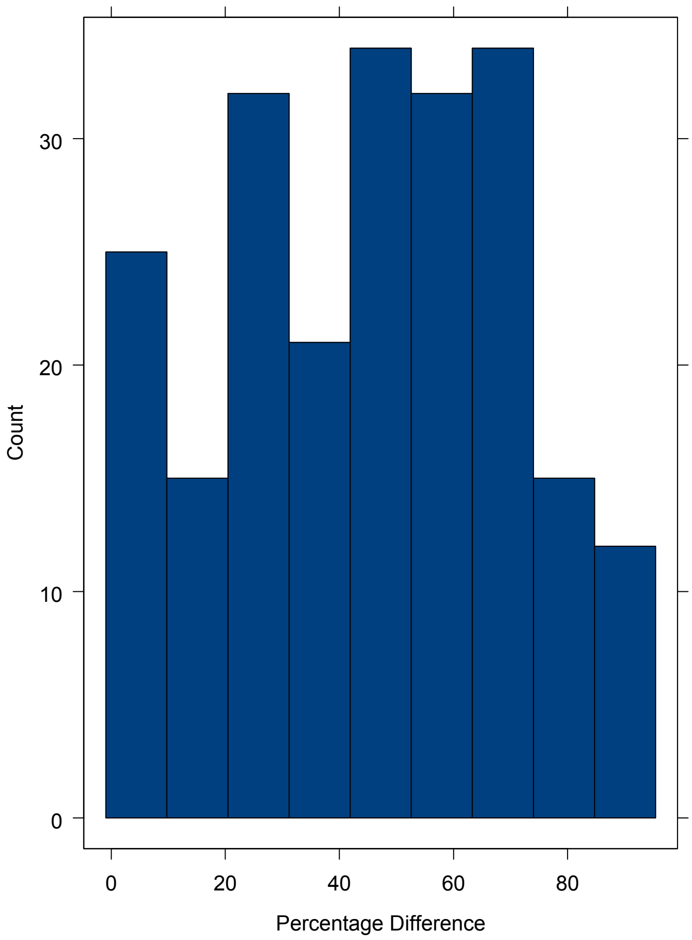

Figure 3 Histogram of the percentage difference in mean abundance between successive time points from all of the first 24 stations.

3. Spatial Interpolation of Water Quality and Contaminants

3.1 *Methodology for Spatial Interpolation*

The geostatistical methodology kriging (Cressie, 1993, Chapters 2 and 3) is used to spatially predict the variables sampled in the bay. Spatial prediction has two components. The first component is the large-scale spatial structure in the data, which models the overall trend in the data. The second component is the small-scale spatial structure in the data. This is the spatial structure that is left when the overall trend, or large-scale spatial structure, has been accounted for. Figure 4 helps to illustrate via an example the large-scale and small-scale spatial components. For simplicity, it is assumed that the system of interest is one-dimensional, so sampling can be done on a linear transect. The green points represent the observations. The red line represents the large-scale spatial structure, which in this example is quadratic. When the small-scale spatial structure is included, the black line results. Notice how the general shape is the same as that of the large-scale spatial structure but at a local level it can deviate from the large-scale spatial structure. The deviation is due to the small-scale spatial structure.

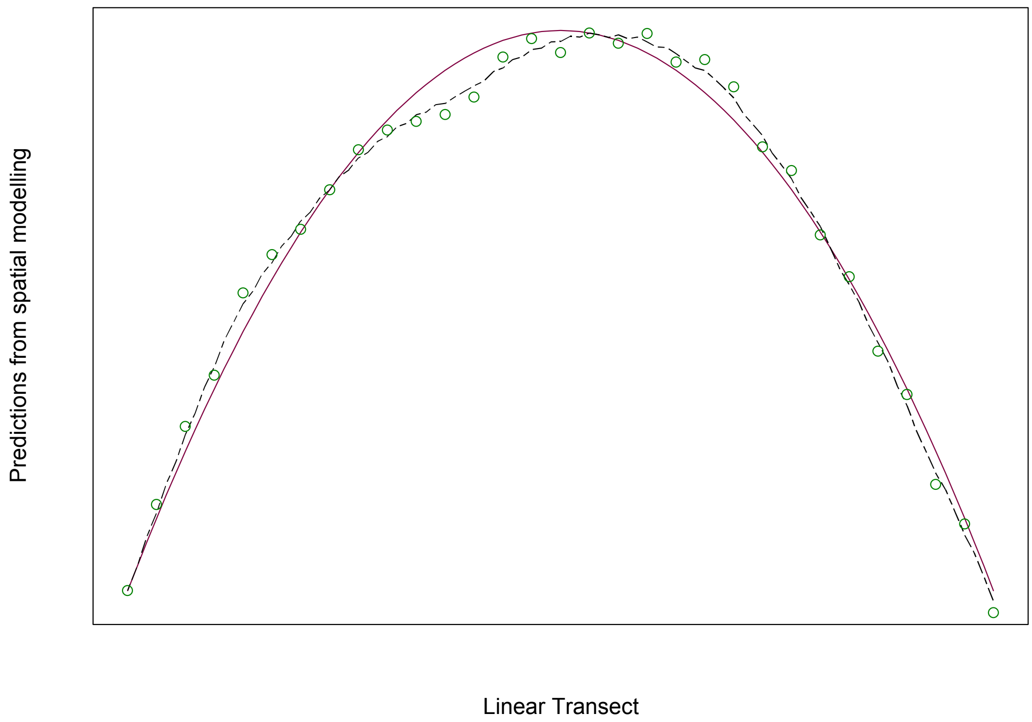

Figure 4 Large and small scale components for a one-dimensional system (an example). The red line represents the large-scale spatial structure, the black line the large-scale and small-scale spatial structure combined, and the green dots represent the observed values.

Accounting for the small-scale spatial structure involves semi-variogram modelling of the residuals that result when the large-scale spatial structure is removed from the data. From the fit of the semi-variogram to the residuals it is possible to predict the small-scale spatial structure. The residuals are calculated as the observed value at a particular station subtracted from the estimated large-scale spatial trend value at that station. As an example, Figure 5 presents the empirical and fitted semi-variogram for the intensive water quality salinity data. The semi-variogram shows how the variation changes between points at different distances apart. Notice in Figure 5 that points that are not more than a distance of 0.012 degrees apart (distance calculated based on decimal longitude and latitude values) have a small semi-variogram value (gamma < 0.03), suggesting that these points are similar, while points that are further apart, such as greater than a distance of 0.035, have a semi-variogram value approximately 0.05, suggesting that these points are not as similar.

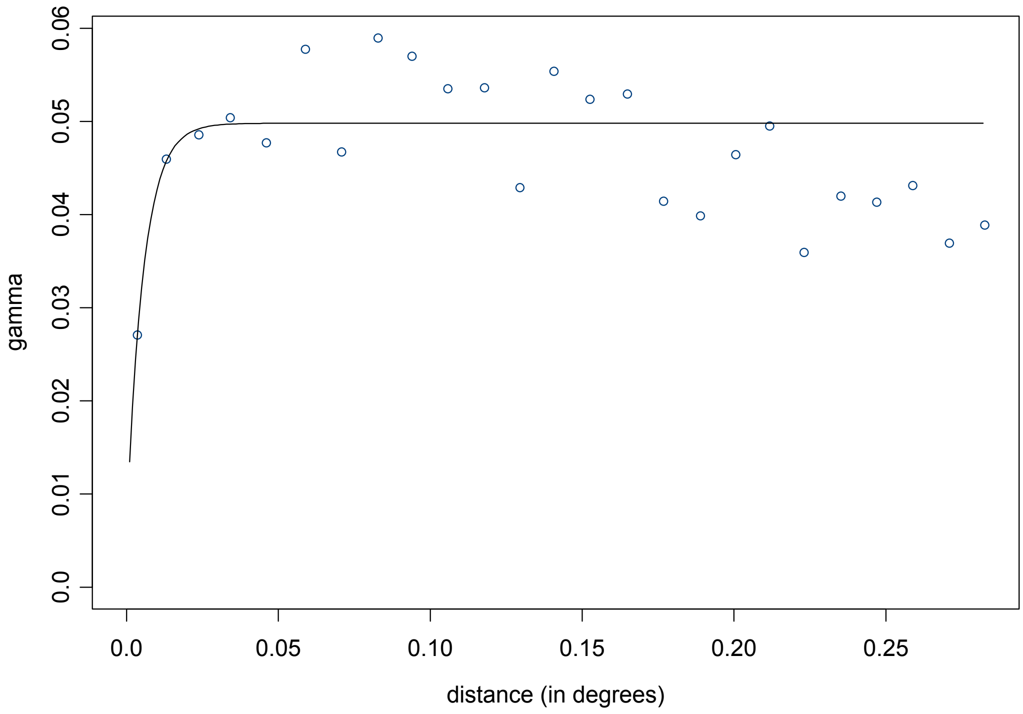

Figure 5 The empirical and fitted semi-variogram for the intensive sampling water quality salinity data.

Modelling the semi-variogram requires the estimation of the range, the sill and the nugget effect. The range represents the distance at which the data are no longer correlated, the sill represents the variance, and the nugget effect represents micro-scale (very small-scale) spatial structure or measurement error (error that would result if the measurement were repeatedly taken at the same station). For the model fitted in Figure 5 the range is estimated to be 0.02, the sill to be 0.05 and the nugget 0.006.

For information on the semi-variogram and geostatistical spatial modelling when the data, or some transformation of the data, are assumed to be approximately Gaussian distributed, see Cressie (1993). This assumption was made for all the variables analysed except for the percentage of sediment of size less than 60 μm. The spatial analysis of these percentage data is based on the application of geostatistical techniques to non-Gaussian data. The modelling of non-Gaussian data is commonly performed using generalised linear models. (See McCullagh and Nelder (1989) for information on generalised linear models, and Gotway and Stroup (1997) for information on spatial analyses for generalised linear models.)

3.2 *Data Available for Analysis*

Water quality readings were taken in the Port Curtis area in August 2001 and February 2002 at 50 stations, with replicates at six stations for August 2001 and at five stations for February 2002 (Refer to Appendix A for details). A number of variables were measured, with some having most readings below detection limit. Spatial maps are generated only for those variables that have no more than a few observations below detection limit, with observations below detection assigned a value just less than the actual detection limit. For the water quality surveys in August 2001 and February 2002 the variables that fall into this category are: pH, salinity, fluoride, arsenic and selenium.

Sediment samples were taken in the Port Curtis area in September/October 2001 and March 2002 at 50 stations, with replicates at five stations for both surveys (Refer to Appendix A for details). A large number of the readings for silver and cadmium were below detection limit for both surveys, so these two variables were not analysed. Spatial maps were generated for the variables: antimony, arsenic, chromium, copper, nickel, lead, zinc and mercury because few if any of the readings for these variables were below detection limit. It is important to note that for the September/October 2001 data approximately 70% of the sediment samples were taken on 19 September and the remaining samples were taken three weeks later. Hence the maps for the variables in this survey should be examined with caution because the prevailing conditions when the samples were taken in September may not have corresponded to those three weeks later in October.

The same cautionary note applies to the intensive water quality maps. The intensive water quality samples were taken over a six week period from mid July 2002 to the beginning of September 2002 at 177 stations (Refer to

Appendix A for details). Since the prevailing conditions over this six week period may have changed, the maps for the intensive water quality variables should be viewed with caution. The intensive water quality variables analysed are: temperature, conductivity, salinity, dissolved oxygen (mg/L), pH and oxidation/reduction potential (ORP). The maps for the intensive water quality variables are based on the average value over depth for each station.

In September/October 2001 and March 2002 samples of sediment were also taken and the percent of sediment falling into four classes was calculated: greater than 1 mm, greater than 125 μm but less than 1 mm, greater than 60 μm but less than 125 μm, and less than 60 μm. Toxicologists generally assume that the bio-available fraction of contaminants is found in sediment of size less than 60 μm (see ANZECC/ARMCANZ, 2002, Chapman *et al*., 1998, and USEPA, 2002). Consequently only maps for the percent of sediment of size less than 60 μm are generated.

Maps have been generated on a grid of 0.002 degrees apart, giving the effect of continuous colour fill at this resolution. For mapping purposes, sample stations in Port Curtis and between the mainland and Curtis Island were included in the analyses. Stations more than a few hundred metres up rivers and creeks are excluded from the spatial mapping. Different processes may be affecting these stations hence they are best removed from the spatial analyses.

3.3 *Spatial Prediction and Coefficient of Variation Maps*

The September 2001 and March 2002 prediction maps for the percent of sediment that is of size less than 60 μm can be found in Figure 6, and Figure 7 respectively. An examination of these two figures reveals a marked difference. For example, a greater percentage of sediment is of size less than 60 μm in March 2002 than in September 2001 for the area between the mainland and the bottom of Curtis Island. It is difficult to say why this is the case. This difference could possibly be caused by a number of events such as large rainfall and runoff events, dredging or rough weather. Another possibility could be that the distribution of sediment size is very variable for small distances, thus resulting in different maps for samples collected at nearby sites. There is a suggestion of this latter possibility in the data. For example, for site 39 in September 2001 the first sample at this site has 0.3 percent of the sediment greater than 1 mm, 4.9 percent greater than 125 μm but less than 1 mm, 5.7 percent greater than 60 μm but less than 125 μm, and 89.1 percent less than 60 μm. The duplicate sample for this site has 16.4 percent, 53.3 percent, 14.0 percent and 16.3 percent in the corresponding sediment size classes. A similar disparity exists for the two samples taken at site 31 in September 2001.

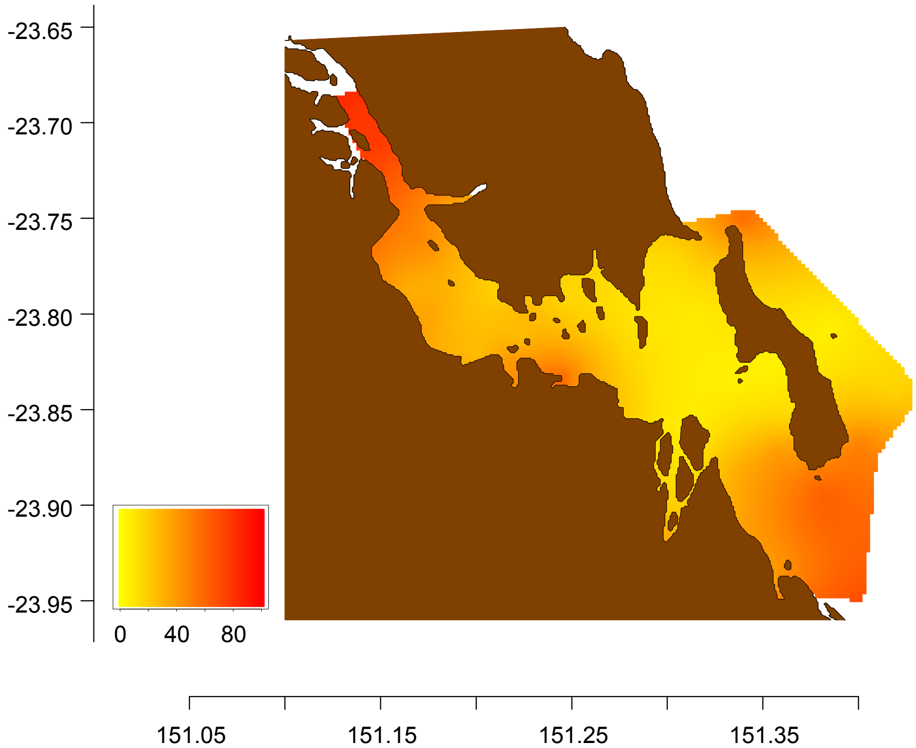

Figure 6 September 2001 prediction map for percent of sediment < 60 (μm).

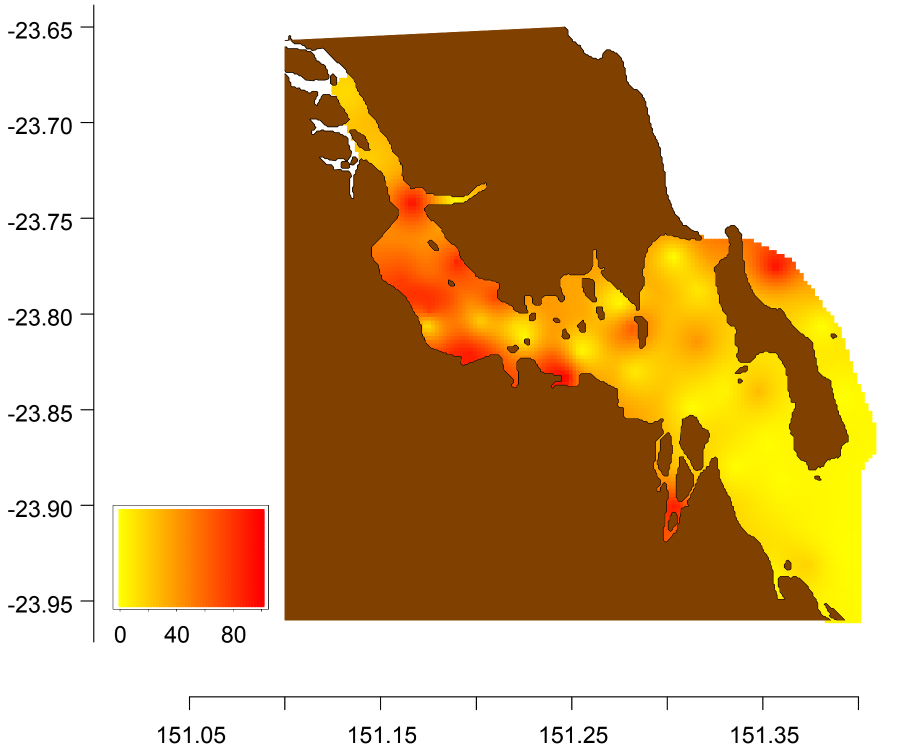

Figure 7 March 2002 prediction map for percent of sediment < 60 (μm).

An examination of the other prediction maps in Appendix D reveals that there can be differences between the maps of the corresponding sediment variables in September 2001 and March 2002, with some areas having high values in one map but not in the other. The same can be said for the prediction maps of the water quality variables in August 2001 and February 2002.

To accompany the prediction maps we have plotted the coefficient of variation using the same grids as the predictions. The coefficient of variation at a station is defined as:

$$\frac{\text{standard error of the prediction}}{\text{prediction}} \times 100\%. \qquad (2)$$

Along with the predictions from the semi-variogram fit, we get standard errors associated with these predictions. Small coefficient of variation values suggest that the variability of the prediction is small relative to the prediction value, while large values suggest that the variability of the prediction is large relative to the prediction value.

The coefficient of variation maps reveal another interesting result. An examination of the coefficient of variation maps reveals that the predictions for the variables from the sediment samples have relatively greater variability than the predictions for the variables from the water quality samples. This point is illustrated by comparing the coefficient of variation maps for arsenic from the sediment samples in September 2001 (Figure 8) and March 2002 (Figure 9) with those for arsenic from the water quality samples in August 2001 (Figure 10) and February 2002 (Figure 11). For the sediment plots (Figure 8 and Figure 9) most of the coefficient of variation values fall in the range 25 to 50 percent. For the water quality plot for February 2002 (Figure 11) all the coefficient of variation values are less than or equal to 10 percent and for the August 2001 (Figure 10) all the coefficient of variation values are less than 25 percent.

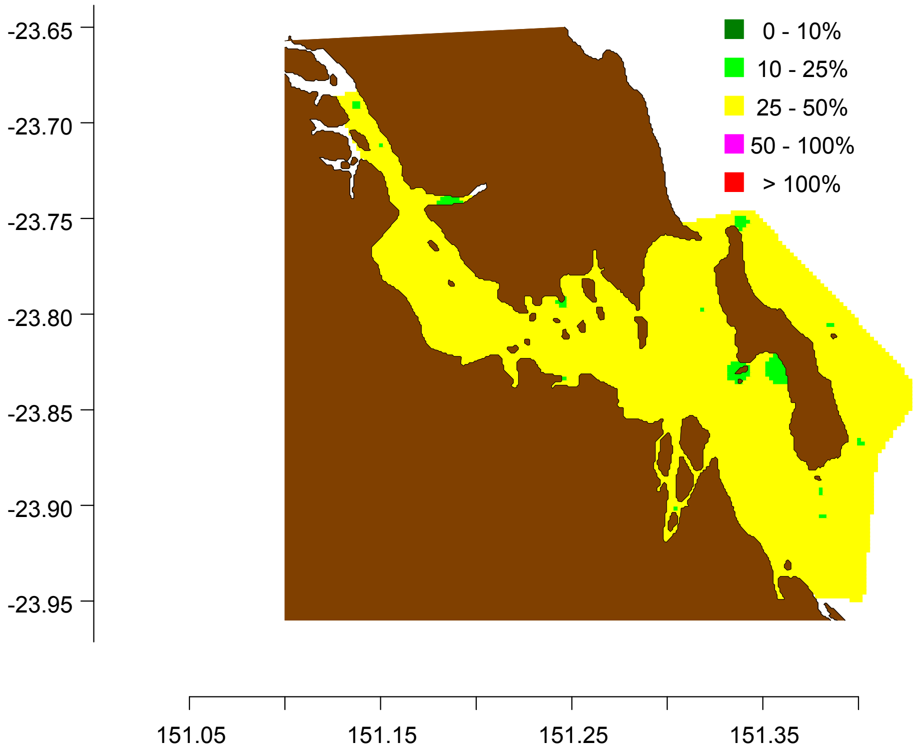

Figure 8 September 2001 coefficient of variation map for sediment arsenic.

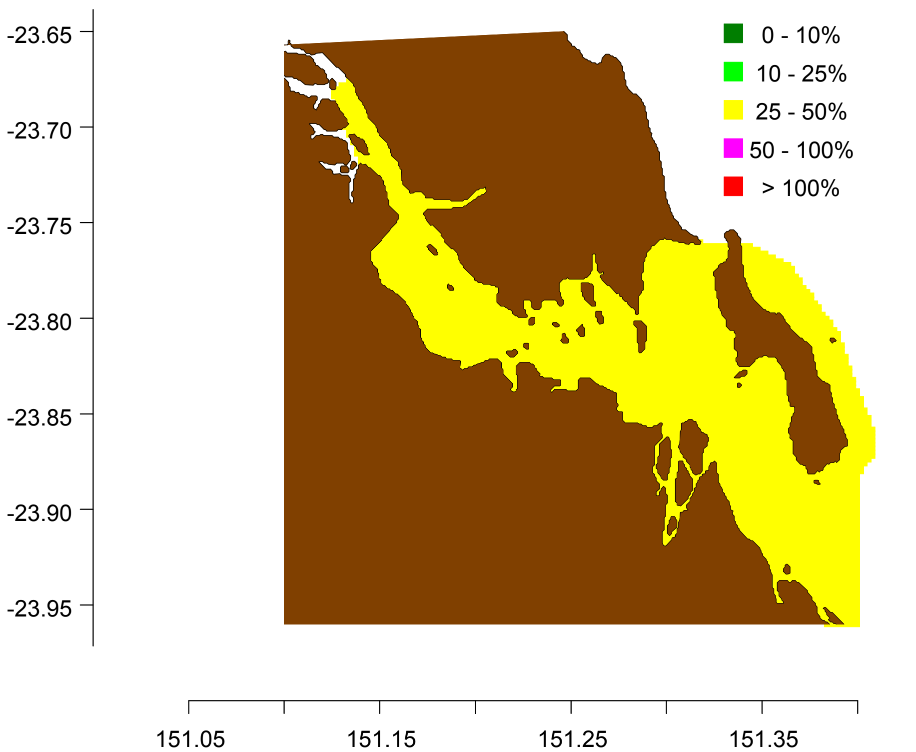

Figure 9 March 2002 coefficient of variation map for sediment arsenic.

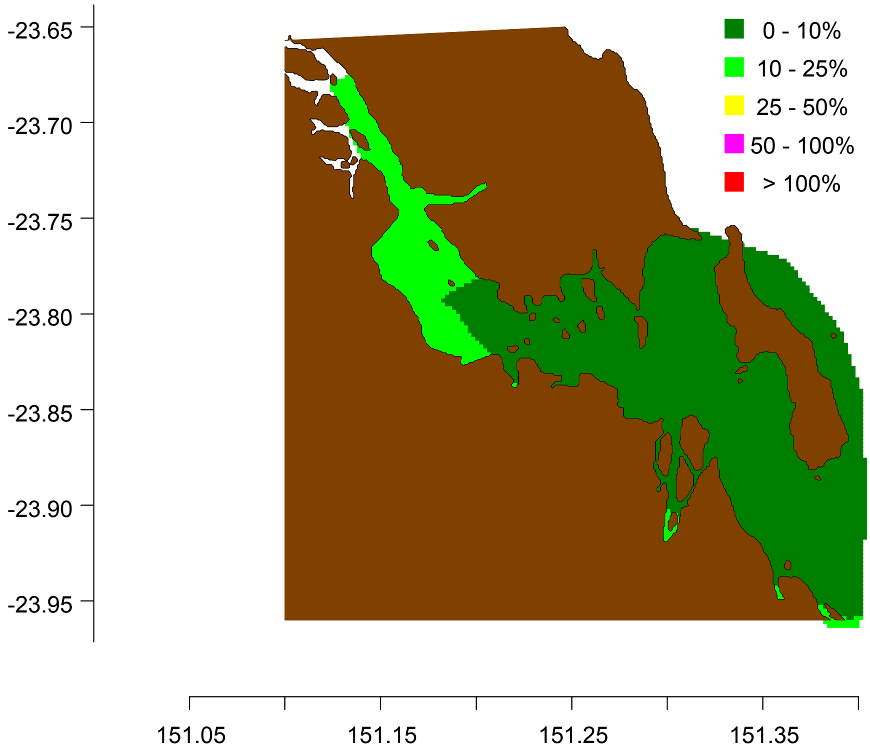

Figure 10 August 2001 coefficient of variation map for water quality arsenic.

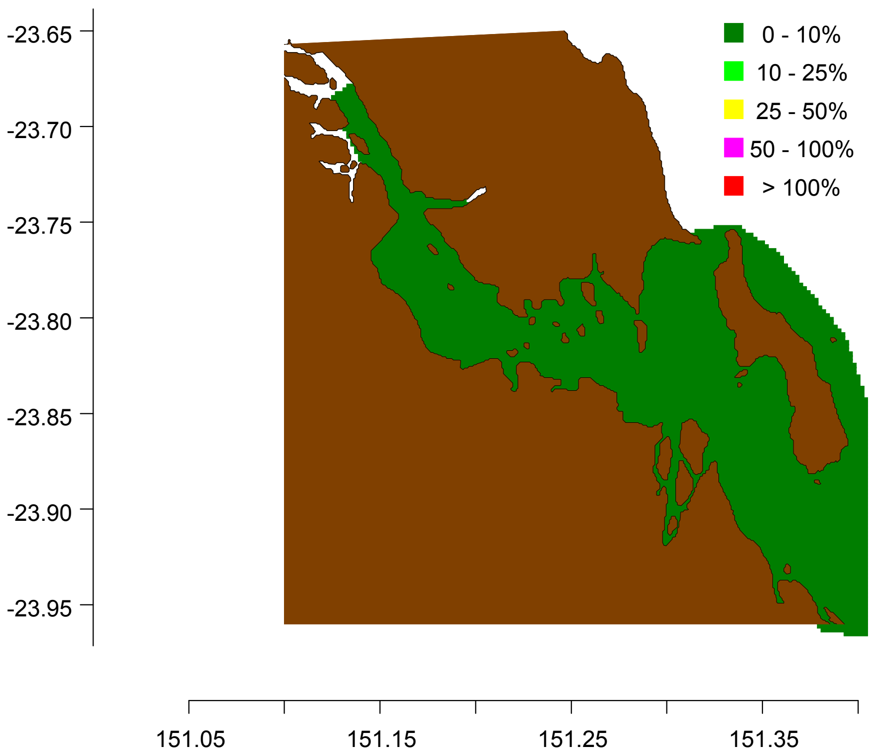

Figure 11 February 2002 coefficient of variation map for water quality arsenic.

4. Recommendations for Monitoring Throughout Port Curtis

The statistical investigations conducted as part of this project can be used to inform 1) the design of an ecosystem health monitoring program involving water quality parameters, contaminants and macrobenthos, 2) the further development of conceptual process-response models for Port Curtis, and 3) the water resource planning process for this coastal system.

Optimal Number of Grabs for Macrobenthos Sampling

The choice of the number of grab samples to take during sampling of macrobenthos at a particular sampling station depends on how great a percentage difference amongst the sampling periods is required from the monitoring program. The appropriate percentage difference for detection should be considered in conjunction with the objectives of the monitoring program.

The variability in the historical macrobenthos data suggests that 10 grab samples enable detection of a 60% difference in abundance (significance level, α=0.05 and Power=0.9). If detection of a larger percentage difference is required (eg 75% or 90%), then a smaller number of grab samples could be taken. This may be relevant for instance if the objective of the monitoring program is to detect major changes in the abundance of macrobenthos. However, for more subtle changes in macrobenthos abundance (eg less than 60% difference), more than 10 grabs samples per sampling event would be required. This more intensive sampling requirement may also suggest the inability of the monitoring program to detect subtle changes in macrobenthos abundance within Port Curtis. This finding should be considered seriously if the objective of the monitoring program is to detect subtle changes in the abundance of macrobenthos.

Spatial Interpolation of Water Quality and Contaminants

As evidenced from the coefficient of variation maps, sediment predictions within the port were generally found to be more variable than predictions for the water quality parameters. To address these higher levels of variability more sampling points within the port would be required to reduce the sediment prediction variability to the range currently exhibited by the water quality parameters. An initial focus on increasing the intensity of sampling stations in the eastern section of the port may be warranted as higher coefficient of variation values were generally found in this section of the port.

The spatial modelling results for each parameter considered also provide the necessary information for considering optimal spatial configuration of stations within Port Curtis, known as spatial power analysis. Here optimal would be assessed as minimizing the level of variability associated with different spatial intensities of sampling effort. The consideration of spatial power analysis is beyond the scope of this report, however with all the spatial modelling now completed an interaction between spatial modelers and stakeholders to ascertain different spatial configurations of relevance would enable a thorough investigation of optimal spatial configurations to be conducted. These spatial power analyses would provide stakeholders with the level of confidence a monitoring design could achieve for detecting change across a given set of monitoring parameters.

Temporal Frequency of Sampling

When taking into account the historical data available for statistical analysis, recommendations about a relevant temporal frequency of sampling are beyond the scope of this report. To address the level of sampling frequency required for sampling either macrobenthos, water quality parameters or contaminants an intensive sampling program with finer scale temporal sampling than twice yearly is required (eg monthly). These finer scale data can then be considered at various coarser scales of temporal frequency and the associated level of variability at these various scales (monthly, bimonthly, quarterly) investigated.

In addition, monitoring data collected for all relevant parameters over a series of years is necessary for understanding the level of natural variability in the system. Knowledge of the natural variability can then enable confident inferences to be made about the impact of known or unknown sources of variation in the system (eg seasonality, pollution sources, etc).

5. References

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Appendix A

A listing of the data sets identified for analysis during this project have been outlined below and provided as CD with this report.

Description of Data Set	Provided by	Filename
Historical Macrobenthos Data: 30 stations at which 10 replicate samples were made at each of 11 dates from November 1995 to November 2000. Identified to species level with numbers of individuals recorded per grab sample. Data were collated to form overall abundance (or richness) at a station. Longitude and latitude values for each of the 30 stations are provided in the EXCEL™ spreadsheet using those outlined in the CQU report entitled "Port Curtis Integrated Macrobenthic Monitoring".	Centre for Environmental Management, Central Queensland University on behalf of Port Curtis Stakeholders	Macrobenthos data.xls Macrobenthos Station Locations.xls
Pilot Grid Sampled Water Quality Data: Samples taken over a 6-week period from mid July 2002 to beginning of September 2002. Parameters measured (those in **bold** were used for subsequent spatial interpolations): • depth, dissolved oxygen (% saturated), turbidity • **temperature, conductivity, salinity, dissolved oxygen (mg/l), pH, oxidation/reduction potential (ORP)**	Centre for Environmental Management, Central Queensland University	jul_sep03 water quality.xls

Water Quality Data: 50 stations sampled in August 2001 and February 2002, with replicates at 6 stations in August and 5 stations in February. Parameters measured (those in **bold** were used for subsequent spatial interpolations): • aluminium, cadmium, copper, chromium, iron, manganese, nickel, lead, zinc, total cyanide, depth, TBT (only measured Feb 2002) • **pH, salinity, fluoride, arsenic, selenium**	CSIRO Energy Technology in collaboration with Co-operative Research Centre for Coastal Zone Estuary and Waterway Management	aug01 water quality.xls feb02 water quality.xls
Sediment Data: 50 stations sampled in September/October 2001 and March 2002, with replicates 5 stations for both surveys. 70% of September/October 2001 samples were taken on 19th September and remaining samples taken 3 weeks later. Parameters measured (those in **bold** were used for subsequent spatial interpolations): • cadmium, silver • **antimony, arsenic, chromium, copper, nickel, lead, zinc, mercury, percentage of sediment less than 60 µm**	CSIRO Energy Technology in collaboration with Co-operative Research Centre for Coastal Zone and Estuary Management Centre for Environment Management - Central Queensland University	march02 sediment contaminants.xls sep01 sediment contaminants.xls march02 sediment size.xls sep01 sediment size.xls

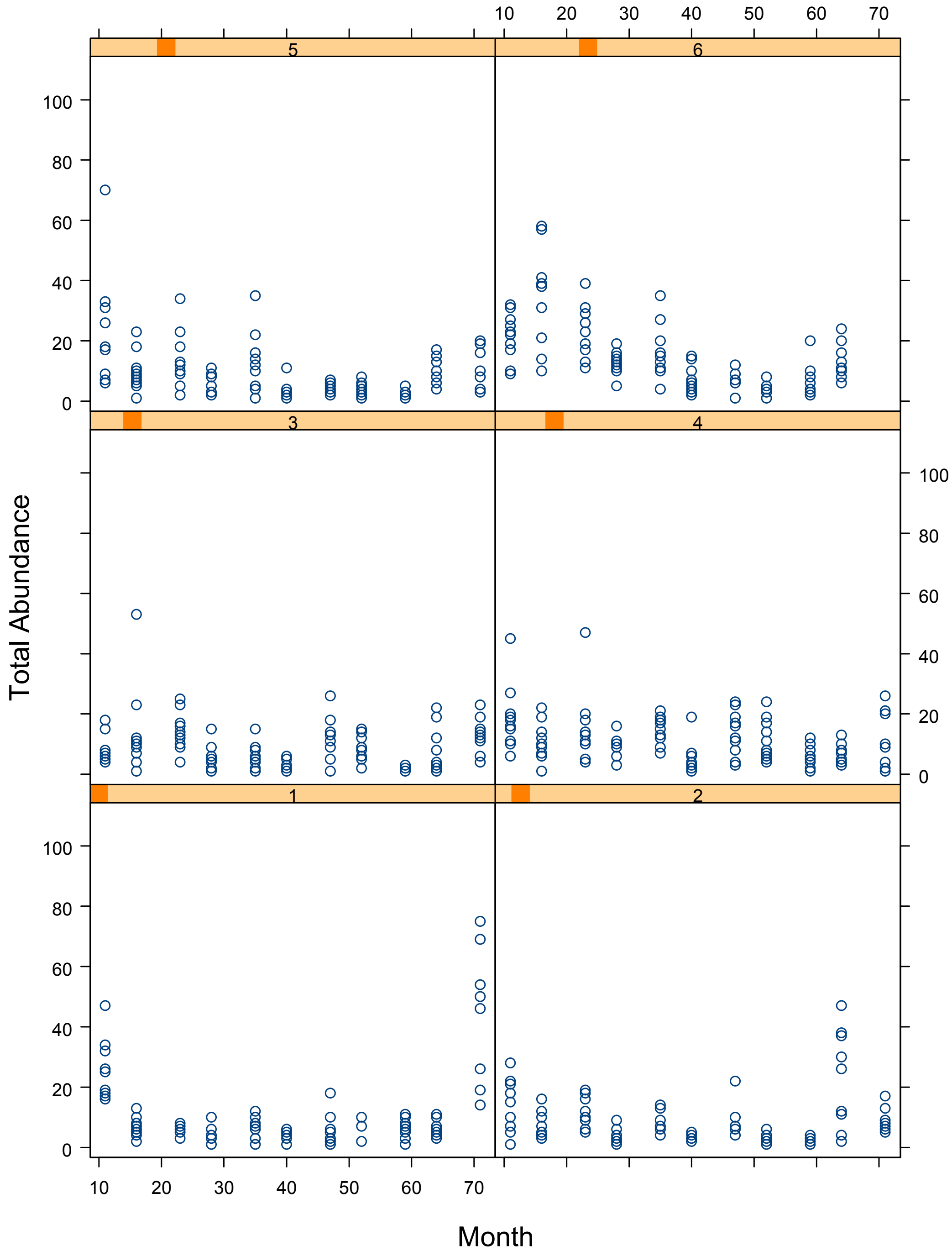

Figure B.1 Time Series plot for Stations 1-6. Ten replicate values are presented for each month. Note that the x-axis is a running month of the year index, starting at 11 for November 1995 and ending at 71 for November 2000. Note November 2000 data for Station 6 has not included on this plot due to the impact of the large abundance values on plot interpretation.

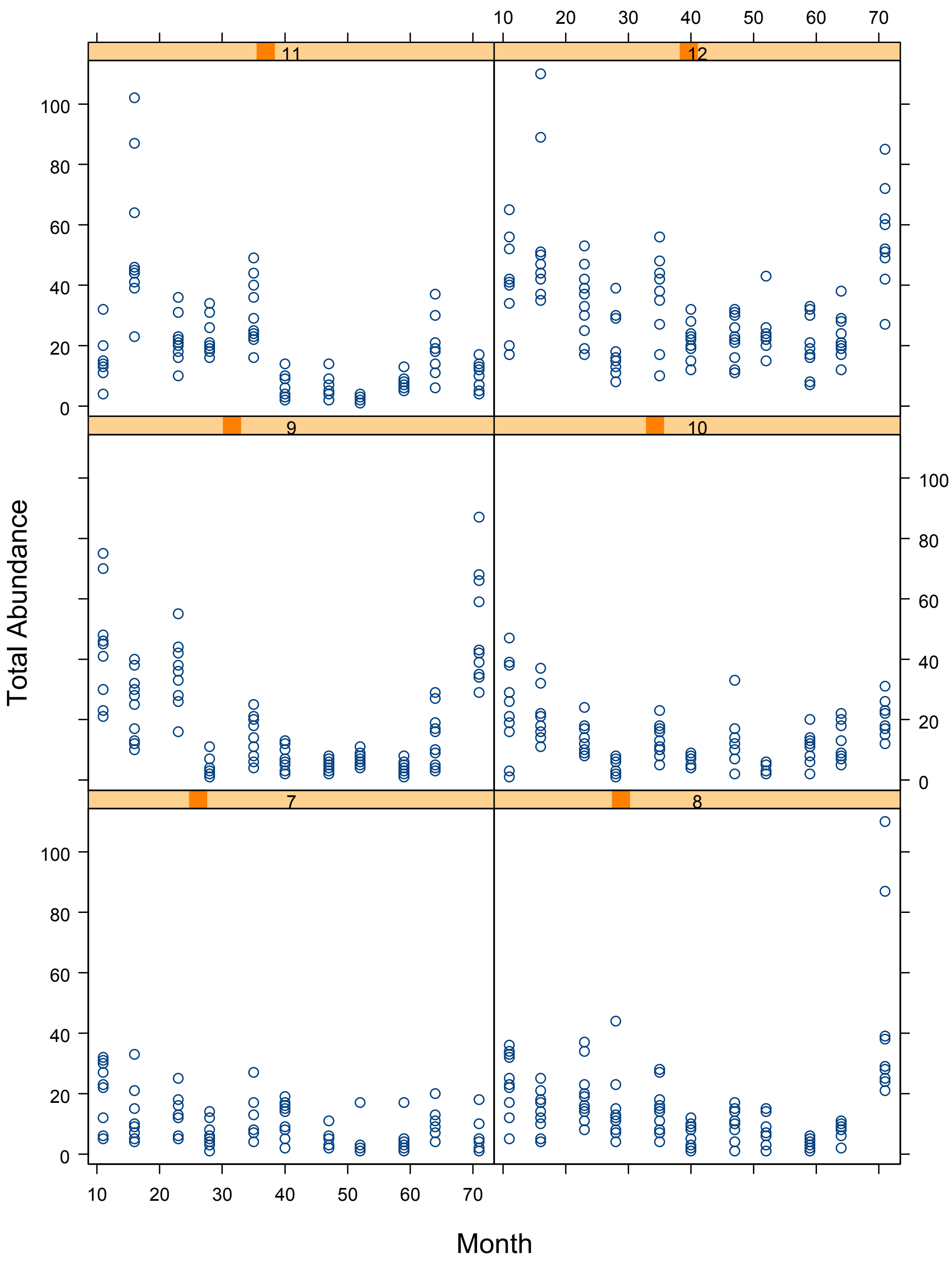

Figure B.2 Time Series plot for Stations 7-12. Ten replicate values are presented for each month. Note that the x-axis is a running month of the year index, starting at 11 for November 1995 and ending at 71 for November 2000.

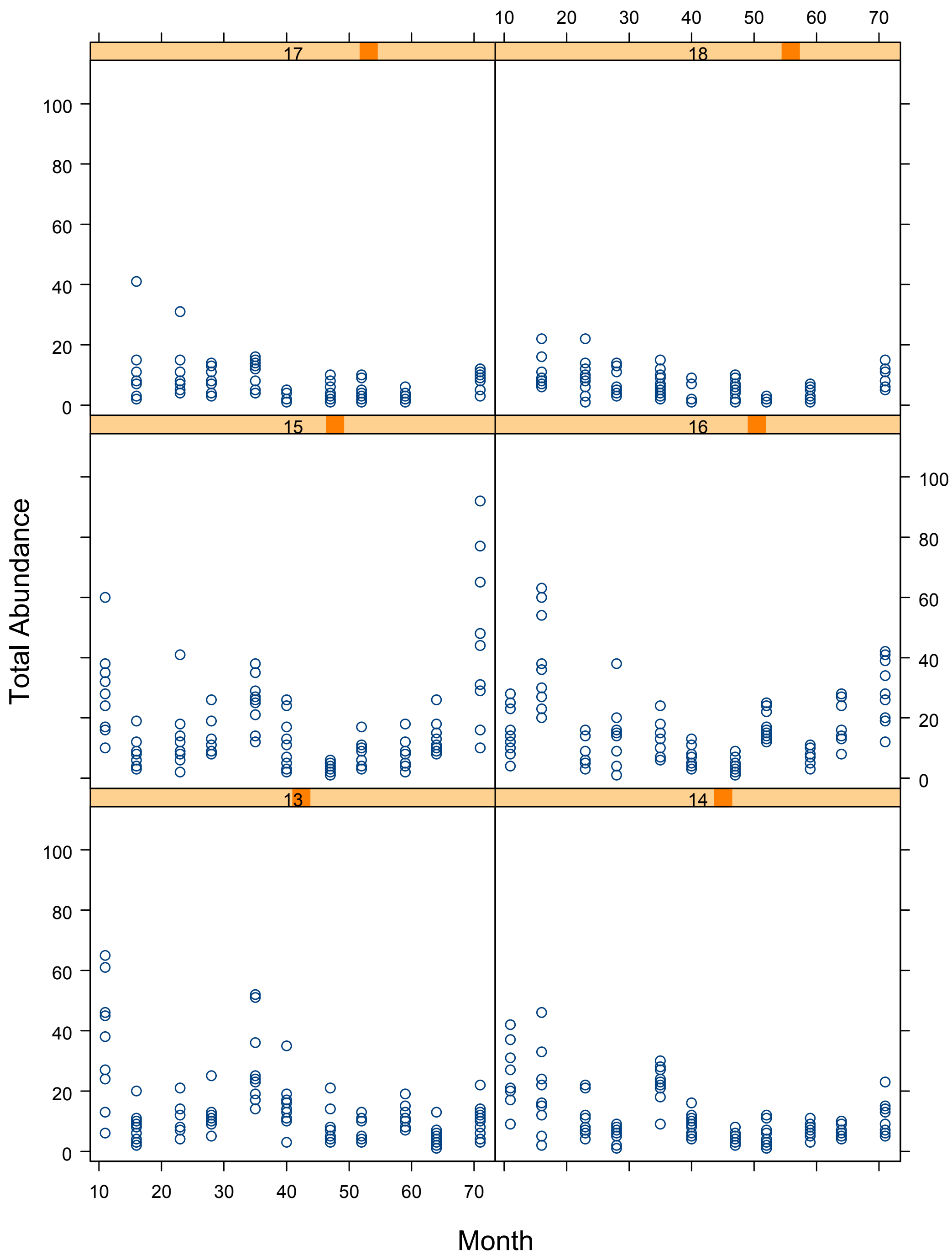

Figure B.3 Time Series plot for Stations 13–18. Ten replicate values are presented for each month. Note that the x-axis is a running month of the year index, starting at 11 for November 1995 and ending at 71 for November 2000.

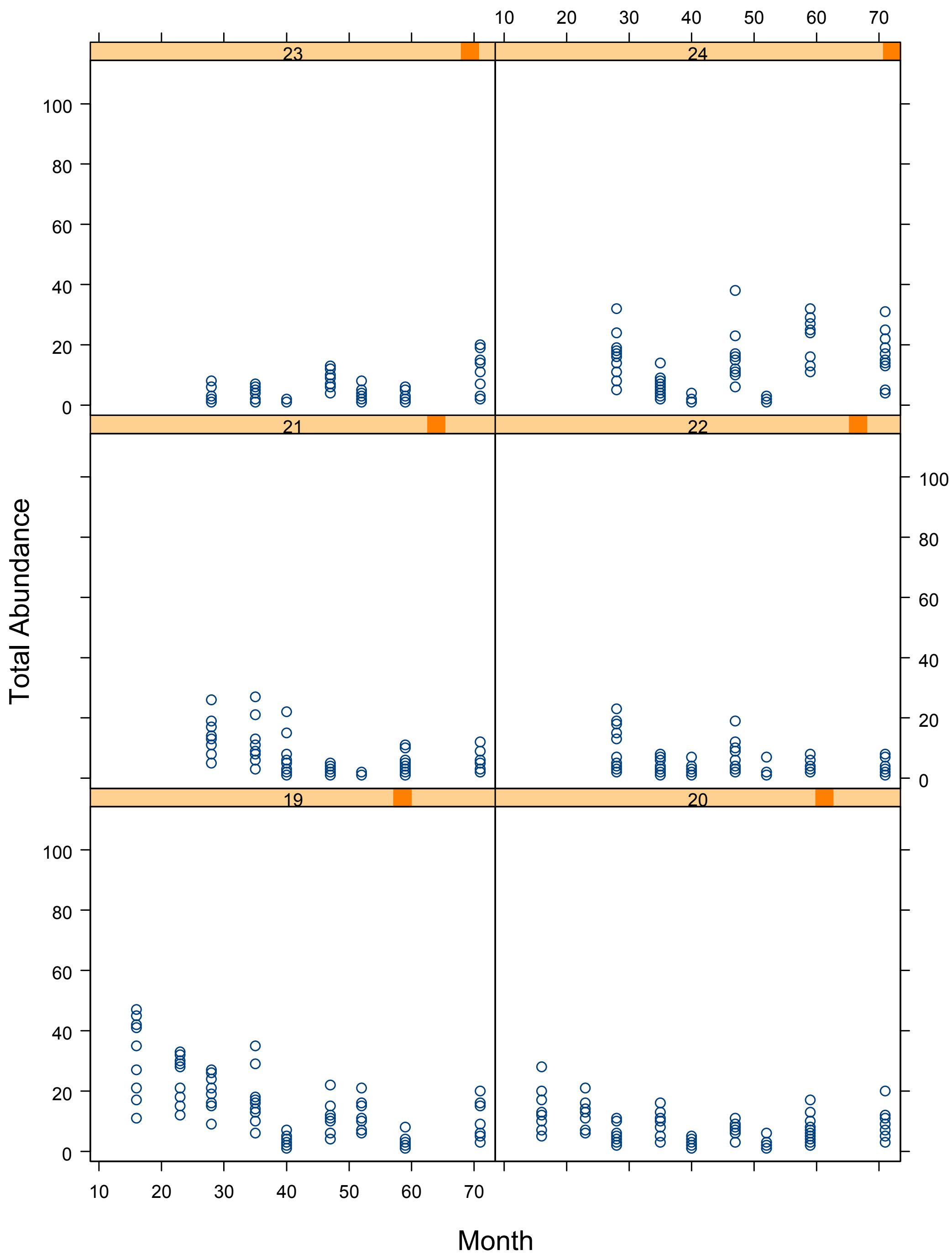

Figure B.4 Time Series plot for Stations 19-24. Ten replicate values are presented for each month. Note that the x-axis is a running month of the year index, starting at 11 for November 1995 and ending at 71 for November 2000.

Appendix C

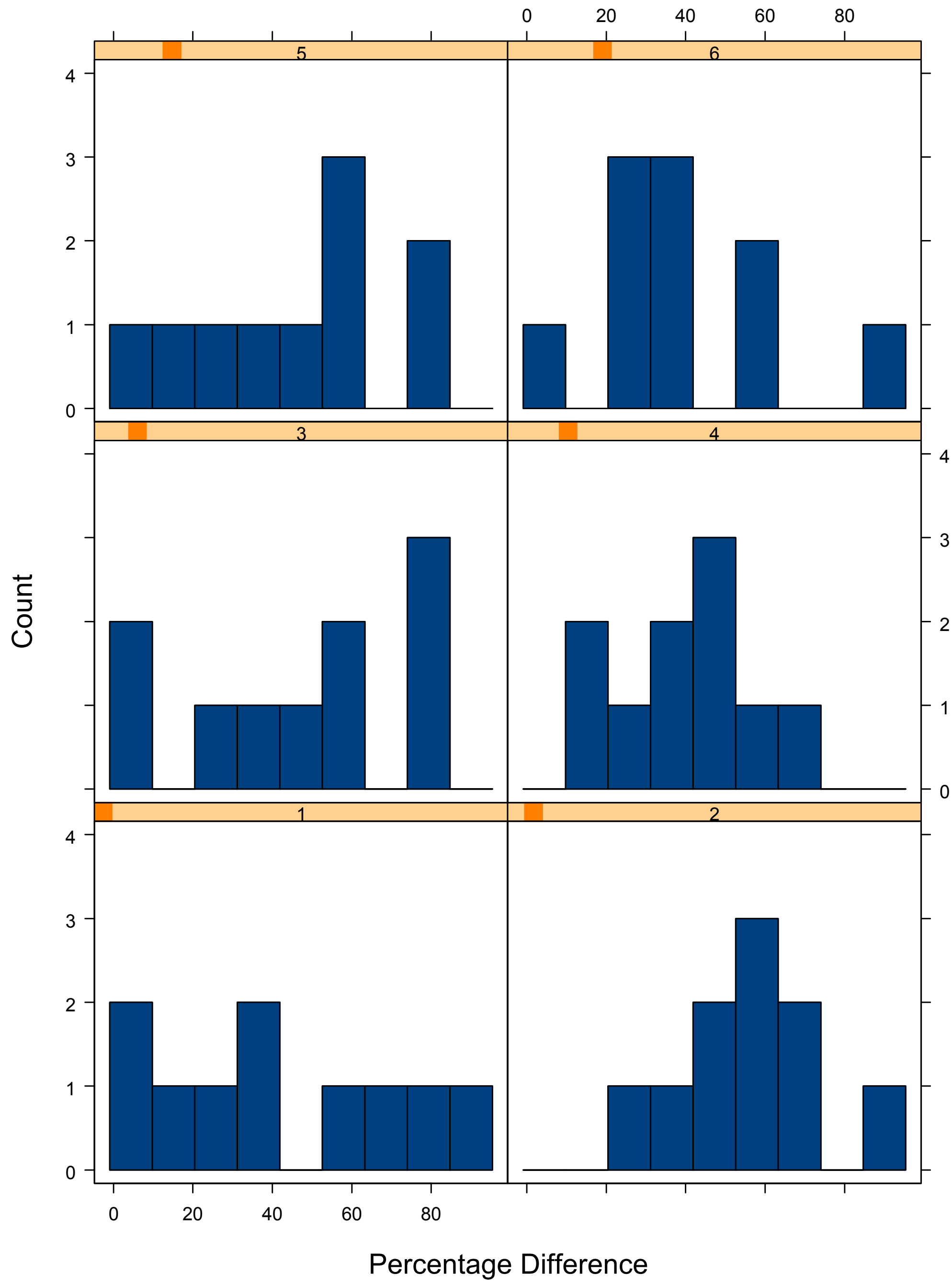

Figure C.1 Histograms of Percentage Difference [100(1-p)] for Mean Abundance at Stations 1-6.

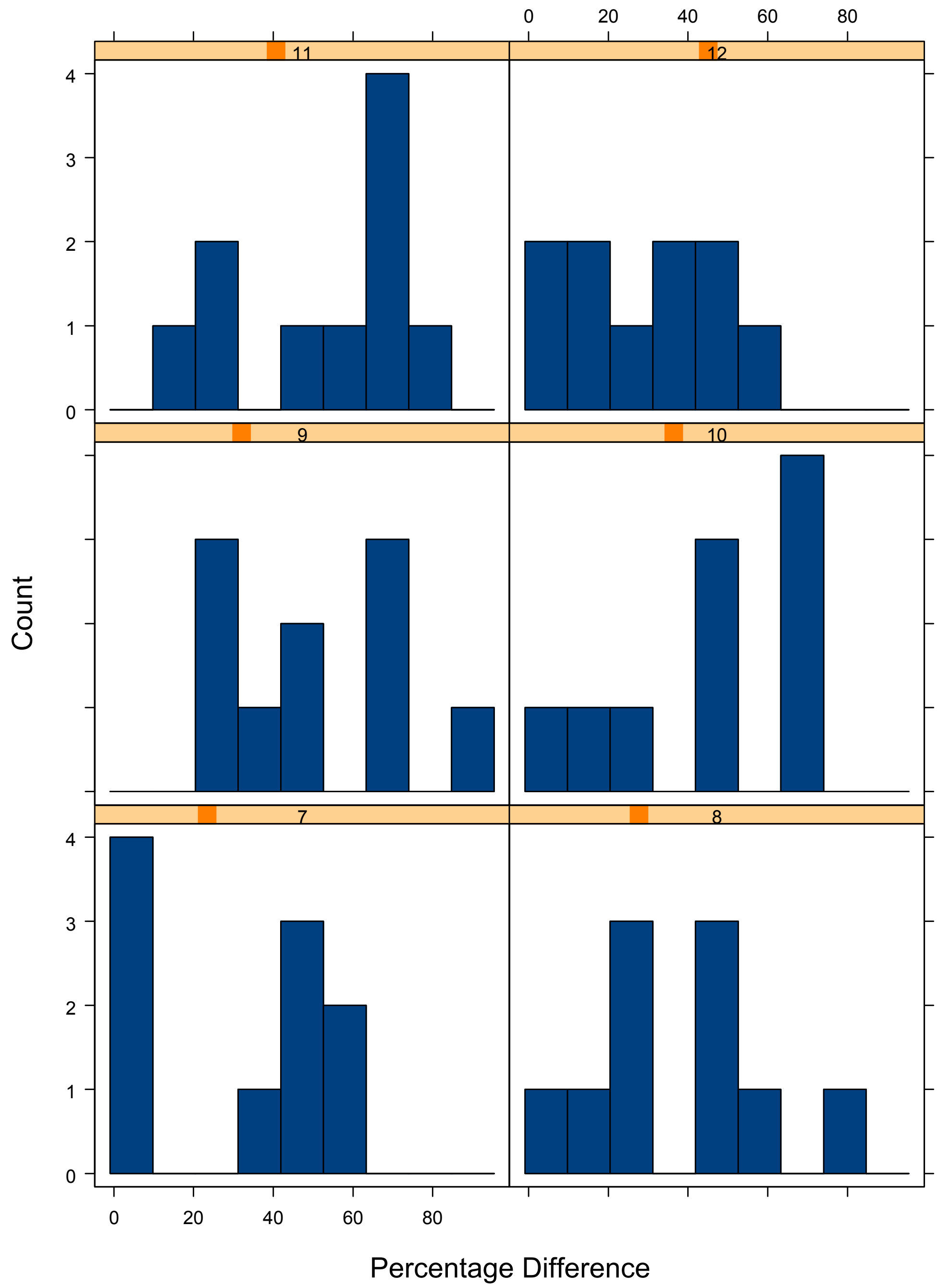

Figure C.2 Histograms of Percentage Difference [100(1-p)] for Mean Abundance at Stations 7-12.

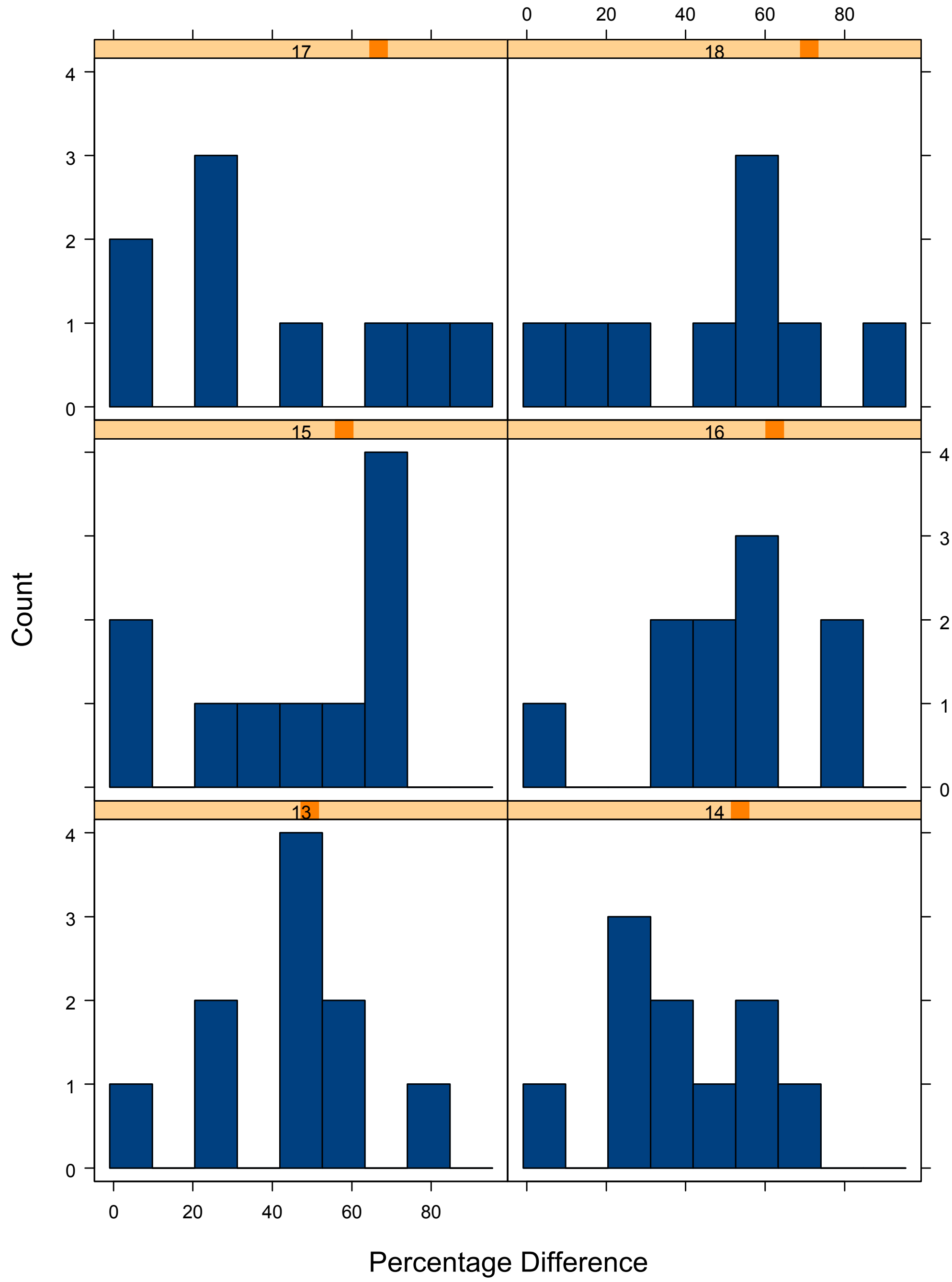

Figure C.3 Histograms of Percentage Difference [100(1-p)] for Mean Abundance at Stations 13-18.

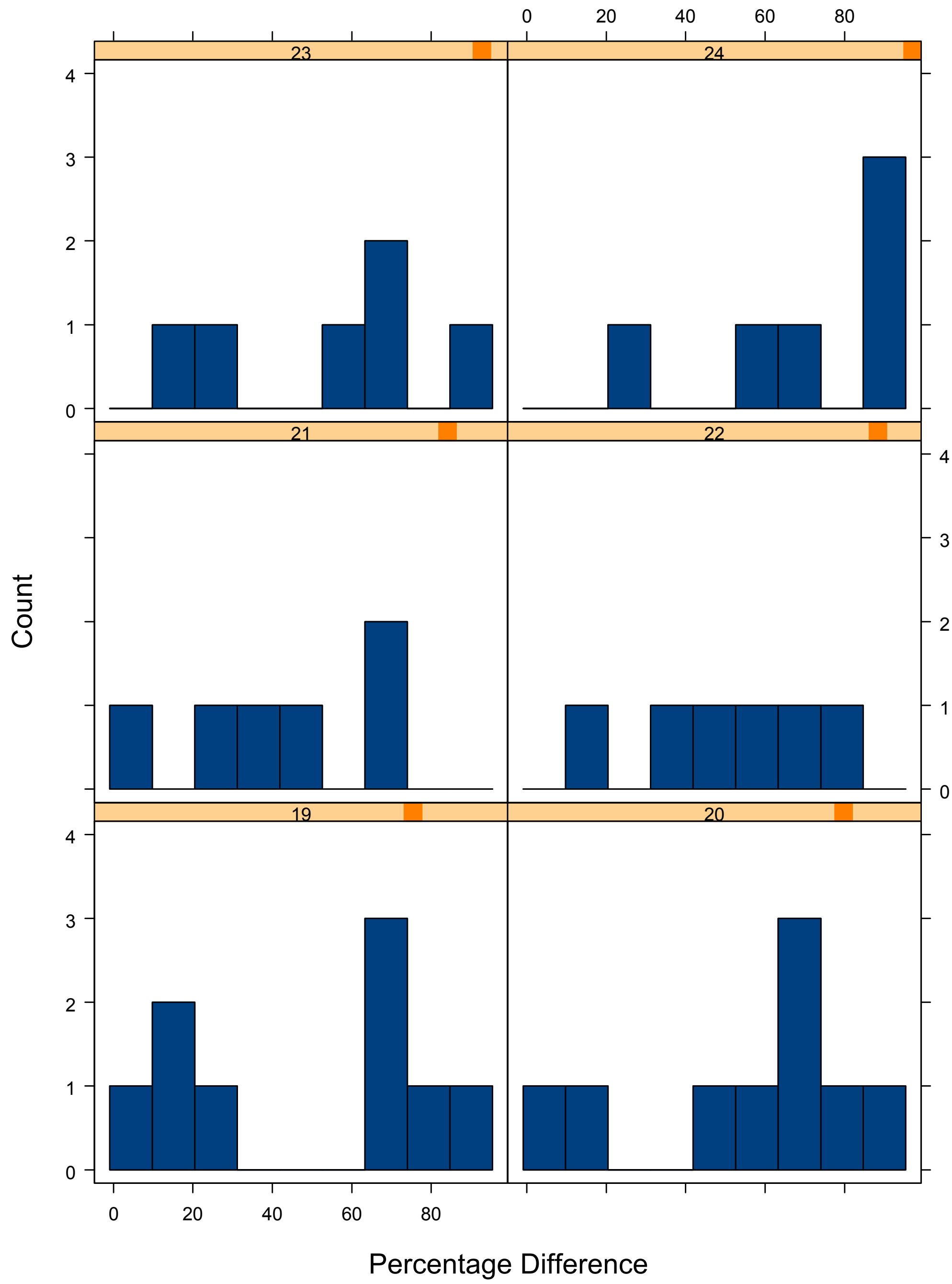

Figure C.4 Histograms of Percentage Difference [100(1-p)] for Mean Abundance at Stations 19-24.

Appendix D