5.0 MODEL EVALUATION PROCEDURES

This section describes the procedures used to evaluate the performance of the meteorological and photochemical models using the routine and special studies surface and aloft aerometric data for the 26-28 June and 17-19 July 1991 LMOS episodes.

5.1 Evaluation Approach

A rigorous model evaluation consists of two components. The ***operational evaluation*** entails an assessment of the model's ability to estimate correctly surface meteorological or air quality variables largely independent of whether the actual process descriptions in the model are accurate. The operational evaluation essentially tests whether the predicted surface meteorological and air quality fields are reasonable, consistent and agree adequately with routinely available observations. In this study, the operational evaluations focus on the various model's reliability in reproducing hourly-average surface wind speed, wind direction, temperature, mixing ratio and ozone concentrations across the 4.0/4.5 km "urban" LMOS analysis domain.

The ***scientific evaluation*** addresses the realism of the meteorological and air quality processes simulated by the models through testing the model as an entire system (i.e., not merely focusing on surface wind and temperature or ozone predictions) as well as its component parts. The scientific evaluation seeks to determine whether the model's behavior, in the aggregate and in its component modules, is consistent with prevailing theory, knowledge of physical processes, and observations. The main objective is to reveal the presence of bias and internal (compensating) errors in the model that, unless discovered and rectified, or at least quantified, may lead to erroneous or fundamentally incorrect decisions based on model usage.

Ideally, the scientific evaluation consists of a series of diagnostic and mechanistic tests aimed at: (a) examining the existence of compensatory errors, (b) determining the causes of failure of a flawed model, (c) stressing a model to ensure failure if indeed the model is flawed, (d) provide additional insight into model performance beyond that supplied through routine, operational evaluation procedures.

Practically, a rigorous scientific evaluation is seldom feasible due to the absence of the specific measurements needed to test the process modules (e.g., soil moisture, Reynold=s stress measurements, PBL heights, trace gas species, and so on). Accordingly, the overall mode performance evaluation in this study is largely limited to operational testing of the MM5 and RAMS models= primary meteorological outputs (i.e., wind speed, wind direction, temperature, and moisture) and the CAMx and MAQSIP models' predictions of ozone and NOx. However, some components of the scientific evaluation of the CAMx and MAQSIP models is possible through examination of ground-level and aloft primary and product species and species ratios. In addition, corroborative analyses involving joint analysis of emissions inventory estimates, air quality model predictions and ambient measurements adds to the scientific evaluation.

The testing procedures used here include those employed in other regional model evaluations (see, for example, Steyn and McKendry, 1988; Ulrickson and Mass, 1990; Tesche and McNally, 1993a,b, 1996a,b; McNally and Tesche, 1996a,b, 1998; Seaman and Stauffer, 1996; Seaman et al., 1997). These analysis procedures are incorporated into the Model Performance Evaluation, Analysis, and Plotting Software (MAPS) system (McNally and Tesche, 1994) which also includes a variety of other statistical and graphical testing methods for photochemical and meteorological models (Tesche et al.,1990; ARB, 1992; EPA, 1991). Tables 5-1 through 5-4 list the specific numerical measures and graphical tools used to evaluate surface and aloft meteorological and air quality model predictions. Below, we introduce the statistical and graphical procedures used to test the models. All of these performance measures and graphical procedures were employed in the evaluations although due to reporting limitations, only the most pertinent results are presented and discussed in this report.

5.1.1 Statistical Measures

As noted, the operational evaluation process includes the calculation and analysis of several routine statistical measures and the plotting of specific graphical displays to characterize the basic performance attributes of the models. Below, we define the specific statistical measures that are used in the evaluation of the meteorological and photochemical models.

Mean and Global Statistics. Several statistical measures are calculated as part of the meteorological and photochemical model evaluations. In some of the definitions below, the variable Ö represents a model-estimated or derived quantity, e.g., wind speed, temperature or concentration. The subscripts e and o correspond to model-estimated and observed quantities, respectively. The subscript i refers to the ith hour of the day.

Mean Estimation (M_e). The mean model estimate is given by:

$$M_e = \frac{1}{N} \sum_{i=1}^{N} \Phi_{ei}$$

where N is the product of the number of simulation hours and the number of ground-level monitoring locations providing hourly-averaged observational data. $\ddot{O}_{ei}$ represents the model-estimate at hour i.

Mean Observation (M_o). The mean observation is given by:

$$M_o = \frac{1}{N} \sum_{i=1}^{N} \Phi_{oi}$$

Here, $\ddot{O}_{oi}$ represents the observations at hour i.

Average Wind Direction. Because wind direction has a crossover point between 0 degrees and 360 degrees, standard linear statistical methods cannot be used to calculate the mean or standard deviation. Evaluations by the EPA (Turner, 1986) suggest that the method proposed by Yamartino (1984) performs well in estimating the wind direction standard deviation. Specifically, this quantity is calculated by:

$$s_a = \arcsin(b)\ [1 + 0.1547\ b^3]$$

where:

$$b = \left[\ 1.0 - \ [(\overline{\sin\ a})^2 + (\overline{\cos\ a})^2\ ]\ \right]^{1/2}$$

Here, a is the measured hourly or instantaneous wind direction value.

Standard Deviation of Estimation (SDe). The standard deviation of the model estimates is given by:

$$SD_e = \left[\ \frac{1}{N}\sum_{i=1}^{N} |\Phi_{ei} - M_e|^2\ \right]^{1/2}$$

Standard Deviation of Observations (SDo). The standard deviation of the observations is given by:

$$SD_o = \left[\ \frac{1}{N}\sum_{i=1}^{N} |\Phi_{oi} - M_o|^2\ \right]^{1/2}$$

Least Square Slope and Intercept Regression Statistics. A linear least-squares regression is performed to calculate the intercept (a) and slope (b) parameters in the following equation:

$$\hat{\Phi}_{ei} = a + b\ \Phi_{oi}$$

This regression is performed for each set of hourly (or instantaneous) data to facilitate calculation of several error and skill statistics.

Difference Statistics. Several difference statistics are calculated, based principally on hourly residuals of model estimates and observations.

Residual (d_i). For quantities that are continuous in space and time (i.e., wind speed, temperature, pressure, pbl height, species concentrations) difference (or residual) statistics are very useful.

Difference statistics are based on the definition of a residual quantity. A mixing ratio residual, for

$$d_i = c_e(x_i, t) - c_o(x_i, t)$$

example, is defined as:

where d_i is the i-th residual based on the difference between model-estimated (c_e) and observed (c_o) mixing ratio at location x and time i.

Standard Deviation of Residual Distribution (SDr). The standard deviation of the residual distribution is given by:

$$SD_r = \left(\frac{1}{N-1} \sum_{i=1}^{N} (d_i - MBE)^2 \right)^{0.5}$$

where the residual is defined as:

$$d_i = c_e(x_i, t) - c_o(x_i, t)$$

and MBE is the first moment, i.e., the mean bias error, defined shortly. This statistic describes the "dispersion" or spread of the residual distribution about the estimate of the mean. The standard deviation is calculated using all estimation-observation pairs above the cutoff level. The second moment of the residual distribution is the variance, the square of the standard deviation. Since the standard deviation has the same units of measure as the variable (e.g., meters/sec for wind), it is used here as the metric for dispersion. The standard deviation and variance measure the average "spread" of the residuals, independent of any systematic bias in the estimates. No direct information is provided concerning subregional errors or about large discrepancies occurring within portions of the diurnal cycle although in principle these, too, could be estimated.

Accuracy of Peak Model Estimates (A). Five related methods are used to evaluate the accuracy of the model's estimate of the maximum value of a spatially distributed variable. This may be, for example, temperature, wind speed, pressure, or concentration. In the definitions below we use the peak one-hour average mixing ratios for discussion purposes; however, these measures may be applied to other meteorological variables as well.

Several accuracy measures are used because there are different, informative, and plausible ways of comparing the peak measurement on a given day with model estimates. These five accuracy measures provide complimentary tests of the model's performance.

Paired Peak Estimation Accuracy. The paired peak estimation accuracy, A_{ts}, is given by:

$$A_{ts} = \frac{c_e(\hat{x}, \hat{t}) - c_o(\hat{x}, \hat{t})}{c_o(\hat{x}, \hat{t})} 100\%$$

A_{ts} quantifies the discrepancy between the magnitude of the peak one-hour average mixing ratio measurement at a monitoring station, $c_o(\hat{x},\hat{t})$, and the estimated mixing ratio at the same location, $\hat{x}$, and at the same time, $\hat{t}$. Model estimates and observations are thus "paired in time and space." The paired peak estimation accuracy is a stringent model evaluation measure. It quantifies the model's ability to reproduce, at the same time and location, the highest observed mixing ratio during each day of the episode. The model-estimated mixing ratio used in all comparisons with observations is derived from bi-linear interpolation of the four ground level grid cells nearest the monitoring station.

A_{ts} is very sensitive to spatial and temporal misalignments between the estimated and observed mixing ratio fields. These space and time offsets may arise from spatial displacements in the transport fields resulting from biases in wind speed and direction, problems with simulation of water vapor phase changes, precipitation processes, or subgrid-scale phenomena that are not intended to be resolvable by mesoscale prognostic models.

Temporally-Paired Peak Estimation Accuracy. The temporally-paired peak estimation accuracy, A_t, is given by:

$$A_t = \frac{c_e(x,\hat{t}) - c_o(\hat{x},\hat{t})}{c_o(\hat{x},\hat{t})} \, x \; 100\ \%$$

A_t quantifies the discrepancy between the highest measurement at a monitoring station and the highest model estimate at the same station or any other grid cell within a distance of, say, 25 km. This measure examines the model's ability to reproduce the highest observed value in the same subregion at the correct hour.

Spatially-Paired Peak Estimation Accuracy. The spatially-paired peak estimation accuracy, A_s, is given by:

$$A_s = \frac{c_e(\hat{x},t) - c_o(\hat{x},\hat{t})}{c_o(\hat{x},\hat{t})} \, x \; 100\ \%$$

A_s quantifies the discrepancy between the magnitude of the peak one-hour average measurement at a monitoring station and the highest estimated value at the same monitor, within 3 hours (before or after) the peak hour.

Unpaired Peak Estimation Accuracy. The unpaired peak estimation accuracy, A_u, is given by:

$$A_u = \frac{c_e(x,t) - c_o(\hat{x},\hat{t})}{c_o(\hat{x},\hat{t})} \, x \; 100\ \%$$

A_u quantifies the difference between the magnitude of the peak one-hour average measured value and the highest estimated value in the modeling domain, whether this occur at a monitoring station or not. The unpaired peak estimation accuracy tests the model's ability to reproduce the highest observed value anywhere in the region. This is the least stringent of the above four peak estimation measures introduced thus far. It is a weak comparison relative to the previous ones but is useful in coarse screening for model failures. This measure quickly identifies situations where the model produces maximum values in the region that significantly exceed the highest observed values within the network.

Average Station Peak Estimation Accuracy. The average station peak estimation accuracy, A, is given by:

$$\overline{A} = \frac{1}{N}\sum_{i=1}^{N} |A_{si}|$$

where:

$$A_{si} = \frac{c_e(\hat{x}_i, t) - c_o(\hat{x}, \hat{t})}{c_o(\hat{x}, \hat{t})} \times 100\ \%$$

Here, x_i is the ith monitoring station location. A is calculated by first determining the spatially-paired peak estimation accuracy, Asi, at each monitoring station. Thus, the average station peak estimation accuracy is simply the mean of the absolute value of the A_{si} scores, where the temporal offset between estimated and observed maxima at any monitoring station does not exceed three hours.

Mean Bias Error (MBE). The mean bias error is given by:

$$MBE = \frac{1}{N}\sum_{i=1}^{N} (c_e(x_i, t) - c_o(x_i, t))$$

where N equals the number of hourly estimate-observation pairs drawn from all valid monitoring station data on the simulation day of interest.

Mean Normalized Bias Error (MNBE). The mean normalized bias error, often just called the bias, is given by:

$$MNBE = \frac{1}{N}\sum_{i=1}^{N} \frac{(c_e(x_i, t) - c_o(x_i, t))}{c_o(x_i, t)} \times 100\ \%$$

Mathematically, the bias is derived from the average signed deviation of the mixing ratio (or temperature) residuals and is calculated using all pairs of estimates and observations above the cutoff level.

Mean Absolute Gross Error (MAGE). The mean gross error is calculated in two ways, similar to the bias. The mean absolute gross error is given by:

$$MAGE = \frac{1}{N} \sum_{i=1}^{N} |c_e(x_i, t) - c_o(x_i, t)|$$

Mean Absolute Normalized Gross Error (MANGE). The mean absolute normalized gross error is:

$$MANGE = \frac{1}{N} \sum_{i=1}^{N} \frac{|c_e(x_i, t) - c_o(x_i, t)|}{c_o(x_i, t)} \text{ x } 100\ \%$$

The gross error quantifies the mean absolute deviation of the residuals. It indicates the average unsigned discrepancy between hourly estimates and observations and is calculated for all pairs. Gross error is a robust measure of overall model performance and provides a useful basis for comparison among model simulations across different model grids or episodes. Unless calculated for specific locations or time intervals, gross error estimates provide no direct information about sub-regional errors or about large discrepancies occurring within portions of the diurnal cycle.

Root Mean Square Error (RMSE). The root mean square error is given by:

$$RMSE = \left[\frac{1}{N} \sum_{i=1}^{N} |\Phi_{ei} - \Phi_{oi}|^2 \right]^{1/2}$$

The RMSE, as with the gross error, is a good overall measure of model performance. However, since large errors are weighted heavily, large errors in a small subregion may produce large a RMSE even though the errors may be small elsewhere.

Systematic Root Mean Square Error ($RMSE_S$). A measure of the model's linear (or systematic) bias may be estimated from the systematic root mean square error given by:

$$RMSE_s = \left[\frac{1}{N} \sum_{i=1}^{N} |\hat{\Phi}_{ei} - \Phi_{oi}|^2 \right]^{1/2}$$

Unsystematic Root Mean Square Error ($RMSE_U$). A measure of the model's unsystematic bias is given by the unsystematic root mean square error, that is:

$$RMSE_u = \left[\frac{1}{N} \sum_{i=1}^{N} |\Phi_{ei} - \hat{\Phi}_{ei}|^2 \right]^{1/2}$$

The unsystematic difference is a measure of how much of the discrepancy between estimates and observations is due to random processes or influences outside the legitimate range of the model.

A "good" model will provide low values of the root mean square error, RMSE, explaining most of the variation in the observations. The systematic error, $RMSE_s$ should approach zero and the unsystematic error $RMSE_u$ should approach RMSE since:

$$RMSE^2 = RMSE_u^{\ 2} + RMSE_s^{\ 2}$$

It is important that RMSE, $RMSE_s$, and $RMSE_u$ are all analyzed. For example, if only RMSE is estimated (and it appears acceptable) it could consist largely of the systematic component. This bias might be removed, thereby reducing the bias transferred to the photochemical model. On the other hand, if the RMSE consists largely of the unsystematic component ($RMSE_u$), this indicates further error reduction may require model refinement and/or data acquisition. It also provides error bars that may used with the inputs in subsequent sensitivity analyses.

Skill Measures. Three model skill measures are calculated, principally for the meteorological models.

Index of Agreement (I). Following Willmont (1981), the index of agreement is given by:

$$I = 1 - \left[\frac{N\ (RMSE)^{\ 2}}{\sum_{i=1}^{N} \left(|\Phi_{ei} - M_o| + |\Phi_{oi} - M_o| \right)^2} \right]$$

This metric condenses all the differences between model estimates and observations into one statistical quantity. It is the ratio of the cumulative difference between the model estimates and the corresponding observations to the sum of two differences: between the estimates and observed mean and the observations and the observed mean. Viewed from another perspective, the index of agreement is a measure of how well the model estimates departure from the observed mean matches, case by case, the observations' departure from the observed mean. Thus, the correspondence between estimated and observed values across the domain at a given time may be quantified in a single metric and displayed as a time series. The index of agreement has a theoretical range of 0 to 1, the latter score suggesting perfect agreement.

RMS Skill Error ($Skill_e$). The root mean square error skill ratio is defined as:

$$Skill_E = \frac{RMSE_u}{SD_o}$$

Variance Skill Ratio ($Skill_{var}$). The variance ratio skill is given by:

$$Skill_{Var} = \frac{SD_e}{SD_o}$$

5.1.2 Graphical Tools

Many features of model simulations are best analyzed through graphical means. In addition to revealing important qualitative relationships, graphical displays also supply quantitative information. The main graphical displays used to analyze the meteorological and air quality model performance results include:

> The temporal correlation between estimates and observations;

> The spatial distribution of estimated ground-level fields;

> The correlation among hourly pairs of estimates, observations and residuals;

> The variation in bias and error estimates as functions of time and space;

> The degree of mismatch between volume-averaged model estimates and point measurements; and

> Log p/Skew-T plots of wind, temperature and mixing ratio.

These plotting methods are exemplified in the many recent model evaluation studies cited in the reference section.

5.2 Meteorological Model Evaluation Methodology

The goal of the MM5/RAMS model inter-comparison was to (a) assess whether and to what extent confidence may be placed in the MM5 and/or RAMS modeling systems to provide wind, temperature, mixing, moisture, and radiation inputs to the CAMx and MAQSIP models for the 26-28 June 1991 and 17-19 July 1991 LMOS episodes, and (b) to compare and contrast the performance of the two models amongst themselves. We re-emphasize that the term "modeling system " refers to the main MM5 or RAMS source code, its preprocessor and data preparation programs, the mapping routines, and the supporting data base. Two factors limit the technical rigor with which the two models can be compared:

> **Inconsistent Grid Domains and Resolutions Between the MM5 and RAMS Applications:** In the planning of the MM5 modeling under CRC Project A-11 and the Illinois EPA RAMS3c modeling studies, there was apparently no coordination in the choice of grid domains and horizontal resolution. For example, the MM5 grid nesting scheme consists of horizontal grid scales of 4 km, 12 km, and 36 km, respectively. In

contrast, the RAMS nesting scheme employs nests of 13.5 km and 4.5 km resolution. In addition to this inconsistency between the horizontal scale of resolution (i.e., 4 km vs. 4.5 km; 12 km vs. 13.5 km), the domains chosen at each horizontal scale differ widely. For example, the RAMS modeling domain at 13.5 km scale most closely corresponds to the MM5 domain at 36 km scale. The result of this inconsistency between horizontal grid resolution and domain scale is that direct comparisons between models at the same or similar horizontal grid resolutions or over comparable physical domains is not possible.

> **Evaluation Based on Processed Meteorological Fields Rather than Raw Model Output:** Ideally, the evaluation of the meteorological models would be performed in two stages: with the direct output from the prognostic model, and with the final input to the air quality model. Since neither the MM5 or RAMS models were operated on the identical grid meshes as the CAMx or MAQSIP air quality models, some form of mapping of the meteorological files onto the air quality grids is necessary. Since these intermediary processors modify the prognostic model outputs in potentially important ways, an evaluation before and after is vital. However, due to resource constraints, only the simplest form of comparison was feasible: inter-comparing the air quality model-ready MM5 and RAMS meteorological files rather than a comparison between the prognostic model outputs.

Chapter 6 presents the highlights of the MM5 and RAMS comparative performance evaluation. Full details of the investigation are presented in the companion report by Tesche and McNally (1999).

5.3 Photochemical Model Evaluation Methodology

The objective of the CAMx and MAQSIP model evaluations was to test the models' ability to reliably estimate ground level and aloft ozone, precursor, and product species concentrations based on routine and special studies measurements collected in the Lower Lake Michigan during the 26-28 June and 17-19 July 1991 LMOS field programs. As part of this testing process, specific sensitivity simulations are included to examine the response of the model=s to prescribed VOC and/or NOx emissions reductions as well as to changes in grid nesting structure and the use of sub-grid-scale paremeterizations of point source plumes (i.e., Plume-in-Grid treatments). In analyzing the evaluation results, we seek to identify areas of similarity and dissimilarity in the two model=s responses. The air quality model evaluation will be carried out in two-phased process beginning with the simplest comparisons of model estimates and observations, progressing to more illuminating analyses of model sensitivity and uncertainty.

5.3.1 Phase 1: Initial Screening

Phase 1 consists of an initial screening of the ground level ozone results for both episodes. This initial screening is aimed at identifying obvious flaws or deficiencies in the base case model simulations than require immediate, focused diagnostic analyses. If such deficiencies are not found it does not mean that the simulation base case is declared acceptable; rather, it indicates that the analysis shifts for more stressful testing of model performance (Phase 2 described below). The graphical procedures we find most useful include the following:

> Spatial mean time series plots;

> Time series plots at particular monitoring stations;

> Daily maximum ground-level tile plots;

> Scatterplots of hourly prediction/observation pairs; and

> Time series plots of mean normalized bias and gross error.

Useful statistical metrics (including those most commonly employed in the literature) include the accuracy of daily peak unpaired (time and space) prediction, daily mean normalized bias, daily mean normalized gross error, and the average (across all monitoring stations) of the daily peak unpaired prediction accuracy. In the aggregate, these four statistical measures and five graphical displays have been found to be a reliable set of procedures for assessing whether a particular simulation suffers from obvious flaws and/or performance problems. Lacking such a finding, one moves to the more rigorous and informative second phase of the evaluation.

We note that there has been (and continues to be) a tendency to terminate the model evaluation activity if the ozone performance results for the above metrics meet or exceed EPA=s so-called performance goals (EPA, 1991). However, ample experience has shown that model simulations passing EPA=s performance goals for accuracy, bias and error may still possess significant flaws and vice versa. Accordingly, in this study we place only very limited weight on whether the CAMx and MAQSIP evaluation results meet or surpass the EPA goals. Experience in modeling, we believe, is a better guide in judging the acceptability of a photochemical model base case.

5.3.2 Phase 2: Refined Evaluations

Phase 2 entails a more extensive evaluation of the base case model performance using, to the fullest extent possible, all available surface and aloft data for ozone, precursor species (VOCs and oxides of nitrogen), and pertinent ratios of precursor and/or product species. This refined evaluation is aimed at stressing the model to ascertain whether more subtle flaws or deficiencies in the base case model simulations exist than are revealed through simple inspection of the surface ozone results. If such deficiencies are not found in a models performance (say, for a precursor species such as PAR or NO) it does not necessarily mean that the overall simulation should be declared unacceptable; rather, it indicates that potential need to explore the matter further. For example, it would be unreasonable to expect a regional-scale model to perform well for NO concentrations immediately downwind of a major roadway segment since the model=s chemistry and physics are not formulated to treat such microscale phenomena. Certainly available data bases do not support such localized performance testing.

The chemical species to be evaluated in Phase II include ozone, PAR, NO_2, NOx, and NO_{xp}. where the latter species is actually the sum of NOx and PAN. These species will be evaluated at the surface and aloft contingent upon data availability (see below). Additional graphical displays will be employed for these precursor/product species similar to those used in Phase 1 for ozone. These new displays will be generated for the full set of precursor/product species presently available in the 1991 LMOS data base. Displays for species ratios (e.g.,O_3/NO_x, PAR/NO_x, and PAR/NO_{xp}) will also be developed. A full set of graphical displays and statistical results will be archived for each model configuration (CAMx/MM5, CAMx/RAMS, MAQSIP/MM5) and base case.

Supplemental graphical procedures to be used in Phase II include:

> Spatial maps of aircraft traverses over Lower Lake Michigan with superimposed time series plots of aircraft altitude, O_3 and NO_x concentration measurements;

> Maps of integrated ozone and NOx mass fluxes across transport planes;

> Time series plots of total mass accumulation rates at the ground and aloft.

If possible, we will compute 8-hr average ground level ozone performance statistics. Finally, appropriate statistical and graphical displays will be used to compare the output of the CAMx and MAQSIP models for each grid structure/emissions change simulation to help to identify the similarities and differences in model response to grid structure and/or emissions changes.

5.3.3 Available Aerometric Data for the Evaluations

Several reports from the LMOS program have described the air quality data collected and analyzed as part of the study (see, for example, Luria et al., 1992; Uthe et al., 1992; Main et al., 1993; Korc et al., 1993). Here we summarize briefly the surface and aloft air quality data available for our analysis.

Surface Air Quality Data

Data files containing hourly-averaged concentration measurements at numerous stations were provided by LADCo for both modeling episodes. These data sets were reformatted for use by MAPS. For the 26-28 June, 1991 episode, the following numbers of surface monitoring stations were represented in the data sets provided: ozone (68), NO (25), NO_2 (27), NO_x (27), and VOCs (15). A total of 10 stations had co-located measurements of NO_X and VOCs. For the 17-19 July, 1991 episode, the following numbers of surface monitoring stations were available: ozone (69), NO (24),

NO_2 (27), NO_x (27), and VOCs (15). As before, a total of 10 stations had co-located measurements of NO_x and VOCs.

Aloft Air Quality Data

Data sets from the various aircraft flights were also provided by LADCo. These sets were analyzed with the "Flying Data Grabber" routines in MAPS, producing a set of observation files that could be compared with corresponding photochemical model output. For the 26-28 June, 1991 episode, the total number of aircraft flights available for analysis included: ozone (29), NO (30) and NO_x (27). For the 17-18 July period, the available flights included: ozone (18), NO (18) and NO_x (17). Aircraft data were not collected on 19 July, 1991.