Ozone Exposure Assessment in a Southern California Community

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An ozone exposure assessment study was conducted in a Southern California community. The Harvard ozone passive sampler was used to monitor cohorts of 22 and 18 subjects for 8 weeks during the spring and fall of 1994, respectively. Ozone exposure variables included 12-hr personal O_3 measurements, stationary outdoor O_3 measurements from a continuous UV photometer and from 12-hr Harvard active monitors, and time–activity information. Results showed that personal O_3 exposure levels averaged one-fourth of outdoor stationary O_3 levels, attributable to high percentages of time spent indoors. Personal O_3 levels were not predicted well by outdoor measurements. A random-effect general linear model analysis indicated that variance in personal exposure measurements was largely accounted for by random error (59–82%), followed by inter-subject (9–18%) and between-day (9–23%) random effects. The microenvironmental model performs differently by season, with the regression model for spring cohorts exhibiting two times the R^2 of the fall cohorts (R^2 = 0.21 vs. 0.09). When distance from the stationary monitoring site, elevation, and traffic are taken into account in the microenvironmental models, the adjusted R^2 increased almost twofold for the fall personal exposure data. The low predictive power is due primarily to the apparent spatial variation of outdoor O_3 and errors in O_3 measurements and in time–activity records (particularly in recording the use of air conditioning). This study highlights the magnitude of O_3 exposure misclassification in epidemiological settings and proposes an approach to reduce exposure uncertainties in assessing air pollution health effects. *Key words*: active sampler, exposure assessment, ozone, passive sampler, time–activity pattern. *Environ Health Perspect* 105:58–65 (1997)

The current National Ambient Air Quality Standard (NAAQS) for ozone (O_3), 0.12 ppm, is based on the health effects due to acute exposures of 1 hr as measured by continuous monitors. However, exposures to O_3 for up to 8 hr at less than 0.12 ppm have been shown to result in progressive and significant changes in respiratory function in exercising individuals (*1–3*), suggesting that the current O_3 standard may not sufficiently protect public health. In response, one of the alternative O_3 standards being considered by the EPA is the 8-hr average concentration (*4*). The use of the integrated passive monitor to obtain exposures greater than 1 hr can greatly enhance our ability to determine the dose–response relationship for acute exposures to O_3. The 12-hr O_3 measurements are biologically significant when combined with the retention factor of O_3 in the deep lung and the ventilation rate to produce the 12-hr delivery dose of O_3 (*5*). Our recent epidemiologic study showed that these O_3 dose estimates, not 1-hr maximum O_3 measures at the stationary site, were associated with respiratory symptoms and inhaler use among asthmatics (*5*). Using the 12-hr personal measurements significantly reduces the magnitude of expected exposure misclassification in studies that have relied solely upon O_3 measurements from outdoor stationary site monitors to represent personal exposure to O_3.

Previous studies (*6–9*) that examined short-term (12-hr) personal O_3 exposures have involved relatively short monitoring periods, generally less than 5 days, or monitored less than five subjects simultaneously. Epidemiological research on the acute and adverse respiratory effects of O_3, on the other hand, generally involves repeated daily measurements over several weeks or months in larger cohorts (panel studies). To examine personal O_3 exposure and its determinants in a setting directly relevant to epidemiological research, the present exposure assessment study was integrated into two consecutive asthma panel studies. More precisely, this study involved daytime (12-hr) personal O_3 monitoring in cohorts of 23 and 18 subjects for two 8-week periods during the spring and fall of 1994, respectively. Extensive outdoor active monitoring throughout the study region was conducted during the fall period. Because of the diverse geographical characteristics of the study area, it was possible to examine variations of O_3 concentrations in a three-dimensional domain.

The purpose of this study was to investigate personal O_3 exposures among subjects during both spring and fall seasons in the Alpine area and to investigate the feasibility of using ambient O_3 measurements from one outdoor fixed site as well as the activity patterns from the subjects to pre-

dict personal O_3 exposures. This study further examined the influence of outdoor temperature on activity patterns and the effects of activity patterns on personal O_3 exposure levels. In addition, the extent of the effects of outdoor O_3 spatial variation on the predictive power of personal exposure models was investigated.

Methods

This study was conducted in the Alpine area of San Diego county, California. Alpine (population ~12,000) is located approximately 20 miles east of San Diego. Residents of the Alpine community live around or above the base of the average air inversion layer (1,200 ft or 366 m above sea level) (*10*). High levels of O_3 above 120 ppb have been measured on many days per year and a permanent government monitoring site (using a continuous UV photometric O_3 analyzer) has been in operation since 1981.

The Harvard O_3 passive sampler was used for personal monitoring. The principle of the sampler is oxidation of nitrite (NO_2^-) by O_3 to form nitrate (NO_3^-), which is quantified by ion chromatography (*11*). Field blanks (n = 184) and duplicate samples (n = 52) were used for quality assurance and quality control (QA/QC). The limit of detection (LOD), calculated as three times the standard deviation of the field blank values, was 17 ppb of O_3 for the 12-hr average samples. The uncertainty, defined as the variance of difference between duplicates divided by $\sqrt{2}$ (*12*), was 3 ppb.

Subjects recruited for the spring study included 9 males (mean age = 18 years; range = 10–38) and 13 females (mean age = 24 years; range = 10–47). Of these subjects, 13 were pediatric subjects and 9 were adults. Informed consent was obtained from all subjects who were monitored simultaneously from 9 May to 3 July 1994. During the fall, 18 subjects were monitored simultaneously from 6 September to 31 October 1994. These subjects included 11 males (mean age = 16 years; range = 9–38) and 7

females (mean age = 21 years; range = 9–38). Of these, 13 were pediatric subjects and 5 were adults. Fourteen subjects had been previously monitored in the spring. The monitoring duration was approximately 12 hr, starting when subjects awoke, generally between 6 and 8 A.M. Subjects were given clock-shaped time–activity diary forms to record activities (time indoors and outdoors, in Alpine area or outside Alpine area), the level of physical activities, and the use of air conditioning. The time resolution of the diary is 15 min.

The study area is located in a complex terrain, with an altitude ranging from less than 600 ft in the west to over 2,000 ft in the northeast (Fig. 1). During the fall study, in addition to the San Diego County Air Pollution Control District (APCD) monitoring sites at Alpine and El Cajon (west of Alpine), the Harvard O$_3$ active monitor (*13*) was used at 12 other outdoor locations chosen on the basis of providing a representative range of traffic volume and elevation in the community (Table 1). Passive samplers were collocated with four active monitors. The monitoring duration for the active samplers was 12 hr; samples were taken every other day (*n* = 22). The active monitor, based on the same chemical principle as the passive sampler, was designed to improve the passive method (*13,14*). This active sampler used a hollow tube denuder attached to a small personal pump (Model PAS-500, Spectrex Corp., Redwood City, CA). The denuder system consisted of a 1.4 cm (inside diameter) × 10 cm (length) etched borosilicate hollow glass tube attached to a personal pump, which maintained a constant sampling rate of 65 ml/min.

Samples were validated by examining the field and laboratory records and were removed when records justified it (e.g., broken or wet samples, unused samples, etc.). The LOD for the active method was 0.5 ppb for 12-hr monitoring during the fall study. The mean difference between the collocated active monitors was 3 ± 9 ppb (uncertainty = 7 ppb; *r* = 0.83). The mean difference between the collocated active and passive measurements were 0.2 ± 16 ppb (not different from zero; *r* = 0.48). Although the active monitors were designed to be an improved method, it was speculated that they exhibited leakage at the inlet and outlet connections in the system. Therefore, for data analysis, active measurements were vigorously screened for anomalies by removing outliers, which are defined as measurements over the 90th or under the 10th percentiles of the ratio of active to continuous measurement.

The data analysis was conducted in three major steps:

1. Descriptive statistics were performed for both spring and fall samples. Geometric means and standard deviations were calculated when skewed distributions were observed.

2. Personal exposure modeling was performed using time–activity patterns to account for differences in exposure across various microenvironments. General linear models (GLM) were used to examine random effects of day and subject on personal exposures. Personal exposure models were then developed using the microenvironmental exposure concept and multiple regression techniques. For microenvironmental modeling, average personal O$_3$ exposure is predicted as the sum of outdoor and indoor exposures:

$$\hat{E} = (0.8 \times C_o)F_o + (0.3 \times C_o)F_i \quad \text{(Model 1)}$$

where $\hat{E}$ = predicted personal exposures, C_o = outdoor O$_3$ concentration measured at the Alpine APCD site, F_o = fraction of time spent outdoors during the daytime period, and F_i = fraction of time spent indoors (without A/C) during the daytime period.

Model 1 assumes negligible O$_3$ exposures while subjects were indoors with air conditioning (A/C) on because of closed windows/doors and air filters known to scavenge O$_3$ (*15*). The coefficients in the model are based on our earlier study results (*9*) in which the home outdoor O$_3$ levels were, on average, 80% of those measured at the closest outdoor monitoring sites and the mean indoor-to-outdoor ratio was 0.3.

In addition, multiple regression models were used to predict personal exposures ($\hat{E}'$) and to compare with results from Model 1:

$$\hat{E}' = \alpha_1 \times C_o \times F_o + \alpha_2 \times C_o \times F_i + \alpha_3 \times C_o \times F_a \quad \text{(Model 2)}$$

where F_a = fraction of time spent indoors with A/C on. The split sample approach (*16*), in which samples were randomly split into two groups for model construction, was used to examine model reliability. Colinearity also was examined by calculating the condition index.

3. Factors considered to affect the prediction power of the microenvironmental

models were examined and included: outdoor spatial variation, indoor O$_3$ concentration variation, and the measurement error resulting from analytical error and from subjects' compliance. Note that there is currently no true gold-standard measure of personal O$_3$ exposures. The passive monitor, in spite of being the most direct measure of personal O$_3$ exposure, has not been validated in natural settings in which the study subject is freely mobile. The personal passive measurements were used in this paper as a reference value for personal exposures.
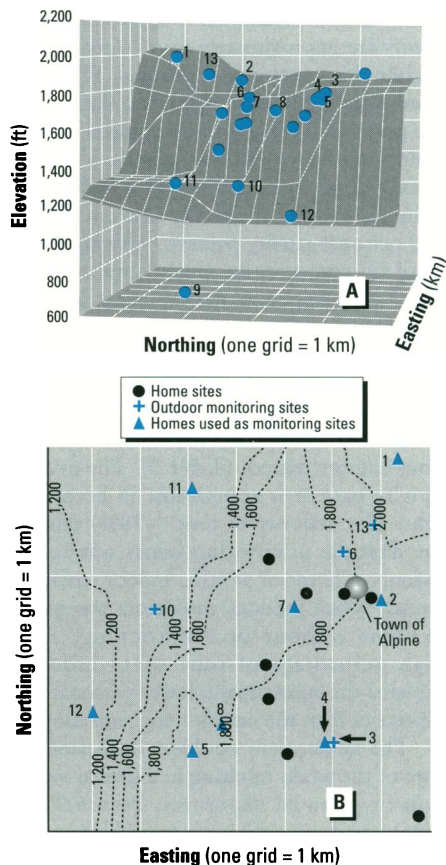

Figure 1. (A) A three-dimensional view of the study area (northing to the left for easy viewing). Filled circles represent the location of the 18 subjects' homes, the Alpine APCD site (numbered 13), and the 12 additional outdoor monitoring sites (numbered from 1 to 12). (B) The projected two-dimensional topography for the Alpine area (northing upward for conventional viewing).

Table 1. Stationary monitoring sites selected to represent the range of average weekday traffic volume and elevation in the community

Traffic volume	Elevation (ft above sea level)			
	>2,000	1,750–2,000	1,250–1,750	775–1,250
>30,000 (high)	—	Site 2	Site 6(S)	Site 9
20,000–30,000 (medium)	Alpine APCD site 13	Sites 3(S) and 4	Site 7	Sites 10(S) and 11
<20,000 (low)	Site 1	Site 5	Site 8	Site 12

Site 13 is the Alpine Air Pollution Control District continuous monitoring site; sites 3, 6, 10 were located at schools (S), while other sites were located outside subjects' homes.

Results

Descriptive statistics. During the spring monitoring period (56 days), hourly outdoor O_3 concentrations measured at the Alpine APCD site ranged between 1 and 147 ppb, averaging 49 ± 26 ppb. During the 56 12-hr daytime periods, there were 7 hr (in 5 days) when hourly O_3 concentrations exceeded the NAAQS. In the fall study, the average hourly outdoor O_3 concentration was lower than that in the spring. It ranged between 0 and 118 ppb, averaging 45 ± 20 ppb and never exceeding the NAAQS. Table 2 shows the descriptive statistics for both spring and fall 12-hr integrated samples. Outdoor measurements are approximately four to five times higher than personal exposures. Figure 2 demonstrates the variability of the daily average personal exposures across subjects for the spring and fall monitoring periods. Variance among subjects differs by day due to the variation in daily outdoor O_3 concentrations and personal activity patterns. Although personal O_3 exposures are much lower on average than continuous measurements in both seasons, the contrast is notably greater in the fall (Fig. 2B vs. 2A).

The difference between personal exposures and outdoor continuous measurements can be partly explained by the time–activity pattern (Table 3). The overall activity pattern is comparable in both seasons. The majority of time (~70%) during the daytime monitoring hours was spent indoors at home or at other indoor environments. When indoors, most time was spent at home without air conditioning. This high percentage of time spent indoors explains the substantially lower personal O_3 exposures than the outdoor concentrations.

The hours spent outdoors fluctuated by days of the week, resulting in a similar variation in personal exposures. Personal O_3 exposures during the spring are highest on Saturdays and lowest on Mondays and Tuesdays. The mean personal exposure on Saturdays is 22.6 ppb, while the mean on other weekdays and Sundays is 17.3 (two-sample *t*-test *p*<0.001). A similar trend was observed for outdoor O_3 measurements at the Alpine APCD site. This weekend effect has been observed in several California cities and has been attributed to weekday to weekend emission reductions in NO_x and nonmethane hydrocarbon (due to less commuter driving), which result in reduction in O_3 formation (*17*). Using the GLM for personal exposures and controlling for the subject effect, the effect of days of the week was found to be significant for both personal O_3 exposures (*p*<0.001) and activity pattern (percent time spent outdoors) (*p*<0.001) in both seasons. Evidently, personal O_3 exposures over weekends were elevated due to the

greater number of hours spent outdoors and reinforced by higher outdoor O_3 levels on Saturdays and Sundays.

Modeling personal exposures. Factors that affect personal O_3 exposures were further examined with random effects GLM in which personal O_3 exposures were regressed on day of study and subject. Day-of-study and subject effects were found to be significant in both seasons (*p*<0.01). The day-of-

Table 2. Statistics for the spring and fall O_3 samples collected from subjects, the Alpine air pollution control district (APCD), the 4 colocated passive monitoring sites, and the 12 additional active monitoring sites

	Spring		Fall			
	Passive	Continuous	Passive		Active	Continuous
	Personal[a]	APCD site	Personal[a]	Stationary	Stationary	APCD site
Number	90.4	56	741	77	231	56
Mean	13.6	63.1	10.5	45.1	44.0	54.5
Median	15.5	59.7	12.7	42.9	44.9	54.5
SD	2.5	16.3	2.5	15.5	15.2	12.1

[a]Geometric statistics were justified given a lognormal distribution.
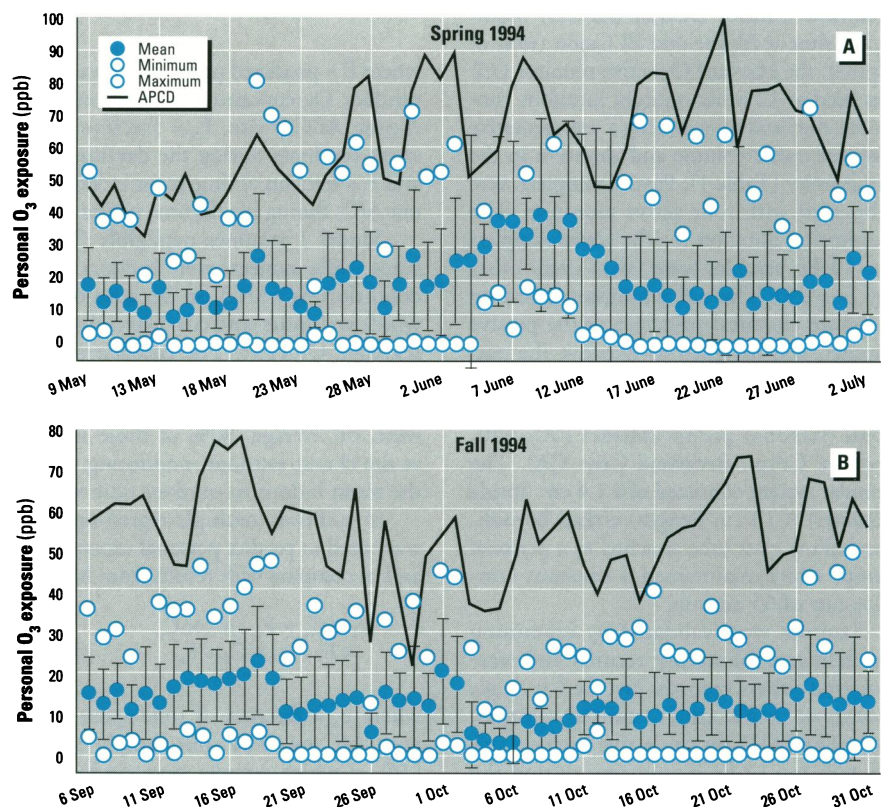

Figure 2. The daily average personal exposures across subjects. Error bars indicate SD. The outdoor Alpine air pollution control district (APCD) measurements are shown as the solid line.

Table 3. The fraction of time spent in different microenvironments during spring and fall monitoring periods[a]

Microenvironment	Air conditioning	Spring Mean ± SD	Fall Mean ± SD
Home outdoors	—	0.22 ± 0.19	0.20 ± 0.14
Outdoors in other areas	—	0.05 ± 0.13	0.03 ± 0.10
Home indoors	Off	0.59 ± 0.27	0.62 ± 0.24
	On	0.05 ± 0.15	0.07 ± 0.17
Other indoors	Off	0.05 ± 0.14	0.03 ± 0.09
	On	0.01 ± 0.06	0.01 ± 0.03
Left San Diego County	—	0.01 ± 0.10	0.00 ± 0.03
Missing or unclear data	—	0.01 ± 0.07	0.03 ± 0.14

[a]Statistics are for average time fractions across 22 subjects in the spring and 18 subjects in the fall.

study effect is a manifestation of the daily variation in outdoor O_3 concentrations and the average activities of subjects, as well as meteorological factors such as temperature, which impacts photochemical oxidation rates, subject activities, and A/C use. The subject effect reflects the variation in time–activity patterns from one subject to another. The random error accounts for unmeasured determinants of personal O_3 exposure not predicted by the subject and day variables, such as variation within activity patterns of individual subjects, compliance, and measurement errors. For spring personal exposures, the random error accounts for 59% of the variance (R^2) of individual observations, while intersubject and between-day variations comprise 18% and 23% of the variance, respectively. For fall personal exposures, the random error accounts for most (82%) of the variation in personal exposure measurements (intersubject R^2 = 9%; inter-day R^2 = 9%). These large random errors are due partly to the variation in day-to-day individual activities as well as to the low O_3 measurements.

Spring personal exposures. The results of the above GLM analysis indicate the importance of the individual activities in personal O_3 exposure modeling. This concept is illustrated with microenvironmental models that include the time–activity information as well as outdoor O_3 measurements. The predictive equation (Model 1) explains 20% (R^2 = 0.20) of the variance in the measured personal O_3 exposures. The slope of the regression line for Model 1 is almost unity (0.99 ± 0.02). The mean of the predicted values is 27.6 ppb, while the mean of the measured values is 24.7 ppb. For comparison, the regression model with the outdoor measurements (C_o) at the Alpine APCD site as the sole predictor for personal exposures resulted in an R^2 of 0.04 only ($p<0.001$).

The multiple linear regression equation (Model 2), which includes indoor exposures with A/C on, results in an R^2 of 0.21 (Table 4). The coefficient for outdoor exposure was 0.52, smaller than the 0.8 used in Model 1. This difference may be due to the variation in elevation and traffic counts in the community and thus the differences in outdoor O_3 concentrations between home and the Alpine APCD site. The coefficient for indoor exposures without A/C is comparable to the mean Toronto indoor/outdoor ratio (0.3). The coefficient for indoor exposures with A/C on (0.22; $p<0.001$) implies that indoor exposure exists even when windows are closed and the A/C is on. The R^2 value for Model 2 is low; however, when Model 2 is constructed for each subject, the resultant R^2 values range between 0.07 and 0.85. This indicates that the variation in the ability of the model to predict individual exposures is large and may be attributable to the performance of the sampler as well as the subjects' compliance to the monitoring protocol. The reliability of Model 2 is further validated using the split sample approach (*16*). The difference in R^2 values between the models that use two randomly split data sets is 0.03, and the difference in R^2 between Model 2 and the models that use either split data set is less than 0.02.

Fall personal exposures. The same modeling effort was carried out for fall personal exposures. First, outdoor measurements, C_o at the Alpine APCD site, are used to predict personal exposures (Ê), resulting in an R^2 of 0.07 (Ê = 0.23 C_o; $p<0.001$). A similar R^2 of 0.06 ($p<0.001$) is found when Model 1 is used to predict personal exposures, with model predictions generally overestimating personal exposures (estimated = 20.5 ± 7.9 ppb; measured = 12.7 ± 10.2 ppb; n = 663). The slope of the regression line for the predicted versus measured values is 1.06 ± 0.03. This higher random error in the fall model as opposed to the spring model may be attributable to the lower personal O_3 exposures, which may result in a higher measurement error.

The multiple linear regression model (Model 2) results in an R^2 of 0.09 (Table 4). The split sample approach also was used to examine the model reliability. The difference in R^2 values between the split data sets is 0.01, demonstrating the reliability of the model. For Model 2, the regression coefficients from the fall data are smaller than those used for Model 1. In particular, the coefficient for indoor exposure with A/C off (E_i) is smaller than that with A/C on (E_a). The adequacy of the regression model regarding potential colinearity problems was further examined by calculating the condition indices. Results show small condition index values for all independent variables (≤ 8), indicating that colinearity is not a problem in the models and that coefficients are stable; however, we suspect that the regression coefficients for indoor exposures with A/C on or off are inaccurate. It was observed during the study that despite instructions, young subjects might not have accurately recorded the use of A/C at school. The following sections investigate further possible modeling errors for the fall study results.

Time–Activity Patterns Versus Exposures

The results of our study show that peak O_3 concentrations occur at times when subjects are likely to be outdoors, as shown in Figure 3. Therefore, peak exposures should occur between 11 A.M. and 1 P.M., when subjects were likely to be outdoors. However, even at the peak of the outdoor activity profile, less than 35% of the time was spent outdoors. Therefore, subjects were generally not exposed to the high outdoor O_3 concentrations as would have been measured by the outdoor monitors.

In addition to the hour of the day, whether subjects spent their time outdoors also depended on the temperature. As shown in Figure 4, outdoor activities increase with temperature between 50 and 70°F. When the temperature is higher than
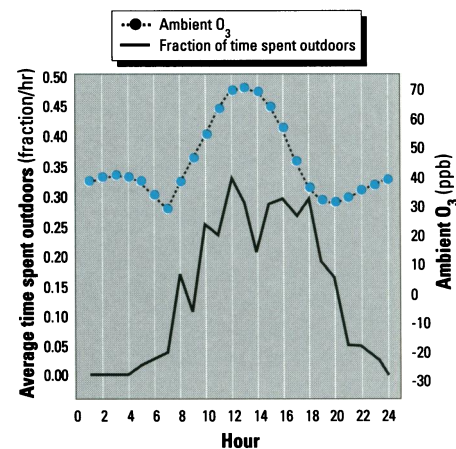

Figure 3. The average outdoor activity profile (fraction of time spent outdoors during each hour) and the outdoor O_3 concentrations in the fall. (Note that the tails of the activity profile span over the nominal 12-hr daytime monitoring period to include activities from those who awoke early or late.)

Table 4. Coefficients and R^2 values for Model 2 using the entire data set for predicting personal O_3 exposures in spring and fall

Season	Variable	Coefficient	Number	Mean	Model		R^2
					F-value	p-value	
Spring	E_o	0.52 ± 0.02*	523	24.69	45.36	<0.0001	0.21
	E_i	0.33 ± 0.01*					
	E_a	0.22 ± 0.04*					
Fall	E_o	0.39 ± 0.03*	652	12.79	21.38	<0.0001	0.09
	E_i	0.18 ± 0.01*					
	E_a	0.25 ± 0.04*					

Abbreviations: E_o, outdoor exposure; E_i, indoor exposure without air conditioner; E_a, indoor exposure with air conditioner on.
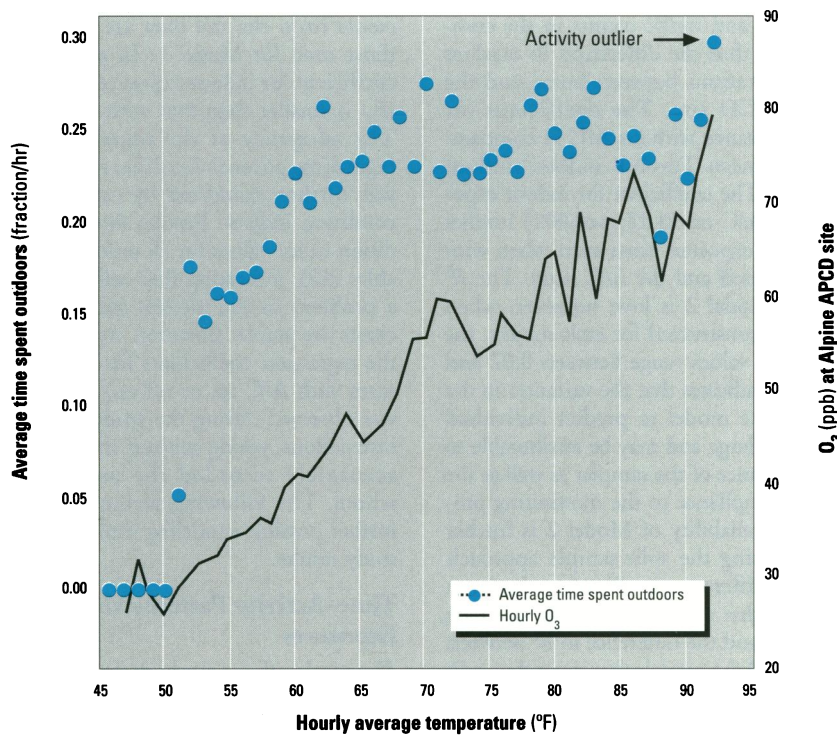*$p<0.001$.

Figure 4. Average fraction of time in the hour spent outdoors for all subjects and outdoor O_3 concentrations measured at the Alpine air pollution control district (APCD) site as a function of temperature.
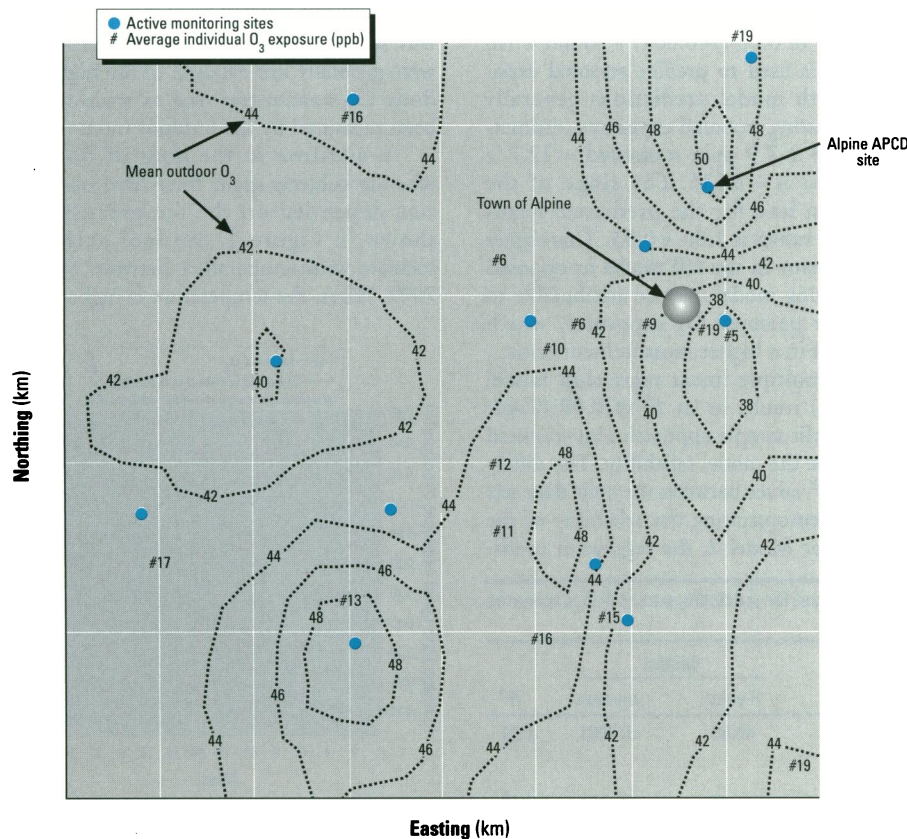

Figure 5. Contour plot of the average outdoor O_3 concentrations measured at the 13 outdoor active sites over the fall study period. # Indicates the average exposure for each individual during the fall, shown at the subject's home location. APCD, air pollution control district.

70°F, outdoor activities reach a plateau and decrease slightly at very high temperatures except for one high outdoor-activity outlier, which occurred primarily (95% of the observations) on Saturdays. Subjects tend to remain indoors to escape high temperatures; thus they unintentionally avoid high O_3 exposures. We expected that the percentage of A/C usage would be high while subjects were indoors and outdoor temperatures were high, especially during school hours. Although the reported A/C usage (percent of time A/C on while subjects are indoors) and the corresponding hourly outdoor temperature are well correlated ($R^2 = 0.88$), no more than 35% of the subjects reported using A/C even when the temperature exceeded 90°F. While this may be true at home when electricity costs are a concern, it should not be the case at the four schools in the area where the A/C is operated either manually by teachers or automatically. Reporting errors could have contributed to the low percentage of A/C use, which in turn results in an overestimation of personal O_3 exposure in the above models. To adjust for this potential bias, we developed a model by assuming that there is a linear relationship between A/C use and outdoor temperature and that most A/Cs are on at temperatures greater than 80°F. However, with this A/C model, the predictive power (R^2) of Model 1 was not improved, although the mean of the predicted values is closer to that measured. We also further examined the first term in Model 1 ($0.8 \times C_o \times F_o$), i.e., the spatial variation in O_3 exposure in relation to the stationary site levels.

Spatial Variation

Continuous measurements. Because of the high altitude, O_3 concentrations at the Alpine APCD site (622 m, mean O_3 = 54 ppb) are always higher than those at the nearby El Cajon APCD site (200 m, mean O_3 = 41 ppb). In addition, O_3 levels at these two locations did not follow the same trend. The correlation between these two continuous measurements depends on the averaging time period. The R^2 for hourly O_3 concentrations at these two sites is 0.38. The R^2 decreases when longer averaging durations for O_3 concentrations are used, especially when averaging duration extends into early morning (before 7 A.M.) or late evening (after 7 P.M.). It is possible that the radiation inversion layer may at times be lower than the Alpine APCD site, especially after sunset and before sunrise. In this case, O_3 aloft did not mix with the air underneath, resulting in higher O_3 concentrations at the higher altitude Alpine APCD site than at the El Cajon APCD site. This observation may explain in part

the low R^2 for exposure models based on stationary measurements.

Active measurements. The spatial pattern of outdoor O_3 concentrations in the Alpine area is further examined using the active O_3 measurements at the additional monitoring sites (Fig. 1). The contour plot for the average outdoor O_3 concentrations in fall (Fig. 5) shows that sites near the town of Alpine have the lowest O_3 concentration while sites at the highest elevations have the highest O_3 concentration. Table 5 summarizes O_3 concentrations at different elevations and traffic conditions. The mean outdoor O_3 concentrations at elevations less than 600 m are comparable. The mean concentration for sites located at elevations greater than 600 m is on average 10 ppb higher than others. Ozone concentrations at locations in low to medium traffic areas are on average 5 to 6 ppb higher than those located in heavy traffic areas. The GLM results indicate that after controlling for the effect of day of study, both traffic ($p<0.01$) and elevation ($p<0.001$) trends are significant. To predict O_3 concentrations at the active sites, continuous measurements at the Alpine APCD site are first used as the only predictor in a regression model ($R^2 = 0.49$). However, the multiple regression model, which includes traffic conditions (1, light; 2, medium; 3, heavy), distance between the active and Alpine APCD sites, and elevation, only improves the predictions slightly ($R^2 = 0.53$).

Personal measurements. The cross-sectional correlation was calculated to further compare personal exposures with the Alpine APCD site measurements. The R^2 varies substantially by subject, ranging between 0 and 0.25. The low R^2 may be attributed in part to the spatial variability in outdoor O_3 concentrations. Figure 6 shows the relationship between individual R^2 values and the distance between the subject's home and the Alpine APCD site. A decreasing correlation with distance for possibly two groups of subjects is observed. The first group, above the fitted curve, exhibits a higher correlation with the Alpine measurements even at distance as far as 12 km. The second group shows a rapid decrease in R^2 with distance. Most subjects in the first group (five out of six) live in areas with low to medium traffic, which are comparable to the traffic conditions at the Alpine APCD site. This contrasts with the second group, with subjects living in areas with medium to heavy traffic.

To examine the effect of this spatial variability, the microenvironmental model is modified by adding predictive factors, including traffic conditions, three-dimensional distance from the home (or school for students during weekdays) to the Alpine APCD site, and the difference in

Table 5. Summary statistics of O_3 concentrations at different elevations (grouped for equal sample size) and traffic density

Parameter	Level (m)	Ozone concentration (ppb)				
		No.	Mean	SD	Minimum	Maximum
Elevation	<400	57	42.0	14.8	9.7	71.6
	500–550	58	42.9	14.0	12.4	64.1
	551–600	69	43.7	16.0	9.0	97.0
	601–700	76	53.0	13.3	17.5	77.6
Traffic	Low	75	46.4	15.8	14.8	97.0
	Medium	101	45.0	14.6	9.7	73.3
	High	57	40.5	14.1	9.0	68.4

SD, standard deviation.

elevation between the home (or school) and the Alpine APCD site (Table 6). Because subjects tended to be outdoors during O_3 peak hours (Fig. 3), the daily 1-hr maximum O_3 concentration is also used as a predictor. The ability to predict personal exposures for the models using the APCD site 12-hr mean O_3 (Model 3, Table 6) is not notably different from that using the APCD site 1-hr maximum O_3 measurements (Model 4, Table 6).

When distance, difference in elevation, and traffic conditions are added (Model 5, 6, Table 6), the adjusted R^2 increased twofold. To advance the modeling effort, school site measurements as well as the spatial interpolation model predictions, including kriging and inverse distance predictions, were used to predict outdoor O_3 concentrations. The predicted values were then used in Models 5 and 6 (Table 6) to replace C_o. However, these models did not improve the R^2 values.
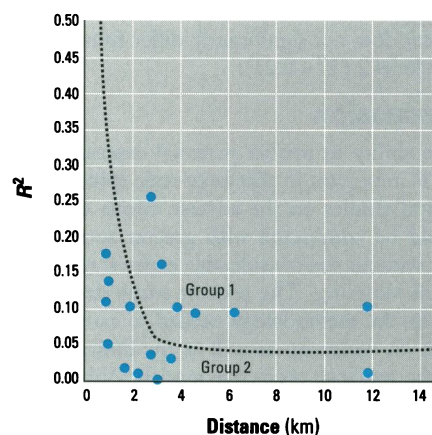

Figure 6. R^2 for personal exposures and the Alpine air pollution control district (APCD) site measurements for individual subjects as a function of the three-dimensional distance between the subjects' home and the Alpine APCD site. (Note that subjects did not always stay home and that the distances are only an approximation.) Curve fit: $R^2 = 0.04 + e^{-0.95x}$.

Table 6. Microenvironmental models for personal exposures during the fall study period

Model	Variable	Major predictor (C_o)	Coefficient	Adjusted R^2
3	Intercept	Mean O_3	0.52 ± 1.78	0.10
	E_o		0.36 ± 0.05**	
	E_i		0.17 ± 0.03**	
	E_a		0.23 ± 0.05**	
4	Intercept	Maximum O_3	0.52 ± 1.58	0.11
	E_o		0.25 ± 0.03**	
	E_i		0.13 ± 0.02**	
	E_a		0.16 ± 0.03**	
5	Intercept	Mean O_3	3.59 ± 2.85	0.17
	E_o		0.32 ± 0.04**	
	E_i		0.19 ± 0.03**	
	E_a		0.21 ± 0.05**	
	Traffic		-2.37 ± 0.79*	
	Distance		1.43 ± 0.42**	
	dZ		0.02 ± 0.01**	
6	Intercept	Maximum O_3	3.45 ± 2.72	0.19
	E_o		0.22 ± 0.03**	
	E_i		0.13 ± 0.02**	
	E_a		0.14 ± 0.03**	
	Traffic		-2.29 ± 0.78*	
	Distance		1.45 ± 0.42**	
	dZ		0.02 ± 0.01**	

Abbreviations: E_o, outdoor exposure, $C_o \times F_o$; E_i, indoor exposure without A/C, $C_o \times F_i$; E_a, indoor exposure with A/C on, $C_o \times F_a$; Traffic, traffic condition near subject's home (high, medium, and low); Distance, distance between home and the Alpine APCD sites (km); dZ, elevation difference between home and the Alpine APCD sites (m). C_o is the 12-hr mean (Model 3, 5) or hourly maximum (Model 4, 6) O_3 concentration at the Alpine APCD site.
*p-value <0.01.
**p-value <0.001.

Colinearity was examined for all models. The highest correlation between the independent variables is 0.64 between distance and elevation difference. The tolerance values for all independent variables are greater than 0.1 and the condition index values are smaller than 20. Therefore, colinearity is not evident for any models. For the spring model, when additional variables for distance, elevation, and traffic conditions were added to predict 12-hr personal exposures, the R^2 (adjusted R^2 = 0.22; significant predictors include outdoor and indoor exposures, traffic, and distance) does not significantly differ from that of Model 2 (R^2 = 0.21).

Discussion

The ability to predict personal exposure to O_3 is important in that large-scale epidemiological studies on the adverse effects of O_3 could be conducted with greater accuracy but without the considerable expense of personal sampling. The present study demonstrates the methodology needed to carry out such an endeavor, as well as the limitations of the resultant predictive models. Although the models reported here are unlikely to fulfill the need for accurate exposure assessment in an epidemiological setting, they do provide valuable insight into the determinants of O_3 exposure and the relevance of outdoor stationary site measurements to exposure.

For instance, personal exposures to O_3 were found to differ by the days of the week. More time is spent outdoors on weekends, when outdoor O_3 concentrations are higher, than on weekdays. During the daytime period, more time is spent outdoors during the period when outdoor O_3 peaked. Personal exposures are therefore enhanced by such activity patterns. Nevertheless, subjects do not spend a significant percentage of time outdoors (<35% at the peak of the activity profile). Since most of the time is spent indoors, cumulative indoor O_3 exposures are important. Indoor O_3 concentrations, however, vary with the ventilation conditions and home characteristics. Although deposition of O_3 on clothes may result in a reduced personal measurements on the passive sampler (12), the analysis on time–activity pattern suggests that the low personal exposure is not an artifact but a manifestation of the low fraction of time spent outdoors.

The R^2 between the Alpine and El Cajon APCD sites ranged between 0.37 and 0.53, while the R^2 for Models 1 through 6 ranged between 0.08 and 0.22. The lower R^2 values for these microenvironmental models can be explained by the fact that the outdoor monitors are fixed and thus easier to predict while subjects move around different microenvironments with various O_3 concentrations. In

addition, personal exposure measurements were not made at fixed times and durations. The analyzed personal measurements include sampling durations between 9.6 and 14.4 hr (within a 20% range of 12 hr), starting between 6 and 10 A.M. Furthermore, the low R^2 may also result from the measurement error due to different effective collection rates of the passive sampler in various environments (12). Correlations between personal exposures and the outdoor measurements varied among subjects due to various activity patterns and geographical and demographic characteristics near the home, school, or workplace. Intrasubject variance and monitoring error probably account for most of the variability in personal exposures. Less than 40% of the variance in personal O_3 exposure was attributed to intersubject and day-of-week variabilities.

Based on outdoor concentrations obtained from the Alpine APCD site and time–activity information collected from the subjects, simple personal exposure models predict 20% and 6% of the variability in the measured personal exposures in spring and fall, respectively. Although such predictive powers are low, the models are reliable when assessed by the split sample method. Inaccurate time–activity information on the use of air conditioning might have contributed to the low R^2. Efforts will have to be made in the field to correct this A/C reporting error, such as taking daily air exchange rate measurements or collecting information on A/C use from workplaces and the school. In addition, the spatial variation of O_3 also resulted in variation in personal O_3 exposures in the study area. By adding factors that are associated with the spatial variation to the simple personal exposure models, the R^2 was markedly improved from 0.06 to 0.19 for the fall data. Similar modeling efforts, however, only resulted in a minimal improvement of the predictions for the spring data. It is possible that measurement error from the personal monitor and the time–activity records accounts for most of the variance in personal measurements.

Conclusions

Key findings of this study include the following:

• Personal O_3 exposure differs dramatically (by fourfold on average) from outdoor stationary O_3 measurements (Fig. 2) and is not predicted well by these outdoor measurements (R^2 = 0.07 or less).
• There is considerable intersubject variability in personal O_3, which is partially explained by differences in percent of time spent outdoors.
• Models perform differently by season;

microenvironmental Model 1 and multiple regression Model 2 for spring cohorts have two to three times the R^2 of the fall cohorts.
• The fall, but not the spring, model was markedly improved by adjusting for distance from the outdoor stationary site.

Recent studies (8,9,18,19) that examine associations between personal exposures and outdoor measurements found similar values for R^2. Thus, microenvironmental models including outdoor O_3 concentrations and simple personal activity information are improvements in estimating personal exposures over models including only outdoor stationary site measurements. Predicting personal exposures was further improved by the inclusion of microenvironmental variables such as spatial variation and workplace (e.g., school) exposures in the present and past O_3 modeling studies (9). However, it remains to be shown to what degree such predictive models enhance the ability to detect the adverse respiratory health effects of O_3 in an epidemiological study that would otherwise rely on outdoor stationary site O_3 measurements.

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