Chapter 8

Spatial and Temporal Analysis of Surface Ozone in Urban Area: A Multilevel and Structural Equation Model Approach

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/50417

1. Introduction

Photochemical smog, first identified in Los Angeles in the late 1940s, nowadays is a widespread phenomenon in many of the world's population centers (Jenkin & Chemitshaw, 2000). Photochemical smog occurs when primary pollutants (nitrogen oxides - NOx and volatile organic compound – VOC created from burning of fossil fuel and biomass) interact in the presence of sunlight to produce a mixture of hazardous secondary pollutants (Stern, 1973). Major constituent of photochemical smog is surface (ground-level) O_3, which is not emitted directly into the atmosphere but formed as the product of photochemical reactions of its precursors, NOx and VOC (Seindfeld & Pandis, 1998). At the same time, pollutants also interacts each other to form other secondary pollutants as like acidifying substance and also particulates.

Concentration of atmospheric gases involved in forming O_3 and nitrogen oxides (NO_x) changes rapidly with wind speed and direction, ambient air temperature, humidity and solar radiation. Chemical reactions of O_3 production and destruction progresses take place at the same time. O_3 concentrations are affected mainly by photochemical reactions, transport and diffusion process. The photochemical reactions are related to meteorological factors such as solar radiation, temperature and concentration of pollutants. In general, O_3 is closely related to the pollutants like NO_2, NO and NO_x according to photochemical oxide interaction in local environment (Wang, 2003). The relationship between precursor pollutants and O_3, thus differ from one place to another due to the emission distribution and meteorology (Zhang & Kim, 2002). It is critical to understand the variability of ozone concentration across location and time.

In a spatial and temporal analysis, it is noteworthy to first clarify several technical terms: heterogeneity, variability, variation and variance. Heterogeneity refers to phenomenon that actual concentration measured at monitoring station changes across individual measurement. This study especially deals with the unobserved heterogeneity. It is well known that variance is a statistical term, representing the degree of variation. The variability means the fact that something being likely to vary. In this study, the later three terms are especially an aggregate of measurement` (or monitoring station`) heterogeneity. To quantitatively assess the properties of unobserved heterogeneity at various situations, we focus on various components, which correspond to the degree of variation caused by unobserved heterogeneity within monitoring station and also among locations by using monitoring data. We use regression-based method a multilevel model to capture temporal variations and spatial heterogeneity caused by land-use characteristics surrounding monitoring stations and its impact on surface ozone. A multilevel analysis was applied to analyze (a) daily event when peak concentration of ozone occurred, (b) daily average concentration of ozone and (c) possibility of phenomena of ozone weekend effect in Jakarta city represented by systematically day-to-day variation of event of peak ozone and daily average concentration of ozone.

In tropical regions, high O_3 level may be expected due to high rate of precursor emissions from anthropogenic and biogenic sources coupled with high sunlight intensity. Yet, there is only a limited research about tropical tropospheric O_3 focusing on Asian cities. The lack of systematic monitoring data of O_3 and its precursors is one of the barriers to scientific research for photochemical smog in most of the developing Asian countries (Zhang & Kim, 2002). In the context of urban areas, NO_2, NO and NO_x, which are generally highly associated with primary sources of air pollution, come from both mobile sources (automobiles) and stationary sources (e.g., household sector and industrial sector). An understanding of ozone (O_3) behavior near surface layer is essential for a study of pollution oxidation processes in urban area (Monoura, 1999). Ground level O_3 is formed from its precursors by complex and non-linear photochemical reaction in presence of sunlight. O_3 concentrations are very difficult to model because of the different interactions between pollutants and meteorological variables (Sousa, 2007).

Concerning the methods of analysis, although several multiple regression models are available to analyze urban air pollution especially surface O_3. It is however difficult to apply these models to deal with the complex cause-effect relationships among meteorological factors, primary pollutants under different wind conditions, and their influences on surface O_3. Therefore, our proposed structural equation model can flexibly represent the aforementioned causal interactions aspects. The development of such models usually involves the choice of appropriate model structures and nonlinear data transformation methods. Then, a spatial and temporal analysis was performed based on our structural equation model with latent variables. A spatial analysis based on spatial pattern is also carried out at two major land use types (i.e., suburban area-SU and central urban area (CA), and a roadside area-RA in central business district in Jakarta City. A temporal analysis was done at roadside station in central Jakarta by considering seasonal and weekly variations.

2. Literature review and methodology

2.1. Relationships between surface ozone and its precursors

In the O_3-NOx system, the dominant chemical reactions in the atmosphere are described below :

$$NO_2 + hv \rightarrow NO + O \quad (1)$$

$$O + O_2 + M \rightarrow O_3 + M \quad (2)$$

$$NO + O_3 \rightarrow NO_2 + O_2 \quad (3)$$

M represents N_2 or O_2 or another third molecule that absorbs excess energy and consequently stabilizes the O_3 molecule formed (3). The time scale of reaction (2) is very small (~10-6s) relative to the scales of reactions (1) and (3) (~100s and 30s, respectively) (Monoura, 1999). This is the result of O_3 destruction by NO in the nitrogen dioxide photolytic cycle, which is effective at a close distance to NO source due to its short cycle time (about several minutes) (Jenkin, 2000). Since the conversion from NO to NO_2 involving reactive hydrocarbons and the OH radical usually takes several hours, the higher concentration of O_3 is observed in both weekdays and weekend in dry season (Seinfeld & Pandis, 1998).

It is known that O_3 concentration and NO concentration show a logarithmic relationship, and the relationship between O_3 and NO_2 observed at the same time shows a typical linear function. A power function relationship is found between NO and NO_2 observed at the same time (Monoura, 1999). O_3 levels are negatively relevant to nitric oxide and positively to nitrogen dioxide, weakly affected by carbon monoxide (CO) and hardly affected by sulphur dioxide (SO_2) and respirable suspend particles (RSP). A case study in Hong Kong confirms a strong linear relationship between O_3 and NO_2/NO concentration in 1999 and 2000 (Wang, 2003).

High emission of NO from automobile traffic should be the major reason for low O_3 at the curbside (roadside) and lower O_3 at ambient monitoring station. In a city like Bangkok where the emission of NO from traffic is rather uniformly spread over a large area, the processes of O_3 destruction (by NO) and formation should be competing at any locations. Therefore O_3 level is found to be high over the city except for the very heavy traffic center and curbside where the O_3 destruction by NO is significant (Zhang & Kim, 2002).

2.2. Meteorological factors influencing surface ozone

The meteorological conditions of a region (e.g., sunlight, temperature, wind speed, and other factors) also directly affect the formation of O_3. In general, episodes of high O_3 concentration are associated with slow-moving, high barometer pressure weather system. Clear skies, sunshine, and warm conditions usually accompany high-pressure system, accelerating the photochemical formation of O_3 (Rubin, 2001). The relationship between the meteorological variation and daily maximum O_3 concentration can be well represented by a linear function (Gardner & Dorling, 1998).

Solar radiation

O_3 production is dependent on solar radiation, and consequently solar radiation intensity and O_3 concentration usually show positive correlation (Monoura, 1999).

Ambient air temperature

Meteorologically, high temperature is frequently associated with high pressure, stagnant conditions that lead to high O_3 concentration at vertical level (Seinfeld & Pandis, 1998). The rate of photochemical reaction increases as air temperature rises. In many O_3 prediction models, air temperature was found to be the strongest single predictor of O_3 concentration (Boriboonsomsin & Uddin, 2005). In urban and metropolitan areas, paved surface, high-rise building and other constructed surfaces cause air temperature to be higher due to the heat transfer of these surfaces.

Wind speed and direction

Wind speed associated with high-pressure system is typically low. Therefore pollutants stay longer over urban areas and accumulate in the atmosphere (Rubin, 2001). Calm or light winds allow more emissions to accumulate over large area, which result in higher concentration of O_3 precursors. O_3 formation and transport is a complex phenomenon, and O_3 concentration depends on wind speed and direction among others (Hubbard & Cobourn, 1998). The dispersion of air pollutants is roughly inversely related to wind speed (Zhang, 2002). Higher wind speeds promote the dispersion of O_3 concentrations (Sanchez-ccoyllo, 2006). Wind direction is also highly related to O_3 level, for example, downwind locations of precursor emission sources are strongly inclined to high concentration of surface O_3.

Precipitation

Precipitation is one of O_3 destruction mechanisms due to a wet deposition. In this study, precipitation is expressed as relative humidity level. Most tropical rain forest countries such as Indonesia have high relative humidity, especially during night time and wet season.

2.3. Development of surface ozone model in urban areas

2.3.1. Existing model

Various models have been developed to describe the relationship among factors to surface ozone. These models include simple contingency tables, multiple linear and non-linear regression models, time series techniques (Benarie, 1980), artificial neural network approaches and fuzzy logic based methods (Wang, 2003). Linear regression model is a classical and easily applied method. It uses a linear combination of factors to explain the ozone behavior. Artificial neural network approach is capable of modeling complex nonlinear phenomena, but its main drawback is that it results in a 'black box' model which it isn't easy to interpret or justify. Fuzzy logic also allows one to model complex nonlinear phenomena (Peton, 2000). Since fuzzy logic is based on a set of empirical rules, the inherent cause-effect relationships and interactions among factors of the ozone cannot be flexibly incorporated. Time series technique is suitable to capture the temporal change of ozone itself, but they are not capable of incorporating the influential factors into the models.

Multiple regression models have been commonly used for describing the ozone in the last few decades (Boriboonsomsin, 2005). Gardner and Dorling (2000) found that the relationship between meteorological variables analyzed and the daily maximum ozone concentration could be well represented by a linear model. Linear regression gives a first-order approximation of a non-linear function, is easy to calculate and very robust (Geladi, 1999). However, it is quite difficult to apply such linear regression models to properly capture the nonlinear relationships among variables, and to represent the inherent cause-effect relationships and interactions in the model structure. Therefore, it is required to establish an alternative surface ozone model.

2.3.2. Multilevel analysis

Multilevel models are the expansion of classical regression model which data were classified in groups, thus allow coefficients to vary for each group. This has been a popular approach applied in many fields, such as properties and its relation to PM_{10} (Pattenden et al., 2000), pure properties aspect (Gelfanda et al., 2007), and land use fields for crops (Overmars K.P., and Verburg P.H. 2006). The benefits of multilevel models are allows random variations and explanatory variables to be incorporated inside the model at different levels.

Multilevel models are considered as a regression model in which the ultimate power lays on the regression coefficients that are given a probability model (Gelman and Hill, 2007). The second-level has parameters of its own which are estimated from data. Varying coefficients across different levels are a critical difference from classical regression models. Also, those varying coefficients serve as a model as well. Although classical regression models sometimes are also able to accommodate varying coefficients by using explanatory variables, however multilevel models has one ultimate attractive feature that it allows for modeling of the variation between groups, which classical regression is incapable off.

The multilevel model essentially treats multiple hierarchical and cross-classifications unobserved heterogeneities by introducing corresponding variation components. To describe the variations concentration pollutant *i*, in multilevel analysis, the model buildings strategies can be either top-down and bottom-up (J.J Hox, 2010). In this study, we select bottom-up approach in which analysis starts with a simplest model and proceed by adding parameters. Concretely speaking, first, we start with model without explanatory variables (called *Null* model). This model, the intercept-only model, can be defined as follows:

$$Y_{ij} = \gamma_{00} + \mu_{oj} + \varepsilon_{ij} \tag{4}$$

where γ_{00} is regression intercept and μ_{oj} and ε_{ij} are residuals at group-level and individual-level (Here, "group level" means monitoring sites, and "individual level" means measurements within the same station), following the normal distribution with mean 0 and variances $\sigma_{\mu 0}^2$ and σ_e^2, respectively. Using *Null* model, it possible to clarify reason of "why the concentrations are fluctuates?" based on the component of variance. It is also gives estimate of interclass correlation (ρ) among measurements in stations. The interclass correlation (ICC, δ) is estimated as follows:

$$\sigma_{\mu 0}^2 / (\sigma_{\mu 0}^2 + \sigma_e^2) \quad (5)$$

Second, we analyze a model with all explanatory variables (called as the *Full* model). This model is expressed as follows:

$$Y_{ijk} = \gamma_{00} + \gamma_{l0}X_{ijk} + \mu_{oj} + \varepsilon_{ij} \quad (6)$$

Where Y_{ijk} is dependent variable concentration of pollutant *i* at monitoring station *j* of measurement *k.* γ_{00} and $\gamma_{\lambda 0}$ are unknown parameters, X_{ijk} indicates explanatory variables including monitoring station` *j* attributes (e.g., emission intensity which reflected by systematically day-to-day variation, open space area nearby station, etc), atmospheric situations (e.g., presence or concentration of other pollutants), temporal attributes (e.g., annual variation and seasonal variation). Parameters μ_{oj} and ε_{ij} represent random components which indicate inter- monitoring location variation and inter-measurement variation within same location respectively. In this step, we assess the contribution of explanatory variables. The significance of each predictor can be tested and also possible to assess what changes occur in the first-level and second-level variance terms. We use chi-square test based on the deviances of *Null* and *Full* models to test the assumption whether variation across group is significant. Whenever explanatory variables introduced, we expect the variance $\sigma_{\mu 0}^2$ and σ_e^2 to go down or in other words the introduced explanatory variables explain part of measurements and part of monitoring station variances.

2.3.3. Structural equation model with latent variables

This paper also proposes to apply a structural equation model with latent variables to capture the complex cause-effect relationships and interactions in photochemical process. Structural equation model (SEM) is a modeling technique that can handle a large number of the observed endogenous and exogenous variables, as well as (unobserved) latent variables specified as linear combinations (weighted averages) of the observed variables (Golob, 2003). The models play many roles, including simultaneous equation systems, linear causal analysis, path analysis, structural equation models, dependence analysis, and cross-legged panel correlation technique (Joreskoq, 1989). It is a confirmatory, rather than explanatory method, because the modeler is required to construct a model in term of a system of unidirectional effects of one variable on another. SEM is used to specify the phenomenon under study in terms of putative cause-effect variables and their indicators. Following the descriptions by Jöreskog and Sörbom (1989), the full model structure can be summarized by the following three equations.

Structural Equation Model:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{7}$$

Measurement Model for y:

$$y = \Lambda_y \eta + \varepsilon \tag{8}$$

Measurement Model for x:

$$x = \Lambda_x \xi + \delta \tag{9}$$

Here, $\boldsymbol{\eta'} = (\eta_1, \eta_2, ..., \eta_m)$ and $\boldsymbol{\xi'} = (\xi_1, \xi_2, ..., \xi_m)$ are latent dependent and independent variables, respectively. Vectors η and ξ are not observed, but instead $\boldsymbol{y'} = (y_1, y_2, ..., y_p)$ and $\boldsymbol{x'} = (x_1, x_2, ..., x_q)$ are observed dependent and independent variables. $\boldsymbol{\zeta, \varepsilon, \delta}$ are the vectors of error terms, and $\mathrm{B}, \Gamma, \Lambda_x, \Lambda_y$ are the unknown parameters.

An important feature of SEM is that it can calculate not only direct effects, but also total effect (Golob, 2003). Direct effect is the link between a productive variable and the variable that is the target of the effect, which corresponds to an arrow in a path diagram. These direct effects embody the causal modeling aspect of SEM. Total effects are defined to be the sum of direct effects and indirect effects, where the indirect effects represent the sum of all the effects along paths between two variables that involve intervening variables. Advantages of SEM compared to most other linear-in-parameter statistical methods include the following capabilities: (1) treatment of both endogenous and exogenous variables as random variables with error of measurement, (2) latent variables with multiple indicators, (3) test of a model overall rather than coefficients individually, (4) modeling of mediating variables, (5) modeling of dynamic phenomena such as habit and inertia (Golob, 2003). One can see that SEM has a very flexible model structure to simultaneously represent various interdependent variables. Therefore, in this study, we adopt the SEM to model and analyze surface ozone in Jakarta City.

The model was built using 11 observed variables that consisted of three meteorological factors (SR, T and RH), two wind factors (WS and WD), five primary pollutants (NO, NO_2, CO, SO_2 and PM_{10}) and a surface O_3. The four latent variables $\xi_1, \eta_1, \eta_2, \eta_3$ as shown in Figure 1 represents these four groups of variables respectively. ξ_1 indicates an exogenous latent variable, and η_1, η_2, η_3 are the endogenous latent variables. The latent variable η_3, which is defined by using both O_3 and its precursor NO, describes the photochemical matters in this study.

Since the SEM still possesses a linear model structure, to capture the non-linear relationship between some variables, here several observed variables need to be properly transformed. The empirical observations results of Jakarta air quality data indicates that the relationship between O_3 concentration and NO concentration may be explained by a negative logarithm function and the relationship between NO and NO_2 by a logarithm function. In addition, the existing research (Monoura, 1999) suggests that the relationship between O_3 and NO_2 is best described by a linear function. The non-linear phenomena is represented by a natural logarithm (LN) function, therefore the pollutant NO is transformed into a new variable LN_NO. LN_NO, NO_2, CO, SO_2 and PM_{10} are specified in one-to-one relationships with the latent variables "Primary Pollutants" (η_2). This latent variable η_2 is specified to represent the influence of primary pollutants emitted from both gasoline and diesel vehicles. The latent variable "Photochemical" (η_3) corresponds to several chemical reactions in photochemical process (Seinfeld & Pandis, 1998).

For the structural equation model with multiple endogenous variables, especially with latent variables, model estimation becomes more challenging, and quite a few different methods have been developed (Golob, 2003). The most commonly used estimation methods are maximum likelihood (ML), general least squares (GLS), weighted least squares (WLS), asymptotically distribution free weighted least squares (ADF or ADF-WLS) and elliptical re-weighted least squares (EGLS or ELS). The most often used estimation method is ML, which maximizes joint probabilities that the observed covariance are drawn from a population that has its variance-covariance generated by the process implied by the model, assuming a multivariate normal distribution.

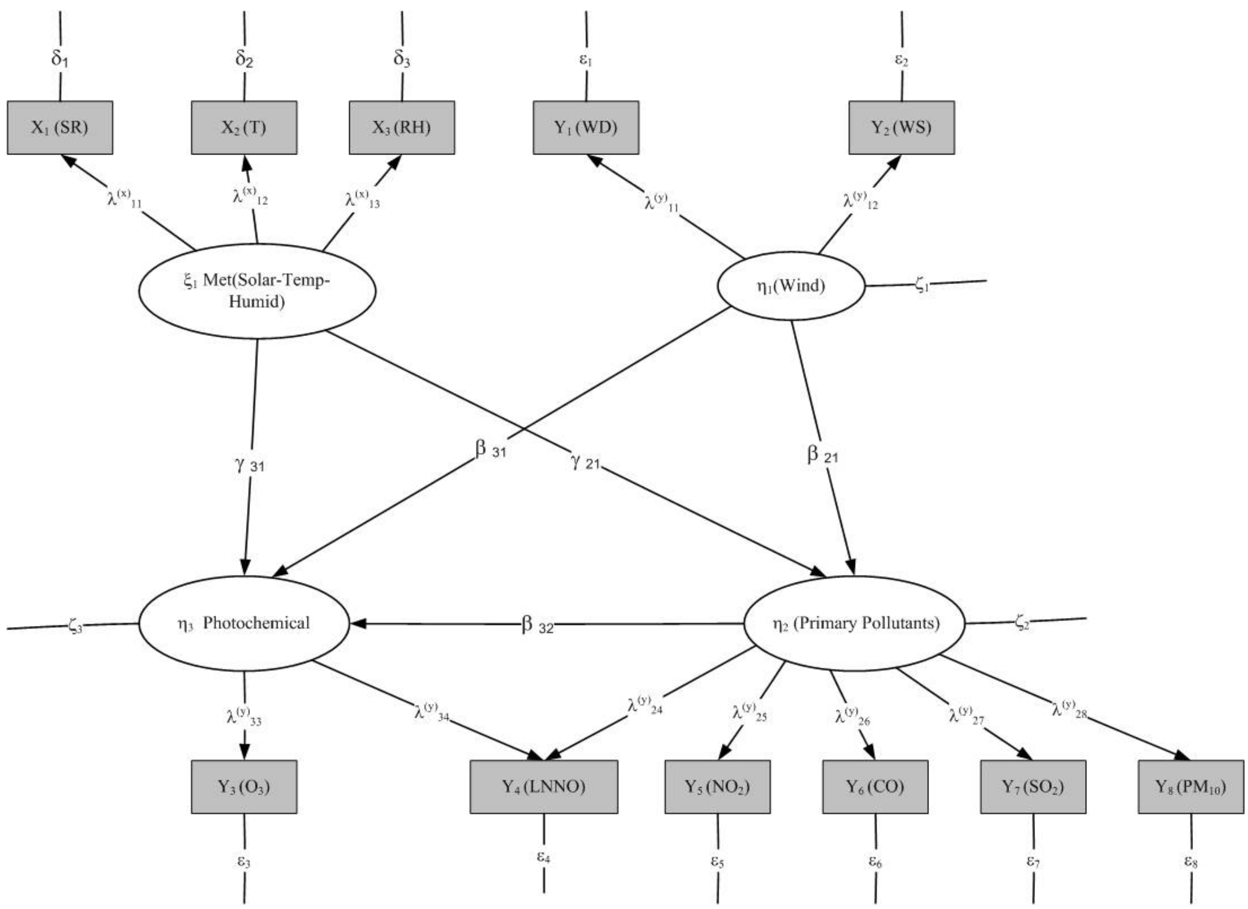


Figure 1. Air Pollutants Interactions Model for Jakarta City

Several criteria have been developed for assessing overall goodness-of-fit of a structural equation model and are used to determine how well one model performs than others. Such model accuracy indices includes: (a) root mean square residual (RMR), (b) standardized RMR (SRMR), (c) the goodness-of-fit index (GFI), (d) adjusted goodness-of-fit index (AGFI) which adjusts GFI for the degree of freedom in the model, and (e) the parsimony-adjusted goodness-of-fit index (PGFI). In this study, the GFI and AGFI are used to assess the models and to compare model results for different areas. Nowadays, there are several software that can estimate the structural equation models. The Analysis of Moment Structure (AMOS) software, which has a very attractive and user-friendly interface is used for this study.

In the work by Boriboonsomsin and Uddin (2005), they incorporated precursor emissions (mobile sources and stationery sources) into the model and found that traffic is highly associated with the change of O_3 concentration. The traffic behaviors are strongly influenced by land use type, which in the behavior of pollutant species are reflected as spatial and temporal variables such as location of stations and systematically day-to-day variation. It assumed that day-to-day variation has linear relationship with traffic data and it is expected lower emission intensity occurs on weekend as result of decreasing vehicle usage on weekend days. Furthermore, we also assumed that variation of emission intensity especially in weekend days will affect simultaneously on concentration of primary pollutants in weekend days. Then, this study examines those impact on secondary pollutants ozone.

3. Study area and data

3.1. Description of study area

Jakarta is comprised of 664 km^2 land area and stretchs along the coast of the Java Sea. The topography is very flat with a mean elevation of seven meters above sea level. Jakarta is a part of the greater Metropolitan Jabodetabek (Jakarta, Bogor, Depok, Tangerang and Bekasi) area. Jakarta's climate is generally tropical. The 'rainy/wet' season starts from November to March and 'dry' season from May to September. A few weeks in April and October are the transition period between dry and wet seasons, respectively.

The Jakarta Office of Environment (Bapedalda DKI Jakarta and later BPLHD DKI Jakarta) has regularly monitored the air pollution in Jakarta since 1985. At the beginning, twelve manual monitoring stations that are located at housing, industrial, recreation and mixed areas measures sulphur dioxide (SO_2), nitrogen oxides (NOx), and total suspended particulate (TSP) (Haq, 2002). Those stations are operated on a rotational basis, and the parameters are measured for twenty-four hours every eight days at each manual monitoring station (Syahril, 2002). Since 1992, Jakarta has another six continuous monitoring stations which consist of four ambient fix stations and two roadside fix stations. The fix monitoring stations records air quality every 10 minutes. At the end of 2001, another six new monitoring stations were activated which consist of five ambient fix stations and one mobile roadside station. These stations equipped with measurement analyzers to monitor NO, NO_2, NO_x, SO_2, CO, O_3 and PM_{10} every 30 second. The fix stations are centrally connected to data computer at Jakarta Office of Environment and the data are transferred every half an hour.

No	Monitoring Stations	Location	Land-use
A	Ambient Stations (Fixed Station)		
1	Gelora Bung Karno (Senayan)	Central Jakarta	City center-commercial area (CBD)-
2	Kemayoran	North Jakarta	Commercial & Industry-Urban Fringe
3	Kantor Walikota Jakarta Timur	East Jakarta	Residential – Sub urban
4	Pondok Indah	South Jakarta	Residential – Urban fringe
5	Kantor Walikota Jakarta Barat	West Jakarta	Commercial and residential area-Sub Urban
B	Roadside (Mobile) Station		
1	Casablanca	Central Jakarta	Central business district (CBD)

Table 1. Air Quality Monitoring Stations in Jakarta City

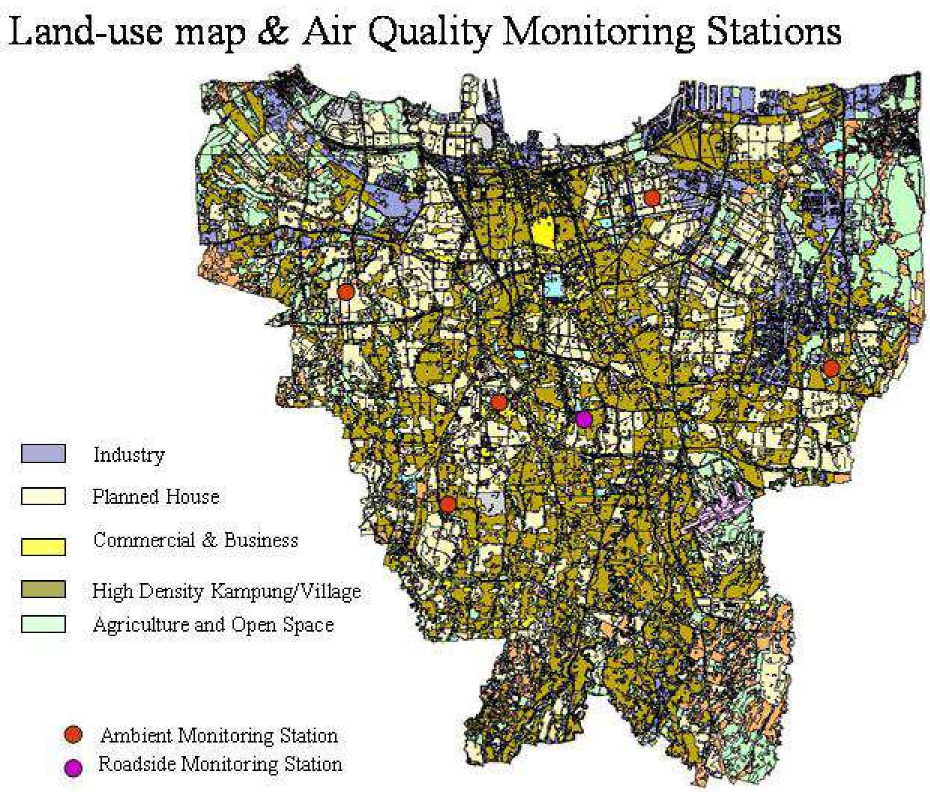


Figure 2. Air Quality Monitoring Stations in Jakarta city

Nowadays, only the latest five fix stations that remains to provide air quality data on daily basis for parameters CO, NO, NO_2, SO_2, PM_{10}, and O_3. The data are used to calculate the Pollutants Standard Index (PSI), which are subsequently published on data displays to the public. In-situ meteorological data i.e. solar radiation (SR), temperature (T), relative humidity (RH), wind speed (WS) and direction (WD) are also recorded using the basic meteorological sensors, which are installed at 10 meter height above the ground. Four data displays are located at Gambir (central Jakarta), Kelapa Gading (east Jakarta), Pondok Indah (south Jakarta) and Grogol (west Jakarta). Figure 2 and Table 1 provides detail information on the stations location.

This study used air quality data for weekday and weekend at wet and dry season in 2001-2003 from five fixed ambient monitoring stations and the roadside street-level ambient monitoring station. The general ambient air quality monitoring stations are located more than 100 meters away from main roads and the roadside street-level ambient air quality monitoring station is located 5-10 meter from the main road. The five of monitoring stations are Senayan (Central Jakarta), Kemayoran (North), Pondok Indah (South Jakarta), Walikota Jakarta Barat and Walikota Jakarta Timur (East station). The West Station (SUW) is located 20 km from city center and represents suburban area at western part of Jakarta. The East Station (SUE) is located 25 km from city center and represents suburban area in eastern part of Jakarta. The Senayan Station (CA) is located at city sport facilities in Jakarta's central business district area. This station is nearby the heaviest traffic roads in Jakarta (Jl Sudirman and Jl Gatot Subroto). The North Station (NUF) and South Station (SUF) are represents urban fringe area non-CBD in north and south Jakarta. Finally, the Roadside Station (RA) is located at the Jakarta Office of Environment on Jl Casablanca, which is also located in central business district area.

These all stations were selected to make a spatial and temporal analysis of the surface O_3 behavior in Jakarta city. Analysis was performed for several set situations as provided in table 2.

No	Type of Analysis	Approach	Data
1	Spatial and temporal variations of daily peak concentration of ozone (analysis of events)	Multilevel Analysis	Events of peak concentration of ozone at five six stations on 2001 to 2003.
2	Spatial and temporal variations of daily average concentration of	Multilevel Analysis	Daily average concentration at five fixed station in 2001-2003. Parameter: PM_{10},SO_2,CO, O_3,NO_2, and NO
3	Spatial and temporal Analysis of causal interaction among pollutants	Structural Equation Model	Spatial Analysis: Three stations at West Jakarta (SA), Central Jakarta (DA) and mobile station (RA) in Dry season 2003 Temporal Analysis: Seasonal variation and weekly variation at Roadside station (RA) in 2003.

Table 2. Distribution of data in Spatio-Temporal Analysis

3.2. Ambient air quality monitoring data in Jakarta city

Table 3 summarizes the data availability for diurnal analysis from six current monitoring stations in Jakarta. Due to technical failure, the data from North and South Stations were incomplete, therefore only the data from the four remaining stations were used in this diurnal analysis. The weekly variation for dry and wet seasons in year 2003 that start from 00.30 a.m. on Monday and end at 24.00 on Sunday were identified. The data time interval is 30 minutes, therefore 336 average concentration data should be available in a week for each corresponding hour and day in a week. The results of analysis for pollutants O_3 is discussed below.

Locations	Data Avialability			
	Dry Season		Wet Season	
	Weekdays	Weekend	Weekdays	Weekend
East	5520	2208	6240	2496
West	3648	2496	3456	2496
Central	5568	2160	4128	1632
Roadside (Central)	5760	2352	5520	2208
North	NA[1]	NA[1]	NA[1]	NA[1]
South	NA[1]	NA[1]	12 [2]	NA[1]

Note: NA[1]: Not available for NO and NO_2
12[2] : Limited data for NO and NO_2

Table 3. Data availability for diurnal analysis

Figures 3 and 4 show weekly variations of average O_3 concentrations at each station during wet and dry seasons in year 2003, respectively. The concentrations of O_3 increased after the sunrise and reached the highest level at around 10:00-12:00 a.m. in all the locations. We found only a single peak of O_3 occurs in a day. It is obvious that the formation of O_3 was coincided with the abrupt dropped of NO concentrations after sunrise. During the daytime, the O_3 production was faster than the O_3 consumption. During this period, some O_3 might be transported from the upper atmosphere to the ground level accompanied by convection in the mixing layer (Monoura, 1999). The highest average concentration for dry season was identified at the Central Station (CA), but not for wet season. The average concentration of O_3 showed a seasonal variation, which average concentrations for dry season were slightly high. Although the highest daytime O_3 concentration during wet and dry season is measured at the East Station, the lowest concentrations were also measured at the same location.

The findings for O_3 concentration variation seems in agreement with the Hubbard & Cobourn (1998) finding that indicates that unlike primary pollutants, the O_3 concentration does not show obvious weekly cycles. Unlike CO and SO_2 which showed a weekly cycle with lower concentration during the weekend at the Roadside Station (RA), the O_3 concentration remained stable. The findings reveal that the ambient air quality standard for 1-hour O_3 (200 ug/m^3-1hr, Governor Decree of DKI Jakarta no 551/2001) was exceeded several times at all the locations.

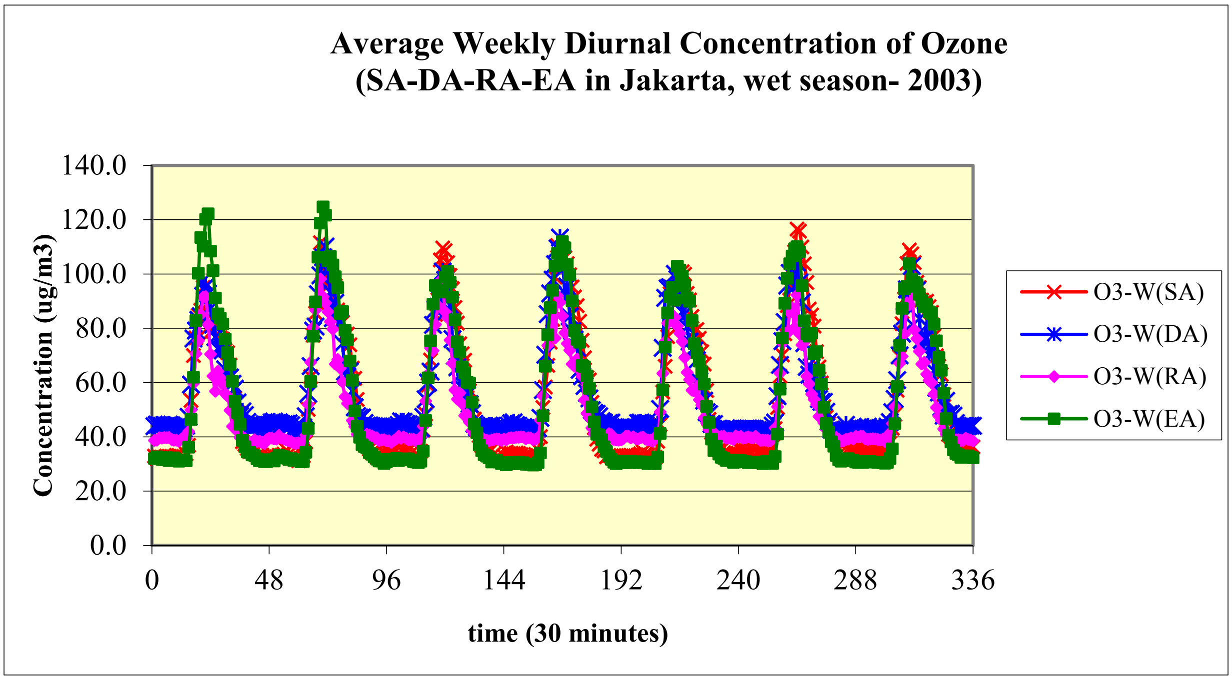


Figure 3. Weekly variations of average O_3 concentrations during wet season in 2003

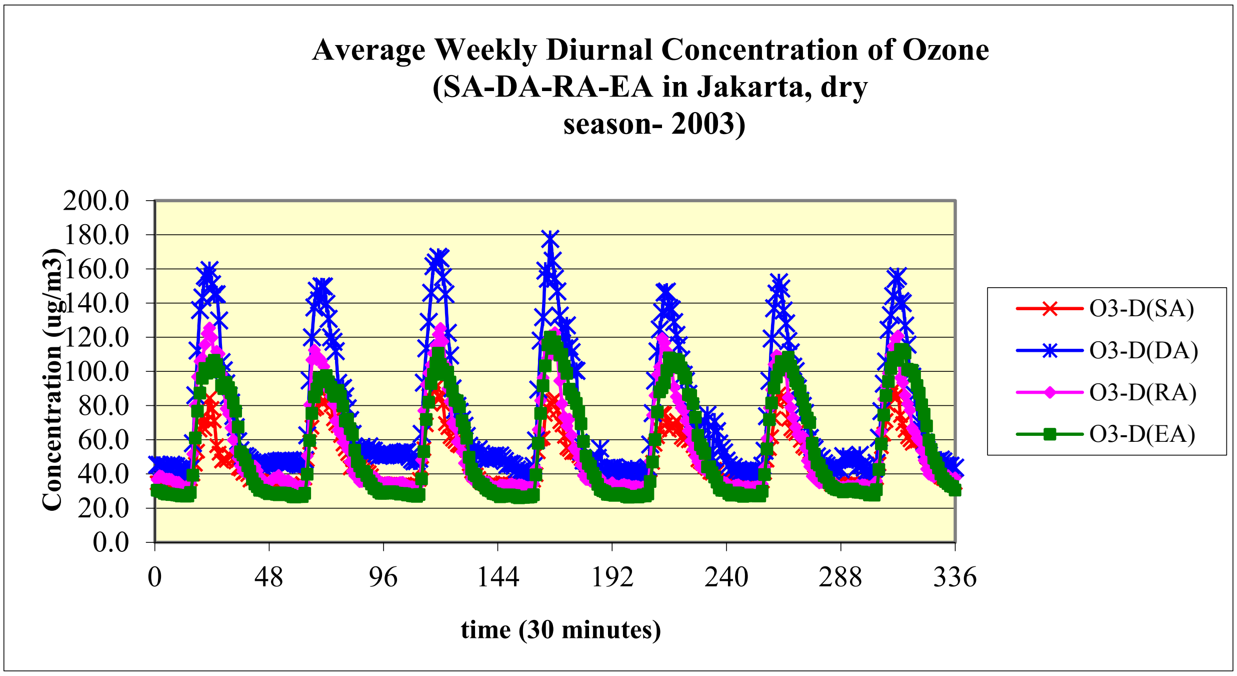
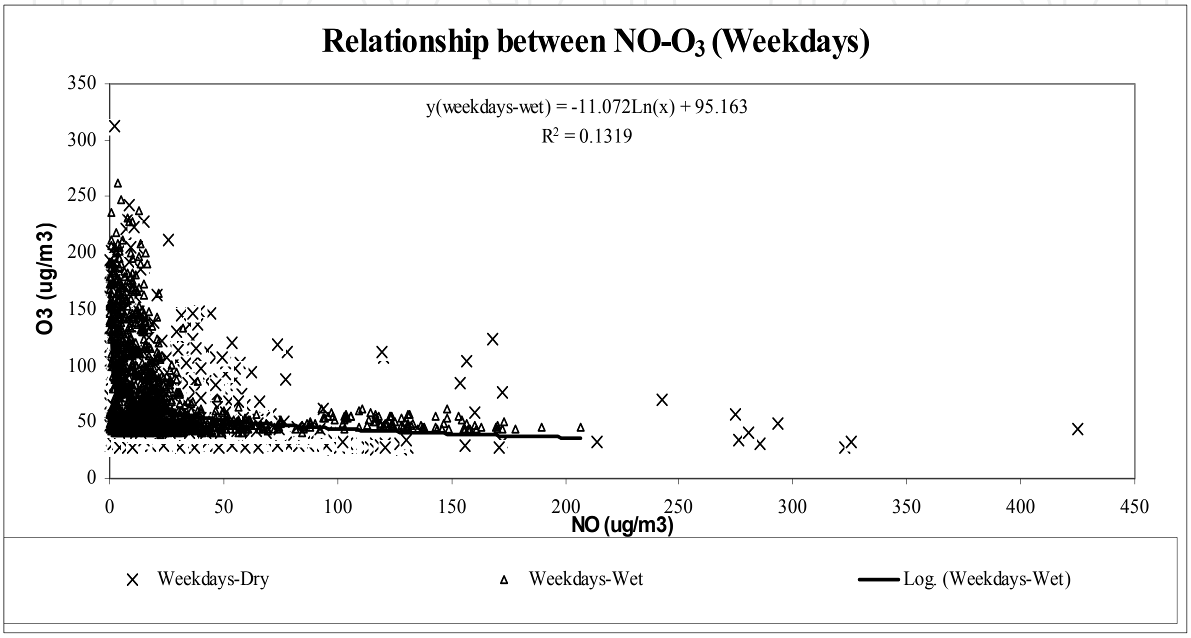


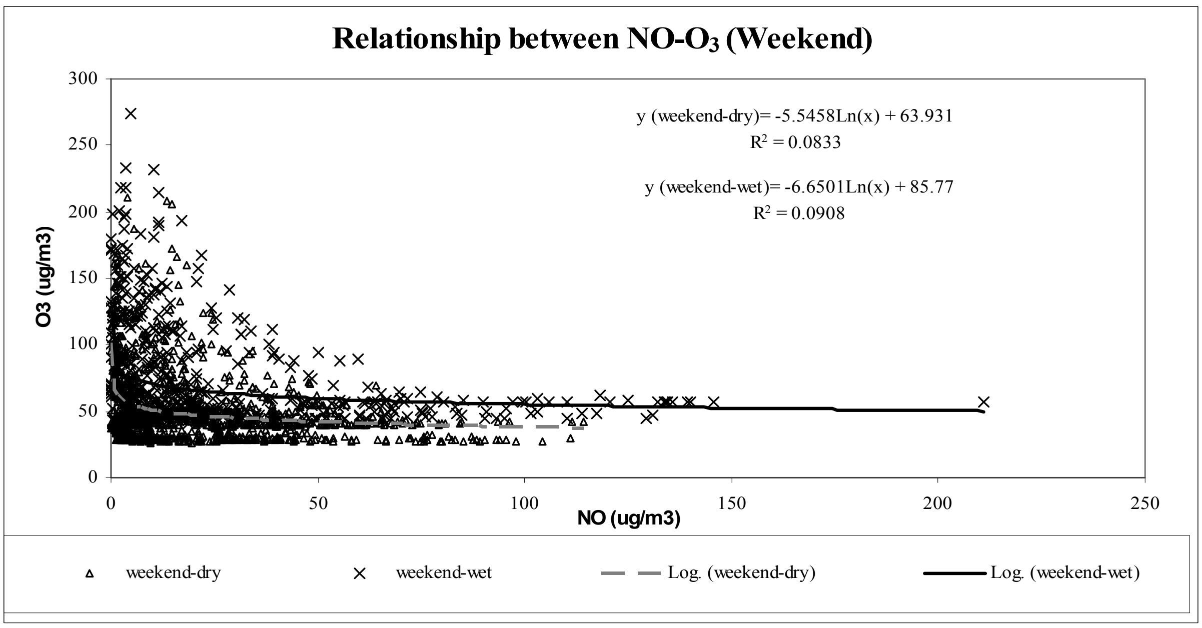
Figure 4. Weekly variations of average O_3 concentrations during dry season in 2003

3.3. Observed causal interaction among pollutants

In order to enhance understanding of the surface O_3 behavior in Jakarta, it is necessary to examine the relationships among O_3 precursors and meteorological factors. Figure 5 shows the relationship between NO and O_3 at the Roadside Station., A logarithmic relationship is observed between O_3 concentration and NO concentration as indicated in solid lines. The highest R^2 0.1319 is obtained for weekday-wet season. O_3 formation is solar radiation (SR) dependent. Figure 6 shows the relationships between O_3 and SR that are linear at three different areas. The highest R^2 value is found for weekday-dry season. Some observed relationships between O_3-NO, NO_2-NO and O_3-SR might be derived from the reactions (1) ~ (3) as mentioned earlier in the paper and follow the basic photochemical cycle of NO, NO_2, CO, O_3 and SR (Seinfeld & Pandis). These observations are helpful to develop and understand the structure of surface O_3 model for urban roadside in Jakarta city.

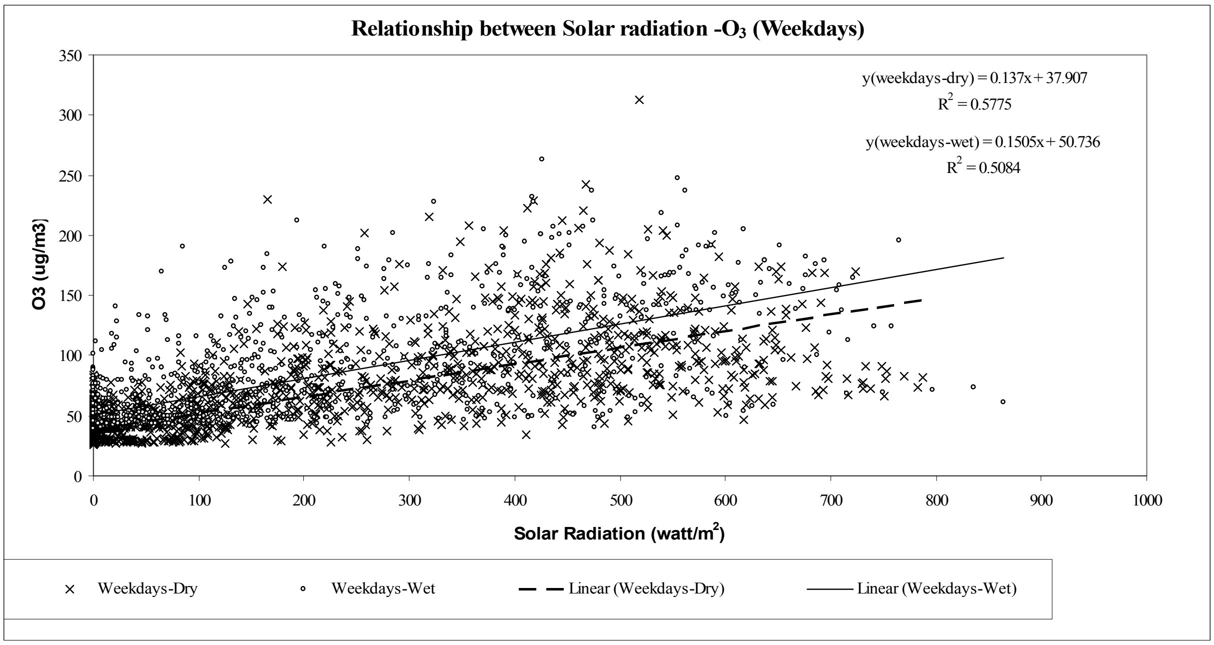


(a) Relationships between O_3 – NO for Weekday Situations

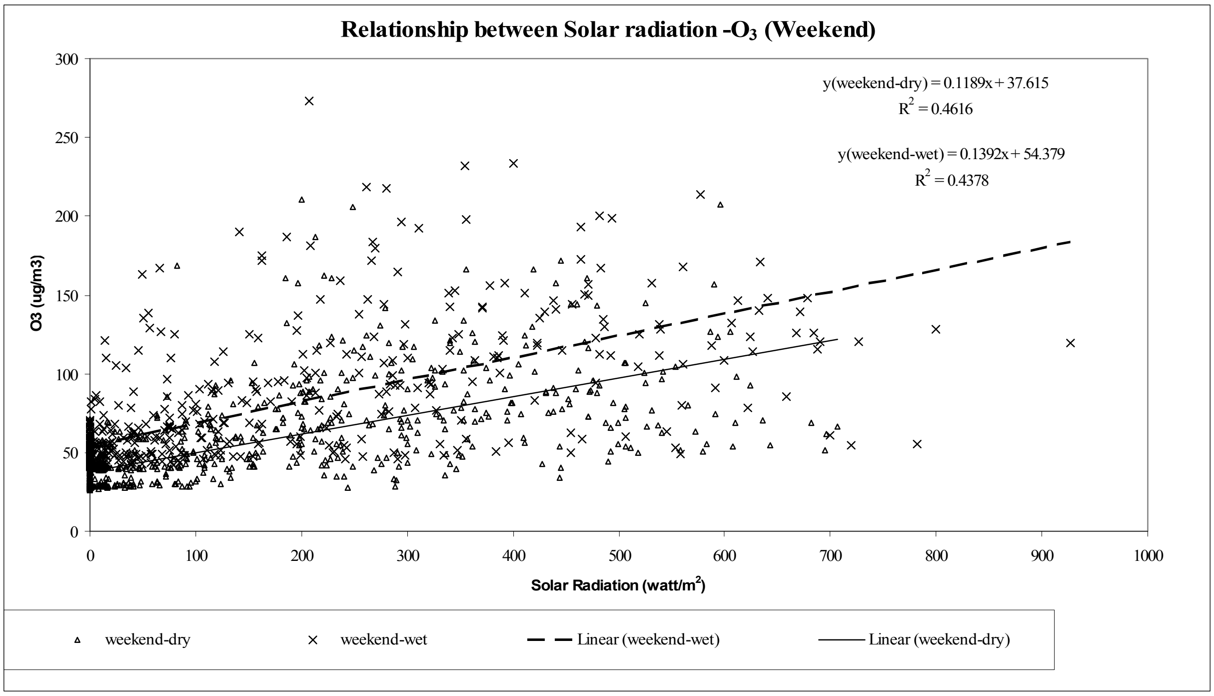


(b) Relationships between O_3 – NO for Weekend Situations

Figure 5. Relationships between O_3 – NO at roadside station in 2003



(a) Relationships between O_3 – SR for Weekday Situations



(b) Relationships between O_3 – SR for Weekend Situations

Figure 6. Relationships between O_3 – SR at roadside station in 2003

4. Result and discussion

This section discuss about estimation results for several issues mentioned in above. It is organized as follows. First part discuss about spatial and temporal analysis by multilevel approach and secondly spatial and temporal analysis of causal interaction among factors in urban ambient air pollution. In the first part, there are two main topics to be analyzed which are (a) daily event of peak concentration of ozone, when it happened and (b) analysis of daily average ozone concentration. In the second part, spatial and temporal analysis was done by using the proposed structural equation model.

4.1. Spatial and temporal analysis by multilevel approach

4.1.1. Spatial and temporal variation of Events of Daily Peak Concentration of ozone

The dependent variable, time of daily peak concentration of surface ozone is expressed in minute counted from midnight as zero. First, the *Null* model is estimated for intercept (location) only and the result is presented in Table 4. Estimation result show only small variation (1.7%) of event of daily peak concentration due to different location in Jakarta city. Next step, it is necessary to examine how much of unobserved variance of random component can be explained by observed information. We use half model (spatial and temporal information) and full model (spatial, temporal and systematic day-to-day variation) to examine unobserved variance. Both two models show zero random component of inter-monitoring which means there is no variation among locations. The selected variable of observed information successfully explained all unobserved variance of random component (1.7%) of the *Null* model.

Comparing the *Null*, *Half* and *Full* models as shown in table 4, we could conclude that variation of event when peak concentration of ozone happened mostly caused by locations. The dummy variable of Sub-urban and Urban-fringe show the event of peak concentration ozone in Sub-urban and Urban Fringe usually 38 and 40 minutes later than Central Business District (urban core/central Jakarta) around 688 minutes from midnight or 11:28 am. The temporal variations are insignificant in all temporal variables which are long-term (annual), seasonal and weekly (day-to-day variation). Looking at systematically day-to-day variation, by using event peak on Tuesday, Wednesday and Thursday as the references, we could see there are insignificant different among other days. This result support the findings for O_3 concentration variation seems in agreement with the Hubbard & Cobourn (1998) finding that indicates that unlike primary pollutants, the O_3 concentration does not show obvious weekly cycles.

4.1.2. Spatial and temporal variation of Daily Average Concentration of ozone

The dependent variable, daily average concentration of surface ozone is expressed in ug/m^3 as also measured by automatic ambient air monitoring stations. First, the *Null* model is estimated for intercept (location) only and the result is presented in Table 5. Estimation result shows variation around 22.6% due to different specific characteristic among monitoring station which contribute to the variation of daily average concentration. The rest parts are due to variations inside the boundary nearby stations which influence on ambient air pollution measured at the stations. Next step, it is necessary to examine how much of unobserved variance of random component can be explained by observed information. We use half model (spatial and temporal information) and full model (spatial, temporal and interaction with other pollutants in ambient air) to examine unobserved variance. In the *Half* model we could found there is no significant different among location (spatial impact). The estimation results of dummy variable Sub-urban and Urban fringe are insignificant. As for temporal aspect, long-term aspect (annual impact) shows positive and significant which mean daily average concentration of ozone increase year by year significantly. It shows consistent result (positive and significant) in the *Full* model. In the full model, we also found the positive significant impact of dummy variable wet season on surface ozone concentration.

No	Description	Null Model	Half model: Spatial & Temporal	Full Model: With systematic day-to-day
I	**Fixed Part**			
A	**Intercept (Location)**	706.243(84.95)	688.521(112.17)	687.298(104.22)
B	**Spatial**			
1	Sub-Urban (Dummy)		38.111(6.47)	38.147(6.48)
2	Urban Fringe(Dummy)		40.553(6.34)	40.614(6.35)
C	**Temporal**			
1	Long-term (Year)		-3.013(-1.28)	-3.007(-1.28)
2	Seasonal (Dummy wet season)		-7.862(-1.55)	-7.894(-1.56)
3	Weekly Weekend (Dummy)		0.580(0.100)	
D	**Systematic day-to-day variation**			
1	Monday			-6.660(-0.86)
2	Friday			12.450(1.62)
3	Saturday			-6.644(-0.86)
4	Sunday			10.316(1.33)
II	**Random Part**			
	σ_e^2 (Within monitoring)	21527.55	21518	21489
	$\sigma_{\mu 0}^2$(Inter-monitoring)	374.16	0	0
III	**Model Performance**			
	AIC	43456	16060	14499
	BIC	43474	16104	14570
	-2*Log likelihood	43450	43406	43382
	Degree of freedom	3	8	11
	No of Samples	3390	3390	3390

Note: ( ) → t-statistic

Table 4. Model of Daily Event of Peak Concentration of Ozone (Peak O_3)

Looking at *Full* model, the model performance is increase based on some indicators such as AIC, BIC and log likelihood estimation. The inter-monitoring location` variances also decrease from 22.5 % (*Null* model) to 8.2% in the *Full* model and selected observed variables show meaningful information to explain unobserved variance properties. Instead of spatial and temporal variables, the interaction effect of pollutants on surface ozone is also significant. By using *Full* model, we successfully explore the significant impact of ozone precursors (NO_2 and NO) and PM_{10}. We leave other two parameters (SO_2 and CO) since the estimation results show insignificant effects of these two parameters on daily average concentration of ozone. Daily average concentration of PM_{10} slightly increase ozone concentration while in contrast, NO_2 will decrease ozone concentration. The ratio between NO and NO_2 is crucial factor since it give a negative and significant impact on ozone. This result leads to policy maker to manage the ratio NO and NO_2 to decrease ozone concentration in urban area. Finally, we also found accumulation impact on surface ozone concentration. By using dummy variable of prior day concentration (t-1), this dummy variable significantly shows a positive sign which mean today`s average concentration of ozone is significantly affected by yesterday` concentration, a time series dependent concentration phenomena. We leave systematic day-to-day variation in *Half* and *Full* model since this variables are insignificant. This result also support the findings for O_3 concentration variation seems in agreement with the Hubbard & Cobourn (1998) finding that indicates that unlike primary pollutants, the O_3 concentration does not show obvious weekly cycles. We can preliminary conclude that there is no ozone weekend effect phenomena in Jakarta city.

4.2. Spatial analysis on causal interaction by structural equation model

4.2.1. Spatial analysis

The model for the Sub-urban west (SUW) shows the highest GFI (AGFI) value of 0.787 (0.629), followed by that for the RA with the value of GFI (AGFI) 0.770 (0.600). The model for the CA has the lowest GFI (AGFI) of 0.731 (0.533). Peton (2000) highlights that environmental data usually have some measurement and sampling errors. These errors may due to the disordered operation of measurement equipments, some missing observations, and some very small observed data that fluctuated around the detection limit of monitoring equipments and also sometimes irrelevant measurements. Thus, this kind of measurement issues might influence model performance. Indeed, the calculated GFI and AGFI values for this model imply that the model is statistically acceptable. Among the three models, the sub-urban model performance is the best.

For all of the structural equation models and measurement models, it is found that all the parameters are statistically significant at the 1% or 5% level. This finding indicate the validity of the postulated model structure in this case study. The log-transformed variable LN_NO is also statistically a meaningful parameter. All the signs of the estimated parameters are intuitive and consistent with expectations. It can be imagined that positive parameter indicating the influence of “Primary Pollutants” on “Photochemical” might be also logical, considering that at the SUW, other than the pollutants from mobile sources, stationary sources (e.g., household and industrial emissions) also contribute to the air pollutants. Indeed, this findings need to be further explored when the data is available.

No	Description	Null Model	Half model: Spatial & Temporal	Full Model: With pollutants interactions
I	**Fixed Part**			
A	**Intercept (Location)**	50.125(10.12)	42.627(3.848)	8.722(1.97)
B	**Spatial**			
1	Sub-Urban (Dummy)		-13.255(-0.992)	-4.513(-0.96)
2	Urban Fringe(Dummy)		-18.743(-1.401)	-6.873(-1.45)
C	**Temporal**			
1	Long-term (Year)		9.383(12.333)	3.410(6.27)
2	Seasonal (Dummy wet season)		-1.370(-1.472)	2.186(3.32)
3	Weekly Weekend (Dummy)		1.077(1.054)	0.909(1.370)
D	**Interaction with other pollutants**			
1	PM_{10}			0.129(9.68)
2	NO_2			-0.056(-2.76)
3	NO			0.050(1.50)
E	**Atmospheric Condition**			
	Ratio NO/NO_2			-2.046 (-4.02)
F	**Accumulation Impacts**			
	Prior day concentration			0.669 (40.88)
II	**Random Part**			
	σ_e^2 (Within monitoring)	416.43	384.38	160.559
	$\sigma_{\mu 0}^2$(Inter-monitoring)	121.47	118.34	14.333
III	**Model Performance**			
	AIC	16060	16060	14499
	BIC	16104	16104	14570
	-2*Log likelihood	16213	16044	14473
	Degree of freedom	3	8	13
	No of Samples	1826	1826	1826

Note: ( ) → t-statistic

Table 5. Model of Daily Average Concentration of Ozone (O_3)

The latent variable “Photochemical” consistently receives the largest influence from the latent variable “Meteorology” at all the locations (see Table 6). This is consistent with the scientific evidences about photochemical reactions as described earlier in this chapter. O_3 is the secondary pollutant, which is chemically transformed from the primary pollutants and the dominant driving forces for such chemical transformation are meteorological factors. Among the meteorological factors, humidity has a negative effect on “Photochemical” in contrast to solar radiation and temperature, which have positive effects. It is also found that parameter of wind speed has a negative value and parameter of wind direction (i.e., degree from the north) is positive. Since wind speed is usually slow, and major wind comes from the north direction in Jakarta City, wind speed and direction works in the same way to increase the O_3 production. Primary pollutants, on the one hand, produce the O_3, but on the other, they cause O_3 destruction too. The latent variable “Wind” shows the second largest influence on the “Photochemical”, followed by the latent variable “Primary Pollutants”. “Primary Pollutants” shows positive influence on the “Photochemical” at the SUW, but negative at CA & RA because major precursors of O_3 are NO, NO_2 and CO, the increase in “Primary Pollutants” usually results in the reduction of O_3 production. Accordingly, negative influence at city center (CA & RA) is intuitive. On the other hand, the higher loading of PM_{10}, then lower loading of major precursors NO, NO_2 and CO at SUW. To verify the influence of PM_{10} on major precursors NO, NO_2 and CO, we also tried to incorporate such influence in the model structure, but we failed to get reasonable estimation results. Then it is difficult to clarify the reason why the influence of “Primary Pollutants” on the “Photochemical” is positive at the SUW. However, because of the negative interaction between PM_{10} and major precursors NO, NO_2 and CO, it seems that the influence of “Primary Pollutants” on the “Photochemical” is also dependent on the relative magnitude of each pollutant. This should be further explored in the future.

Concerning the interactions among the “Meteorology”, “Wind” and “Primary Pollutants”, it is found that “Meteorology” negatively affects “Primary Pollutants” at all the locations, “Wind” has positive influence on “Primary Pollutants” at the SUW and the RA, but negative at the CA. Looking at the total effects as shown in Table 7, one can see that at the SUW and the RA, influence of “Meteorology” on “Photochemical” is clearly larger than “Wind”, however, “Meteorology” and “Wind” have almost equal influence at the CA.

4.2.2. Temporal analysis

Observing the model accuracy indices (i.e., GFI and AGFI), the model for weekdays-wet season shows the highest GFI (AGFI) value 0.845 (0.724), followed by the model for weekend-wet season with the value of GFI (AGFI) 0.822 (0.683) and than followed by the model for weekdays-dry season with the value of GFI (AGFI) 0.783 (0.612). The model for weekend-dry season has the lowest GFI (AGFI) 0.775 (0.599). Despite the possible measurement and sampling errors, the GFI and AGFI values indicate the model is statistically acceptable. Among all models, the model accuracy for the weekday-wet season is the best.

Covariances				Weekdays - Dry Season					
				Sub-Urban (SUW)		CBD (CA)		Roadside (RA)	
Primary ($\acute{\eta}_2$)	<---	Met (ξ_1)	γ_{21}	-0.017		-0.142	***	-0.080	***
Primary ($\acute{\eta}_2$)	<---	Wind ($\acute{\eta}_1$)	β_{21}	0.547	***	-0.072	***	0.180	***
Photochem ($\acute{\eta}_3$)	<---	Wind ($\acute{\eta}_1$)	β_{31}	0.420	****	0.683	***	0.156	***
Photochem ($\acute{\eta}_3$)	<---	Met (ξ_1)	γ_{31}	0.816	****	0.759	***	0.743	***
Photochem ($\acute{\eta}_3$)	<---	Primary ($\acute{\eta}_2$)	β_{32}	0.109	***	-0.040	**	-0.142	***
SR (X_1)	<---	Met (ξ_1)	$\lambda^{(x)}_{11}$	0.685	***	0.796	***	0.793	***
T (X_2)	<---	Met (ξ_1)	$\lambda^{(x)}_{12}$	0.972	***	0.969	***	0.980	***
RH (X_3)	<---	Met (ξ_1)	$\lambda^{(x)}_{13}$	-0.967	***	-0.930	***	-0.952	***
WD (Y_1)	<---	Wind ($\acute{\eta}_1$)	$\lambda^{(y)}_{11}$	0.664	***	0.494	***	0.995	***
WS (Y_2)	<---	Wind ($\acute{\eta}_1$)	$\lambda^{(y)}_{12}$	-0.977	***	-0.672	***	0.617	***
LN NO (Y_4)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{24}$	0.548	***	0.525	***	0.719	***
NO_2 (Y_5)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{25}$	0.688	***	0.659	***	0.684	***
CO (Y_6)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{26}$	0.790	***	0.831	***	0.944	***
SO_2 (Y_7)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{27}$	0.210	***	0.311	***	0.368	***
PM_{10} (Y_8)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{28}$	0.777	***	0.469	***	0.449	***
O_3 (Y_3)	<---	Photochem ($\acute{\eta}_3$)	$\lambda^{(y)}_{33}$	0.795	***	0.879	***	0.979	***
LN NO (Y_4)	<---	Photochem($\acute{\eta}_3$)	$\lambda^{(y)}_{34}$	-0.660	***	-0.642	***	-0.231	***
GFI				0.787		0.731		0.770	
AGFI				0.629		0.533		0.600	
df				37		37		37	
Sample Size				1916		3179		2145	
Notes : *** Significant at 1 %; ** Significant at 5%									

Table 6. Estimation Results of Spatial Analysis (comparison among locations)

Components	Dry Season											
	Sub-Urban (West Jakarta-SUW)				CBD (Central-CA)				Roadside (JAM/Mobile-RA)			
	Met (ξ_1)	Wind ($\acute{\eta}_1$)	Primary ($\acute{\eta}_2$)	Photochem ($\acute{\eta}_3$)	Met (ξ_1)	Wind ($\acute{\eta}_1$)	Primary ($\acute{\eta}_2$)	Photochem ($\acute{\eta}_3$)	Met (ξ_1)	Wind ($\acute{\eta}_1$)	Primary ($\acute{\eta}_2$)	Photochem ($\acute{\eta}_3$)
Primary ($\acute{\eta}_2$)	-0.017	0.547	0.000	0.000	-0.142	-0.072	0.000	0.000	-0.080	0.180	0.000	0.000
Photochem ($\acute{\eta}_3$)	0.814	0.480	0.109	0.000	0.765	0.686	-0.040	0.000	0.754	0.131	-0.142	0.000
O_3 (Y_3)	0.647	0.382	0.086	0.795	0.673	0.603	-0.035	0.879	0.738	0.128	-0.139	0.979
PM_{10} (Y_8)	-0.013	0.425	0.777	0.000	-0.066	-0.034	0.469	0.000	-0.036	0.081	0.449	0.000
SO_2 (Y_7)	-0.003	0.115	0.210	0.000	-0.044	-0.022	0.311	0.000	-0.029	0.066	0.368	0.000
LN NO (Y_4)	-0.547	-0.018	0.476	-0.660	-0.566	-0.478	0.550	-0.642	-0.232	0.099	0.752	-0.231
NO_2 (Y_5)	-0.011	0.376	0.688	0.000	-0.093	-0.047	0.659	0.000	-0.055	0.123	0.684	0.000
CO (Y_6)	-0.013	0.432	0.790	0.000	-0.118	-0.060	0.831	0.000	-0.075	0.170	0.944	0.000
WS (Y_2)	0.000	-0.977	0.000	0.000	0.000	-0.672	0.000	0.000	0.000	0.617	0.000	0.000
WD (Y_1)	0.000	0.664	0.000	0.000	0.000	0.494	0.000	0.000	0.000	0.995	0.000	0.000
RH (X_3)	0.685	0.000	0.000	0.000	0.796	0.000	0.000	0.000	0.793	0.000	0.000	0.000
T (X_2)	0.972	0.000	0.000	0.000	0.969	0.000	0.000	0.000	0.980	0.000	0.000	0.000
SR (X_1)	-0.967	0.000	0.000	0.000	-0.930	0.000	0.000	0.000	-0.952	0.000	0.000	0.000

Table 7. Estimated Standardized Total Effects of spatial analysis

For all of the structural equation models and measurement models, it is found that all the parameters are statistically significant at the 1% or 5% level. This findings indicate that the the postulated model structure in this case study is valid. In addition, the log-transformed variable NO (LN_NO) is also statistically a meaningful parameter. All the signs of the estimated parameters are intuitive and consistent with expectations. It can be imagined that positive parameter indicating the influence of "Primary Pollutants" on "Photochemical" might be also logical, considering weather/meteorological situations, also contribute to the reaction of air pollutants in roadside. Needless to say, this findings need to be further explored when the data is available.

The latent variable "Photochemical consistently receives the largest effect from the latent variable "Meteorological" at all the situations (see Table 8). This is consistent with the scientific evidences about photochemical reactions as described earlier in this chapter. O_3 is the secondary pollutant which is chemically transformed from the primary pollutants and the dominant driving forces for such chemical transformation are meteorological factors. Among the meteorological factors, humidity has negative effect on "Photochemical", in contrast to solar radiation and temperature that have a positive effect. The signs of these parameters seem in agreement with the photochemical process described earlier in this chapter. It is also found that latent variable "Wind" has a negative value during wet season, in contrast to a positive value during dry season, since the wind direction are on the opposite direction seasonally. The wind comes from South East (57 %) and North West (47.4%) during dry season and wet season, respectively.

The Roadside Station is located in the south part of the nearest pollutants source (Casablanca Road) , we preliminary identify that during wet season the wind direction from North West carry the "Primary Pollutants" more intensive than during in dry season. On the one hand, primary pollutants produce the O_3, but on the other hand also cause O_3 destruction. The latent variable "Wind" shows the second largest influence on the "Photochemical", followed by the latent variable "Primary Pollutants" during wet season. On the contrary, "Primary Pollutants" shows the second largest influence on the "Photochemical", followed by the latent variable "Wind" during dry season period. The "Primary Pollutants" shows negative influence on the "Photochemical" for weekday-dry, weekday-wet and weekend-dry season, because major precursors of O_3 are NO, NO_2 and CO. The increase in "Primary Pollutants" usually reduces O_3 production. Accordingly, negative influences for weekday-wet, weekdays-dry and weekend-dry season are intuitive. The "Primary Pollutants" shows positive influence on the "Photochemical" for weekend-wet season, but not significant for all confidence level (see Table 8). Therefore, the data for weekend-wet season in particular should be further explored to explain the positive value. The load of CO is the highest among other pollutants SO_2, NO, NO_2 and CO for all situations. The influence of CO has been incorporated into the model structure to verify its effect to the model especially for weekend-wet season, but all the estimation results are below the reasonable confidence level, despite the fact that .the emission source (road) is relatively close to the monitoring station. The influence of meteorological factors seems more dominant than primary pollutants. Indeed, this should be further explored in the future.

Concerning the interactions among the "Meteorological", "Wind" and "Primary Pollutants", it is found that "Meteorological" and "Wind" positively affects "Primary Pollutants" for all data sets. The influence of "Meteorological" on "Photochemical" is obviously larger than the "Wind" and "Primary Pollutants" for all situations as depicted in Table 9 and 10.

Estimated Free Structural Parameter				Weekdays Dry season		Weekdays Wet Season		Weekend Dry Season		Weekend Wet season	
Wind ($\acute{\eta}_1$)	<---	Met (ξ_1)	γ_{11}	-0.156	***	0.679	***	-0.237	***	-0.129	
Primary ($\acute{\eta}_2$)	<---	Met (ξ_1)	γ_{21}	0.02		0.027		0.117		0.005	
Primary ($\acute{\eta}_2$)	<---	Wind ($\acute{\eta}_1$)	β_{21}	0.363	***	0.479		0.305	***	0.538	***
Photochem ($\acute{\eta}_3$)	<---	Wind ($\acute{\eta}_1$)	β_{31}	0.118	****	-0.315	***	0.075	*	-0.054	
Photochem ($\acute{\eta}_3$)	<---	Met (ξ_1)	γ_{31}	0.769	****	0.971	***	0.777	***	0.761	***
Photochem ($\acute{\eta}_3$)	<---	Primary ($\acute{\eta}_2$)	β_{32}	-0.17	****	-0.142	***	-0.163	***	0.022	
SR (X_1)	<---	Met (ξ_1)	$\lambda^{(x)}_{11}$	0.795	***	0.724	***	0.775	***	0.796	***
T (X_2)	<---	Met (ξ_1)	$\lambda^{(x)}_{12}$	0.975	***	1	***	0.978	***	0.989	***
RH (X_3)	<---	Met (ξ_1)	$\lambda^{(x)}_{13}$	-0.949	***	-0.95	***	-0.963	***	-0.958	***
WD (Y_1)	<---	Wind ($\acute{\eta}_1$)	$\lambda^{(y)}_{11}$	0.979	***	0.441	***	0.724	***	0.453	***
WS (Y_2)	<---	Wind ($\acute{\eta}_1$)	$\lambda^{(y)}_{12}$	0.473	***	0.855	***	0.525	***	0.383	***
LN NO (Y_4)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{24}$	0.742	***	0.551	***	0.629	***	0.525	***
NO_2 (Y_5)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{25}$	0.737	***	0.786	***	0.711	***	0.94	***
CO (Y_6)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{26}$	0.91	***	0.936	***	0.991	***	0.962	***
SO_2 (Y_7)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{27}$	0.206	***	0.673	***	0.239	***	0.329	***
PM_{10} (Y_8)	<---	Primary ($\acute{\eta}_2$)	$\lambda^{(y)}_{28}$	0.411	***	0.512	***	0.4	***	0.563	***
O_3 (Y_3)	<---	Photochem ($\acute{\eta}_3$)	$\lambda^{(y)}_{33}$	0.962	***	0.946	***	0.967	***	0.93	***
LN NO (Y_4)	<---	Photochem($\acute{\eta}_3$)	$\lambda^{(y)}_{34}$	-0.254	***	-0.408	***	-0.243	***	-0.317	***
Goodness-of-fit index (GFI)				**0.783**		**0.845**		**0.775**		**0.822**	
Adjusted Goodness-of-fit Index (AGFI)				**0.612**		**0.724**		**0.599**		**0.683**	
df				37		37		37		37	
Estimation Method : Maximum Likelihood											
Notes : * Significant at 1 % ; * significant at 10%**											

Table 8. Estimation Results of Temporal Variations at Roadside of Jakarta City

Variables	Weekdays Dry Season Met (ξ_1)	Dry Season Wind ($\acute{\eta}_1$)	Dry Season Primary ($\acute{\eta}_2$)	Dry Season Photochem ($\acute{\eta}_3$)	Wet Season Met (ξ_1)	Wet Season Wind ($\acute{\eta}_1$)	Wet Season Primary ($\acute{\eta}_2$)	Wet Season Photochem ($\acute{\eta}_3$)
Wind ($\acute{\eta}_1$)	-0.156	0	0	0	0.679	0	0	0
Primary ($\acute{\eta}_2$)	-0.037	0.363	0	0	0.352	0.479	0	0
Photochem ($\acute{\eta}_3$)	0.757	0.056	-0.17	0	0.708	-0.383	-0.142	0
O_3 (Y_3)	0.728	0.054	-0.164	0.962	0.669	-0.362	-0.135	0.946
PM_{10} (Y_8)	-0.015	0.149	0.411	0	0.18	0.245	0.512	0
SO_2 (Y_7)	-0.008	0.075	0.206	0	0.237	0.322	0.673	0
LN NO (Y_4)	-0.219	0.255	0.786	-0.254	-0.095	0.42	0.609	-0.408
NO_2 (Y_5)	-0.027	0.268	0.737	0	0.277	0.376	0.786	0
CO (Y_6)	-0.033	0.33	0.91	0	0.33	0.448	0.936	0
WS (Y_2)	-0.074	0.473	0	0	0.58	0.855	0	0
WD (Y_1)	-0.152	0.979	0	0	0.3	0.441	0	0
RH (X_3)	-0.949	0	0	0	-0.95	0	0	0
T (X_2)	0.975	0	0	0	1	0	0	0
SR (X_1)	0.795	0	0	0	0.724	0	0	0

Table 9. Estimated standardized total effects of surface O_3 model for Jakarta City (weekday)

Variables	Weekend							
	Dry Season				Wet Season			
	Met (ξ_1)	Wind ($\acute{\eta}_1$)	Primary ($\acute{\eta}_2$)	Photochem ($\acute{\eta}_3$)	Met (ξ_1)	Wind ($\acute{\eta}_1$)	Primary ($\acute{\eta}_2$)	Photochem ($\acute{\eta}_3$)
Wind ($\acute{\eta}_1$)	-0.237	0	0	0	-0.129	0	0	0
Primary ($\acute{\eta}_2$)	0.045	0.305	0	0	-0.065	0.538	0	0
Photochem ($\acute{\eta}_3$)	0.752	0.026	-0.163	0	0.766	-0.042	0.022	0
O_3 (Y_3)	0.727	0.025	-0.158	0.967	0.713	-0.039	0.021	0.93
PM_{10} (Y_8)	0.018	0.122	0.4	0	-0.036	0.303	0.563	0
SO_2 (Y_7)	0.011	0.073	0.239	0	-0.021	0.177	0.329	0
LN NO (Y_4)	-0.154	0.186	0.668	-0.243	-0.277	0.296	0.518	-0.317
NO_2 (Y_5)	0.032	0.217	0.711	0	-0.061	0.506	0.94	0
CO (Y_6)	0.044	0.303	0.991	0	-0.062	0.518	0.962	0
WS (Y_2)	-0.124	0.525	0	0	-0.05	0.383	0	0
WD (Y_1)	-0.171	0.724	0	0	-0.059	0.453	0	0
RH (X_3)	-0.963	0	0	0	-0.958	0	0	0
T (X_2)	0.978	0	0	0	0.989	0	0	0
SR (X_1)	0.775	0	0	0	0.796	0	0	0

Table 10. Estimated standardized total effects of surface O_3 model for Jakarta City (weekend)

5. Conclusion

Surface ozone is potentially high in Jakarta, serious problem and getting worse every year. In this paper, a spatial and temporal analysis of surface ozone related issues were done by two major approach multilevel analysis and structural equation model. A spatial and temporal analysis was conducted by using time series data, which were collected at the existing air quality monitoring stations in Jakarta city from 2001 to 2003.

This paper first applied a multilevel analysis to examine the variation properties affect on event of daily peak ozone concentration. Secondly, we analyze variations properties on daily average surface ozone concentration by introducing observed information related to spatial aspect and temporal aspect. The year of measurement, seasonal and weekly variables were selected to represent long-term, medium/seasonal-term and day-to-day (short term) variation of daily average ozone concentration. Finally, we established a structural equation model, which can endogenously incorporate various cause-effect relationships and interactions among meteorological factors, wind, and primary pollutants, which affect on a half-hour concentration of surface ozone. The established model also incorporated non-linear relationships existing in the observed variables. Using the data collected from the above-mentioned fixed monitoring stations in Jakarta City, the effectiveness of the established model is empirically confirmed. The best model for spatial analysis, that it has the highest goodness-of-fit index, is the one for the suburban area. As for temporal analysis, the model effectiveness was empirically tested using the air quality data from Roadside Station in Central Jakarta. The best model indicated with the highest goodness-of-fit index, was the one for the weekdays during wet season.

The event of daily peak ozone concentration is singular and usually occurred at 11.28 am in central business district of Jakarta city. These events will be slightly late at sub-urban monitoring stations and urban fringe around 38 to 40 minutes later than central Jakarta. The events of daily peak concentration of ozone are almost stable in all measurement period. We couldn`t found variations among year of measurement, among dry and wet seasonal variations and also among days in a week. In contrast, by using daily average concentration we couldn`t find significant impact of location which mean location properties are minor factor on daily average concentration of surface ozone occurs in Jakarta city. The main factors affects on daily average concentration are temporal aspects and the presence of other pollutants. The medium and long-term variations are significantly increase ozone concentration. In contrast, short-term (day-to-day) variation is insignificant. This analysis shows the tendency of daily average surface ozone concentration in Jakarta city are increase year by year and getting worse. The expected washing phenomena caused by rain are smaller than the emission increase due to traffic jam or chaotic traffic situation on the rainy situation in Jakarta city. As results, daily average concentration of surface ozone concentration measured at wet season is slightly high than dry season. The influence of precursor pollutants on surface ozone concentration shows the logical reason and accumulation process of daily average surface ozone concentration was exist in the urban ozone atmospheric conditions.

The establishment of causal interaction in urban ozone atmospheric condition was successfully captured by proposed structural equations model. The proposed structural equation model also examine by empirical data for very short term concentration of ozone in Jakarta city. The structural equation model incorporates various cause-effect relationships and interactions among meteorological variables, wind, and primary pollutants, which affect the surface O_3. The model also incorporated the existing non-linear relationships in the observed variables. The model effectiveness was empirically tested and the best model was defined for the one that has the highest goodness-of-fit index, which was the one for the suburban area and weekdays-wet season` model. In micro urban environment studies, all models used in this study showed that meteorological variables consistently had the largest influence on photochemical, followed by the wind conditions and lastly the primary pollutants. Among the meteorological variables, relative humidity had a negative influence while solar radiation and temperature had positive influences. The model estimations demonstrated that the influence of meteorological factors on photochemical was definitely larger than the wind conditions at all situations.

Primary pollutants had a negative influence for all temporal situations in roadside area except for the weekend during wet season. It seems that PM_{10} behaved quite differently compared to the other primary pollutants at the suburban area and city center, i.e. the higher the PM_{10} load, the lower the major precursors NO, NO_2 and CO loads. On the roadside area in the city center, It is found that CO concentration was the highest among the other primary pollutants for all situations. In addition, the higher the CO load, the lower the other major precursors (NO and NO_2) loads.

Further study should be carried out to combine both spatial and temporal issues and causal interaction among factors on surface ozone concentration at urban areas. A study based on multilevel structural equation model should be conducted to solve these issues.

This understanding can assist the policy maker in the developing O_3 pollution control strategies.

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Acknowledgement

This research is partially supported by Global Environmental Leadership Program at Graduate School of International Development and Cooperation, Hiroshima University, Japan.

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