# Chapter 7

# Modeling the Effect of Traffic Count on Commuters' Exposure to PM

This chapter discusses the effect of traffic count on commuters' exposure to PM. The chapter covers the modeling of section-wise and real-time PM for commuters and explores the optimal combination of factors for modeling PM concentrations.

## 7.1 Background

Past studies have examined various factors influencing motorcyclists' exposure to PM. The studies and the factors considered in their analysis are illustrated in the Literature Review Section. Maximum number of studies considered AC, TT, IR, ID, PHT and OPHT as their primary factors for modeling and assessing the PM exposure for motorcyclists. Though these studies considered those factors and found satisfactory results, there is a limited number of studies available that explored the traffic count factor. The properties of a cycle (in terms of exposure to air pollutants) are similar to a motorcycle, as both of the modes are open modes of travel. As limited articles are available to review, the effect of traffic count on cyclists' PM exposure from past studies is reviewed here. It is common knowledge that an increase in vehicles increases air pollution levels. However, Adams et al. (2001) reported that traffic count (per hour) negatively correlated with on-road PM levels during winter in London (UK). The reason for the anomaly in the relationship between traffic count and PM levels was not explained in the study. Hatzopoulou et al. (2013) reported that the counts (vehicle/min) of diesel vehicles (sum of buses and trucks) were associated with a smaller increment in $PM_{2.5}$, while the automobile counts were the insignificant determinant of cyclists' PM levels. Thus, the objective of the study is to analyze the effect of section-wise and real-time traffic count on motorcyclists' exposure to on-road PM levels.

## 7.2 Data Analysis

### 7.2.1 Vehicle Detection

The traffic composition needed to be extracted and saved in a database before they could be used to model their effect on PM concentrations. Thus, vehicle detection was required to extract the vehicle compositions from traffic videos. The vehicle detection process was carried out by two methods i.e., manual and automatic. The manual vehicle detection involved a moving observer method, while the automatic vehicle detection involved image processing using the YOLOv5, a popular object detection model.

### 7.2.2 Manual Vehicle Detection

The manual vehicle detection process was carried out, which involved a moving observer method. As mentioned earlier in Chapter 3, the data collection was carried over four routes. The traffic count and parameters were different along different parts of the routes. The reason might be due to the presence of multiple traffic intersections. These are the places along the routes at which the traffic pattern changes due to the merging and diverging of vehicles. Thus, the routes were divided into various sections before proceeding with vehicle counting. Here, one section is the length between two consecutive traffic intersections. In total, 37 sections were present along these four routes (Fig. 7.1). The sections were labeled in x-y format. Here, x is the route number, while y is the corresponding section number of the respected route.

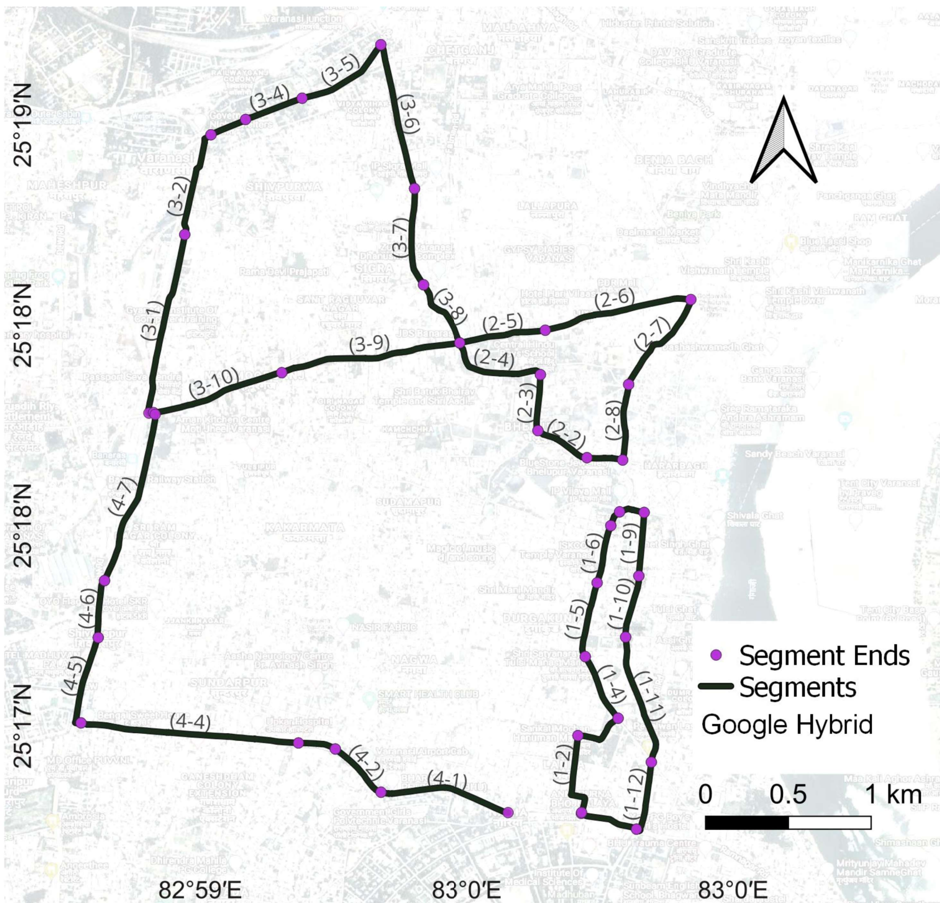



Fig. 7.1 Representation of study routes in terms of various sections.

A data entry sheet was made for entering information adhering to the moving observer method, such as time duration, vehicle composition or classifications and their counts. The vehicle types, such as Auto-Rickshaw (M3W), Motorcycles/Bike (M2W), Bus, Car (LMV), LCV, HCV, and TOTO were considered in the data extraction. The data was stored in the computer database after the data entry for several data collection days and trips were completed. The flow chart for manual vehicle detection and counting is shown in Fig. 7.2.

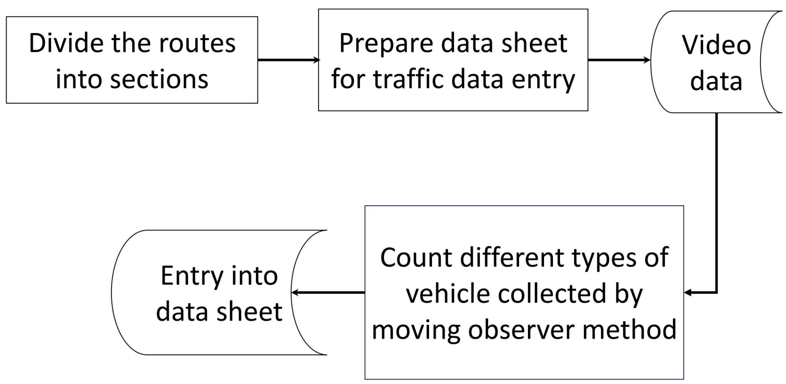



Fig. 7.2 Steps for manual vehicle counting.

### 7.2.3 Automatic Vehicle Detection

The automatic vehicle detection process is carried out in two stages. In the first stage, the real-time (second-wise) image frames were extracted from the traffic videos using Python codes. The example of the extracted image is shown in Fig. 7.3. The frames were read one by one in a loop, and the image frames were taken every second. The frames were saved in a modified file name. The naming of each frame was dependent upon the starting date and time of the traffic video data collection. The collected video data files were named in the format of the starting date and time of the data collection, i.e., yyyy-mm-dd_hh-mm-ss (date_time). The first image extracted from the video files had the same name as the name of the video file. The next extracted image files were renamed by adding one second to the file name, and the process went on till the video extraction was completed fully. For example, if the data was collected on 15th January 2022 at 10 h 15 m 58 s, the first extracted image from the video was renamed as 2022-01-15_10-15-58. Then, the second and third images were renamed as 2022-01-15_10-15-59 and 2022-01-15_10-16-00, respectively. The process continued till all the images from the complete video were extracted and renamed.

Fig. 7.3 Example of an extracted raw image using Python.

In the second stage, an object identification model, YOLOv5, was used to get the traffic composition and their counts from each of those extracted images. The same vehicle classifications were considered in automatic vehicle detection, like manual vehicle detection. The YOLOv5 model was trained and tested before it could be used to get traffic composition details for the whole data set of extracted images. A total of 10000 extracted images were used for training and testing the performance of YOLOv5. The YOLOv5 was trained using 70% of images (7000 numbers), while the performance of the model was tested using 30% of images (3000 numbers) by two methods. The methods included the confusion matrix (Fig. 7.4) and precision-recall curve (Fig. 7.5).

The confusion matrix is a tools that evaluate the performance of the model by comparing the predicted vehicle classes with the actual vehicle classes. Vehicle class detection involves not just the accuracy of detected classes but also the localization of detected vehicles. Finally, the matrix helps in understanding how well the model is detecting vehicle classes by presenting a detailed breakdown of true positives, false positives, false negatives and true negatives for each vehicle class.

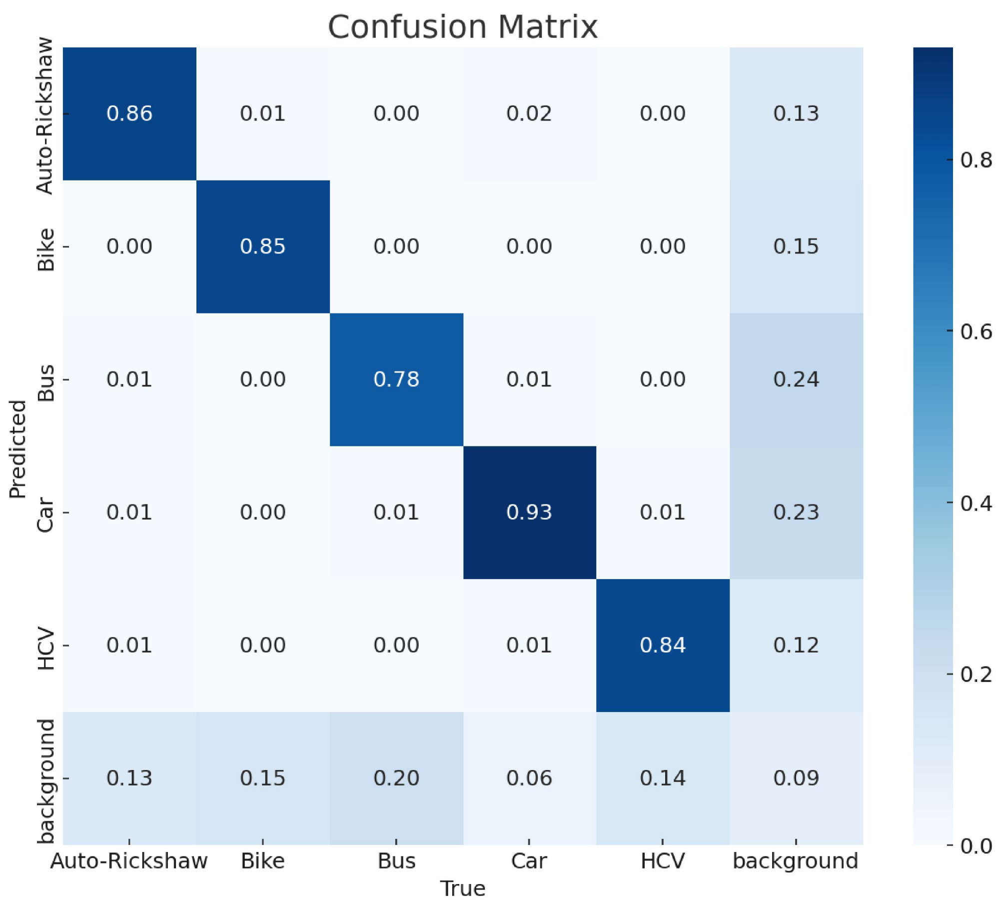



Fig. 7.4 Performance evaluation YOLOv5 by confusion matrix.

The precision-recall curve is a graphical representation used for evaluating the performance of classification models, particularly in places where the classes are imbalanced. In object detection models like YOLOv5, the precision-recall curve helps in understanding the trade-off between precision and recall across different confidence thresholds. Precision is the ratio of true positive object detections to the total number of object detections (both true positives and false positives). It finds the answer to actual correct predictions of total positive predictions made in the process. Recall is the ratio of true positive object detections to the total number of actual positive detections (both true positives and false negatives). It finds the answer to actual correct predictions of total actual positive instances. As shown in Fig. 7.5, the mAP stands for mean average precision for all vehicle classes in the extracted images dataset. It provides a single numerical value that summarizes the performance of the precision-recall trade-off for all object classes. The one tested image showing different vehicle classifications is presented in Fig. 7.6. The vehicle classifications and their counts were stored in an Excel file in CSV format. The flow chart for automatic vehicle detection and counting is shown in Fig. 7.7.

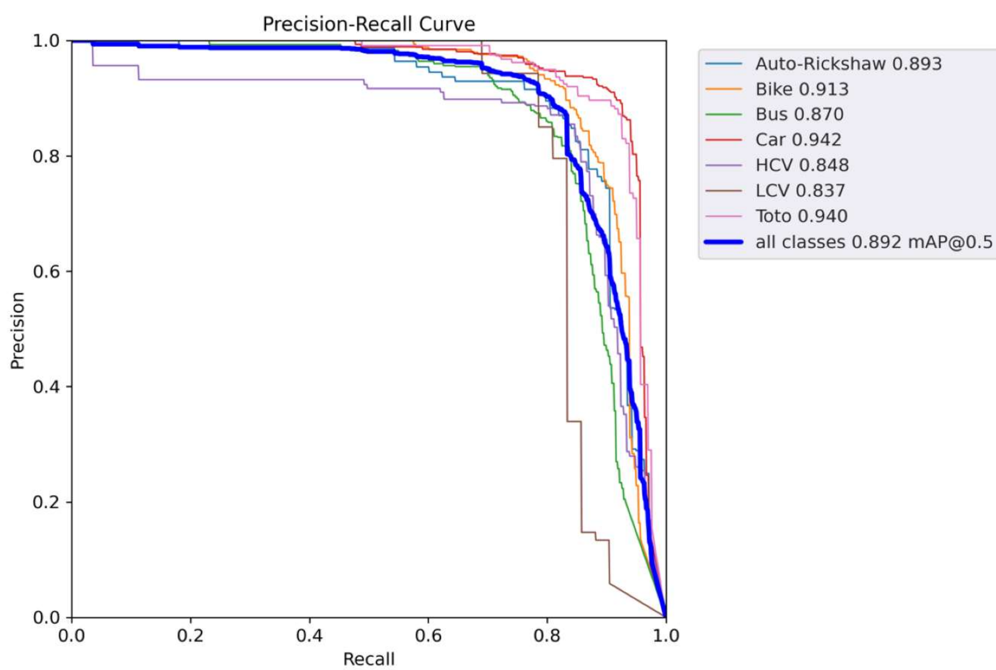



Fig. 7.5 Performance evaluation of YOLOv5 by Precision-Recall Curve.

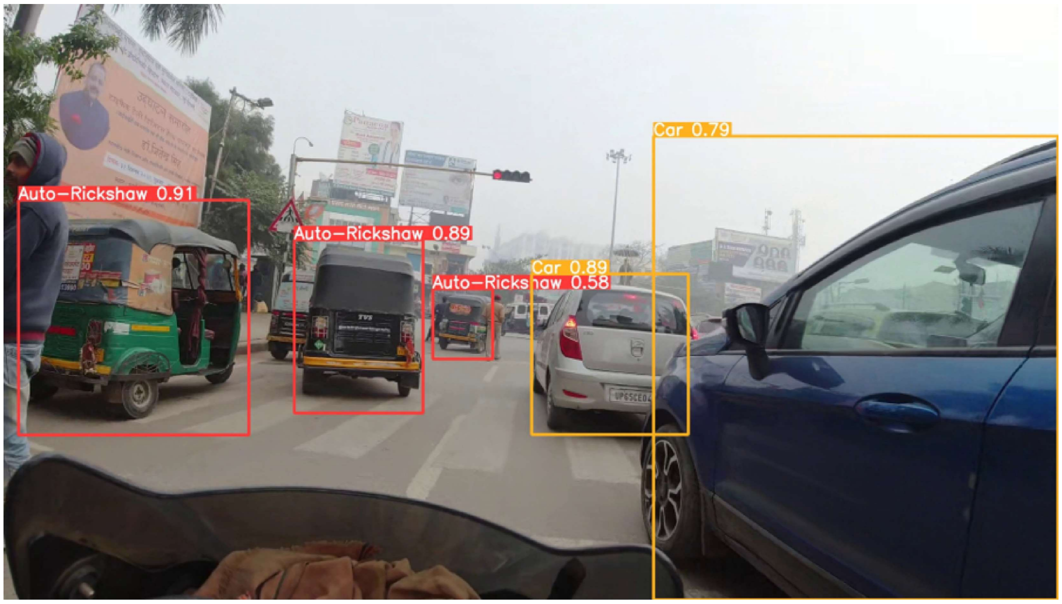



Fig. 7.6 Vehicle classification by YOLOv5.

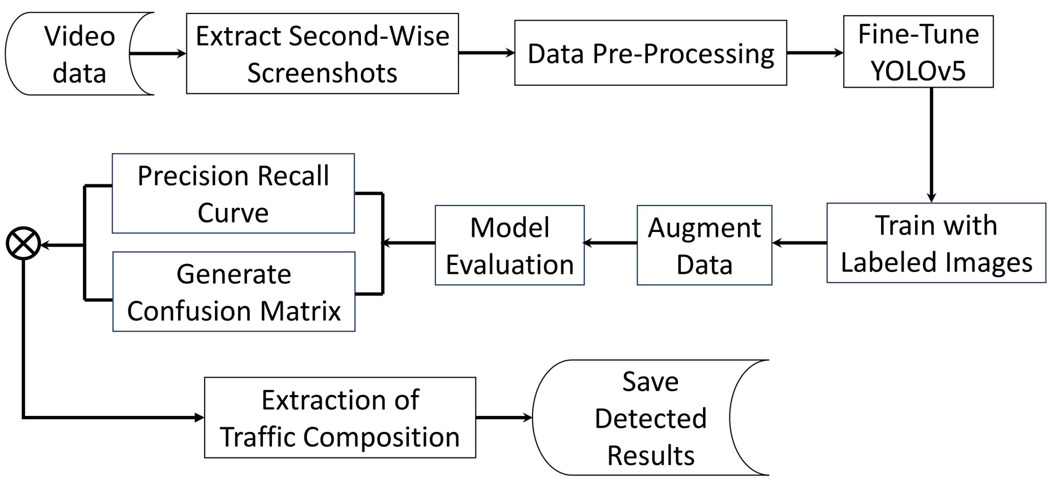



Fig. 7.7 Steps involved in automated vehicle counting.

### 7.2.4 Statistical Analysis

The statistical analysis included single variate and mixed-effect linear regression. Single variable linear regression works on the fixed effect of independent variables, while mixed-effect linear regression works on both fixed and random effects of independent variables. The fixed factors influence the response variable, while the random factors introduce variability.

## 7.3 Results and Discussion

### 7.3.1 Section-Wise PM Exposure Summary Statistics

Table 7.1 and 7.2 summarizes the on-road PM statistics across various route sections for the whole study duration. The highest median $PM_{2.5}$ (161 µg $m^{-3}$) and $PM_{10}$ (342 µg $m^{-3}$) concentrations were found along R2 across S15 and S19, respectively. S31 (along R4) was found to be the cleanest section among other sections, with 97 and 179 µg $m^{-3}$ of $PM_{2.5}$ and $PM_{10}$ concentrations, respectively. The maximum number of sections with comparatively higher and lower PM concentrations belongs to R2 and R4, respectively, compared to the rest of the sections (Fig. 7.8). Thus, the PM concentrations along R2 and R4 were higher and lower compared to other routes. As mentioned before, the CPCB, India, categorized $PM_{2.5}$ ($PM_{10}$) concentration (in µg $m^{-3}$) ranges from 0 to 30 (0 to 50) as good, from 31 to 60 (51 to 100) as satisfactory, from 61 to 90 (101 to 250) as moderate, from 91 to 120 (251 to 350) as poor, from 121 to 250 (351 to 430) as very poor and more than 250 (430) to be severe (CPCB, 2015). Considering the $PM_{2.5}$ concentration of sections, the PM level of the worst section (S15: 161 µg $m^{-3}$) comes under the very poor category, while the PM level of the cleanest section (S31: 97 µg $m^{-3}$) comes under the poor category. In summary, we can conclude that all sections are not safe to travel. Long-term exposure to these high PM levels will have serious effects on human health. Thus, policymakers and urban planners should work on the methodologies to reduce the on-road PM level immediately.

### 7.3.2 Performance Evaluation of PM Exposure Models using Section-Wise Traffic Count

**Single Variable Linear Regression Models**

As mentioned Literature Review Section, the prominent factors such as meteorology factors (AT, RH and Season), traffic factors (PHT and OPHT), ventilatory factors (IR and ID), street configurations (LU only) and AC were already explored for the motorcyclists in the study location by Behera et al. (2023). The current study explored the possible effect of traffic counts on particulate exposure for motorcyclists during commuting in the study area. Table 7.3 and 7.4 presents the section-wise $PM_{2.5}$ and $PM_{10}$ linear regression models for PM exposure concentration. The linear regression model was fitted using section-wise traffic flow that was converted into PCU/hr. As mentioned earlier, the segment-wise traffic was calculated using a moving observer method. For each trip, the traffic count was estimated for each segment. Suppose we use count/hr instead of PCU/hr it would not give weightage to bigger (larger project area) vehicles such as HCV and LMV, which generally emit higher pollutants compared to other vehicles and are also more responsible for resuspension. PCU provides a measure that reflects the size of the vehicles. The estimates for PCU/hr ($PM_{2.5}$: 0.008 and $PM_{10}$: 0.012) were found to be a very small comparison to intercepts ($PM_{2.5}$: 142.28 and $PM_{10}$: 267.83). Thus, it can be assumed that the section-wise traffic was not significantly correlated with the PM exposure concentrations. In addition, the models were also found insignificant, with the R-squared values were found to be close to 0.

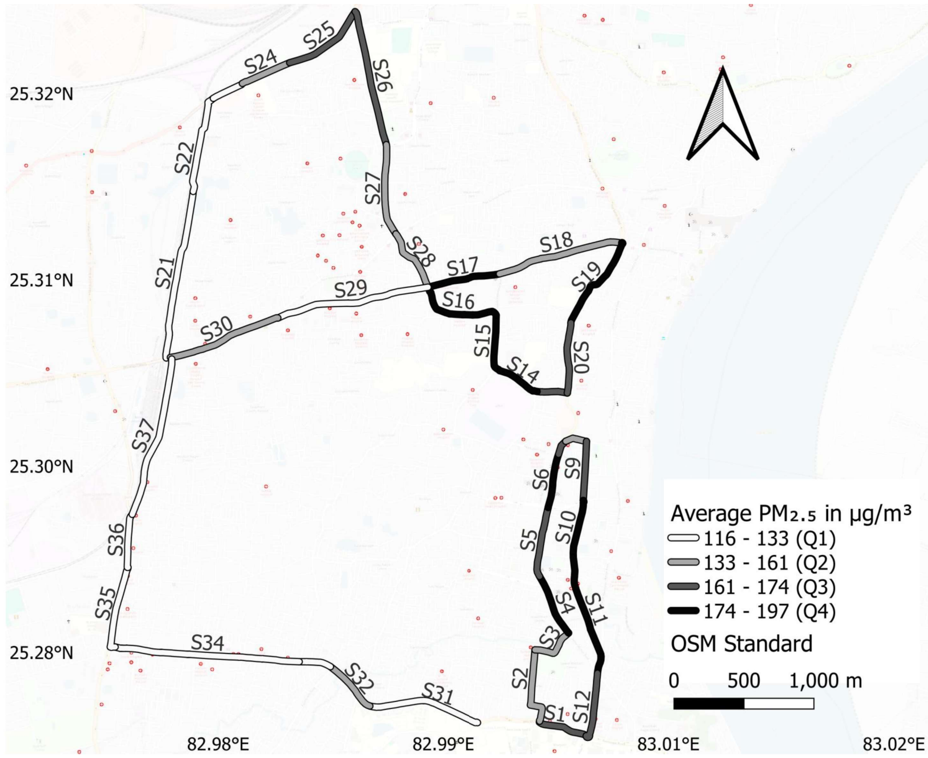
The study by Adams et al. (2001) found an insignificant (p-value: 0.75) Pearson correlation coefficient (0.03) of $PM_{2.5}$ exposure for cyclists in London (UK) (Adams et al.,

Table 7.1 Summary of on-road $PM_{2.5}$ concentration across all route sections (µg $m^{-3}$).

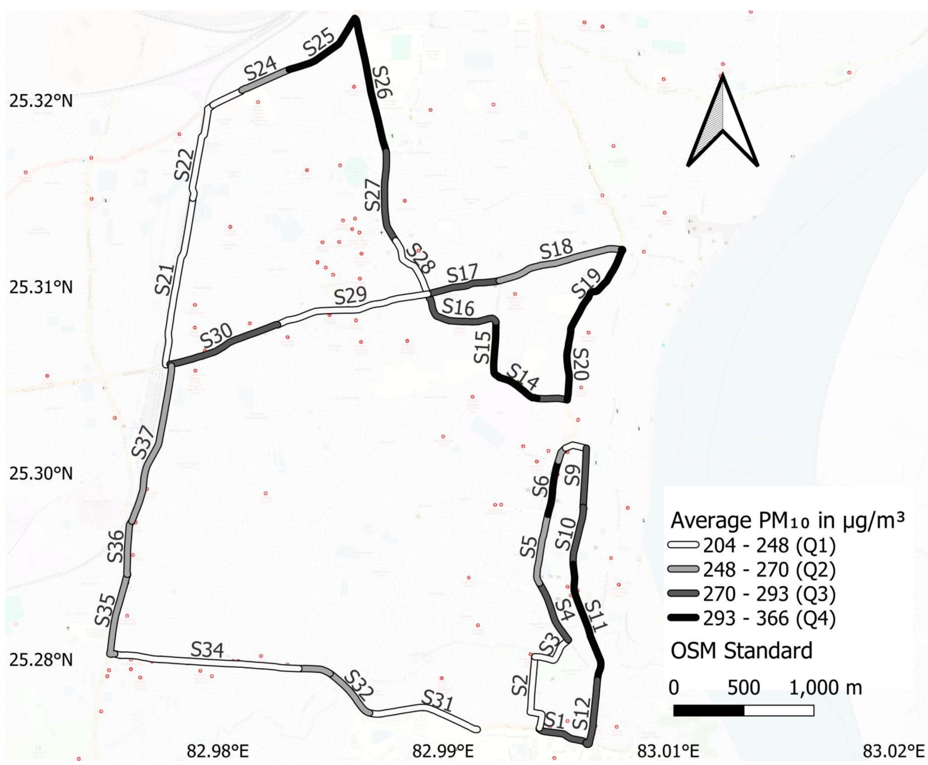
| Route Number | Section Number | Mean (SD) | Median | 2.5% - 97.5% | Min - Max |
|---|---|---|---|---|---|
| R1 | S1 | 170 (104) | 136 | 48 - 465 | 29 - 597 |
| | S2 | 153 (106) | 115 | 36 - 459 | 28 - 592 |
| | S3 | 148 (102) | 113 | 37 - 465 | 30 - 597 |
| | S4 | 177 (114) | 139 | 46 - 513 | 33 - 597 |
| | S5 | 174 (112) | 136 | 45 - 493 | 29 - 598 |
| | S6 | 179 (114) | 141 | 42 - 469 | 28 - 595 |
| | S7 | 169 (120) | 121 | 39 - 476 | 31 - 581 |
| | S8 | 161 (110) | 119 | 34 - 478 | 27 - 580 |
| | S9 | 173 (115) | 133 | 38 - 477 | 28 - 590 |
| | S10 | 180 (118) | 142 | 36 - 490 | 29 - 578 |
| | S11 | 184 (119) | 141 | 46 - 503 | 35 - 598 |
| | S12 | 173 (115) | 134 | 45 - 517 | 35 - 596 |
| R2 | S13 | 165 (107) | 135 | 36 - 442 | 22 - 590 |
| | S14 | 175 (116) | 136 | 46 - 485 | 33 - 579 |
| | S15 | 197 (116) | 161 | 56 - 499 | 35 - 595 |
| | S16 | 185 (116) | 146 | 44 - 487 | 21 - 598 |
| | S17 | 179 (112) | 142 | 38 - 444 | 19 - 594 |
| | S18 | 159 (104) | 123 | 40 - 438 | 21 - 590 |
| | S19 | 177 (107) | 148 | 42 - 444 | 21 - 595 |
| | S20 | 170 (110) | 139 | 36 - 457 | 22 - 595 |
| R3 | S21 | 132 (92) | 103 | 36 - 403 | 20 - 596 |
| | S22 | 128 (96) | 98 | 30 - 414 | 19 - 595 |
| | S23 | 133 (97) | 104 | 36 - 437 | 22 - 574 |
| | S24 | 155 (94) | 135 | 36 - 416 | 23 - 586 |
| | S25 | 172 (106) | 144 | 43 - 462 | 22 - 598 |
| | S26 | 173 (105) | 149 | 44 - 460 | 23 - 597 |
| | S27 | 155 (102) | 126 | 41 - 447 | 24 - 597 |
| | S28 | 136 (87) | 112 | 38 - 385 | 22 - 595 |
| | S29 | 125 (89) | 101 | 34 - 397 | 20 - 595 |
| | S30 | 144 (98) | 116 | 36 - 425 | 22 - 595 |
| R4 | S31 | 116 (75) | 97 | 26 - 321 | 16 - 568 |
| | S32 | 136 (84) | 114 | 32 - 358 | 19 - 546 |
| | S33 | 133 (78) | 118 | 34 - 334 | 17 - 558 |
| | S34 | 123 (80) | 103 | 26 - 345 | 16 - 590 |
| | S35 | 132 (85) | 113 | 27 - 360 | 15 - 585 |
| | S36 | 128 (80) | 112 | 30 - 345 | 20 - 577 |
| | S37 | 133 (85) | 114 | 28 - 353 | 15 - 593 |

Table 7.2 Summary of on-road $PM_{10}$ concentration across all route sections (μg $m^{-3}$).

| Route Number | Section Number | Mean (SD) | Median | 2.5% - 97.5% | Min - Max |
|---|---|---|---|---|---|
| R1 | S1 | 290 (155) | 261 | 82 - 666 | 37 - 959 |
| | S2 | 248 (154) | 215 | 59 - 644 | 38 - 965 |
| | S3 | 241 (131) | 214 | 66 - 581 | 39 - 925 |
| | S4 | 275 (146) | 250 | 78 - 623 | 44 - 952 |
| | S5 | 270 (150) | 246 | 75 - 638 | 36 - 963 |
| | S6 | 312 (172) | 281 | 72 - 726 | 36 - 963 |
| | S7 | 258 (158) | 224 | 56 - 633 | 40 - 958 |
| | S8 | 240 (131) | 213 | 56 - 532 | 35 - 907 |
| | S9 | 291 (171) | 254 | 56 - 667 | 33 - 956 |
| | S10 | 293 (173) | 266 | 54 - 694 | 33 - 964 |
| | S11 | 298 (162) | 266 | 84 - 681 | 48 - 961 |
| | S12 | 279 (159) | 246 | 78 - 662 | 48 - 966 |
| R2 | S13 | 276 (156) | 244 | 75 - 659 | 38 - 966 |
| | S14 | 303 (174) | 261 | 86 - 775 | 47 - 958 |
| | S15 | 328 (157) | 300 | 109 - 701 | 63 - 951 |
| | S16 | 288 (145) | 261 | 83 - 634 | 40 - 952 |
| | S17 | 273 (148) | 250 | 72 - 622 | 40 - 954 |
| | S18 | 267 (134) | 241 | 82 - 569 | 39 - 966 |
| | S19 | 366 (180) | 342 | 95 - 801 | 42 - 966 |
| | S20 | 308 (162) | 280 | 74 - 682 | 38 - 966 |
| R3 | S21 | 244 (153) | 201 | 69 - 684 | 38 - 966 |
| | S22 | 220 (140) | 179 | 61 - 626 | 33 - 958 |
| | S23 | 242 (153) | 199 | 72 - 679 | 37 - 965 |
| | S24 | 267 (152) | 230 | 81 - 670 | 46 - 955 |
| | S25 | 350 (195) | 306 | 97 - 834 | 56 - 966 |
| | S26 | 330 (184) | 289 | 88 - 802 | 45 - 966 |
| | S27 | 284 (155) | 248 | 86 - 681 | 49 - 966 |
| | S28 | 236 (126) | 208 | 72 - 562 | 41 - 934 |
| | S29 | 228 (135) | 191 | 71 - 593 | 36 - 966 |
| | S30 | 293 (171) | 243 | 86 - 741 | 36 - 966 |
| R4 | S31 | 204 (114) | 179 | 47 - 486 | 22 - 899 |
| | S32 | 266 (152) | 229 | 64 - 659 | 25 - 961 |
| | S33 | 263 (150) | 230 | 68 - 646 | 24 - 955 |
| | S34 | 226 (128) | 194 | 53 - 561 | 24 - 923 |
| | S35 | 257 (152) | 223 | 56 - 632 | 22 - 959 |
| | S36 | 266 (146) | 237 | 74 - 639 | 36 - 950 |
| | S37 | 262 (165) | 221 | 62 - 713 | 22 - 966 |




(a)




(b)

Fig. 7.8 Average (a) $PM_{2.5}$ and (b) $PM_{10}$ exposure along different sections of the study routes.

2001). The study used a surrogate of traffic data by getting the traffic data from the UK Department of the Environment, Transportation and the Regions (DETR), which could be one of the reasons behind the lower correlation. Similarly, Hatzopoulou et al. (2013) considered a constant traffic count at each count point instead variable traffic count, which might lead to a lower correlation between traffic count and $PM_{2.5}$ levels. Again, Kaur and Nieuwenhuijsen (2009) found a lower Spearman correlation (0.15) between traffic count and $PM_{2.5}$ exposure. Traffic count explained very little variability in $PM_{2.5}$ concentrations in past studies, including the current study. Thus, the linear regression is not sufficient enough to get a statistically determinant model. Therefore, the current study modeled the PM exposure using mixed effect linear effect by incorporating other suitable factors along with the traffic counts.

Table 7.3 Linear regression for section-wise $PM_{2.5}$ exposure models.

| Variables | Estimate | Std. Error | t-value | p-value |
|---|---|---|---|---|
| **Intercept** | 142.28 | 4.368 | 32.577 | 0.000 |
| **PCU/hr** | 0.008 | 0.003 | 2.740 | 0.006 |

*Note: R-squared: 0.006, Adjusted R-squared: 0.005*

Table 7.4 Linear regression for section-wise $PM_{10}$ exposure models.

| Variables | Estimate | Std. Error | t-value | p-value |
|---|---|---|---|---|
| **Intercept** | 267.83 | 7.540 | 35.520 | 0.000 |
| **PCU/hr** | 0.012 | 0.005 | 2.468 | 0.014 |

*Note: R-squared: 0.005, Adjusted R-squared: 0.004*

**Mixed-Effect Linear Regression Models**

There were various categorical variables, such as route and section number, travel direction, month, season, time interval, speed and temperature interval or bin, which had significant effects on on-road PM exposure. Thus, a mixed-effect linear regression was performed on the data to achieve a better fit. Different combinations of categorical variables were used as random effects in the regression, while traffic count (in PCU/hr) was used as a fixed effect. The hit and trial were continued until getting a better model performance (higher R-squared value). The model performance for the $PM_{2.5}$ exposure models was evaluated for both fixed and random effects, as shown in Tables 7.5 and 7.6, respectively. In addition, the model performance for the $PM_{10}$ exposure models was evaluated for both fixed and random effects, as shown in Tables 7.7 and 7.8, respectively. These tables also present the marginal and conditional R-squared values. The marginal R-squared indicates the proportion of variance explained by the fixed effects, while the conditional R-squared indicates the proportion of variance explained by the fixed and random effects together. section number, time interval and season were used as the random effects. The mixed-effect models gave a comparatively better fit against normal linear regression with a conditional R-squared of 0.700 and 0.434 for $PM_{2.5}$ and $PM_{10}$, respectively. However, the correlations between $PM_{2.5}$ ($PM_{10}$) and traffic count were found to be negative, with -0.099 and -0.178, respectively. Again, the estimates for $PM_{2.5}$ ($PM_{10}$) were found to be -0.006 (-0.005), respectively. The specific reason for negative correlations and estimates is not identified yet.

Table 7.5 Mixed-effect linear regression for section-wise $PM_{2.5}$ exposure models (fixed effects).

| **Fixed Effects** | **Estimate** | **Std. Error** | **t-value** | **p-value** |
|---|---|---|---|---|
| **Intercept** | 155.66 | 39.84 | 3.907 | 0.040 |
| **PCU/hr** | -0.006 | 0.003 | -2.093 | 0.040 |

*Note: Marginal R-squared: 0.002*

Table 7.6 Mixed-effect linear regression for section-wise $PM_{2.5}$ exposure models (random effects).

| Random Effects | Variance | Std. Deviation |
|---|---|---|
| **Section Number** | 439 | 20.95 |
| **Hour of Day** | 1014 | 31.84 |
| **Season** | 4365 | 66.07 |
| **Residual** | 2500 | 50.00 |

*Note: Conditional R-squared: 0.700*

Table 7.7 Mixed-effect linear regression for section-wise $PM_{10}$ exposure models (fixed effects).

| Fixed Effects | Estimate | Std. Error | t-value | p-value |
|---|---|---|---|---|
| **Intercept** | 276.59 | 45.07 | 6.114 | 0.010 |
| **PCU/hr** | -0.005 | 0.006 | -0.795 | 0.430 |

*Note: Marginal R-squared: 0.001*

Table 7.8 Mixed-effect linear regression for section-wise $PM_{10}$ exposure models (random effects).

| Random Effects | Variance | Std. Deviation |
|---|---|---|
| **Section Number** | 1417 | 37.64 |
| **Hour of Day** | 1736 | 41.66 |
| **Season** | 5226 | 72.29 |
| **Residual** | 10921 | 104.51 |

*Note: Conditional R-squared: 0.434*

### 7.3.3 Performance Evaluation of PM Exposure Models using Real-Time Traffic Count

**Single Variable Linear Regression Models**

The real-time PM forecast is one of the primary objectives of the study. Thus, both real-time $PM_{2.5}$ and $PM_{10}$ concentrations were modeled using real-time traffic counts.The summary of the $PM_{2.5}$ and $PM_{10}$ model are shown in Table 7.9 and 7.10, respectively. Similar to the section-wise PM exposure models, the real-time exposure models were also found insignificant, with the R-squared values close to 0 ($PM_{2.5}$: 0.014 and $PM_{10}$: 0.011). Thus, the study failed to model real-time on-road PM concentration using linear modeling. Thus, the study tried the mixed-effect modeling again, as the modeling approach was found suitable against modeling section-wise PM levels.

Table 7.9 Linear regression for real-time $PM_{2.5}$ exposure models.

| Variables | Estimate | Std. Error | t-value | Pr (>\|t\|) |
|---|---|---|---|---|
| **Intercept** | 134.62 | 0.48 | 281.65 | < 2e-16 |
| **Auto Rickshaw** | 11.97 | 0.29 | 40.87 | < 2e-16 |
| **Bike** | 7.06 | 0.31 | 23.07 | < 2e-16 |
| **Bus** | 9.05 | 2.56 | 3.54 | 0.0004 |
| **Car** | 2.75 | 0.27 | 10.16 | < 2e-16 |
| **HCV** | 0.64 | 0.76 | 0.85 | 0.3937 |
| **LCV** | 14.27 | 2.34 | 6.10 | 1.04e-09 |
| **Toto** | 12.78 | 0.75 | 16.99 | < 2e-16 |

*Note: Multiple R-squared: 0.014, Adjusted R-squared: 0.014*

**Mixed-Effect Linear Regression Models**

The real-time $PM_{2.5}$ and $PM_{10}$ were modeled using mixed-effect modeling, considering real-time traffic counts as the fixed effect. Similar to section-wise mixed-effect models, section number, time interval, speed and temperature bin were also considered for random

Table 7.10 Linear regression for real-time $PM_{10}$ exposure models.

| Variables | Estimate | Std. Error | t-value | Pr (>\|t\|) |
|---|---|---|---|---|
| **Intercept** | 254.91 | 0.81 | 315.91 | < 2e-16 |
| **Auto Rickshaw** | 18.03 | 0.49 | 36.47 | < 2e-16 |
| **Bike** | 9.89 | 0.52 | 19.13 | < 2e-16 |
| **Bus** | 15.87 | 4.32 | 3.68 | 0.0002 |
| **Car** | 0.51 | 0.46 | 1.12 | 0.2635 |
| **HCV** | 6.58 | 1.28 | 5.16 | 2.53e-07 |
| **LCV** | 32.30 | 3.95 | 8.18 | 2.82e-16 |
| **Toto** | 16.55 | 1.27 | 13.03 | < 2e-16 |

*Note: Multiple R-squared: 0.011, Adjusted R-squared: 0.011*

effects in the real-time PM modeling. Table 7.5 and 7.7 represent the model summary of fixed effects for $PM_{2.5}$ and $PM_{10}$, respectively, whereas Table 7.6 and 7.8 represent the model summary of random effects for $PM_{2.5}$ and $PM_{10}$, respectively. The mixed effect model gave a comparatively better fit with the conditional R-squared of 0.548 and 0.313 for $PM_{2.5}$ and $PM_{10}$, respectively.

Table 7.11 Mixed-effect linear regression for real-time $\log PM_{2.5}$ exposure models (fixed effects).

| Variables | Estimate | Std. Error | t-value | Pr (>\|t\|) |
|---|---|---|---|---|
| **Intercept** | 4.806 | 0.169 | 28.384 | 0.000 |
| **Auto Rickshaw** | 0.034 | 0.002 | 22.497 | 0.000 |
| **Bike** | 0.006 | 0.002 | 3.671 | 0.000 |
| **Bus** | 0.005 | 0.013 | 0.410 | 0.682 |
| **Car** | 0.013 | 0.001 | 8.973 | 0.000 |
| **HCV** | 0.015 | 0.004 | 4.036 | 0.000 |
| **LCV** | 0.081 | 0.012 | 6.950 | 0.000 |
| **Toto** | 0.025 | 0.004 | 6.634 | 0.000 |

*Note: Marginal R-squared: 0.002*

Table 7.12 Mixed-effect linear regression for real-time log$PM_{2.5}$ exposure models (random effects).

| Groups | Name | Variance | Std. Dev. |
|---|---|---|---|
| **Section Number** | Intercept | 0.008 | 0.088 |
| **Speed Bin** | Intercept | 0.002 | 0.041 |
| **Time Interval** | Intercept | 0.036 | 0.190 |
| **Temperature Bin** | Intercept | 0.198 | 0.444 |
| **Residual** | | 0.201 | 0.448 |

*Note: Conditional R-squared: 0.548*

Table 7.13 Mixed-effect linear regression for real-time log$PM_{10}$ exposure models (fixed effects).

| Variables | Estimate | Std. Error | t-value | Pr (>\|t\|) |
|---|---|---|---|---|
| **Intercept** | 5.388 | 0.103 | 52.447 | <2e-16 |
| **Auto Rickshaw** | 0.031 | 0.002 | 19.633 | <2e-16 |
| **Bike** | 0.004 | 0.002 | 2.150 | 0.0316 |
| **Bus** | 0.002 | 0.013 | 0.135 | 0.8927 |
| **Car** | 0.018 | 0.002 | 11.905 | <2e-16 |
| **HCV** | 0.032 | 0.004 | 7.905 | 2.69e-15 |
| **LCV** | 0.010 | 0.001 | 8.108 | 5.20e-16 |
| **Toto** | 0.021 | 0.004 | 5.324 | 1.01e-07 |

*Note: Marginal R-squared: 0.003*

Table 7.14 Mixed-effect linear regression for real-time log$PM_{10}$ exposure models (random effects).

| Groups | Name | Variance | Std. Dev. |
|---|---|---|---|
| **Section Number** | (Intercept) | 0.015 | 0.122 |
| **Speed Bin** | (Intercept) | 0.008 | 0.089 |
| **Time Interval** | (Intercept) | 0.019 | 0.139 |
| **Temperature Bin** | (Intercept) | 0.060 | 0.245 |
| **Residual** | | 0.225 | 0.475 |

*Note: Conditional R-squared: 0.313*

## 7.4 Summary

Multiple factors have been considered for PM exposure studies for motorcyclists. However, there is a limited amount of research available that considers the effect of traffic count on motorcyclists' PM levels while commuting. Thus, the study aims to investigate the possible effect of traffic count average and real-time PM concentration. Thus, an exposure study was conducted for 8 months by traversing with motorcycles along various routes in the densely populated city of Varanasi. The effect of the traffic counts was analyzed and modeled using two types of linear regression models, i.e., single variable and mixed-effect linear regression models. The following conclusions were made from the analysis.

1. The section-wise and real-time vehicle counts alone cannot predict on-road particulate exposure concentration. Various factors such as atmospheric temperature, relative humidity, season of the year and travel at different hours of the day were found to be good predictors.

2. Mixed-effect linear regression was found to be an effective PM exposure model instead of single variable linear regression models while considering traffic count and other predictors together.