Chapter 4

Study Design and Data Collection

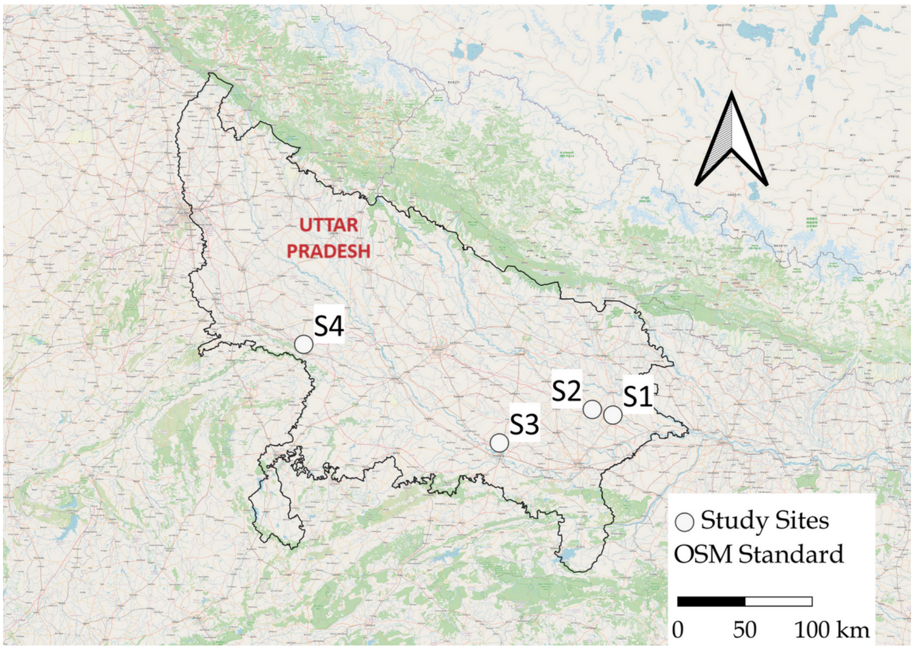
4.1 Preface

Conflict indicators are derived from microscopic traffic parameters. Safety assessment using such measures will depend on the accuracy of data. Tracking vehicles and capturing conflict indicators from the video data is challenging in a heterogeneous traffic condition due to heterogeneity in vehicles and disorderness in traffic movements. An elaborate description of video data collection, and vehicle trajectory extraction is discussed in this chapter.

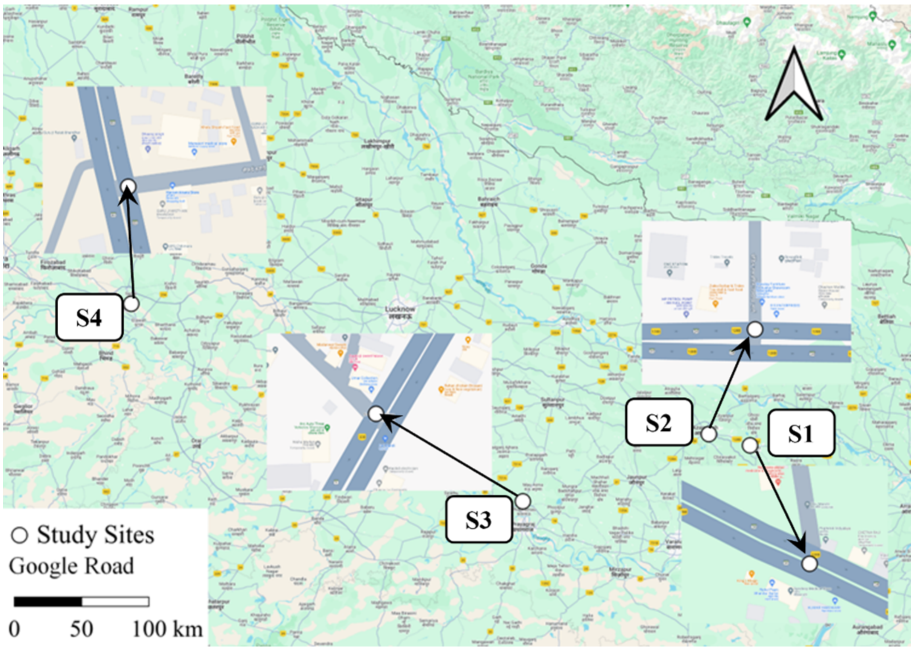
This chapter is divided into 3 sections. The detail of site selection and video data collection is presented in Section 4.1. Vehicle trajectory extraction is presented in the Section 4.2. Finally the descriptive statistics of the data is presented in Section 4.3.

4.2 Details of Study Sites

To examine how conflict indicators vary with vehicle size and lateral interactions, a videographic survey was conducted at four unsignalized T-intersections on 4-lane divided highways in India. The approach width, median width, and shoulder width were 7.2 m, 2 m, and 1.5 m respectively. The sites (Fig. 4.1a and Fig. 4.1b) being high crash locations (blackspots) were ideal for a conflict study. Crash data for these blackspots were provided by the State Road Authority called Uttar Pradesh Public Work Department (UPPWD). Blackspot is defined as a road section of 500 m length or a junction that has the number of road crashes higher than the Average Annual Total Crashes (AATC) computed for the candidate road section. More precisely, Blackspot is a road section of 300–500 m length that has an abnormally high number of road crashes showing a pattern of crash types due to some underlying local risk factors [196]. To identify the blackspots, one of the first tasks is to identify that location in the road network or road corridor where the number of road crashes are above average. Considering the heterogeneity in the traffic volume, composition, speed and land use patterns, a uniform guiding value cannot be applied across the country for identifying blackspots and the guiding rationale has to be state-specific as well as according to the road class. In order to arrive at the average value for a state and specific road class; in the absence of quality and reliable data, a simple method based on annual average total crashes has been proposed to determine the criterion for finding blackspots in various states [196].



(a) location



(b) roadway geometry of study sites.

Fig. 4.1 Study sites map (a) location and (b)roadway geometry of study sites.

The details about these sites are presented in Table 4.1. At these sites, the traffic was lane free and was composed of a variety of motorized and non-motorized vehicles.

Because of this heterogeneity, it was possible to capture various interactions and inter-modal conflicts between vehicle pairs. To cover a wider area of the intersections, the video camera was set on the top of nearby buildings. Fig.4.2 shows the camera view of these sites.

Fig. 4.2 Camera view of the study sites

To collect a representative sample of vehicular interactions at these sites, video data were recorded from 9:00 am to 1:30 pm on each location capturing both peak and off-peak traffic interactions. At each location 4.5 hours of video data was recorded, which resulted in a total 18 hours of data. The video graphic survey were conducted on different days in January 2021. The data at all sites were collected in normal weather conditions with good visibility.

4.3 Video Data Extraction

Tracking vehicles and capturing proximity indicators is challenging in a heterogeneous traffic scenario because of multiple vehicle types (different sizes, motorized and non-motorized) and lane-free driving behaviour. Also, automated vehicle trajectory extraction

Table 4.1 Details of Study sites

Characteristics	Site 1	Site 2	Site 3	Site 4
Name of location (City)	Barlai (Mau)	Bethuli (Azamgarh)	Sorawn (Prayagraj)	Saifai (Etawa)
Latitude	25.972159	26.046506	25.602261	26.903604
Longitude	83.5154413	83.212876	81.846701	78.970360
Reported fatal crashes in 2018	4 crashes, 4 fatalities	4 crashes, 4 fatalities	7 crashes, 24 fatalities	10 crashes, 10 fatalities
Land use pattern	Agricultural and residential	Commercial and residential	Commercial	Commercial and residential
Median opening	60 m	60 m	30 m	60 m
Length of the study section	60.3 m	54.1 m	67.2 m	66.8 m

is challenging in heterogeneous traffic where a variety of motorized and non-motorized vehicles have similar size and vehicles often move with oversized loads which changes effective size. In addition, trajectories of two small vehicles moving together or pedestrians moving in groups may be identified as one and hence trajectory extraction would be erroneous. Variation in illumination, road user occlusion and shadows are other issues which arise while tracking vehicles [195].

4.3.1 Trajectory extraction using Tracker

In this study, a semi-automated method was used to extract vehicle trajectories from videos. A trained observer identified and manually tracked the vehicles across multiple frames at desired frame rate by using an open-source software called Tracker [63]. Vehicle positions were marked at every 10 frames i.e., at a time interval of 0.33 s. Tracking and calibrating motion of objects is easier with such tools. It can generate trajectories from video data recorded at oblique angles which is especially useful in situations when it is not possible to have a camera view orthogonal to the traffic movement. Gu et al. [166] used Tracker for extracting vehicle trajectories from UAV (unmanned aerial vehicle) photography on an interchange merging area. They used lane marking as reference for calibrating the distance travelled in longitudinal direction. The authors suggested Tracker as a prominent tool for manual trajectory extraction. Snapshot of the trajectory extraction using Tracker software along with extracted vehicle trajectories are depicted in Table 4.2 and Fig.4.3 respectively.

Table 4.2 Extracted Vehicle Trajectory Data

Time (sec)	**X(m)**	**Y(m)**	**VehID**	**Type**
40.00	16.27	7.95	24	car
40.33	18.93	7.93	24	car
40.67	21.3	7.93	24	car
41.00	23.67	7.92	24	car
41.33	26.62	7.84	24	car
41.67	30.21	7.71	24	car

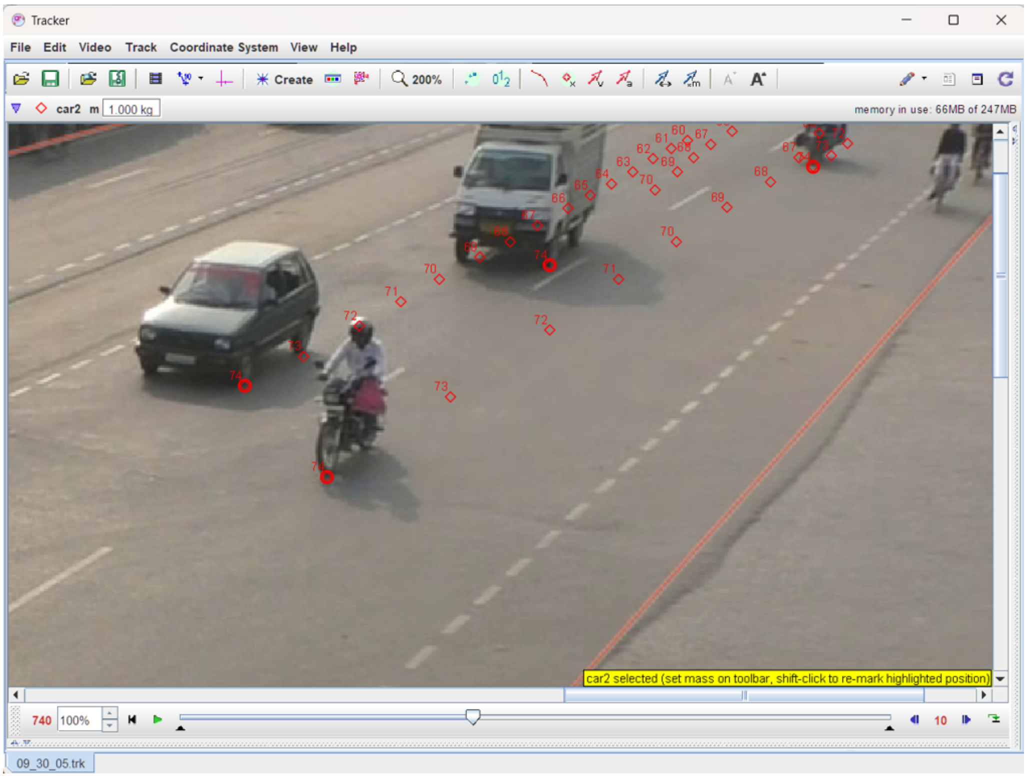


Fig. 4.3 Trajectory Extraction using Tracker Software.

Correction for vehicle size and tracking point

Correction for vehicles dimensions were applied for more accurate computation of conflict indicators. Vehicles were tracked at the front wheel and correction for tracking point were applied to shift the tracking point to the front-center of vehicle. Average vehicle sizes used in this study are mentioned in Table 4.3.

Table 4.3 Vehicle class and their average dimensions

Vehicle type	Vehicle class	Length (m)	Width (m)
Motorbikes, scooter	Light vehicle (LV)	1.87	0.64
Three-wheeler motor rickshaw, electric rickshaws	Light vehicle (LV)	3.20	1.40
Car	Medium vehicles (MV)	3.72	1.44
Big car, jeep	Medium vehicles (MV)	4.48	1.80
Light commercial vehicles, Vans	Medium vehicles (MV)	6.10	2.10
Tractor with trailer	Heavy vehicle (HV)	7.40	2.20
Bus	Heavy vehicle (HV)	10.10	2.43
Truck (Two-axle/ three-axle)	Heavy vehicle (HV)	7.50	2.35
Multi axle trucks	Heavy vehicle (HV)	15.24	2.44

Image to real coordinate transformation

Tracker can generate precise trajectory when the movement is one dimensional. Gu et al. [166] used Tracker for extracting vehicle trajectories from UAV (unmanned aerial vehicle) photography on an interchange merging area. They used lane marking as reference for calibrating the distance travelled in longitudinal direction. Although it is possible to use Tracker for creating a trajectory of two-dimensional motion, it does not allow the transformation of image coordinate to real world coordinates in two dimensions.

Human eyes and cameras have perspective view of the objects and the world. Owning to this we see near objects bigger than far objects. The perspective transform converts a

3-D world into a 2-D world. In a technique proposed by Bleyl [197] a photographic image of a plane object taken with an oblique camera can be transformed into an orthogonal projection. Based on that technique, the equations relating the photo coordinates with the real world coordinates can be written as

$$X = \frac{C_1 + C_2 x + C_3 y}{C_4 x + C_5 y + 1} \tag{4.1a}$$

$$Y = \frac{C_6 + C_7 x + C_8 y}{C_4 x + C_5 y + 1} \tag{4.1b}$$

The transformation involves 8 coefficients $C_1, C_2, \ldots, C_8$ transformation as mentioned in Eqn. (1). For given real-world points (X,Y) on the field and the corresponding points (x,y) in the image coordinate system, two equations can be written down for each pair. Therefore, four pairs of points on the field and the corresponding points in the photo are sufficient to obtain eight equations which can be solved using the Gauss elimination method. In this way, the coefficients $C_1, C_2, \ldots, C_8$ are obtained. No three of these points should be collinear.

4.3.2 Data Processing

Errors and occlusions in manual data extraction might lead to noise. Smoothing the raw data and eliminating miss-click mistakes are the first steps in data processing. To smooth the trajectories, cubic splines with a degree of freedom of six were employed, following the methodology of Wang, Xu, and Dai [186]. Total 9972 vehicles were manually tracked using Tracker software at the 4 study sites. Few vehicles could not get tracked for the whole stretch due to occlusion. Therefore, vehicles were initially filtered based on minimum trap length for which individual vehicles were tracked. Further, as recommended by Punzo, Borzacchiello, and Ciuffo [198], the retrieved trajectories were also checked for the maximum feasible jerk of 15 m/s3 and the minimum inter-vehicle spacing of zero, which denotes a crash. Based on these criteria, about 17 percent of trajectories were discarded. The flowchart for generating vehicle trajectory from video data is presented in Fig.4.4. The final dataset resulted in 8326 vehicle trajectories, which were used for further analysis in this thesis.

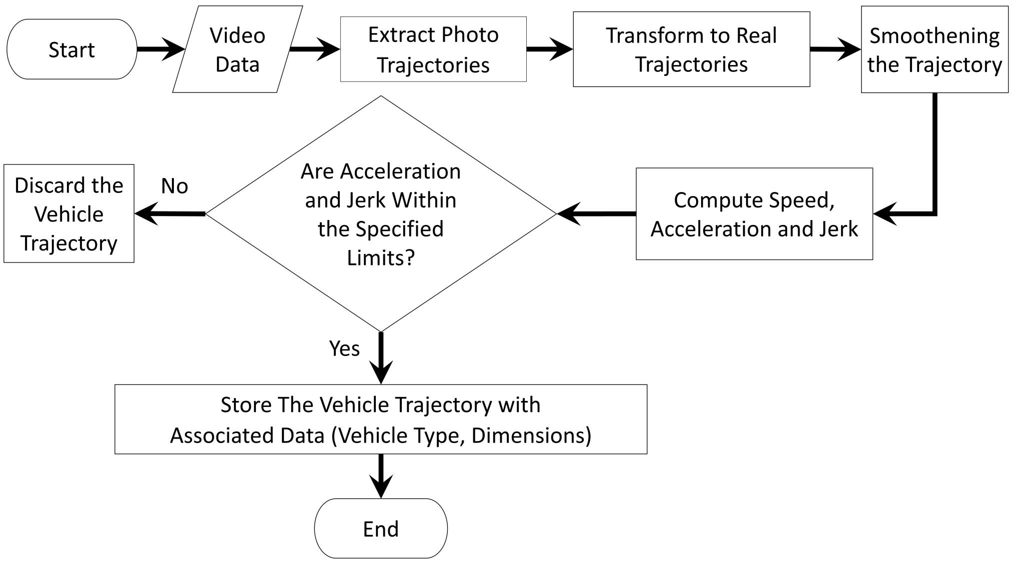


Fig. 4.4 Extracting and Cleaning Vehicle Trajectories.

Further, it was required to check the accuracy of trajectories in relation to actual vehicle trajectories. In this regard, free-flowing vehicles that cross the study section without any evasive action (deceleration, acceleration, swerving) were identified from videos. The extracted vehicle trajectories were validated by comparing observed speed (v_o) with the speed (v_d) derived from the trajectories. The observed speed was computed by dividing the length of the study section with the time taken by a vehicle to cross it. A linear regression model was fitted $(v_o$ versus $v_d)$ as shown in Fig.4.5. The R-squared value (0.99) was close to 1, and the Y-intercept (0.089) was small. These results support the accuracy of the extracted trajectory. Using Eqn.4.2-Eqn.4.4, as suggested by Fu et al. [199], the following additional metrics were computed: Mean relative error (MRE), Relative precision error (RPE), and Relative accuracy error (RAE) were found to be 0.0061, 0.0063, and 0.00032, respectively. Since, the errors were small, the extracted trajectories were used for further analysis.

$$\text{Mean Relative Error (MRE)} = \frac{1}{100}\sum_{i=1}^{n}\frac{|v_d - v_0|}{v_0} \tag{4.2}$$

$$\text{Relative Precision Error (RPE)} = \frac{1}{100}\sum_{i=1}^{n}\frac{|v_d - (\text{Y intercept}) - v_0|}{v_0} \tag{4.3}$$

$$\text{Relative Accuracy Error (RAE)} = \frac{1}{100}\sum_{i=1}^{n}\frac{|\text{Y intercept}|}{v_0} \tag{4.4}$$

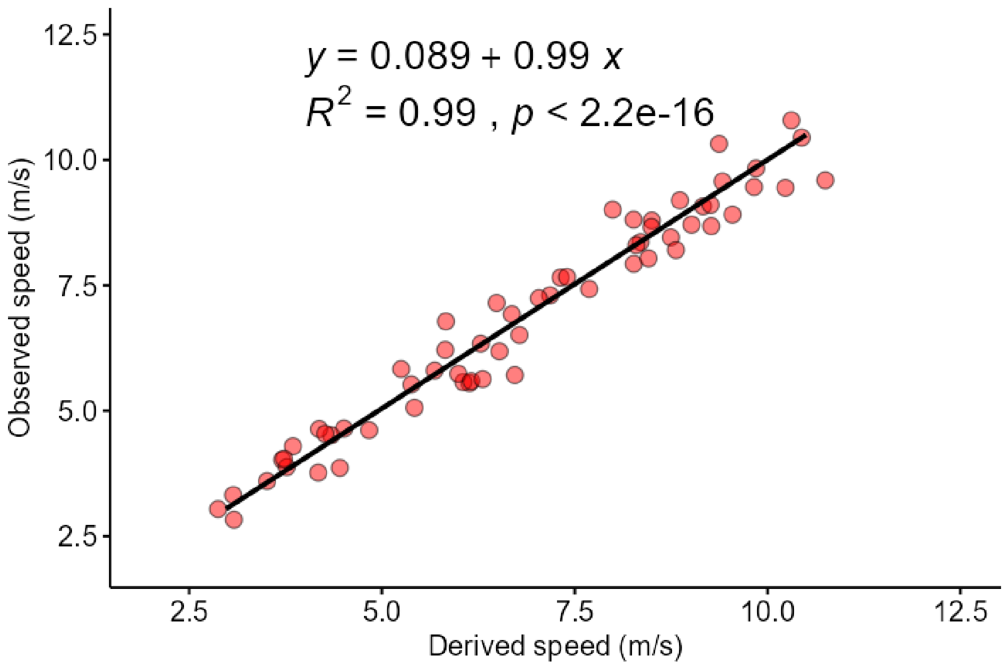


Fig. 4.5 Relationship between derived and observed vehicle speeds.

4.4 Data Summary

The extracted trajectory data included 8326 vehicles comprising of motorized two-wheeler (M2W), motorized three-wheeler (M3W), cars, light commercial vehicles (LCVs), tractors, trucks, and buses. Vehicles were grouped into three classes, namely (1) light vehicles (LV), (2) medium vehicles (MV), and (3) heavy vehicles (HV) based on their size. Motorized two and three-wheeler were kept in the light vehicle category. Medium vehicles included standard cars, big cars, and LCVs. Heavy vehicles included buses, tractors with trailers, and trucks. The vehicular composition and speed distribution at each site are presented in Fig.4.6. The descriptive statistics of the vehicle speed in each category is presented in Table 4.4.

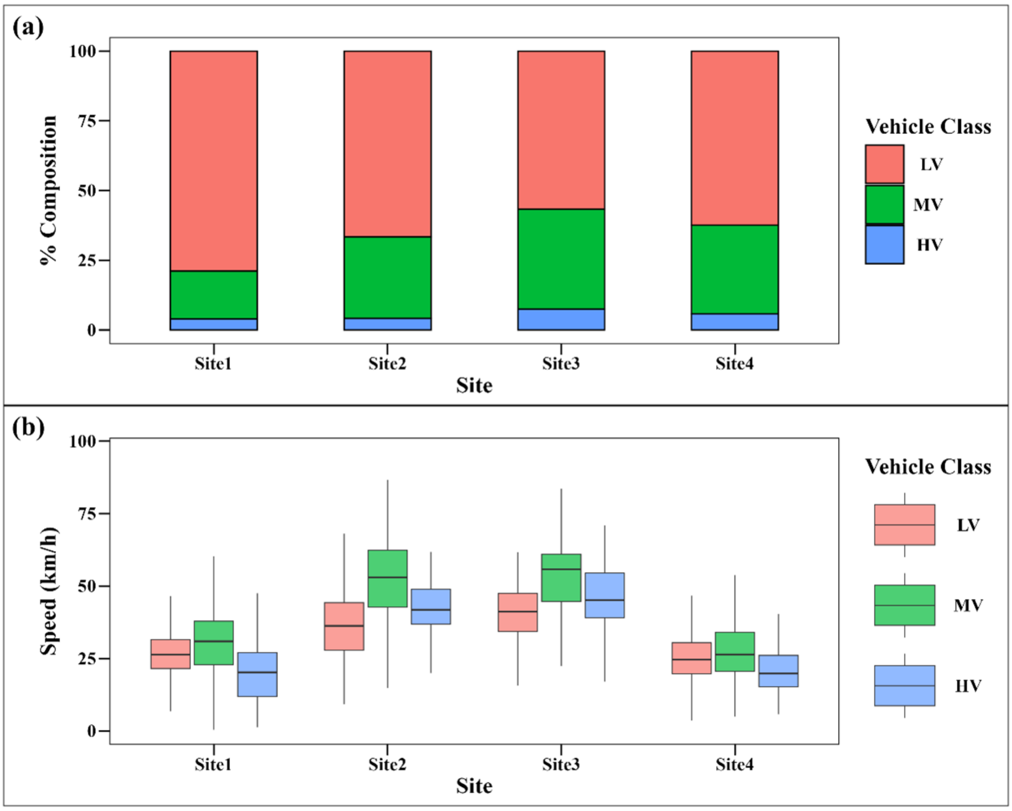


Fig. 4.6 (a) Vehicle composition and (b) speed variation at different sites.

Two and three-wheelers maintained significantly lower speed than cars and LCVs. Buses and heavy goods vehicles also moved relatively slowly as compared to cars and LCVs. Further, vehicle speed at site 1 and site 4 are lower than other sites because of the commercial area around these locations. Since the composition of buses and heavy goods vehicles was significantly small (4 to 6%) at all sites, the sample size for interaction

Table 4.4 Descriptive statistics of vehicle speeds

Vehicle class	Sample size	Mean Speed (kmph)	SD (kmph)	Median Speed (kmph)
Light vehicles (LV)	5942	26.53	9.56	25.63
Medium vehicles (MV)	1975	33.13	14.8	31.35
Heavy vehicles (HV)	409	28.78	15.21	25.56

involving theses (HV-HV, HV-LV, and LV-HV) were small, therefore, not considered in the present study.