A real-time crash risk estimation framework for signalized intersections

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Presenter

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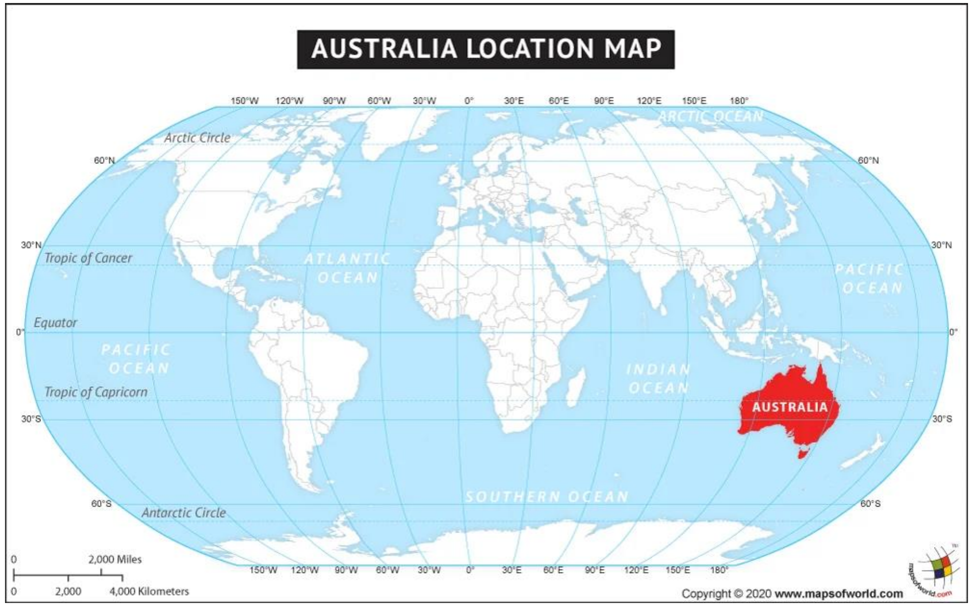
Smart Transport Safety Research Lab

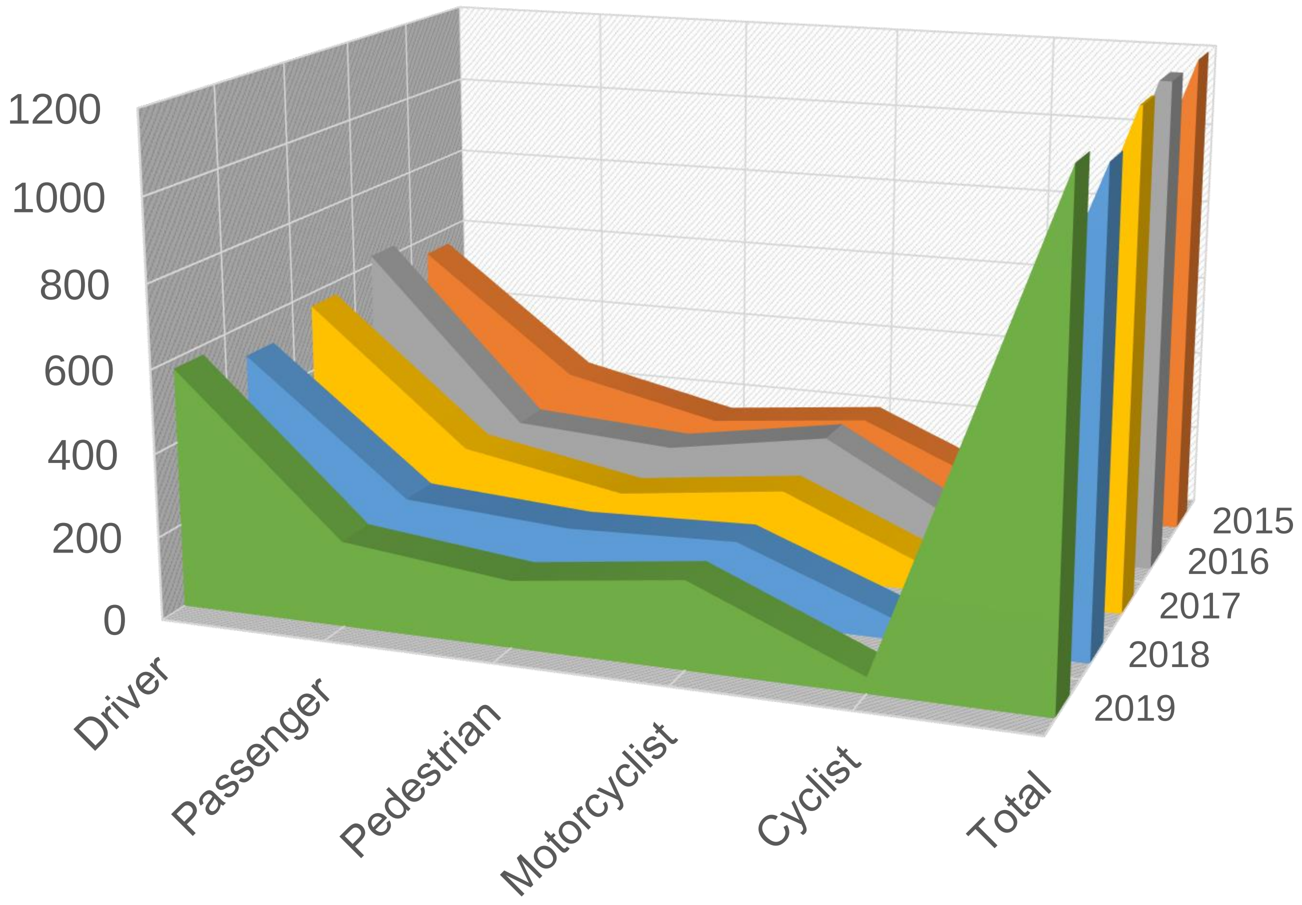
Background

- In Australia, ***1195 people killed*** and ***39,330 hospitalised*** annually (BITRE 2019)

- Social cost of road crashes = **$29.7 billion** (BITRE 2009) ***≈1.3% of Australia's GDP***



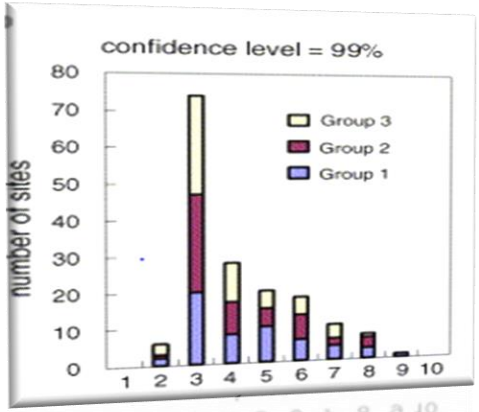
Road Crash Deaths by Road User Type in Australia



Challenges in Road Safety Analysis

Reactive Crash-based Analysis

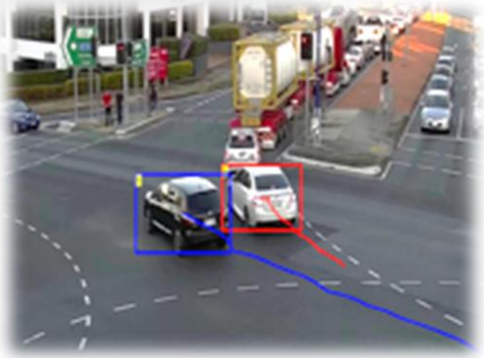
Crash Occurred in 2014



Analysis done in 2019

Implementation ?

Proactive Conflict-based Analysis



Conflict Observed...

...Rapid Analysis

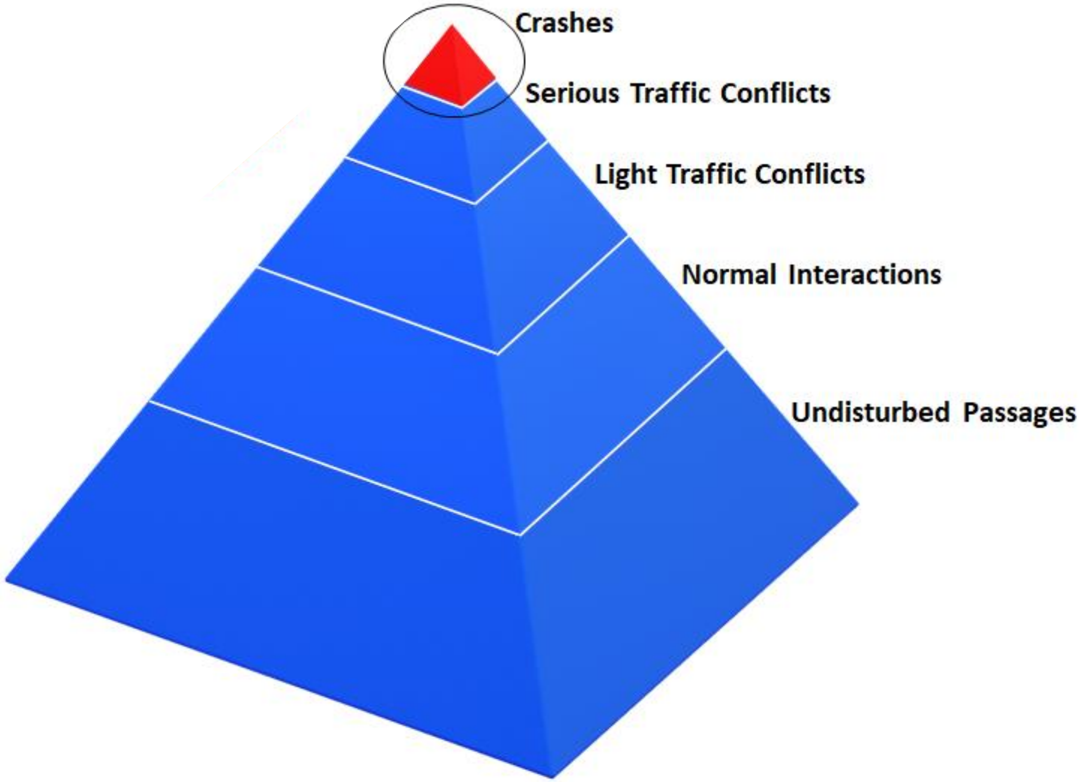
Ready for Action!

Traffic Conflicts:
Dangerous traffic interactions, potential road crashes

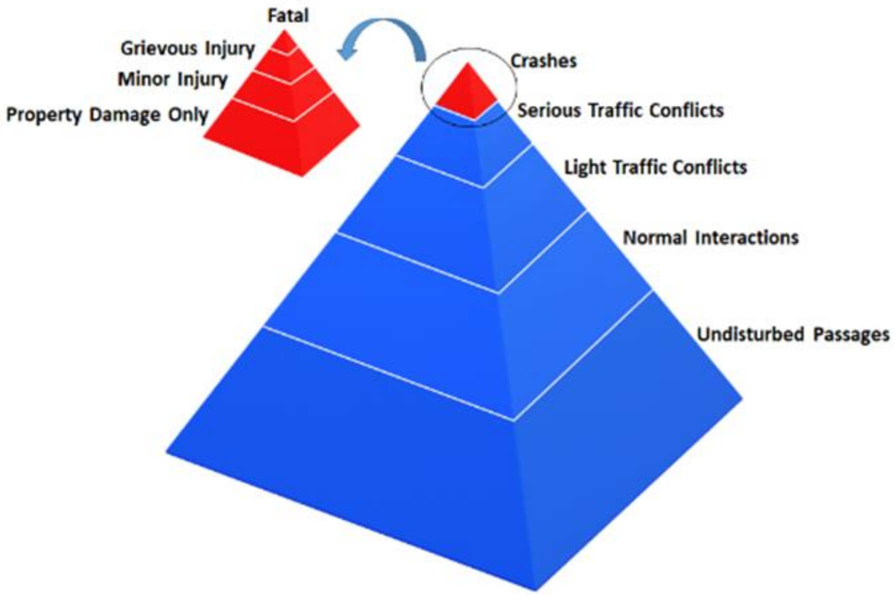
Road Crashes:
End results of traffic conflicts

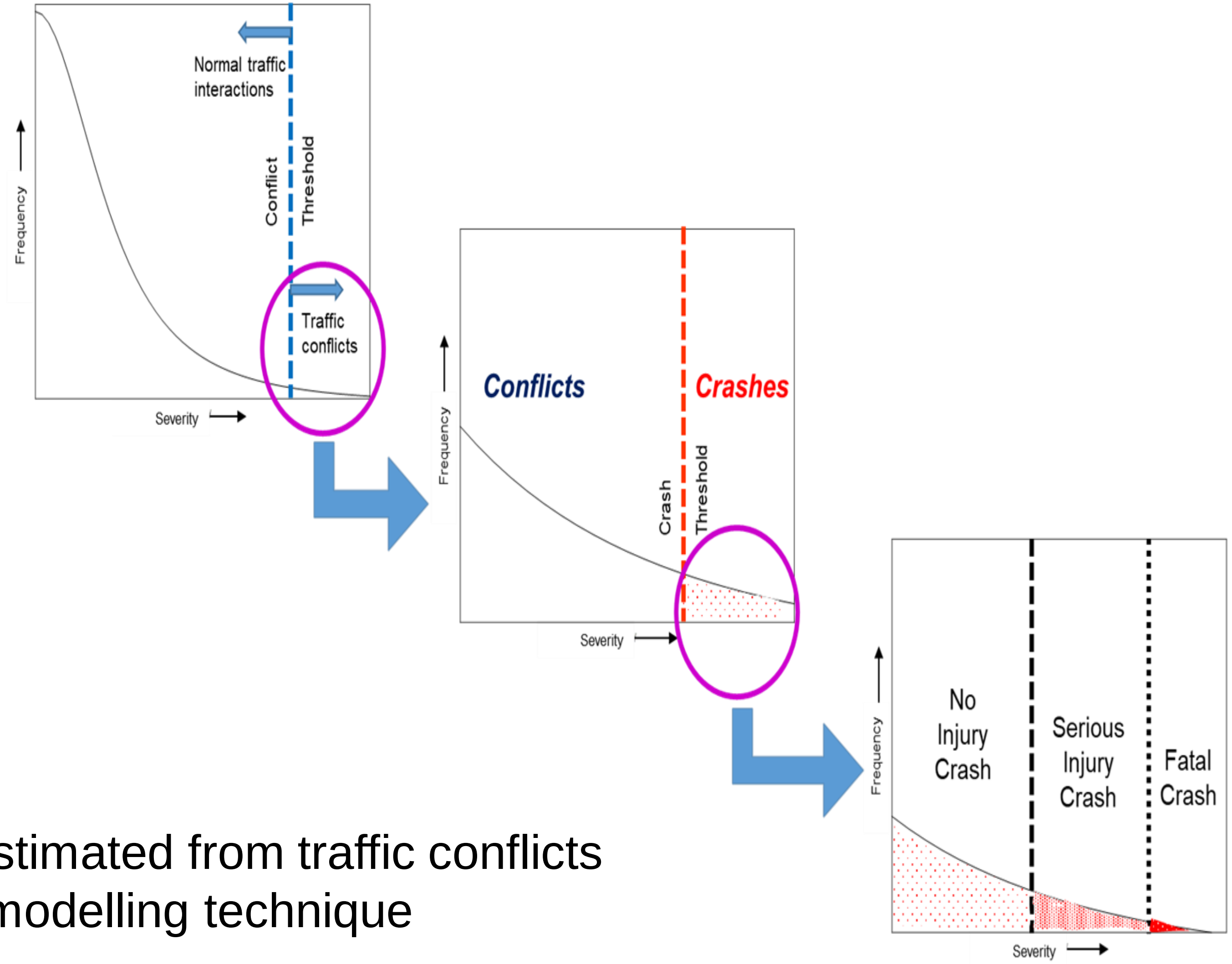
Courtesy: LJ Raggy (https://www.youtube.com/watch?v=Xx7NCbzxIzI)

Safety Pyramid of Traffic Events



Safety Pyramid of Traffic Events





- Crashes (unobserved extremes) can be estimated from traffic conflicts (observed extremes) with an appropriate modelling technique

Objective

To develop a real-time crash risk estimation framework using traffic conflicts

- How can Extreme Value Theory be leveraged to obtain real-time crash risk?
- How crash risk varies with different time periods of the day (e.g., peak vs. off-peak hours)?
- Does incorporating a covariate in the model yield better fit and crash estimates?

Methodology

➔Extreme Value Theory to model traffic extremes at the signal cycle level

➔Given that z_{ij} corresponds to the maximum value of a traffic conflict indicator for cycle *i* at site *j*, a GEV distribution function can be written as

$$G(z_{ij} < z|\mu_{ij}, \phi_{ij}, \xi_{ij}) = exp\left(-\left[1 + \xi_{ij}\left(\frac{z - \mu_{ij}}{exp(\phi_{ij})}\right)\right]^{-1/\xi_{ij}}\right)$$

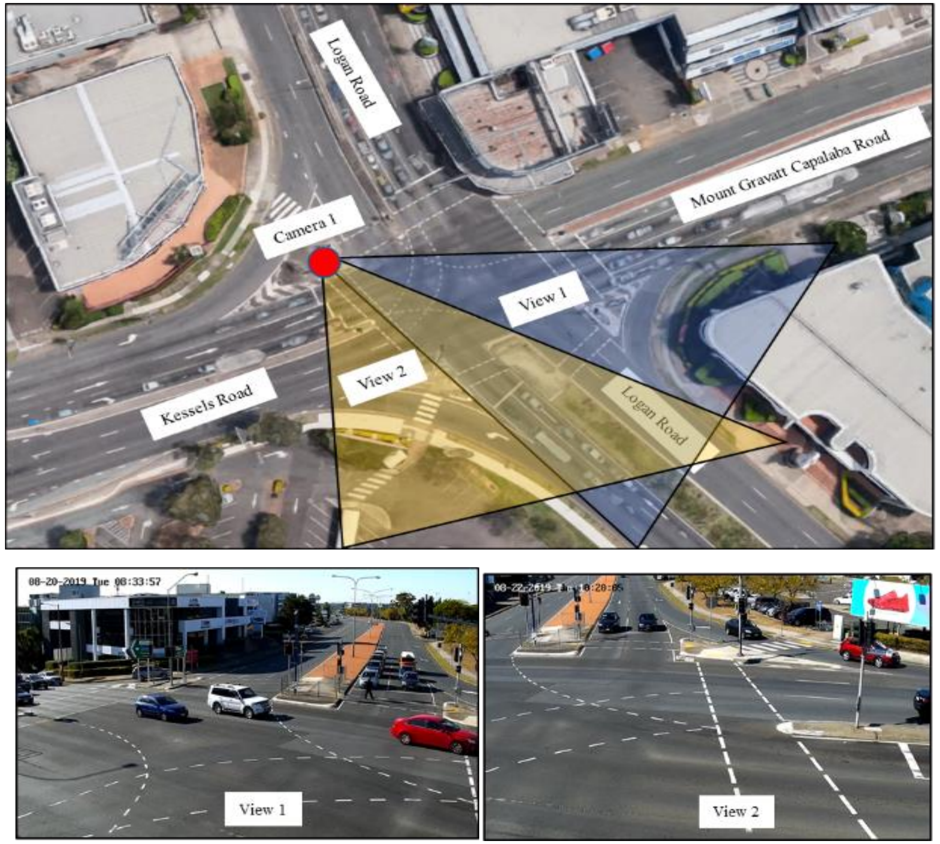
where μ, σ, and ξ represents location, scale ($\phi = log\sigma$), and shape parameters

Data Collection

Video recording of traffic
movements at intersections

Data Collection

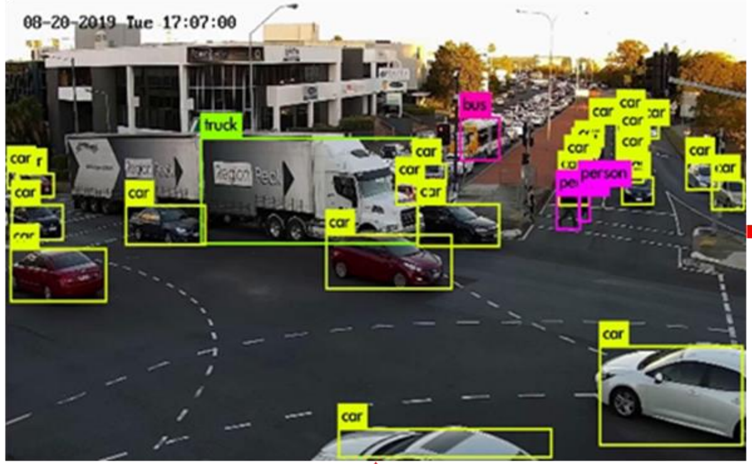
A total of 96 hours of traffic videos from a four-legged signalized intersection in Brisbane, Australia



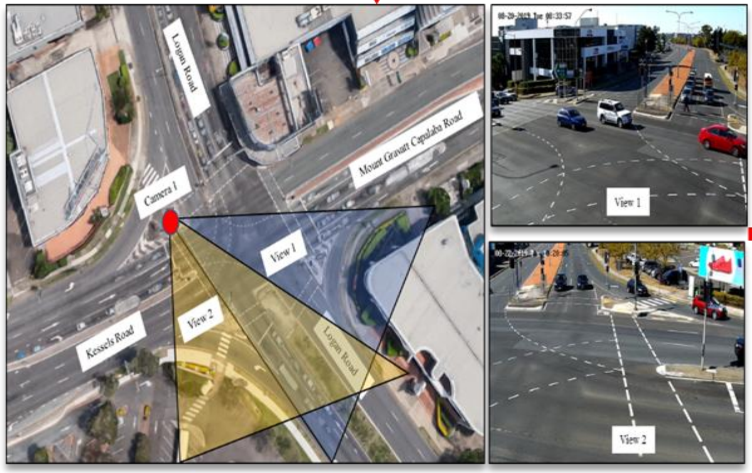
AI-based Traffic Conflict Data Extraction

1. Setting up cameras at vantage points

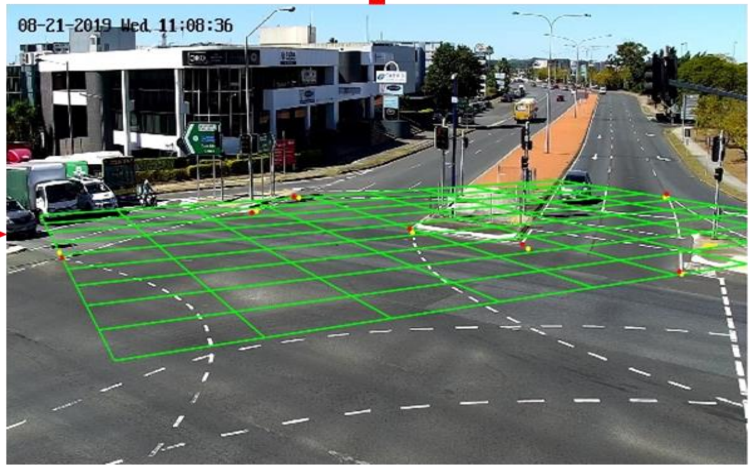
4. Road user detection using Yolo-v4.0



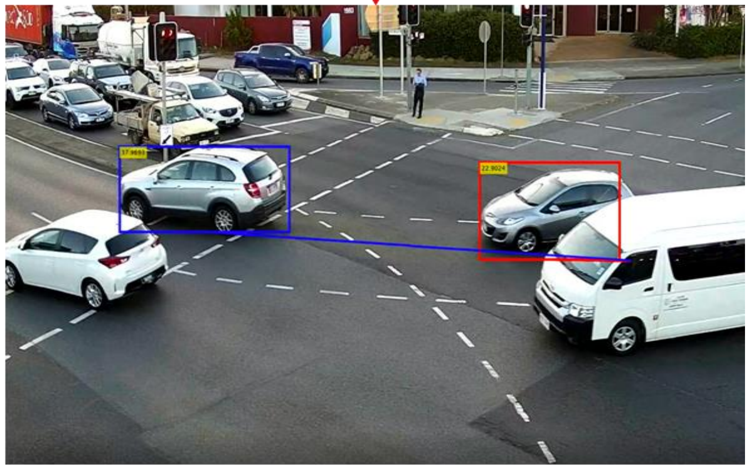
5. Road user tracking using DeepSORT



2. Video observation of targeted traffic movements

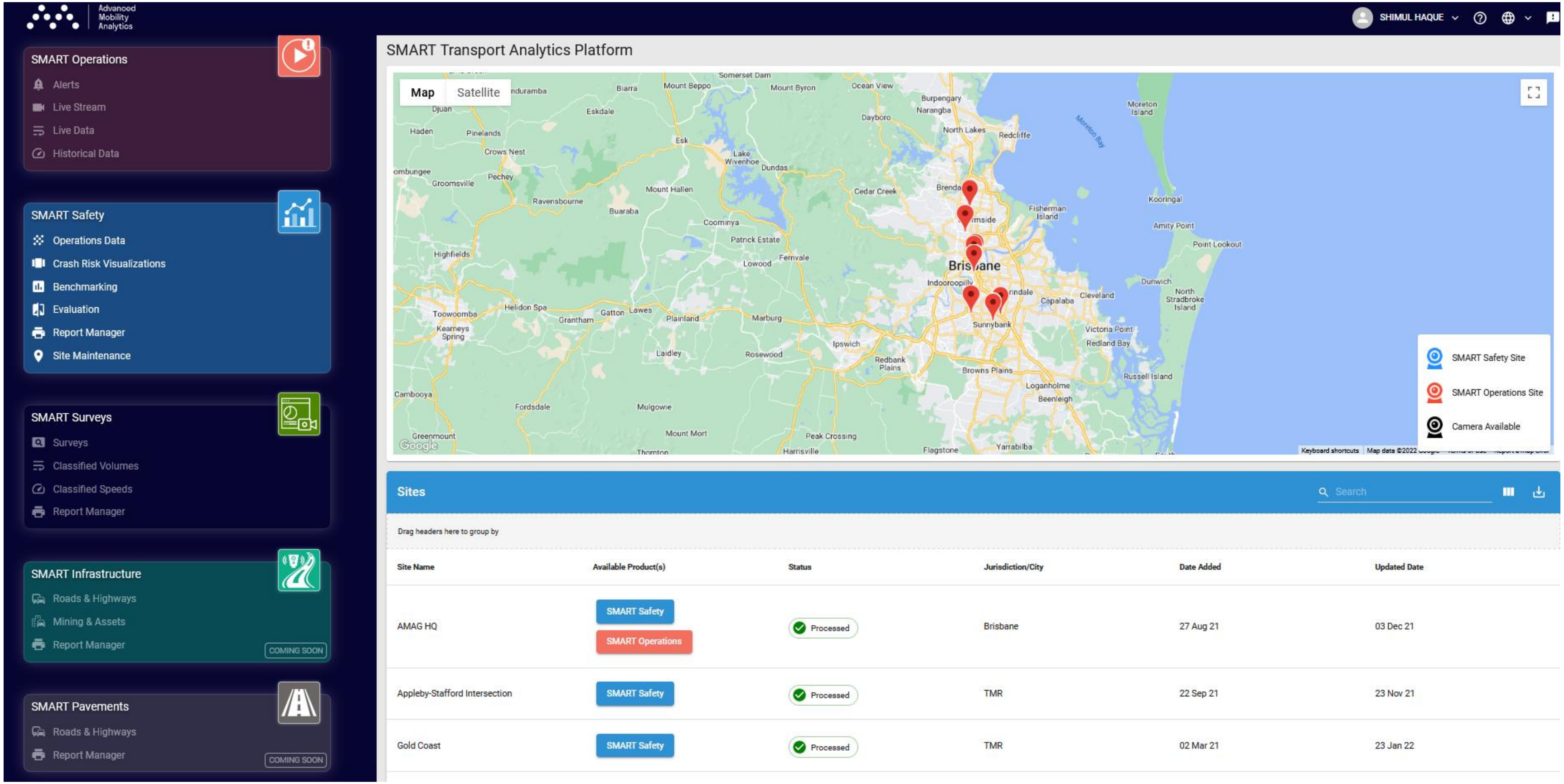


3. Camera calibration and homography matrix generation

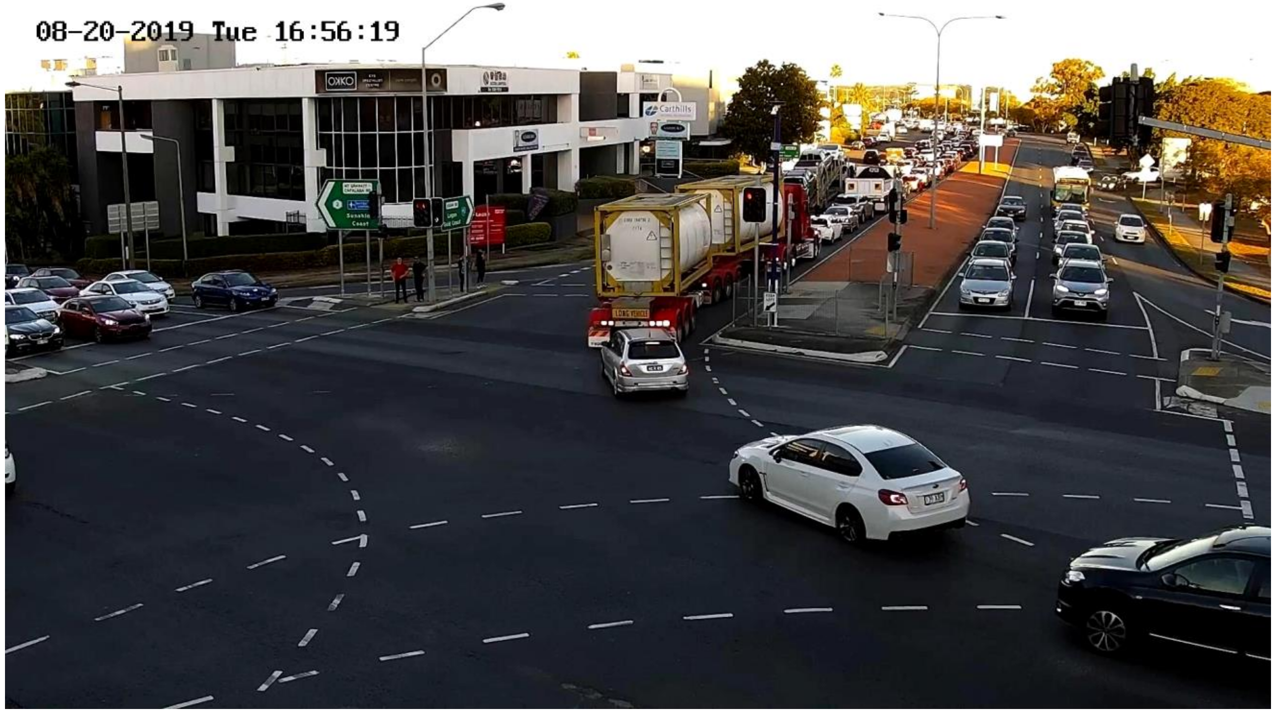


6. Extracting traffic conflicts (all interactions with time-to-collision ≤ 3 s)

Advanced Mobility Analytics Group (AMAG)



AI-based Traffic Conflict Data Extraction



Traffic conflict indicator

Modified time-to-collision (MTTC)

$$MTTC = \frac{\Delta s \pm \sqrt{\Delta s^2 + 2\Delta a (x_{LV} - x_{FV} - D_{LV})}}{\Delta a},$$

Δs= relative speed, Δa= relative acceleration, x_{LV} & x_{FV} = positions of leading and following vehicles, D_{LV} = length of leading vehicle

Parameter	Statistics	
	Mean	Standard deviation
Number of cycles	444	
V (volume count per cycle)	13.13	4.51
MTTC (s)	1.25	0.29
Total rear-end conflict	2,915	
Crash record (2015 – 19)	9	

Results

Three separate Bayesian hierarchical models are estimated

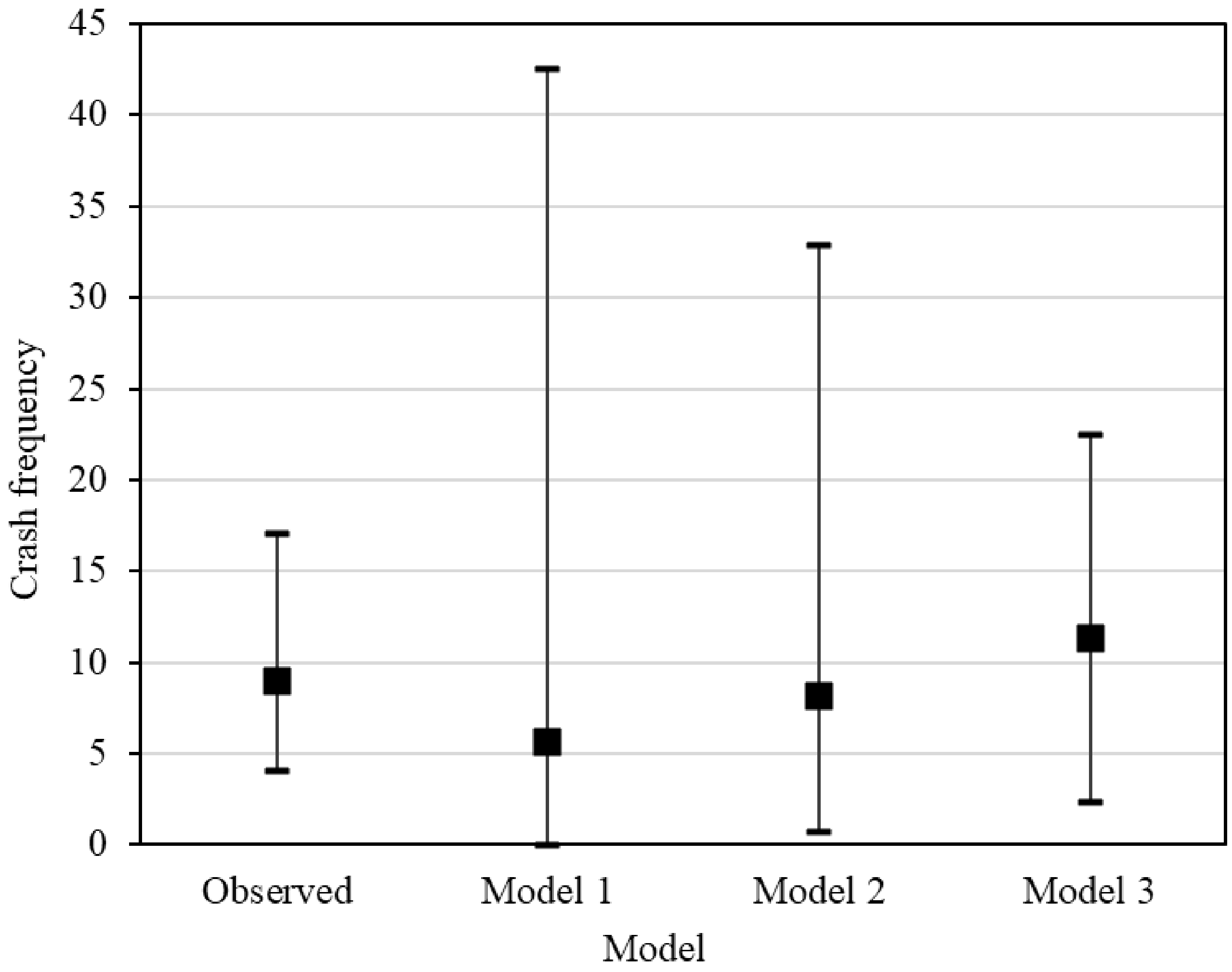
$$G(z_{ij} < z|\mu_{ij}, \phi_{ij}, \xi_{ij}) = exp\left(-\left[1 + \xi_{ij}\left(\frac{z - \mu_{ij}}{exp(\phi_{ij})}\right)\right]^{-1/\xi_{ij}}\right)$$

- ➢A stationary model
- ➢A model with traffic volume as a covariate to the scale parameter
- ➢A model with traffic volume as a covariate to the location parameter

Results

Model	Parameter	location		scale		shape	DIC
		μ_0	μ_V	σ_0	σ_V	ξ_0	
Stationary	mean	-0.5391	—	0.2588	—	-0.4734	1107.77
	s.d.	0.0048	—	0.0040	—	0.085	
	2.50%	-0.5489	—	0.2510	—	-0.4894	
	97.50%	-0.5298	—	0.2667	—	-0.4566	
Model with covariate in scale	mean	-5.5398	—	-4.3589	0.500	-0.4714	1095.27
	s.d.	0.005	—	0.0208	0.010	0.0079	
	2.50%	-5.5482	—	-4.3947	-0.514	-0.4895	
	97.50%	-5.529	—	-4.3197	0.522	-0.4569	
Model with covariate in location	mean	-0.5572	0.0020	0.2571	—	-0.4644	1086.74
	s.d.	0.006	0.0002	0.0037	—	0.0075	
	2.50%	-0.5301	0.0018	0.2503	—	-0.4771	
	97.50%	-0.5057	0.0011	0.2644	—	-0.449	

Results



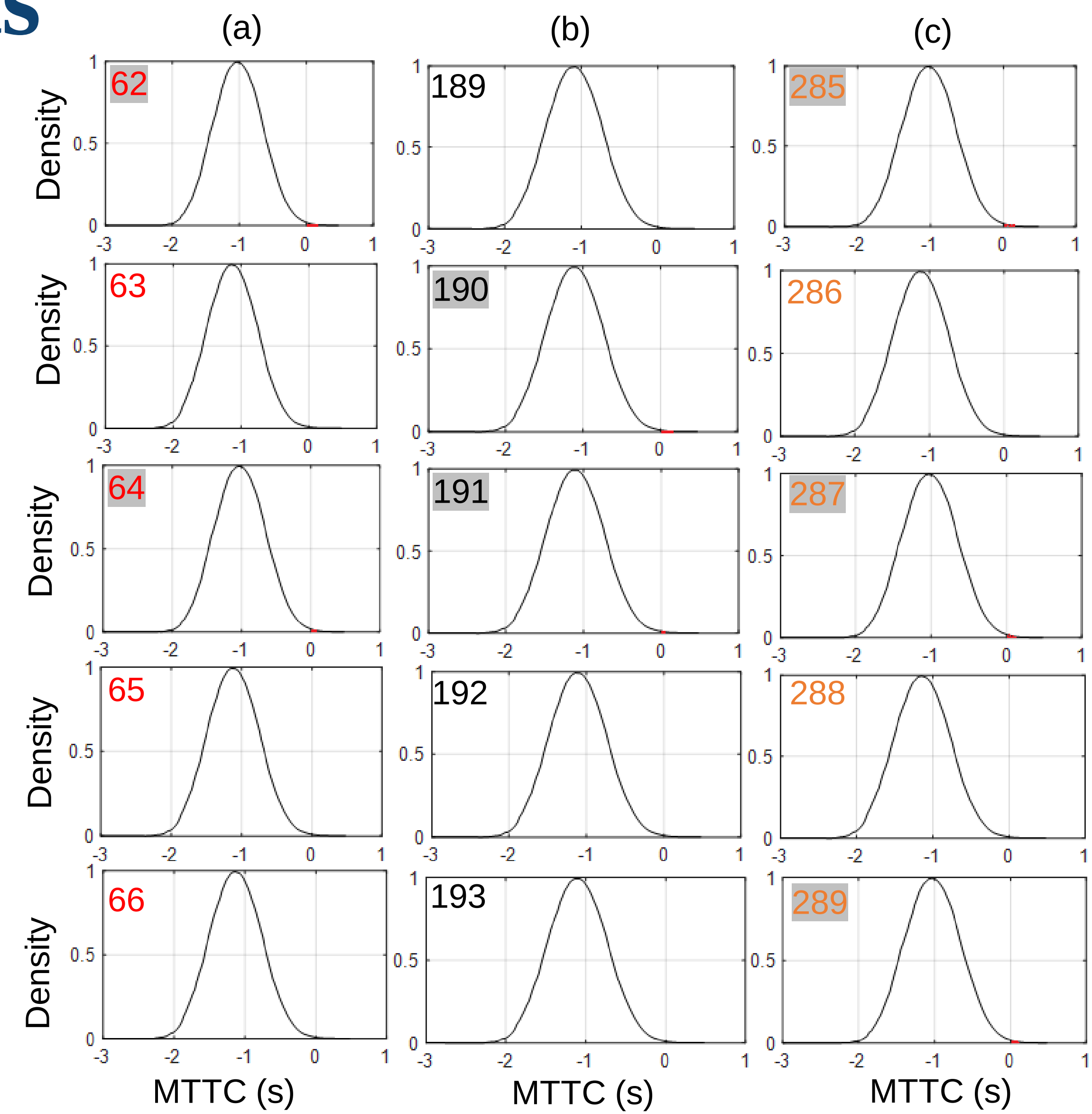
Model 1: Stationary Model

Model 2: With traffic volume as a covariate in the scale parameter

Model 3: With traffic volume as a covariate in the location parameter

Results

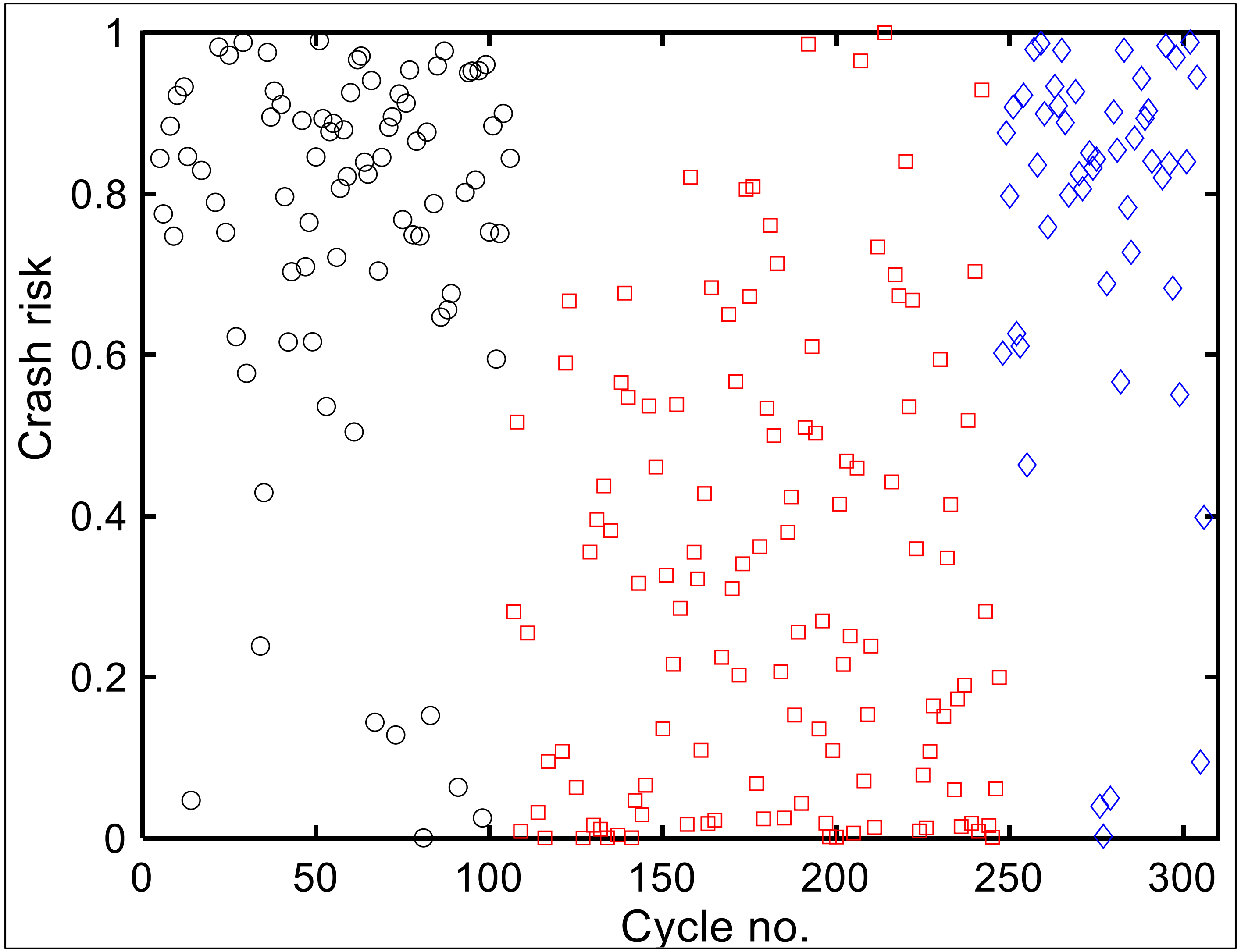
- ➢Tail of a GEV distribution ending after the negated MTTC = 0 indicates a positive crash risk
- ➢Greyed Cycles have positive crash risk (and are risky cycles)
- ➢Kolmogorov–Smirnov test to compare the equality of distributions across signal cycles
- ➢Cycles with positive crash risk are significantly different from other cycles



Results

➔Crash risk varies across the time of the day

➔This difference in variation is statistically significant



Conclusions

- Extreme Value Theory provides a good framework to estimate real-time crash risk from traffic conflicts

- Non-stationary models are preferable

- The suitability of traffic conflict indicators for other crash types needs to be rigorously tested.