RSS2026
Road Safety & Simulation
23-26 June 2026, Naples, Italy

Are telematics-based harsh occurrences associated with street-level visual features? A case study of motorway intersections.

Paper 213

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INTRODUCTION AND OBJECTIVES

Recent technological advancements have reshaped road safety assessment. AI-powered models can detect interactions between road users from multiple sources, enabling a shift from crash data alone to **surrogate measures of safety (SMoS)**. Beyond new data types, **road telematics** (Boylan et al., 2024), derived from mobile phone or in-vehicle sensors, offer geo-positioning and behavioural monitoring over time as a major crash-risk indicator.

In parallel, open data sources such as **Street View Imagery (SVI)**, with near-global coverage by Google, Baidu Maps and Mapillary, allow extraction of environmental attributes via Computer Vision models.

This work explores the association between SVI-derived environmental elements (extracted via semantic segmentation) and telematics-based harsh events from mobile phone sensor data.

DATA CURATION AND PROCESSING

Telematics data was provided by Oseven (www.oseven.io), a Greek company offering smartphone-based telematics solutions. The dataset comprises **322 trips** collected between **March 2021 and March 2025** in the Gorizia region (Italy/Slovenia border), providing **per-second geolocation, speed and harsh event occurrence**. Data was fully anonymised per GDPR.

Road network data (nodes/edges) was collected from **OpenStreetMap (OSM)** via OSMnx (Python). Most harsh events concentrated around intersections, leading us to restrict the analysis to **motorway junctions** (at least one primary/motorway road), and with at least **two trips**, to avoid individual-behaviour bias. This yielded **98 junctions**.

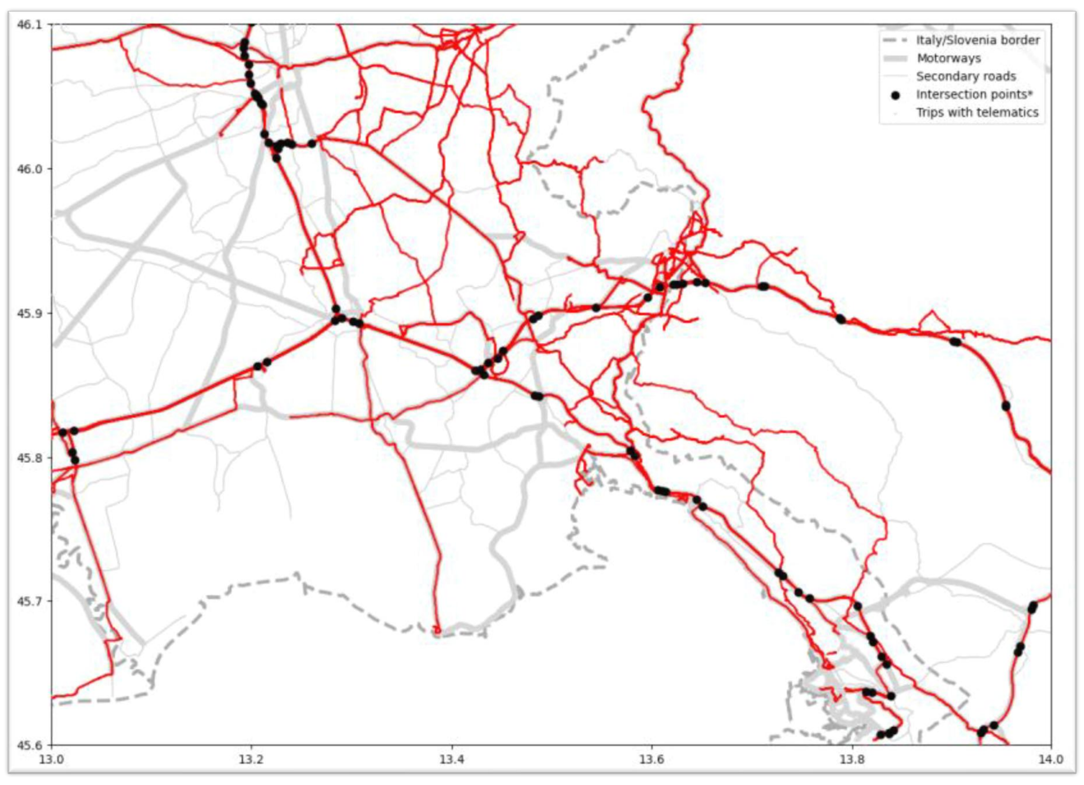

Fig. 1. Study area near Gorizia (IT/SL border) with 322 telematics trips and 98 motorway junctions highlighted.

Environmental data was drawn from Mapillary. A spatial join retrieved images within a 50m radius of each junctions, consistent with the telematics geofence, yielding **101 images** in total (3 junctions had 2 images; pixel rates were averaged). Images were processed using **DeepLabV3+** (Chen et al., 2018) with a ResNet-50 encoder, trained on Cityscapes data (Cordts et al., 2016) via Segmentation Models PyTorch (Iakubovskii, 2019) on an NVIDIA RTX-2080 GPU. Training ran for 58 epochs (early stop after 10 non-improving epochs). **Best IoU: 0.5881** across 19 classes.

ANALYSIS METHODOLOGY

Analysis proceeded in two rounds: (1) **Spearman rank correlation** between individual environmental elements and harsh events; (2) **count regression** (Poisson and Negative Binomial) using arithmetic log-ratio (ALR) transformation relative to road pixels, to handle compositional data constraints. Telematics variables (number of trips, mean speed) were also tested as explanatory variables.

RESULTS AND DISCUSSION

Table 1. Spearman rho table

Variable	Spearman ρ	p-value	p-value (BH)
Road	0.1770	0.0813	0.5147
Sidewalk	0.1241	0.2235	0.7121
Building	-0.0345	0.7356	0.8735
Wall	0.0395	0.6995	0.8735
Fence	-0.0014	0.9893	0.9893
Pole	-0.0382	0.7091	0.8735
Traffic light	0.0906	0.3748	0.7121
Traffic sign	-0.0043	0.9662	0.9893
Vegetation	0.1092	0.2844	0.7121
Terrain	-0.2339	0.0204	0.3885
Sky	0.0146	0.8868	0.9893
Person	0.0630	0.5379	0.8735
Rider	-0.0477	0.6413	0.8735
Car	-0.1790	0.0778	0.5147
Truck	0.1077	0.2913	0.7121
Bus	-0.1058	0.2999	0.7121
Train	-0.0532	0.6030	0.8735
Motorcycle	-0.0913	0.3711	0.7121
Bicycle	-0.1239	0.2240	0.7121

The Spearman-rho output showed no strong correlation between individual environmental variables and harsh-event occurrence. The only variable significant at the 5% level was **terrain** (rho = -0.2339, p = 0.020), but this could not be confirmed after Benjamini-Hochberg correction. Results do not rule out non-linear relationships; no impediment to regression analysis was identified.

Mean harsh events per junction = **0.35;** variance = **1.96** (considerable overdispersion). Three model families were tested: Poisson, NB with estimated alpha, and NB with alpha fixed = 1. Variables were aggregated into five categories to address compositional constraints: **construction** (building, wall, fence); **flat** (sidewalk, terrain); **poles and signs** (pole, traffic light, traffic sign); **nature** (vegetation, sky) and **road users** (person, rider, car, bus, train, truck, motorcycle, bicycle).

Four variable configurations were tested:

(1) all ALR variables + trips as offset;
(2) ALR aggregated + trips as offset;
(3) ALR aggregated + trips directly;
(4) ALR aggregated + trips + mean speed.

Model fit was evaluated via log-likelihood (LL), AICc, and BIC (Table 2). **Poisson consistently outperformed Negative Binomial**, supported by very low estimated alpha values and NB convergence issues. Including trips directly (rather than as offset) improved fir further, especially when combined with mean speed (pseudo-R^2 = **0.54** vs. 0.37 for SVI-only). However, adding trips and speed reduced the statistical significance of the SVI-derived variables.

RESULTS AND DISCUSSION

Table 2. Model fit comparison

Model	Variables used	Alpha	AICc	BIC	LL
Poisson	All	0	128.3420	-318.9659	-41.2976
Poisson	Aggregated	0	112.7693	-360.7311	-50.1672
Poisson	With trips	0	111.4521	-359.6879	-48.3938
Poisson	With trips and speed	0	105.0355	-363.7935	-44.0511
NB	All	1	136.4259	-327.9652	-45.3396
NB	Aggregated	5.855*10-6	114.7693	132.4293	-50.1672
NB	Aggregated	1	116.8745	-373.8093	-52.2198
NB	With trips	1.623*10-8	113.4521	133.4725	-48.3939
NB	With trips	1	115.5369	-372.7864	-50.4388
NB	With trips and speed	1	107.3726	-378.6397	-45.2200

Table 3. Regression coefficients

Model	Number trips as offset		Number of trips and speed as variables	
	β	p-value	β	p-value
Constant	-7.3278	0.000	-1.8787	0.199
Constr.	0.3165	0.049	0.2894	0.168
Flat	-0.2593	0.000	-0.1549	0.010
Poles and signs	-0.0598	0.475	-0.1098	0.217
Nature	0.6816	0.117	1.1323	0.027
Road users	-0.4889	0.005	-0.2778	0.156
Trips count			0.0222	0.000
Mean speed			-0.0294	0.003
Pseudo-R^2	0.3730		0.5431	
AICc	112.7693		105.0355	

Across model specifications, **flat variables** (terrain, sidewalk) consistently showed negative coefficients significant at 95% confidence: higher proportions of open/unobstructed space are associated with fewer harsh events. Poles and signs showed high p-values throughout, likely due to limited variance in their pixel proportions relative to road pixels.

CONCLUSIONS

Spearman correlation tests did not confirm a direct linear relationship between individual environmental attributes and harsh-event frequency. However, count regression models achieved reasonable fit (pseudo-R^2 = 0.37 with SVI variables only; 0.54 with added telematics variables).

Key findings:

- Poisson provided better fit than Negative Binomial across all configurations.
- A greater prevalence of flat-terrain pixels (terrain, sidewalk) consistently predicts **fewer harsh events**.
- Number of trips and mean speed strengthen predictive power but reduce significance of SVI variables.

Limitations: small dataset (98 junctions) limits generalisability; Mapillary image quality is variable; no temporal analysis; segmentation model IoU (0.5881) is below SOTA; single geographic area.

ACKNOWLEDGEMENTS

This project has received funding from the Union's Horizon Europe research and innovation European programme under grant agreement No 101119590.

IVORY

European Commission