From Crash Data to Risk Fields

How Traffic Research in Geography Helps Us Understand Road Safety

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Original research question:
Which factor influence crash fatality most, road slope? Road curvature? Or other variables?

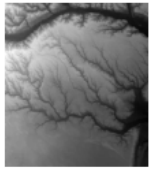
Future question: Where/which road could be more dangerous?

Two prerequisite knowledge:

1. **DEM (Digital Elevation Models) Data**
2. **(Linear) Regression Model**

DEM Data

Digital Elevation Models, or DEMs, are three-dimensional models of the "bare earth" surface, showing **elevation** and **topography** without trees, buildings, or other objects. DEMs are created from a variety of sources. USGS DEMs used to be derived primarily from topographic maps. Those are being systematically replaced with DEMs derived from high-resolution lidar and IfSAR (Alaska only) data.



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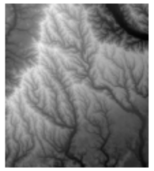

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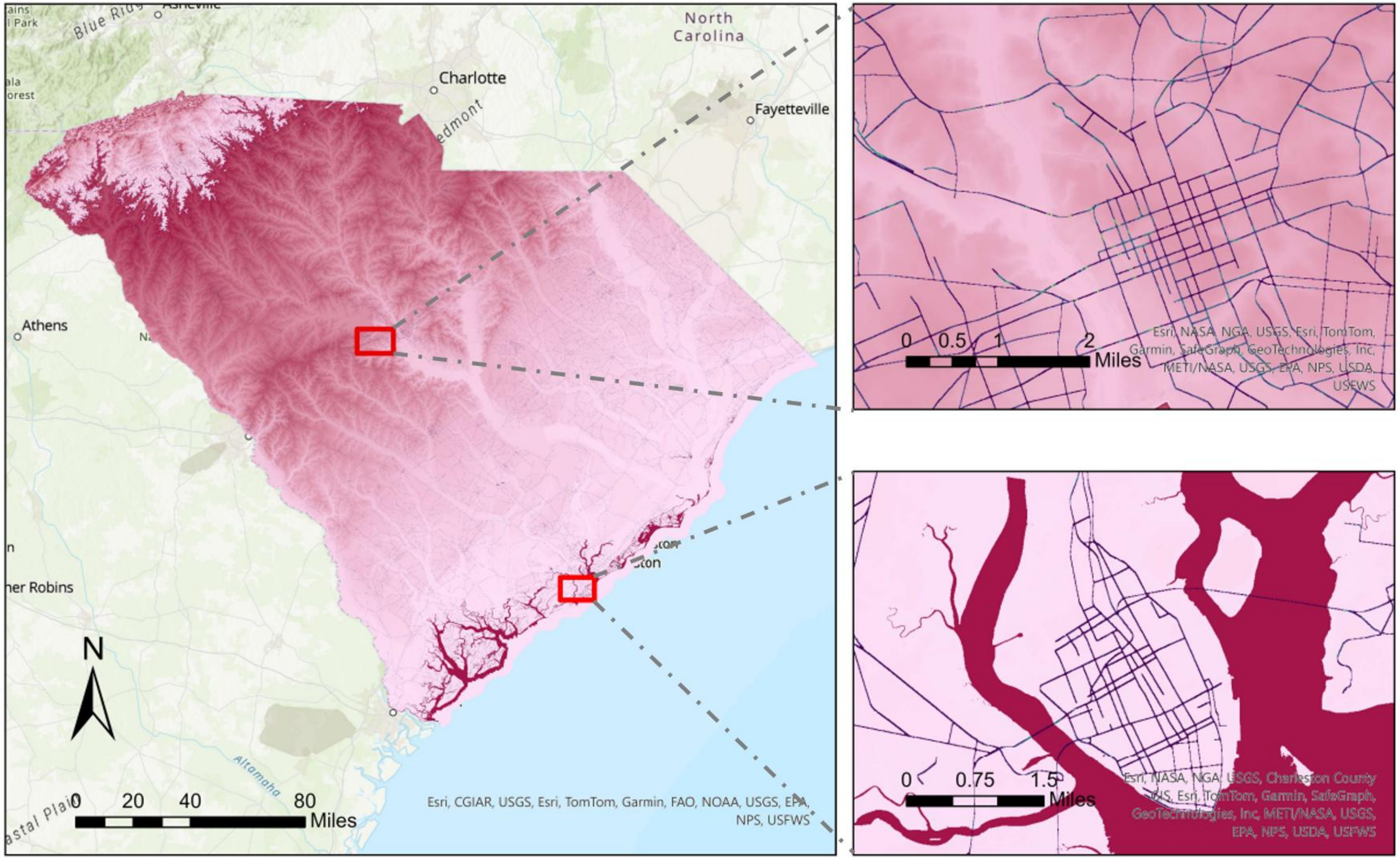

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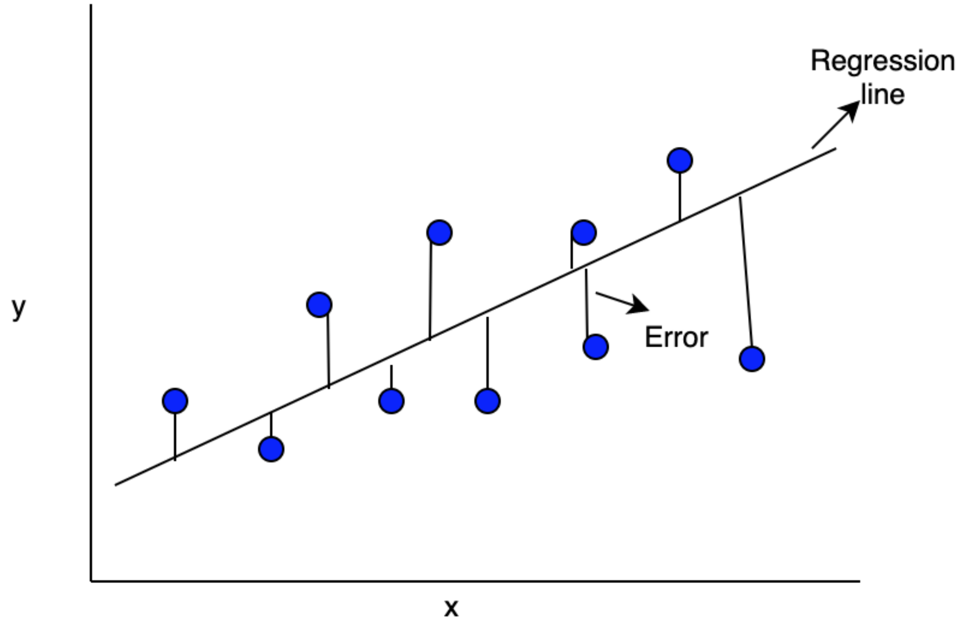
https://www.earthdata.nasa.gov/topics/land-surface/digital-elevation-terrain-model-dem

https://apps.nationalmap.gov/downloader/

Regression model

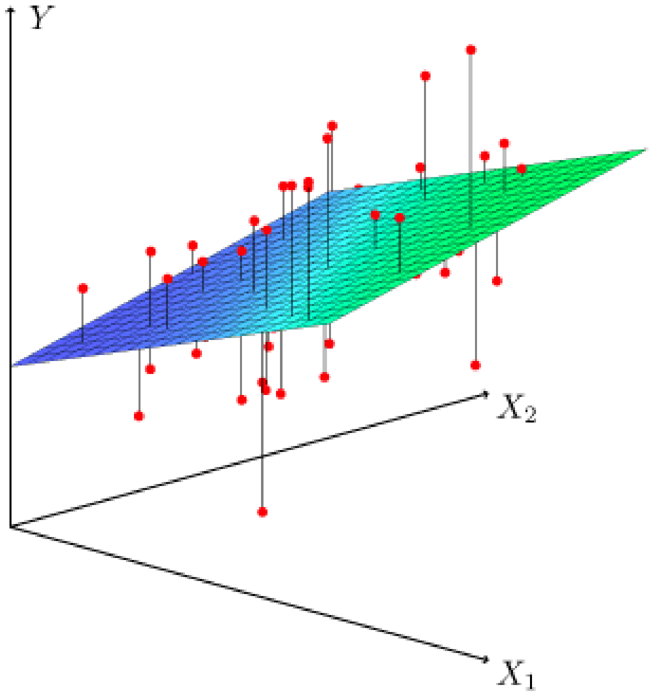
People use Regression model for finding relationship, **Inference**, or prediction

1) See how variables connect to each other.
2) **See if a relationship is real or just luck.**
3) Guess future numbers.



The model we use: Inhomogeneous Poisson point process

For today: Think it as a *Linear regression*



$$Y_i = \beta_0 + \beta_1 X_1 + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

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Inhomogeneous Poisson point process (IPPP)

$$\log \lambda(s) = \beta_0 + \beta_1 X_1(s) + \cdots + \beta_p X_p(s) = X(s)^T \beta$$

$\lambda(s)$: intensity function, Represents the density or rate of event occurrence at position *s*.

Log-Likelihood Function of IPPP

$$\log L(\beta) = \sum_{i=1}^{n} \log \lambda(s_i) - \int_W \lambda(s)\, ds$$

$$= \sum_{i=1}^{n} X(s_i)^T \beta - \int_W exp\left(X(s)^T \beta\right) ds$$

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

1. Why use Poisson?

Because we are dealing with **counting rare, independent events**.

- **No negatives, whole numbers only:** You can observe $0,1,2,$or 10trees or car crashes in an area, but never -3or 2.4.
- **Natural fit for counts:** The standard bell curve (Normal distribution) assumes numbers can be negative and continuous. The Poisson distribution is built specifically for non-negative integers ($0,1,2,\ldots$) where occurrences happen independently at a certain average rate.

2. Why use a Point Process?

Because the **exact location** (x, y)**of each event is the data itself**.

- In classic statistics, the locations are fixed first (like choosing 50 pre-set weather stations) and then measuring a value at each one (like temperature).
- In spatial point patterns (trees in a forest, disease cases in a city, lightning strikes), the **locations where things appear are random and informative**. A point process models both *how many* events happen and *where* they choose to appear across continuous space.

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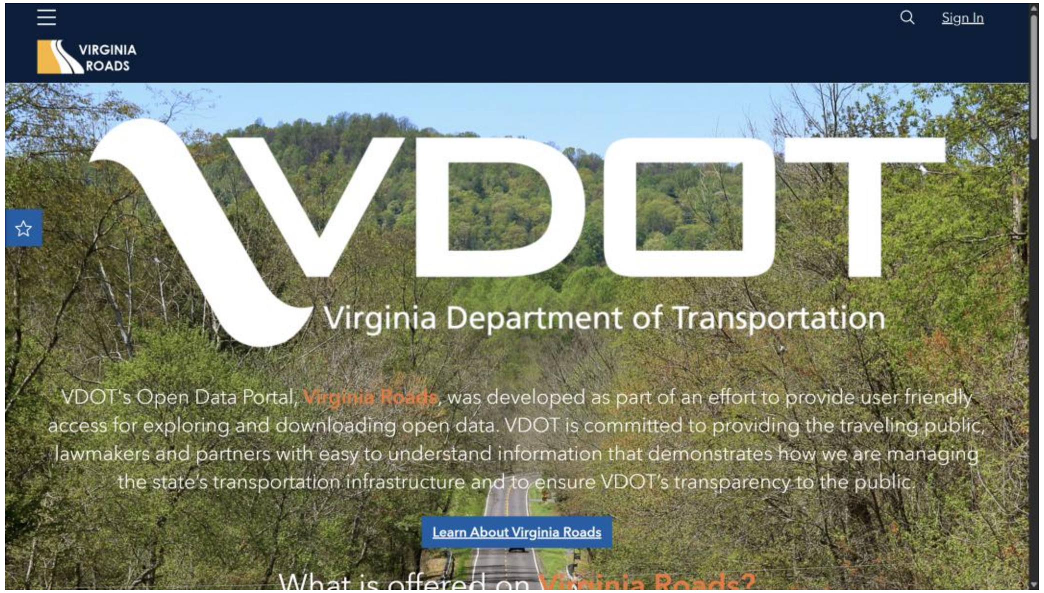
Data & Data processing

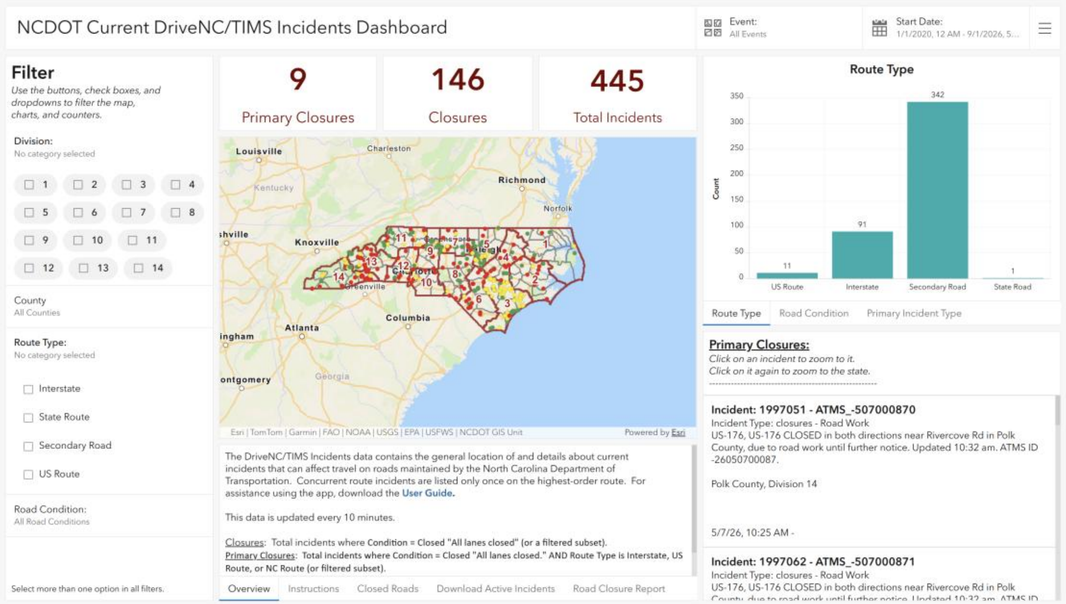
DOT DATA

https://www.scdot.org/travel/travel-mappinggis.html

Table 1
Description of variables used in the analysis.

Variable	Description
Dependent Variable	
FatalCrash	Binary indicator for fatal crash (1 = fatal crash, 0 = background point)
Road Design	
Log (Slope)	Log-transformed road slope (in degrees), derived from DEM
Log(Curvature^{-1})	Log-transformed inverse road curvature (radius of fitted arc, in meters)
Dynamic Road Conditions	
Work Zone	Indicator for presence of a work zone (1 = yes, 0 = no)
Wet Surface	Indicator for wet or slippery surface condition (1 = wet, 0 = dry)
Log (AADT)	Log-transformed Average Annual Daily Traffic (normalized/interpolated)
Temporal and Environmental Factors	
Night	Indicator for nighttime crash (1 = night, 0 = day)
Weekend	Indicator for weekend crash (1 = Saturday/Sunday, 0 = weekday)
Bad Weather	Indicator of adverse weather (e.g., rain, snow)
Vehicle Characteristics	
Commercial Vehicle (CMV) Involved	Indicator for commercial motor vehicle involvement (1 = CMV, 0 = otherwise)





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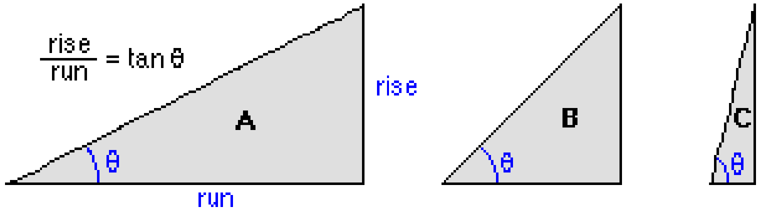
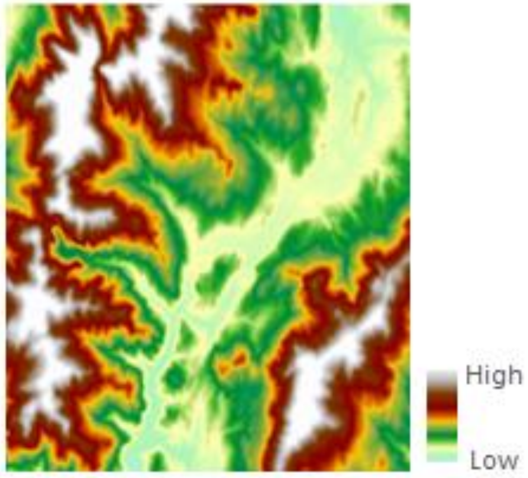
Road Slope

Degree of slope = θ

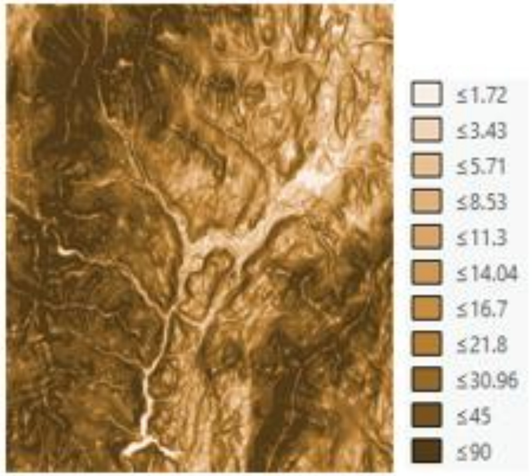
Percent of slope = $\frac{\text{rise}}{\text{run}} * 100$



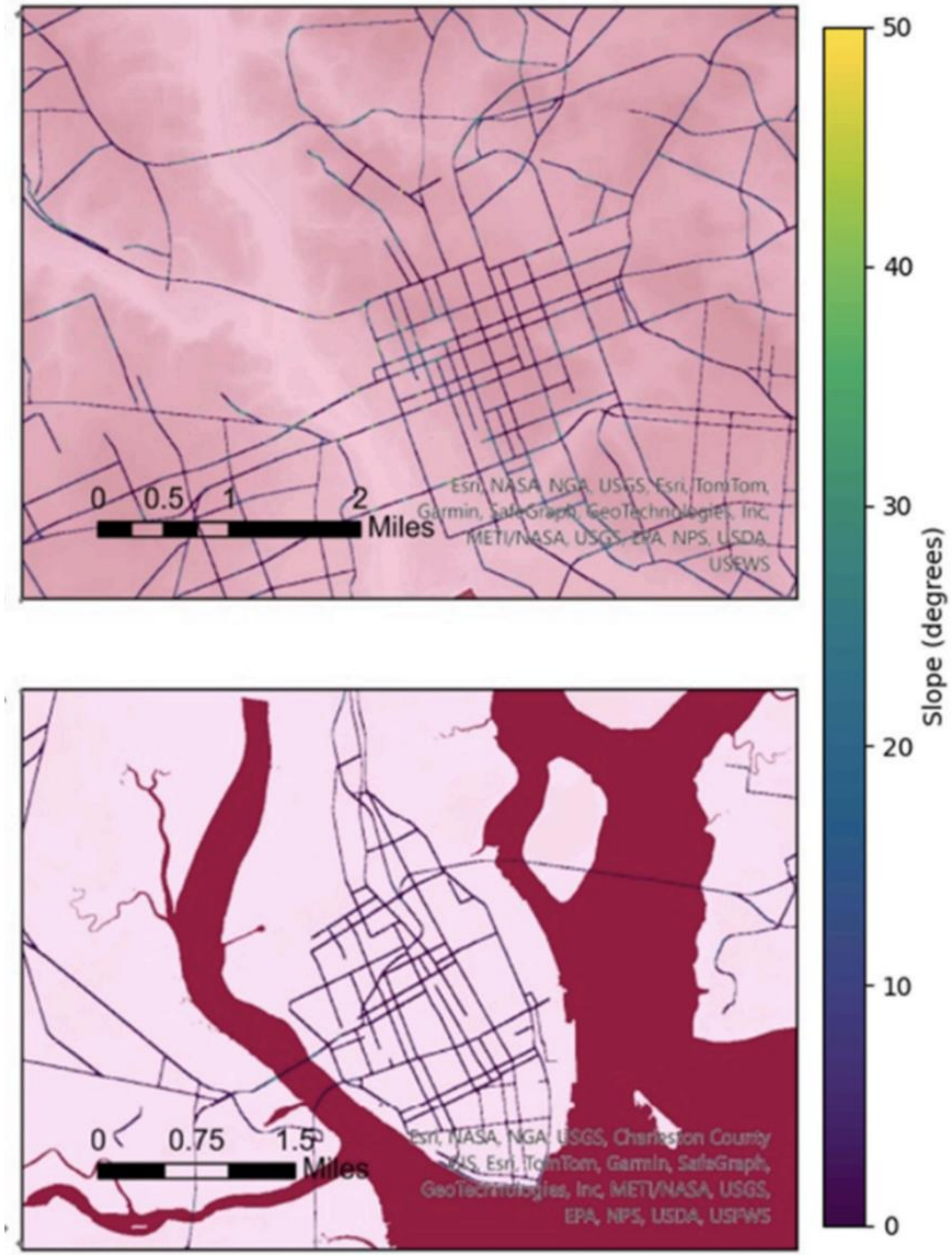
	A	B	C
Degree of slope =	30	45	76
Percent of slope =	58	100	373



Input elevation raster



Output slope raster
(in degrees)



https://pro.arcgis.com/en/pro-app/3.6/tool-reference/spatial-analyst/how-slope-works.htm

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Road curvature

The radius of an equivalent circle represents the road curvature at a given point.

In practice, we approximate this radius using the circle defined by the three nearest neighboring points along the road.

Curvature = 1/Radius

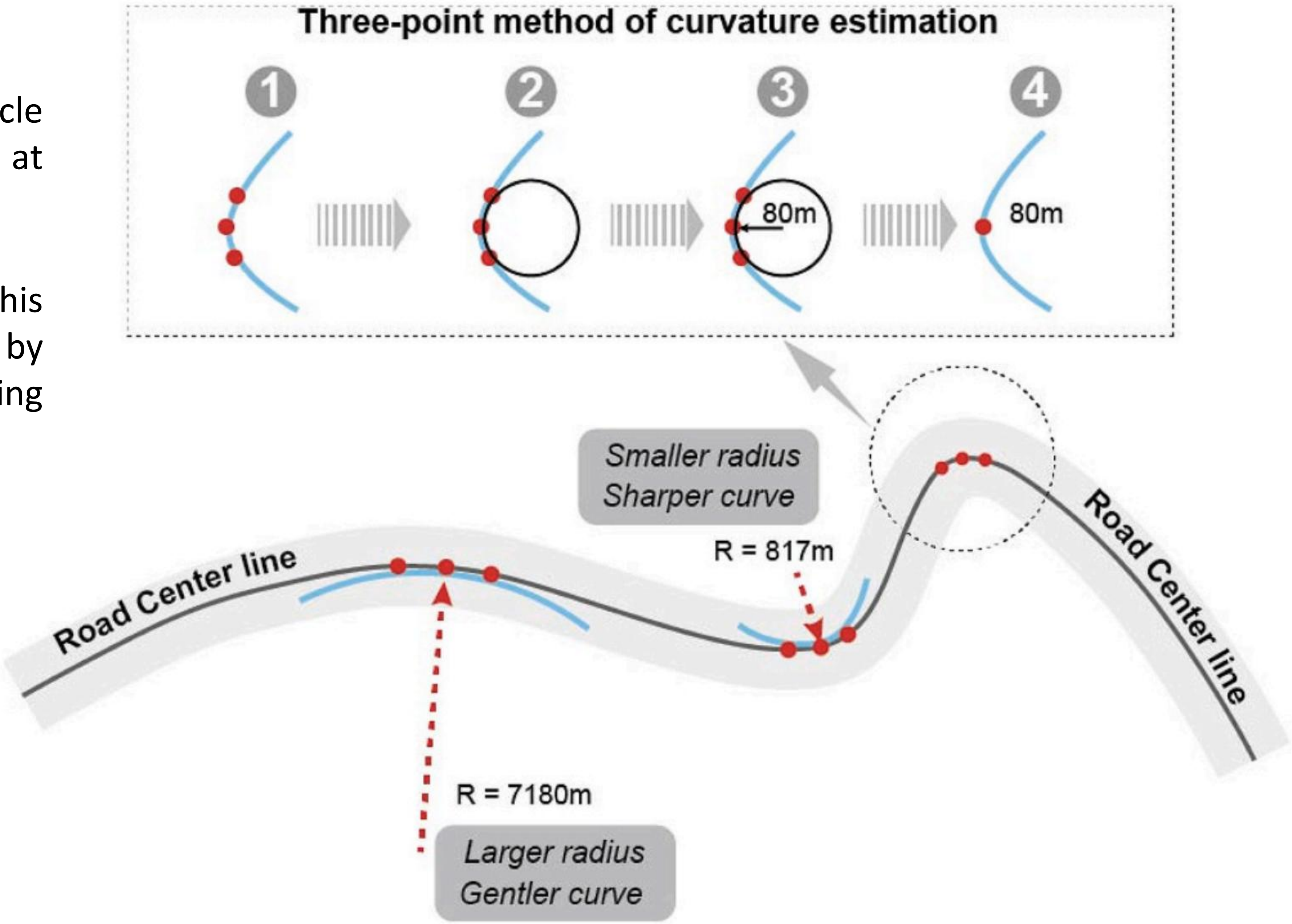

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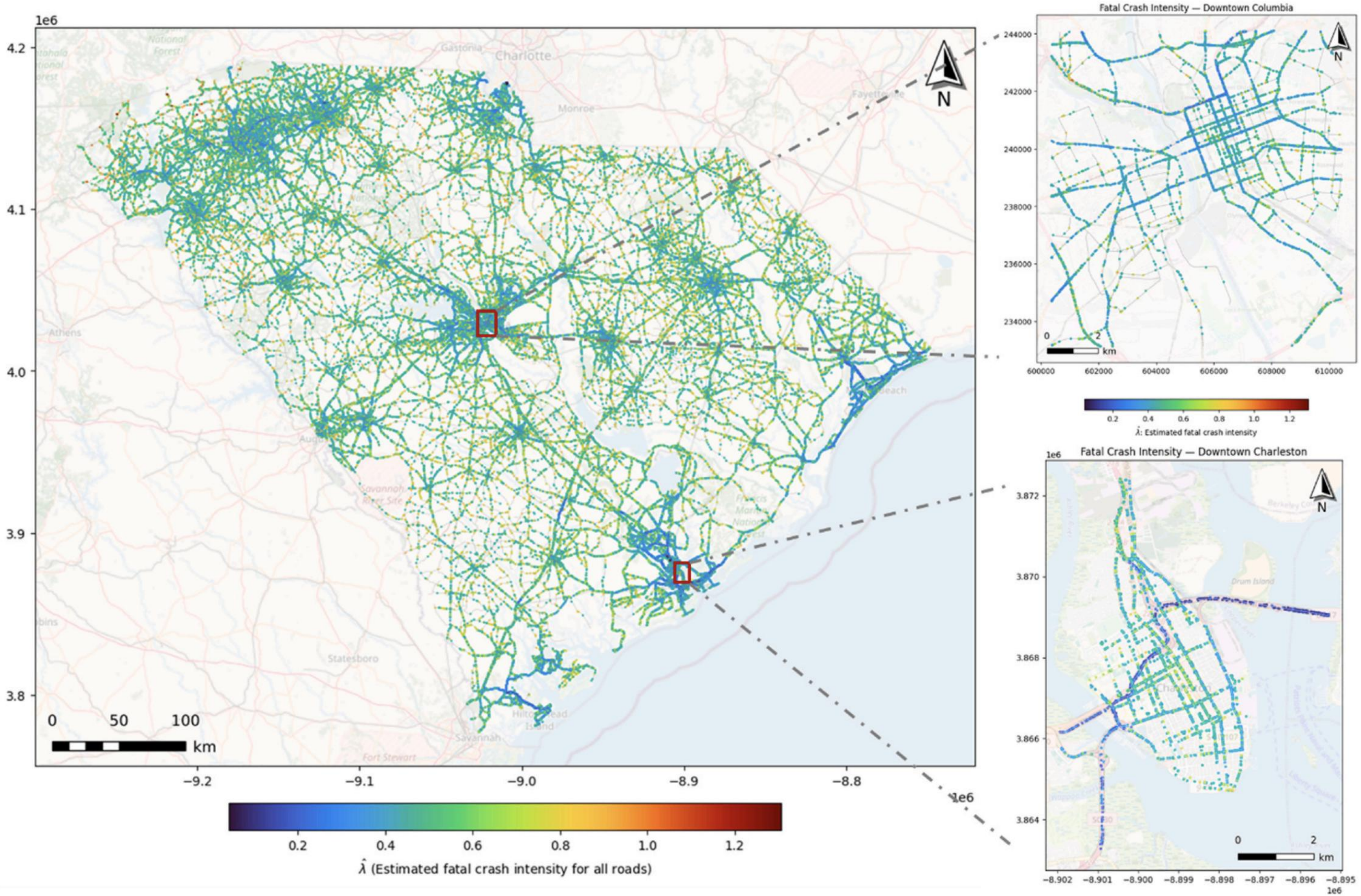
Table: Variable definitions in the analytical dataset

Variable	**Description**
`Slope`	Road slope (degrees), derived from DEM
`Night`	Indicator for nighttime crash ($1 = $ yes, $0 = $ no)
`Surface`	Indicator for wet surface condition ($1 = $ wet, $0 = $ dry)
`Workzone`	Indicator for work-zone presence ($1 = $ yes, $0 = $ no)
`AADT`	Average Annual Daily Traffic (normalized)
`Curvature`	Road curvature (arc radius in meters)
`Road`	Road class (e.g., interstate, local)
`death`	Fatal crash indicator ($1 = $ fatal, $0 = $ non-fatal)

$$Y_i\,(\text{death}) = \beta_0 + \beta_1 X_1(slope) + \beta_2 X_2(night) + \cdots + \beta_n X_n + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}\left(0, \sigma^2\right)$$

Results

Result: Fatal Intensity (λ) map



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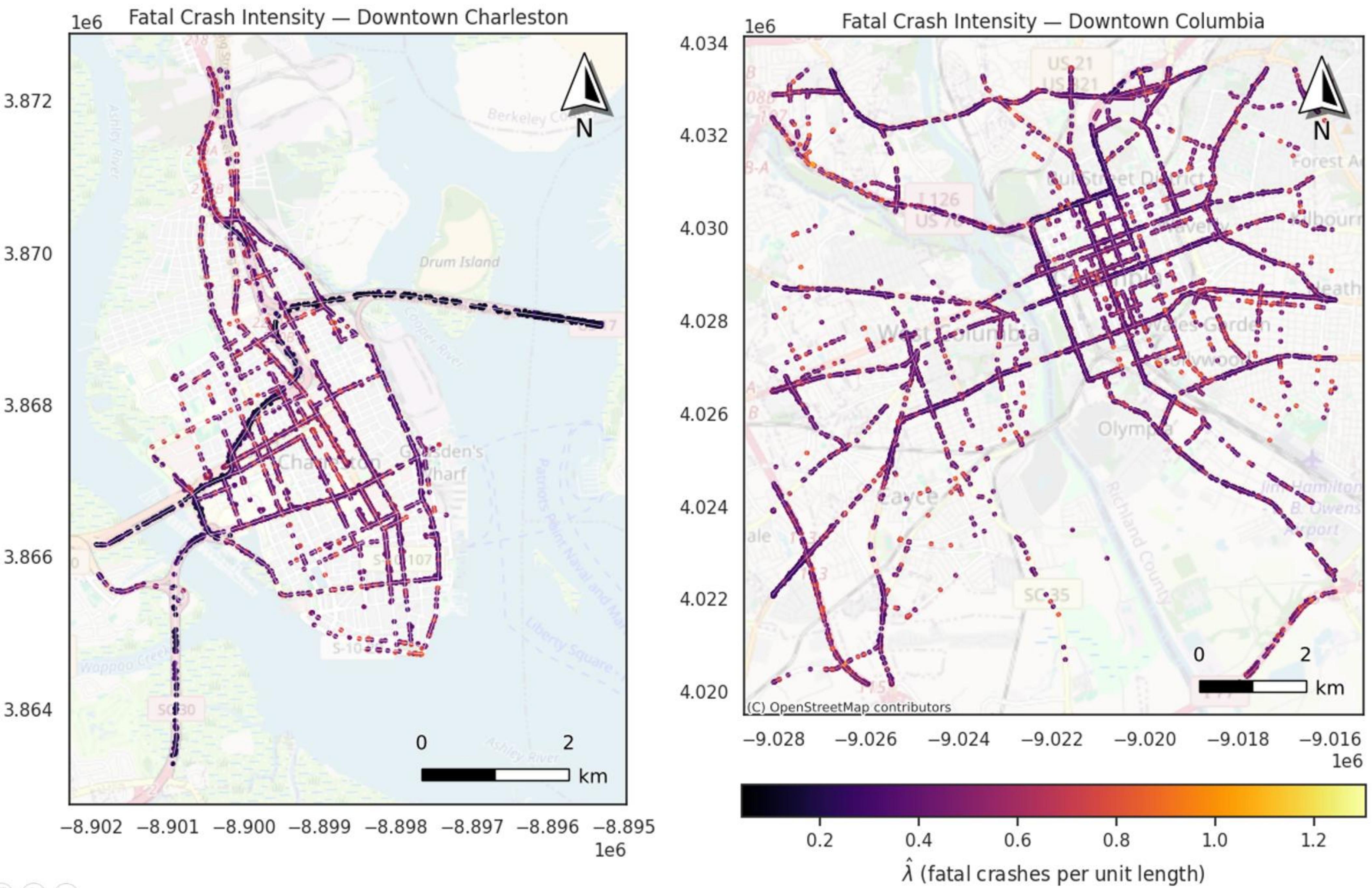

Fatal Crash Intensity — Downtown Charleston
1e6
3.872
3.870
3.868
3.866
3.864
−8.902
−8.901
−8.900
−8.899
−8.898
−8.897
−8.896
−8.895
1e6
N
Drum Island
0
2
km
Fatal Crash Intensity — Downtown Columbia
1e6
4.034
4.032
4.030
4.028
4.026
4.024
4.022
4.020
−9.028
−9.026
−9.024
−9.022
−9.020
−9.018
−9.016
1e6
N
0
2
km
(C) OpenStreetMap contributors
0.2
0.4
0.6
0.8
1.0
1.2
$\hat{\lambda}$ (fatal crashes per unit length)

Result: Tables show how variable influence road fatal crash results

Table 2

Poisson point process model using log-transformed variables (all road types).

	Estimate	Std. Error	z-value	p-value
DV: FatalCrash				
Road Design				
Log(Slope)	0.063	0.014	4.512	<0.001 ***
Log$\left(\text{Curvature}^{-1}\right)$	−0.025	0.013	−1.941	0.052 •
Dynamic Road Condition				
Work Zone1	0.205	0.095	2.159	0.031 *
Wet Surface	−0.049	0.045	−1.093	0.274
Log (AADT)	−0.865	0.018	−47.609	<0.001 ***
Temporal and Environmental Factors				
Night	0.570	0.027	21.394	<0.001 ***
Weekend	0.159	0.032	4.885	<0.001 ***
Bad Weather	0.049	0.042	1.167	0.243
Vehicle Characteristics				
CMV Involved	0.812	0.043	18.801	<0.001 ***
Intercept	1.618	0.136	11.914	<0.001 ***

Sample Size (N): 602,955; signifiance codes: <0.001 '***' <0.01 '**' <0.05 '*' <0.1 '•'

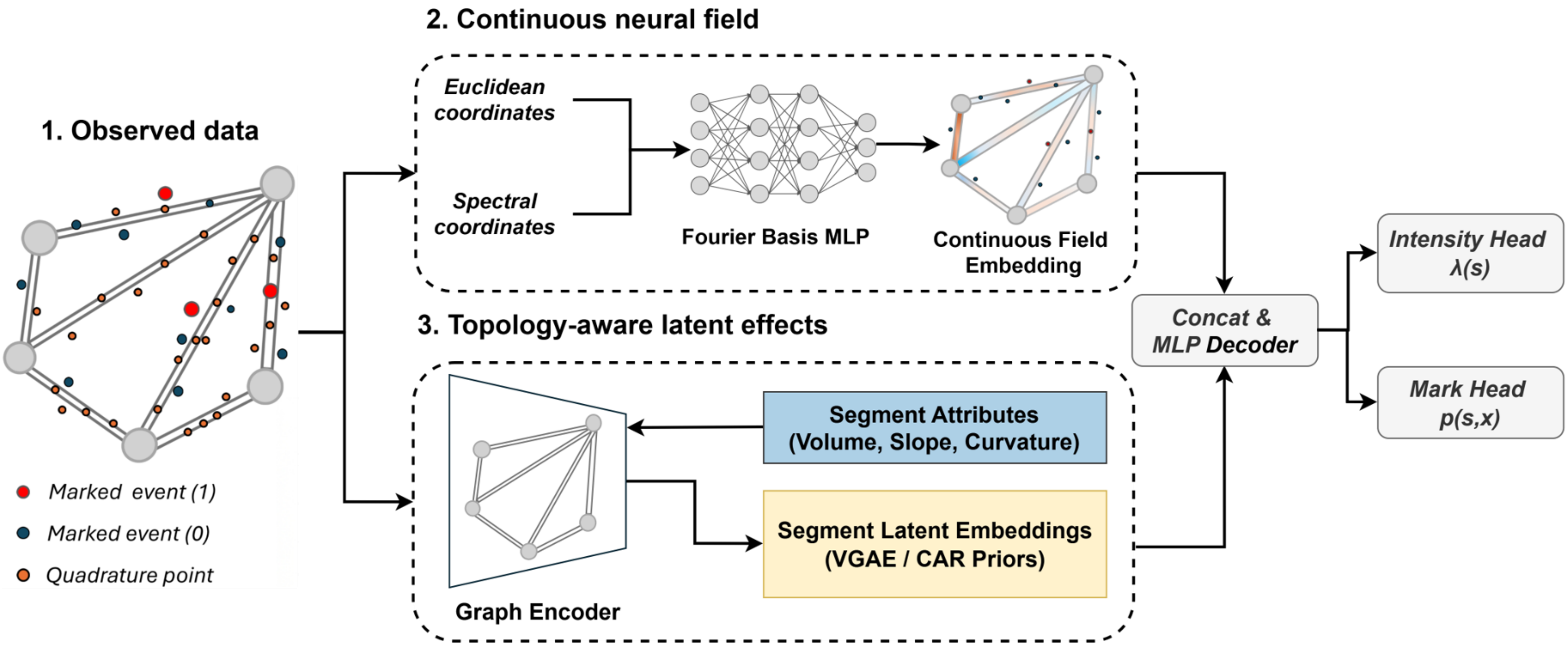
Poisson model estimates by road type with log-transformed variables.

DV: FatalCrash	Stratified model of highways			Stratified model of local roads		
	Estimate	**Std. Err.**	**p**	**Estimate**	**Std. Err.**	**p**
Road Design						
Log (Slope)	0.0646	0.0185	<0.001***	0.0546	0.0247	0.027*
Log($Curvature^{-1}$)	−0.0065	0.0156	0.675	−0.0901	0.0197	<0.001***
Dynamic Road Condition						
Work Zone	0.1222	0.1108	0.270	0.3498	0.2985	0.241
Wet Surface	−0.0446	0.0582	0.444	−0.1503	0.0924	0.104
Log (AADT)	−0.9164	0.0289	<0.001***	−0.9904	0.0260	<0.001***
Temporal and Environmental Factors						
Night	0.7062	0.0339	<0.001***	0.6932	0.0494	<0.001***
Weekend	0.2109	0.0406	<0.001***	0.1745	0.0607	0.004**
Bad Weather	0.0267	0.0563	0.635	0.1113	0.0858	0.195
Vehicle Characteristics						
CMV Involved	0.8978	0.0522	<0.001***	0.7893	0.1033	<0.001***
Intercept	1.7431	0.2512	<0.001***	2.2809	0.1884	<0.001***

Sample Size (N): Highway = 438,200, Local = 291,810; Pseudo R^2: Highway = 0.227, Local = 0.333; significance codes: <0.001 '***' <0.01 '**' <0.05 '*'.

Paper link: https://www.sciencedirect.com/science/article/pii/S0143622826001633

Ongoing work



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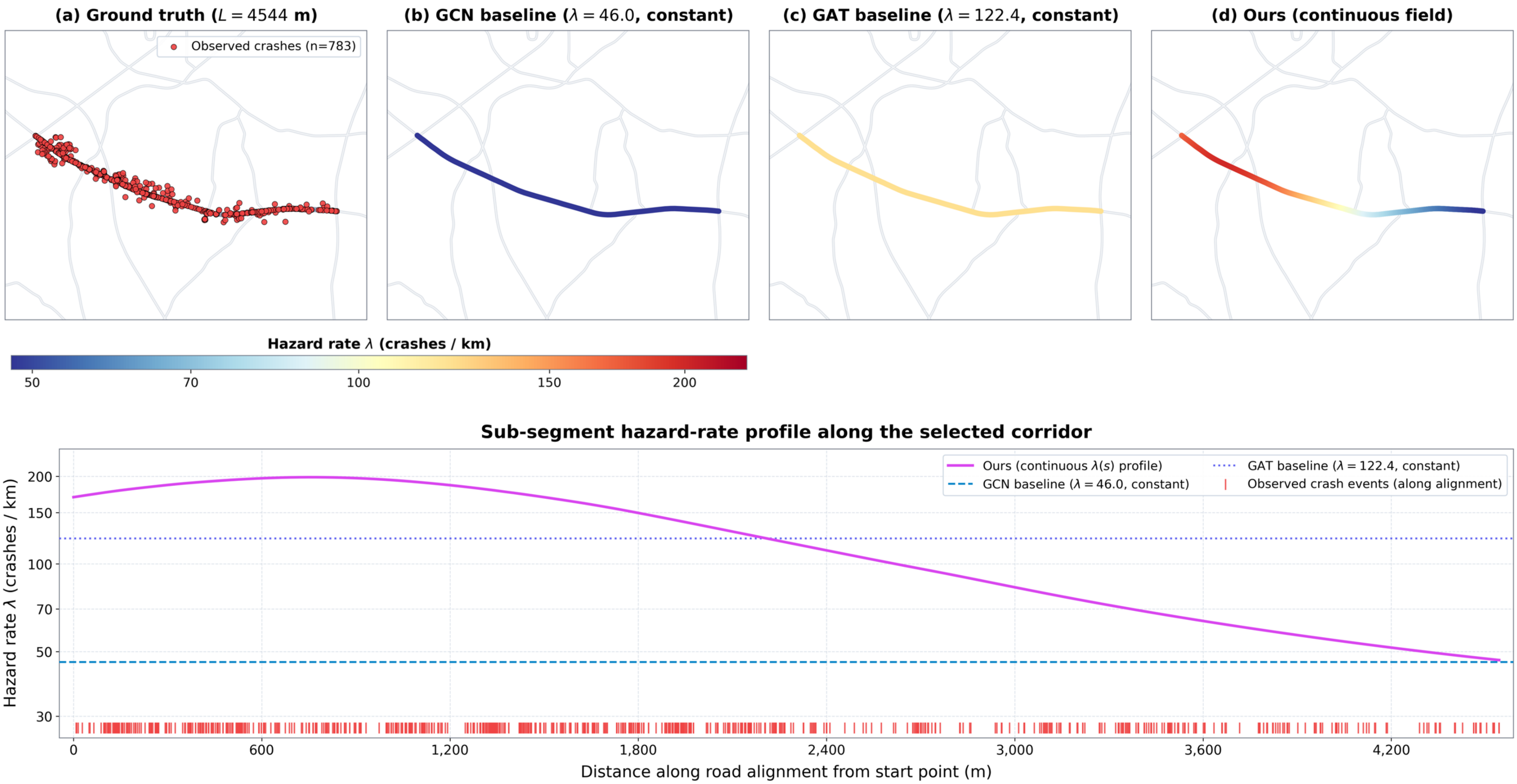
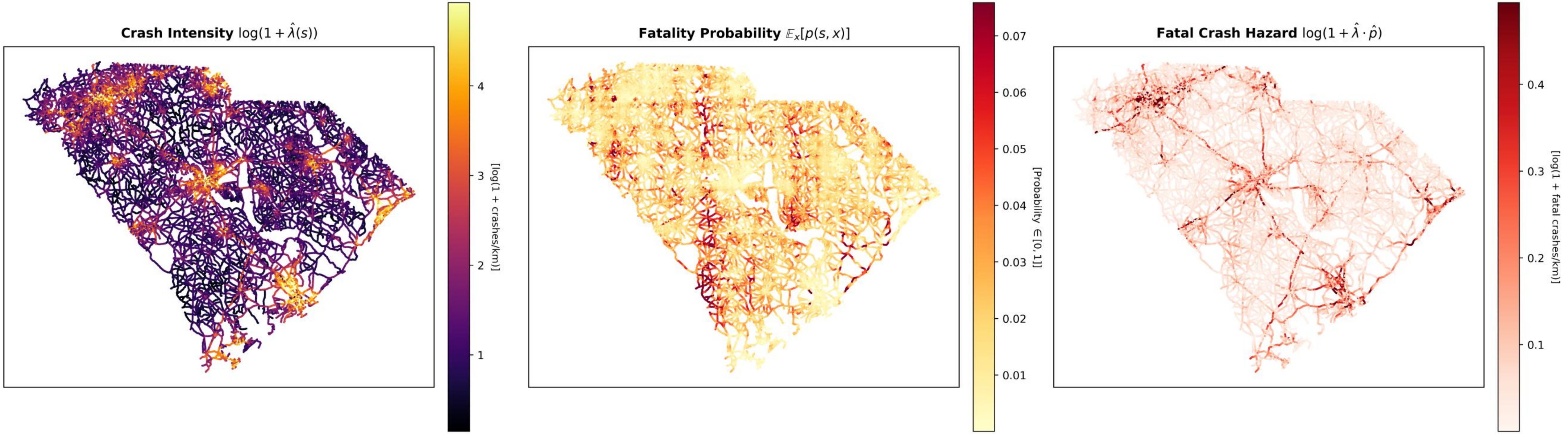


(a) Ground truth (L = 4544 m)
Observed crashes (n=783)
(b) GCN baseline (λ = 46.0, constant)
(c) GAT baseline (λ = 122.4, constant)
(d) Ours (continuous field)
Hazard rate λ (crashes / km)
50
70
100
150
200
Sub-segment hazard-rate profile along the selected corridor
Ours (continuous λ(s) profile)
GCN baseline (λ = 46.0, constant)
GAT baseline (λ = 122.4, constant)
Observed crash events (along alignment)
Hazard rate λ (crashes / km)
200
150
100
70
50
30
0
600
1,200
1,800
2,400
3,000
3,600
4,200
Distance along road alignment from start point (m)



Deep learning model provide more accurate & better results.

However, the results would be less explainable.

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Questions?

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