Maximizing Safety: Smart Autonomous Path Planning to Reduce Harm from Crashes

By: Zayan Hassan

Problem

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$1.4 Trillion in damages from car accidents in 2019

Damages from crashes is not minimized

Models do not focus on best expected value outcome

Fixing gap can decrease harm to people, vehicles, and infrastructure

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Research Question

How can environmental-based model switching compare to traditional single-model use with regards to monetary damages and harm to people in a crash?

Goal

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Improve Road Safety

Addresse ethical gaps in autonomous driving

Minimize harm and preserve infrastructure

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Definitions

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Single / Ensemble Model

CARLA Simulator

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Assumptions

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CARLA is accurate

Utilitarianism Ethicality should be used

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Hypothesis

Environmental-based model switching is able to reduce monetary damages and harm to people in a crash when compared to single-model algorithms.

Literature Review

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Ensemble models are not viable (Cho et al., 2020)

Semantic Gaussian Filtering (Zhou et al., 2025)

Graph-Temporal Convolutional Model (Chen et al., 2025)

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Inquiry Method

The proposed inquiry method is **Experimental** Research Design.

Rationale

I picked experimental design because I already have clear-cut independent and dependent variables. My independent variable will be the model that I use, while the dependent variable will be the associated average harm across all tests.

Inquiry Method

The proposed inquiry method is **Experimental** Research Design.

Best Fit

Experimental Research Design is the best for my research because it allows me to draw conclusions about causal relationships which is vital for improving my final algorithm.

Methodology

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Create the ensemble model

Select maps to use

Run each model 5 times on each map and record raw data

Convert raw data into calculated damage values

Analyze data using a bayesian hierarchical model

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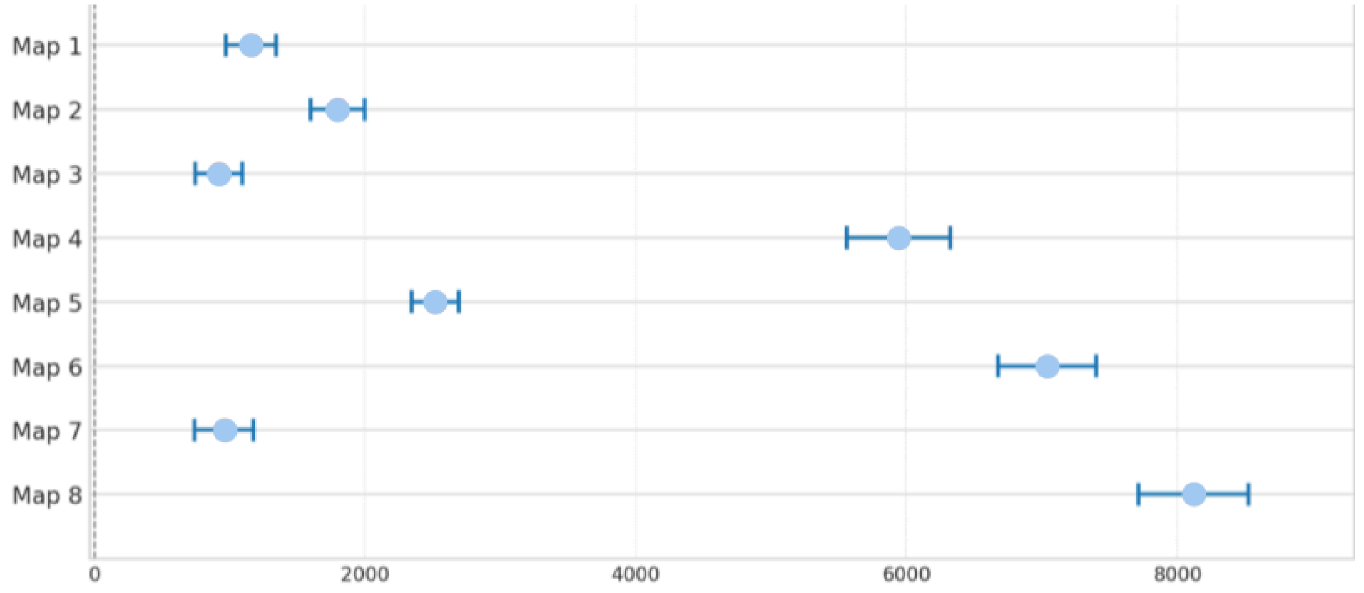
Data

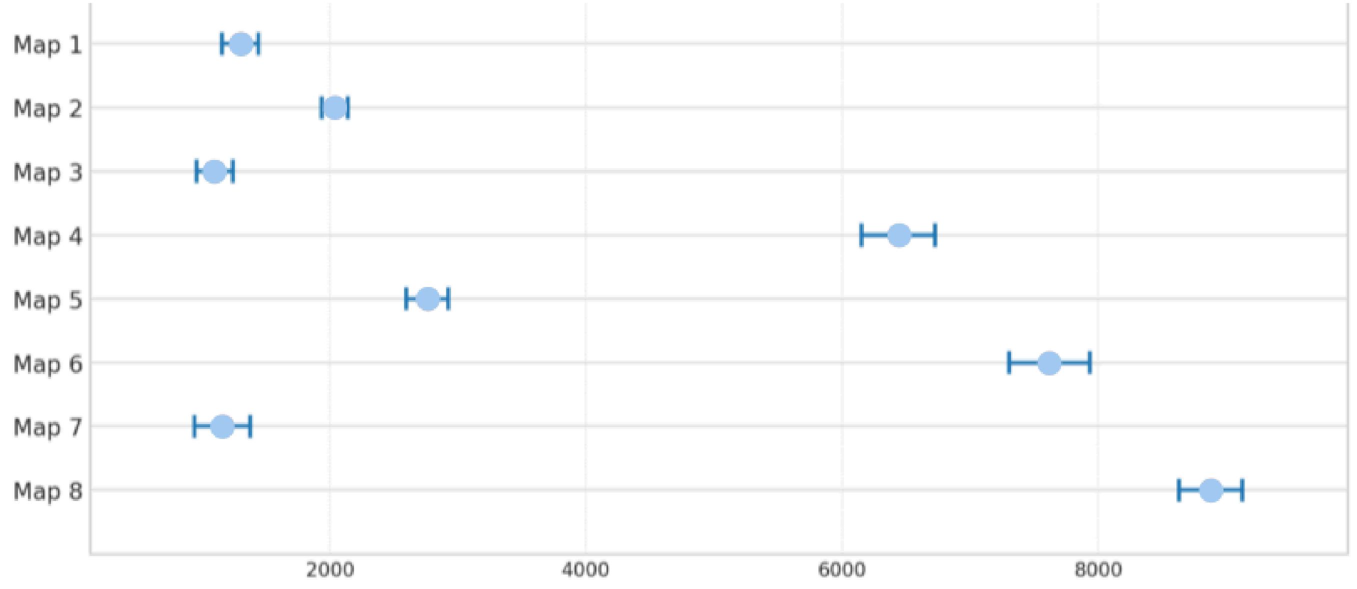
CARLA 2024 Model	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
Map 1	$1,500.00	$1,100.00	$1,400.00	$1,300.00	$1,200.00
Map 2	$2,200.00	$1,900.00	$2,100.00	$2,000.00	$2,000.00
Map 3	$1,300.00	$900.00	$1,200.00	$1,100.00	$1,000.00
Map 4	$6,900.00	$6,100.00	$6,600.00	$6,400.00	$6,200.00
Map 5	$3,000.00	$2,600.00	$2,900.00	$2,700.00	$2,600.00
Map 6	$8,100.00	$7,200.00	$7,800.00	$7,600.00	$7,400.00
Map 7	$1,500.00	$900.00	$1,300.00	$1,100.00	$1,000.00
Map 8	$9,300.00	$8,600.00	$9,000.00	$8,800.00	$8,700.00

My Model	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
Map 1	$1,400.00	$900.00	$1,300.00	$1,200.00	$1,000.00
Map 2	$2,100.00	$1,500.00	$1,900.00	$1,700.00	$1,800.00
Map 3	$1,200.00	$700.00	$1,000.00	$900.00	$800.00
Map 4	$6,500.00	$5,400.00	$6,200.00	$5,900.00	$5,700.00
Map 5	$2,800.00	$2,300.00	$2,600.00	$2,500.00	$2,400.00
Map 6	$7,600.00	$6,500.00	$7,200.00	$6,900.00	$7,000.00
Map 7	$1,300.00	$700.00	$1,100.00	$900.00	$800.00
Map 8	$8,800.00	$7,600.00	$8,300.00	$8,000.00	$7,900.00

95% Confidence Interval for Mean Damage - Ensemble Model

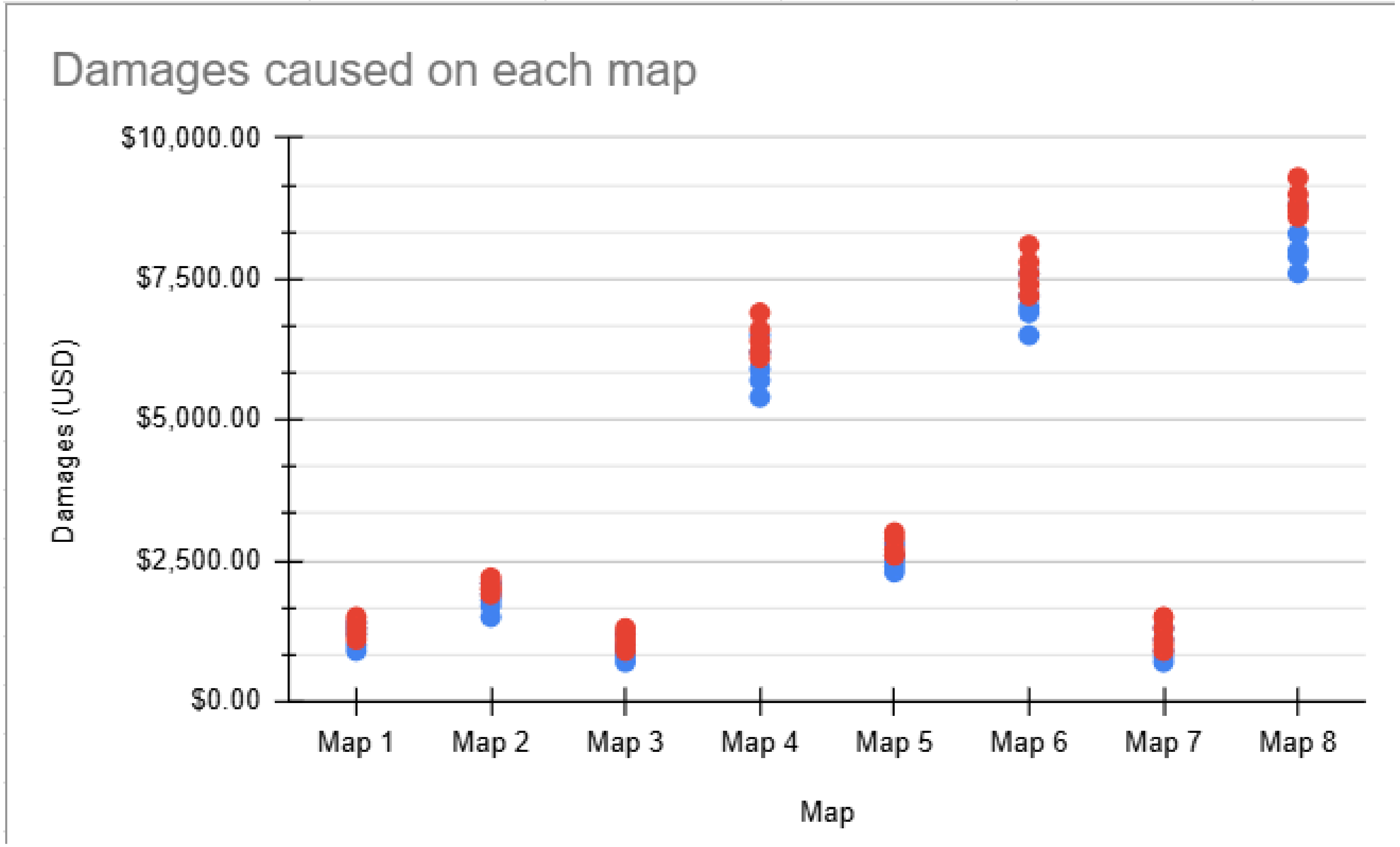


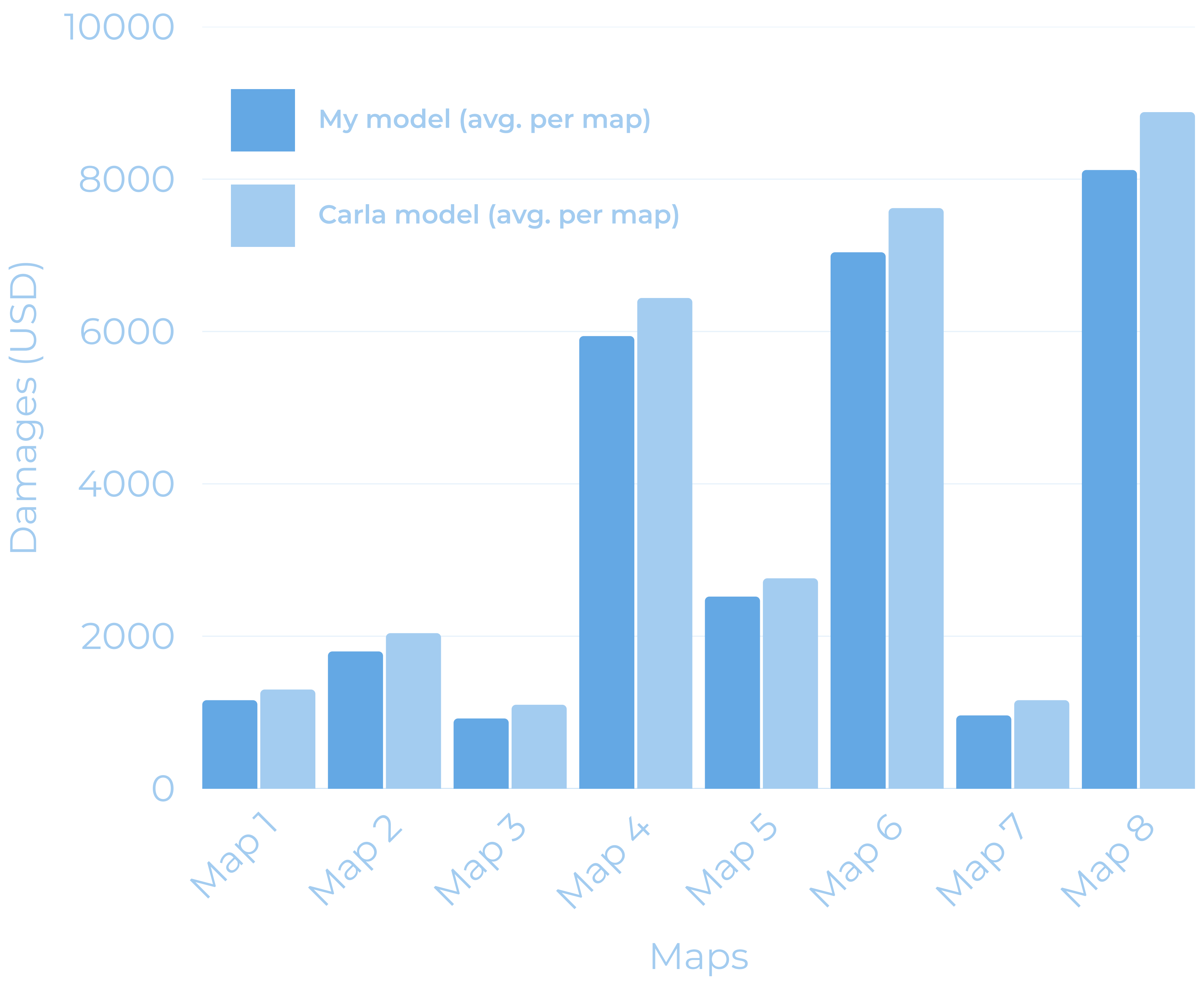
95% Confidence Interval for Mean Damage - Single Model

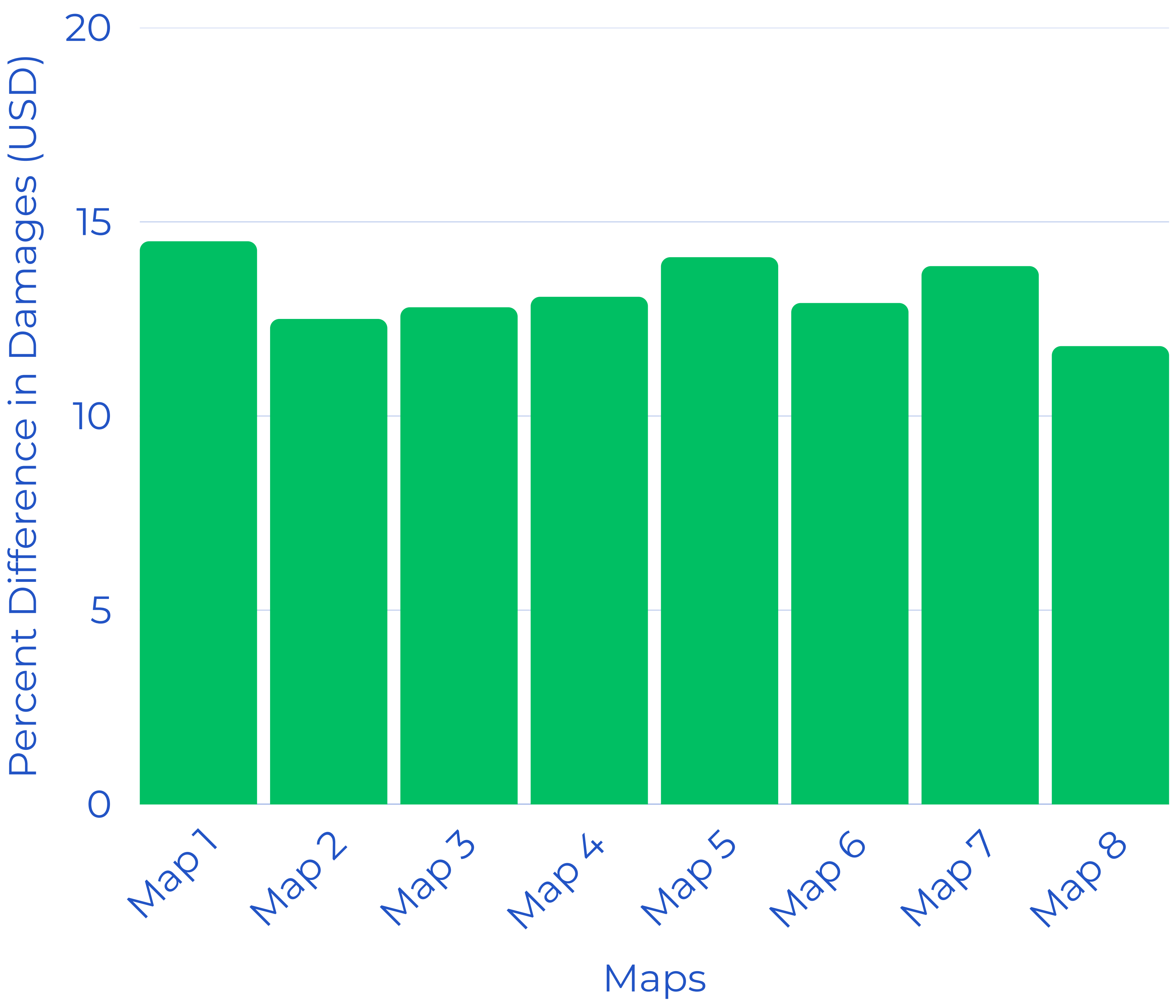


Red - CARLA Model

Blue - My Model




10000
8000
6000
4000
2000
0
Damages (USD)
My model (avg. per map)
Carla model (avg. per map)
Map 1
Map 2
Map 3
Map 4
Map 5
Map 6
Map 7
Map 8
Maps

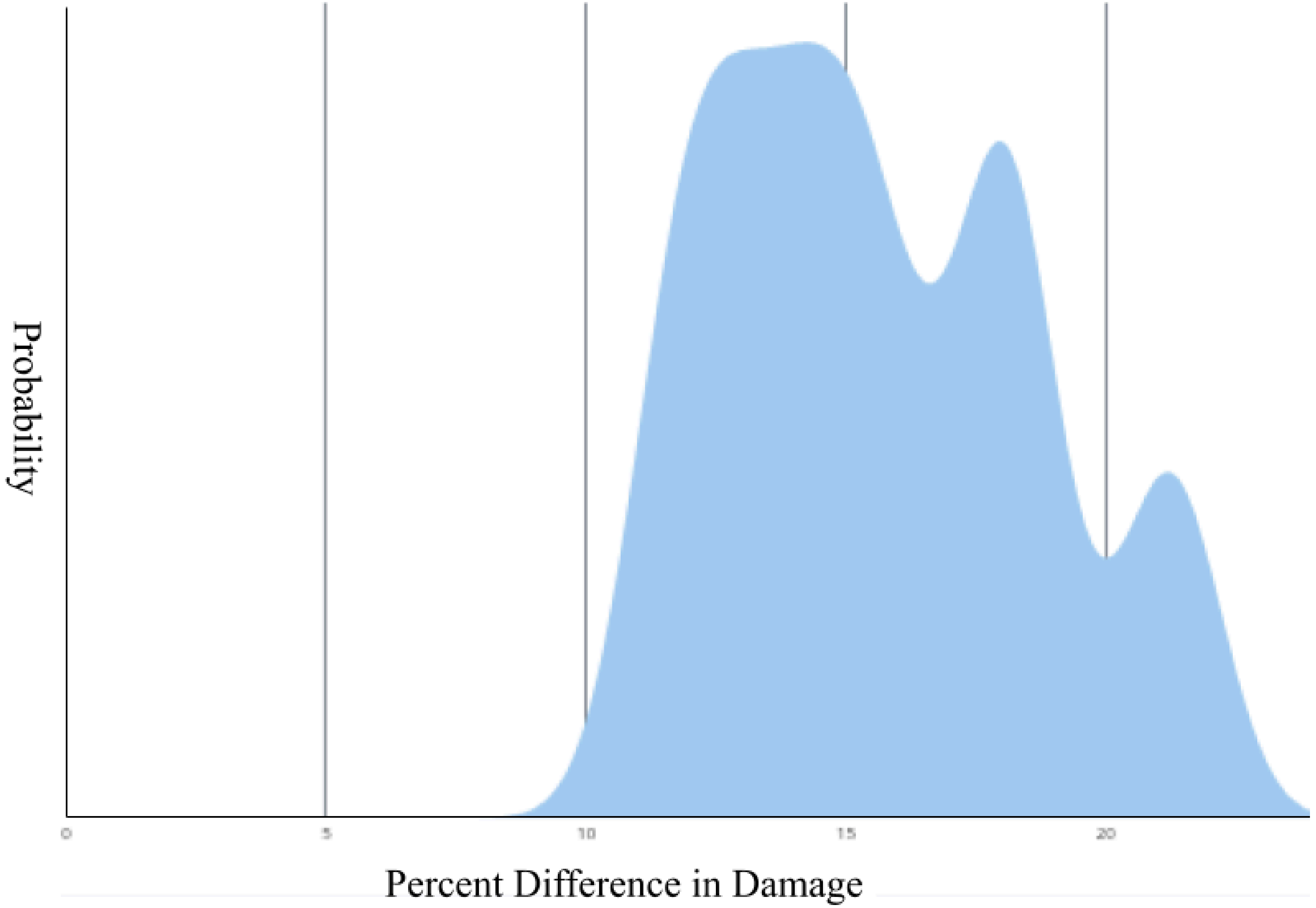

20
15
10
5
0
Percent Difference in Damages (USD)
Map 1
Map 2
Map 3
Map 4
Map 5
Map 6
Map 7
Map 8
Maps

```python
import numpy as np
import pymc as pm
import arviz as az

ensemble = np.array([
    [1400,  900, 1300, 1200, 1000],
    [2100, 1500, 1900, 1700, 1800],
    [1200,  700, 1000,  900,  800],
    [6500, 5400, 6200, 5900, 5700],
    [2800, 2300, 2600, 2500, 2400],
    [7600, 6500, 7200, 6900, 7000],
    [1300,  700, 1100,  900,  800],
    [8800, 7600, 8300, 8000, 7900],
])

carla = np.array([
    [1500, 1100, 1400, 1300, 1200],
    [2200, 1900, 2100, 2000, 2000],
    [1300,  900, 1200, 1100, 1000],
    [6900, 6100, 6600, 6400, 6200],
    [3000, 2600, 2900, 2700, 2600],
    [8100, 7200, 7800, 7600, 7400],
    [1500,  900, 1300, 1100, 1000],
    [9300, 8600, 9000, 8800, 8700],
])
y = np.concatenate([ensemble.flatten(), carla.flatten()])
vehicle = np.concatenate([
    np.zeros(40),
    np.ones(40)
])
map_idx = np.tile(np.repeat(np.arange(8), 5), 2)
with pm.Model() as model:
    alpha_global = pm.Normal("alpha_global", mu=4000, sigma=3000)
    beta_global  = pm.Normal("beta_global", mu=0, sigma=2000)
    sigma_alpha = pm.HalfNormal("sigma_alpha", sigma=2000)
    sigma_beta  = pm.HalfNormal("sigma_beta", sigma=1500)
    alpha_map = pm.Normal("alpha_map", mu=alpha_global, sigma=sigma_alpha, shape=8)
    beta_map  = pm.Normal("beta_map",  mu=beta_global,  sigma=sigma_beta,  shape=8)
    mu = alpha_map[map_idx] + beta_map[map_idx] * vehicle
    sigma = pm.HalfNormal("sigma", sigma=1000)
    y_obs = pm.Normal("y_obs", mu=mu, sigma=sigma, observed=y)
    t = pm.sample(2000, tune=2000, target_accept=0.9, random_seed=67, progressbar=False)
b = t.posterior["beta_global"].values.flatten()
eb = np.mean(b > 0)
cb = np.mean(b < 0)
d = b.mean()
print(f"Ensemble better {eb:.3f}")
print(f"CARLA better {cb:.3f}")
print(f"damage difference {d:,.0f}")
```

13% better with a 91% posterior probability



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Environmental-based model switching is able to reduce monetary damages and harm to people in a crash when compared to single-model algorithms.

Conclusions

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Improvement is percentage-based

The ensemble model performs better

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Implications

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Ensemble models have real world application

Potential to spark academic discussions over ethicality principles

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Limitations

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Testing occured in a simulation

Posible errors in damage calculation

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References

Cho, J., Kim, D., & Park, S. (2020). *Improving trajectory planning through probabilistic SLAM for autonomous vehicles in dynamic environments.* Robotics and Autonomous Systems, 132, 103617. https://doi.org/10.1016/j.robot.2020.103617

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Thank You