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# Modelling the impact of road infrastructure on cycling moving speed

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## 1 Introduction

Cycling for transport is increasingly recognised as a key solution for achieving a healthier and more sustainable future (Celis-Morales et al., 2017; Handy et al., 2014). It not only offers an active and environmentally friendly mode of travel (Buehler et al., 2020) but can also be faster than other modes for short trips, particularly in CBDs and during peak hours (Gossling, 2020). Despite these benefits, cycling remains underutilised in many cities, prompting growing interest in understanding cyclist behaviour and the barriers that deter people from cycling (Molenberg et al., 2019; Biernat et al., 2018).

One of the key factors influencing the decision to cycle is travel time, with studies showing that time spent cycling, especially on roads without dedicated bike lanes, is valued more highly than time spent using other modes of transport (Borjesson and Eliasson, 2012; Wardman et al., 2007). To reduce cycling travel times, strategies like improving street connectivity and optimising cycling infrastructure have been explored (Handy et al., 2014; Ahmad et al., 2020). One promising intervention is the implementation of green wave signal timing, which minimises disruptions for cyclists by synchronising traffic lights along main cycling routes. This strategy has been successfully implemented in cities like Copenhagen and Groningen, resulting in significant travel time reductions for cyclists (Zhang and Blokpoel, 2018; City of Copenhagen, 2014).

This study aims to address the gap in city-scale models that simulate more realistic cycling speeds by investigating the association between road characteristics and cycling speed in Melbourne. Using an agent-based model, we simulate the potential impact of optimising traffic signals on the main cycling corridors feeding into the Melbourne CBD. The findings contribute to an understanding of how improvements to road infrastructure could enhance cycling speeds and reduce travel times in cities with low cycling uptake, such as Melbourne.

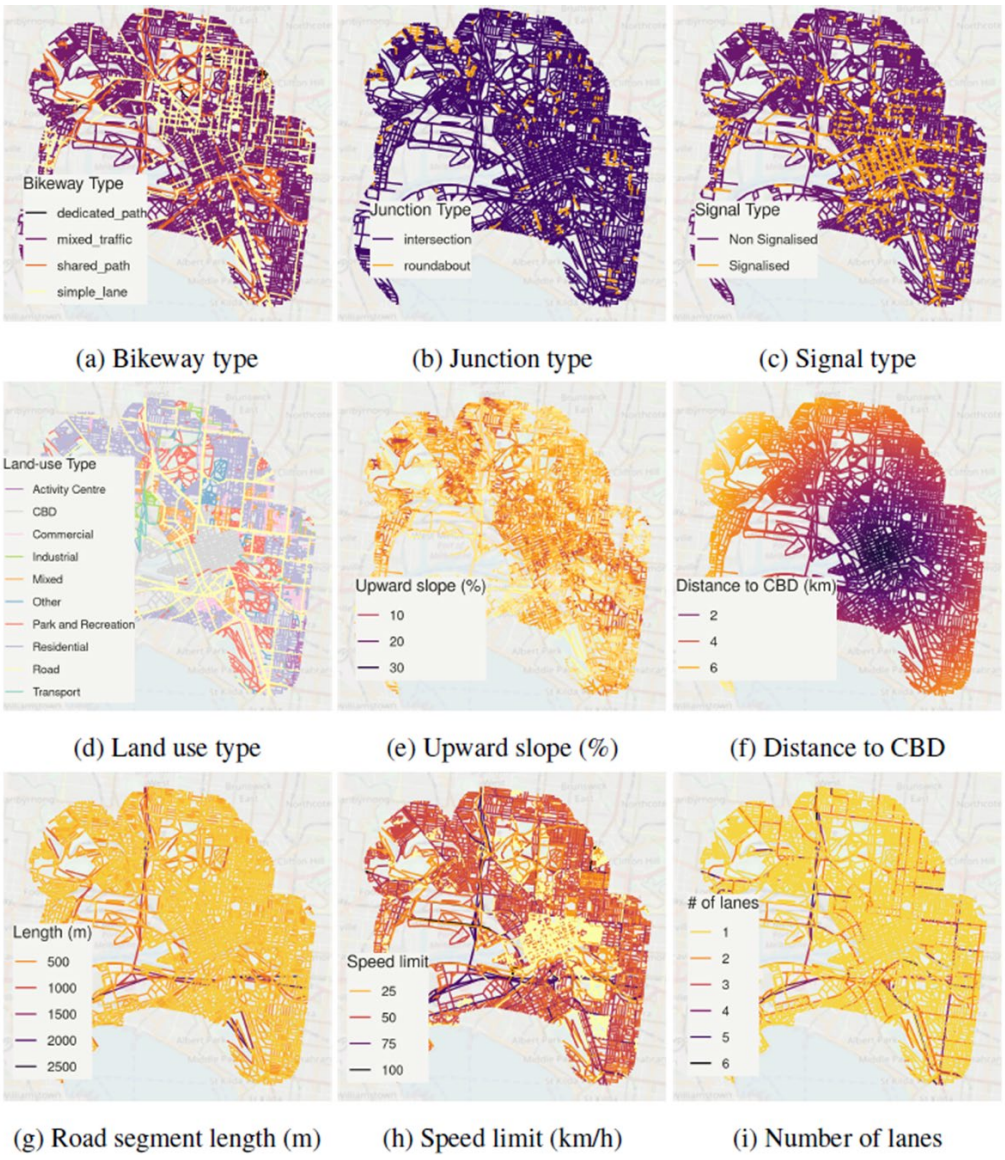
## 2 Methodology

To estimate cycling speed, two models were developed: a least squares Linear Regression (LR) model and a Random Forest (RF) regression model. Each model offers distinct advantages: while the LR model provides a simple, interpretable way to assess the relationship between road attributes and cycling speed, it assumes linearity, which limits its predictive accuracy. In contrast, the RF model, which does not assume linear relationships, offers superior predictive power but is considered a “black box”. After testing both models, the RF model, with an optimal set of hyperparameters (mtry = 3, min_n = 4), showed better predictive accuracy.

To build the models, aggregated data from Strava Metro for March 2021 was used, capturing over 250,000 cycling trips tagged as "commute" across Greater Melbourne. The data were filtered to focus on road segments with a minimum of 20 unique cyclists and average speeds between 5 km/h and 50 km/h. Predictor variables, such as bikeway type, junction type, slope, speed limits, and road length, were used to estimate average cycling speed for both

models. Figure 1 illustrates the physical attributes added to road segments within Melbourne's central area.

**Figure 1: Attributes added to the selected road segments (base map from OpenStreetMap)**

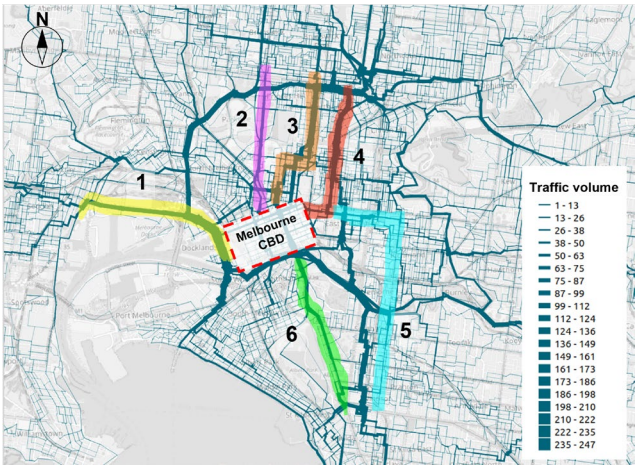



The data set was split into a training set of 28,387 data points and a test set of 9,464 points, using stratified sampling based on average cycling speed. For the RF model, grid-based hyperparameter tuning with 20 parameter sets was performed, resulting in RMSE = 4.41 and $R^2$ = 0.498. The selected RF model was then used to predict cycling speeds across the entire network. To validate the predictions, the results were compared to real-world cycling speed data from traffic sensors.

The next phase extended an agent-based transport model, AToM, developed for Melbourne (Jafari et al., 2024), by integrating the predicted cycling speeds from the RF model. This model was calibrated to simulate weekday transport for a 10% sample of Melbourne's population.

A case study was conducted to examine the potential impact of optimising traffic signals for major cycling corridors feeding into Melbourne's CBD during the AM peak. Six key corridors were selected for testing this intervention (Figure 2), which modelled a "green wave" scenario by reducing the negative impact of traffic signals on cycling speed. The simulation was run for 200 iterations, allowing agents to find their optimal routes.

**Figure 2: AM peak hour cycling traffic volume from the simulation model with the identified feeder corridors highlighted (base map from OpenStreetMap)**




# 3 Main findings

The LR model demonstrated that several road attributes were significant predictors of cycling speed ($p < 0.001$). Notably, cycling on roads with mixed traffic or signalised intersections was strongly associated with reduced speeds. Both uphill and downhill slopes negatively affected cycling speed, which was unexpected for downhill slopes, suggesting complex interactions with road infrastructure. Positive contributors to cycling speed included road length and proximity to the CBD. Overall, the model achieved a moderate fit with R2 = 0.3154 and an RMSE of 4.69.

The RF model provided greater predictive accuracy, identifying signal type, distance to the CBD, and slope as the most influential factors on cycling speed. The RF model outperformed the LR model with R2 = 0.454 and RMSE = 4.11, capturing a more nuanced relationship between road attributes and speed. Particularly interesting was the impact of traffic signals, which had a strong negative influence on cycling speed. The RF model's prediction accuracy was much higher than the constant cycling speed assumptions typically used in simulation models, making it a valuable tool for future research.

When the RF model was applied in the agent-based simulation, the most notable result was the potential benefit of a green wave intervention for cyclists. As shown in Table 1, optimising signal timings along key corridors feeding into the Melbourne CBD led to an average 6.2% reduction in moving travel time and a 4.1% increase in cycling volume. Among the corridors, the sixth corridor saw the largest decrease in travel time (-9.5%), while the first corridor had the highest increase in cycling volume (11.1%), indicating that certain routes stand to benefit more from such interventions. These findings highlight the significant impact that targeted infrastructure changes can have on cycling efficiency and uptake, especially in urban environments.

**Table 1: Average AM peak travel time of cyclists using the corridors and bicycle traffic volume on the selected corridors before and after the intervention**

| Corridor | Travel time | | | Bicycle traffic volume | | |
|---|---|---|---|---|---|---|
| | Before | After | Change (%) | Before | After | Change (%) |
| **1** | 18.0 | 16.7 | -7.4 | 292 | 325 | 11.1 |
| **2** | 13.6 | 12.6 | -6.7 | 105 | 99 | -5.5 |
| **3** | 21.6 | 21.0 | -2.7 | 321 | 326 | 1.6 |
| **4** | 20.4 | 19.7 | -3.1 | 192 | 191 | -0.4 |
| **5** | 22.9 | 21.2 | -7.5 | 114 | 125 | 9.6 |
| **6** | 19.8 | 17.9 | -9.5 | 124 | 128 | 3.3 |
| **Average** | 19.4 | 18.2 | -6.2 | 191.2 | 199 | 4.1 |

# 4 Discussion

The comparison between the LR and RF models highlighted that the RF model offered superior predictive accuracy. The LR model revealed that longer roads, roundabouts, and unsignalised junctions were associated with faster cycling speeds, confirming previous research (Clarry et al., 2019). Notably, the RF model found signal type, distance to the CBD, and slope as the most important predictors, emphasising the significant role of signalised junctions in influencing cycling speeds. This shows the need for effective signal control strategies to optimise cyclist flow.

One particularly interesting finding was the variability in the effectiveness of the green wave intervention across different corridors feeding into Melbourne's CBD. For example, some corridors, like the sixth, saw significant reductions in travel time (up to 9.5%), while others, like the first, experienced the largest increase in cycling volume (11.1%). This suggests that the best strategy for implementing green wave signal timing may depend on the corridor's specific goals, whether to reduce travel time for current cyclists or encourage new cyclists from nearby roads.

Additionally, the findings highlighted the balance between minimising cycling delays and ensuring better network connectivity. While green wave interventions might benefit key commuter routes, increasing junctions can improve overall connectivity and accessibility, particularly for local trips. This balance aligns with the Movement and Place framework, where different road types require different interventions. For major commuter corridors, reducing delays with green wave strategies is ideal, but for local cycling routes, connectivity and accessibility may take precedence.

Another interesting result was the finding that both uphill and downhill slopes were associated with lower cycling speeds in the LR model, a surprising outcome for downhill sections, suggesting that braking to maintain safe speeds could be a factor. This highlights the importance of considering road safety alongside speed improvements when designing interventions.

Although the study focused on built-environment attributes, it did not account for individual cyclist characteristics, such as physical fitness and bike type, which likely contribute to speed variations. Addressing this in future research could provide even more accurate simulations. Moreover, incorporating detailed traffic signal timing into the model would likely show a greater impact of green wave strategies, further enhancing the potential for cycling speed improvements across Melbourne's network.

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