Eco-Aware Route Planning in Okinawa: A Case Study on the Impact of Gradient

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Abstract

The global climate crisis has entered a critical phase, with scientific consensus indicating meaningful emission reductions must occur within this decade to limit global warming to 1.5°C above pre-industrial levels. Road transport remains a major contributor, accounting for roughly 15% of global anthropogenic CO_2 emissions. In Japan, passenger car transports alone generated approximately 101 million metric tonnes of CO_2 in 2019. Okinawa bears a share of this burden with 858,004 registered passenger cars among roughly 1.38 million residents (Stats-Japan, 2024). Applying the US EPA's standard figure of 4.6 metric tonnes of CO_2 per passenger vehicle per year, Okinawa's private car fleet alone is estimated to generate approximately 3.95 million metric tonnes of CO_2 annually.This paper presents "Eco-Mode", a navigation framework built on OpenRouteService (ORS) to address this challenge. Building on the established relationship between road gradient and fuel consumption (Huang & Peng, 2018), we score per-segment emissions using a tiered gradient-based factor derived from Jiang et al., 2025, applying a routing algorithm constrained by travel time to identify the lowest-emission path. Across 20 routes spanning short urban trips to inter-city journeys, the Eco Drive route achieves a mean CO_2 reduction of 9.8% (median 10.75%), with a mean travel time increase of 5.3%. Given a fleet of one million vehicles statewide, even partial adoption could yield reductions of thousands of tonnes of CO_2 annually at negligible infrastructure cost.

1. Introduction

The transport sector accounts for approximately 15% of global anthropogenic CO_2 emissions, with individual passenger vehicles contributing nearly 45% of all transport related emissions (González et al., 2019, Ritchie, 2020). While international policies have focused on fleet electrification and fuel standards, routing optimization represents an immediately deployable strategy with already in place infrastructure reducing the carbon emissions of vehicles. Navigation systems that minimize travel time rather than fuel consumption tend to guide drivers onto high speed roads with unefficient gradient profiles. Neglecting possible emission savings with a time cost.

Eco-routing has been investigated across a range of network scales and vehicle classes. Boriboonsomsin et al. (Boriboonsomsin et al., 2012) presented an eco-routing navigation system combining road network with vehicle specific emission factors to identify the most fuel efficient path between an origin and a destination. At the network level, Ahn and Rakha (Ahn and Rakha, 2013) conducted a case study of eco-routing in Cleveland and Columbus, Ohio, reporting fuel savings between 3.3% and 9.3% relative to travel time minimizing strategies, while noting that the benefit of eco-routing is sensitive to network configuration. Rakha et al. (Rakha et al., 2012) developed population and agent based eco-routing algorithms, observing fuel savings of approximately 15% on a small test network at the cost of increased travel time, consistent with the time-fuel trade-off addressed in this paper. Zeng et al. (Zeng et al., 2020) extended eco-routing to account for a probabilistic travel time budget, solving the resulting constrained shortest path problem with a Lagrangian relaxation based heuristic. Fanti et al. (Fanti et al., 2021) proposed an eco-route planner specifically for heavy duty vehicles, while Schröder and Cabral (Schröder and Cabral, 2019) developed a GIS based three dimensional routing model to estimate and reduce CO_2 emissions from distribution transport. A broader review of vehicle fuel consumption models suitable for eco-driving and eco-routing applications is provided by Zhou et al. (Zhou et al., 2016) (Kubička et al., 2016), who classify existing models by transparency and discuss their respective trade-offs between accuracy and computational cost. Building on this body of work, the present study distinguishes itself by applying a time-constrained eco-routing framework specifically to a topographically constrained island network, and by examining population-scale impacts under three adoption scenarios.

Okinawa presents a compelling case for eco routing. Unlike mainland Japanese prefectures that have extensive rail networks, Okinawa's 1.38 million residents relies overwhelmingly on private vehicles (Stats-Japan, 2024). This means even a marginal improvement in routing efficiency produces a large aggregate impact. A 1% reduction in per trip fuel consumption, applied across the full commuting population, translates to hundreds of thousands of litres of fuel saved and thousands of tonnes of CO_2 emissions avoided annually. The leverage available through routing software, which requires no infrastructure changes and no driver behaviour change beyond following a revised path, is therefore high in this context.

In this paper we propose an Eco-mode method for real time navigation systems. And we develop a reference implementation using OpenRouteService (ORS). The system scores candidate routes using a fuel consumption model derived from the empirical findings of Huang and Peng (Huang and Peng, 2018), chosen for its empirical calibration against real world driving data, compatibility with ORS network attributes, and established constrained eco-routing framework. The model applies a travel time constraint and presents the result to users alongside the standard fastest route.

This study addresses three objectives. First, we apply a time constrained eco-routing framework to Okinawa, selected as a case study because its topography produces road gradients sharper and more variable than those seen in prior eco-routing studies, and evaluate the resulting CO_2 savings. Second, we quantify these savings across a set of trip types, ranging from short urban routes to long inter-city routes. Third, given Okinawa's high car dependency relative to mainland Japan, we evaluate the population-scale impact of adoption.

Section 2 describes the fuel consumption model, the routing logic, and the constraint formulation. Section 3 presents results from our 20 test routes. Section 4 discusses the population scale implications and system limitations, finally Section 5 concludes the paper.

Nomenclature

Symbol	Description	Unit/Value
GMR formulation (theoretical motivation, Section 2.1–2.2)		
π_k	Mixing coefficient for component k	[0, 1]
μ_k	Mean vector of Gaussian component k	-
Σ_k	Covariance matrix of Gaussian component k	-
α_0	Dirichlet prior hyperparameter	Variable
$w_k(x)$	Posterior component weight (GMR)	[0, 1]
Operational routing model (Section 2.3–2.4)		
w_t	Travel time weighting parameter	[0, 1]
ε	Relative time constraint threshold	0.10 (10%)
$g(x_i)$	Total transition cost for road link i	-
$c(x_i)$	Estimated fuel consumption for link i	[kg]
$t(x_i)$	Expected travel time for link i	[s]
T_{eco}	Total travel time of the eco-route	[s]
T_{fastest}	Total travel time of the fastest route	[s]

2. Methodology

2.1 Fuel Consumption Modeling via GMR

This section presents the fuel consumption model underlying Eco-Mode. We begin with the Gaussian Mixture Regression (GMR) framework of Huang and Peng (2018), which motivates our treatment of road grade as the primary input variable. We then explain in Section 2.2 why this model could not be used for Okinawa, and describe the tiered gradient-based method used in its place.

The core of the proposed Eco-Mode scoring system is a fuel consumption model adapted from Huang and Peng (2018), who developed a nonparametric framework for estimating expected fuel consumption across a road network. Their model was trained and validated on 321,945 naturalistic driving trips from 2,468 drivers in Ann Arbor, Michigan, covering over 3.7 million kilometres, and achieved a Mean Absolute Percentage Error (MAPE) of 10.08% , superior to both average speed parametric models (MAPE: 37.63%) and power balance models (MAPE: 46.22%) (Huang and Peng, 2018). The modelling framework uses Gaussian Mixture Regression (GMR) to estimate the fuel consumption given a set of road link variables. The key insight of GMR is that rather than fitting a regression function directly, the model learns the joint probability density of both inputs and outputs, then derives the regression function from that joint density. This allows the model to capture the relationship between road grade and fuel consumption without manual feature engineering.

2.1.1 Joint Distribution Model

Following Huang and Peng (2018), let X denote the vector of road link input variables and Y denote the fuel consumption output. The joint distribution of inputs and outputs is modelled as a Gaussian Mixture Model (GMM):

$$P(X, Y|\theta) = \sum_k \pi_k \cdot \mathcal{N}(X, Y|\mu_k, \Sigma_k) \tag{1}$$

where π_k is the mixing coefficient for component k, and $\mathcal{N}$ denotes the multivariate Gaussian distribution with mean μ_k and covariance Σ_k. The conditional expectation of fuel consumption given a set of observed road link variables x is then derived as the GMR regression function:

$$\begin{aligned} f(x) &= E[Y|X = x] \\ &= \sum_k w_k(x) \left[\mu_{Y,k} + \Sigma_{YX,k} \cdot \Sigma_{XX,k}^{-1} \cdot (x - \mu_{X,k})\right] \end{aligned} \tag{2}$$

where the posterior component weight $w_k(x)$ is computed from the marginal density of X. This formulation, taken directly from the framework of Huang and Peng (2018), provides a nonparametric estimate of expected fuel consumption for any road link characterized by the input features listed in Section 2.1.2.

2.1.2 Input Variables

The fuel consumption estimate for each road segment is a function of the following variables:

1. Average speed [m/s] - a proxy for congestion level and aerodynamic drag
2. Speed change [m/s] - captures kinetic energy loss in stop-and-go cycles
3. Average road grade [rad] - captures gravitational load on the engine
4. Link length [m] - scales the per unit cost to a per segment cost

Of these, road grade is the most relevant variable to Okinawa's terrain. Huang and Peng's results show a near linear relationship between road grade and Fuel Consumption Rate (FCR). In our implementation, this coefficient is applied as a slope emission factor to each decoded route segment, using elevation data sourced from the ORS API.

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2.2 Parameter Estimation: Variational Inference

A practical challenge in fitting a GMM is the specification of the number of components K. Huang and Peng (2018) address this by adopting a Bayesian Variational Inference (VI) approach, which treats model parameters as hidden random variables and uses a Dirichlet prior over the mixing coefficients π. As the Dirichlet prior hyperparameter α_0 is set small and the sample size grows, the mixing coefficient for any redundant component converges to zero:

$$\lim_{n\to\infty} E(\pi_k) = \lim_{n\to\infty} \frac{\alpha_0 + N_k}{K\alpha_0 + N} = 0 \quad (3)$$

This automatic pruning of empty components means the model does not require crossvalidated component selection, an important advantage when fitting separate models for multiple speed limit categories. The model is less sensitive to initialisation than neural network approaches and produces a simpler, more interpretable final structure (Huang and Peng, 2018).

In our implementation, we initially tested a GMR model following the Huang and Peng framework, using elevation derived road grade as an input feature. This prototyping stage confirmed the relationship reported by Huang and Peng, that fuel consumption rises non-linearly with positive road grade, but fitting a full Gaussian Mixture Model for Okinawa was constrained by the lack of a comparable driving dataset for the prefecture. Huang and Peng's own model was trained on 321,945 trips from 2,468 drivers, which we do not have for Okinawa. We therefore replaced the GMR component with the slope-emission function described in Section 2.4. Calibrated against the gradient-fuel relationship reported by Jiang et al. (2025). GMR remains the theoretical basis motivating our treatment of road grade as the primary variable. The tiered function is the operational approximation actually used to score routes in this study.

2.3 Constrained Eco-Routing Logic

The routing algorithm follows the travel time constrained eco routing strategy described in Huang and Peng (2018), Section 2.3. The transition cost g assigned to each road link is defined as a weighted combination of expected fuel consumption and travel time:

$$g(x_i) = (1 - w_t) \cdot c(x_i) + w_t \cdot t(x_i) \quad (4)$$

the tiered-function estimated fuel consumption link for $x_i, t(x_i)$ is the expected travel time, and w_t is a weighting parameter. For the fastest time route, $w_t = 1$ (pure time minimisation). For the unconstrained eco route, $w_t = 0$ (pure fuel minimisation). In our constrained implementation, w_t is modulated by a sigmoid function of the cumulative travel time, enforcing a constraint that the eco route's total duration does not exceed the fastest route duration by more than ε:

$$T_{\text{eco}} \leq T_{\text{fastest}} \cdot (1 + \varepsilon) \quad (5)$$

In this study we set ε = 0.10. Routes that would require more than a 10% increase in travel time relative to the fastest path are rejected regardless of their fuel score, ensuring that the Eco Drive recommendation remains a practical choice for daily commuters.

2.4 Slope Emission Factor Implementation

In our implementation, the ORS API returns route geometry in the form of longitude, latitude and elevation coordinates.

If we implemented this only between the start and destination points, a route with a climb immediately followed by a matching descent can average out the slope as if the route was flat. To prevent this, we compute the horizontal distance via the Haversine formula and the elevation difference, yielding a slope percentage in every 30 meters until the route is finished.

This slope is then mapped to a fuel emission factor using a tiered approximation derived from empirical findings in (Jiang et al., 2025) research Impact of Road Gradient on Fuel Consumption of Light-Duty Diesel Vehicles, which reports nonlinear effects of road gradient on fuel consumption, consistent with similar gradient-fuel relationships reported elsewhere (Xu et al., 2020, Borisov et al., 2019, Carrese et al., 2013, Posada-Henao et al., 2023, Qi et al., 2024, Fan et al., 2022):

$$\text{factor} = \begin{cases} 0.10 & \text{if slope} \leq -6\% \\ 0.20 & \text{if } -6\% < \text{slope} \leq -4\% \\ 0.50 & \text{if } -4\% < \text{slope} < 0\% \\ 1.00 & \text{if } 0\% \leq \text{slope} < 3\% \\ 1.80 & \text{if } 3\% \leq \text{slope} < 5\% \\ 2.20 & \text{if } 5\% \leq \text{slope} < 7\% \\ 2.40 & \text{if slope} \geq 7\% \end{cases} \quad (6)$$

These factors reflect experimental observations indicating that fuel consumption increases significantly for uphill gradients above 3–4%, reaching approximately 1.8–2.0× at 4% and over 2.2× at 6%, while steep downhill segments can reduce fuel consumption to near zero due to engine braking and reduced load.

The total equivalent fuel consumption for a route is computed as the sum of horizontal distances weighted by their corresponding emission factors, multiplied by the baseline flat road emission rate of 120 g CO_2/km for an average sized gasoline passenger vehicle. This scoring function is applied to all candidate routes returned by ORS, and the lowest scoring route within the time constraint is designated as the Eco Drive recommendation.

Note that the slope coefficients in Equation 6 are derived from a diesel vehicle study (Jiang et al., 2025). While the baseline emission rate above assumes a gasoline vehicle, consistent with the EPA reference figure used in Section 4. We treat the relative slope factor applied to the flat road baseline, as fuel type independent. CO_2 figures reported throughout this paper use gasoline as the reference fuel type.

2.5 System Architecture and Data Pipeline

The proposed Eco-Mode framework operates through a decoupled four-stage pipeline: data acquisition, topographic enrichment, cost estimation, and pathfinding.

Initially, the road network geometry is fetched via the OpenRouteService (ORS) API, which interfaces with OpenStreetMap (OSM) contributors' data(OpenStreetMap contributors, 2017). Rather than generating a single route per query, we request up to three alternative candidate routes from ORS's alternative-routes feature for each route. Using a target count of 3, a share factor of 0.6 (limiting how much any two candidates may overlap), and a weight factor of 1.4 (bounding how much longer an alternative may be relative to the fastest route). Each candidate is independently scored using the function described in Section 2.4. The Normal Drive recommendation is the candidate with the lowest travel time, and the Eco Drive recommendation is the candidate with the lowest CO_2 score among those satisfying the time constraint in Equation 5. During the second stage, topographic enrichment is performed using a Digital Elevation Model (DEM). The system extracts the Z-coordinate for every vertex in the route geometry. Allowing for the calculation of segment-specific gradients as defined in Section 2.4.

In the third stage, tiered gradient-based scoring (Equation 4) is applied to each edge. Finally, the Dijkstra-based A* search algorithm (Zhang et al., 2016) identifies the optimal path that minimizes the total cost $g(x_i)$ while respecting the time constraint ε.

3. Results and Discussion

3.1 Benchmark: Huang and Peng (2018) Routing Results

Before presenting our results gathered by analyzing the Okinawa region, we summarise the routing outcomes from Huang and Peng's Ann Arbor study as a benchmark. Table 1 reproduces their key findings across four routing strategies applied to 3,031 routes.

Strategy	Fuel (kg)	Time (s)	Saving
Shortest distance	0.4809	611.4	9.5%
Fastest time	0.5312	554.5	Baseline
Unconstrained eco	0.4576	601.0	13.9%
Constrained eco-routing	**0.5038**	**559.5**	**5.2%**

Table 1. Expected fuel consumption and travel time by routing strategy, reproduced from Huang and Peng (2018). Fuel saving is relative to the fastest time baseline.

These results establish two important reference points. First, the constrained eco routing strategy achieves a 5.2% average fuel saving with only a 0.9% increase in travel time. Second, Huang and Peng note that 55% of constrained eco routes are geometrically identical to the fastest route. This means that even in a dense, grid based urban network, the majority of eco routing benefit comes not from finding a different road but from scoring the same road differently and, when multiple options exist, selecting the geometrically distinct option with the better gradient profile.

Note that Huang and Peng do not report a numeric ε value in their paper. The 5.2% saving and associated time increase are outcomes of their (undisclosed) constraint setting. Our ($\varepsilon = 0.10$) (Section 2.3) is set independently for the Okinawa implementation

3.2 Representative Route Example

Before presenting results across our 20 route sample (Section 3.3), we first illustrate the framework's behaviour on a representative route within central Okinawa using ORS with elevation data (Route 6 in Table 3). The normal drive (fastest time) and eco drive routes were calculated and scored using the function described in Section 2.4. Results are presented in Table 2.

Strategy	Distance (km)	Duration (min)	Est. CO_2 (kg)
Normal Drive	24.05	34.7	2.58
Eco Drive	22.02	35.8	2.31
Efficiency Gain	-8.4%	$+3.1\%$	-10.5%

Table 2. Comparative routing outputs for a representative central Okinawa journey. CO_2 estimates use a baseline rate of 120 g/km for an average sized gasoline vehicle, adjusted by the slope emission factor.

The Eco Drive path is 2.03 km shorter than the Normal Drive (22.02 km vs. 24.05 km), reflecting a route with a lower average gradient (2.70% vs. 3.14%) and a lower peak elevation (83 m vs. 94 m). The marginal increase in travel time is 1.1 minutes (66 seconds), equivalent to a 3.1% penalty, well within the 10% constraint ($\varepsilon = 0.10$) from Equation 5. The estimated CO_2 saving is 0.27 kg per trip, a 10.5% reduction, comparable to the 5.2% average reported by Huang and Peng for their constrained eco routing across the Ann Arbor network.

As Section 3.3 shows, this route's savings sits just above the 9.8% mean observed across our samples.

3.3 Multi-Route Validation

To assess how consistently the framework performs across different trip types, we tested 20 routes across Okinawa, ranging from short urban trips (under 5 km) to long inter-city journeys (over 45 km), including the representative route discussed in Section 3.2. Across this sample, the Eco Drive route achieved a mean CO_2 saving of 9.8% (median 10.75%) relative to Normal Drive, with a mean travel time penalty of 5.3%. Savings ranged from 0.9% to 18.0%. Table 3 summarises results across all 20 routes.

Route ID	Distance (km)	CO_2 Saving (%)	Time Penalty (%)
1	21.54	0.9	+2.7
2	19.90	3.8	+5.1
3	23.18	14.4	+2.2
4	48.44	18.0	+1.4
5	22.99	11.0	+3.2
6	24.05	10.5	+3.1
7	26.84	16.6	+6.7
8	30.05	12.2	+7.7
9	95.25	1.7	+1.3
10	32.74	4.0	+8.5
11	33.09	2.2	+8.1
12	43.38	15.2	+3.4
13	42.59	13.4	+7.4
14	41.52	8.2	+9.9
15	47.79	4.6	+9.3
16	46.65	15.4	+9.5
17	4.95	5.8	+8.4
18	21.62	11.8	+4.1
19	5.27	9.4	+2.6
20	47.52	17.0	+1.0
Mean	—	**9.8**	**+5.3**
Median	—	**10.75**	**+4.6**

Table 3. CO_2 savings and travel time penalty of the Eco Drive route relative to Normal Drive across 20 routes sampled across Okinawa.

The least efficient result in our sample was Route 1 (21.54 km), where the Eco Drive achieved only a 0.9% CO_2 reduction for a 2.7% time penalty. Here the eco and normal routes diverge almost immediately and do not rejoin until near the destination, yet this separation produced almost no fuel benefit: the eco route's average gradient (3.33%) was actually higher than the normal route's (2.33%). This illustrates a limitation of route-level divergence as a proxy for fuel savings, two physically distinct paths can still carry similar or even worse slope costs, and the algorithm will still select whichever is more efficient even when the margin is negligible.

The most efficient result was Route 4 (48.44 km). Where the Eco Drive achieved an 18.0% CO_2 reduction for a travel time penalty 1.4%. The eco route's average gradient (1.98%) was lower than the normal route's (3.08%), and its elevation range was less (89 m vs. 126 m peak elevation), indicating the algorithm found a flatter alternative.

Map data © OpenStreetMap contributors.

Figure 1. Comparative visualization of the lowest-efficiency Eco Drive result (Route 1, 0.9% reduction), illustrating a case where route divergence did not translate into meaningful fuel savings. Blue: Normal Drive, Green: Eco Drive.

It is worth noting that Route 4 connects the Okinawa Institute of Science and Technology (OIST) to Naha Airport. Given the volume of OIST-affiliated travel along this route, adopting the Eco Drive recommendation on this specific route alone could yield a fuel saving of 18% per trip.

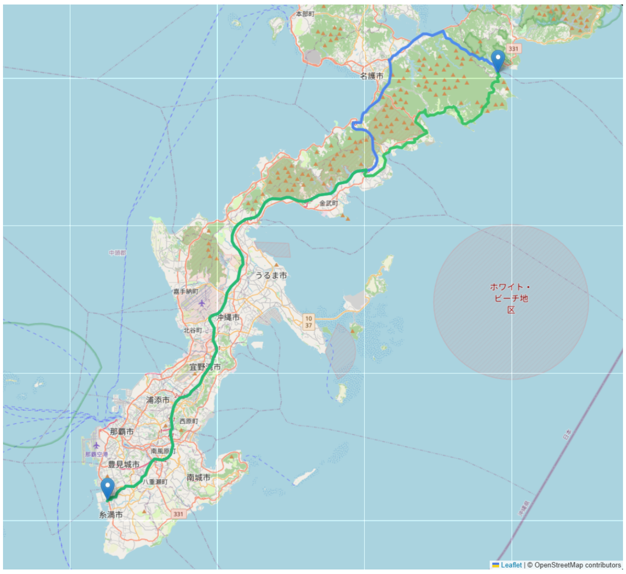
Route 9 (95.25 km) was the longest trip in the sample, yet its efficiency gain was among the smallest, achieving 1.7% CO_2 reduction for a 1.3% travel time penalty. Despite the eco route being 2.4 km shorter than the normal drive (92.85 km vs. 95.25 km), its average gradient (3.66%) was slightly higher than the normal route's (3.54%). Indicating the shorter path did not correspond to a flatter route. This result reinforces the pattern observed in Route 1, a longer trip length does not guarantee larger fuel savings.

3.4 Network Topology Constraint: The Linear Corridor Problem

Okinawa's road network has two parallel roads along the island, National Route 58 along the west coast and Route 329 along the east. These roads carry most of the north-south traffic. For most long-distance trips across the central or northern part of the island, ORS keeps returning the same route. Whether we optimize for time, distance, or fuel efficiency, there isn't a better option for the algorithm to offer. Huang and Peng found something similar: 55% of their eco routes were geometrically identical to the fastest route. In Okinawa's more constrained road network this proportion runs higher for long trips, with most routes over 30 km converging on a single option. For these trips, the Eco Drive card shows the fuel estimate for the one available route, scored the same way as every other candidate.

Map data © OpenStreetMap contributors.

Figure 2. Visualization of the highest efficiency Eco route (Route 4, 18.0% reduction), where a flatter coastal alternative yielded a large CO_2 saving for only 1.4% additional travel time. Blue: Normal Drive, Green: Eco Drive.



Map data © OpenStreetMap contributors.

Figure 3. Visualization of Route 9 (95.25 km), the longest route in the sample, where 1.7% CO_2 reduction was achieved. Blue: Normal Drive, Green: Eco Drive.

3.5 Impact of Sub-tropical Topography on Emission Variance

The mean 9.8% reduction observed across 20 route sample, compared to the 5.2% average reported by Huang and Peng

(2018), can be attributed to the higher variance in road gradients within the Ryukyu archipelago. Unlike the relatively flat terrain of the Midwestern United States, Okinawa's topography is characterized by a central limestone plateau spine running the length of the main island, with elevations reaching 200-500 meters, flanked by narrow coastal plains typically less than 2 km wide. This results in either traversing steep interior hills or circuitous coastal routes. The island's geological foundation consists primarily of Ryukyu limestone with elevation changes over short horizontal distances. The central Route 330, which connects Naha to the mid-island urban corridor, climbs approximately 120 meters over a 5 km segment through the Urasoe-Ginowan plateau, producing sustained gradients of 4-6%. In contrast, the coastal Route 58 maintains elevations below 50 meters for most of its length, with maximum grades rarely exceeding 2%.

3.6 Route Diversity Analysis

To assess whether divergence between the Normal Drive and Eco Drive routes reliably predicts CO_2 savings, Table 4 compares the average gradient differential against the resulting saving for the three routes discussed in detail in Section 3.3.

Route ID	ΔAvg. Gradient (pp)	CO_2 Savings (%)
1	$+1.00$	0.9
4	-1.10	18.0
9	$+0.12$	1.7

Table 4. Average gradient differential (Eco Drive average gradient minus Normal Drive average gradient, in percentage points) versus resulting CO_2 savings.

All three routes have distinct Eco Drive paths. Route 4's eco path lowers average gradient by 1.10 percentage points relative to Normal Drive, resulting in an 18.0% CO_2 saving. Route 9's eco path is 2.4 km shorter than Normal Drive but raises average gradient by 0.12 percentage points, limiting its saving to 1.7%. Route 1's eco path raises average gradient by a full percentage point, consistent with its 0.9% saving (Section 3.3).

These results indicate that for Eco Drive to yield meaningful CO_2 savings it must satisfy at least one of two conditions: a reduction in total route distance sufficient to lower cumulative emissions independent of gradient, or a reduction in average gradient relative to the Normal Drive path. Route 9 satisfies the first condition but not the second, and its saving remains small; Route 1 satisfies neither condition, and its saving is negligible. Route 4 lowers the average gradient by 1.10 percentage points and its saving is the largest observed in the sample.

4. Population-Scale Impact Analysis

4.1 Okinawa's Car Dependency as a Force Multiplier

Okinawa's car dependency amplifies the environmental impact of even modest per trip fuel savings. The prefecture has a population of approximately 1.38 million and 858,004 registered passenger cars (Stats-Japan, 2024). Assuming 70% of the registered passenger car fleet is in daily use, the daily fleet of active commuter vehicles is estimated at approximately 600,000 cars on any given weekday.

Applying the mean eco routing saving of 9.8% in CO_2 observed across our 20 route validation sample (Section 3.3) to a 10 km round trip baseline, the per vehicle daily saving is approximately 0.118 kg CO_2 (based on 1.2 kg for a 10 km round trip at the 120 g/km flat road baseline rate from Section 2.4). Across 600,000 vehicles, this represents a potential daily reduction of approximately 70.8 tonnes of CO_2, or approximately 17,700 tonnes annually, assuming 250 commuting days per year. Table 5 presents a scenario analysis for three adoption rates.

Adoption Rate	Vehicles Affected	Annual Fuel Saved (L)	CO_2 Reduction (tons)
10%	∼60,000	∼0.76 million	∼1,760
30%	∼180,000	∼2.29 million	∼5,290
50%	∼300,000	∼3.82 million	∼8,820

Table 5. Annual emission reduction scenario analysis at three adoption rates, based on the 9.8% mean per-trip CO_2 saving observed across 20 routes (Section 3.3), a 10 km daily round trip commute assumption and an estimated 600,000 vehicle commuter fleet (Section 4.1). Figures assume full compliance with the Eco Drive recommendation.

These projections highlight the asymmetry between individual level saving (0.118 kg per daily round trip, which a driver might dismiss as negligible) and the aggregate impact (thousands of tonnes annually).

5. Conclusion

This study has presented a practical Eco-Mode routing framework for Okinawa, inspired by the empirically-established slope-to-fuel-consumption relationship reported by Huang and Peng (2018) and implemented via a travel time constrained routing formulation using a tiered gradient-based scoring function. Tested across 20 routes spanning short urban trips to long inter-city journeys, the framework achieves a mean CO_2 reduction of 9.8% (median 10.75%) with a mean travel time increase of 5.3%.

The population scale significance of this result is amplified by Okinawa's structural car dependency. At a 30% system adoption rate, the framework is projected to reduce annual CO_2 emissions by approximately 5,290 tonnes, a contribution to the prefecture's carbon reduction targets through software alone, without any change to the vehicle fleet or transport infrastructure.

Two limitations merit explicit acknowledgement. First, the slope emission coefficients are transferred from Huang and Peng's Ann Arbor calibration rather than estimated from Okinawa specific driving data. A local calibration study using vehicle data from Okinawa would improve accuracy.

Second, Okinawa's road network constrains the availability of geometrically distinct alternative routes on long north-south journeys. Future work will address both limitations through local data collection and integration with real time traffic information to balance gradient avoidance against congestion driven fuel cost.

It is worth noting that in the terminology of environmental philosophy, this framework represents a reformist intervention (Kırışık, 2013): it reduces trip emissions through routing optimization without requiring any change to consumption patterns, vehicle ownership, or driving behaviour beyond following a suggested route. Such technological interventions can reduce emissions at scale, as Section 4 demonstrates.

Our source code and the 20 routes used for validation are publicly available at: https://github.com/EnisSard/EcoRoute-Okinawa.

5.1 Future Research Directions

While the current framework provides a "Green" baseline, three avenues for further research are identified. First, the integration of real-time traffic data is essential. Currently an optimal route may be recommended while being heavily congested. If idling time exceeds the fuel saved by avoiding a hill, the net environmental benefit may be nullified. Integrating Live Traffic APIs would allow for a dynamic weighting of w_t.

Second, the model currently assumes a standard internal combustion engine (ICE). Future iterations should incorporate specific power-train models for Electric Vehicles (EVs). For EVs, the "Eco" logic is inverted on downhill segments due to regenerative braking, where a steep decline may actually be preferred to recharge the battery.

Third, extending the framework to multi-modal eco-routing represents a promising direction. Under this approach, a single journey would be decomposed into discrete legs, with each leg assigned the lowest emission modal option available. Segments proximate to cycling infrastructure or within comfortable walking distance would be allocated to those modes, contributing zero CO_2 emissions, while the remaining legs retain the fuel optimised vehicle routing developed here. This decomposition would require integration with pedestrian and cycling network graphs alongside the existing ORS road network. A unified cost function that converts modal emissions, travel time, and physical effort into a single metric. Finally, a pilot study involving Okinawa residents is planned to determine the "Value of Green Time". Specifically, the maximum ε users are willing to accept in exchange for carbon credits or fuel savings.

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Map data copyrighted OpenStreetMap contributors and available from https://www.openstreetmap.org. Routing and elevation services were provided by openrouteservice.org by HeiGIT.

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