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Optimization of CO_2 Emission Taxation in Switzerland Using Machine Learning

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Abstract. This research aims to improve the taxation of CO_2 emissions from internal combustion engine passenger cars using a Machine Learning (ML) approach. The current tax system in Switzerland relies heavily on WLTP type-approval values, which often differ from real-world fuel consumption and emissions, limiting its effectiveness.

Using European OBFCM data and the citiwatts.eu dataset [1], the study develops predictive models to estimate actual fuel consumption and CO_2 emissions based on technical vehicle characteristics such as mass, engine power, and displacement. Ensemble algorithms, including LightGBM and Random Forest, demonstrate strong predictive accuracy, showing that ML can reliably approximate real driving emissions.

To validate the model, a qualitative assessment was conducted through a Delphi study with mobility experts, surveys of Swiss corporate fleet managers, and interviews with politicians from multiple parties. This ensured that the findings are grounded in practical, political, and economic realities.

The results indicate the need to revise local and national vehicle taxation to better reflect real emissions and to more rigorously assess plug-in hybrid vehicles, whose environmental impact is often underestimated. The research proposes a differentiated, science-based tax framework aligned with actual vehicle performance, improving both environmental effectiveness and fiscal fairness.

It also recommends enhancing consumer awareness and replacing the A–G energy labeling scale with more precise, continuous indicators.

Keywords: CO_2 taxation, Machine Learning, Internal combustion vehicles, Environmental taxation, Real-world consumption, Delphi method, Sustainable mobility

1 Introduction

Passenger cars account for 60.6% of CO_2 emissions from the European transportation sector [2] (see Figure 1).

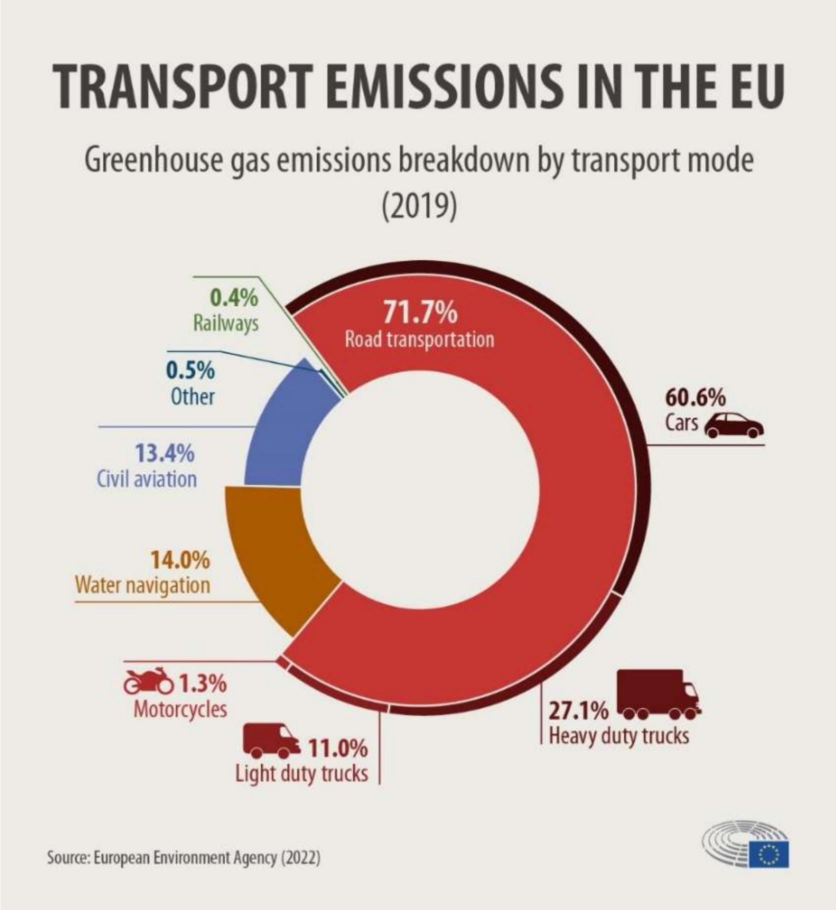

Figure 1**. Transport emissions in Europe **[2]

Human activities, such as agriculture, industrial cooling, fuel combustion, and domestic consumption, have increased water vapor emissions indirectly through warming processes, thereby leaving an increasingly evident human footprint on the climate and weather patterns [3]. Water vapor feedback has a cumulative effect that doubles the initial warming and causes nonlinear amplification that can triple or quadruple the warming when interacting with other feedback mechanisms such as cloud formation or surface albedo [4].

Climate change results from an energy imbalance: the Earth absorbs more energy from solar and cosmic radiation than it re-emits back into space, leading to an accumulation of energy [3]. Two major greenhouse gases, carbon dioxide (CO_2) and water vapor, are essential for sustaining life but also significantly contribute to enhancing the greenhouse effect [3]. Among them, water vapor is the most significant greenhouse gas because it has a much greater thermal capacity and energy transport function than nitrogen, oxygen, or even CO_2 [3].

Tax policy thus plays a key role in reducing CO_2 emissions from internal combustion passenger vehicles. However, CO_2 emission taxes do not always account for the main characteristics of vehicles. The various vehicle taxation systems in Switzerland, which are determined by the local state (cantons), create inconsistencies in promoting environmentally sustainable choices and sometimes result in disproportionate taxation of certain vehicle types [5].

Moreover, this suggests that factors other than fuel consumption influence CO_2 emissions. Therefore, this study aims to improve the tax calculation process using machine learning algorithms to analyze the relationships between vehicle characteristics and their actual emissions, relying on reliable data from the European Commission on passenger vehicles.

The main objective is to design a fair and efficient tax framework based on solid data. The sub-objectives include:

- Identifying key variables that influence emissions
- Proposing recommendations based on reliable predictive models

This study does not cover the political implementation of taxes. As such, the primary limitation of the project lies in the willingness of stakeholders to adopt the recommendations, a factor that is not addressed in this research.

One of the main risk factors for the machine learning model is the limited access to data [6], especially due to:

- The lack of real fuel consumption data for internal combustion passenger vehicles alone
- The fact that real-world CO_2 consumption data does not include the vehicle's full lifecycle, from production to disposal
- Insufficient information on how vehicles are used by individuals, such as route types, road conditions, or elevation changes along trips

1.1 Vehicle Taxation Based on CO_2 in the EU

Vehicle taxation is a key factor in the progress made in reducing emissions and in determining current emission levels. All the countries studied have different fiscal systems. They apply various vehicle-related taxes, with varying tax bases and rates [7]. This study compares vehicle taxation across these countries (see Figure 2) and identifies several essential features for fair and low-carbon taxation [7]. In particular, it examines [7] :

- Registration taxes
- Acquisition taxes
- Recurring ownership taxes
- Taxation of company cars
- Fuel taxes

Countries that have implemented well-designed CO_2-based taxes, particularly on vehicle registration, achieve much better results in terms of reducing average CO_2 emissions [7].

However, significant room for improvement remains in all countries, and further progress is essential [7]. It is still uncertain whether the European target of an average of 95 gCO_2/km will be achieved [7]. Moreover, a large part of the progress achieved so far exists only on paper. CO_2 emission values measured in laboratories increasingly diverge from real-world values observed on the road [7].The gap between these two figures rose from 14% in 2006 to 42% in 2016 [7].

Runkel et al. [7] indicate that this gap is widening because laboratory-measured emissions (homologated values) do not reflect the real-world behavior of vehicles. In other words, even if tests show decreasing emissions, real driving conditions generate much higher levels. This means that the reduction in CO_2 emission values has had a much smaller impact on actual road-sector emissions [7]. This gap also undermines the effectiveness of CO_2-based fiscal policies [7].

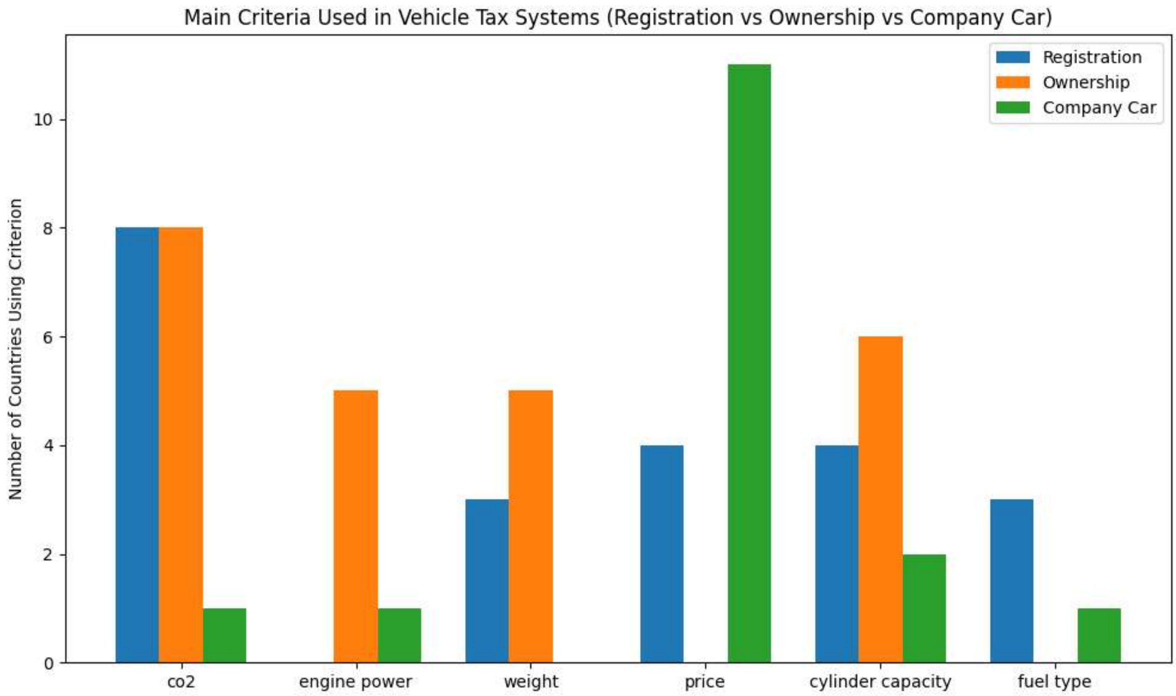

Figure 2**. Passenger Car Taxation in the EU28 + NO, CH (CO_2 and fuel-consumption-related taxes highlighted)* ***[7]

In EU member states, fuel taxes vary considerably [8]. In 2019, gasoline tax rates in some countries (the Netherlands, Italy, Finland, and Greece) were about twice as high as the minimum levels set by European regulations [8]. In contrast, in countries such as Bulgaria, Hungary, and Poland, gasoline taxes barely exceeded these minimum thresholds [8].

These differences in taxation between countries lead to variations in fuel prices, encouraging "fuel tourism" [8] : consumers cross borders to buy fuel in countries where it is cheaper. This phenomenon affects not only tax revenues but also the composition of the vehicle fleet in some countries.

Compared to diesel used for commercial activities and other fossil fuels, tax breaks applied to gasoline and diesel for passenger cars remain modest [8]. As a result, the environmental impact of fuel taxes in EU member states is not overly negative [8]. An analysis of tax rates between 2010 and 2019 shows that taxation levels on gasoline and diesel generally increased during this period [8].

To influence consumers' purchasing decisions, acquisition taxes are more effective than annual ownership taxes [7]. Consumers tend to place more importance on immediate costs than on future taxes, which they perceive with uncertainty [7].

2 Methodology

This chapter outlines the methodology adopted for this research. The approach combines a literature review, empirical analysis through machine learning modeling, and qualitative surveys among mobility sector stakeholders. This triangulation enhances understanding of the link between CO_2 taxation, fleet behaviors, and technical variables determining real-world vehicle emissions.

2.1 Literature Review

The work began with an extensive review of vehicle taxation systems based on CO_2 emissions in Europe. This step included systematic exploration of academic databases, institutional reports, and policy documents. The goal was to map existing tax regimes, assess their environmental effectiveness, redistributive effects, and social acceptance.

This synthesis was refined through multiple revisions in collaboration with thesis supervisor Dominique Genoud. The state of the art was organized thematically and by region, covering:

- CO_2 or weight-based taxation mechanisms
- Environmental and behavioral effectiveness
- Equity and redistributive considerations
- Consumer behavior in vehicle purchasing
- Differences between official and real emissions
- Integration of machine learning into carbon taxation

The result was a detailed thematic table of contents serving as the analytical foundation for empirical work.

2.2 Qualitative Study on Vehicle Fleets

Since company fleets make up a large share of the passenger vehicle market, a qualitative study explored how companies manage and electrify their fleets. This process proved complex due to limited transparency within the industry.

Several Swiss companies were contacted (SPIE, Vebego, ISS, Hirslanden, Spitex, Coop, Swiss Post, L'Oréal, Carvolution, Honegger, Manor, Groupe E, Migros, Philip Morris, Microelectronic, Busch, BAT, Syngenta, BASF, Raiffeisen, Lonza, BCV, UBS, Bucherer, Bolliger Immobilier, Conciergeservice, Nestlé, Novartis, Swatch Group, etc.). However, most either:

- Did not respond, despite follow-ups,
- Stated they had no fleet,
- Or were not authorized to share the information.

Only Migros, Swiss Post, Mobility, Europcar, and the Swiss army participated. Four of them have over 1000 cars in their fleet, while only one has between 500 and 1000 vehicles in their fleet. Due to limited responses, a non-probabilistic sample was used, a methodological limitation that reflects real-world data access challenges.

2.3 Machine Learning Modeling

Parallel to the qualitative study, a quantitative analysis was conducted using a European dataset on real vehicle fuel consumption. The goal was to build a predictive model estimating real consumption (and indirectly CO_2 emissions) based on technical variables.

The flow below (see Figure 3) represents all the data processing and analysis steps, organized sequentially to transform raw data into usable results, integrating operations such as import, preparation, modeling, and export (see Figure 3).

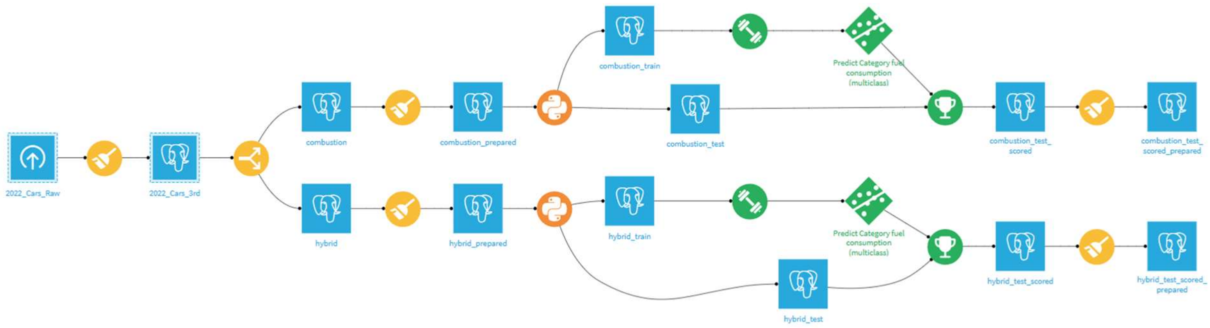

***Figure 3**. Data processing and analysis steps*

This was done incrementally. The steps included:

- Dataset preparation and cleaning (handling missing data thresholds: 0–5%, 5–15%, >30%)
- Univariate and bivariate analysis on quantitative (mass, power, displacement, consumption) and qualitative (fuel type, country, brand) variables
- Building multiple ML algorithms (clustering, regression, prediction), including:
    a. Simplification of target variables (low, medium, high consumption)
    b. Class rebalancing
    c. Hyperparameter tuning (including via ChatGPT)
    d. Prediction error evaluation
    e. Comparison of real vs official data

The results identified the most influential variables in real fuel consumption, providing useful insights for public policy and industry.

2.4 Validation via Delphi Method

To compare algorithm results with expert knowledge, a Delphi-based questionnaire was developed. It was submitted to a panel of mobility experts:

- Dr. Manuele Margni (HES-SO Valais-Wallis, School of Engineering)
- Mr. Gabriel Magnaval and his team (Paul Scherrer Institute)
- Mr. Philippe Burri (Vehicle Service, Neuchâtel)
- Mr. Yannick Giroud (Vehicle Service, Vaud)
- One expert recommended by the faculty

Other specialists were contacted but did not respond. Only the experts listed above participated.

2.5 Political Validation

A shorter second questionnaire targeted political representatives to assess the model's feasibility and acceptability. Two national parliamentarians responded:

- Mr. Thomas Hurter (SVP)
- Mr. Christophe Clivaz (Les Verts)
- Ms. Christelle Sierro Fardel (PLR)

Other politicians involved in CO_2-related legislation were also contacted, but only the above responded.

These contributions helped partially validate the model, identify areas for improvement, and discuss its potential for real-world policy application.

3 Comparison with State-of-the-Art Results

The findings of this research align with the main conclusions from existing literature. On one hand, the gap between real-world and laboratory-measured emissions is well confirmed: discrepancies range from 20% to 50%, as reported by Fontaras and Tietge [9]. This confirms the relevance of using real-world consumption data to develop reliable predictive models.

On the other hand, the role of vehicle weight as a discriminating variable aligns with studies advocating for mass-based taxation, particularly in France and the Netherlands [10].

The machine learning model results generally converge with the state-of-the-art (see Table 1): technical factors (weight, power, displacement) and fuel type remain predominant. However, current literature places more emphasis on the use of onboard sensors for real-time prediction, which goes beyond the limits of approaches relying solely on declared or official technical specifications.

Table 1**. Comparison Between the ML Model and the Literature **[7], [11], [12], [13], [14], [15]

Criteria	Machine Learning	State of the Art
Main variable	Fuel type / WLTP emissions	Real-world fuel consumption
Technical variables	Power, displacement, mass	Engine size, number of cylinders
Use of embedded data	Not directly integrated	Highly valued (OBD-II, PEMS)

Moreover, the use of machine learning techniques to model emissions, as proposed by Niroomand, Yin, and Al-Nefaie [16], [17], [18], is confirmed here as an effective tool for anticipating energy behavior. Finally, the qualitative survey results echo common concerns in carbon tax literature regarding fairness [19], [20], [21], [22] and social acceptability[19], [21], [23]. The perceived lack of attractiveness of government incentives [24] and skepticism about TCO parity [25] illustrate the ongoing challenges in the energy transition, despite some momentum in public sectors like the military.

This opens up perspectives for a dynamic taxation system based on embedded empirical measurements rather than declarative official values.

4 Synthesis of ML Model Results

This synthesis confirms that the ML model offers a robust approach to predicting and classifying vehicle CO_2 emissions based on their intrinsic characteristics (see Table 2). It also supports the relevance of a differentiated tax policy based on precise, individualized predictions aligned with the technical realities of the Swiss and European vehicle fleets.

***Table 2**. Summary of the Machine Learning Model*

Category	Main Results
Datasets	**OBFCM european dataset**. Technical characteristics and real consumption of vehicles.
Key **Correlations**	• Total distance traveled ↔ Total fuel consumed • Average consumption ↔ CO_2 emissions (WLTP) • Engine power ↔ Engine displacement • Electric range ↔ Reduction in overall consumption
Influential **Variables**	• **With official** data: **WLTP emissions** = most **important variable**

	• **Without official** data: **Fuel type**, **powertrain** mode, vehicle **mass**, engine **power**, engine **displacement**
Algorithmic **Performance**	Best performance achieved with **ensemble learning algorithms** such as LightGBM (F1-Score: 0.970 (± 0.001), Random Forest (F1-Score: 0.967 (± 0.001), and Gradient Boosted Trees (F1-Score: 0.966 (± 0.002).
Observed **Limitations**	To overcome the **difficulty** of distinguishing the **intermediate consumption levels**, a **continuous approach** will provide **better results**.
Recommendations	• Increase the **volume** and **quality** of **data**. • Integrate **additional variables** (e.g., driving cycle, detailed electric consumption). • Adjust **classification thresholds** and **hyperparameters**
Political & **Fiscal** Impact	**Machine Learning** enables precise association of **technical characteristics** with **emissions** and helps define **tax brackets** better calibrated to the **environmental performance of vehicles**.

The analysis of the European OBFCM dataset highlighted several significant trends in real-world fuel consumption and its technical determinants. Strong correlations were observed, particularly between total distance traveled and fuel consumed, and between average consumption and WLTP CO_2 emissions. Vehicle mass, engine power, displacement, and fuel type emerged as key factors influencing environmental performance. Notably, greater electric range tends to significantly reduce overall consumption, underscoring the role of plug-in hybrid technologies in the energy transition.

The machine learning modeling emphasized the relative importance of variables depending on model configuration. When official data is included, WLTP emissions become the most influential; in their absence, attributes such as fuel type and powertrain mode dominate. These results suggest future iterations should include more rigorous data cleaning and expanded training datasets.

5 Results of the Fleet Manager Survey

The summary table presents an overview of the main trends observed from fleet manager responses (see ***Table*** 3). It provides a quick view of key dimensions analyzed, such as fleet size, major barriers to electrification, and perceptions regarding total cost of ownership (TCO) and public incentives.

This table highlights that upfront costs, range limitations, and charging infrastructure are the most common obstacles. It also notes the moderate increase in electric vehicle share in fleets from 2020 to 2025, and the marginal role of resale value from combustion vehicles in funding the transition. Lastly, it reveals that TCO parity is reached for some even with small fleets, while others believe it’s only possible with very large fleets.

Table 3. *Responses from Fleet Managers in Switzerland*

Question	Main Result
Fleet size	Majority > 1,000 vehicles
Main barriers	Upfront purchase price, range, infrastructure
Public charging network	Improved but still insufficient
Range perception	Average, score of 3.6/5
Competitive TCO	Improving, but still variable
Public incentives	Not very attractive: 2.2/5
EV maintenance training	Still insufficient
TCO parity	Reached from < 50 vehicles for some

EV progress 2020–2025	From 0–10% to 11–25%, one case at 51–75%
Financing via resale of ICE	Largely marginal (0–10%)

These results show that despite progress, the transition to electric fleets remains hindered by high initial costs and logistical constraints. Public support and technical training are still considered inadequate. However, economic gains are already noticeable in certain fleet configurations, especially from 50 vehicles onwards for more advanced fleet operators.

6 Validation Using the Delphi Method for Mobility Experts

This first round provided broad trends and initial areas of agreement, particularly emphasizing the need to focus on real CO_2 emissions and modernize taxation criteria. Future rounds aimed to refine these insights and reach the 80% consensus threshold.

The second round achieved consensus on several key points, including the need to better differentiate of hybrids vehicles, focus on real-world emissions, and integrate new technical criteria. The third and final round aimed to consolidate these decisions and propose final recommendations.

The third and final round aimed to confirm or refine the consensus points from previous rounds and close open debates (see Table 4). The same five mobility experts were consulted. The questions focused on validating:

- The final relevance of criteria for CO_2 taxation,
- The selection of complementary environmental criteria,
- The definitive method for categorizing hybrid vehicles.

The same methodological rule applied: any criterion or proposal reaching 80% agreement was considered a final, validated consensus.

Table 4. *Expert mobility responses (Final Round)*

Question	Consensus / Final Response
Importance of engine displacement	No consensus: useful only for combustion engines
Importance of curb weight	Strong consensus: central criterion for CO_2 taxation
Importance of engine power	Consensus: not very relevant
Complementary criteria	Drive cycle recognized but not essential if real-world data is available
Hybrid categorization	Total consensus: multi-criteria classification based on size, electric range, real emissions, and energy consumption

This final round concluded the Delphi method with consolidated consensus on several key points:

- Vehicle weight is a robust fiscal lever,
- Real-world CO_2 emissions remain the fairest basis for taxation,
- Power and engine displacement are outdated or secondary criteria for environmental evaluation, particularly due to the high efficiency of hybrid batteries,
- For hybrids, a multi-criteria approach ensures fairer and more adaptable classification aligned with technological evolution.

7 Political Validation

A questionnaire was sent to three Swiss political representatives from each party, SVP (federal), Les Verts (federal), and PLR (municipal). Addressing their positions on CO_2 vehicle emission taxation and incentives for the energy transition. The responses highlight the distinct political orientations of each party on climate and mobility-related fiscal issues (see Table 5).

Table 5*. Political representatives' responses*

Topic	SVP (Federal)	Les Verts (Federal)	PLR (Municipal)
CO_2 priority	Low (2/5)	Very high (5/5)	High (4/5)
Current taxation effective	Yes	No	No
Inspired by French model	Undecided	Yes	Cautious
EV incentives	No	Yes (bonus-malus)	No
Real-use taxation barriers	Federalism	Industrial lobbying	Federalism
Revision of A–G thresholds	No	Yes	Yes

The PLR response comes from a municipal councilor, unlike the federal representatives from SVP and Les Verts.

These three visions illustrate distinct political philosophies:

- **SVP** adhere to a liberal, federalist approach with little desire for further regulation.
- **Les Verts** support strong public intervention and a complete overhaul of fiscal tools to encourage ecological transition.
- **PLR** favor pragmatic, market-based adaptation, while remaining open to conditional improvements.

Each approach poses specific risks:

- **SVP**'s strategy may delay adaptation to international climate standards, increase tax policy fragmentation, and weaken Switzerland's ecological competitiveness due to lack of innovation incentives.
- **Les Verts**' interventionist path may face limited social acceptability, especially if fiscal measures are viewed as punitive. Political and industrial resistance could also slow implementation.
- **PLR**'s moderate route risks inadequate or unstructured response to the climate crisis, resulting in partial measures that may fall short of Switzerland's 2030–2050 climate goals.

8 Comparison with the Study by Gabriel Magnaval

The comparison (see Table 6) between this thesis and the scientific publication by Gabriel Magnaval [26] reveals two complementary approaches to studying vehicle energy consumption and emissions.

Table 6*. Comparison of study objectives* ***[26]***

Aspect	Master's Thesis	Gabriel Magnaval's Article
Main Objective	Develop a predictive model using Machine Learning (ML) to optimize CO_2 vehicle taxation in Switzerland.	Construct a parametric and physical analytical model to calculate vehicle energy consumption in Life Cycle Assessment (LCA).

Research Focus	Fiscal and environmental approach to taxing real-world vehicle emissions.	Limitations of existing LCA databases, lack of granularity, and need for regional and technological adaptation.

A relevant next step would be to directly integrate physical parameters from Magnaval's model into the ML framework by combining the explanatory power of physics with the predictive efficiency of data-driven methods.

- Using physical variables in ML can better capture emission mechanisms, reducing overfitting and extrapolation errors.
- Physical inputs increase transparency and explainability, crucial for policymaking.
- This hybrid approach adapts better to local policies and technological variations.

Physical parameters from PETRAUL, e.g., efficiency coefficients, specific emission factors, behavioral indicators that could serve as additional ML input features. This would improve forecasting of policy impacts and anticipate behavior-based variations (e.g., from light-weighting or driving style)

9 Recommendations

At the conclusion of this study, several recommendations can be made for policymakers and stakeholders in the Swiss automotive sector:

1 **Implement a differentiated taxation system based on real-world fuel consumption**
The current tax system often relies on homologation values that poorly reflect actual usage. Machine Learning algorithms enable the estimation of real-world consumption based on reliable technical characteristics such as vehicle mass, engine displacement, or power.

2 **Include vehicle mass and power in fiscal brackets**
These variables have a significant impact on real CO_2 consumption and emissions. A taxation framework that incorporates them would be fairer and more environmentally sound.

3 **Avoid reliance on the A–G energy scale**
This work did not use the A–G energy labeling scale because its class distinctions are too narrow and do not reflect actual differences in consumption or emissions. This categorization lacks the precision required to train a reliable Machine Learning model, which depends on continuous and detailed data for accurate predictions.

4 **Ensure continuous monitoring using OBFCM data**
The development of onboard fuel consumption monitoring systems (OBFCM) presents an opportunity to regularly reassess the relevance of tax scales based on real-world data.

5 **Further research on hybrid and electric vehicles**
Findings indicate that plug-in hybrids tend to have underestimated real-world emissions. A tailored fiscal framework should more accurately account for these discrepancies.

6 **Raise consumer awareness**
Fiscal measures should be accompanied by public awareness campaigns to help users understand the environmental impact of their vehicle choices.

7 **Standardize taxation across local states (cantons)**
The proposed fiscal model could help harmonize tax practices among Swiss cantons, avoiding regional disparities and inconsistencies.

10 Synthesis and conclusion

This research aims to optimize the taxation of CO_2 emissions from internal combustion passenger vehicles in Switzerland by leveraging the potential of machine learning, complemented by qualitative validation through the Delphi method and political interviews. The ambition is to propose a fairer and more effective tax framework, one that reflects actual fuel consumption and aligns with current climate challenges. As the datasets used are European, the study can be easily extended to other countries.

The machine learning models developed, particularly LightGBM and Random Forest, demonstrate strong predictive capabilities for combustion vehicles. These models improve the classification of vehicles based on their real-world emissions. However, performance remains limited for plug-in hybrid vehicles due to the lack of behavioral data such as charging frequency or electric mode usage. This data gap hinders prediction accuracy and underscores the need to enrich datasets to better model mixed powertrains.

The Delphi method scientifically validates model parameters and collects insights from mobility, environmental, and public policy experts. This approach confirms the relevance of the explanatory variables while highlighting the need for better model interpretability to ensure their acceptance by decision-makers. In parallel, the political validation reveals a wide range of partisan positions, from the SVP's opposition to further regulation, to Les Verts' call for a tax overhaul, and the PLR's pragmatic stance.

Several key challenges emerged throughout the research. Data is not always well understood or utilized in political circles. The political perspectives gathered are not fully representative, with some cantons or viewpoints underrepresented. Moreover, the absence of behavioral variables limits the ability to precisely predict real consumption, especially for hybrids.As a result, it is crucial to develop a hybrid model combining machine learning with physical modeling, such as the one proposed by Gabriel Magnaval, to strengthen predictive robustness. It is also necessary to gather more data on real vehicle usage, either through OBFCM systems or industrial partnerships.

Finally, a regulatory and legal framework for the validation of predictive models should be established, for instance, through a national consumption observatory. This research thus proposes an innovative and cross-disciplinary method, combining artificial intelligence with human expertise to address the challenges of environmental taxation. It represents a first step toward a tax system that is more adaptive, equitable, and capable of evolving alongside changing behaviors, technologies, and climate goals.

Ultimately, this approach calls for enhanced collaboration among researchers, public authorities, industry, and civil society to build a fiscal system aligned with both environmental objectives and market realities.

Usage of Artificial Intelligence (AI)

Generative Artificial Intelligence (AI) tools were used in a limited and supportive capacity during the preparation of this work. Specifically, AI-assisted tools were employed to improve the clarity and readability of certain sentences through minor linguistic reformulations. In addition, AI was used to assist in the summarization and visualization of existing content, such as transforming textual or tabular information into structured tables or graphical representations (e.g., converting tables into graphs) to facilitate the presentation of data.

In particular, the tool ChatGPT (version GPT-5.3, OpenAI) was used for these limited editorial and formatting tasks. The tool was not used to generate original research content, develop methodological approaches, conduct analyses, or formulate interpretations and conclusions. All research design, analytical work, and intellectual contributions presented in this study are the sole responsibility of the author.

Data availability statement

The data underlying this study are primarily based on the **On-Board Fuel Consumption Monitoring (OBFCM)** framework made available through the European Environment Agency (EEA). Aggregated datasets and methodological documentation used to support the analysis can be accessed via the EEA's public portal on real-world vehicle emissions: https://climate-energy.eea.europa.eu/topics/transport/real-world-emissions/intro

Underlying and related material

This work is connected to the research context of the **"OpenGIS4ET – Open Geographic Information System for Energy Transition" (2021–2026)** project [SI/502364], funded by the Swiss Federal Office of Energy (SFOE). The project supports the development of open, spatially explicit data infrastructures for analyzing energy transition pathways, which provides an important contextual framework for integrating transport energy data into broader sustainability assessments :

SFOE. (2021-2026). "OpenGIS4ET – Open Geographic Information System for Energy Transition" [Research project SI/502364]. Swiss Federal Office of Energy.

The Hotmaps project (open source mapping and planning tool for heating and cooling): https://www.hotmaps-project.eu

Author contributions

Huy-Duc Nguyen: Conceptualization; Methodology; Data Curation; Software; Formal Analysis; Investigation; Visualization; Writing – Original Draft; Writing – Review & Editing. He designed the research framework, prepared and analyzed the OBFCM dataset, implemented the machine-learning models, interpreted the results, and drafted the manuscript.

Prof. David Wannier: Supervision; Methodology; Validation; Writing – Review & Editing; Project Administration. He provided scientific guidance, contributed to the refinement of the methodological approach, reviewed and validated the analytical results, and supported the preparation of the work for international dissemination.

Prof. Dominique Genoud: Supervision; Validation; Writing – Review & Editing. He oversaw the research progression, contributed to critical review of the findings, and ensured the academic rigor and coherence of the study.

Competing interests

The authors declare that they have no competing interests.

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