Spatio-Temporal Dynamics of Electric Vehicle Adoption in Quebec: A Bayesian Hierarchical Approach

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1 Introduction

The global shift to electric vehicles (EVs) is accelerating, driven by the need to reduce transportation-related greenhouse gas emissions and improve urban air quality (1). However, EV adoption rates vary significantly across regions due to economic, climatic, and societal factors (2). While China and Europe lead in EV uptake, Canada lags behind despite transportation accounting for 26% of its total emissions (3). To address this, Canada has introduced the "Electric Vehicle Availability Standard," targeting 20% EV sales by 2026, 60% by 2030, and 100% by 2035 [1]. Challenges to EV adoption in Canada include harsh winters affecting battery performance (4), high upfront costs, limited charging infrastructure, and grid integration issues (5).

Extensive research has explored global EV adoption, identifying key drivers such as financial incentives, charging infrastructure, socioeconomic factors, government policies, and consumer behaviour (6). Economic incentives, such as rebates and tax exemptions, promote EV uptake, while robust charging infrastructure reduces range anxiety (7, 8). Socioeconomic conditions and government interventions play significant roles, and consumer perceptions regarding performance and convenience further influence adoption (4). Regarding predictive models, studies have utilised spatial regression, Poisson models, and Bayesian frameworks to forecast EV adoption (9). While global research highlights the importance of policy and infrastructure, Canadian-specific studies remain limited. For instance, Ahmadi et al. (10) linked socioeconomic factors to EV uptake in Ontario, while Renaud-Blondeau et al. (11) emphasised the role of charging infrastructure in Montreal.

Despite this body of research, few studies have examined the spatio-temporal dynamics of EV adoption within Canada. This gap limits our understanding of regional disparities, the influence of local policies, and environmental factors on adoption patterns. The lack of region-specific analyses hampers the development of targeted, data-driven strategies to address unique local barriers and opportunities for EV adoption.

This paper aims to critically evaluate EV adoption rates in Quebec, Canada, to inform data-driven strategies that support the country's sustainable transportation goals. We address existing gaps using a Bayesian hierarchical framework with Poisson regression, incorporating spatial and temporal random effects to capture complex dependencies across regions and time. This approach enhances predictive accuracy and offers a versatile methodology applicable to diverse geographical contexts. Our main contributions are threefold: (i) Developing a robust Bayesian framework for spatio-temporal EV adoption analysis, (ii) Identifying key factors influencing EV adoption and

[1] More information can be found at: https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/sources-sinks-executive-summary-2023.html

regional disparities, and (iii) Providing evidence-based recommendations for targeted policy interventions. In this context, by integrating comprehensive datasets and advanced modelling techniques, this study provides valuable insights for policymakers and stakeholders aiming to implement EV adoption strategies in Canada and beyond.

2 Data Description

2.1 Vehicle Registry Data

This study examines the adoption of EVs by combining data on battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). The EV adoption data were obtained from the Société de l'Assurance Automobile du Québec (SAAQ) for the period 2013–2020 across 412 geographic areas in Quebec. Figure 1 (a) illustrates the temporal trend of EV adoption rates, demonstrating a consistent year-over-year increase. Notably, BEVs have surpassed PHEVs in adoption rates since 2019. Figure 1 (b) presents the distribution of vehicle counts by Forward Sortation Area (FSA) in 2020, which exhibits a long-tail trend. Given this distribution, a Poisson distribution is employed to model the EV adoption rate in this study.

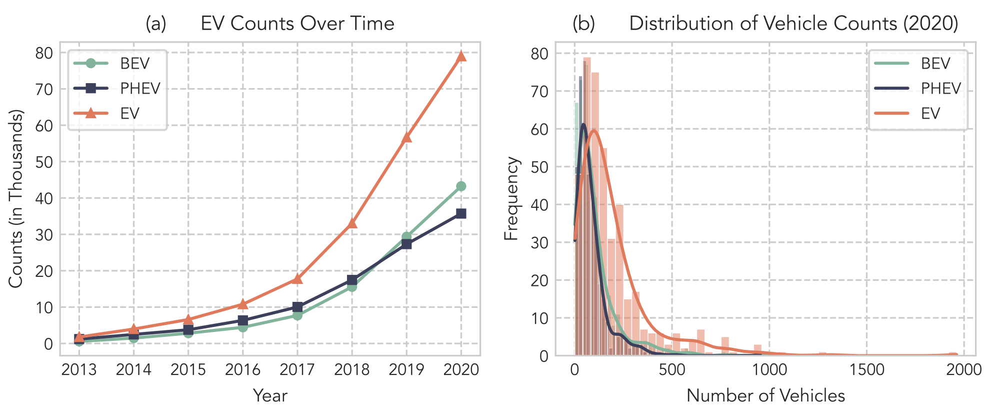

Figure 1 – *Temporal evolution of EVs in Quebec: (a) Counts over time and (b) Distribution of EV counts.*

In addition to temporal trends, EV adoption often demonstrates spatial autocorrelation, commonly referred to as the neighbor effect—where the adoption patterns of neighboring areas influence the likelihood of consumers adopting EVs. Figure 2 illustrates the spatial distribution of EV adoption in 2020. The map reveals that adoption rates are notably higher in the outskirts of the Montreal Metropolitan Area. To examine the spatial correlation of EV adoption across regions, we employed Moran's I, a measure of spatial autocorrelation. The analysis revealed moderate positive clustering ($I = 0.37$, $p = 0.001$), indicating that EV adoption tends to cluster geographically.

2.2 Influential Data

The census data used in this study were obtained from the 2016 Canadian Census [2]. To predict EV adoption rates, we included key variables such as total population, gender distribution, age groups (e.g., percentages of individuals aged 30–49 and 50–64), household types (e.g., percentages of detached homes and single-person households), and employment-related metrics (e.g., employment rate and the proportion of individuals working from home). We also incorporated data on immigrant populations by origin (e.g., the United States, China, and Europe), educational attainment, and

[2] https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/index-eng.cfm

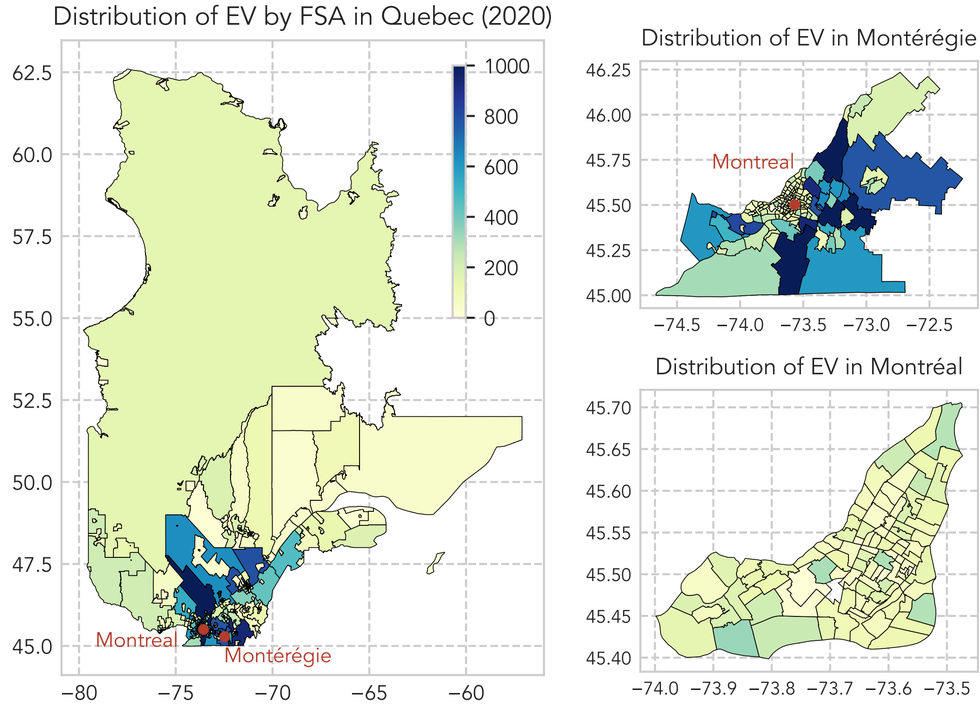

Figure 2 – *Spatial distribution of EVs by FSA in Quebec (2020).*

socio-economic factors such as household income and transportation habits. Additionally, weather-related variables, including average annual temperature and precipitation, were included to assess their potential impact on transportation patterns and EV adoption.

3 Method

To analyse spatio-temporal trends in EV adoption, we propose a Bayesian hierarchical framework (12). This model accounts for spatial and temporal dependencies, offering robust insights into adoption patterns. The mathematical formulation is briefly described in the following.

Let Y_{nt} denote EV adoption in region n at year t, then Y_{nt} can be modeled by a Poisson distribution:

$$Y_{nt} \sim \text{Poisson}(E_{nt}\lambda_{nt}), \tag{1}$$

where E_{nt} is the expected adoption and λ_{nt} the relative adoption rate. Then, the logarithm of λ_{nt} is modeled by a regression model:

$$\ln(\lambda_{nt}) = \mathbf{x}_{nt}^{\top}\boldsymbol{\beta} + \phi_{nt}, \tag{2}$$

where $\mathbf{x}_{nt}$ includes inflencial factors described in Section 2.2, $\boldsymbol{\beta}$ are the regression coefficients with prior $\beta_k \sim \mathcal{N}(0, 1000)$, and ϕ_{nt} are the spatio-temporal random effects capturing residual dependencies. To model the random effects ϕ_{nt}, a Gaussian Markov Random Field (GMRF) is applied:

$$\phi_t|\phi_{t-1} \sim \mathcal{N}(\alpha\phi_{t-1}, \sigma^2 Q^{-1}(\rho, W)), \tag{3}$$

where α is the temporal autocorrelation, σ^2 the variance, and $Q(\rho, W)$ the spatial precision matrix. The following weakly informative priors are specified for the hyperparameters:

$$\alpha \sim \mathcal{U}[0,1], \quad \rho \sim \mathcal{U}[0,1], \quad \sigma \sim \mathcal{U}[0,1000].$$

Model estimation is performed using Markov Chain Monte Carlo (MCMC) simulation, combining Gibbs sampling and Metropolis-Hastings steps. This framework captures spatial and temporal dependencies in this context, accounting for unobserved confounders. Parameters α and ρ control temporal and spatial correlations, respectively, enabling dynamic analysis of EV adoption trends from both temporal and spatial perspective.

4 Final Remarks

This study aims to advance understanding the spatio-temporal dynamics of EV adoption in Quebec. By integrating vehicle registry data with demographic and environmental variables and employing a Bayesian hierarchical framework, we seek to address gaps in existing literature related to regional and temporal variations in EV uptake. The proposed approach will enable the identification of key factors influencing EV adoption and help uncover spatial and temporal patterns that may inform targeted policy interventions. While the current work focuses on Quebec, the methodology is designed to be adaptable to other regions, providing a flexible tool for broader applications in sustainable transportation research. Future analyses will offer insights into the role of socioeconomic conditions, infrastructure, and environmental factors in shaping EV adoption trends. This prospective framework lays the groundwork for data-driven strategies to support the transition to low-emission mobility systems.

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