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ESTABLISHMENT OF PUBLIC CHARGING STATIONS: FACTORS FOR THEIR HIGH DIFFUSION IN NORWAY

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Original scientific paper

Abstract: The transportation sector is a major contributor to greenhouse gas emissions, and Norway is one of the leading countries in transitioning to zero and low-emitting private transportation. In 2022, over 80% of new cars sold there were electric or hybrid. This study explores the dynamics between public charging infrastructure and EV diffusion in Norway. Though home charging in Norway is widespread, public infrastructure plays a role, too. This study investigates factors influencing their link to EV adoption. The study employs a multifaceted approach in leveraging municipality-level data from 2020 to 2022. Initial Ordinary Least Squares (OLS) regression provided a baseline understanding, followed by hot spot analysis to identify spatial clusters of high and low EV adoption. Geographically Weighted Regression (GWR) and Multilevel Geographically Weighted Regression (MGWR) unveiled finer-grained local variations in the public charging infrastructure-EV diffusion relationship across 356 municipalities and 11 counties. Municipalities with more stations exhibit higher EV usage. This study underscores the significance of developing public charging infrastructure for EV adoption. Additional influencing factors, such as EV cost, availability of new models, and public perception, are also identified. The findings offer valuable insights for policymakers and stakeholders promoting EV adoption.

Keywords: Public charging stations, Electrical vehicles, Norway.

JEL classification: Q54, R40, L90

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Introduction

The transportation sector contributes to almost 16% of all greenhouse gases emitted globally. Thus, this has also pressured governments to limit the manufacture and use of cars and other emitting vehicles in the market and adopt various measures and strategies to accommodate non-emitting electric vehicles on the streets. The European Union and many other organizations are working to make the transportation sector more sustainable, thus focusing on using EVs as an alternative to traditional combustion engine vehicles (Illmann & Kluge, 2020). With the introduction of EVs in the market and increased consumer demand, the development of charging infrastructures has also become a necessary commodity. Despite the economic challenges, many countries follow ambitious plans for charging infrastructure to support the mass adoption of EVs (Baumgarte et al., 2021).

Norway has become one of the leading countries in transitioning to zero and low-emitting private transportation to meet the zero-emission goals (Fevang et al., 2021; Schulz & Rode, 2022). This has a long history from 1970 to 1990, when the Government funded private companies to research and produce Norway's first modern EV prototype, followed by their outstanding subsidies for testing in the following decade. The testing included the provision of incentives and support to encourage the commercialization of electric vehicles. After 2009, while Norwegian EV manufacturers went through bankruptcy, many other manufacturers and players entered the market that made EVs affordable to people (Mersky et al., 2016). National Transport Plan 2018-2029 by the Norwegian Ministry of Transport also stated a goal that all new cars registered after 2025 should be electric. This policy has also led to an increased EV market in Norway (Norsk-Elbilforening, 2022). The Norwegian Government started building public charging stations in 2009 (Mersky et al., 2016), resulting in over 80% of the new passenger cars sold in Norway in 2022 being either hybrid or all-electric (McKinsey & Company, 2023). With the highest EV adoption rate in the world, Norway is towards massive development of infrastructures and charging stations across the country and has established more than 28000 charging points across the country (NOBIL, 2023).

While Norway ranks among those with the highest share of home charging availability, the availability of public charging infrastructures also affects EV adoption (Schulz & Rode, 2022). EV adoption has changed over time and is influenced by the availability of charging opportunities. A wide network of public chargers for people's daily commute and longer travel makes EV mass adoption much more attractive (Anjos et al., 2020). Other factors, such as improved cost competitiveness with internal combustion engine vehicles, the availability of numerous new brands and models, and peoples' perceptions towards environmental conservation, also assist in the mass adoption of EVs. This increase in EV demand and market also requires developing charging infrastructure. Overall, deploying facilities and infrastructures for the charging of vehicles is among the strategic measures to increase the EV market in many countries.

This study consists of municipality-level data between 2020 and 2022 that will be used for various statistical analyses and compare them. It will also visually display the relationship between the availability of public charging infrastructures and EV diffusion in 356 municipalities (communes) and 11 counties (files) in Norway. It also aims to analyze the EV market in Norway, identify the various factors that drive public charging infrastructure, and provide evidence of its significance/ impact on EV adoption based on the results of those models.

Literature research

Electric vehicle adoption and its share in the market are found to be associated significantly with several factors, such as the socio-economy of the people in the area or country, financial and other incentives to the consumers, the availability of charging infrastructure and the presence of companies (Lemphers et al., 2022). The global demand for the reduction in emissions from the transport sector forces the different levels of government to plan and implement policies and measures to support and promote battery-powered electric vehicles and the development of several infrastructures to accommodate them on the street. Hidrue et al. (2011) mentioned that technological issues such as high initial purchase cost, battery cost, driving range, charging times, and limited charging infrastructure were some of the causes that people did not prefer to shift from traditionally fueled vehicles to electric in the initial days. Still, the recent advancements in the technology and mass production of EVs will attract more consumers (Hidrue et al., 2011).

Socio-demographic factors for EV adoption

As Rogers (1995) mentioned, consumer adoption of an innovation (e.g. EVs) is due to their knowledge of the innovation, attitude toward it and the decision to adopt it or not. High EV adoption is connected with the consumers' income and education and varies with socio-demographic characteristics (Hidrue et al., 2011; Westin et al., 2018). A study in Norway shows drivers of EVs tend to have higher education than others, and this may also be related to the high motivation for environmental issues (Chen et al., 2020). Studies by Beresteanu & Li (2011) show financial incentives and support to consumers are highly correlated with EV sales, while Diamond (2009) and Zhang et al. (2013) found that higher prices of fuel and operation, not consumer subsidies were associated with increased adoption of EV (Sierzchula et al., 2014).

In addition, survey studies by Li et al. (2017) also show people with full-time jobs, living outside large cities, have a place to charge at home and live in multiperson households who want to buy electric vehicles (Fevang et al., 2021). A similar study in Germany to identify likely buyers of EVs found that middle-aged people living in outskirts or suburbs with technical professions are more likely to benefit economically from an EV due to their regular annual mileage and would thus go for EVs (Westin et al., 2018). Homeownership also gives EV owners access to parking or a driveway, with the possibility of home charging facilities, and thus supports EV adoption in outer parts of the big cities and urban areas. This higher home ownership and car ownership also results in geographic clusters in EV adoption, as found in Birmingham, UK (Westin et al., 2018). Jansson et al. (2017) mentioned in their study that adopting private vehicles has a neighbour effect. They showed that the influence of neighbours, close family and co-workers and geographical proximity to other adopters also relates to adoption decision (Westin et al., 2018).

According to Sovacool et al. (2019), a study in Nordic countries shows that the income of people living in those areas is highly correlated with EV ownership, use and interest. They found that higher income levels are associated with car ownership, and higher income groups demand more from their cars and are willing to pay more for them (Sovacool et al., 2019). While some other studies in Nordic countries show more than half of the early adopters of EVs have a yearly income of 600,000 NOK or higher, with 20 % of the individuals reaching above 1,000,000 NOK, they indicate income levels to be insignificant for EV adoption (Chen et al., 2020).

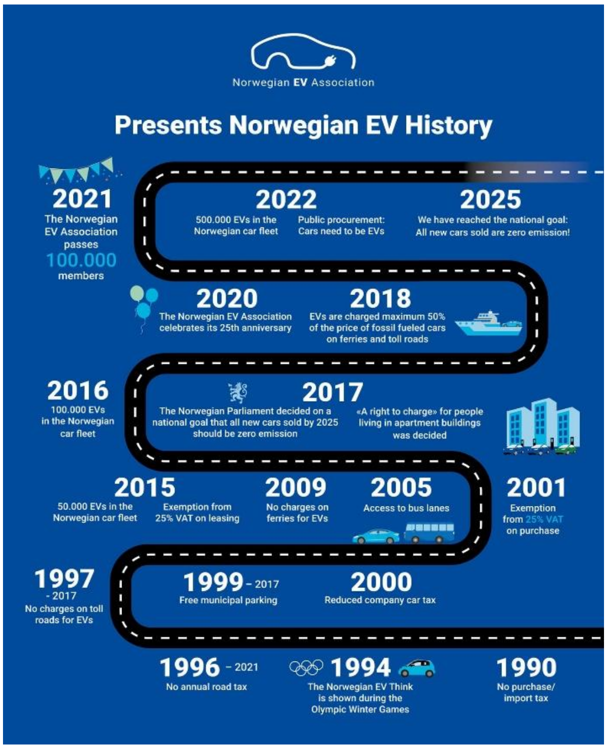
Similarly, they also found in their study in Nordic countries that political orientation is less connected to EV ownership but shows that political leaning has some impact on EV interest. They also found that car ownership is higher among conservatives and democrats, followed by liberals' orientation, and left parties are more concerned with design and engineering aspects. In contrast, the right parties are concerned with the costs and the environmental impact of cars. Regarding EVs, the range is more important to those on the right, while charging-related issues are essential for all orientations (Sovacool et al., 2019). Overall, EV adoption appears to be influenced by the socio-economy of the EV users, considering that they tend to have higher socio-economic status and, therefore, can afford investments in EVs.

Policies and Incentives for EV diffusion in Norway

Norway, with its strong economy, high income and standard of living, makes people afford the costs of electric vehicles. Effective economic and social initiatives, a reliable power grid, and demographics have made EV adoption successful (McKinsey & Company, 2023). The high environmental awareness and concern for climate change in Norwegian society has also led to a positive attitude toward sustainable transportation. More people adopting EVs make it socially accepted (Bjerkan et al., 2016). According to SSB Norway and the European Commission, it took four years (2008-2011) to sell the first 10,000 EVs in Norway, which is sold in 4 weeks in 2022 (McKinsey & Company, 2023).

High EV diffusion in Norway is the result of outstanding support and subsidies from the government. Transport policies in Norway aim to reduce carbon emissions from vehicles and thus play a differentiating factor between the adoption of EVs and conventional fueled vehicles (Chen et al., 2020). While Norway lacks an auto manufacturing industry, the growth in the country's oil and gas industry has encouraged business leaders and politicians to look for opportunities in other sectors. Lots of water resources and abundant hydropower production also play a vital role in the environmental movement in reducing fuel-powered vehicles on the road. A solid organisational support system has also facilitated the development of EV driven economy (Lemphers et al., 2022).

Figure 1: Norwegian EV Policy



Source: Norsk Elbilforening

In the 1990s, when state support started providing financial incentives to purchase EVs through reduced taxes, later policies with free charging, parking, tolls and ferries increased convenience for EV users (Norsk-Elbilforening, 2022). Norsk Elbilforening, the EV user group in Norway, educates its members regarding benefits, insurance, and legal advice and provides an open-access database of EV charging stations. These work with environmental groups and municipalities and thus show their interest in the electrification of transportation in Norway (Lemphers et al., 2022). Norwegian society has powerful norms towards the environment and its preservation, and thus, policymakers and political parties do not oppose any EV policies and 'Green State' targets.

Availability of charging infrastructure and demand from the consumers

Electric vehicle adoption and diffusion are infrastructure-dependent adoptions. It is highly dependent on the number of facilities available to the users. A study by Rostad Sæther (2022) on data from 32 European countries from 2009 to 2019 shows that charging infrastructure growth increases the EV market significantly (Sæther, 2022). Therefore, the optimal electric vehicle support policy should usually consist of subsidizing the infrastructure such as charging stations, electric grids, etc. The inclusion of social networks effect by policymakers and infrastructure developers while planning new facilities is also a must for optimal policy. The model developed by Sæther (2022) predicted that if 150 fast chargers are built per 100 km of highway, the EV market share will increase by 3% and 5% if 400 fast chargers are built. Moreover, it was also mentioned that Norway had already built 655 fast charging stations per 100 km highway in 2019 and thus suggested that policymakers need to focus on funding, regulations and political conditions to attract more private companies and public entities to improve the charging network and infrastructure for electric mobility (Sæther, 2022). The public and private sector cooperation has also provided support for market-driven funding development projects and acts as a bridge to reduce the gap in funding infrastructure solutions.

The availability of home charging is also an essential factor in the increased diffusion of electric vehicles in Norway. Figenbaum and Nordbakke (2019) found that 80% of electric vehicle owners charge their vehicles at home because of the high availability of private parking spaces (Schulz & Rode, 2022). While public fast charging is about three to four times more expensive than home charging (Norsk-Elbilforening, 2022), public charger density in Norway has also steadily increased from 0.6 public chargers for every 1000 inhabitants in 2009 to 2.8 in 2019 (NOBIL, 2023). They are installed with at least two fast chargers for every 50 km in all major transport corridors to support long-distance driving (Figenbaum, 2020). Access to these charging facilities and their presence on high-use roads make electric vehicles more accessible and flexible, and they support long-distance trips. Fast chargers in the area where EV owners live or travel to work also help complement home charging and thus positively influence the perception towards EVs over Internal Combustion Engine vehicles (Figenbaum, 2020). Most typical locations for fast chargers in Norway are at or next to fuel stations, food stores, shopping centres, cafes, etc. (Feigenbaum, 2019).

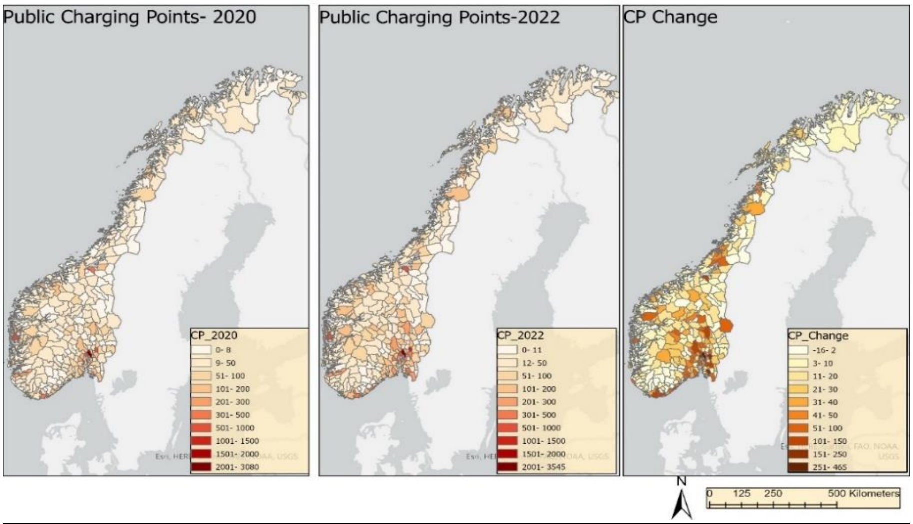
Most of the public charging points in Norway are established and operated by private companies with support and incentives from the Norwegian government. However, a growing trend of private fast-charging operators without governmental support in the larger cities and along the major highways shows pure commercial decisions based on consumer demand. Research in the US mentioned the users' equity for EV infrastructures, where many neighbourhoods with high population but low median household income face charging deserts with very few or no charging stations and thus prefer nonelectric vehicles (Iravani, 2022).

Methodology

Data

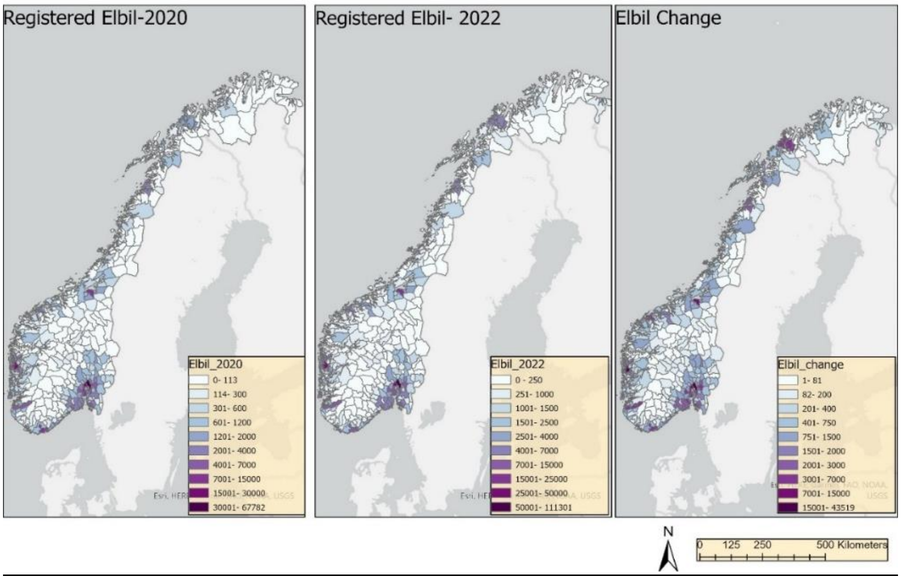
Detailed information and data regarding the electrification of transportation in Norway were obtained from Statistics Norway and NOBIL (accessed on 14th Nov 2023). The data consisted of the total population, voters, number of established charging points, number of registered electric vehicles, number of commuters for jobs, and median income of households in every 356 municipalities of Norway. The data for 2020 and 2022 are considered to identify the trends and changes in these two years.

Figure 2: Spatial representation of Public Charging Points



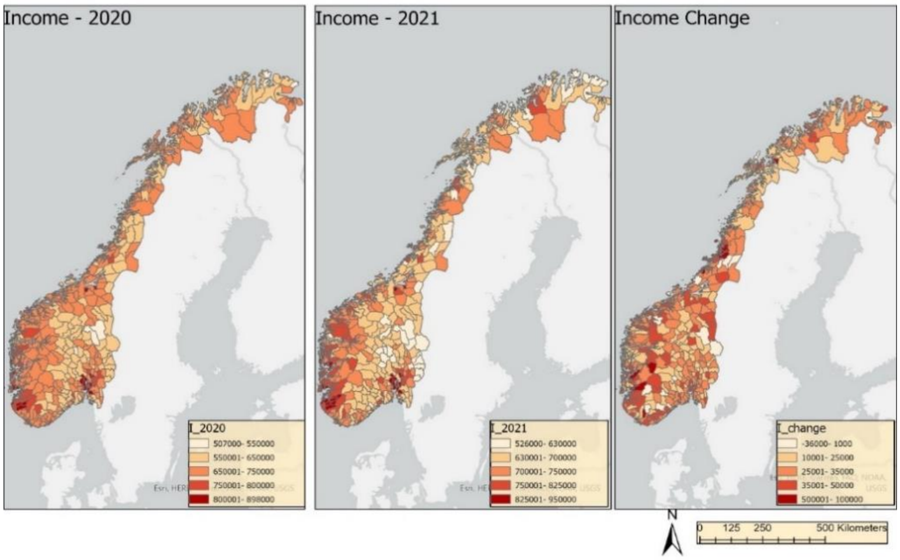
Variable	Obs	Mean	Std. dev.	Min	Max
CP_2020	356	47.80056	182.9046	0	3080
CP_2022	356	67.03933	213.142	0	3545
CP_Change	356	19.23876	38.08326	-16	465

Figure 3: Spatial Representation of Elbil registration



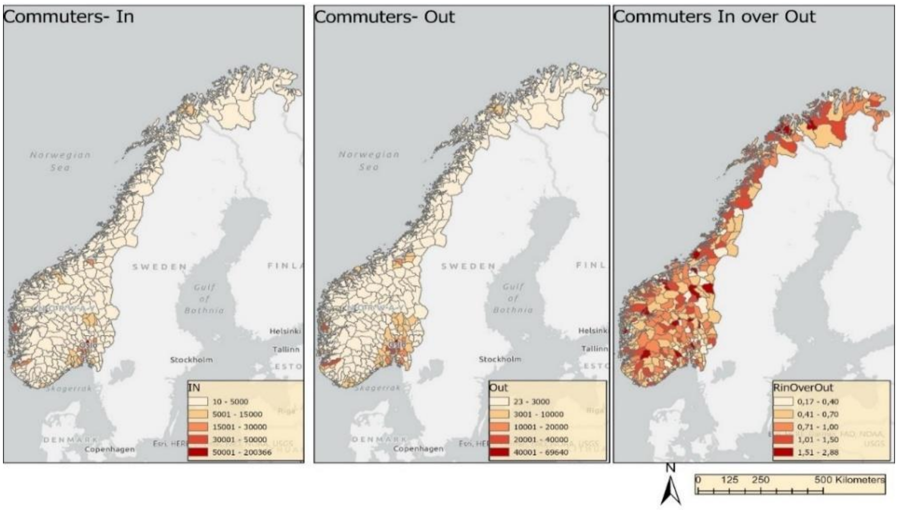
Variable	Obs	Mean	Std. dev.	Min	Max
Elbil_2020	356	954.9747	4276.1	0	67782
Elbil_2022	356	1682.876	6966.426	5	111301
Elbil_change	356	727.9017	2703.975	1	43519

Figure 4: Spatial Representation of Income



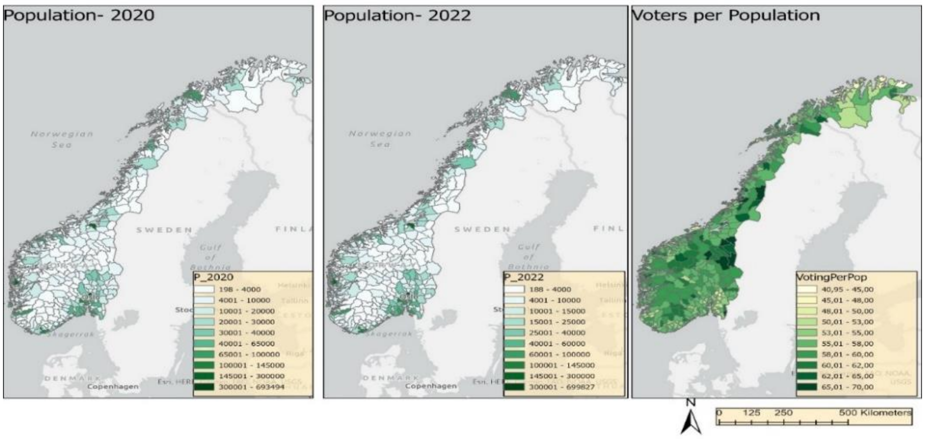
Variable	Obs	Mean	Std. dev.	Min	Max
I_2020	356	677969.1	70700.45	507000	898000
I_2021	356	707154.5	74754.78	526000	941000
I_change	356	29185.39	13359.15	-36000	95000

Figure 5: Spatial representation of commuters



Variable	Obs	Mean	Std. dev.	Min	Max
IN	356	2711.548	11766.79	10	200366
Out	356	2725.32	5900.933	23	69640
RinOverOut	356	.7519458	.4069053	.171429	2.877168

Figure 6: Spatial representation of Population and Voters



Variable	Obs	Mean	Std. dev.	Min	Max
P_2020	356	15077.47	44325.37	198	693494
P_2022	356	15239.52	44838.26	188	699827
VotingPerPop	356	57.22148	3.879301	40.95455	69.63109

Methodological Framework

The statistical data is cleaned up with MS Excel and later imported to ArcGIS to visualize the spatial distribution. For the statistical analysis' easiness, understandability and easy-to-interpret results from the regression model, charging points and the number of electric vehicles were converted to per 100K capita for every municipality. Similarly, to test the significance of voters in the area for the change in charging points, a variable voter per population was created from the number of voters and total population in each municipality. The variable Rinoverout with a ratio of commuters in over out in every municipality were also created to identify its effect on the establishment of charging stations.

Statistical Framework

OLS Regression

Ordinary least squares (OLS) regression is used to estimate the relationship between one or more independent and dependent variables. This method aims to minimize the sum of square differences between the observed and predicted values. Linear Regression and Ordinary Least squares are often used to refer to the same kind of statistical model as both describe the relationship between the dependent and independent variable by a straight line. The best-fitting line is the line that minimizes the sum of the squared errors. When a dependent variable is rarely explained by only one independent variable, OLS regression is used as a multiple regression that attempts to explain a dependent variable using more than one independent variable.

Our study for the change in charging points is assumed to be related to several (more than one) independent variables and thus OLS regression could be one of the solutions to identify the standard residuals for individual kommune. The independent (explanatory) variables VotingperPop, Elbil per 100K capita 2022, Income 2021 and the ratio of commuters in over out (Rinoverout) from the feature class (dataset) were used to model, explain, and predict the dependent variable (CP per 100K capita 2022) in ArcGIS pro.

Geographically Weighted Regression

Traditional regression assumes a constant relationship of the model's parameters over space. GWR is a spatial analysis technique that considers non-stationary variables and models the local relationships between the predictors and outcome of interest (Brunsdon et al., 1998). It is an outgrowth of OLS regression that adds a level of modelling by allowing the relationships between the variables to vary by locality and space. It also captures the variation by calibrating a multiple regression model. At different locations in the study area, the explanatory variables impact the dependent variables differently. Thus, it accounts for spatial autocorrelation of variables and constructs a separate OLS equation for every location in the dataset. So, to calibrate a GWR model at any one location, data are 'borrowed' from the nearby locations and weighted according to the distance from the regression point (Fotheringham et al., 2017), allowing all coefficients to change at a similar rate across the study area.

Multiscale Geographical Weighted Regression

MGWR is used to explore spatial heterogeneity, model local spatial processes, minimize overfitting, mitigate concurvity, and reduce bias in parameter estimates (Oshan et al., 2020). It evolved from GWR by allowing different neighbourhoods and bandwidth for different variables, where a small bandwidth indicates that the spatial process changes quickly from location to location (Zhou et al., 2023). MGWR are helpful for large datasets containing several hundred features where the dependent variable shows spatial heterogeneity. Unlike GWR, where if one explanatory variable uses a definite neighbour, all other explanatory variables must also use the same number of neighbours, MGWR allows the coefficient to vary over space and varies across different explanatory variables.

For this study, the effect of individual explanatory (independent) variables on the dependent variable from the dataset (feature class) is run through both GWR and MGWR, and the results are compared between these two models. Features containing numeric values were considered, and missing values in the dependent or explanatory variables were excluded from the analysis by the models. A continuous (Gaussian) model with a Golden Search neighbourhood selection option for several neighbours in the neighbourhood type parameter was done to categorize the neighbourhoods based on the denseness and sparseness of the features.

Multilevel Regression Model

Multilevel models are used to find the relationship between 2 or more independent variables and the corresponding dependent variable. It helps to predict the trends and future values, forecast the effects, and identify the strength of the impact. These models are particularly appropriate for the data that are organized at more than one level. The units of analysis or data at the lower level are nested within the aggregate units at the upper level. In this study, units of analysis are data for municipalities (kommunes), and aggregate units are data for counties (folks). These models can also be used on data with many levels, but 2-level models are more common, and the dependent variable is examined at the lowest level of analysis (Wikipedia, 2023). When the observations at the municipality level are independent of each other, ordinary single-level regression analysis is conducted, but in this study, there may be an influence of the county-level factors. Thus, a two-level mixed-effect regression analysis is conducted. The number of charging points in any fylke may be higher or lower than the average for all fylkes regardless of other factors being equal. Then within the same fylke, kommunes has a difference in the number of charging points. In multilevel analysis, charging points in fylkes are assumed to be sampled from a distribution of the average of charging points in all fylkes.

Results and Discussions

Optimized Hot Spot Analysis

The optimized hot spot analysis tool in ArcGIS helped identify significant clusters of high values (hot spots) and low values (cold spots) based on the z-score, p-value, and confidence level for change in charging points. The result showed that the eastern part of Norway (more specifically municipalities in Oslo, Viken, Vestfold and Telemark and some parts of Vestland and Agder fylkes showed a high concentration of change in charging points whereas some parts of Vestland and northern parts of Norway displayed low concentration in the change in charging points. The rest of the parts of Norway had no significant relative change in the established charging points. This result leads to investigating factors and their relation or effect to the increased charging points in different kommunes of Norway. One of the assumptions for this difference may be establishing charging points more focused on people traversing the major transport corridors. The major highways and motorways (E6, E16, E18, E134, etc.) in the eastern and southern parts of Norway are used not only by locals but also by people travelling long distances and significant big cities. We considered it not to be the only cause, and thus, several statistical analyses were performed to find the effect and significance of increased public charging points.

The ordinary least squares regression model produced a relatively low adjusted R2 (0.020547) lower than multiple R2 (0.031583). This shows a very low correlation and variance between the variables used in the model, and some of the independent variables could be more useful to the model. This low value of R2 also explains a tiny proportion of variance in the dependent variable. The model also shows that the ratio of commuters travelling in and out has a relatively positive, significant relationship with the establishment of charging stations, followed by the ratio of voters per population. The model displayed that registration of electric vehicles is significantly less, but the positive relationship and income of the people have minimal and adverse relationships with the charging points.

Figure 7: Optimized Hot Spot Analysis

Ordinary Least Square (OLS) Regression

Summary of OLS Results

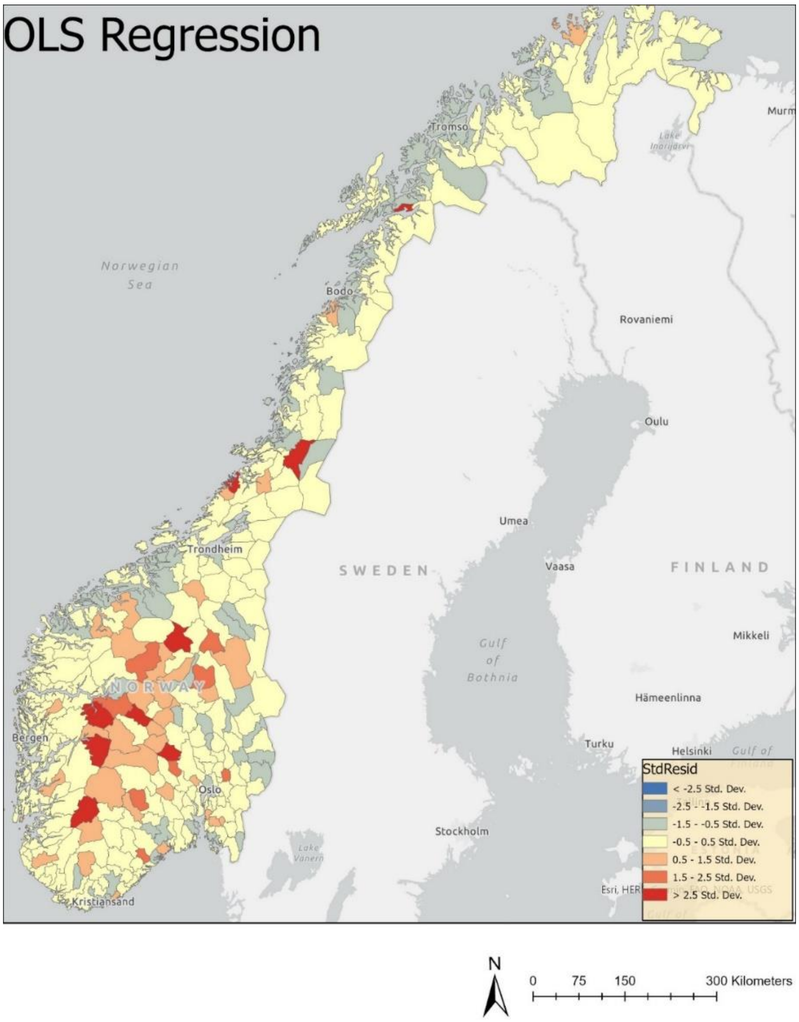
Variable	Coefficient[a]	StdError	t-Statistic	Probability[b]	Robust_SE	Robust_t	Robust_Pr[b]	VIF[c]
Intercept	350,359519	814,221594	0,430300	0,667255	760,838478	0,460491	0,645461	--------
VOTINGPERPOP	16,001272	11,235975	1,424111	0,155315	9,911185	1,614466	0,107337	1,051803
ELBIL_PER_100KCAPITA_2022	0,002994	0,016416	0,182355	0,855404	0,014845	0,201648	0,840306	2,092226
I_2021	-0,001210	0,000814	-1,487386	0,137824	0,000727	-1,665348	0,096746	2,047666
RINOVEROUT	254,394973	105,932991	2,401471	0,016836*	109,351730	2,326392	0,020553*	1,028620

OLS Diagnostics

Input Features	Kommunes	Dependent Variable	CP_PER_100KCAPITA_2022
Number of Observations	356	Akaike's Information Criterion (AICc)[d]	5777,623705
Multiple R-Squared[d]	0,031583	Adjusted R-Squared[d]	0,020547
Joint F-Statistic[e]	2,861836	Prob(>F), (4,351) degrees of freedom	0,023747*
Joint Wald Statistic[e]	11,536257	Prob(>chi-squared), (4) degrees of freedom	0,021154*
Koenker (BP) Statistic[f]	2,722093	Prob(>chi-squared), (4) degrees of freedom	0,605354
Jarque-Bera Statistic[g]	11179,568683	Prob(>chi-squared), (2) degrees of freedom	0,000000*

The standardized residual of the model, which represents the strength of the difference between observed and expected values, shows that 109 out of 356 kommunes have positive results that explain the higher number of charging stations established than predicted by the model, while the remaining kommunes had negative values that explain lower charging points than predicted. However, some of the kommunes had very high positive values (>4); thus, other factors were associated with establishing charging points. The above results assume the relationship is constant across the study area. Therefore, GWR and MGWR were applied to the same explanatory variables to differentiate the prediction between the models.

Figure 8: OLS regression



Geographically Weighted Regression (GWR) and Multiscale GWR

Model Diagnostics

Statistic	GWR	MGWR
R-Squared	0,4593	0,5460
Adjusted R-Squared	0,2776	0,4340
AICc	969,0858	907,8479
Sigma-Squared	0,7217	0,5656
Sigma-Squared MLE	0,5407	0,4540
Effective Degrees of Freedom	266,7290	285,7936

Optimal GWR Bandwidth: 53 (K nearest neighbors).

The R^2 increased to 0.4593 in the GWR model and 0.5460 in the MGWR model from 0.020547 in the OLS model. Similarly, AIC decreased to 969.0858 and 907.8479 respectively for GWR and MGWR models from 5755.0085 for the OLS model. This shows that the MGWR model outperformed the other model and thus all the spatial relationships change at a similar rate on a regional scale. GWR uses 53 neighbours as an optimal bandwidth to feature relationships on the local modal.

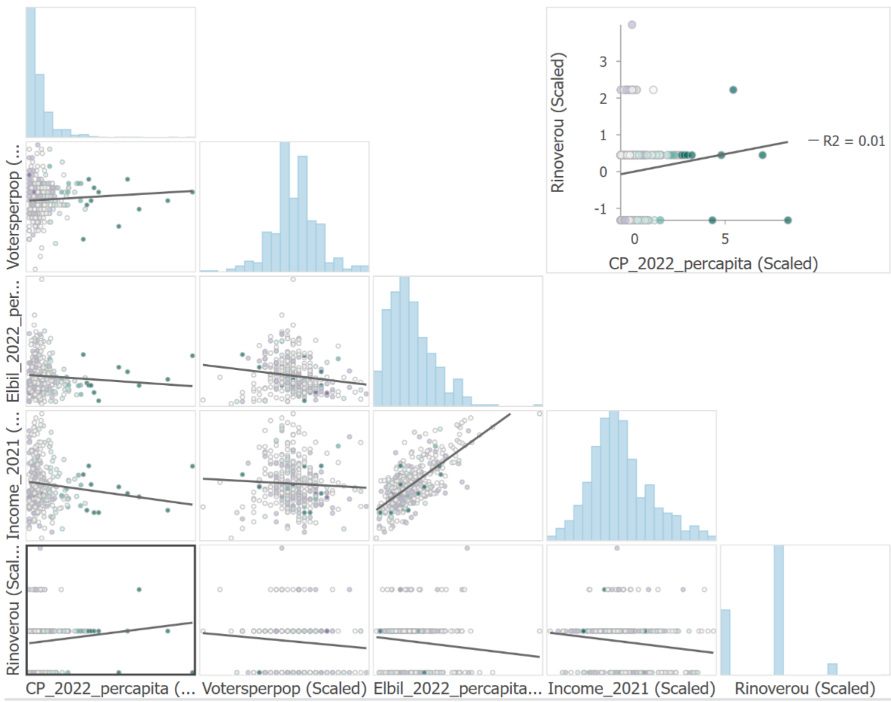
In MGWR, the ratio of voters per population operates at a global scale with 231 neighbors, the ratio of commuters in over out operates on a regional scale with 53 neighbors, and the number of elbil registered and income operates on a local scale with 41 and 30 neighbors respectively.

Summary of Explanatory Variables and Neighborhoods

Explanatory Variables	Neighbors (% of Features)[a]	Significant (% of Features)[b]
Intercept	41 (11,52)	31 (8,71)
Votersperpop	231 (64,89)	83 (23,31)
Elbil_2022_percapita	41 (11,52)	8 (2,25)
Income_2021	30 (8,43)	6 (1,69)
Rinoverou	53 (14,89)	11 (3,09)

a: This number in the parenthesis ranges from 0 to 100%, and can be interpreted as a local, regional, global scale based on the geographical context from low to high.
b: In the parentheses, the percentage of features that have significant coefficients of an explanatory variable.

Relationships between Variables



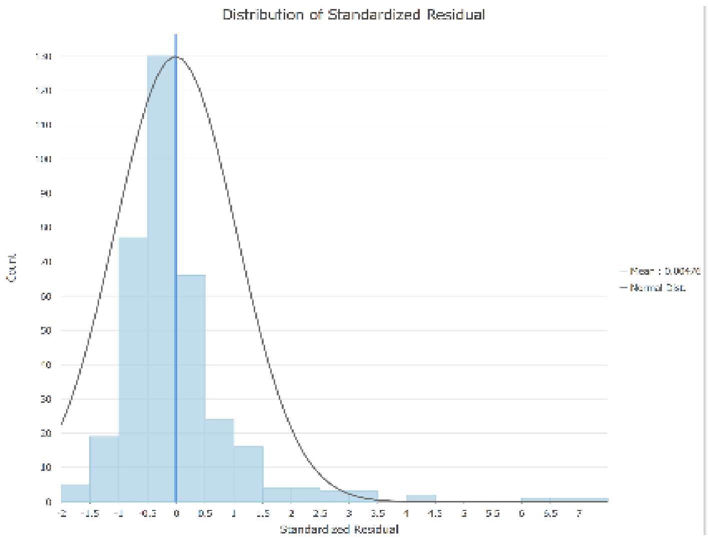


Figure 9 shows that both GWR and MGWR model predicts a positive coefficient and positive relationship of voters per population for the majority of the kommunes in northern Norway, as indicated by the red colour, and a negative coefficient and negative relationship for the majority of the kommunes located in central and eastern Norway with yellow colour. Both maps from the models indicated a positive coefficient and relationship between several voters per population and the establishment of public charging points for most kommunes in northern Norway. In contrast, most commuters in central and eastern Norway show a negative association with the voters and the establishment of public charging points.

Moreover, the MGWR model indicated that the voters per population in central Norway have significance for establishing public charging points while the rest of Norway is not significant. This could lead to an assumption that for central and some parts of eastern Norway, changes in the number of voters might be one of the determining factors in establishing public charging points. In contrast, other factors might be more critical for the rest of the country.

Similarly, Figure 10 shows both models calculated mixed coefficients across different regions for public charging points due to elbil registration per capita. The central and southern parts of Norway showed high positive coefficient and thus positive relationship between the number of EVs per capita and the establishment of public charging points while northern part shows lower and non-significant relationship between these variables.

However, both maps show a strong relationship between the variables in northern and eastern parts and MGWR showed that some kommunes in Viken and Vestland had high significance of elbil per capita for establishing the public charging points.

Figure 9: GWR vs MGWR- Voter_per_Pop

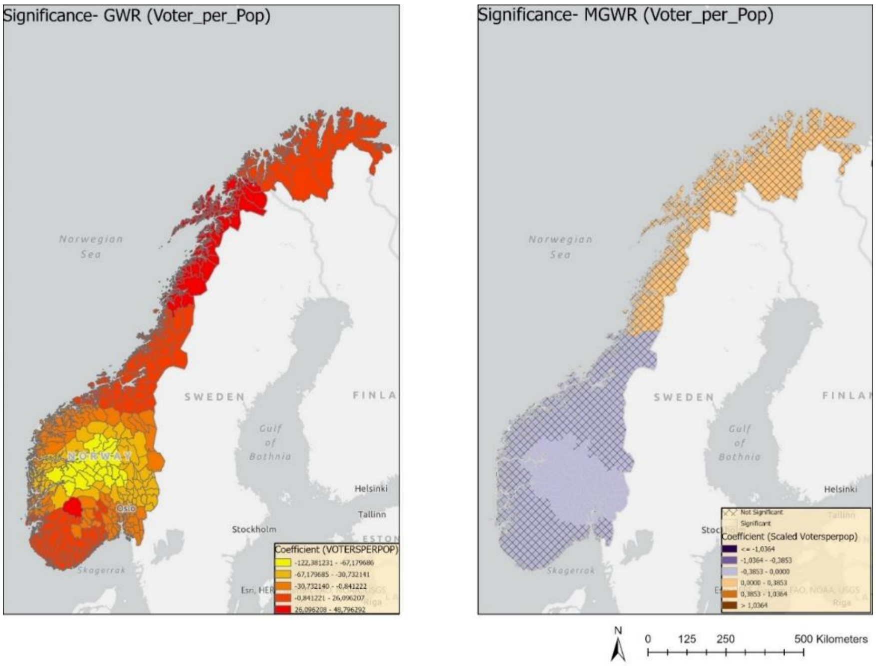
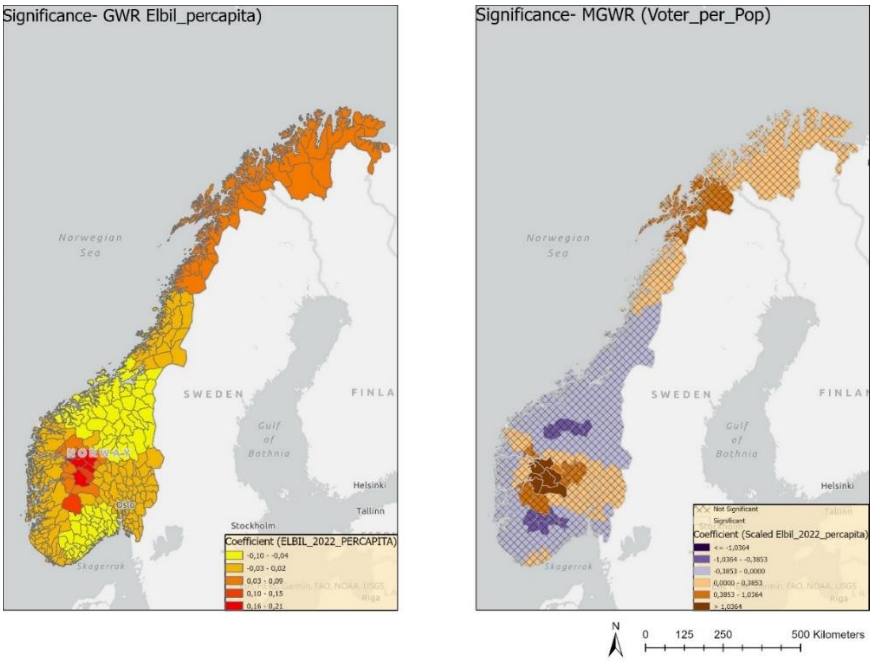


Figure 10: GWR vs MGWR- Elbil_percapita



For the effect of income in establishing charging points, both models calculated negative coefficients (as shown in Figure 11), and MGWR showed that Ulvik and Eidfjord communes in Vestland and Nesbyen, Flå and Krødsherad kommunes in Viken folks had the significance of income to the charging points.

Figure 11: GWR vs MGWR- Income

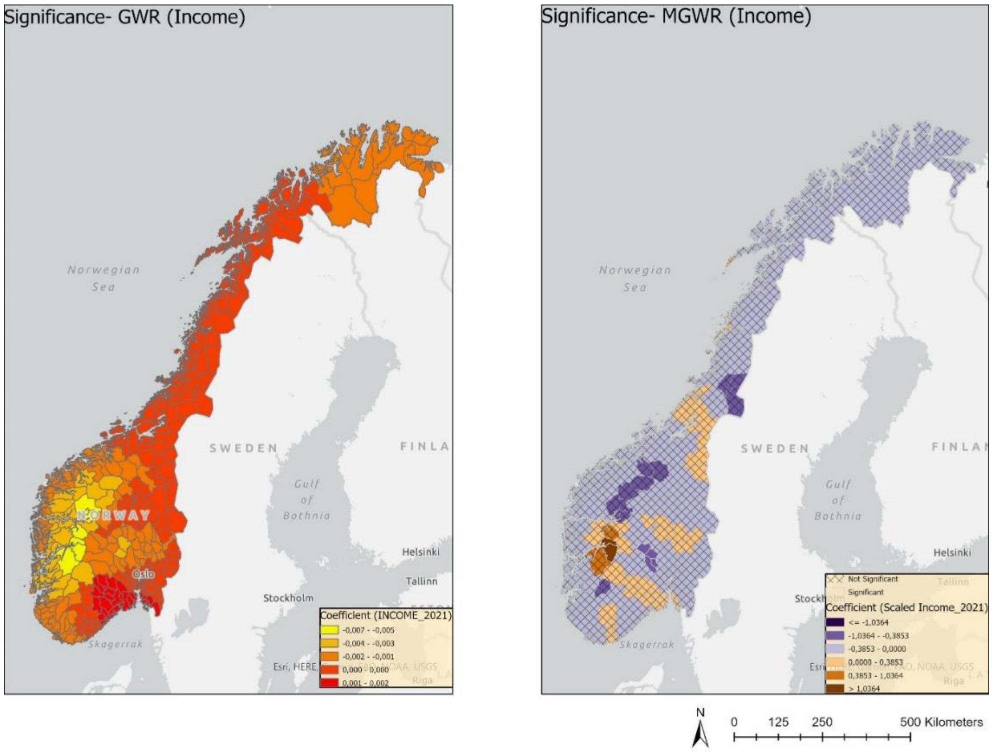
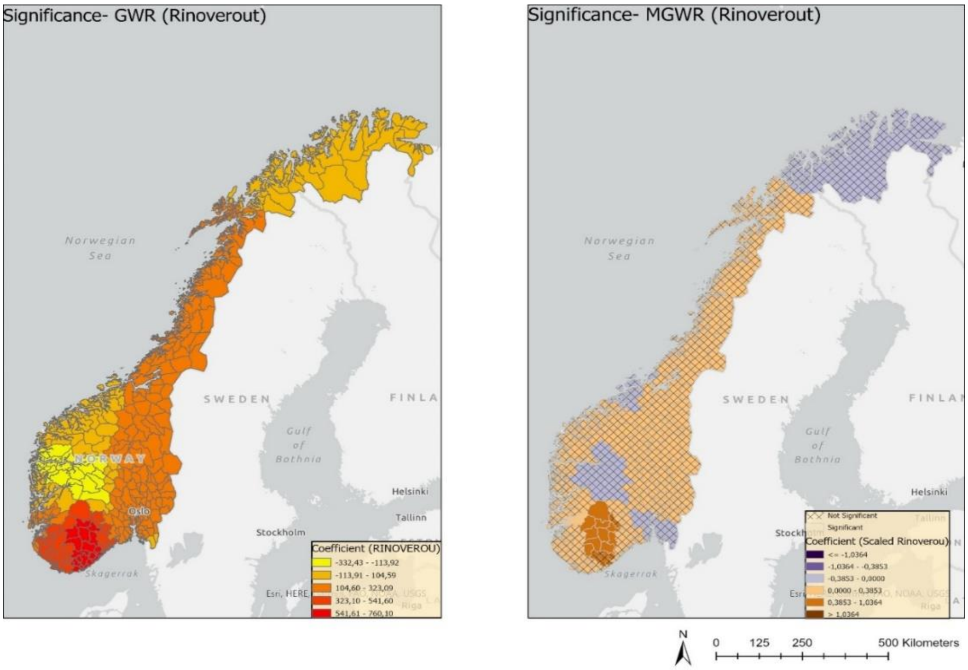


Figure 12, the map by GWR and MGWR for the effect of commuters travelling for the job to the charging points, shows a positive coefficient for the northern kommunes and most of the eastern kommunes, with some exceptions in central Norway. This shows the positive relation between the ratio of commuters and the charging points. The kommunes with higher positive coefficients are among the big cities of Norway and have a higher positive ratio for commuters travelling in and out. However, MGWR showed that only some kommunes in southern Norway have the significance of commuters for charging points.

Figure 12: GWR vs MGWR- R inoverout



Multilevel Regression Model

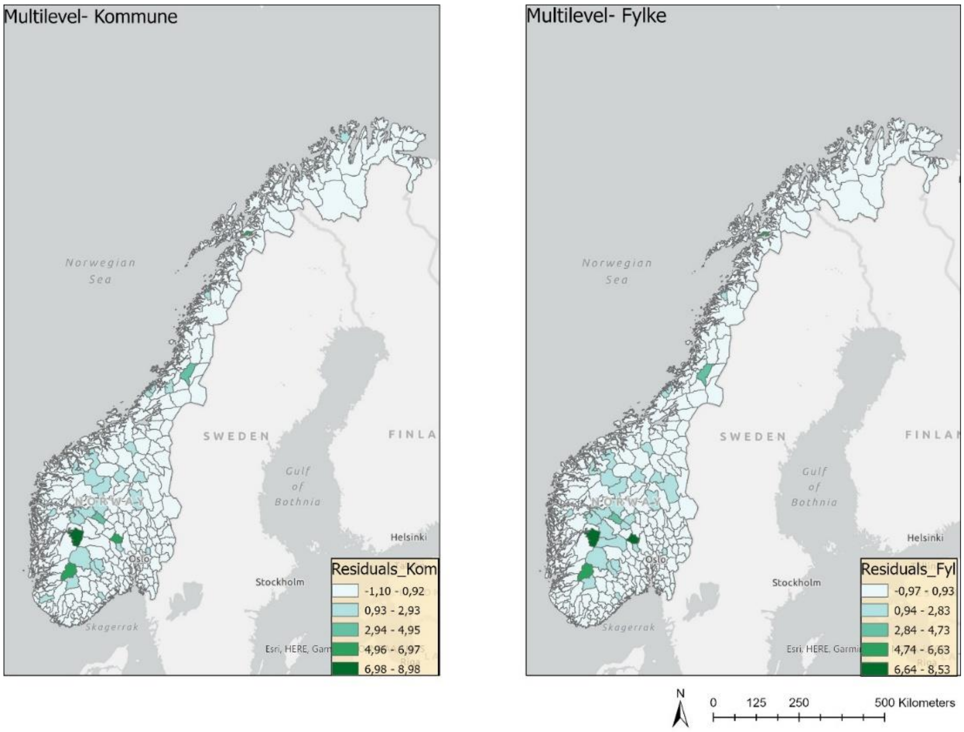
The multilevel regression model with 2 levels, first-level (kommune) and second-level (fylke) shows little difference in the standardized residuals with and without considering the fylke level. Like the global linear regression model, the multilevel regression model showed that the ratio of commuters had a solid positive relationship followed by voting per population. This indicates that areas with more commuters and voters will likely have more public charging points. However, elbil registration was found to have a slightly negative relationship with the charging points in the fylke level followed by the median income of the people. This indicates that areas with more registered electric vehicles and income do not necessarily have more public charging points.

The model predicted that the ratio of commuters is significant in establishing charging points. The random effect at the fylke level is comparatively lower (42718.37) with a standard error of 27337.27 compared to the random effect at the kommune level (592321.6) and standard error of 45059.74. This vast difference in the random effect and low value for the LR test vs one-level ordinary linear regression shows that the variables used for these models are insignificant and that establishing public charging points is more consistent at the fylke level than the kommune level. It also shows that these factors may not be the primary drivers in the decision-making process, and other factors might be considerable.

```
. mixed CP_per_100kcapita_2022 || Fylke: || Fylke:

Performing EM optimization ...

Performing gradient-based optimization:
Iteration 0:  Log likelihood = -2886.2815
Iteration 1:  Log likelihood = -2886.2815

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =    356
Group variable: Fylke                           Number of groups  =     11
                                                Obs per group:
                                                              min =      1
                                                              avg =   32.4
                                                              max =     51
                                                Wald chi2(0)      =      .
Log likelihood = -2886.2815                     Prob > chi2       =      .

------------------------------------------------------------------------------
CP_per_100k~2 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
--------------+---------------------------------------------------------------
        _cons |   609.4112   62.89721     9.69   0.000     486.1349    732.6874
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
Fylke:                (empty)|
-----------------------------+------------------------------------------------
Fylke: Identity              |
                  var(_cons) |   21231.99   17311.32      4295.077    104956.8
-----------------------------+------------------------------------------------
               var(Residual) |   631181.2   47954.86      543854.6    732529.7
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 4.25          Prob >= chibar2 = 0.0197
```

```
. mixed CP_per_100kcapita_2022 VotingPerPop Elbil_per_100kcapita_2022 I_2021 Rin
> OverOut || Fylke: || Fylke:

Performing EM optimization ...

Performing gradient-based optimization:
Iteration 0:  Log likelihood = -2877.3644
Iteration 1:  Log likelihood = -2877.3644

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =    356
Group variable: Fylke                           Number of groups  =     11
                                                Obs per group:
                                                              min =      1
                                                              avg =   32.4
                                                              max =     51
                                                Wald chi2(4)      =  19.34
Log likelihood = -2877.3644                     Prob > chi2       = 0.0007

------------------------------------------------------------------------------
CP_per_100k~2 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
--------------+---------------------------------------------------------------
 VotingPerPop |   12.28403    11.4063     1.08   0.282    -10.07192    34.63997
Elbil_per_1.. |  -.0213314    .016886    -1.26   0.206    -.0544274    .0117645
       I_2021 |  -.0011304   .0008566    -1.32   0.187    -.0028094    .0005485
   RinOverOut |   309.3908   103.3173     2.99   0.003     106.8927     511.889
        _cons |   611.6281   844.8713     0.72   0.469    -1044.289    2267.546
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
Fylke:                (empty)|
-----------------------------+------------------------------------------------
Fylke: Identity              |
                  var(_cons) |   42718.37   27337.27      12186.96    149738.7
-----------------------------+------------------------------------------------
               var(Residual) |   592321.6   45059.74      510274.7    687560.8
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 10.65         Prob >= chibar2 = 0.0005
```

Figure 13: Multilevel Regression Model



Spatial mapping of the standardized residuals for the fylke level showed slight differences in the charging points by the same explanatory variables on several kommunes. However, the changes were not very significant and thus changes (addition and/or removal) of some variables could lead to a better model and significant results for the changes.

Conclusion

This study applied various statistical methods to characterize the spatial distribution of electric charging points using 356 kommunes in Norway. It helped us improve our understanding of the factors that influence the establishment of charging points and helped us understand the differences between different methods that could be used in explaining spatial data. The various methods were performed differently and could have been better for prediction. It was challenging to interpret the results and the differences between methods, and this could be related to the high correlation between the explanatory variables used in the study. Weighted regression methods such as GWR and MGWR were helpful to get results that were beyond the capacity of traditional linear regression models.

As suggested in many previously conducted research, detailed investigation and use of MGWR may help policymakers and developers plan and policymaking to establish more charging points to accommodate electric vehicles on the road. This method could be used to assess and improve the robustness of the explanatory variables and the model. The lower values of AIC, AICs, and improved R2 value by MGWR provided a better model fit, and the results from this model were also able to address and solve issues of multicollinearity of the variables.

Regardless of the factors that were taken into consideration to examine the effect on electric charging points, all models based on the provided dataset predicted a high number of charging points would be established or will be established at the high-use transport corridors. This was also found in the optimized hot spot analysis results, which considered changes in charging points between 2020 and 2022. Most of the models developed in this study supported it statistically. They showed the ratio of commuters associated with the higher number of charging points, while median income was not crucial for increased charging points. This was also in line with some literature highlighting the increased use of electric vehicles commuting to or from jobs because of the high availability of charging facilities between the destinations.

Apart from the factors taken for this study, some other underlying factors might be highly influential in increasing public charging points. While the independent variables weren’t explained much by the OLS model, the same independent variables produced significant variance in both the GWR and MGWR models; most likely, the relationship between the variables varies across space. It would also be beneficial to look at the residuals, spatial autocorrelation and statistical significance of coefficients, add more relevant variables and explore other spatial regression techniques that would be more suitable for this context.

Limitations and Further Study

The primary goal of our research has been to identify the numerous factors driving the development of public charging infrastructure and establish its critical role in promoting electric vehicle (EV) adoption. To better understand the complexities of infrastructure growth, this study examined various socioeconomic, policy-driven, and demographic variables. However, certain methodological limitations that might improve further investigations in this field must be acknowledged.

Given Norway's position as one of the world's leading countries in EV usage, the patterns observed here may only partially represent trends in other countries with different economic profiles, policy environments, and cultural attitudes toward environmental issues. Our study's two-year span and exclusive focus on Norway provide a thorough, localized understanding but limit the range of our findings' applicability.

Our methodological approach has limitations. The reliance on quantitative data provides a solid foundation for statistical analysis but may not capture the full range of qualitative factors influencing individual EV adoption decisions. Personal attitudes toward technology, environmental concerns, and the influence of social groups could all contribute to a better understanding, but they were outside the scope of this study.

Long-term studies following EV adoption trends over a longer period could extend these findings. Research across cultures could validate our findings' applicability in various contexts, providing a global perspective on the transition to electric mobility. Qualitative research could uncover consumer motivations and barriers, providing a complete view of numbers and spatial analysis alone.

Including a broader set of variables may also improve future models. Elements such as technological advancements in EVs and charging infrastructure, policy changes, and shifts in global environmental attitudes can greatly change the pattern of EV adoption and infrastructure development. By addressing these limitations and broadening the scope of research, future studies can provide a larger, more detailed plan for the transition to sustainable transportation.

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IZGRADNJA JAVNE INFRASTRUKTURE PUNJAČA: FAKTORI NJOHOVE SNAŽNE DIFUZIJE U NORVEŠKOJ

Apstrakt: Saobraćajni sektor je glavni faktor koji doprinosi emisiji gasova staklene bašte, a Norveška je jedna od vodećih zemalja u prelasku na privatni transport sa nultom emisijom i niskim emisijama. 2022. godine, preko 80% novih automobila prodatih u ovoj zemlji je bilo električnih ili hibridnih. Ova studija istražuje dinamiku između javne infrastrukture za punjenje i difuzije električnih vozila u Norveškoj. Iako je kućno punjenje u Norveškoj široko rasprostranjeno, javna infrastruktura takođe igra značajnu ulogu. Ova studija istražuje faktore koji utiču na njihovu vezu sa usvajanjem EV. Studija koristi višekriterijumski pristup u korišćenju podataka na nivou opština od 2020. do 2022. Inicijalna regresija običnih najmanjih kvadrata (OLS) pružila je osnovno razumevanje, praćena analizom vrućih tačaka da bi se identifikovali prostorni klasteri visokog i niskog EV usvajanja. Geografski ponderisana regresija (GVR) i višestepena geografski ponderisana regresija (MGVR) otkrile su finije lokalne varijacije u odnosu javne infrastrukture za punjenje i difuzije EV u 356 opština i 11 okruga. Opštine sa više stanica pokazuju veću upotrebu EV. Ova studija naglašava značaj razvoja javne infrastrukture za punjenje za uvođenje električnih vozila. Identifikovani su i dodatni faktori uticaja, kao što su EV troškovi, dostupnost novih modela i percepcija javnosti. Nalazi nude vredne uvide za kreatore politike i zainteresovane strane koji promovišu usvajanje EV.

Ključne reči: javne stanice punjača, električna vozila, Norveška.

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Asim Lamsal, a bachelor's graduate in Civil Engineering in 2013, a master's degree in Innovation Management from the University of Oslo, Norway in 2020 and currently a master's student in Smart Mobility and Urban Analytics (SMUA) at Oslo Metropolitan University, Oslo, Norway is keen on research and studies related to sustainability, urban mobility and spatial analytics. With the working experience of more than 5 years in the engineering industry, he is passionate about sustainable urban mobility solutions and urban analytics. Lamsal has actively engaged and participated in research projects related to smart urban mobility systems and the optimization of urban transportation networks.

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