Residential demand response enrollment scenarios: A geospatial case study of Finland

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***Abstract*—The transition of a conventional energy system to a sustainable one requires the availability of flexible loads on the consumption side. Coupling several individual residential consumers can provide a high degree of flexibility, which can help the energy system during times of need. This paper aims to analyze the potential enrollment of Finnish residential consumers in demand response by using an agent-based model. The motivators determining consumer enrollment are personal satisfaction, the neighborhood effect, and the social effect. In this paper, the geospatial dataset of Finland including the EV registrations are utilized and simulated for the year 2019. A sensitivity analysis is performed to analyze the effect of varying parameters in the simulation. The results highlight the high enrollment rates during the beginning of the year and lower enrollment rates during the summer months.**

***Index Terms*—Demand response, Agent-based modeling, Residential consumers, Decision-making, geospatial analysis**

I. INTRODUCTION

The need for flexibility within the energy system is of utmost importance with the rapid increase in installations of intermittent renewable energy in the electricity system. Residential sector corresponds to roughly a quarter of the overall electricity consumption in the EU. Though the amount of flexible electricity is limited in a single household, but when several households are coupled together can assist the electrical grid during the time of need. Additionally, the increase in installations of solar PV systems and the electrification of the heating and transport sector has raised the amount of flexibility which can be extracted from a residential household. With such advancements happening in a widespread scale in the near future, the residential sector plays an important role in providing flexibility services.

Demand Response (DR) is a potential solution which aids in the transition towards a sustainable grid. With DR, Direct Load Control (DLC) is preferred over Implicit DR by residential consumers due to a higher flexibility of quantity, location, and timing of flexibility [1]. DR has been employed for decades in the industrial and commercial sectors but have been not extensively used within the residential sector. One possible reasoning is the lack of understanding of residential consumers' willingness to participate in such programs. Parrish et al. [2] conducted an in-depth literature review on the motivators for residential consumers' willingness to enroll in demand response. The findings highlight the importance of both personal and social factors (financial gains, influence from friends and neighborhood).

In order to evaluate residential consumers' enrollment in DR, Sridhar et al. [3] developed a tool based on Agent Based Modelling (ABM) in which each residential consumer is treated as an individual agent and have their own personal and social factors influencing their decision to enroll in DR. This paper builds on the same methodology proposed by Sridhar et al. while incorporating the geospatial dataset for the inhabitants of Finland obtained from Statistics Finland. The geospatial dataset incorporates the socio-economic dataset of all residential consumers in 1 kilometer square resolution across Finland.

II. MODEL DESCRIPTION

The model employed in this study builds upon the model introduced by Sridhar et al. [3], and its structure is described in this section. The model is divided into two main components: (1) the Home Energy Management System (HEMS) and (2) the Agent-Based Model (ABM). The HEMS utilizes mixed-integer linear programming to schedule household loads for consumers. The flexible loads considered in this study include bidirectional electric vehicle (EV) charging, a heat pump (HP), photovoltaics (PV) coupled with a battery energy storage sys-

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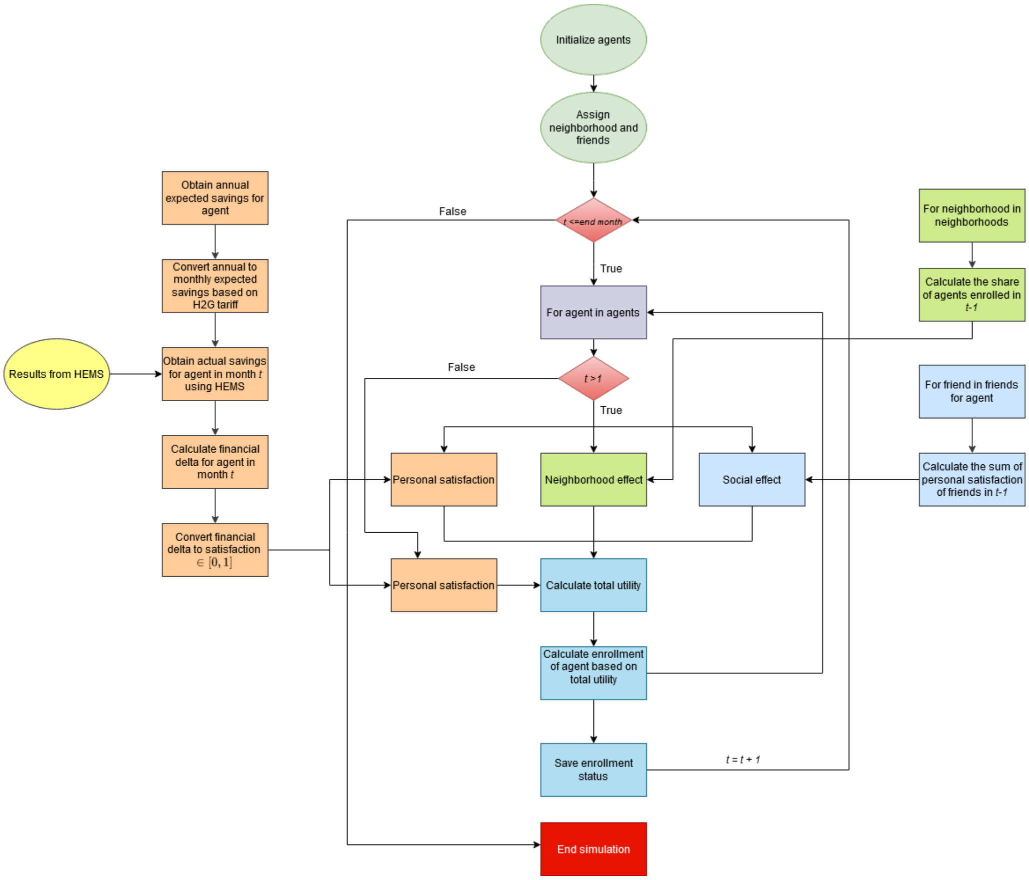

Fig. 1: Flowchart of ABM [3]

tem (BESS), a washing machine (WM), a dishwasher (DW), and a tumble dryer (TD). The primary objective of the HEMS is to maximize financial savings through energy arbitrage by utilizing flexible loads. The HEMS schedules the flexible loads of consumers based on the day-ahead electricity prices, and for simplification, consumers are assumed to accept the proposed schedule. The HEMS runs daily for each household according to their available flexible loads, which can be employed in DLC DR. The equations governing the operation of flexible appliances, along with associated parameters, decision variables, the objective function, and constraints, are provided in detail in [3]. The outputs of the HEMS yield the schedule for flexible appliances across all consumers and indicate the potential financial savings if consumers participate in DLC DR.

The ABM simulates consumer enrollment in DLC DR. In this model, each consumer is treated as an individual agent, randomly assigned to a neighborhood with random friends. Consumer enrollment is determined based on their total utility value (on a scale from 0 to 1), the consumer is considered to enroll in DLC DR if their total utility is greater than their threshold value (dependent on consumer subgroups based on consumer socioeconomic). The total utility is derived from three factors: (1) personal satisfaction (PS), (2) neighborhood effect (NE), and (3) social effect (SE). The personal satisfaction of each consumer is determined by their financial savings obtained through HEMS operation and their expected annual savings (randomly assigned based on the size of flexible loads in their household; further details are available in [3]). The neighborhood effect is based on the proportion of agents/consumers from the same neighborhood who were enrolled in DLC DR during the previous month. The social effect reflects the average personal satisfaction of the agent's friends during the previous month. The total utility is calculated using equation 1.

$$u_{i,j}^{Total} = \frac{w_i^{PS} * u_{i,j}^{PS} + w_i^{NE} * u_{i,j}^{NE} + w_i^{SE} * u_{i,j}^{SE}}{w_i^{PS} + w_i^{NE} + w_i^{SE}} \qquad (1)$$

The total utility (defined as $u_{i,j}^{Total}$ for consumer i in month j) is calculated as the convex combination of the utilities of PS, NE, and SE, given by (1).

The operation of the ABM is illustrated in Fig. 1.

III. EXPERIMENTAL SETUP

In order to explore the residential consumers' enrollment rates in DLC DR determined by the HEMS–ABM tool proposed above, the following experimental setup is examined:

- The Finnish socioeconomic geospatial dataset is considered, which yields 4,108,740 residential consumers above 18 years who are eligible to enroll in DR.

- Each agent is considered to be in an individual household, making their own decision to enroll in DLC DR.
- The neighborhoods are based on the registered municipality of the agent, and the total number of municipalities considered based on the geospatial dataset are 311.
- Each consumer has four friends randomly assigned, out of which two friends are coming from the same neighborhood and two friends from outside the neighborhood of the consumer.
- The day-ahead prices of the year 2019 are used in the simulation in the ABM to avoid the abnormal price levels during the European energy crisis. The consumers in the ABM are assumed to have a spot price contract to ensure maximum financial benefits for their energy arbitrage. The electricity buying costs are based on the spot market prices and are calculated as:

$$\lambda_t^{buy} = \lambda_t^{spot} * (1.24) + 8.035 \text{ c/kWh}, \tag{2}$$

where λ_t^{buy} is the cost of electricity to be bought by the consumer from the grid at time t based on the spot prices λ_t^{spot} in c/kWh, and 24% is added to take into account the value added tax. The additional costs correspond to the retailer's margin, electricity distribution cost, and electricity tax for small-scale consumers [4]–[6].
- The electricity selling price from the consumer to the grid is represented as H2G in Fig. 1, and it is calculated as

$$\lambda_t^{sell} = \lambda_t^{spot} - 0.25 \text{ c/kWh}, \tag{3}$$

where λ_t^{sell} is the selling price of electricity by the consumer to the grid at time t based on the spot prices λ_t^{spot} in c/kWh, and the retailer's margin of 0.25 c/kWh is removed from this selling price [5], [6].
- All consumers have a WM (Bosch WAX32GH4GB with a daily consumption of 0.4038 kWh), a TD (Bosch WTU8769SSN with a daily consumption of 0.6657 kWh), and a DW (Bosch SMV6ZCX42E with a daily consumption of 0.57534 kWh) at their disposal to be used in DLC DR [7].
- The consumers who own an EV, has the possibility to use bidirectional charging having a capacity of 65 kWh [8] with a daily usage of 50 km between 09:00 and 18:00, corresponding to 10 kWh/day [3].
- The share of consumers having an HP for heating is assumed to be 60%, and it is randomly assigned. The indoor temperature can be varied between 19°C and 22°C; the thermodynamic properties of the household are reported in detail in [3]. Additionally, the same thermal model is used for all houses having electric heating. The dataset is split into 7 different regions and the outdoor temperature dataset for the entire region is based on a selected spot as highlighted in Fig. 2. The highlighted spots are representing the main cities in each region, and they are as follows: Mariehamn, Helsinki, Tampere, Kuopio, Oulu, Rovaniemi and Inari.
- The share of consumers having a PV and BESS system (5 kW PV panels with 20 kWh BESS capacity) is assumed to be 10%, and it is randomly assigned. The PV profile was generated using PV GIS developed by Suri et al. [9].
- The expected annual savings of consumers are randomly assigned, and their limits are obtained based on [3], [10] and can be seen in Table I (the HP savings are in order from southern to northern Finland).

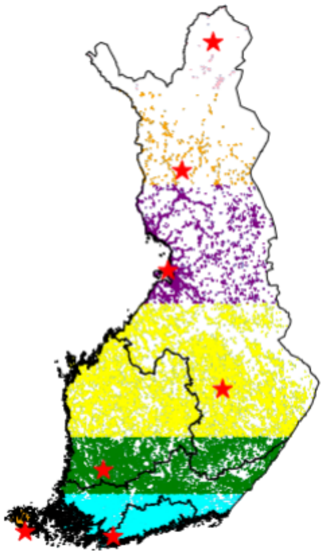

Fig. 2: Finnish geospatial dataset with representing stations highlighted for regions

TABLE I: Range of expected annual savings based on regions (€/anum)

Location	HP	EV	Appliances
Mariehamn	(60,400)	(60,250)	(10,50)
Helsinki	(60,400)		
Tampere	(85,425)		
Kuopio	(85,425)		
Oulu	(110,500)		
Rovaniemi	(135,475)		
Inari	(150,500)		

- Consumers are grouped into adopters, followers and neutral based on k-means clustering used by Sridhar et al. [11]. The adopters are consumers who are easily willing to enroll in DR; Followers are consumers who need more benefits from DR than adopters; Neutral are consumers who do not have any particular inclination towards DR. As a result, the threshold for adopters, followers and neutral are 0.3, 0.4 and 0.5 respectively.
- Consumers can decide to enroll or disenroll in DLC DR on a monthly basis, and their enrollment is based on their total utility from the previous month. There are no restrictions on the number of times a consumer can enroll or disenroll from the program.

IV. RESULTS AND DISCUSSION

Based on the above experimental setup, the ABM was simulated for the electricity prices for the year 2019; the geospatial enrollment rates of consumers in DLC DR in Finland are shown in Fig. 3 and the geospatial figures for different consumers based on EV registrations can be seen in Appendix section A.

As shown in Fig. 3, the enrollment trends for various consumer types can be observed. For all consumers in Finland, the enrollment rate started at approximately 20% at the beginning of the year and steadily increased until May. This rise can be attributed to the onset of spring and an increase in price volatility, which encouraged consumer participation. The highest enrollment rate occurred in May, reaching 42% overall. However, this trend declined during the summer months, when electricity prices were close to zero, resulting in minimal personal satisfaction and, consequently, lower consumer enrollment. The lowest enrollment rate was recorded in August, at around 15%, with a slight increase toward the end of the year as prices began to rise again.

Similar patterns were observed across different consumer groups based on the availability of flexible loads. Consumers with heat pumps (HP) exhibited a higher enrollment rate, peaking at 65% in April, and reaching a low of 14% in August, following a trend similar to that of all consumers. For consumers with photovoltaic (PV) systems coupled with battery energy storage systems (BESS), the highest enrollment rate of 99% occurred between April and June, coinciding with maximum PV production, which facilitated easier enrollment. However, during the winter months, the enrollment rate for these consumers dropped to nearly 0%. Consumers with electric vehicles (EVs) showed a trend similar to that of all consumers, with the highest enrollment rate of 98% in May and a minimum of 58% in September.

To assess the impact of varying model parameters, a sensitivity analysis was conducted by modifying the parameters as outlined in Table II. The parameters considered are the expected annual savings of a consumer (which is changed by multiplying the factor shown in Table II), share of HP consumers (shown as a percentage of entire population), share of PV+BESS consumers (shown as a percentage of entire population) and the threshold value for different consumer subgroups (adopters;followers;neutral).

TABLE II: Sensitivity analysis parameters

Parameter	Δ_1	Δ_2	Δ_3	Δ_4	Δ_5
Annual Expected Savings	0.7	0.85	1	1.15	1.3
HP Consumers	20%	30%	40%	50%	60%
PV+BESS Consumers	10%	15%	20%	25%	30%
Threshold	{0.2;0.3;0.4}	{0.25;0.35;0.45}	{0.3;0.4;0.5}	{0.35;0.45;0.55}	{0.4;0.5;0.6}

The enrollment rates for all consumers in demand response (DR) for the months of May and August, with varying parameters, are depicted in Fig. 4a and Fig. 4b, respectively.

A clear direct relationship is evident between the share of HP consumers and PV+BESS consumers and the enrollment rate. Conversely, an indirect relationship can be observed between expected annual savings and the consumer threshold on enrollment rates. The low consumer threshold had a significant influence on the enrollment rates in August.

Given the inherent randomness in the model, a Monte Carlo analysis would ideally be required. However, due to computational complexity and the similar trends previously noted in the results by Sridhar et al. [3], a ±10% variation in consumer enrollment can be considered in this simulation.

V. CONCLUSION

This study extends the understanding of consumer enrollment in DLC DR programs by analyzing the influence of flexible household loads and consumer behavior. This paper utilizes an agent based modelling approach to simulate consumer enrollment over the span of 1 year. The geospatial dataset of Finland is considered, and the results are simulated for 2019 year. The enrollment patterns in Finland show seasonal variation, with higher participation in spring and lower in summer, driven by electricity price fluctuations and financial savings. The geospatial dataset can be further utilized to check the enrollment patterns in different regions and can be utilized to understand the enrollment patterns while providing insights to increase DR adoption.

Consumer groups with flexible loads, such as HP, PV+BESS, and EVs, displayed distinct enrollment trends. HP consumers had peak enrollment in spring, while PV+BESS consumers showed maximum participation during high PV generation periods, illustrating the importance of renewable integration. EV owners followed the general trend of all consumers, with notable participation in May and a reduction in late summer.

A sensitivity analysis revealed a direct relationship between the share of HP and PV+BESS consumers and enrollment rates, while expected annual savings and consumer thresholds had an indirect influence. Geospatial datasets were instrumental in mapping neighborhood effects and social influence on enrollment decisions, providing additional insights into localized consumer behavior. Although a full Monte Carlo analysis was not performed, a ±10% variation in enrollment rates is consistent with prior studies.

In conclusion, this study emphasizes the potential of residential flexibility in DR programs and highlights the flexibility of the ABM while having access to geospatial dataset to explore in-depth regional analysis. Targeted strategies, including financial incentives and social influence mechanisms, will be essential to enhance DR participation.

VI. ACKNOWLEDGMENT

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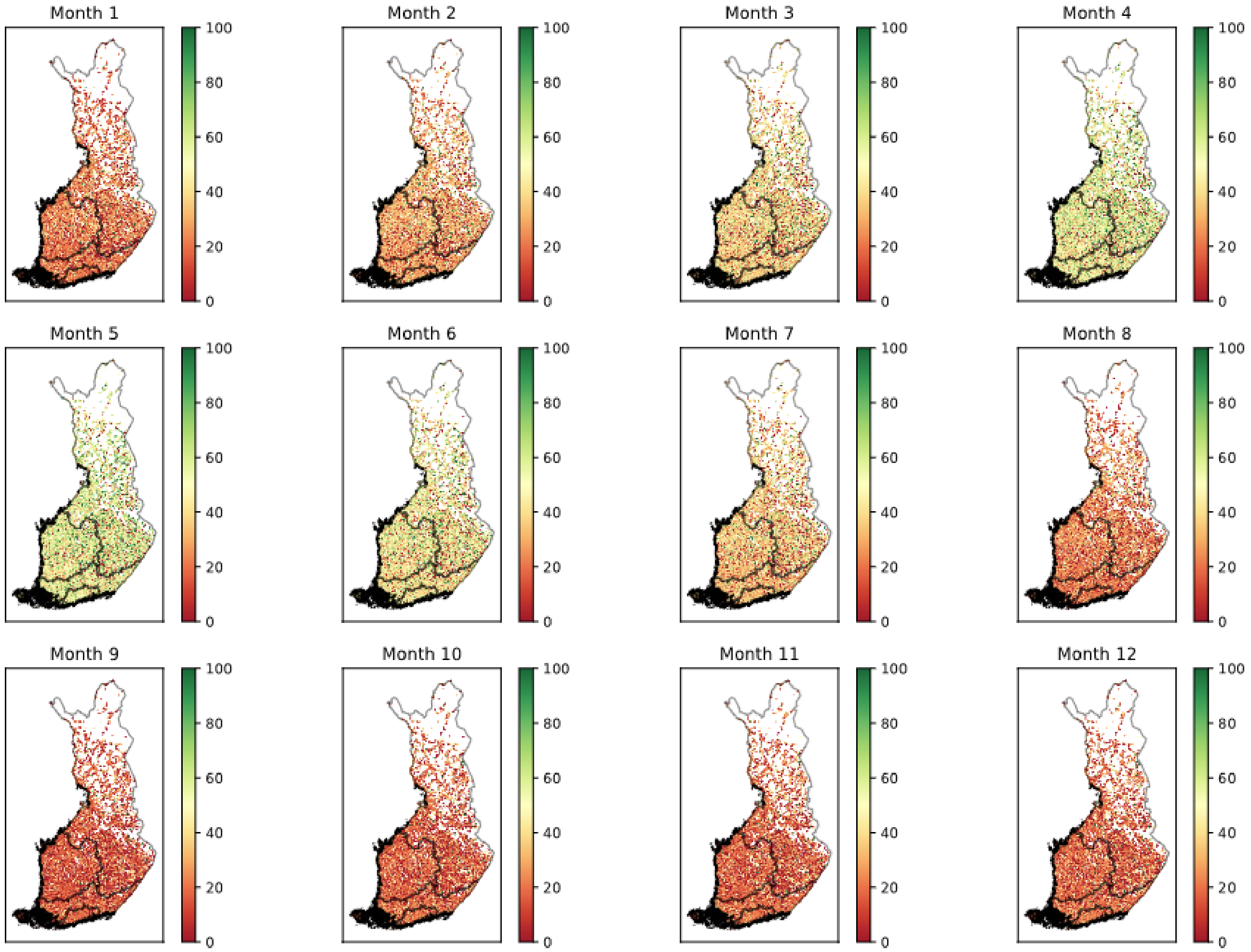
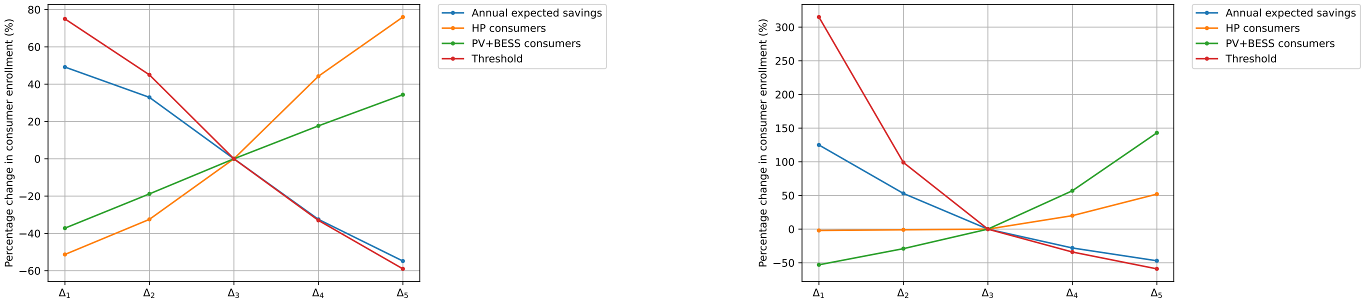


Fig. 3: Monthly enrollment rates of consumers in Finland



(a) Consumer enrollment in May

(b) Consumer enrollment in August

Fig. 4: Sensitivity analysis

REFERENCES

[1] X. Xu, C.-f. Chen, X. Zhu, and Q. Hu, "Promoting acceptance of direct load control programs in the united states: Financial incentive versus control option," *Energy*, vol. 147, pp. 1278–1287, 2018.

[2] B. Parrish, R. Gross, and P. Heptonstall, "On demand: Can demand response live up to expectations in managing electricity systems?," *Energy Research & Social Science*, vol. 51, pp. 107–118, 2019.

[3] A. Sridhar, S. Honkapuro, F. Ruiz, J. Stoklasa, S. Annala, and A. Wolff, "Residential consumer enrollment in demand response: An agent based approach," *Applied Energy*, vol. 374, p. 123988, 2024.

[4] "Verkkopalveluhinnasto." https://pkssahkonsiirto.fi/wp-content/uploads/pkss_verkkopalveluhinnasto_01072022.pdf. Accessed 21/11/2023.

[5] "Electricity products and prices." https://www.helen.fi/en/electricity/electricity-products-and-prices. Accessed 24/11/2023.

[6] “Electricity price comparison.” https://www.sahkonhinta.fi/. Accessed 21/11/2023.

[7] A. Sridhar, S. Honkapuro, F. Ruiz, S. Annala, and A. Wolff, “Assessing the economic and environmental benefits of residential demand response: A finnish case study,” in *2022 18th International Conference on the European Energy Market (EEM)*, pp. 1–6, IEEE, 2022.

[8] V. Tikka, *On Load Modeling of Electric Vehicles—Energy System Viewpoints*. Doctoral dissertation, LUT University, 2024. Available at https://lutpub.lut.fi/bitstream/handle/10024/166753/Ville

[9] M. Suri, T. Huld, T. Cebecauer, and E. D. Dunlop, “Geographic aspects of photovoltaics in europe: contribution of the pvgis website,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 1, no. 1, pp. 34–41, 2008.

[10] A. Sridhar, S. Honkapuro, F. Ruiz, J. Stoklasa, S. Annala, A. Wolff, and A. Rautiainen, “Toward residential flexibility—consumer willingness to enroll household loads in demand response,” *Applied Energy*, vol. 342, p. 121204, 2023.

[11] A. Sridhar, S. Honkapuro, F. Ruiz, J. Stoklasa, S. Annala, A. Wolff, and A. Rautiainen, “Residential consumer preferences to demand response: Analysis of different motivators to enroll in direct load control demand response,” *Energy Policy*, vol. 173, p. 113420, 2023.

APPENDIX A
GEOSPATIAL ENROLLMENT FIGURES

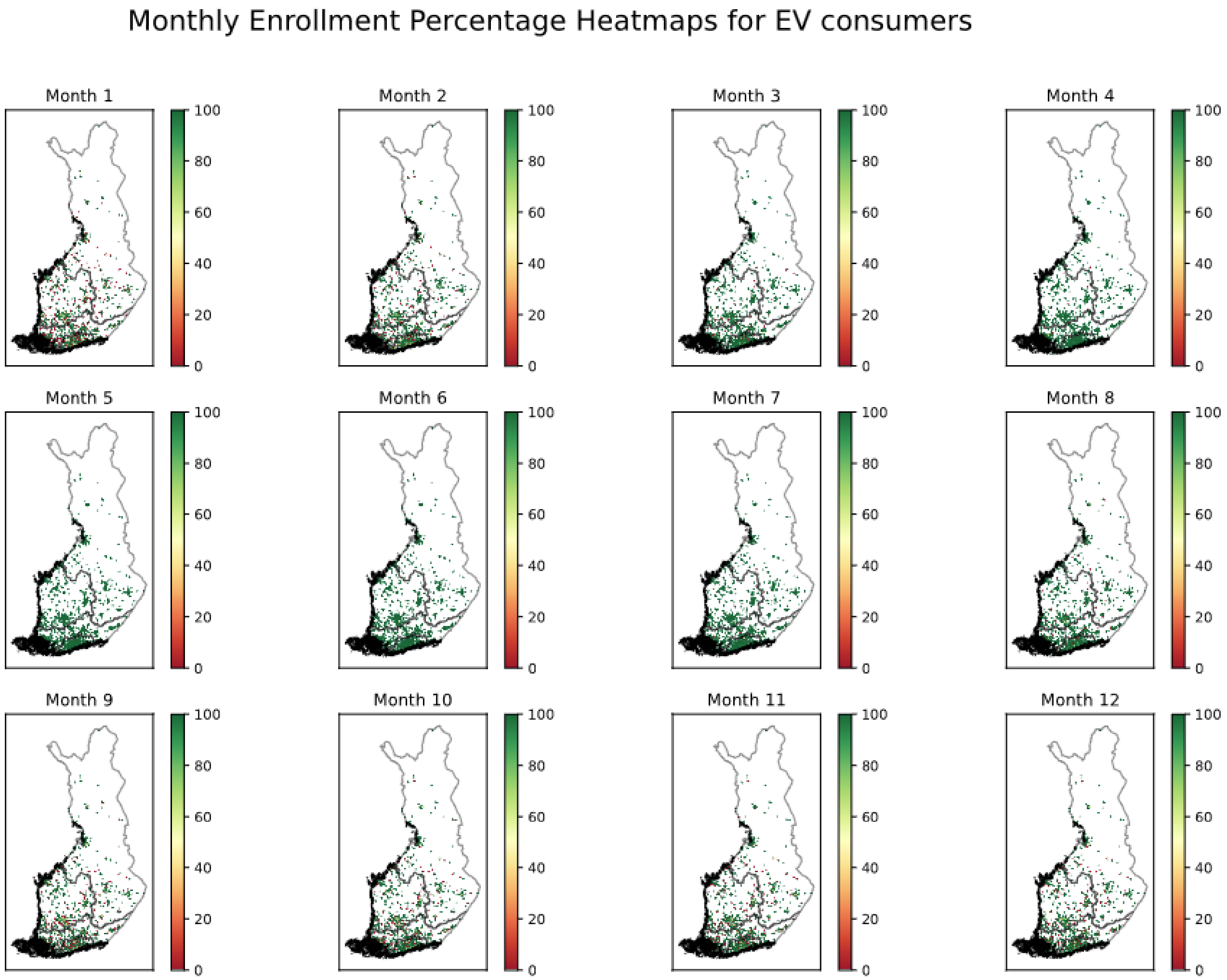


Fig. A.1: Geospatial enrollment rate of EV consumers in Finland