reviewed paper

# Spatial Planning on Electricity – What smart meter data can tell us about spatial structures

*Dirk Engelke, André Biskup*

(Prof. Dr. Dirk Engelke, OST Eastern Switzerland University of Applied Sciences, dirk.engelke@ost.ch)
(André Biskup, OST Eastern Switzerland University of Applied Sciences, andre.biskup@ost.ch)

DOI: 10.48494/REALCORP2025.6107

## 1 ABSTRACT

Spatial planning approaches such as densification, the 15-minute city, or net-zero initiatives increasingly promote and necessitate mixed-use land allocations. Traditionally, land use was segmented into distinct categories such as residential, industrial, commercial, or transportation. This zoning-based approach provided clear guidance on expected spatial functions and human activities within designated areas. However, as mixed-use developments become more prevalent, the conventional distinction between living, working, and other activities becomes increasingly blurred. Consequently, traditional zoning regulations use more and more mixed-use zoning to regulate spatial impacts. But the knowledge of spatial impact does not fit the need for coordination and regulation. The dynamics of urban life require planning instruments that go beyond static land-use maps and embrace real-time and usage-based data to inform spatial policies.

To address this challenge, planning authorities require an empirical foundation that captures real-world spatial usage and interactions. Conventional spatial data from federal or state topographic offices primarily describe physical land features but lack insights into actual usage patterns. This gap is increasingly critical as mixed-use developments grow in scale and complexity. The key challenge is no longer defining land use but understanding how space is utilized in real-time to inform better regulatory measures. Additionally, understanding peak hours of electricity consumption can provide indirect yet valuable insights into mobility patterns, working behaviors, and residential activity shifts.

Smart meter data offers a novel and dynamic source of information to bridge this gap. As Engelke (2017) states, "Not only more accurate and up-to-date geodata is available for planning, but also unprecedented knowledge about the actual use of space." By capturing detailed electricity consumption at the household level, smart meters provide indirect but valuable insights into human presence, activity patterns, and the intensity of land use. The mandatory rollout of smart meters presents an unprecedented opportunity to integrate high-resolution temporal data into spatial planning. The EU has decided in 2009 to implement smart meter in all member states, and e.g. Germany decided obligatory smart meters in all households by 2023. Switzerland intends to cover 80% of Swiss households by 2027.

Aggregated smart meter data at neighborhood or district levels allows planners to assess deviations between planned and actual land use, thus informing evidence-based policy adjustments and regulatory interventions. This integration has the potential to refine urban planning strategies, providing a data-driven approach to analyze urban vitality, the success of mixed-use developments, and urban energy efficiency.

Moreover, leveraging smart meter data can help policymakers refine zoning laws and introduce dynamic zoning approaches that adapt to real-time conditions. Instead of relying solely on traditional land-use maps, urban planners can create policies based on actual demand, energy efficiency, and mobility behaviors. For example, if a neighborhood exhibits a sharp increase in electricity consumption during typical work hours, it may indicate the presence of informal office spaces or remote work trends that challenge conventional zoning assumptions. By using smart meter data to validate and adjust planning regulations, cities can enhance the efficiency of land use, reduce urban sprawl, and support more sustainable forms of development.

This paper explores the potential of smart meter data for spatial planning, identifying its strengths, limitations, and future research needs. Using open data from the Swiss Lucerne region as a case study, the paper investigates how temporal spatial structures can be derived from electricity consumption data. The objective is not merely to analyze a specific case but to examine the broader applicability of such data in addressing spatial planning challenges. Furthermore, this research contributes to the debate on how digitalization and real-time data streams can enhance planning effectiveness, ensuring that cities remain adaptable and resilient in the face of growing urbanization and climate challenges.

Keywords: data science, smart city, spatial planning, smart meter data, energy

## 2 LITERATURE REVIEW ON SMART METER AND MOBILITY DATA

The spatiotemporal analysis of data enables the mapping, understanding, and optimization of complex dynamics of human behavior (represented by their energy consumption) and spatial patterns. Given the fact that there is rarely literature on the interaction between energy consumption and spatial patterns, but various studies on analyzing energy data, this paper examines these different methodological approaches and their implications for spatial planning.

Kragh-Furbo and Walker (2018) highlight how digital transformation in electricity metering generates fine-grained, high-resolution data, offering a deeper understanding of energy consumption patterns. This data not only enables more precise allocation of responsibilities in energy systems but also allows for new forms of governance and demand-side management strategies. The performative consequences of this transformation are particularly relevant for policymakers seeking to integrate data-driven insights into regulatory frameworks. Additionally, the ability to track energy usage at a granular level provides a means to optimize energy efficiency and support sustainable urban development.

In the domain of mobility research, Wang & Huang et al. (2019) demonstrate how spatiotemporal analysis of GPS-based taxi data helps identify urban traffic patterns. Their innovative visualization techniques, such as chord diagram plots, effectively represent origin-destination flows across multiple spatial scales. These findings underscore the interdependencies between mobility behavior and spatial structures, offering valuable input for sustainable urban planning. Moreover, by integrating mobility data with energy consumption data, planners can create a more comprehensive understanding of urban activity dynamics.

The methodological approaches to analyzing smart meter data are diverse. The Swiss Federal Office of Energy (SFOE, 2016) has developed classification and clustering algorithms that derive household characteristics based on consumption profiles. Machine learning techniques, enriched with additional data sources such as meteorological and demographic information, enable more precise energy advisory services and system efficiency improvements. Similarly, Wang & Henri et al. (2020) propose an activity-based modeling approach, leveraging smart meter data to recognize household activities and their temporal dynamics. These studies illustrate how electricity consumption data can extend beyond traditional energy management and contribute to broader urban planning applications. By employing advanced machine learning techniques, smart meter data can be further refined to predict future energy demands and urban mobility needs.

Peng et al. (2021) advance this field by developing a high-resolution predictive model based on potential flow theory. Their entropy-based indices quantify clustering intensity and meteorological dependencies, improving the accuracy of energy demand forecasting. This approach is particularly relevant for integrating smart meter data into spatial planning, as it provides predictive insights into future consumption trends and their spatial implications. The ability to anticipate future energy demands can aid in the planning of decentralized energy systems and localized energy production, fostering more resilient urban environments.

Alternative approaches in the analysis of urban mobility data provide complementary perspectives. Wang & Huang et al. (2019) apply interactive visualization techniques to large-scale trajectory datasets, enabling a granular understanding of traffic flows and their spatial distributions. Data-driven modeling strategies incorporate machine learning to classify and predict movement patterns, highlighting the synergies between energy consumption and mobility behaviors. Building on this, Wang & Lu et al. (2022) propose that generative intelligence models frameworks (AI) can enhance smart data analysis, e.g. in the field of mobility, by simulating emergent urban dynamics in response to infrastructure changes. These models generate probabilistic scenarios that allow planners to explore different land-use and transport policy outcomes, thus shifting the focus from static analysis toward an iterative, scenario-based planning methodology.

The reviewed literature demonstrates that smart meter data can serve as a crucial resource for uncovering spatial and temporal dynamics. The spatiotemporal analysis of smart meter and cab data shows how data-driven approaches can contribute to the optimization of urban systems. While smart meter data is mainly used for energy efficiency and forecasting, cab data offers unique insights into urban mobility patterns. Both approaches benefit from innovative methods such as machine learning, visualizations and interactive analysis tools. The integration of space and time in data analysis opens up new perspectives for the sustainable planning and management of urban infrastructures. In particular:

- Fine-grained energy consumption insights – Smart meter data enables detailed analysis of household activities and urban energy demands.
- Visualization as a planning tool – Innovative visual methods bridge the gap between complex data and practical applications for spatial planning.
- Integration with mobility data – Linking smart meter data with mobility patterns provides a more holistic perspective on urban dynamics, allowing for improved infrastructure planning and service provision.

By synthesizing these findings, this paper builds on existing methodologies to explore the applicability of smart meter data in spatial planning, with a particular focus on their impact on regulatory frameworks and future urban development strategies.

## 3 CASE STUDY

The insights gained from literature review will now be further examined in a case study. The selected case study region is the Swiss Lucerne Region, which offers a diverse range of spatial typologies – from rural areas to peri-urban agglomerations and the urban periphery of the core city of Lucerne. This diversity provides an ideal setting to analyze spatial dynamics and Smart City developments across different settlement structures. For this case study, an open data dataset containing smart meter data from the Swiss energy provider Centralschweizerische Kraftwerke is available (CKW 2024). These data will be systematically analyzed to assess spatial patterns, digital infrastructure, and governance strategies related to Smart City concepts. By leveraging these data-driven insights, the study aims to deepen the understanding of how digitalization and spatial planning interact across different territorial contexts within the Lucerne Region.

### 3.1 Case study region

#### 3.1.1 Dataset Description

The used anonymized smart meter dataset consists of aggregated electricity consumption measurements from households across the CKW service area. To protect consumer privacy, the dataset includes only anonymized meter IDs and does not contain personally identifiable information. Additionally, large industrial consumers have been filtered out to ensure that the analysis focuses on residential and small commercial energy consumption patterns. The dataset includes the following key attributes:

Anonymized Meter ID: Unique identifier for each smart meter (text format).

Area Code: Postal code of the service area (categorical data).

Timestamp: UTC-based timestamp marking the beginning of a 15-minute measurement interval (ISO-8601 format).

Number of Meters: Count of smart meters aggregated per area (integer format).

Energy Consumption (kWh): Total measured electricity consumption in kilowatt-hours (continuous variable).

The data covers an observation period of one representative week in 2024 (calendar week 45), a period chosen to avoid anomalies caused by public holidays or school vacations. The temporal resolution of 15-minute intervals provides fine-grained insights into energy consumption trends, allowing for detailed spatiotemporal analysis.

#### 3.1.2 Spatial Context of the Case Study

The case region includes the western part of Lucerne, the surrounding commuter catchment area, as well as peri-urban and rural areas to the west of Lucerne. These areas encompass municipalities classified as major centers and secondary centers of major centers according to the ARE municipality typology. Additionally, the case region includes municipalities situated along the A2 freeway, categorized as belts of major centers within the ARE typology, as well as agricultural municipalities, some of which are located within the UNESCO Entlebuch Biosphere Reserve. In total, it comprises 116 zip code areas within nearly 80 municipalities, three of which belong to the municipality of Lucerne itself.

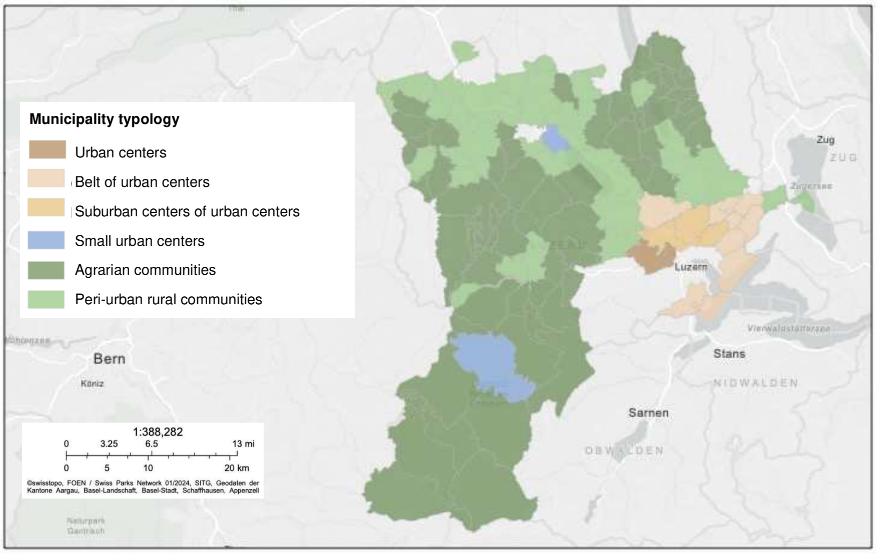


Fig. 1: Case study region with municipality categories of the zip code areas

To assess the suitability of smart meter data for spatial planning purposes, both temporal and spatio-temporal patterns in the data must be identified. The analysis begins with the examination of temporal patterns. For this purpose, selected municipalities are analyzed based on spatial categories, and behavioral patterns are derived from daily consumption trends observed on weekdays and weekends. In a subsequent step, spatio-temporal analyses are conducted.

To determine which community typologies – such as those related to commuter behavior – can be inferred from smart meter data, an average consumption pattern is first established across all days and all zip code areas within the study region. By comparing individual municipalities to this average daily consumption pattern, those exhibiting particularly distinct spatial consumption trends are identified. From this group, three municipalities displaying significant deviations from the average pattern are selected for further discussion.

The analysis initially focuses on temporal patterns. The following municipalities have been selected as representative examples of different spatial categories. The statistical methods used to identify these municipalities are not elaborated upon in this paper:

Willisau: Agricultural municipality with a predominantly rural character

Dagmersellen: Peri-urban rural municipality with direct freeway access to Lucerne via the A2

Root: Located within the commuting belt of major urban centers, adjacent to Lucerne

The locations of these three municipalities are depicted in Figure 2.

To bridge the transition from the case study region and dataset description to the analysis of temporal energy consumption patterns, it is essential to outline the methodological framework guiding this research. The study aims to examine how smart meter data can enhance spatial planning by revealing underlying patterns of human activity and land use. Building upon the literature review, which highlighted the potential of energy consumption data for spatial analysis, this research applies empirical methods to test these concepts in the specific context of the Lucerne region. The approach includes statistical evaluations of energy consumption trends, spatial clustering techniques to detect functional land-use variations, and comparative analyses across different municipal typologies. By structuring the investigation in this manner, the study seeks to answer key research questions: How do electricity consumption patterns correspond with land use functions? To what extent can these patterns refine existing planning paradigms? These inquiries will be explored through both temporal and spatio-temporal analyses in the following sections.

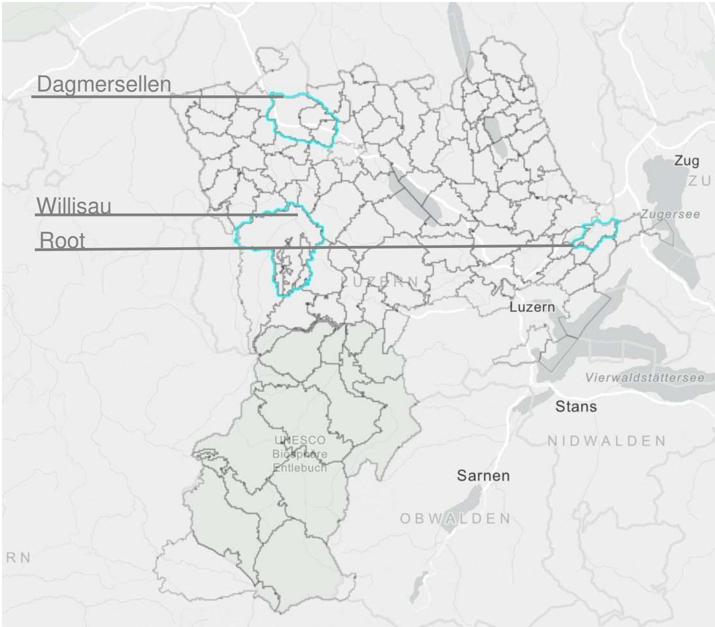


Fig. 2: Case study region and exemplary municipalities

### 3.2 Temporal representation of smart meter data

For improved readability, the daily electricity consumption patterns for Monday and Sunday are presented below, representing typical weekday and weekend consumption behaviors. Electricity consumption is displayed per capita and is derived from the average daily consumption patterns across all municipalities within the study region. The per capita electricity consumption is presented as an indexed value. It is important to note that the same calculation can also be applied per device instead of per capita. Since both approaches share the same total consumption value and the same proportional daily mean value, the relative deviations remain identical regardless of whether the consumption is indexed per capita or per device. Thus, the choice of unit does not affect the interpretation of consumption dynamics. The consumption patterns of the four exemplary municipalities are illustrated in Figure 3:

The daily consumption patterns observed in the analyzed municipalities reflect underlying spatial structures, population densities, and the functional characteristics of the settlements. These patterns provide critical insights for spatial planning, particularly concerning land-use diversity, mobility flows, and energy infrastructure.

Willisau, a predominantly rural municipality characterized by agricultural activities, exhibits a remarkably uniform consumption pattern throughout the week. There is little variation between Monday and Sunday, with only a slight increase in morning consumption, presumably linked to agricultural work. This stability indicates low commuting dynamics and a largely homogeneous pattern of land use. The spatial structure of Willisau is strongly shaped by its agricultural character, which is reflected in a low diversity of activities and a predominantly locally anchored population.

Dagmersellen, benefiting from direct highway access to the A2 leading to Lucerne, exhibits an even more pronounced commuter profile. On weekdays (Mondays), consumption peaks are particularly distinct in the morning and evening, while Sundays show a significant decline in consumption. The municipality's spatial function as a residential area for commuters is reinforced by its strong transport connectivity. Additionally, Dagmersellen demonstrates increased midday activity, suggesting the presence of work-related or service-oriented functions.

Root, located in the agglomeration of a major metropolitan center and adjacent to Lucerne, displays a particularly notable pattern. On weekdays (Mondays), electricity consumption remains high throughout the day but decreases in the evening. During weekends (Sundays), overall consumption is lower and more evenly distributed. This consumption behavior suggests that Root functions not merely as a residential municipality but also accommodates a significant number of workplaces or home-office activities.

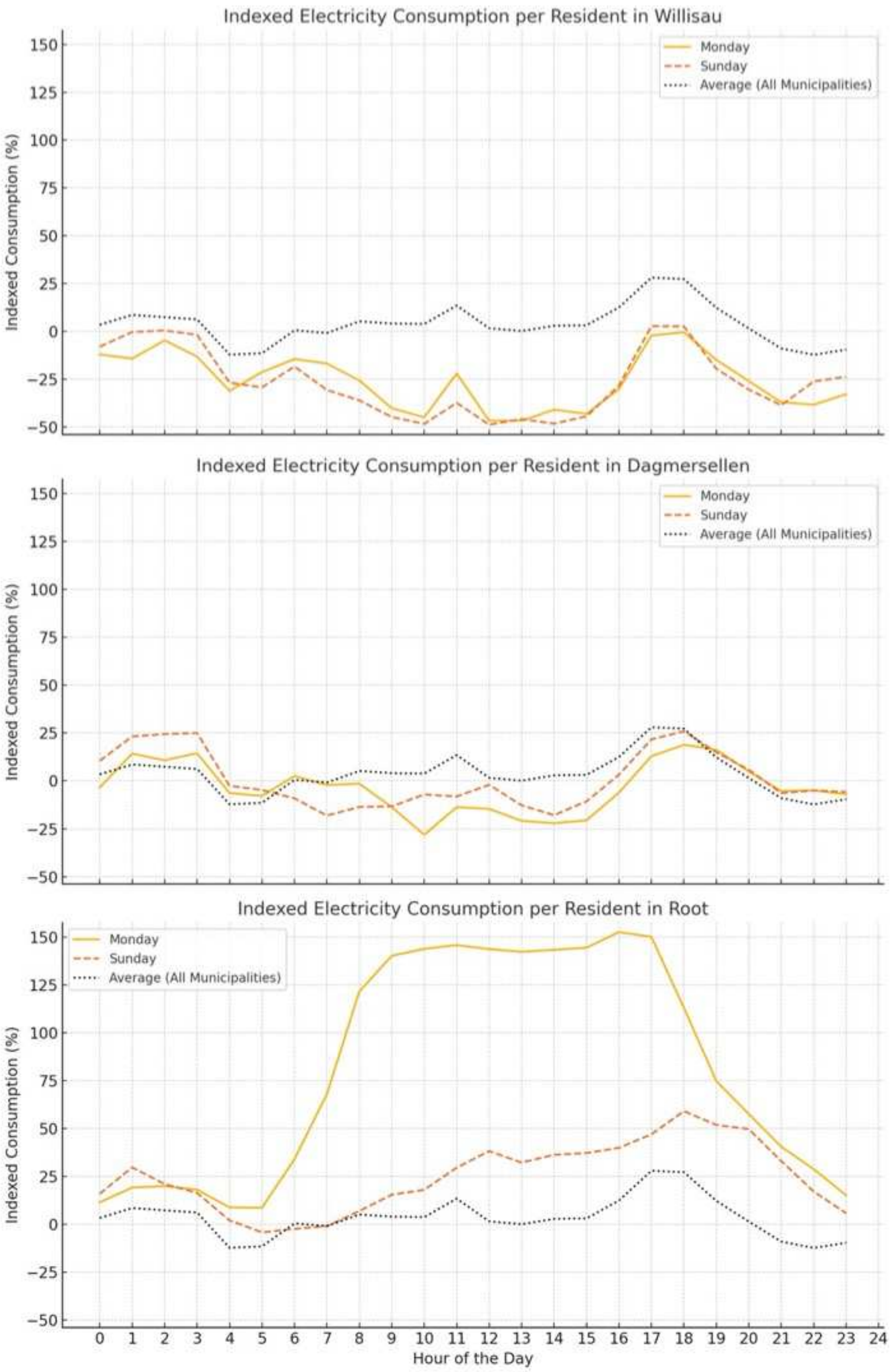


Fig. 3: Daily patterns of indexed energy consumption

Overall, the observed consumption patterns enable inferences about the spatial structures and the socio-economic functions of the municipalities. From a spatial planning perspective, these findings offer valuable indications for the development of tailored strategies in energy supply, mobility, and land-use planning. Such strategies should consider the specific characteristics of each municipality to enhance sustainability and efficiency in urban and regional development.

These findings directly address the gap outlined in Chapter 1. While traditional spatial planning has relied on zoning laws to regulate land use and by this behavior, the increasing prevalence of mixed-use developments necessitates a more dynamic approach that incorporates real-time data. Smart meter data contributes to this by offering empirical evidence of actual space utilization, enabling planners to identify discrepancies between intended and real-world usage. The integration of smart meter data into spatial planning thus facilitates the development of adaptive zoning strategies, enhances infrastructure planning, and ensures a more efficient allocation of resources. By providing a more nuanced understanding of urban energy consumption, this approach strengthens the ability of planners to design sustainable and responsive urban environments. The next section will further examine how spatio-temporal analyses refine our understanding of urban energy use.

### 3.3 Spatio-temporal representation of smart meter data

In addition to analyzing temporal consumption patterns and identifying municipalities that deviate significantly from the average daily energy consumption pattern, the following spatial patterns are examined the spatio-temporal representation of smart meter data.

To achieve this, deviations from daily electricity consumption are visualized for all zip-code areas in a certain municipality. Specifically, quarter-hour intervals indicate whether consumption in a given interval deviates from the daily average in the respective postal code area. With one exception, deviations of plus or minus 25 percent are considered the average for each postal code area. This approach enables the identification of overarching spatial patterns within the study region, independent of individual municipalities. The analysis follows a key computational step of calculation of the nornmalized mean value per ZIP code per day. To establish a baseline (“zero point”) for each ZIP code, the mean value for each day and postal code is determined. This enables the visualization of relative deviations, indicating increases or decreases in consumption relative to the daily mean for each ZIP code. The calculation is structured as follows, where 96 represents the total number of 15-minute intervals per day:

$$\text{Normalized mean value per ZIP code per day} = \frac{\sum \text{Normalized consumption per device per day per ZIP code}}{96}$$

For simplification, this paper presents consumption patterns at three distinct time points: Monday at 6 a.m., 11 a.m., and 5 p.m., which represent key moments in the weekday work rhythm. Due to the data format of the source data, the times are in UTC. So the local time in Switzerland at that period of the year is UTC +1 hour, so 7, am 12 noon, 18/ 6 pm. These are subsequently compared to the same time points on a weekend day (Sunday) to illustrate differences in consumption dynamics. In figure 4 on the spatio-temporal distribution on weekdays (Monday) as well as on figure 5 on weekends (Sunday).

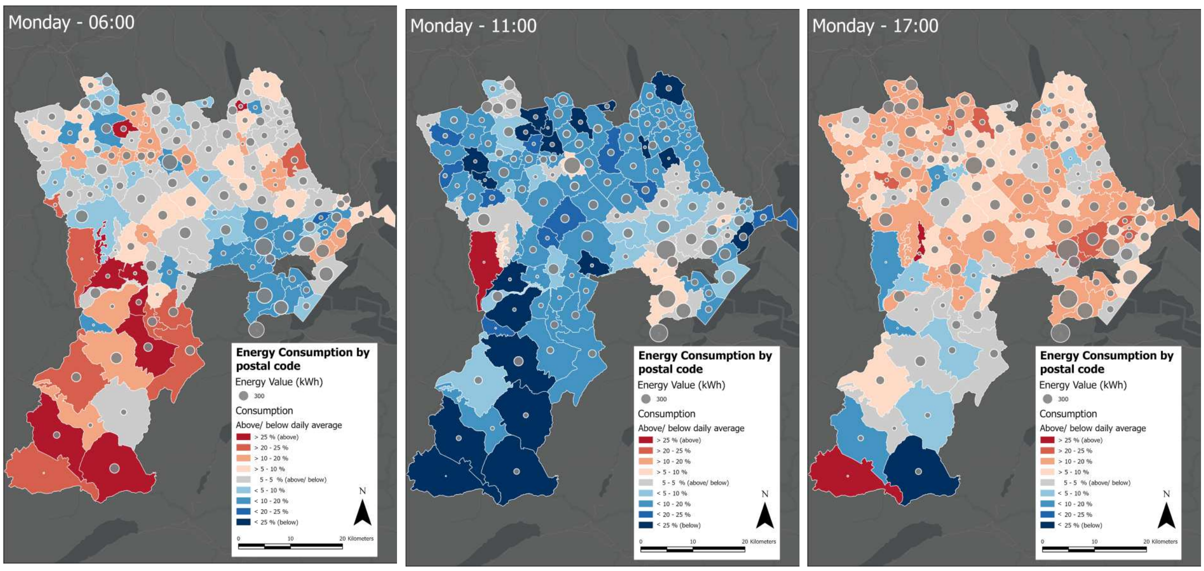


Fig. 4: Spatio-temporal distribution on weekdays (Monday)

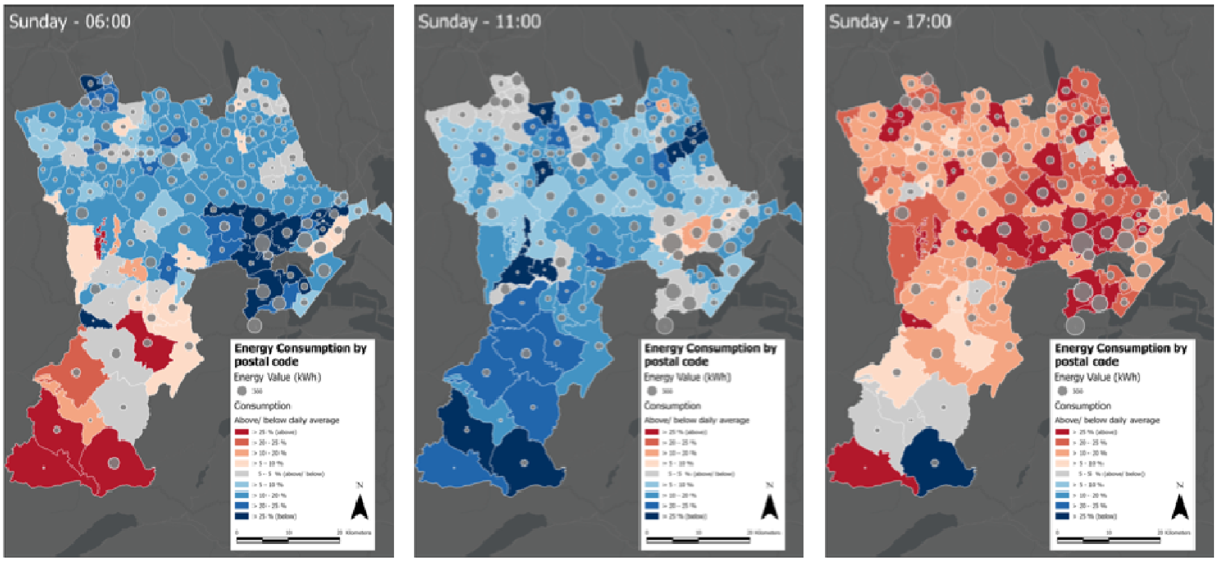


Fig. 5: Spatio-temporal distribution on weekends (Sunday)

A clear distinction emerges within the study region, which consists of two sub-areas. The northern part is strongly influenced by the municipality of Lucerne and comprises urban centers, suburban agglomeration, and other rural communities – effectively forming the commuter catchment area of Lucerne.

Monday, 6 a.m. – Electricity consumption in this northern sub-area is generally below the daily average. Notably, closer proximity to the urban core correlates with even lower consumption levels, whereas in more distant regions, certain postal code areas already exhibit above-average consumption at this early hour.

Monday, 11 a.m. – By late morning, consumption across most of this northern region remains below average, while the belt surrounding Lucerne shows comparatively higher electricity consumption.

Monday, 17:00/ 5 p.m. – By early evening, a general increase in consumption is observed across the entire region. The peri-urban belt around Lucerne shows the highest deviations from the daily average, indicating intensified household and workplace-related activities.

These emerging spatial patterns illustrate a clear daily cycle: the region "wakes up" in the morning, experiences a peak in commuting-related activity towards the urban center, sustains activity levels in the center throughout the day, and then undergoes a shift back towards suburban and peri-urban areas in the evening.

In contrast, the southern sub-area of the study region, characterized by predominantly agricultural communities, exhibits markedly different consumption patterns. These differences highlight the varying spatial functions of municipalities, which have implications for energy planning, mobility strategies, and land-use planning.

Sunday, 11 a.m. – Energy consumption remains low across the study region. In rural areas, patterns resemble those of weekdays, while urban and peri-urban areas show significantly lower demand, indicating a delayed start to activities.

Sunday, 11 a.m. – Overall energy demand remains below Monday levels, particularly in urban centers where commercial activity is reduced. Rural areas show steadier consumption, maintaining household and agricultural energy use.

Sunday, 17:00/ 5 p.m. – Energy use increases again, with a stronger residential focus compared to weekdays. Sunday’s evening consumption surpasses Monday’s in most areas, reflecting a shift toward leisure and home-based activities. The overall pattern highlights a slower start to the day and a more pronounced evening peak in residential zones.

The spatio-temporal representation of smart meter data refines the understanding of energy consumption by linking daily load curves to spatial distribution, complementing Chapter 2.1’s focus on temporal trends. Unlike Chapter 2.1, which identifies peak consumption times, this section on spatio-temporal representation reveals how spatial discrepancies indicate varying land-use functions and mobility dynamics. In this paper, we picked the definitions of the classes to use as examples. For further investigation, both the time intervals and the class widths must be statistically substantiated. As mentioned, the purpose of this study is to investigate the general suitability of smart meter data for spatial planning. And these insights show how smart meter data uncovers deviations between planned and actual land use, supporting data-driven adjustments in zoning and infrastructure planning.

## 4 CONCLUSION

This paper has demonstrated that smart meter data provides a valuable resource for spatial and transportation planning by enabling the mapping of spatial structures and identifying consumption patterns that align with or deviate from planned land use. Addressing the research gap, the study has shown how smart meter data extends beyond traditional zoning approaches by offering empirical insights into real-world energy usage in a region.

The literature review set the base of temporal and spatio-temporal data analysis in spatial planning, emphasizing that traditional spatial data sources are insufficient for capturing dynamic land use and mobility behaviors. Smart meter data fills this void by providing high-resolution temporal and spatial insights, which are particularly relevant in assessing the effectiveness of mixed-use planning strategies. The integration of energy consumption patterns with land-use data supports a more responsive and adaptive approach to zoning and infrastructure development.

The temporal analysis of smart meter data revealed daily consumption patterns that correspond to commuting behaviors and urban activity rhythms. It showed how commuter catchment areas exhibit higher energy demand earlier in the day, reflecting outbound mobility trends, while core urban areas experience increased consumption later as workers return home. These findings confirm that energy consumption serves as an indirect but effective indicator of human mobility and land-use functions, offering a complementary perspective to transport planning models.

The spatial-temporal analysis extended these insights by demonstrating how electricity consumption varies not only over time but also across different urban structures. It illustrated how energy use differs between urban, peri-urban, and rural areas, confirming that mixed-use zones exhibit distinct and fluctuating consumption patterns compared to purely residential or commercial areas. The observed spatial heterogeneity reinforces the necessity of integrating real-world data into planning frameworks, ensuring that zoning regulations and infrastructure investments align with actual usage patterns rather than static land-use designations.

Future research should focus on enhancing data aggregation methodologies in order to further improve the applicability of smart data data in spatial planning, such as smart meter data. The aggregation of household-level data at the street or neighborhood level would provide greater spatial granularity, enhancing its utility for land-use decision-making.

A key challenge remains the anonymization and representativeness of smart meter data. Ensuring that datasets maintain privacy while still delivering accurate spatial insights is crucial for their widespread adoption in planning processes. As finer spatial granularity is explored, it is essential to develop robust privacy-preserving techniques. This includes differential privacy and federated learning approaches that allow analysis without compromising individual data. Additionally, compliance with legal frameworks such as GDPR and national data protection laws must be ensured to balance analytical value with ethical considerations. Further investigation is required to validate the extent to which smart meter data accurately reflects mixed-use dynamics and whether additional contextual datasets, such as socioeconomic or mobility data, should be integrated to enhance analytical precision.

To improve the robustness of the findings, additional Smart City data sources should be integrated for validation. These could include mobility data from transport systems, socio-economic indicators, or sensor-based environmental data to cross-reference and contextualize energy consumption patterns. By incorporating these datasets, spatial planning decisions can be more accurately informed, and potential biases in smart meter data can be identified and addressed. Furthermore, a multi-source data validation approach would enhance the predictive capabilities of smart energy analysis, ensuring its relevance for diverse urban and rural contexts.

Beyond data aggregation, future research should also explore advanced aggregating, modeling and predictive analytics to enhance the utility of smart data in spatial planning. Generative AI models provide an opportunity to aggregate and simulate urban dynamics based on smart data like mobility and energy data, offering scenario-driven approaches rather than static analyses. These models allow planners to explore different zoning, transport, and infrastructure interventions by generating adaptive predictions that account for policy shifts and behavioral changes. The integration of such AI-driven frameworks could significantly improve spatial planning decisions and long-term resilience strategies.

Ultimately, this study underscores the necessity of incorporating smart data into spatial planning to enable data-driven policy adaptations. In an era where urban environments are becoming increasingly dynamic, traditional land-use planning methods must evolve to reflect actual usage patterns rather than relying solely on predefined zoning categories. Particularly in mixed-use developments, where spatial functions overlap and evolve over time, static zoning frameworks are no longer sufficient. A more dynamic, data-driven approach can provide planners with continuous feedback on urban activity patterns, enabling more responsive governance and adaptive infrastructure investments. The future of spatial planning will not be defined solely by regulatory land-use frameworks, but increasingly by data-supported governance that guides human behavior and their spatially effective activities.

## 5 REFERENCES

BUNDESAMT FÜR ENERGIE BFE. (2016). Smart-Meter-Datenanalyse für automatisierte Energieberatungen.

BUNDESAMT FÜR STATISTIK BFS (2024): Gemeindetypologie 2020 mit 9 Kategorien, URL: https://www.bfs.admin.ch/bfs/de/home/statistiken/querschnittsthemen/raeumliche-analysen/raeumliche-gliederungen/raeumliche-typologien.assetdetail.31265019.html (abgerufen ab 08.01.2025, 11:00 Uhr)

BUNDESAMT FÜR STATISTIK BFS (2022): Ständige Wohnbevölkerung nach Postleitzahl, Jahr 2022, URL: https://www.bfs.admin.ch/asset/de/26565300 (abgerufen ab 08.01.2025, 11:05 Uhr)

CENTRALSCHWEIZERISCHE KRAFTWERKE CKW (2024): Open Data Smart Meter Energie Verbrauchsdaten, URL: https://open.data.axpo.com/%24web/index.html (abgerufen am 08.01.2025)

ENGELKE, D. (2017): Die Digitalisierung definiert den Raum neu. In: Bundesamt für Raumentwicklung (ARE): Forum Raumentwicklung 2/17

KRAGH-FURBO, M., & WALKER, G. (2018). Electricity as (Big) Data: Metering, spatiotemporal granularity and value. Big Data & Society, 5(1), 2053951718757254. https://doi.org/10.1177/2053951718757254

NIU, Z., WU, J., LIU, X., HUANG, L., & NIELSEN, P. S. (2021). Understanding energy demand behaviors through spatio-temporal smart meter data analysis. Energy, 226, 120493. https://doi.org/10.1016/j.energy.2021.120493

PENG, J., KIMMIG, A., NIU, Z., WANG, J., LIU, X., & OVTACHAROVA, J. (2021). A flexible potential-flow model based high resolution spatiotemporal energy demand forecasting framework. Applied Energy, 299, 117321. https://doi.org/10.1016/j.apenergy.2021.117321

WANG, D., LU, C.-T., & FU, Y. (2022). Towards Automated Urban Planning: When Generative and ChatGPT-like AI Meets Urban Planning. https://arxiv.org/abs/2304.03892

WANG, H., HENRI, G., TAN, C.-W., & RAJAGOLAL, R. (2020). Activity Detection And Modeling Using Smart Meter Data: Concept And Case Studies. 1–5. https://doi.org/10.1109/PESGM41954.2020.9281746

WANG, H., HUANG, H., NI, X., & ZENG, W. (2019). Revealing Spatial-Temporal Characteristics and Patterns of Urban Travel: A Large-Scale Analysis and Visualization Study with Taxi GPS Data. ISPRS International Journal of Geo-Information, 8(6), 257. https://doi.org/10.3390/ijgi8060257