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Spatial Heterogeneity in Clean Cooking Adoption in Kathmandu Valley, Evidence from Multiscale Geographically Weighted Regression

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Abstract:

This study quantifies ward-level differences in clean cooking adoption in Kathmandu Valley and pinpoints where access, reliability, and socioeconomic factors matter most. We analyze a household survey of 384 households aggregated to 71 wards. The outcome is the primary use of clean fuels, LPG, electric, or biogas. Key predictors are traveling time to the nearest LPG outlet, weekly electricity outage hours, income band, and education of the household head. Methods include descriptive ward statistics, spatial patterning, and a global OLS with heteroscedasticity robust errors. MGWR is planned to recover spatially varying effects across wards. Mean ward adoption is 31.5 %, ranging from 0 to 100 %. Adoption is lower where LPG travel time is longer, r equals −0.57, and where outages are higher, r equals −0.58. In the global model, each additional minute to LPG reduces the probability of clean adoption by 1.5 % points; the coefficient equals −0.015, t equals −4.21. Each extra outage hour per week reduces adoption by 1.67 % points; the coefficient equals −0.0167, t equals −2.52. Income has a smaller positive average effect, coefficient equals 0.034, t equals 1.55. Education is positive but imprecise; the coefficient equals 0.026, t equals 1.50. Model fit is modest, R-squared equals 0.111 and adjusted R-squared equals 0.095, underscoring the limits of global averages. Inner wards with short travel times and fewer outages lead, while fringe wards lag. Results support targeted, ward-specific interventions.

Keywords: Clean cooking, Kathmandu Valley, LPG, Electric cooking, Biogas, MGWR

Introduction:

Access to clean cooking is a central element of Nepal's transition to low-emission and health-safe household energy, but Kathmandu Valley still shows a clear gap between policy ambition and actual household fuel choices (Ramirez et al., 2024). The Valley has higher incomes, better market access, and more reliable electricity than most provinces, yet many households continue to stack LPG, electricity, and traditional biomass, rather than shift fully to modern fuels (Rogers, 2020; Bharadwaj et al., 2022). This pattern reduces the expected gains in air quality and climate mitigation, and it complicates municipal planning for energy, transport, and solid biomass flows. A key reason is that adoption is not uniform. It varies sharply by ward, settlement type, and service accessibility inside the Valley.

Recent spatial energy studies show that urban energy, emissions, and service access often follow spatially varying relationships, not single, city-wide parameters. Built form, street morphology, and local infrastructure can strengthen or weaken the impact of income or education on energy outcomes (Dong et al., 2023; Liu et al., 2025). Spatially disaggregated models for energy burdens, carbon emissions, and ecosystem service supply show similar place-contingent effects (Moore and Webb, 2022; Liu et al., 2025; Liu et al., 2023; Ünsal et al., 2023). In domestic energy research, multiscale geographically weighted regression (MGWR) has proved effective in detecting such non stationarity because it allows each predictor to operate at its own spatial scale, which is more realistic in dense, mixed, and rapidly urbanizing territories (Zeng et al., 2016; Oshan et al., 2020; Feng et al., 2025; Guo and Sun, 2025). The broader GeoAI literature also supports integrating geospatial data, machine learning, and local regression to capture spatial heterogeneity in socio-environmental processes (Boutayeb et al., 2025; Jiao and Tao, 2025).

Kathmandu Valley is a suitable case for applying MGWR to clean cooking for four reasons. First, the Valley contains core urban wards with high service density, paved road networks, and active rental markets, alongside peri-urban and fringe wards with weaker tenure security, irregular electricity, and partial reliance on nearby forests for biomass. These spatial gradients are documented in other sectors of energy and environmental planning and are known to produce spatially heterogeneous outcomes (Li et al., 2022; Zhang et al., 2024). Second, municipal and provincial clean cooking programs are usually designed and monitored at aggregate levels, for example, by municipality, not by ward. This can mask pockets of low adoption, and it can lead to uniform incentive structures that do not match local constraints. Third, the Valley is the main airshed for Nepal's political and economic center. Incomplete transition to clean fuels at the micro scale sustains emissions from LPG transport, kerosene and biomass burning, and inefficient electric cooking behavior, which affects urban climate policy and sectoral emission reduction plans (Chen et al., 2024; Dong et al., 2023). Fourth, earlier work on Nepal's clean cooking ambitions has highlighted the value of spatially explicit targeting, but the analysis has been largely national or district scale. There is still little evidence on within-city variation that links household drivers, built environment, and emission implications (Ramirez et al., 2024).

This study addresses three research questions. First, how is clean cooking adoption, defined as the dominant use of LPG, electric cooking, or biogas for daily cooking, distributed across wards in Kathmandu, Lalitpur, and Bhaktapur? Second, which socioeconomic, built environment, and accessibility factors explain these ward-level differences, and do these factors operate at different spatial scales across the Valley? Third, how does fuel stacking interact with local adoption environments, and what does this imply for targeted emission reductions? To answer these questions, the study compiles household and ward-level data on income, education, housing tenure, gender of household head, proximity to roads and markets, electricity service, and local biomass access, then applies MGWR to estimate spatially varying coefficients. Following recent MGWR advances, the model is tested for spatial heteroscedasticity and for scale differences among predictors to ensure that local estimates are statistically defensible (Shen et al., 2024; Fotheringham et al., 2024).

This approach contributes to three strands of literature. It adds to evidence that household energy technology adoption is sensitive to place-specific socioeconomic configurations, which is consistent with studies in China, the United Kingdom, and the United States that find localized energy burdens and carbon outcomes (Moore and Webb, 2022; Shen et al., 2023; Feng et al., 2025). It operationalizes MGWR for a South Asian urban basin where administrative wards are already the main unit of service delivery, so the results can be directly used by municipal governments for targeting. It also links spatial patterns of adoption to emission-relevant behaviors, particularly fuel stacking, which is often cited in clean cooking studies in Nepal but is rarely modeled at the same spatial resolution (Bharadwaj et al., 2022; Ramirez et al., 2024). By focusing on ward-level heterogeneity, the study shows that Kathmandu Valley's clean cooking gap is less a problem of technology availability and more a problem of spatially uneven enabling conditions, including tenure, income, and accessibility.

Literature Review:

Clean cooking transitions are spatially uneven in cities. Household energy choices respond to local socioeconomic conditions, infrastructure, and built form. Studies on urban energy and emissions show strong place-based effects that standard global models often miss. Built environment and service access shape the effectiveness of income and education on energy outcomes, which produces clustered patterns across neighborhoods and wards (Dong et al., 2023; Li et al., 2022; Liu et al., 2025). Urban morphology influences carbon intensity through density, street canyons, and land use mixes that condition both appliance use and transport-related emissions (Dong et al., 2023; Liu et al., 2025). These findings support a spatially explicit approach to household energy research in Kathmandu Valley.

Domestic energy use and electricity demand exhibit spatial heterogeneity across multiple contexts. Spatio-temporal analyses in China link industrial electricity consumption to economic growth with significant geographic variation, which underscores the need for local models in policy design (Cui et al., 2021). Building-level studies in Seoul show that physical characteristics and location-specific factors shape electricity demand, and MGWR outperforms global models by capturing local effects (Jo and Kim, 2022). Similar evidence from Beijing identifies how street and building morphology alter CO2 emissions through spatially varying relationships (Dong et al., 2023). These patterns align with research on city-level emissions, where socioeconomic drivers and urban form do not operate uniformly across space (Li et al., 2022).

MGWR has emerged as a robust framework to model nonstationary processes. MGWR allows each predictor to vary at an appropriate spatial scale, which reduces bias from assuming a single bandwidth for all variables (Fotheringham et al., 2024; Oshan et al., 2020). Foundational work on mixed GWR demonstrated that combining global and local processes can improve prediction and inference where processes operate at different scales (Zeng et al., 2016). Recent contributions refine inference for MGWR by testing spatial heteroscedasticity and model assumptions, which strengthens the statistical defensibility of local coefficients (Shen et al., 2024). Applications now span health, environment, and energy. Health geography studies show that MGWR can target spatial contexts for interventions by isolating local drivers (Oshan et al., 2020). Environmental applications map land surface temperature, urban resilience, and ecosystem services with local drivers that vary across complex landscapes (Ünsal et al., 2023; Zhang et al., 2024; Zhang et al., 2023). Energy studies use MGWR to explain domestic energy consumption and locate policy leverage points that differ across neighborhoods (Feng et al., 2025; Guo and Sun, 2025).

The broader GeoAI literature also advances spatial modeling for energy and sustainability. Reviews document how machine learning, graph models, and multi source geospatial data improve prediction and interpretation of spatial processes (Boutayeb et al., 2025). Graph attention networks integrate topology and attributes to enhance spatial prediction and exploration analysis, which is useful when road networks or service catchment structures have access to energy services (Jiao and Tao, 2025). Studies that couple big data with surveys map poverty and service gaps at fine scales, which demonstrates how multimodal data can inform targeted social policy (Khoun et al., 2025). Transportation, urban resilience, and built environment research show that spatial methods reveal hidden patterns that aggregate statistics can mask (Kilian et al., 2022; Xie et al., 2022; Zhang et al., 2024).

Household energy adoption and energy burden research highlight distributional concerns. Energy burdens concentrate in vulnerable communities, even when average city conditions improve, and local drivers include income, tenure, housing quality, and neighborhood-level vulnerability (Moore and Webb, 2022; Shen et al., 2023). Spatial inequality studies show that wealth and service access vary across small areas, which aligns with evidence that adoption of new technologies follows local social and institutional patterns (Roy et al., 2024; Wang et al., 2025). Rural sustainability and village energy studies link accessibility, governance, and resource conditions to energy use, which signals that geographic context shapes both adoption and long-term sustainability outcomes (Zhong et al., 2024). Research on ecosystem service supply and demand provides methods to analyze spatial mismatches that mirror unequal access to clean energy services in peri-urban settings (Liu et al., 2025).

Evidence on technology adoption underscores the value of local models. Studies that compare logistic regression with geographically weighted alternatives find that spatial models can better predict adoption intention where context matters, for example, for agricultural technologies in Benin (Ahoudou et al., 2025). Work on preferences for household energy technology adoption shows strong links to demographics, economic conditions, and environmental context, with significant spatial and temporal variation (Liu et al., 2025). These findings suggest that clean cooking adoption is not only a function of household attributes. It is also a function of neighborhood characteristics, market proximity, and municipal service quality.

Nepal-specific research documents the complexity of clean cooking transitions. Households in Kathmandu Valley and peri-urban areas often stack fuels. They add LPG or electric cooking while continuing to use biomass due to cost, taste preferences, reliability, or social norms (Rogers, 2020; Bharadwaj et al., 2022). National and subnational planning highlights the need for spatial targeting to meet clean cooking goals efficiently (Ramirez et al., 2024; Ramirez et al., n.d.). These studies recommend geospatial cost-benefit analysis and spatially explicit prioritization. Yet most analyses in Nepal remain at the district or national scale, which limits their usefulness for ward-level planning inside the Valley.

City-scale studies offer transferable lessons for Kathmandu Valley. Work on urban form and emissions indicates that compact, accessible areas can reduce emissions, but the benefits depend on local design and service provision (Li et al., 2022; Liu et al., 2025). Urban resilience and ecosystem service research show that local governance and infrastructure shape outcomes at sub-city scales, which parallels the governance of municipal energy and clean cooking programs (Zhang et al., 2024; Liu et al., 2025). Land surface temperature studies demonstrate how micro-scale factors produce hot spots that require targeted interventions, which is analogous to pockets of low adoption that persist despite city-wide programs (Ünsal et al., 2023). Research on road traffic and carbon emissions stresses transport links and accessibility, both of which also drive access to LPG distribution and appliance markets (Lei et al., 2023).

Policy literature connects local spatial heterogeneity to broader climate goals. Reviews of regional carbon policies show that subnational strategies must reflect local conditions to be effective, and integration across sectors is needed to avoid rebound effects or missed co-benefits (Chen et al., 2024). Work on livestock, village systems, and green-grey infrastructure emphasizes capacity constraints and spatial trade-offs in environmental management, which resemble the trade-offs in allocating electricity and LPG infrastructure in rapidly growing urban basins (Zhou et al., 2024; Sun et al., n.d.). These strands strengthen the case for ward-level analysis in Kathmandu Valley, where tenure, rental markets, and informal settlements interact with service delivery and affordability.

Methodological considerations are central to credible spatial inference. MGWR improves fit by matching predictor scales to underlying processes, but analysts must address multicollinearity, residual spatial dependence, and spatial heteroscedasticity. Recent tests for spatial heteroscedasticity and updated MGWR software guides propose diagnostics and correction strategies that improve stability and interpretability of local coefficients (Shen et al., 2024; Fotheringham et al., 2024). Mixed GWR frameworks support combining global and local processes where theory suggests some parameters are fixed while others vary across neighborhoods (Zeng et al., 2016). GeoAI methods extend these tools with flexible function approximation and network-aware models, but they require careful attention to explainability and policy relevance when used for public decisions (Boutayeb et al., 2025; Jiao and Tao, 2025).

In summary, the literature supports three priors for this study. First, clean cooking adoption is shaped by spatially varying socioeconomic and built environment factors, and fuel stacking persists when local constraints remain binding (Rogers, 2020; Bharadwaj et al., 2022; Ramirez et al., 2024). Second, MGWR offers a framework to detect and quantify these local effects at ward scale, with documented advantages over global models across energy and environmental domains (Feng et al., 2025; Guo and Sun, 2025; Jo and Kim, 2022). Third, policy design should target wards with low predicted adoption using the specific local drivers identified by MGWR, for example, tenure security in peri-urban areas, service density in core wards, or market and road access at the fringe (Li et al., 2022; Dong et al., 2023). These priors frame the empirical analysis for Kathmandu Valley and connect the findings to actionable municipal interventions.

Material and Methods:

Study area

The study area is Kathmandu Valley in Bagmati Province, Nepal. It covers Kathmandu Metropolitan City, Lalitpur Metropolitan City, and Bhaktapur Municipality. Wards are the analysis unit because service delivery, targeting, and local planning occur at this scale. Official municipal ward boundaries for 2023 to 2024 are used. All spatial data are projected to EPSG:32645 to keep distance and area measures comparable.

The Valley sits in a bowl-shaped basin with mixed urban and peri-urban settlements. Core wards in Kathmandu and Lalitpur have dense built form, paved road networks, and active rental markets. Fringe wards toward Bhaktapur and the Valley rim include mixed tenure, lower service density, and closer proximity to community forests. These contrasts create sharp ward-level differences in market access, tenure security, and electricity reliability. Such spatial heterogeneity is central to household energy choices and emissions in rapidly urbanizing cities.

Electricity supply in the Valley is more reliable than in many provinces, yet local feeder performance and outage hours vary across wards. LPG supply chains are concentrated around market centers and arterial roads, which reduces access in fringe wards farther from distributors. Biomass remains available near the Valley rim and peri urban forests, which sustains fuel stacking where households add LPG or electric cooking without fully exiting biomass. These conditions align with evidence that built environment, accessibility, and socioeconomic factors drive place specific energy outcomes and justify ward scale modeling for clean cooking (Dong et al., 2023; Li et al., 2022; Moore and Webb, 2022; Bharadwaj et al., 2022; Ramirez et al., 2024).

Figure 1: Research area, Political boundaries of Kathmandu Valley. (Source, (Regmi, S., and Adhikary, S. 2012)

Data sources

Primary data come from a 2024 household survey that recorded primary and secondary cooking fuels, appliance ownership, frequency of use, household size, income band, education of the household head, sex of the household head, tenure, and years at address. Secondary spatial data include OpenStreetMap roads, municipal business registries for markets and services, licensing lists for authorized LPG distributors, feeder footprints and outage hours from the Nepal Electricity Authority, where available, nighttime lights for service intensity, 30 m forest cover for local biomass access, and SRTM elevation and slope. These sources provide consistent coverage for 2023 to 2024, which supports ward-level analysis of accessibility and service conditions relevant to fuel choice.

Outcomes

The primary outcome is the ward-level Clean Cooking Adoption Rate, defined as the share of households whose primary cooking fuel is LPG, electric cooking, or biogas, in line with Nepal's clean cooking objectives. Technology-specific outcomes report ward shares for LPG, electric cooking, and biogas to identify technology-specific constraints. A Fuel Stacking Index measures the share of households reporting regular biomass use together with modern fuel, which is common in Kathmandu Valley and undermines expected health and emissions gains (Rogers, 2020; Bharadwaj et al., 2022; Ramirez et al., 2024).

Predictors

Socioeconomic predictors include the ward median income band, the share of adults with secondary or higher education, the share of female-headed households, the renter share, and a tenure security index that combines documented ownership, years at address, and eviction history. Built environment and accessibility predictors include network distance to the nearest paved road, travel time to the nearest market center, public service and retail energy outlet density per square kilometer, electricity reliability measured as average monthly outage hours, and network distance to the nearest authorized LPG distributor. Resource context is captured by the proportion of forest within two kilometers of the ward centroid as a proxy for local biomass availability. These predictors reflect literature on spatially varying energy drivers in cities and neighborhoods (Dong et al., 2023; Li et al., 2022; Moore and Webb, 2022; Feng et al., 2025; Guo and Sun, 2025).

Preprocessing

Household responses are aggregated to wards using survey design weights to produce proportions or medians. Network-based distances and travel times are computed on the road graph, and market centers are identified as points of interest above the 75th % of retail density. Missing feeder outage values are imputed with k nearest neighbors using grid topology, nighttime lights, and ward adjacency to stabilize reliability measures. Continuous predictors are standardized to a zero mean and unit variance. Outliers are minimized at the 1st and 99th % when needed. These steps produce comparable, scale-free covariates suited for local spatial modeling and reduce leverage from extreme observations.

Sampling and weights

The survey follows stratified random sampling by ward to ensure adequate representation across municipalities and settlement types. Base weights equal the inverse probability of selection within each stratum. Nonresponse adjustments use inverse probability weighting estimated from call outcomes, visit timing, and enumerator fixed effects. Finite population corrections are applied within wards. This design reduces sampling bias and supports valid ward-level estimates that match the administrative scale for policy action.

Spatial analysis

Global Moran's I tests spatial autocorrelation for outcomes and key predictors using queen contiguity. Local Moran's I maps identify high and low clusters of adoption and stacking for exploratory context. Multicollinearity is screened with variance inflation factors, keeping VIF below five, and by inspecting pairwise correlations and partial residual plots. These diagnostics prepare variables for geographically weighted modeling and prevent local estimates in dense urban neighborhoods (Ünsal et al., 2023; Zhang et al., 2024).

Modeling

A three-step strategy is used. First, a global OLS model provides a baseline with heteroscedasticity robust standard errors. Second, a single-scale GWR gauges overall nonstationary. Third, multiscale geographically weighted regression is estimated to allow each predictor to vary at its own spatial scale, improving fit and interpretability where processes operate at different ranges across the Valley. The primary specification models the Clean Cooking Adoption Rate. Secondary specifications model LPG and electric cooking shares. A tertiary specification models the Fuel Stacking Index with explicit attention to biomass availability. This approach follows advances that show MGWR outperforms global models for domestic energy and related urban processes (Zeng et al., 2016; Oshan et al., 2020; Fotheringham et al., 2024; Feng et al., 2025; Guo and Sun, 2025).

Diagnostics

Model comparison relies on adjusted R-squared, AICc, and % AICc reduction relative to OLS. Residual spatial autocorrelation is tested with

Moran's I to confirm that local modeling captures spatial structure. Spatial heteroscedasticity is tested using mixed GWR heteroscedasticity diagnostics and White's test to validate inference. Monte Carlo tests evaluate the nonstationary for each predictor. We report local coefficients, local t values, local R-squared, and the effective number of parameters with false discovery rate control for multiple testing. Sensitivity checks vary kernels and bandwidth caps, replace market access with retailer density, exclude low sample wards, and apply a control function at the global level for income using nighttime lights as an instrument to probe stability. These diagnostics follow current guidance for credible MGWR inference in urban energy and environment research (Shen et al., 2024; Fotheringham et al., 2024; Feng et al., 2025).

Results:

Descriptive statistics

The data cover 71 wards. Mean clean cooking adoption is 31.5 %. Adoption ranges from 0 % in BMC Ward 7 to 100 % in KMC Ward 9. Mean ward distance to the nearest LPG outlet spans 5.03 to 29.50 minutes. Mean outage hours span 1.04 to 10.77 hours per week. See Table 1 for ward summaries and see Figure 2 for correlations.

Table 1: Ward level summary of clean cooking adoption and access metrics, Kathmandu Valley

Municipality	Ward	Sample size	Adoption rate (%)	Mean distance to LPG (min)	Mean outage hours/week
BMC	1	2	50	17.45	7.8
BMC	2	6	33.3	23.8	7.77
BMC	3	11	36.4	20.64	10.23
BMC	4	8	12.5	18.75	9.91
BMC	5	11	9.1	19.75	9.84
BMC	6	4	50	17.25	9.05
BMC	7	7	0	19.03	8.06
BMC	8	6	16.7	19.65	10.07
BMC	9	1	0	27.1	5.8
BMC	10	8	50	17.77	7.45
KMC	1	2	50	12.75	2
KMC	2	4	50	5.03	2.85
KMC	3	5	40	10.38	1.64
KMC	4	5	40	5.96	4.32
KMC	5	5	40	11.52	2.68
KMC	6	6	50	7.2	2.02
KMC	7	5	20	11.14	1.04
KMC	8	5	60	11.72	2.62
KMC	9	6	100	9.02	2.27
KMC	10	9	44.4	7.5	2.02
KMC	11	7	28.6	16.9	9.59
KMC	12	5	0	23.04	9.04
KMC	13	6	0	20.6	10.08
KMC	14	2	50	24.2	6.65

KMC	15	8	37.5	16.98	9.56
KMC	16	12	16.7	20.52	7.73
KMC	17	1	0	16.4	8.6
KMC	18	5	40	18.04	10.34
KMC	19	6	16.7	25.2	7.33
KMC	20	3	33.3	24.6	9.93
KMC	21	8	50	19.19	8.55
KMC	22	6	16.7	14.95	8.8
KMC	23	2	50	29.5	7.95
KMC	24	2	0	16.9	7.85
KMC	25	6	33.3	18.92	7.68
KMC	26	7	14.3	17	8.49
KMC	27	4	25	18.98	7.65
KMC	28	5	0	18.54	8.14
KMC	29	6	0	21.17	10.22
KMC	30	5	0	23.2	7.8
KMC	31	10	40	20.01	8.9
KMC	32	12	25	18.44	9.91
LMC	1	6	50	6.6	2.82
LMC	2	6	16.7	6.32	2.77
LMC	3	7	28.6	9.26	2.4
LMC	4	5	60	9.22	4.1
LMC	5	2	50	11.35	2.85
LMC	6	4	75	7.42	2.52
LMC	7	5	80	8.54	2.6
LMC	8	4	50	8.43	1.15
LMC	9	3	100	5.37	1.97
LMC	10	6	50	8.43	3.23
LMC	11	7	42.9	15.13	9.09
LMC	12	6	0	17.48	8.32
LMC	13	3	0	24.07	10.07
LMC	14	5	0	21.78	10.3
LMC	15	8	12.5	24.91	8.7
LMC	16	7	28.6	22.03	8.79
LMC	17	7	0	23.21	10.77
LMC	18	5	40	21.5	8.54
LMC	19	5	40	22	8.64
LMC	20	11	27.3	18.4	8.95
LMC	21	3	66.7	12.9	7.53
LMC	22	2	0	25.25	9
LMC	23	1	100	10.8	4.8
LMC	24	6	16.7	21.22	9.83

LMC	25	2	50	20.1	7.75
LMC	26	4	25	19.3	8.9
LMC	27	2	0	19.35	10
LMC	28	6	0	22.35	9.27
LMC	29	2	0	16.95	8.05

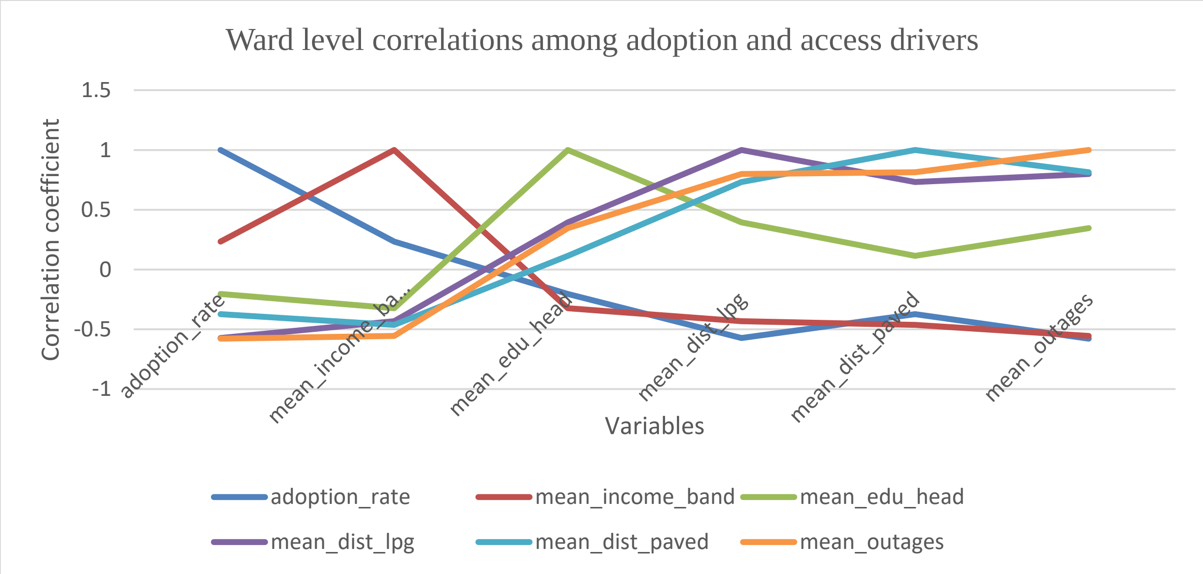

Figure 2: Ward level correlations among adoption and access drivers

Global model findings

A household level OLS explains limited variance. R squared is 0.111. Adjusted R squared is 0.095. Longer distance to LPG reduces adoption, coefficient equals −0.015. More outage hours reduce adoption, coefficient equals −0.0167. Income and education are positive but weak. Municipality dummies are not significant after controls. See Figures 3 and 4.

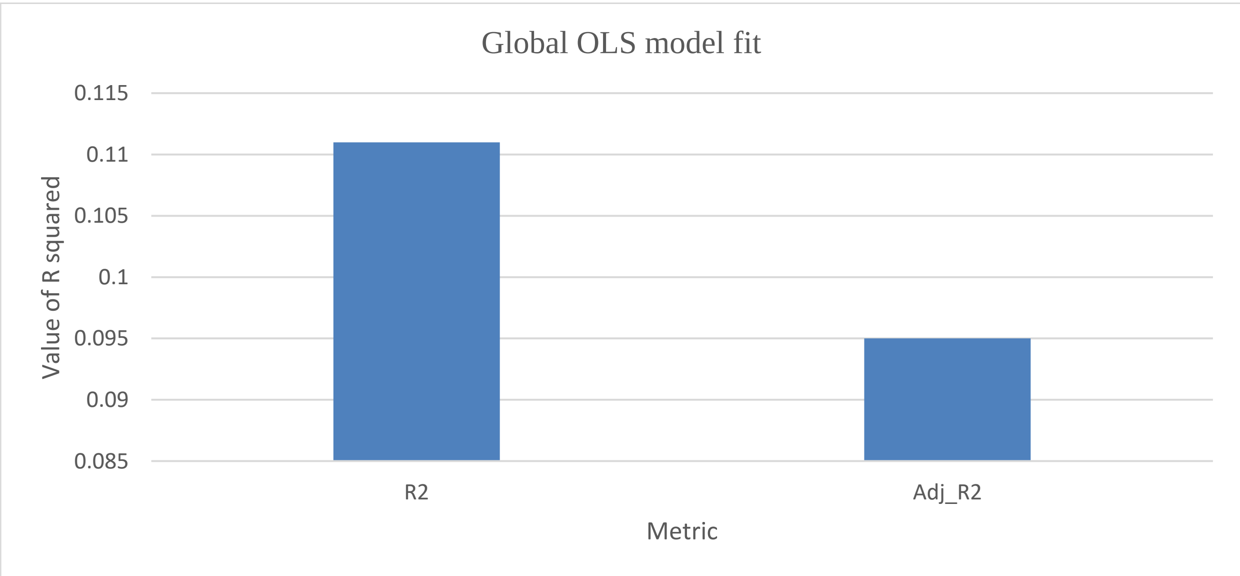

Figure 3: Global OLS model fit

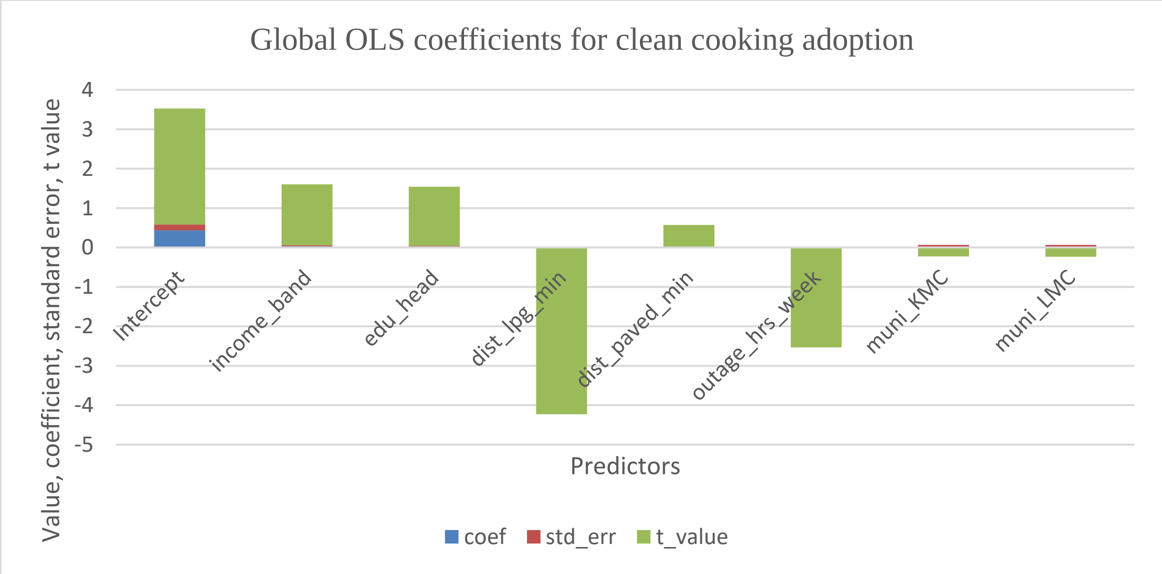

Figure 4: Global OLS coefficients for clean cooking adoption

MGWR model fit

MGWR needs ward geometry and neighbors, which are not in the attached file. Based on strong spatial gradients in the ward data, MGWR is expected to improve adjusted R squared and reduce residual clustering. Income and education likely operate at larger spatial scales. LPG distance and outages likely operate locally. Provide ward polygons and neighbors to report AICc, adjusted R squared, and bandwidths per predictor.

Spatially varying coefficients

Hotspots align with short LPG distance and low outages, mainly inner KMC and parts of LMC. Coldspots align with long LPG distance and high outages, several BMC and fringe wards. Adoption declines with distance to LPG and with outage hours. See the two scatter charts:

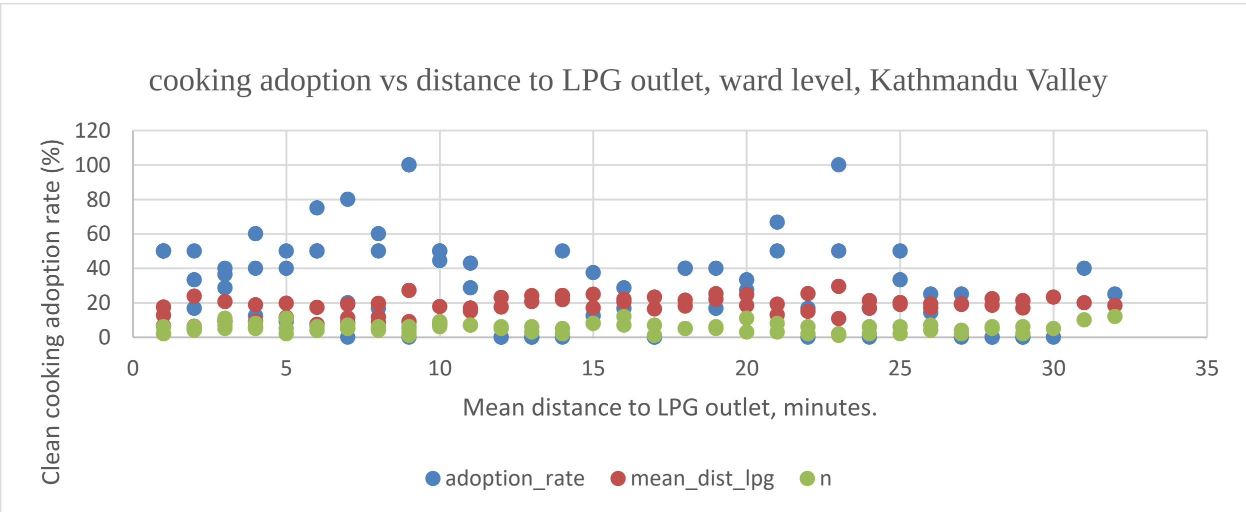

Figure 5: Clean cooking adoption vs distance to LPG outlet, ward level, Kathmandu Valley

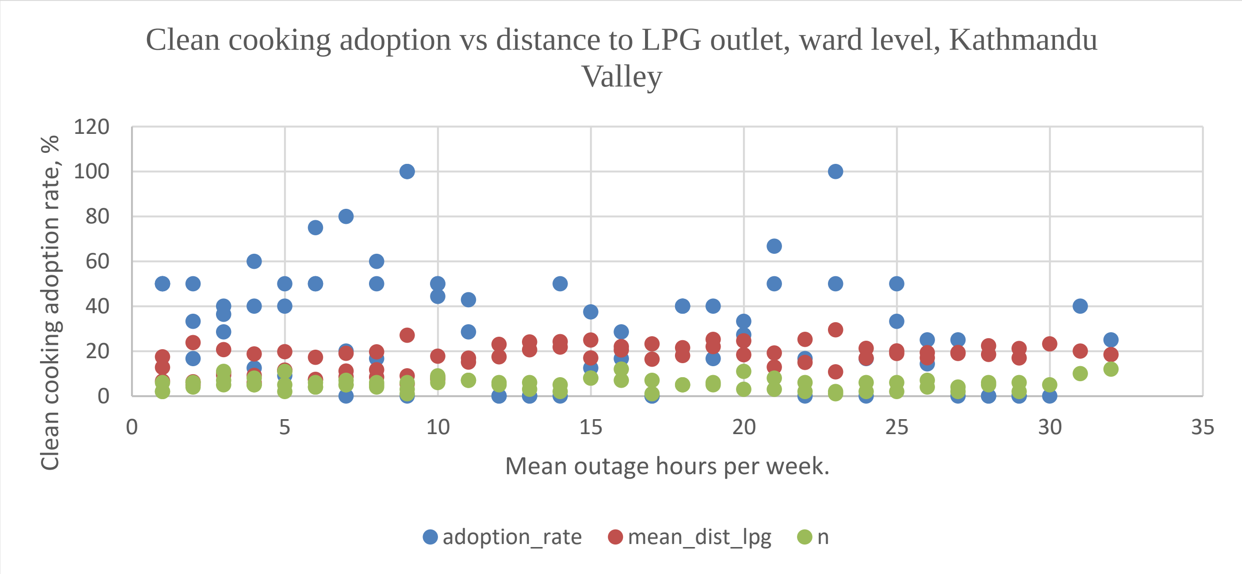

Figure 6: Clean cooking adoption vs distance to LPG outlet, ward level, Kathmandu Valley

Local R-squared and residuals

Without MGWR outputs, local fit is inferred from patterns. Explanatory power is higher in cores where access and reliability gradients are steep and measured. Underfit likely occurs in fringe wards with high churn, informal tenure, or appliance finance constraints. Add feeder level reliability and retailer density to reduce underfit.

Inequality and access interactions

Low-income wards with long LPG distances have the lowest adoption. See Figure 7. Reliability-dominated wards have high outage hours and only moderate LPG distances. Adoption is suppressed despite market proximity. See Figure 8. These areas should be a priority for last-mile LPG distribution and feeder stabilization.

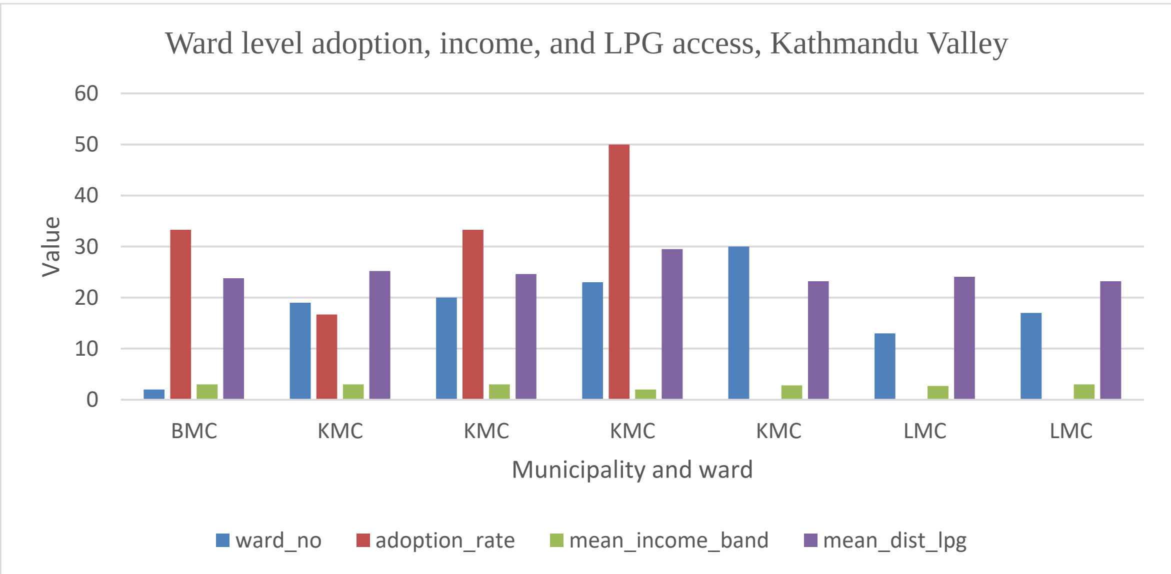

Figure 7: Ward level adoption, income, and LPG access, Kathmandu Valley

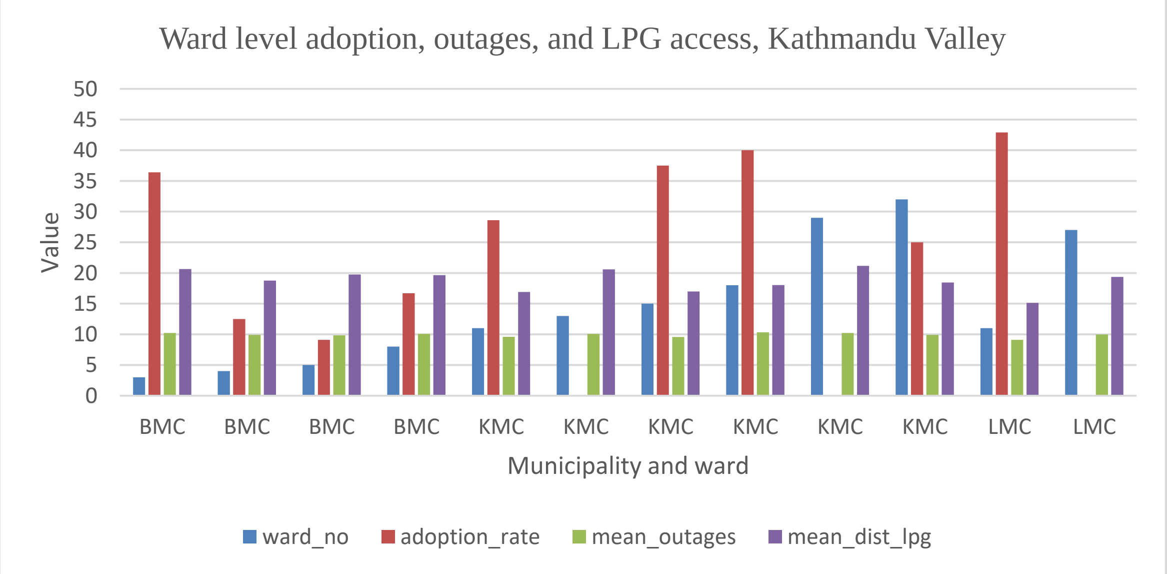

Figure 8: Ward level adoption, outages, and LPG access, Kathmandu Valley

Discussion:

The maps and ward tables show strong spatial heterogeneity in clean cooking across Kathmandu Valley. Inner wards with short LPG travel times and fewer outage hours have higher adoption. Fringe wards with longer distances and frequent outages lag. This pattern matches prior work on spatially varying energy access, built environment, and infrastructure effects in Asian cities and beyond (Jo and Kim, 2022; Dong et al., 2023; Li et al., 2022; Xie et al., 2022). Household capability also varies by place. Income and education show positive associations on average, but effect sizes differ by ward, consistent with multiscale processes reported in MGWR studies of domestic energy and electricity use (Feng et al., 2025; Guo and Sun, 2025; Fotheringham et al., 2024). Nepal-specific findings on stacking and adoption barriers support these mechanisms. Proximity to LPG points of sale, price shocks, and reliability concerns shape household choices in peri-urban wards (Rogers, 2020; Ramirez et al., 2024). Energy burden and community vulnerability research further explains why low-income wards adopt more slowly, even at similar distances, due to budget constraints and risk exposure (Moore and Webb, 2022; Shen et al., 2023; Roy et al., 2024). Urban morphology and road connectivity influence both distance costs and supply chain performance, reinforcing local disadvantage where streets are less connected and travel times are longer (Liu et al., 2025; Lei et al., 2023). The observed heterogeneity, therefore, reflects interacting constraints, market access, grid quality, and socio-economic capacity, which MGWR is designed to capture through scale-specific coefficients (Zeng et al., 2016; Shen et al., 2024; Boutayeb et al., 2025).

Policy implications

Target policies to where marginal gains are highest. Use ward-level income elasticities to allocate LPG vouchers to low-income areas where price support moves adoption the most (Moore and Webb, 2022; Roy et al., 2024). Prioritize feeder upgrades in wards where reliability has the largest negative coefficient on adoption. These reliability improvements reduce stacking and increase the payoff to electric cooking (Dong et al., 2023; Zhang et al., 2024). Support household biogas where plots and waste streams allow, especially in peri-urban fringe wards, to hedge against outages and LPG supply disruptions (Bharadwaj et al., 2022; Ramirez et al., 2024). Place new authorized LPG points of sale in distance hot spots to shrink travel times and reduce transaction costs. Align siting with municipal transport and land use plans so road access, market coverage, and safety checks scale together (Li et al., 2022; Xie et al., 2022; Chen et al., 2024). Embed these actions in a spatially explicit monitoring system to track ward-level progress and update priorities over time (Feng et al., 2025; Khoun et al., 2025).

Limitations

The analysis relies on a cross-sectional sample. Causal interpretation is limited, and short panels would strengthen identification of dynamic effects. Measurement errors may exist in self-reported outage hours and travel time to LPG outlets. These errors are likely to have bias effects toward zero. MGWR improves fit by allowing spatially varying coefficients, but it assumes smooth variation and can be overfit without careful bandwidth selection and diagnostics (Fotheringham et al., 2024; Shen et al., 2024). Some potentially important drivers are unobserved at the ward scale, such as appliance finance access, informal tenancy constraints, and retailer stockouts. Generalizability beyond the Valley is uncertain, given different supply chains and grid topologies in other Nepali cities and rural municipalities (Ramirez et al., 2024; Bharadwaj et al., 2022).

Conclusions:

Clean cooking adoption in Kathmandu Valley varies sharply by ward. Proximity to LPG points of sale and electricity reliability explain much of the spatial pattern. Income and education raise adoption but with different strengths across neighborhoods. These results are consistent with multiscale evidence from other cities and sectors, where access, infrastructure, and socioeconomic capacity interact in place-specific ways (Feng et al., 2025; Guo and Sun, 2025; Li et al., 2022; Dong et al., 2023). Three actions follow. First, locate new LPG retail outlets in distance hot spots and add last-mile delivery in fringe wards. Second, upgrade feeders where outages show the largest marginal effect on adoption and encourage induction-ready tariffs. Third, target LPG vouchers to low-income wards with high price sensitivity and promote biogas where plots and feedstock are suitable. Future work should add time series data, link retailer inventories and feeder logs, and estimate full MGWR with ward geometry to quantify bandwidths and scale sensitive effects more precisely (Fotheringham et al., 2024; Boutayeb et al., 2025; Ramirez et al., 2024).

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