Quantifying the Effects of Spatial Determinants of Cooking Fuel Choices in India

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Abstract
Household energy consumption constitutes approximately 30%, of India's overall energy consumption, with cooking alone accounting for about 40% of this household energy usage. According to the recent consumer survey of India, approximately 30% of the population is still using polluting fuels in India, and several policies like the Pradhan Mantri Ujjwala Yojana have been launched to improve the penetration of LPG as the primary cooking fuel in households. While studies have examined the influence of socio-economic factors on household fuel choices, research focusing on spatial socio-economic dynamics remains limited. This study seeks to fill this gap by investigating the role of regional economies in shaping household cooking fuel preferences, thus addressing concerns related to sustainability and indoor air pollution. This study hypothesises that regional economies might play a significant role in influencing the cooking fuel choice of households. Given the fact that the subsidies and policies governing the cost and distribution of fuel are implemented on national or regional levels, coupled with existing regional disparities in India, studying the influence of spatial variables is imperative. Utilizing Spatial Regression Analysis, specifically the Spatial Lag Model, this research examines the impact of various regional variables on household fuel choices. Findings indicate that GDP per Capita, Built-up Area per 100 sqm, Percentage of main workers in the district and Percentage of households with land ownership exceeding 1 Ha significantly influence the prevalence of LPG usage as the primary cooking fuel in Indian households. For instance, an increase of INR 20,000 in GDP per capita of a district causes a 1% rise in LPG adoption among households in that district. Furthermore, the spatial lag coefficient highlights the spillover effect, indicating that a 1% increase in LPG usage among all the neighbouring districts leads to a 0.42% rise in LPG adoption among the households of the target district. This study underscores the implications of improved technology or new policies on energy usage patterns, suggesting a need for nuanced policy measures tailored to regional disparities. The insights generated from this analysis offer valuable guidance for policymakers and regional planners in formulating targeted interventions to address regional inequalities and promote sustainable development. Additionally, this spatial perspective enables an understanding of resource allocation for efficient regional development. Future research could enhance these findings by incorporating more detailed datasets and refining the Spatial Weights Matrix to account for factors such as connectivity and policy influences..

Keywords
Spatial Regression Analysis, Urban Energy Economics, Household Energy, Cooking Energy

1. Introduction
Approximately 29 percent of the net national energy consumption is in the residential sector, and cooking represents the largest portion of consumption within this sector (IEA, 2020). Specifically, for rural and urban areas, cooking constitutes for 78 percent and 66 percent of the net household energy usage respectively (Yawale et al., 2021).

A business-as-usual scenario of cooking fuel use might lead to approximately 2.7 billion people using unclean fuel by 2030 globally (Stoner et al., 2021). In India, approximately 115 million of its urban population still relying on unclean fuels as of 2012, while only 68.7 percent of utilizes Liquified Petroleum Gas (LPG) for cooking.

Given this substantial reliance on unclean fuels, research has exhaustively examined the factors influencing their usage. The existing literature has extensively explored regression techniques like logistic regression to establish that the household characteristics play an important role in defining household cooking fuel choice, thus suggesting that with the socio-economic upliftment of the household, the population shifts towards using cleaner fuels. Such outcomes often suggest subsidy-based policies to promote cleaner fuel use, specifically in the developing countries like India.

However, the studies on the influence of spatial factors on household cooking fuel usage is limited. Variables like per capita GDP might indicate the overall socio-economic upliftment of a region, and thus might positively influence the uptake of cleaner fuel for cooking in the households. The variables like connectivity and electrification, which show spatial clustering, might also produce errors in in simple regression methods. Moreover, the subsidies and policies governing the cost and distribution of fuel are implemented on national or regional levels. Such uniform policies, coupled with existing regional disparities in India, might not produce the desired results, leading to inequity among population groups and regions. Thus, studying the influence of spatial variables for cooking fuel choice becomes imperative.

This study hypothesises and demonstrates using Spatial Lag Model that spatial factors play a significant role in influencing the cooking fuel choice of households. Thus, suggesting that merely promoting cleaner fuels using schemes like subsidies might not be effectively successful in influencing the household fuel choice. For developing and highly populated countries like India, which aims to reduce its net carbon emission, more efficient and multi-pronged approaches are necessary to reduce emissions. This study provides such opportunity by studying the influence of spatially autocorrelated variables on the uptake of household cooking fuel choices.

2. Literature Review

Studies classify cooking fuels as traditional (unclean or polluting) or modern (clean or non-polluting) fuels (Katutsi, Dickson and Migisha, 2020). Common traditional cooking fuels include biomass, charcoal, coal, and kerosene, while their modern cleaner counterparts typically comprise gas and electricity (Stoner *et al.*, 2021). Apart from the concerns about pollution, efficiency also varies among traditional and modern fuels, with biomass at 8 percent, coal at 18 percent, charcoal at 25 percent, kerosene at 45 percent, and gas and LPG at 50 percent (Dzioubinski and Chipman, 1999).

Research literature has extensively studied the variables influencing households cooking fuel choices. Studies classify these variables into into demographic, economic, consumer attitude, and climatic factors climate (Bhattacharjee and Reichard, 2012). Demographic and economic variables have been extensively studied in the literature (Kastner and Stern, 2015).

The literature has established that the demographic variables such as household size, age of household/head (Yu, Zhang and Fujiwara, 2011; Aslam and Ahmad, 2018; Katutsi, Dickson and Migisha, 2020), gender of household head (Katutsi, Dickson and Migisha, 2020), marital status (Katutsi, Dickson and Migisha, 2020), and level of education (Katutsi, Dickson and Migisha, 2020; Mperejekumana *et al.*, 2021), influence the cooking fuel choices of households.

Similarly, the significant economic variables are GDP (Garba and Bellingham, 2021), employment status, income (Acuner and Özgür Kayalica, 2018; Kuo and Azam, 2019; Katutsi, Dickson and Migisha, 2020), expenditure, land ownership, number employed, type of employment (Liao *et al.*, 2019), credit access (Mperejekumana *et al.*, 2021), ownership of ICT (Acharya and Marhold, 2019), ownership of housing (Pundo and Fraser, 2006; Acharya and

Marhold, 2019), housing type (Pundo and Fraser, 2006; Yu, Zhang and Fujiwara, 2011) and area of housing unit.

Literature has also shown the relationship between use cooking fuels with initial investment cost of modern fuels (Pohekar, Kumar and Ramachandran, 2005; Reddy and Balachandra, 2006), lack of LPG distribution networks (Reddy and Balachandra, 2006), ingrained habits of using traditional fuels like cow-dung or firewood (Sharma, Parikh and Singh, 2019), the availability of Solid Biomass Fuel (SBF) through agricultural produce (Sharma, Parikh and Singh, 2019), culinary preferences (Sharma, Parikh and Singh, 2019), HDI (Dutta and Sahu, 2022), and electrification (Gupta and Pelli, 2021).

These studies have attempted to estimate the influence of various factors on each of the cooking fuel being used in the households. As the fuel choices are polychotomous variable with a dominant category, Multinomial Logistic Regression is a popular regression method in such studies (Danlami, Applanaidu and Islam, 2019; Baek, Jung and Kang, 2020; Katutsi, Dickson and Migisha, 2020; Kapsalyamova *et al.*, 2021; Mperejekumana *et al.*, 2021; Niyonshuti, 2021). Moreover, some works have also employed the Ordered Probit Model (Rahut, Behera and Ali, 2017) and Multiple Discrete-Continuous Extreme Value (Biying, Zhang and Fujiwara, 2012; Yu, Zhang and Fujiwara, 2013; Acharya and Marhold, 2019) for analysis.

However, few research works have attempted to study the influence of spatial factors such as GDP of the region, regional employment type or the extent of urbanisation, specifically using spatial regression analysis methods. Searching for the following code on Scopus outputs 15 studies, only one out of which by Wang *et al.* (2021) suggest that the per capita gross regional product and per capita disposable income of urban residents influence fuel choice of the households.

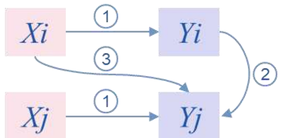
Most of the studies which have used spatial regression analysis in the context of fuel or energy are related to air pollution or electricity consumption. Studies suggest that total population, population density, urbanisation rate, per-capita gross regional product, economic growth, industrial structure, road density and climatic factors influence air pollution (Zhou, Chen and Wang, 2018; Ren and Matsumoto, 2020; Tan *et al.*, 2021). Whereas, income, employment density, ratio of employee in retail department, transit fare, and distance to city centre (Yin, Mizokami and Maruyama, 2013; Li *et al.*, 2022). These studies suggest policy improvements related to spatial pricing policies (Zhang *et al.*, 2023), transition of the economic structure (Ren and Matsumoto, 2020), and influencing built-up and employment density (Yin, Mizokami and Maruyama, 2013). Several variables in these studies are common with the variables which have been found to be significantly influencing the household cooking fuel choices.

Moreover, variables like population density, urbanisation rate, electrification and connectivity exhibit spatial clustering, and hence considering this characteristic is required during analysis. However, the studies focusing on household fuel choices have failed to take the spatial clustering or spatial autocorrelation into account. To address this gap, this study utilises spatial regression method for the analysis.

3. Methodology

Research highlights that the spatial regression models perform better than the Ordinary Least Squares (OLS) regression when there is spatial interaction between the variables (Ward and Gleditsch, 2008). While linear or logistic regression techniques study the relationship between the dependent and corresponding independent variables, the spatial regression models often incorporate the influence of variables corresponding to spatially neighbouring entities (spatial units) on the target variable of the target spatial unit. The description of simple regression models and spatial regression models is shown in Figure 1.

Figure 1 Description of Simple regression and Spatial Regression Techniques



1. Regression Model: $Xi \rightarrow Yi$ or $Xj \rightarrow Yj$
2. Spatial Lag or Lag Y Model (SAR): $Yi \leftrightarrow Yj$
3. Spatial Cross-Regressive or Lag X Model (SLX): $Xi \rightarrow Yj$

As established in the literature, several variables shown to influence household fuel choices significantly might be spatially correlated. To address the spatial influence of such variables, using spatial regression models for this study is required. The influence of the socio-economic variables explored in the previous studies is limited to the same spatial unit, and their influence might not directly extend to the neighbouring spatial units. However, the socio-economic upliftment of the population in the neighbouring spatial unit might also cause a similar development in the target spatial unit, leading to a spill-over effect in the uptake of cleaner fuels for cooking. Since the socio-economic factors of one spatial unit might not affect the fuel choice in the neighbouring spatial unit, the SLX model is out of scope, and the SAR model is used for the study.

The spatial lag model considers the effect of one dependent variable on the neighbouring one, and is represented by the Eq. 1.

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{\beta}\boldsymbol{X} + \boldsymbol{\varepsilon} \qquad \textbf{Eq. 1}$$

where,

y = Dependent Variable
ρ = Spatial Lag Coefficient
W = Spatial Weights Matrix with size a '$n \times n$', where n is the total number of observations
β = Coefficient of Independent Variable
X = Independent Variable
ε = Error

However, it is necessary to find out the extent of spatial autocorrelation in the dataset to perform the spatial regression analysis. Spatial autocorrelation is indexed by calculating Moran's I, which measures the spatial clustering of the variables (Moran, 1950; Cliff, Ord and Cliff, 1981). The value of Moran's I ranges from -1 to +1, negative value representing no clustering or dispersed features, and a positive value representing clustered features, corresponding to a z-score greater than 1.96, at a 0.05 significance level (Ord and Getis, 1995).

4. Data Description and Pre-processing

A district level dataset for 601 districts of India was created for this study. The data was available from various sources listed in Table 1. All the datasets were then transformed at the district level resolution, where districts will be acting as one spatial unit. Since LPG is the predominant fuel choice with 68.7 percent of the Indian population using it as the main cooking

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fuel (MoSPI, 2014), the fraction of households using LPG in the district as their main cooking fuel was considered as the dependent variable for the analysis.

Table 1 Sets of independent variables were considered for the study

S. No.	Variables	Source
Dependent Variables		
1	Fraction of Households using LPG as main cooking fuel	Household Consumption of Various Goods and Services in India, 2011-12, NSS 68th Round, Sch 1.0, Type 2, National Sample Survey Office (NSSO), Ministry of Statistics and Program Implementation (MoSPI, 2014), Government of India
Independent Variables: Spatial Economy		
1	Gross District Product (GDP) (in Crores INR)	NITI Aayog (2016), Government of India (For the states with no data for GDP, the state GDP was distributed according to the population weightage of the districts)
2	GDP per Capita (in Crores INR)	GDP divided by the population of the district (obtained from Census of India, Government of India (MoHA, 2014))
Independent Variables: Household Economic Status		
3	Average Household Expenditure (in Thousands INR)	Household Consumption of Various Goods and Services in India, 2011-12, NSS 68th Round, Sch 1.0, Type 2, National Sample Survey Office (NSSO), Ministry of Statistics and Program Implementation (MoSPI, 2014), Government of India
4	Fraction of Households with more than 1 ha of Land Owned	
Independent Variables: employment types		
5	Fraction of Working Population	Census of India, Government of India (MoHA, 2014)
6	Fraction of Main Workers	
7	Fraction of Agricultural Workers	
Independent Variables: Socio-Demographic Status		
8	Total Population	Census of India, Government of India (MoHA, 2014)
9	Total number of Households	
10	Average Household Size	
11	Fraction of Households with Head having a Graduation Degree	
12	Fraction of Literate Population	
13	Average age of Household Head	Household Consumption of Various Goods and Services in India, 2011-12, NSS 68th Round, Sch 1.0,

		Type 2, National Sample Survey Office (NSSO), Ministry of Statistics and Program Implementation (MoSPI, 2014), Government of India
Independent Variables: Spatial Development		
14	Fraction of Population living in Urban Areas	Census of India, Government of India (MoHA, 2014)
15	Average Night Time Light in W/cm²/sr	Average Night Time Light (NCEI, 2013)
16	Built-up area per 100 m^2 of Land	Built-up density (GHSL, 2023), European Union

Spatial Weights Matrix

The calculation of W matrix is important in determining the model properties. W is defined as a '$n \times n$' matrix, where n is the total number of observations. Creating the W matrix for the study included following steps:

1. Initially, the value of n_{ij} is kept equal to 1 if the i^{th} and j^{th} entries are neighbours. But that ensures that all the neighbouring districts will have a unit impact on a district, essentially meaning that if a district has more neighbours, then it will have more impact on its dependent variable.
2. To overcome the error, row-wise normalisation is done. This ensures that the unit effect is observed. But practically, not every district will provide a uniform impact, and the districts which are highly influential might impact more.
3. To overcome this error, the values were weighted by district GDP and then normalised to ensure justified impacts. The current W matrix can be described as Eq. 2.

$$\boldsymbol{W_{ij} = GDP_j \,/\, \sum_{j=1}^{N} GDP_j} \qquad \textbf{Eq. 2}$$

where,

GDP_j = GDP of the District j

$j \in \{1,2,3,\ldots,N\}$ is the set of neighbouring districts of the district i

Spatial Autocorrelation

It is necessary to find the extent of spatial autocorrelation or clustering in the dataset to perform the spatial regression analysis. The clusters of developed and under-developed regions can be observed primarily through the maps shown in Figure 2 and Figure 3.

Figure 2 Fraction of Households in the district using LPG as Main Cooking Fuel

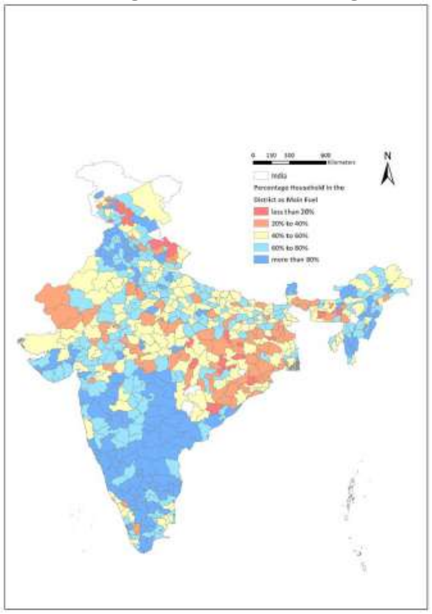
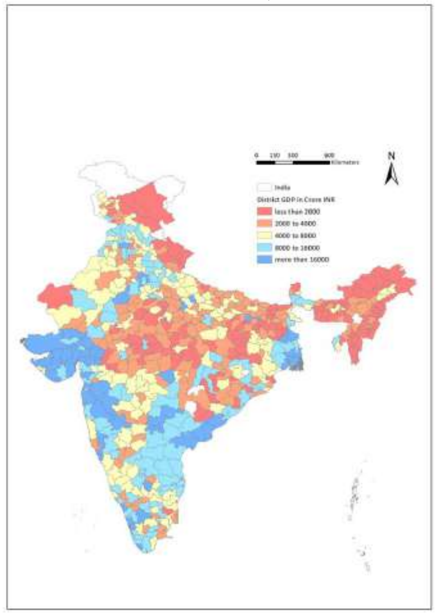


Figure 3 Gross District Product (GDP) (in Crores INR)



To study the extent of clustering, spatial autocorrelation analysis by calculating Moran's Index was done on the dependent variable i.e. Fraction of Households in the district using LPG as the Main Cooking Fuel in Districts as spatial units. The results showed that the value of Moran's I is 0.335299 and the z-score is 22.58 for the Fraction of Households in the 601 districts using LPG, at less than 1 percent likelihood of clustered pattern being result of a random chance.

Correlation Analysis

The correlation analysis is conducted and at least one from each set of correlated variables is to be chosen as the final independent variable. The correlated sets are:

1. GDP, GDP per capita, Total Population, Total number of Households, Fraction of Population living in Urban Areas, Night Time Light Intensity and Built-Up Density are highly positively correlated to each other.
2. The variables describing employment types, Night Time Light Intensity and Built-Up Density are negatively correlated with the Fraction of Households with more than 1 ha of Land Owned.
3. The fraction of main-workers in the district has a higher and positive correlation with all variables depicting higher development than the fraction of the working population in the district.

5. Results and Discussion

High spatial autocorrelation was observed in the dataset and hence the spatial lag model was implemented to consider clustering of the dataset, as suggested by previous research (Yin, Mizokami and Maruyama, 2013). The results of the analysis are depicted in Table 2.

Table 2 Description of Spatial Regression Analysis results for Fraction of Households in District using LPG as Main Cooking Fuel

Variable	**Coefficients**
Constant	-0.16**(0.073)
GDP per Capita in Crores	0.005**(0.002)
Built-up Area per 100 m^2	0.01***(0.002)
Fraction of main workers in the district	0.871***(0.111)
Fraction of households with land owned more than 1 ha	0.238***(0.067)
Spatial Lag	0.42***(0.045)

- Number of Observations: 601
- Number of Variables: 6
- Degrees of Freedom: 595
- Akaike info criterion: -398.995
- Schwarz criterion: -372.603
- Mean dependent var: 0.6178
- S.D. dependent var: 0.2147
- Pseudo R-squared: 0.3839
- Spatial Pseudo R-squared: 0.2752
- Log-likelihood: 205.4975
- Sigma-square ML: 0.0285
- S.E of regression: 0.1687

The results can also be described in the form of Eq. 3:

$$\boldsymbol{y} = \rho \boldsymbol{W y} + \boldsymbol{\beta 1 X1} + \boldsymbol{\beta 2 X2} + \boldsymbol{\beta 3 X3} + \boldsymbol{\beta 4 X4} + \boldsymbol{\varepsilon} \qquad \textbf{Eq. 3}$$

where,

y = Fraction of Households using LPG as the Main Cooking Fuel
ρ = 0.42, W = Spatial Weights Matrix
$\beta 1$ = 0.005, $X1$ = GDP per Capita in Crores
$\beta 2$ = 0.871, $X2$ = Built-up Area per 100 m^2
$\beta 3$ = 0.238, $X3$ = Fraction of main workers in the district
$\beta 4$ = 0.01, $X4$ = Fraction of households with land owned more than 1 ha
ε = -0.16

Four independent variables, namely GDP per Capita, Built-up Area per 100 m^2, Fraction of main workers in the district and Fraction of households with land owned more than 1 ha, were significant. Their description is given below:

1. GDP per Capita in Crores: GDP per capita showed a better significance than net GDP as some of the districts have extremely high or low populations as compared to others. With highly industrialised as well as remote districts present in the dataset, a measure which could depict the economic characteristic at a disaggregate level shows better

results. As the coefficient for the GDP per capita is positive, an increase in the GDP per capita of a district causes a rise in LPG adoption among households in the district.

2. Built-up Area per 100 m^2: Built-up density is a measure of urbanisation as well as accessibility, which ensures the uptake of cleaner fuels. As higher night-time light intensity can be obtained from industries, built-up density showed a higher significance. The positive and significant coefficient shows that if the total built-up land increases, the LPG usage will increase as well, irrespective of all other factors.
3. Fraction of main-workers in the district: The fraction of main-workers depicted the state of employment in the district, and since more stable employment types increase the uptake of cleaner fuels, it provided significant results. The coefficient values depict that a percentage increase in the main workforce of the district increases LPG adoption among households.
4. Fraction of households with land owned more than 1 ha: The average land ownership of Indian households is approximately 1 ha, and better economic well-being increases the uptake of cleaner fuels. Coefficient values depict that an increase in the proportion of households owning up to 1 ha land leads to an increase in LPG usage of the households in the district.
5. Spatial Lag Coefficient: The Spatial Lag Coefficient depicts the effect of LPG usage in neighbouring districts on the target district. Moreover, the effect of independent variables on the LPG usage in the target district also shows up in the coefficient ρ. An increase in LPG usage among all the neighbouring districts leads to a rise in LPG adoption among the households of the target district without any change in the socio-spatial characteristics of the target district. However, LPG usage changes in neighbouring districts with higher GDP would be proportionately higher. However, the value of ρ can also be understood as a limiting factor, meaning any amount of increase in LPG consumption in the neighbouring district cannot lead to more than ρW times of increase in the target district.

6. Policy Implications

In India, subsidy policies like Ujjwala Yojana, which subsidises LPG for a defined socio-economic group, are implemented uniformly nationwide. However, the spatial socio-economic disparity might hinder uniform regional development. Moreover, previous research has extensively explored the influence of socio-economic upliftment on the uptake of non-polluting fuels, suggesting an improvement in such variables to ensure higher uptake of cleaner fuels. However, this research shows the influence of spatial proximity on the uptake of cooking fuels like LPG, indicating a need for nuanced policy measures tailored to regional disparities.

The study indicates that improving the economy or technology or implementing new policies in any urban area might sub-urbanise its periphery by a defined amount. This can be known as an energy usage spill-over effect limited by the value ρW.

Additionally, this spatial perspective enables an understanding of resource allocation for efficient regional development. Such studies can also assess the regional changes in the energy usage scenario after a greenfield development. The insights generated from this analysis offer valuable guidance for policymakers and regional planners in formulating targeted interventions to address regional inequalities and promote sustainable development.

7. Conclusions

This study contributes to the existing literature by introducing the use of the spatial lag model to study the factors influencing cooking fuel choices in households in India. This study quantifies the spatial influence of socio-economic variables and the spill-over effect of LPG usage on its usage in the target spatial units. The findings of this study are:

1. The positive and significant coefficients for GDP per Capita, Built-up Density, State of Employment and Land Holdings in the Spatial Lag Model indicate that an improvement in these variables leads to increased uptake of LPG as the main cooking fuel in Indian households.
2. The spatial lag coefficient indicates that the uptake of LPG as the main cooking fuel in neighbouring districts positively influences the uptake of LPG in the target districts due to the spill-over effect. Moreover, improvements in GDP per Capita, Built-up Density, State of Employment and Land Holdings in the neighbouring districts influence the LPG uptake of those districts, causing an indirect influence on the target districts.
3. Several socio-economic variables previously used in the studies show spatial clustering or autocorrelation, and the phenomenon must be accounted for. The spatial regression models perform well in such cases and explain the effect of variables influencing household cooking fuel choices while accounting for spatial clustering.
4. To promote cleaner fuel usage in households, the policies must consider the spatial aspects of the region, specifically regional economy and spatial inequalities, instead of proposing uniform blanket schemes.

8. Limitations and the Way Forward

Methodologically, inputting variables such as built-up height or forest cover, and considering weightage dependent on connectivity, policies or state boundaries (which govern fuel pricing) for the calculation of the Spatial Weights Matrix might produce better model results. The data resolution can be further improved to achieve better results. Since socioeconomic disparities and heterogeneity exist in India (Reddy and Balachandra, 2006; Balakrishnan, 2016), and barring a few studies, fuel choices of the population in a region has been assumed to be homogeneous, improving on socio-economic variables, specifically in spatial aspects might be helpful for future studies.

Moreover, since that dataset used for the analysis is from 2011-12, it merely depicts the cross-sectional pattern of consumption among Indian Population. A panel analysis might provide even better insights into the fuel usage pattern, impact of new policies such as Ujjwala Yojana, and future policy improvements.

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