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Integrating Specific Emission Factors and Spatial Autocorrelation Analysis to Evaluate Urban Carbon Emissions in Residential and Waste Sectors: A Case Study of Mojokerto City, Indonesia

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ABSTRACT

The rise of urban carbon emissions is being seen as an important global climate change mitigation target, especially for medium-sized cities during rapid urbanization including Mojokerto in Indonesia. Yet almost all the existing studies rely on the basis of macro-scale inventories and overlook micro-spatial variations between urban villages, which cause very little insights into how residential and waste activities drive localized emissions patterns. This study fills this gap through a synergy of the Specific Emission Factor (SEF) method combined with spatial autocorrelation analysis to quantify and map carbon emissions sub-district wise. Empirically generated SEF indicators using the IPCC (2006) Tier 2 method demonstrate 0.278 tons CO_2 /household/year for residential emissions and 0.000579 tons CO_2-eq/person/year for waste emissions. This, was associated with the use of spatial statistical methods (Global Moran's I, Local Moran's I (LISA), and Getis–Ord Gi*) to characterize clusters and hotspots. The findings reveal total annual emissions amounting to 13,439.87 tons CO_2, primarily the former related to the residential sector. A Moran's I value of 0.24 (p = 0.0127) indicated that there was a strong positive spatial autocorrelation, Wates and Kedundung were indicated the emission hotspots and Purwotengah and Sentanan were the cold spots. Results show that Mojokerto carbon emissions are spatially clustered and geographically concentrated, which is indicative of population density and household energy use intensity differences. The findings emphasise the potential of spatially specific mitigation approaches, suggesting that multisectoral and spatio-temporal analyses are necessary to enhance adaptive, context sensitive low carbon urban planning.

Introduction

Climate change is considered to be among the most serious environmental problems of the current century, mainly induced by human activities in cities that have increased the production of greenhouse gases in urban areas, such as carbon dioxide (CO_2) [1]. The global annual average temperature in 2023 had been recorded at 1.45°C higher than the pre-industrial global mean temperature, close to the Paris Agreement's level 1.50 °C standard to serve as a reference point through which to measure mitigation actions [2]. The world mean temperature has risen by approximately 1 °C since 1880 [3]. The effects of climate change are not limited to higher temperatures; they affect ecosystems, human health, and the global economy and social systems [4]. Over 70% of the total global carbon dioxide emissions are from urban processes, including energy use, transportation and waste management, so the city is in the centre of the world's mitigation efforts [5]. Rapidly urbanizing urban centers in developing countries like Indonesia have increased the load for household energy consumption and waste generation, contributing to a substantial environmental pressure on the residential sector [6].

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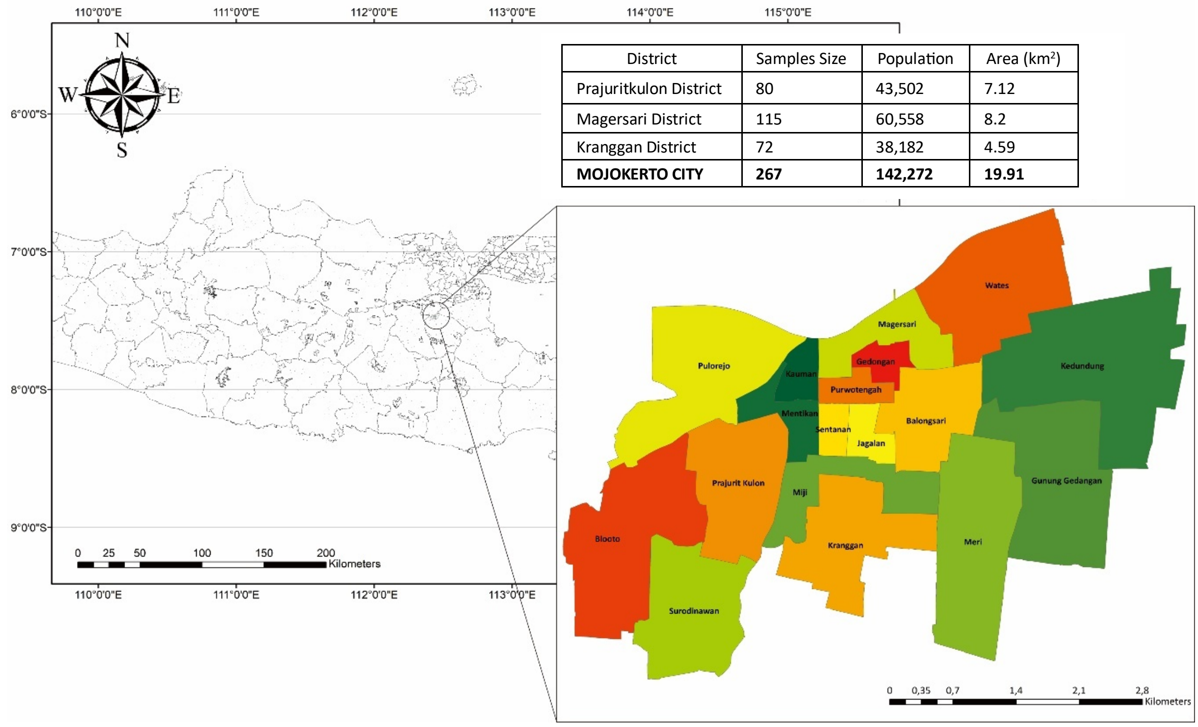
A number of major problems highlight the importance of our research. A majority of the existing research has been aggregate studies, concentrated on cities or provinces and have not considered where spatial variations are taking place at local level (urban villages or neighborhood scale). According to a study conducted among Jakarta population in 2022, household social classes are related to urban community carbon emissions [7]. Additionally, previous studies often separated computation of emission factors from their spatial dimensions. For example, Zhao and Ren [8] found spatial analyses revealed large disparity in household CO_2 emission intensity with regard to northern vs Southern China, but did not formulate an integrative model that combined the specific emission factors with spatial analysis. This limitation underscored the limited study of microscale spatial carbon emissions in medium-sized cities in Indonesia. While previous studies have investigated urban carbon emissions from quantitative and spatial point of view, integrative microscale analyses are still limited. The study's theoretical basis is built upon the requirement of convergence between quantitative and spatial perspectives. The theoretical architecture of this study relies on two major perspectives. First, the activity-based emission inventory and emission factor approach, such as the Tier 2 method from the Intergovernmental Panel on Climate Change [9] provides quantitative estimates of sector emissions. Second, the spatial analytical approach holds that carbon emissions are spatially clustered and interregionally linked, which reflects the complex trade-off between the urban morphology and intensity of carbon emission as demonstrated in international literature [10], while Shi et al. [11] highlighted spatial and temporal variability in carbon emissions from residential buildings in urban cities. Wu and Li [12] found further evidence of the spatiotemporal evolution and emission rate contributing aspects of carbon emissions and underscoring the necessity of combining quantitative, spatial, and temporal approaches for the development of emission distribution. However, a majority of studies have been aggregated or decoupled between the analysis of emission factor and the spatial distribution, and this represents a lack of evidence at the micro-scale level for studying the pattern of carbon emissions in medium-sized Indonesian cities.

The novelty of this study is the integration of specific emission factor calculation combined with sub-district level spatial analysis in methodology in medium-sized urban as compared with low-countries as well as in the Indonesian context of a medium-size country is rarely used in context of developing countries. Earlier studies have only estimated the specific emission factor on the city- or province-level or analyzed spatial emission trends without directly correlating it with specific emission factors. An integrative methodology of such a kind has also been used Gao et al. [13] but its use in medium-sized cities in the Global South is scarce. Hence this research contributes into a knowledge gap about the microscale spatial distribution of carbon emissions and generates methodological novelty by simultaneously combining the quantitative and the spatial approaches. This research has an important practical impact, since the results may inform spatially driven policies for carbon mitigation in urban settings. Against this background, the current work attempts to combine the specific emission factors of the IPCC Tier 2 method with the spatial autocorrelation analysis in order to evaluate the distribution and concentration of carbon emission of the residential and waste sectors in Mojokerto City, Indonesia. Drawing on specific emission factor estimation and spatial statistical techniques (Moran's I and Getis–Ord Gi* among others), this study provides an empirical demonstration of spatial distribution patterns for carbon emissions while creating a foundation for spatially oriented mitigation policies at the urban scale.

Materials and Methods

Study Area

Mojokerto City, which is located in East Java Province of Indonesia between 7°27'0.16" and 7°29'37.11" South latitude, and 112°24'14.3" and 112°27'24" East longitude, is one of Mojokerto's major cities. Situated in the middle of Mojokerto Regency, its core socio-economic and administrative activities are in the core region. According to the Statistics Bureau of Mojokerto City, in 2024, the City of Mojokerto had 142,272 residents. The population of urban villages was dispersed around the town with the highest population density seen in Wates Village (20,379 residents) and a low population density of Purwotengah Village (1,564 residents). As presented in Figure 1, Mojokerto City has 3 subdistricts and each one is composed of 6 urban villages i.e, the total number of urban villages in Mojokerto City is 18. The 3 subdistricts in Mojokerto City are Magersari Subdistrict, Prajuritkulon Subdistrict, and Kranggan Subdistrict. A specific number of samples was collected for each urban village in Mojokerto City, as indicated in Table 3.



District	Samples Size	Population	Area (km²)
Prajuritkulon District	80	43,502	7.12
Magersari District	115	60,558	8.2
Kranggan District	72	38,182	4.59
MOJOKERTO CITY	**267**	**142,272**	**19.91**

Figure 1. Description of the Study Area and Sampling Framework. The main map shows the location of Mojokerto City, located in East Java Province, Indonesia, between 7°27′0.16″ and 7°29′37.11″ south latitude, and 112°24′14.3″ and 112°27′24″ east longitude. The inset map shows the 18 urban villages in Mojokerto City along with their administrative boundaries. The inset table lists the names of the 3 subdistricts in Mojokerto City along with the number of samples to be studied, the population, and the area size.

Data Collections

The information for this study was derived from two primary and secondary datasets systematically compiled for the computation of Specific Emission Factors (SEF), carbon emission estimation, and spatial analysis of Mojokerto City. The core data were household fuel consumption (annual LPG and natural gas usage), daily household waste production (data collected through household survey in 2025). The secondary data, that includes population and household statistics, was obtained from government authorities from the Statistics Bureau of Mojokerto City. All datasets were combined for modeling household dynamics and waste pattern, as well as demographic characteristics influencing carbon emission levels in the study area. The data on consumption of fuel used by households were collected through the stratified random sampling process in this study, as the population of interest is based on the population size of administrative area strata. Samples were given randomly to each stratum to have a representative coverage of the study area. The number of sampling points was obtained through the formula developed by Krejcie and Morgan [14] (Equation 1). This approach allowed for the proportional representation of households across different population densities, ensuring statistical reliability and minimizing sampling bias.

$$n = \frac{X^2 NP\,(1-P)}{(N-1)d^2 + X^2 P(1-P)} \tag{1}$$

where n = total number of samples in the study area (households); N = total population in the study area (households); X^2 = chi-square value corresponding to the desired confidence level (X = 1.28 for 90% confidence; X = 1.64 for 95%; X = 2.58 for 99%); P = population proportion (ranging from 0.5 to 0.99); and d = margin of error or level of precision (5–10%). Based on Krejcie and Morgan's (1970) formula, a 95% confidence level, a population proportion of 0.5, and a margin of error of 5% were applied, resulting in a total of 267 samples distributed across 18 urban villages in Mojokerto City. Samples were randomly selected from each urban village to ensure proportional representation. The number of samples in each urban village was calculated using Equation 2.

$$ni = \mathrm{n}\,(\mathrm{N}_i/\mathrm{N}) \tag{2}$$

where N_i is the total population of each urban village (households), N is the total household population of the study area, n is the total sample size, and n_i is the number of samples allocated to each urban village, to maximize representativeness throughout the study area, this distribution was proportional to the population size of each urban village. Stratified random sampling was used to control for varied population distribution across Mojokerto's 18 urban villages, resulting in a more precise distribution, by minimizing variance within strata and giving balanced representation to both densely populated and sparsely populated areas. Following Krejcie and Morgan's [14] formula with 95% confidence level, 5% margin of error and p = 0.5, this estimate required a sample size of 267, which yielded enough statistical precision for SEF estimation, meeting the requirements from the IPCC for data quality. Further verification confirmed the sample's representativeness of household energy-use diversity, with fuel-type distributions (LPG at 60.7%, natural gas at 34.5%, mixed at 4.9%) very similar to municipal statistics. A Chi-square Goodness-of-Fit test ($\chi^2 = 0.12$, $p = 0.89$) provided no significant difference between sample and population with variance analysis suggesting that there was a proportional representation of socio-economic variables (including household size, density, and access to energy) across strata. These results validate that this stratified design captures fuel-type heterogeneity, energy-use patterns, and socioeconomic variation, providing representative Tier-2 activity data for IPCC-compliant SEF calculations. Quality Assurance and Quality Control (QA/QC) procedures implemented following the 2006 IPCC Guidelines included a pilot survey, standardized enumerator training, verification of sampling distribution, completeness and consistency checks, validation of extreme fuel-consumption values, cross-checking with municipal statistics, auditing of unit conversions and IPCC default parameters, and a 10% recalculation check using an independent spreadsheet. Together, they ensure that SEF estimation activity data is accurate, consistent and fully traceable.

Analysis of Specific Emission Factors and Carbon Emission Estimation

The Specific Emission Factor (SEF) calculation framework adopted for this study provides a composite approach of fuel-use and waste management sources considering the socio-environmental and geography specificities of Mojokerto City. According to the Tier 2 guidelines of the Intergovernmental Panel on Climate Change (IPCC) [9], our methodological approach is updated based on the empirical observation with a local context that may increase representativeness and lower uncertainty in the estimation of emissions. SEF derivation complies with the method outlined in the 2006 IPCC Guidelines, specifically Volume 2 (Energy) and Volume 5 (Waste) where locally representative activity data is used with country- or site-specific parameters, but default emission factors (EF) and Net Calorific Values (NCV) are retained where local values are not available. This Tier 2 method improves accuracy over the Tier 1 approach by considering household environmental changes such as, energy behavior, waste composition, and technology. In line with IPCC Volume 1, Chapter 2, Tier 2 is preferred whenever subnational activity data is present and spatial emission scales at a finer scale must be quantified.

In the energy sector, the Tier 2 approach calculates gas emissions based on fuel consumption statistics (e.g., based on country-specific emission factors, SEF) rather than default Tier 1 values (IPCC) [9]. The greenhouse gas (GHG) inventory, as discussed in further detail in the IPCC Guidelines uses an approach that calculates emissions by human activity (activity data) and an emission factor (EF) that is a measure of the emissions or removal per unit of activity [15]. Tier 2 calculations in this work utilized more precise local measurements of activity occurring in the study area as well as default IPCC emission factors [16]. The basic formula employed to estimate the total emissions is given in Equation 3.

$$Emission\ CO_2 = AD\ x\ EF \tag{3}$$

The variables in Equation (3) are defined as follows: AD refers to the activity data representing human activities that generate emissions, and EF denotes the emission factor, which measures the number of emissions produced per unit of activity. The equation used to estimate the emissions from energy consumption for each type of fuel is expressed in Equation 4 as follows:

$$Emission\ CO_2 = AD\ x\ EF\ x\ NCV \tag{4}$$

NCV refers to the Net Calorific Value of the fuel, expressed in megajoules per kilogram (MJ/kg). The CO_2 emission factors and Net Calorific Values of each fuel type used in this calculation refer to the default values recommended by the Intergovernmental Panel on Climate Change (IPCC) [9], as presented in Table 1.

Table 1. Default CO_2 Emission Factors and Net Calorific Values (NCV) for Various Fuel Types (IPCC) [9]. The table shows the default carbon dioxide (CO_2) emission factors and net calorific values (NCV) for natural gas, liquefied petroleum gas (LPG), and wood/wood waste according to the IPCC guidelines. The emission factor represents the amount of CO_2 emitted per unit of energy consumed (tons CO_2/TJ), and the NCV indicates the usable energy content of each fuel (TJ/Gg). In this work, these metrics are used to calculate CO_2 emissions from household fuel consumption. The values show that among these fuel types, wood and wood waste have the highest emission factor, while natural gas has the lowest emission factor.

Fuel Type	CO_2 Emission Factor (tons CO_2/TJ)	Net Calorific Value (NCV) (TJ/Gg)
Natural Gas	56.1	48.0
Liquefied Petroleum Gas (LPG)	63.1	47.3
Wood / Wood Waste	112	15.0

The Specific Emission Factor (SEF) for the residential sector was determined using data on fuel consumption for cooking and the total number of households in the study area. The relationship used to estimate the SEF is expressed in Equation 5.

$$SEF\ residential = \frac{Emission\ (ton\ CO_2/tahun)}{Total\ Number\ of\ Household\ Samples} \quad (5)$$

Meanwhile, the emissions generated from solid waste disposed of in landfills can be calculated based on the IPCC Guidelines (2006) using Equation 6.

$$Emission\ CH_4 = (MSW_T\ x\ MSW_F\ x\ MCF\ x\ DOC\ x\ DOC_F\ x\ F\ x\ 16/2 - R)\ x\ (1 - OX) \quad (6)$$

The variables in Equation (6) are defined as follows: MSWT represents the amount of municipal solid waste generated (Gg/year), and MSWF is the fraction of waste disposed of in landfill sites. MCF denotes the methane correction factor, and DOC refers to degradable organic carbon (kg C/kg waste). DOCF is the fraction of DOC that undergoes decomposition, and F indicates the fraction of methane (CH_4) in the landfill gas. where R represents the amount of recovered methane (Gg/year), and OX represents the oxidation factor. The conversion of methane (CH_4) emissions to carbon dioxide equivalents (CO_2-eq) can be achieved through two alternative methods: the use of Equation 7 presented below or the application of the Global Warming Potential (GWP) value as defined by the IPCC.

$$Emission\ CO_2 = Emisi\ CH_4\ x\ \left(\frac{1-F}{F} + OX\right) X44/16 \quad (7)$$

The variables in Equation (7) are defined as follows: F represents the fraction of methane (CH_4) in landfill gas, OX denotes the oxidation factor, 44 is the molecular weight of CO_2 (kg/kg-mol), and 16 is the molecular weight of CH_4 (kg/kg-mol). The Specific Emission Factor (SEF) for the waste sector was then calculated based on the number of residents served by the landfill. The relationship used to determine the SEF in the waste sector is expressed in Equation 8.

$$SEF\ waste = \frac{E}{Nt} \quad (8)$$

The Equation (8) variables are defined as follows: FES = Specific Emission Factor (tons CO_2-eq /person/year), E = Total emissions from the landfill (tons CO_2-eq/year) and N_t = Number of residents served by the landfill (persons). This equation was applied to calculate the annual per-capita carbon emissions from the waste sector in Mojokerto, Indonesia. After establishing the Specific Emission Factor (SEF) by local empirical test, variances were derived for each fuel type (LPG and Natural Gas (NG)) in the residential sector. Compared to estimates by default IPCC factors, these regional empirical estimates improve the accuracy, representativeness, and contextual relevance of CO2 emissions. The total carbon emissions from household fuel usage were then calculated through Equation 9.

$$Emission\ CO_2 = Total\ number\ of\ households\ x\ SEF\ residential \quad (9)$$

Conversely, the overall carbon emissions of the waste sector were estimated with respect to Equation 10, as given below.

$$Emission\ CO_2 = Total\ population\ x\ SEF\ waste \quad (10)$$

Total carbon dioxide emissions generated by the waste sector can be calculated by multiplying the total population by the Specific Emission Factor (SEF) given in Equation 10.

Uncertainty Analysis and Error Propagation

Calculation of uncertainty was conducted to quantitatively evaluate the variability and potential inaccuracy of the Tier 2 emission estimates for residential energy and waste in accordance with the IPCC Guidelines of 2006. Uncertainties are mainly based on variability of fuel consumption at the household unit level, the stratified sampling design, measurement error and the use of IPCC default parameters such as NCV, EF and methane generation constants. In the residential sector, uncertainty was estimated as the standard deviation of annual LPG and natural-gas consumption and passed through Tier 2 Equation 4. The error propagation was done according to the IPCC uncertainty guidance, given that the uncertainty sources of the fuel consumption variables were considered as statistically independent. In this study, the composite uncertainty was estimated using the root-sum-square method, generally applied in studies in greenhouse gas inventories and emissions assessment [17]. Uncertainties in greenhouse gas inventories tend to be caused by activity data, emission factors, and methodological assumptions; reporting uncertainty ranges generally fall within ±5–20 per cent of good, high-quality inventories[18].

Spatial Analysis of Carbon Emissions

Spatial analysis was performed to investigate both the global and local distribution of carbon emissions in Mojokerto City as well as clusters of high- and low-emitting areas for spatially targeted mitigation solutions. Three spatial statistical techniques were implemented: Global Moran's I, Local Moran's I (LISA), and Getis–Ord Gi. A Queen contiguity spatial weight matrix was employed, as it best describes the morphology of Mojokerto's urban villages with respect to spatial features on side sharing edges or shared vertices. This construction gives more realistic representation of socio-spatial interactions as opposed to rook contiguity or distance-based matrices, especially for irregular and densely populated administrative units. Queen contiguity models spatial dependence in SEF and emission patterns as the spatial connection with various possible neighbourhoods, reflecting household energy-use and waste-generation behaviour in adjacent areas, and being in line with other best practices for fine-scale urban environmental data. Carbon emissions spatial distribution features were investigated using spatial autocorrelation analysis [19]. The Global Moran's I method was adopted to observe the spatial autocorrelation pattern of carbon emissions from the residential and waste sectors in Mojokerto City. This approach shows the correlation of carbon emission values for an area to those in neighboring areas. In Equat, the overall formula for Global Moran's I is presented as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})^2} \tag{11}$$

N (where n = the number of spatial units) y_i and y_j are the carbon emission values at locations i and j (11). The expression w_{ij} is the spatial weight that defines the proximity relationship between regions using the Queen Contiguity matrix. Moran's I index varies from -1 to +1, a large positive value indicates positive spatial autocorrelation or a clustered structure and a negative value is a dispersed spatial pattern. On the other hand, Local Moran's I, also referred to as Local Indicators of Spatial Association (LISA), was used in examining spatial relationships between urban villages at the local level. The formula for Local Moran's I is provided in Equation 12.

$$I_i = \frac{n(y_j - \bar{y})\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{12}$$

The LISA analysis reveals four main categories: High–High (HH) and Low–Low (LL), which represent positive spatial clusters and High–Low (HL) and Low–High (LH), which represent spatial outliers. Using the LISA cluster map, the findings highlight local and spatial characteristics of carbon emission distribution.

Another important aspect is the study applied the Getis–Ord Gi* method which helps to further solidify the results of spatial autocorrelation analysis in detecting the spatial concentration of carbon emission values. This method also reveals which areas have significantly high (hotspots) or low (cold spots) emission intensities. Equations 13 and 14 provide the formulas for Getis–Ord Gi* statistic.

$$G_i^* = \frac{\sum_j w_{ij}x_j - \bar{X}\sum_j w_{ij}}{S\sqrt{\frac{\left[n\sum_j w_{ij}^2 - \left(\sum_j w_{ij}\right)^2\right]}{n-1}}} \tag{13}$$

Where:

$$S = \sqrt{\frac{\sum_j x_j^2}{n} - \overline{X^2}} \tag{14}$$

where x_j is the carbon emission at j and w_{ij} is the spatial weight between the regions, $\bar{x}$ is the global average and n (the total number of spatial units). A large positive Z-score signifies a statistically significant hotspot, and a significantly negative Z-score implies a coldspot.

Results and Discussion

Results

Specific Emission Factors and Estimated Carbon Emissions

From the primary survey of 267 households in Mojokerto City, it was observed that 162 households utilized Liquefied Petroleum Gas (LPG) as their primary cooking fuel, 118 households used Natural Gas (NG) supplied through the government distribution network, and 15 households used a combination of both fuel types.

From Table 3, the calculated SEF values appear to be substantially similar as the mean (with an estimated value of 0.28787 tons CO_2/ household/year). A higher number of households in urban villages generally lead to an increase in total CO_2 emissions. As an example, the Wates Urban Village (6,905 households) emitted the highest amount of carbon at 2,010.84 tons CO_2/year, followed by Kedundung (1,446.98 tons CO_2/year) and Pulorejo (1,041.20 tons CO_2/year). These areas record large domestic and transportation volume concentration with high concentration of domestic and transportation activities, and the carbon emission intensity is greater. On the other hand, with fewer households, regions like Gedongan (822 households) and Purwotengah (577 households), with almost few homes generating emissions 184.24 tons and 170.49 tons CO_2/year respectively, produced rather low emissions. This pattern is suggestive of a linear relationship between the family units per unit and combined carbon emissions.

SEF analysis revealed that each estimate was contained in the 95% Confidence Interval (CI) and this provided valid statistical estimates. Variations in CI widths vary for unit uncertainty levels that result from variable data and sample size differences. Values located on the range 0.29–0.35 for SEF have narrow symmetric intervals, thus they indicate stable estimates with low dispersion, while values at the extreme range (0.23880, 0.24562 and 0.65648) showed wide intervals because there is greater dispersion of the data and they are more sensitive to input drift. In general, the distribution of CI widths were statistically acceptable, indicating that estimation of the SEF process was rigorous even when the precision varied among observational units. As evidenced in the computed results in Table 3, overall, survey uncertainty is consistent across all the different urban villages in the scale of the Specific Emission Factor (SEF) and from 36.69% to 75.14% at times. All these values were in good consistency with household-level emission inventories, therefore it was considered that the behavior of survey-based activity data did not contribute abnormally and unequally to prediction of the SEF. Increased levels of uncertainty, as for Prajuritkulon (75.14%), Magersari (73.59%) and Sentanan (64.88%); are generally reflected in more heterogeneity in household fuel-use behavior, and therefore more likelihood of changing survey variability in the SEF outcome. On the other hand, the relatively low uncertainty level of Pulorejo (36.69%) and Meri (42.62%) corresponds to a more homogeneous energy behavior, which results in lower confidence intervals and uncertainty propagation. The lack of extreme outliers (<10% or >90%) also confirmed the statistical consistency in the spread of uncertainty. From all of these results, it is clear that variability of survey data has been systematically and transparently factored into SEF estimations, lending further strength and credibility to the emission estimates.

Methane (CH_4) emissions from waste generation in Mojokerto City are mainly waste obtained through solid waste disposed at the Randegan Final Disposal Site (TPA Randegan) in Kedundung Urban Village, Magersari District. The Environmental Agency of Mojokerto City (DLH) (2024) recorded the total annual waste generation in the city to be 36,226.07 tons per annum, out of which ~28,824.05 tons or ~79.57% was shipped and collected into the Randegan landfill dump. Carbon dioxide (CO_2) emissions from the Randegan landfill (e.g., Emissions Eq 6 and Emissions Eq 7, Methodology) were estimated using a methodology based on the IPCC (2006) methodology of methane generation, oxidation, and conversion to CO_2 equivalents of solid waste disposal sites. The emissions of methane (CH_4) were determined to be as follows: 3.298 Gg CH_4/year, or 82.448 tons CO_2-eq/year converted to carbon dioxide equivalents (CO_2-eq). In order to calculate the SEF, the emission load per person (or per population unit) service provided by the landfill over the period of the landfill was divided by the population (142,272 inhabitants) served by the landfill. Thus, the specific emission factor (SEF) for the waste sector was identified to be 0.000579 tons CO_2-eq/person/year.

Table 3. Estimation of CO_2 Emissions from the Residential Sector and Sensitivity Analysis. This table describes the projected annual CO_2 emissions attributed to the residential sector for each urban village within Mojokerto City, Indonesia, based on the number of households, survey samples, and the Specific Emission Factors (SEF) in terms of tons CO_2 per household per year. The table also reports the lower and upper emission estimates obtained from SEF uncertainty bounds, combined with sensitivity ranges and percentage variations.

District / Urban Village	Number of Households	Number of Samples	SEF (tons CO_2/Household/year)	SEF_{lower}	SEF_{upper}	Estimated CO_2 Emission (tons/year)	Estimated CO_2 Emission (tons/year) (lower)	Estimated CO_2 Emission (tons/year) (upper)	Sensitivity Range (tons CO_2/year)	Percentage
i	ii	iii	iv	v	vi	vii	viii	ix	x	xi
Prajurit Kulon District										
Surodinawan	3,061	17	0.229	0.180	0.278	701.44	552.45	850.42	297.97	42.48%
Prajuritkulon	2,769	15	0.247	0.154	0.340	683.72	426.83	940.61	513.78	75.14%
Blooto	2,448	13	0.391	0.294	0.489	957.70	718.83	1,196.56	477.73	49.88%
Mentikan	2,277	13	0.253	0.190	0.317	576.88	432.96	720.80	287.85	49.90%
Kauman	1,084	6	0.249	0.185	0.312	269.44	200.77	338.11	137.34	50.97%
Pulorejo	2,933	16	0.355	0.290	0.420	1,041.20	850.22	1,232.19	381.97	36.69%
Magersari District										
Gunung Gedangan	2,865	16	0.259	0.200	0.318	742.62	573.18	912.07	338.89	45.63%
Kedundung	5,471	30	0.264	0.206	0.323	1,446.98	1125.54	1,768.42	642.88	44.43%
Balongsari	2,745	15	0.267	0.191	0.343	731.99	523.14	940.84	417.70	57.06%
Gedongan	822	5	0.224	0.157	0.291	184.24	129.11	239.37	110.25	59.84%
Magersari	2,019	11	0.250	0.158	0.342	505.30	319.36	691.23	371.87	73.59%
Wates	6,905	38	0.291	0.221	0.361	2,010.84	1527.57	2,494.11	966.54	48.07%
Kranggan District										
Kranggan	4,601	25	0.259	0.185	0.334	1,193.52	851.57	1,535.46	683.89	57.30%
Meri	3,101	17	0.235	0.185	0.285	729.40	573.98	884.83	310.85	42.62%
Jagalan	1,029	6	0.239	0.168	0.310	245.72	172.61	318.84	146.23	59.51%
Miji	2,966	16	0.216	0.153	0.279	640.76	454.54	826.97	372.43	58.12%
Sentanan	800	4	0.656	0.444	0.869	525.19	354.82	695.56	340.74	64.88%
Purwotengah	577	4	0.295	0.219	0.372	170.49	126.10	214.88	88.78	52.07%
Mojokerto City (Total)	48,473	267				13,357.42	9,913.57	16,801.27		

Spatial Autocorrelation Analysis of Carbon Emissions

Spatial model of CO_2 emissions at urban-village scale in Mojokerto City has shown marked spatial differences among the districts. The cumulative CO_2 emission in the city is estimated to be 13,439.87 tons/year; the majority of which from the residential sector (13,357.42 tons/year) and 82.45 tons/year from waste sector. Most of the emissions attributed to waste were concentrated in Kedundung Urban Village, where the Randegan landfill is located, showing local emission concentration, calling attention to a need in spatially targeted mitigation planning.

Spatial analysis of CO_2 emission levels between the urban villages in the study area showed that there were spatial variations. Based on the distribution data, the total CO_2 emissions were between 170 and 2,011 tons/year which was displayed as spatially uneven pattern across Mojokerto City. Wates, Kedundung, and Gunung Gedangan were identified as high-emission areas (1,448–2,011 tons CO_2/year), indicating intensive anthropogenic activities likely associated with high population density and waste management operations. In contrast, Gedongan, Kauman, and Purwotengah exhibited the lowest emission levels (170–269 tons CO_2/year), which may reflect the dominance of low-intensity residential zones and less concentrated urban activity.

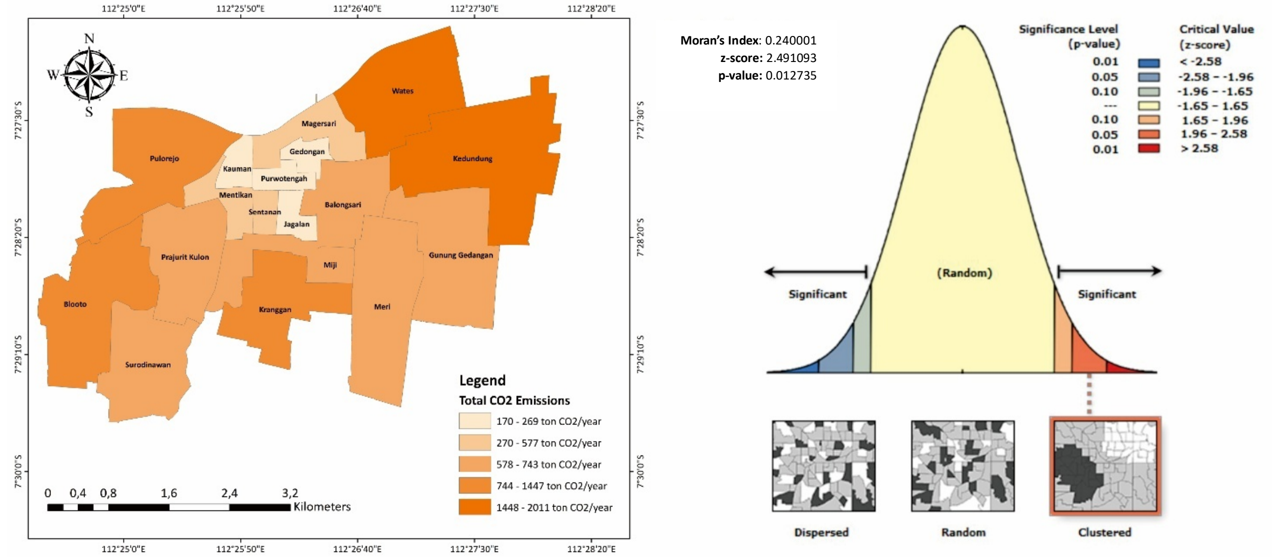


Figure 2. Spatial Distribution Map of Estimated CO_2 Emissions and Global Moran's I Analysis Results. The image on the left displays the boundaries of the urban villages in the city of Mojokerto and the estimated distribution of CO_2 generated by each sub-district. Meanwhile, the image on the right displays the results of the Global Moran's calculation; the Moran's I value was 0.240001, with a corresponding Z-score of 2.491093 and a p-value of 0.012735.

Global Moran's I analysis was conducted on the estimated carbon emissions from the residential and waste sectors at the urban village level in Mojokerto City. Based on the calculation using a Queen contiguity spatial weight matrix in ArcGIS, Moran's I value was 0.240001, with a corresponding Z-score of 2.491093 and a p-value of 0.012735. Since the p-value was < 0.05, the result was statistically significant at the 95% confidence level. Figure 2 shows a positive Z-score (2.49) associated with Moran's I = 0.24, indicating a statistically significant positive spatial autocorrelation, indicating that areas with high carbon emissions tend to be located near other high-emission areas, while low-emission areas are generally adjacent to other low-emission areas. This pattern demonstrates that the distribution of carbon emissions in Mojokerto City is not random but exhibits a spatial clustering tendency.

Conceptually, Moran's I is a global measure of spatial autocorrelation used to evaluate the degree of spatial dependency among regions based on the similarity of observed values occurring simultaneously [20]. In Mojokerto City, this pattern is expected because adjacent urban villages tend to share similar residential characteristics and household energy-use behaviors. These similarities create spatial dependence, whereby the carbon emission intensity of one village is closely related to that of its neighboring areas. Local Moran's I (LISA) analysis was employed to identify the specific locations where spatial autocorrelation occurs, as previously detected by Global Moran's I. While the Global Moran's I indicates a general tendency of spatial clustering, the LISA analysis provides a more detailed explanation of where the "hotspot" and "coldspot" clusters are spatially located [21]. The LISA results revealed four types of spatial relationships: High–High (HH) and Low–Low (LL), which represent positive spatial clusters, and High–Low (HL) and Low–High (LH), which indicate spatial outliers.

Figures 3 show LISA results, indicating that carbon emissions in Mojokerto City do not adhere to a completely homogeneous spatial pattern. Purwotengah and Sentanan were characterized as statistically significant Low–Low (LL) clusters, all other urban villages were considered as non-significant, showing that no spatial association was strong with surrounding areas. LL patterns in Purwotengah and Sentanan highlight the presence of low carbon emissions in two regions with similar low emission areas, driven by lower population density, low-intensity of domestic activities, and the widespread use of cleaner fuels such as natural gas or high-efficiency LPG. On the other hand, the non-significant areas indicate that the emission patterns did not have geographic continuity, likely due to the heterogeneity of characteristics of urban areas (such as population density differences and differences in household energy use practices across Mojokerto City). Getis–Ord Gi* analysis was used to obtain the local intensity of high (hotspot) and low (cold spot) values in the spatial data. In contrast to the Local Moran's I (LISA), which looks at the spatial correlation of the attributes in the same vicinity, a Gi* statistic calculates the local sum (which measures aggregation of neighboring attributes) and then standardizes it with the global mean and standard deviation by determining whether a certain surface corresponds to a statistically significant concentration of high or low values [22].

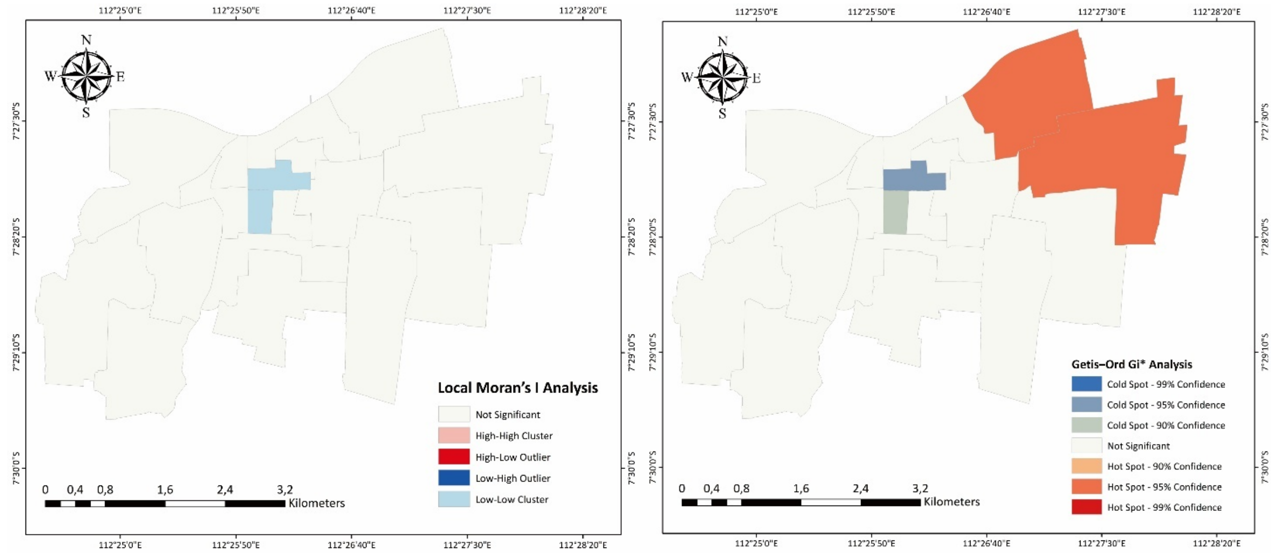


Figure 3. Results of Local Moran's I (LISA) and Getis–Ord Gi* Analyses. The image on the left shows the results of the LISA statistical analysis, which indicate that carbon emissions in Mojokerto City do not follow a completely homogeneous spatial pattern. Purwotengah and Sentanan are categorized as Low–Low (LL) clusters. Meanwhile, the figure on the right displays the results of the Getis–Ord Gi* statistical analysis, which found that Purwotengah is categorized as a coldspot at a 95% confidence level, and Sentanan as a coldspot at a 90% confidence level, while the Wates and Kedundung urban village are considered hotspots at a 95% confidence level, reflecting higher emission levels in clusters of neighboring urban villages with high emissions.

Risk from the spatial distribution of carbon emission results in Mojokerto City was clearly observed by the Getis–Ord Gi* distribution of its intensity (Figure 3). Purwotengah was categorized as a coldspot at 95% confidence level, and Sentanan as a coldspot at 90%, implying a lower emission intensity and similar low emission intensity. On the other hand, the eastern and northern part of the city with specific clusters of areas like Wates and Kedundung were considered hotspots at 95% confidence level, a reflection of higher emission content in clusters of high-emission neighboring urban villages. These findings verify the spatial clustering, with the low emission zones in the central area and high emission areas in the eastern and northern of Mojokerto City. While LISA found only the prominent Low–Low clusters, Getis–Ord Gi detected significant hotspot zones in Wates and Kedundung. This difference mirrors the different statistical goals of local autocorrelation and hotspot detection algorithms.

Discussion

The findings show that residential fuel consumption continues to be the preeminent carbon emission source in Mojokerto City, at a mean SEF of 0.28787 tons CO_2/household/year. This pattern indicates that household energy-use tendencies among urban villages are much the same across different socio-economic situations. The corresponding direct relationship with household numbers further supports the idea that, on balance, urban CO_2 emissions are dependent not on industrial activity as we predict, but on household-level energy-utilization intensity. This discovery is consistent with that of Miao [23] and Hartono et al. [24], who concluded that household dependence on fuel resources, income, and energy access are the most important factors affecting urban residential emissions among developing nations. Local SEF calculations were in good methodological quality as compared to the Indonesian BUR-3 inventory. The residential SEFs for Mojokerto (0.22-0.66 tons CO_2/household/year) sit at the middle-to-lower end in the spectrum of the IPCC-based peer-reviewed literature on other Indonesian cities. On the other hand, the extracted waste-sector SEF (0.000579 tons CO_2-eq/person/year) is much lower than the default FOD assumptions that often factor in high waste generation. This is attributed to waste removal and disposal methods in the area, such as recycling, composting and informal waste diversion, which lowers the proportion of degradable organic carbon available for the landfill. Similar results were obtained from Asyifa and Wijayanti [25], who found that municipalities with an operational community-based waste diversion program had greatly reduced methane emissions. Those similarities also support the evidence for why in many contexts, locally based SEFs should in fact obtain better and context-specific estimates of emission than defaults at the national level.

Spatial analysis indicates that Wates and Kedundung form significantly high-emission clusters. That this is the case can be explained by a number of structural features. First, both sites have the highest population density in Mojokerto (>12,000 people/km²), which consequently results in high domestic energy demands. Second, the emissions are strongly influenced by heterogeneity in the type of fuel. Use of LPG by the community at Wates and Kedundung is still very prevalent because they have not been covered by a natural gas network (18.23% and 54.11%) yet. Since LPG is enriched in carbon and has a different calorific value than natural gas, the emission per unit useful energy is higher. This is similar to the results of Verma et al. [26] and Du et al. [27] presented that the transition from LPG to PNG directly lowers household carbon footprints in the case of highly populated urban areas. In addition, inter-city variation is influenced by differences in urban–rural appliance efficiency. The hotspot areas, in general, are equipped with contemporary and more energy-efficient appliances. However, the number of appliances and overall energy consumption continue to contribute to higher overall emissions. This is consistent with evidence from Malaysia [28] and multi-city studies in China [29] that suggest the appliance-age distribution is an important predictor of household carbon emissions. In Mojokerto, the differences in efficiency increase the difference between the high-emitted clusters (Wates and Kedundung) and low-emitted coldspots (Purwotengah and Sentanan).

Household emissions are also influenced by socio-economic stratification. Household emissions are also influenced by socio-economic stratification. Higher-income households tend to produce greater total emissions due to greater overall energy consumption. However, poorer households often exhibit higher emission intensity (emissions per unit of energy used) because they rely on less efficient appliances and more carbon-intensive fuels. This dual mechanism was also found in Jiangsu Province [30] and Jabodetabek metropolitan studies [31]; and Mojokerto is characterized by the same socio-economic gradients, which would account for the observed spatial clustering. The remarkable positive spatial autocorrelation in Mojokerto (Global Moran I) and Low–Low and High–High clusters that were established by LISA and Getis-Ord Gi*, implicitly indicate that emission distribution in the city is not dispersed randomly but rather it follows a certain spatial pattern. This geographical distribution corresponds with a previous study in Indonesia and other countries. Azizah et al. [31] found similar High–High clusters in Jabodetabek, especially in areas with a high density of residential and economic activities. Similar clustering patterns were also observed in Anhui Province [32], Zhangdian City [33], Malaysia [28], and some Chinese cities [32]. Collectively, these studies demonstrate that both the population density and fuel-type diversity as well as technological efficiency and the morphology of cities are able to manage the spatial mapping of emissions. Hence, the clustering of the emissions in Mojokerto concurs with the more theoretical reasoning laid out by Zhu and Hu [10], which emphasizes that urban configuration (in which residential density is one aspect) controls spatial carbon patterns. The methodological evolution of Global Moran's I, LISA, and Getis–Ord Gi* to the multi-indicator structure provides a stronger place-based diagnosis of places with emissions hotspots. This triangular approach improves spatial inference, similar to the suggestions put forward by Gao et al. [13] and Xu [30], which indicates that multi-scale spatial metrics can improve HSD accuracy and make it more attributed. The steady High–High classification of Wates and Kedundung is evidence that their structures form a carbon intensity zone.

The implications of these findings for policy are straightforward. Priority for clean-fuel switch programs that expand natural gas networks and household energy efficiency interventions should be given to hotspot areas. Near Kedundung, efforts to reduce methane at Randegan landfill, for example, such as through better waste segregation or capture of landfill gas, would result in substantial mitigation. On the other hand, low-emission regions such as Purwotengah and Sentanan can act as pilot LDCCs (low-carbon demonstration communities) to facilitate clean-energy usage patterns and efficient appliances. This is supported by on-the-ground evidence indicating that, under relatively lower population density, households in these areas engage in more energy-efficient practices, including lower ownership and usage of energy-intensive appliances and more conservative daily energy-use behavior. These practices contribute to reduced emissions and confirm that the identified "cold spot" status reflects actual low-carbon behavior at the community level. The mapping with the SEF-based Tier-2 approach in combination with spatial analysis can thus form a tool, useful for both practical and scientifically based city-specific emission management in medium-sized cities. Finally, we make contributions to the literature by showing that positive spatial autocorrelation of carbon emissions is not only found in large metropolises, but also in medium-sized urban systems such as Mojokerto. Using an urban villages-level analytical framework and considering both residential and waste sectors, the study contributes to filling in an existing gap in Indonesian emission analyses that tend to neglect fine-scale spatial interrelations. These findings echo wider arguments in recent literature [30-33], spatially targeted mitigation measures are necessary to realize equitable and effective urban emissions reductions (especially in rapidly urbanizing areas).

Conclusions

Therefore, this study indicates that the coupling of Specific Emission Factors (SEF) with spatial autocorrelation analysis represents a solid micro-scale method to map the spatial structure of carbon emissions in medium cities such as Mojokerto. This approach resulted in two important results. First, the empirically derived SEF values 0.278 tons CO_2/household/year for the residential sector and 0.000579 tons CO_2-eq/person/year for the waste sector established household energy use as the dominant source of emissions, accounting for 13,357.42 tons CO_2/year of the total 13,439.87 tons CO_2/year. Second, spatial analysis revealed a statistically significant clustered pattern (Global Moran's $I = 0.24$; $p = 0.0127$), Hotspots were consistently identified in places like Wates and Kedundung; coldspots were observed in Purwotengah and Sentanan. These results have direct influence upon urban planning and climate action. This evidence emphasises the need to not only adopt such a uniform climate mitigation policy, but also to have one that is spatially relevant. Drawing from our findings, we encourage prioritisation of household energy-saving and methane-reduction measures in the identified hotspot areas and further solidifying sustainability practices in coldspot zones. Moving forward, to enhance urban climate governance, future research should broaden and strengthen the framework by embedding spatio-temporal dynamics and multisectoral emission sources, so as to enable more adaptive, evidence-based low carbon urban planning.

Author Contributions

TH: Conceptualization, Methodology, Software, Investigation, Writing -Review & Editing; **IM, MPK**: Writing-Review & Editing, Supervision

AI Writing Statement

The authors used ChatGPT (OpenAI) only to refine language and enhance clarity in writing this manuscript. All generated content was reviewed by authors and extensive editing was performed, and the authors are responsible for ensuring the correctness and accuracy of the final manuscript.

Conflicts of interest

No conflicts to declare.

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