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Spatial disaggregation of urban greenhouse gases emission scenarios: Empirical analysis based on an expanded Kaya identity

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ABSTRACT

Cities are increasingly recognized as critical nodes in the global carbon footprint. Accordingly, there is an increasing interest in the measurement of urban emissions to guide climate change mitigation in cities. Traditional greenhouse gas (GHG) inventories often provide a macroscopic view of emissions, obscuring the heterogeneity of cities. Recognizing this gap, this study proposes an expanded Kaya identity to spatially disaggregate the carbon emissions inventory and depicts future urban GHG emissions scenarios. Including additional variables to expand the traditional Kaya identity allows to retrieve a spatialized approximation of the emissions inventory that considers the heterogeneity of the city‘s socioeconomic structure within the model. To contextualize this framework, Bogota, Colombia, was chosen as case study. Following the spatial extent of the planning units of the city as disaggregation extent of the GHG emissions, this article offers a view beyond the limitations of the traditionally aggregated data. Such disaggregation underscores the nature of urban emissions, influenced by the distribution of the population, income levels, and socioeconomic strata. This approach allowed to retrieve a spatialization of the GHG emissions scenarios provided by the local administration with a higher level of granularity and an explicitly spatial methodology. The results facilitate targeted policy interventions for effective urban climate action and the cities' sustainability transition.

1. Introduction

Cities, with their dense populations and industrial activities, are decisive in the narrative of climate change and the global effort for its mitigation and adaptation [1]. Consequently, there is an increasing interest in the measurement of urban GHG emissions. Traditional GHG inventories often present data at a national or city-wide scale, offering limited insight into the spatial distribution of emissions within urban boundaries [2,3]. Such a level of analysis can obscure the distinctions and heterogeneity of the urban landscape, leading to a one-size-fits-all approach in mitigation strategies.

Accounting for carbon emissions towards the monitoring of climate change has been a challenging quest in climate science. In the field of GHG emissions scenarios, a variety of methodologies and models are utilized to predict emissions and their impact on climate change [4]. These models vary in complexity, scale, and the specific GHG processes they simulate [5,6]. Accounting for GHG emissions relies on both top-down and bottom-up methods [7,8] that could be grounded on climate simulation, remote sensing and imagery resources, regression models, macroeconomic models, and hybrid models. Among these, the analysis of urban climate impacts has been typically approached from an aggregated approach due to the limitations of detailed data availability and the complexity of urban systems [3,7].

In the quest to spatialize urban carbon emissions with a detailed granularity, various models have been developed, each leveraging unique methodologies and data sources to assess and predict emissions with spatial specificity [7,9]. The integration of GIS (Geographic Information Systems) with bottom-up modeling of urban form components, such as land use, buildings, and transportation networks, serves as a tool for the assessment of carbon emissions, quantifying emissions from

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buildings, transportation, residences, and vegetation with spatial precision [9–11]. Likewise, advancements in urban carbon metabolism studies have underscored the significance of land management and spatial adjustments in reducing carbon emissions, advocating for a comprehensive analysis that includes natural and socioeconomic components alongside vertical and horizontal carbon flows [12,13]. Also, innovative modeling approaches, such as coupling system dynamics with cellular automata and support vector regression, have been applied to evaluate the impacts of socioeconomic developments and urban spatial structures on carbon emissions, offering insights into how urban planning and spatial optimization can support low-carbon development [11,14].

Crucially, recent decades have witnessed significant advancements in empirical and data-driven methods for urban emissions mapping [15–17]. Machine Learning (ML) models have demonstrated high accuracy in estimating and predicting city-level carbon emissions [18,19], revealing the crucial role of socioeconomic and geospatial data in understanding urban emissions [20,21]. Similarly, Land-Use Regression (LUR) approaches establish statistical relationships between observed emissions and various land-use parameters to provide fine-grained spatial estimations [22,23]. Furthermore, the integration of remote sensing (RS) data, particularly Night-Time Light (NTL) data, has become a widely used proxy for human activity and energy consumption, offering broad spatial coverage and frequent updates for urban emission estimations [24–27]. Guo et al. [19] developed an ML-based model relying on geospatial big data to map spatiotemporal variations in urban CO_2 emissions in Chinese cities. They propose a model that integrates nighttime data, remote sensing environmental indicators, socioeconomic big-data sources, and land use data to model urban emissions in a detailed spatial grid. This model achieved an average accuracy of over 80 %, highlighting the influence of the GDP per capita and urbanization as key drivers contributing to contribute in the increase in CO_2 emissions. Likewise, Wang et al. [23] investigated the spatial distribution and influence of diverse land use and nighttime light data on urban carbon emissions in the Beijing-Tianjin-Hebei Urban Agglomeration through a spatial inversion model. They found that land use data improves the accuracy of carbon emissions spatial disaggregation by analysing carbon inequality distribution through the GINI index, and a gravitational model, employing emissions data from 200 to 2019. The adaptation of high-resolution modeling and mapping techniques, which integrate field measurements with a diverse range of remote sensing data (e.g., LIDAR, GPS, and mobile big data) through data-fusion techniques, offers a detailed view of urban carbon stocks and current emission patterns [23,27,28].

However, while these empirical and observational methods excel at characterizing existing spatial emission distributions, a critical gap persists in their capacity to analyze these high-resolution patterns in future emissions trajectories and policy-relevant socio-economic drivers. Projecting how fine-scale emission drivers could evolve under various future scenarios of population growth, economic development, energy transitions, or specific policy interventions often requires methodologies that account for the underlying drivers of change [15,16, 29]. Furthermore, the complex influence of socioeconomic heterogeneity on future urban emission distributions and its implications for targeted policy remain an underexplored area within many existing spatial models [7,9,23,26]. This demand for extensive data and complex models often poses significant challenges, particularly in terms of resource allocation, availability, and accessibility of information. This challenge is particularly significant in the context of developing countries, where the allocation of resources toward the development and maintenance of complex climate models is often outweighed by pressing needs [29]. Furthermore, the level of data granularity required by these models frequently surpasses the available data resources, further complicating their implementation and widespread adoption [2,29].

Addressing this gap, our study introduces a novel methodological framework for the spatial disaggregation of urban greenhouse gas emission scenarios based on an expanded Kaya Identity. This approach uniquely combines the macro-level, driver-based strength of the Kaya framework with granular spatial data, specifically focusing on socioeconomic strata and income level as key disaggregation factors [30–33].

By expanding the Kaya identity, this study not only considers the traditional factors of population, GDP per capita, energy intensity, and carbon intensity but also incorporates additional variables relevant to the urban context of the case study. This extension of the traditional model allows for capturing the granularity of emissions within the city and considering the socioeconomic structure of the city within the estimation, revealing the spatial distribution of GHG sources with unprecedented clarity at the city scale. Due to these methodological adjustments, this approach yields new insights into urban GHG emissions. It is proposed that urban GHG emission patterns are not merely a function of city-wide aggregate drivers, but are profoundly shaped by the spatial heterogeneity of socioeconomic characteristics that mediate consumption, energy demand, and mobility choices. This expands the traditional Kaya framework to explicitly account for the internal socio-spatial dynamics of cities, offering a deeper understanding of the distribution of emissions and responsibilities within urban systems. Given this background, this work aims to answer the question: What are the spatial patterns of GHG emissions across different urban areas, considering the city's socioeconomic dynamics? To do so, this article aims to develop the innovative application of the Kaya identity model in Bogota, dissecting the city's carbon inventory into smaller spatial units. As the capital and largest city of Colombia, Bogota is home to a diverse population and a range of economic activities, all of which contribute to its carbon footprint. The city's urban development has been marked by rapid growth, leading to challenges such as traffic congestion, air pollution, and social disparities [34,35]. The spatialization of Bogotá's GHG inventory, therefore, not only contributes to the scientific understanding of urban emissions but also to the practical needs of the city in strategizing the sustainability transition. In the context of the case study, the findings provide visual insights for targeted climate action that can be integrated into the city's broader efforts for sustainability transition.

For the academic community, policy designers, and decision makers, the study proposes a replicable methodology that can be easily reproduced to estimate the spatial distribution of urban GHG emissions in other urban contexts. Overall, this article proposes a spatialization of Bogotá's GHG inventory as an innovation in the field of urban sustainability. The expanded Kaya identity model, applied at the scale of the city's Zonal Planning Units (ZPU), represents a significant advancement in the methodology of urban emissions analysis. By providing a granular map of emissions and future scenarios, the research supports the strategic planning necessary for Bogotá to progress as a resilient, sustainable, and inclusive city.

The subsequent sections of this article depict a detailed description of the work. Section 2 presents the description of the case study; Section 3 presents the details of the methodology; Section 4 illustrates the sources and description of the data used in the analysis; Section 5 portrays the results of the spatialization of GHG emissions; Section 6 presents the conclusion and final remarks of the work.

2. Case study

Bogota has an approximate population of 8 million inhabitants [36]. The municipality comprises 75 % rural areas, 23.2 % urban areas, and 1.8 % urban expansion areas. The city is administratively divided into 20 localities, 33 local planning units (LPUs), and 112 ZPUs. Within this urban landscape, Bogotá stands as a city committed to understanding and mitigating its contribution to global GHG emissions. The city's efforts to combat climate change necessitate a detailed understanding of its carbon emissions profile [37].

Bogota is located in the central part of Colombia, on a high plateau in the Andean region, at an altitude of approximately 2640 m above sea level (Fig. 1). This elevation is a major climatic factor, categorizing the

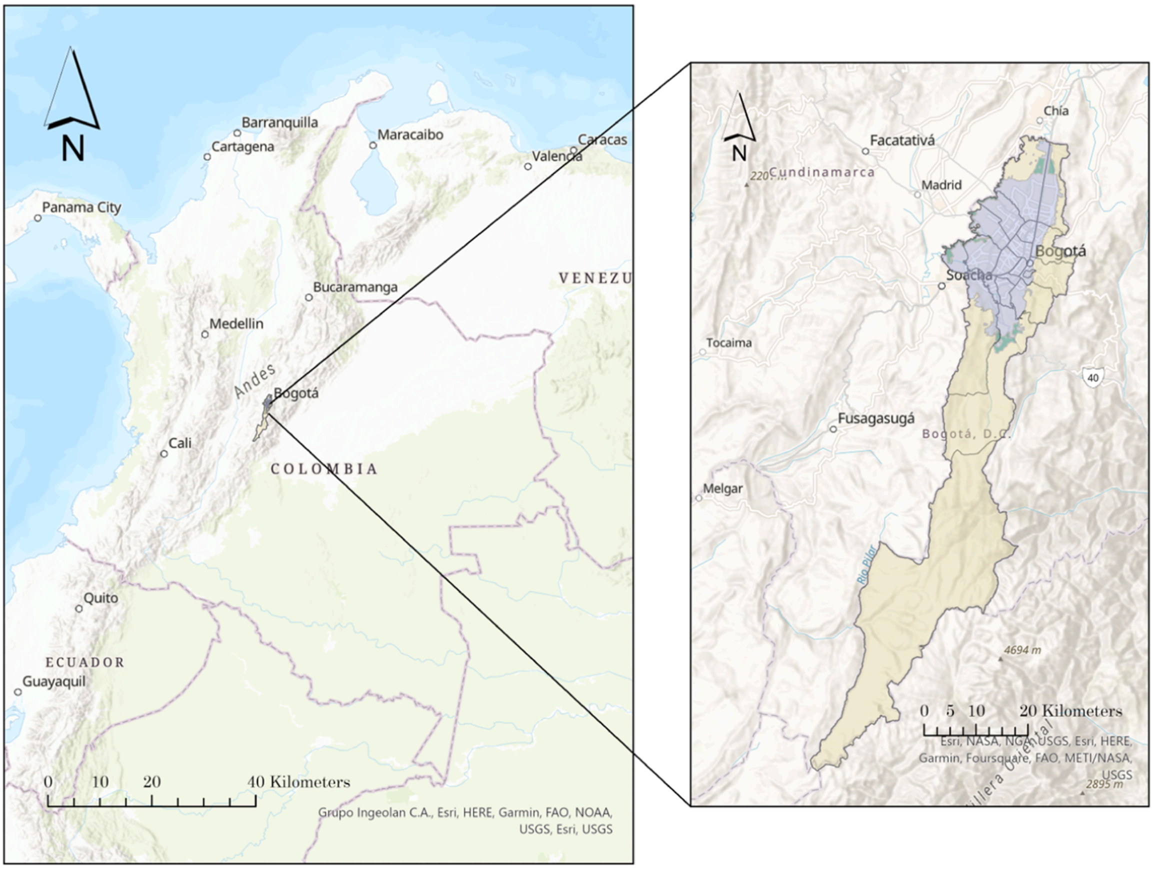

Fig. 1. Geographical context of the case study.

city's climate as a subtropical highland. The climate exhibits a bimodal precipitation pattern with two main rainy seasons (April-May and September-November) and two relatively drier periods (December-March and June-August); daytime temperatures generally range from approximately 14 °C to 20 °C throughout the year [38]. The city has experienced rapid population growth and urbanization, intensifying the strain on housing resources.

Rapid urbanization in the city has given rise to numerous challenges, including mobility congestion, housing affordability, environmental degradation, insecurity, and social inequality. The application of this model to Bogotá is particularly relevant given the city's complex urban dynamics and its commitment to sustainable development [34,35,39].

Bogotá's Climate Action Plan is aligned with the goals outlined in the city's Territorial Ordering Plan (Plan de Ordenamiento Territorial, POT) [37,40], which serves as a blueprint for urban development and land use. The Climate Action Plan's objectives are to reduce greenhouse gas emissions by 15 % by 2024, 50 % by 2030, and to achieve carbon neutrality by 2050. This aligns with the POT's vision for creating a sustainable and resilient urban environment. The POT emphasizes the importance of sustainable urban growth, the conservation of natural resources, and the integration of environmental considerations into all facets of urban planning [40].

The plan highlights the transport sector as responsible for a significant portion of the city's emissions. This supports the POT's initiative for multimodal, inclusive, and sustainable mobility. Efforts to improve urban mobility and reduce congestion not only aim to lower GHG and particulate emissions but also contribute to the broader sustainability goals of reducing the city's carbon footprint and improving air quality, as detailed in the Strategic Plan of Air Management of Bogotá 2030 [41].

The Climate Action Plan and the POT together highlight the need for cross-sectoral collaboration, innovative urban logistics, and data-driven decision-making to ensure the successful transition of Bogotá to a low-carbon economy. This synergistic approach is essential for achieving the city's long-term goals of environmental sustainability, improved public health, and an enhanced quality of life for all residents. A detailed analysis of Bogotá yields valuable insights and ongoing challenges that enrich the wider discourse on urban sustainability.

3. Methodology

This article proposes a methodology structured around a two-stage process illustrated in Fig. 2. The first stage comprised the data collection and pre-processing, and the second stage comprised the implementation of the expanded Kaya identity to spatially disaggregate GHG emissions.

3.1. Theoretical framework

The Kaya Identity, IPAT equation, and STIRPAT model are frameworks used to analyze environmental impacts. They specifically focus on human factors contributing to these impacts, including population, affluence, and technology. Each model has unique features, but they all share the goal of understanding and quantifying the drivers of environmental change [42,43]. Common to all these approaches is their focus on human activities as the primary drivers of environmental impacts, including greenhouse gas emissions, resource consumption, and pollution [42,44]. Also, these methodologies are fundamental decomposition approaches; they decompose and present the factors contributing to environmental impacts into constituent components like population, economic activity, carbon intensity, and technological efficiency.

Furthermore, each of these models serves as an analytical tool for

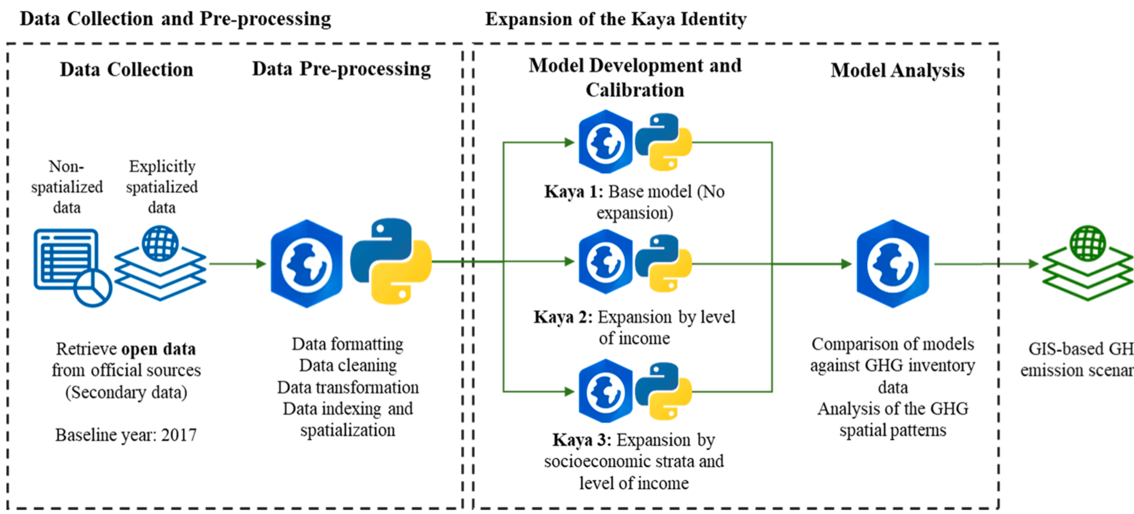

Fig. 2. Methodological framework.

understanding how different factors contribute to environmental changes, facilitating the identification of potential strategies for mitigation [45,46]. While IPAT provides a foundational framework for understanding the broad components contributing to environmental impact, the Kaya Identity offers a more specific formula for dissecting carbon emissions [47,48]. STIRPAT, on the other hand, builds on IPAT's foundation to allow for a more flexible and detailed analysis of the relationships between human activity and environmental changes, making it suitable for stochastic empirical research across various environmental impact assessments [42]. Thus, despite their simplicity, the integration of these models offers a robust analytical framework for understanding and addressing environmental challenges, particularly in regions with limited data availability, such as cities in the Global South.

IPAT Equation:

The IPAT equation ($I = P \times A \times T$) is a straightforward model that describes the impact (I) on the environment as the product of population (P), affluence (A, usually measured as GDP per capita), and technology (T, often measured as impact per unit of GDP). The IPAT model is simple and provides a high-level overview but lacks the flexibility to account for complex interactions between its components or to model specific policy scenarios [30,49].

STIRPAT Model:

STIRPAT is an extension of the IPAT model that allows for more flexibility in the relationships between the components. It is not constrained to a multiplicative form and can incorporate non-linearities and interactions between variables. This makes STIRPAT more adaptable to empirical testing and capable of providing more nuanced insights into the drivers of environmental impacts [49].

Kaya Identity:

The Kaya identity is specifically focused on carbon dioxide emissions and breaks them down into four factors: population, GDP per capita, energy use per unit of GDP (energy intensity), and CO2 emissions per unit of energy (carbon intensity) [47,50]. It is a more detailed decomposition than IPAT, tailored to understanding and addressing climate change by identifying leverage points for reducing carbon emissions.

The methodology relies on the adaptation of the Kaya identity, which expresses GHG emissions as a product of population, GDP per capita, energy intensity, and carbon intensity.

$$\textit{Kaya Identity}: \ CO_2e = \text{Population} * \frac{\text{GDP}}{\text{Population}} \times \frac{\text{Energy}}{\text{GDP}} \times \frac{CO_2e}{\text{Energy}} \tag{1}$$

3.2. Data collection and pre-processing

The data collection involved gathering extensive datasets on demographic distribution, economic activity, and land use across the ZPUs of the city. The model was performed using existing city-wide GHG inventories and validated through comparisons with localized emissions data where available. Table 1 presents the main sources of data for each factor of the implemented expanded Kaya equations. Future scenarios were constructed based on projected changes in the urban parameters influencing emissions, including development plans, policy interventions, and anticipated population growth patterns.

Among the data sources described in Table 1, The primary data source for this study is the official inventory of GHG emissions detailed in Bogotá's Climate Action Plan for the period 2020 to 2050. From this source, critical data such as carbon intensity was derived. The GHG emission baseline year is 2017, so all subsequent data collection was focused on the period from 2017 to 2050.

Table 1
Required data for the general Kaya identity and expanding factors.

Data	Source	Data type	Reference
Kaya Identity			
Carbon emission trajectories	Bogota's Climate Action Plan	GHG Inventory	[37]
Carbon Intensity	Bogota's Climate Action Plan	Derived data	[37]
Population projections	Cadastral data, National Population Census 2018	Secondary data	[36,40,51]
GDP scenarios	Bogotá's medium-term fiscal framework Bogotá's Climate Action Plan	Derived	[37,52]
Zonal planning units	Bogota's Reference map v06.22	Secondary data (GIS - FEATURE CLASS)	[53]
Expanding Factor Kaya Identity			
Household's income per capita	Multipurpose survey 2017 Multipurpose survey 2021	Secondary data	[54–57]
Socioeconomic strata	Bogota's Reference map v09.22	Secondary data (GIS - FEATURE CLASS)	[53]
Land use distribution	Bogota's POT Bogota's Reference Map v12.22	Derived data (GIS - FEATURE CLASS)	[40,58]

The spatialization factors for the emissions are based on official population projections from the 2018 national census. It is important to note that the Gross Domestic Product (GDP) growth scenarios originally used in the Climate Action Plan's technical documents were defined before the COVID-19 pandemic. To account for the long-term economic impacts of the pandemic, this study replaces these initial projections with an updated series of economic growth projections for the city. This substitution introduces the first source of difference between the model's results and the official inventory's theoretical values.

Data for the expansion factors, sourced from various surveys and databases provided by the city administration, required a deeper level of preprocessing. This process involved analyzing and aggregating income values from 2017 to 2021 (pre- and post-COVID) by ZPU. It was also necessary to clean outliers and address missing data. The same spatial indexing process by ZPU was performed for the socioeconomic strata and population time series. Additionally, since the household income data from the surveys was only available for punctual years, it was projected into a time series using the inflation rate as a proxy for the expected growth rate of income.

Overall, these preprocessing strategies were designed to harmonize all available data, ensuring that they were indexed equally for both spatial and temporal dimensions—a critical factor for the development of the disaggregation models.

3.3. Expansion of the kaya identity

Several models have been developed to expand the factors that make up the Kaya Identity, to refine the details of this framework [48,50,59,60]. The expansion of the factors consists of the incorporation of other variables that influence the original terms of the Eq. (1). For instance, Pui K. and Othman J [60] developed and extended the Kaya identity to evaluate the influence of economic, technical, and social aspects on the CO_2 emissions of the energy system in Malaysia. They incorporated factors of the energy mix, investment efficiency, labor, and working population rates, as expanding variables to the original factors of the equation. Furthermore, Zhang X. and Zhang D [28] developed an improved Kaya identity for the estimation of carbon emission projections in construction sites, integrating the changes in land use through time with a genetic algorithm. Mavromatidis et al. [61] developed a modified Kaya identity to propose a multi-scalar decomposition of the Swiss energy system to account for strategies to decarbonize the building sector. They included extra variables into the equation that were relevant to the building sector, such as floor area and the composition of the energy mix in operating buildings.

3.3.1. Kaya 1: base model

The relationships formulated in the Kaya equation allow for disaggregation of GHG data reported by cities on their emissions inventories, based on economic data and the population of the city. The base model for this study consists of the application of the Kaya identity (Eq. (1)) without the expansion of its terms, as a first iteration and methodological foundation. This approach would later be expanded with factors tailored to the specific context of the case study. Expressed for Bogotá, the general equation is written as:

$$\mathrm{E_i} = \mathrm{P_i} * \mathrm{EA_i} * \mathrm{CI_i} \tag{2}$$

Where E_i accounts for the total GHG emissions of the city (ton CO_2e) In the year *i*. P_i Accounts for the population of the city in the year *i*. EA_i Accounts for the factor of economic activity of the city in the year *i*, expressed as the GDP per capita (*millons of COP*) in the current currency of 2005 [37]. *CI* accounts for the carbon intensity in the year *i* relative to the economic activity of the city (GDP), expressed in $\left(\frac{ton\ CO_2e}{\text{millions of COP}}\right)$.

The city's climate action plan 2020–2050 [37] presents the GHG inventory for the baseline year in 2017. This inventory outlines emissions trajectories under a business-as-usual (BAU) scenario, as well as mitigation pathways aligned with Colombia's Nationally Determined Contributions (NDCs) under the Paris Agreement [37,62]. The city's inventory discloses emissions within Scopes 1 and 2, with Scope 1 comprising 91 % of total emissions in the baseline year and Scope 2 accounting for the remaining 9 %. Scope 3 emissions are not reported beyond one simple term in relation to waste incineration, totalling just 1 tCO_2-equivalent [37,63]. Therefore, in this spatial disaggregation of the city's emissions, the analysis was limited to Scopes 1 and 2 to remain consistent with the official reporting framework.

Based on the reported trajectories of GHG emissions of the city [37], the census data providing the projection of population in the city [36,51], and the economic growth scenarios depicted in the climate action plan and the medium-term fiscal framework [37,52] of the city, it is possible to derive the carbon intensity at the city level for each year in the reported official data. Furthermore, to spatially disaggregate the GHG emissions from the city scale into a more granular extent ZPUs, the total GHG emissions of the city for each year (*i*) are expressed as the sum of the local emissions on each of the 112 ZPUs (*j*).

$$\mathrm{E_i} = \sum_{j=1}^{112} E_{j,i} = \sum_{j=1}^{112} \mathrm{P_{j,\ i}} * \mathrm{EA_{j,\ i}} * \mathrm{CI_i} \tag{3}$$

Thus, based on the annual carbon intensity derived from the general expression, the values of the population by ZPU provided on the demographic and cadastral databases of the city [51], and the annual GDP per capita of the city [37,52], it would be possible to estimate a first approximation of granular analysis of the GHG contributions of each ZPU of the city. By applying this model to smaller spatial units within Bogotá, the research captures the heterogeneity of the urban setting. Although this generalized approach offers a way to estimate the respective emissions, it obviates the heterogeneity of the socioeconomic dynamics of a city.

To handle this weakness of the approach and incorporate the effects of the economic structure of the city into the Kaya equation, this research proposes an expansion of the factor of Economic Activity (*EA*) [64] for each ZPU. In this regard, these frameworks generally incorporate adjustment factors related to additional variables relevant to the urban context, such as land use patterns [14,65], life cycle analysis [46], and distributions of socioeconomic activity and wealth [29,66].

3.3.2. Kaya 2: expansion by the level of income

Based on the KAYA equation, the formulation of GHG taking the ZPUs as a spatial unit the ZPUs is:

$$\mathrm{E_{ZPU_i}} = \mathrm{P_{ZPU_i}} * \mathrm{EA_{ZPU_i}} * \mathrm{CI_{c_i}} \tag{4}$$

Where $\mathrm{E_{ZPU_i}}$ (ton CO_2e) is the GHG emissions in the ZPU in the year ***i***. $\mathrm{P_{ZPU_i}}$ Is the Population of the ZPU in the year ***i***. $\mathrm{EA_{ZPU_i}}$ is the Economic activity in the ZPU in the year ***i***. CI_{C_i} is the Carbon Intensity of the city in the year ***i***.

The original equation does not consider the heterogeneous economic structure of the city. This presents the need to depict that some areas of the city have higher economic activity and higher consumption patterns. Hence, a higher contribution to the GHG of each area is affected by this heterogeneity [46,49]. To acknowledge these conditions, it is proposed that a factor of adjustment be included in the term of economic activity for each ZPU. This expansion aims to perform a spatial redistribution of the city's GDP based on the contribution to the economy of each area of analysis. The study presented by Lin et al. [29] performs an empirical analysis of the impacts of urbanization and economic development on the CO_2 emissions in non-high-income countries, like Colombia, and proposes and portrays the use of the household's income as an economic term to estimate the environmental impacts [29]. As an adaptation of this concept, this research proposes an initial expansion of the Economic activity of each ZPU, combining the GDP per capita of the city for each year *i* with an adjustment factor based on the particular household level of income for each ZPU (IAF).

$$EA_{ZPU_i} = IAF_{ZPU} * GDP\ percapita_{Ci} \tag{5}$$

This income level adjustment factor (IAF) is derived from the data on the household's income per capita reported in the Multipurpose surveys of the city [54]. This survey provides a representative sample of the population of Bogota and geolocates every anonymous answer into the ZPU scale. After rigorous data cleaning and preprocessing, the IAF for each ZPU has been defined as the ratio between the mean income per capita of each ZPU (I_{ZPU_j}), and the mean income per capita of the city ($\overline{I_c}$).

$$IAF_{ZPU} = \frac{\overline{I_{ZPU_j}}}{\overline{I_c}} \tag{6}$$

Thus, the Kaya expression to compute the annual (i) GHG contributions of each ZPU (*j),* including the effects of the level of income in the factor of economic activity ($EA_{ZPU_{i,j}}$) is expressed as:

$$E_{ZPU_{ij}} = P_{ZPU_{ij}} * \left(IAF_{ZPU_j} * GDP_{C_i\ percapita} \right) * CI_{C_i} \tag{7}$$

$$E_{ZPU_{ij}} = P_{ZPU_{ij}} * \left(\frac{\overline{I_{ZPU_j}}}{\overline{I_C}} * \frac{GDP_{C_i}}{P_{C_i}} \right) * CI_{C_i} \tag{8}$$

Overall, the final expression of this expansion of the Kaya identity as the total annual GHG emissions in Bogota is:

$$E_i = \sum_{j=1}^{112} \left(P_{ij} * \left(\frac{\overline{I_j}}{\overline{I_C}} * \frac{GDP_{C_i}}{P_{C_i}} \right) * CI_{C_i} \right) \tag{9}$$

3.3.3. Kaya 3: expansion by socioeconomic strata and level of income

In the process of refining the spatial disaggregation of GHG emissions for Bogotá, this paper extends the methodology by incorporating socioeconomic strata as a second supplementary expansion factor in the Kaya Identity. This new consideration portrays a second variable to define the adjustment factor of the term of economic activity of the ZPUs in the city. While the initial expansion integrates household income levels to disaggregate the city's GDP into the 112 ZPUs, as a factor to integrate the complexity of the city's diverse structure, the inclusion of socioeconomic strata enhances this adjustment further.

In Colombia, households are classified through a system of socioeconomic stratification, this classification, which ranges from one (lowest) to six (highest), is based on the evaluation of the conditions of the buildings and the surrounding areas (i.e., geometry, physical characteristics, econometric models for property valuation, and zoning of balanced physical and economic areas) [67]. This system is used by the national government and local administrations to allocate subsidies to public services. As well, it is usually employed to aggregate key indicators like water and energy consumption [68–70], and mobility patterns [71,72] used in the assessment and monitoring of energy efficiency, and sustainable transition policies [68].

Moreover, the socioeconomic stratification system has been broadly used in research as a variable to model or aggregate spatial analyses describing urban mobility patterns [34], urban accessibility [73], public health [34,74], and spatial equity in Bogota [75,76]. Although the stratification is based on the physical condition of housing units and does not directly consider the economic attributes of the inhabitants, it is often used as a proxy for household income, under the assumption that these households and urban environment conditions reflect the inhabitants' payment capacity [33,67]. Cantillo-Garcia et al. [33] provide an overview of applications of socioeconomic stratification as a proxy for household income in Colombia. As well, they developed a set of models for transportation planning in which the socioeconomic strata are used as a proxy of the household income in four Colombian cities, including Bogotá. Fig. 3 portrays the map of Bogota's socioeconomic strata at the urban block scale. It shows a clear spatial pattern of the

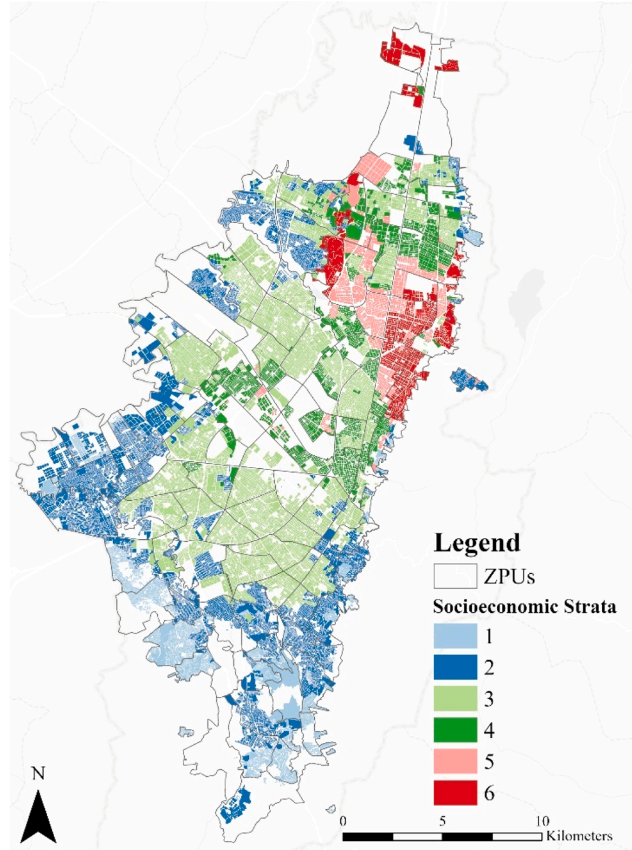

Fig. 3. Socioeconomic stratification.

socioeconomic conditions of the city. High-income areas (strata 5 and 6) are concentrated in the north and north-east of the city; middle-high income areas (stratum 4) are mostly in the north and center of the city; middle-low areas (stratum 3) cover a higher fraction of the territory and are mostly located in the south, west, and a small fraction of scattered areas in the north of the city; and the low-income areas (strata 1 and 2) are located in the periphery of the city, with a predominant concentration in the southern belt, south-west, with some scattered areas in the north-west and north-east periphery.

The need for this methodological expansion arises from the limitations of income level in capturing the complete range of economic activities associated with the built environment and living conditions. Socioeconomic strata serve as a meaningful proxy for capturing diverse urban conditions, encompassing multiple dimensions such as housing quality, access to services, and the state of urban infrastructure, all of which significantly influence patterns of consumption and emissions. In Bogotá, for instance, the city's mobility survey provides modal share data disaggregated by socioeconomic strata from 2011 to 2023, revealing distinct travel behaviours across income groups [72,77–79]. Likewise, Bogota's planning secretariat, as part of the monitoring system of the national public policy on ecourbanism and sustainable construction [80,81], analyzes the indicator of energy consumption in a timeseries from 2012 to 2020, aggregated by socioeconomic strata [68,82]. These examples highlight the value of using socioeconomic strata as a variable for spatially disaggregating GHG emissions, as it is already widely applied in the aggregation and analysis of key emission-related phenomena in the urban context.

i. **Socioeconomic strata and urban transport patterns:** The mobility survey conducted by the local administration analyses Bogota's modal split by socioeconomic strata between 2011 and 2023 [72, 77–79]. These studies indicate that high-income households (strata 5 and 6) primarily rely on private vehicles, which account for over 50 % of their daily trips. In contrast, public transport is among the least used modes, representing only around 10 % of their daily trips, while active transport modes, such as walking (for commutes longer than 15 min) and cycling, constitute approximately 16 %. In contrast, low-income households (strata 1 and 2) do not use private automobiles frequently, with these modes representing just around 5 % of daily trips. Instead, public transport and active modes are predominant, accounting for approximately 45 % and 40 % of daily trips, respectively. Furthermore, middle-income households (strata 3 and 4) show an intermediate pattern, with public transport usage ranging from 30 % to 40 % of daily trips, active modes accounting for 15 % to 30 %, and a higher reliance on private vehicles compared to lower-income groups, ranging from 15 % to 35 % of typical daily trips [77–79]. The referenced data shows a positive correlation between socioeconomic strata and the use of carbon-intensive modes such as private vehicles and taxi services, and a negative correlation with the use of public transport, cycling, and walking. These insights suggest that high-income households are more likely to rely on high-emission transportation options, whereas lower-income households tend to adopt more sustainable alternatives, including public transit and active travel modes.

ii. **Socioeconomic strata and energy consumption patterns:** The city tracks residential electricity consumption per square meter, disaggregated by socioeconomic strata, providing a multi-year dataset [68]. This indicator reveals a consistent downward trend in energy consumption across all six socioeconomic strata starting in 2015, following the adoption of the national public policy on eco-urbanism and sustainable construction [80,83]. An exception occurred in 2020, when mobility restrictions and extended periods of confinement due to the COVID-19 pandemic led to a marked increase in residential electricity use across all strata. Despite the outbreak of the pandemic, one consistent pattern emerges throughout the entire period: high-income households (stratum 6) consistently consume the most electricity, with a multi-annual average approximately 45 % higher than that of stratum 1, the group with the lowest consumption. In addition, this data shows there is a clear positive correlation between socioeconomic strata and energy consumption: each stratum tends to consume more electricity than the one below it, except for 2020, where stratum 1 slightly exceeded stratum 2 by 5 %. Additionally, there is a persistent multiyear consumption gap between low- and lower-middle-income households (strata 1–3) and upper-middle- and high-income households (strata 4–6) that could relate to more efficient energy use, and a more mindful and restrictive use due to economic constraints that could account for energy poverty issues in the lower-classes [84,85].

Although Colombia has made significant progress in decarbonizing its electricity grid, electricity use remains a relevant driver of urban GHG emissions. The consistent correlation between energy consumption and socioeconomic strata underscores the utility of this variable as a spatial proxy to express urban complexity and for disaggregating urban emissions in Bogota.

These examples highlight the value of using socioeconomic strata as a variable for spatially disaggregating GHG emissions, as it is already widely applied in the aggregation and analysis of key emission-related phenomena in the urban context. Likewise, based on the spatial pattern of the socioeconomic strata portrayed in Fig. 3, the inclusion of this variable allows for the representation of economic heterogeneity with a higher degree of granularity in the adjustment factor of the Kaya expansion.

Consequently, the new expression of the Kaya identity will include an economic structure adjustment factor for each ZPU ($ESAF_{ZPU_j}$) as an expansion of the economic activity factor ($\mathrm{EA}_{\mathrm{ZPU}_{ij}}$).

$$\mathrm{E}_{\mathrm{ZPU}_i} = \mathrm{P}_{\mathrm{ZPU}_i} * \mathrm{EA}_{\mathrm{ZPU}_i} * \mathrm{CI}_{c_i} \tag{10}$$

$$\mathrm{E}_{\mathrm{ZPU}_i} = \mathrm{P}_{\mathrm{ZPU}_i} * (ESAF_{ZPU} * GDP\ percapita_{Ci}) * \mathrm{CI}_{c_i} \tag{11}$$

The new economic adjustment for each ZPU ($ESAF_{ZPU_j}$) is defined by a sum of the products of two terms: the ratio between the mean household income per capita for each socioeconomic strata ($\overline{I_{ZPU_j\ SES_k}}$) available in the ZPU, and the mean household income per capita in the city ($\overline{I_c}$); and the ratio between the existing area of each socioeconomic strata in the ZPU ($A_{SES_k\ ZPU_J}$), and the total area categorized on the ZPU (A_{ZPU}).

$$ESAF_{ZPU_j} = \varepsilon \sum_{k=1}^{6} \left(\frac{A_{SES_k\ ZPU_J}}{A_{ZPU}} * \frac{\overline{I_{ZPU_j\ SES_k}}}{\overline{I_c}} \right) \tag{12}$$

$$ESAF_{ZPU_j} = \varepsilon \sum_{k=1}^{6} \left(\frac{A_{SES_k}}{A_{ZPU}} * \frac{\overline{I_{ZPU_j\ SES_k}}}{\overline{I_c}} \right) \tag{13}$$

Finally, the expanded kaya expression to disaggregate the GHG emissions in the city for each year *i.,* following this expansion, follows the equation:

$$\mathrm{E}_i = \sum_{j=1}^{112} \left(P_{i,j} * \left(\varepsilon \sum_{k=1}^{6} \left(\frac{A_{SES_k}}{A_{ZPU}} * \frac{\overline{I_{ZPU_j\ SES_k}}}{\overline{I_c}} \right) * \frac{GDP_{C_i}}{P_{C_i}} \right) * CI_{C_i} \right) \tag{14}$$

4. Results: spatial disaggregation of CO_2 emissions

This section portrays the diverse results of the examination of the spatial disaggregation of GHG emissions in Bogotá. This includes a comparison between the three models described in the methods section. Initially, the analysis compares the totalized annual GHG emissions of each model with the theoretical baseline trajectory of the city [37]. Furthermore, it portrays the spatial patterns of GHG emissions resulting from the three applications.

These disaggregated results represent the most insightful contribution of this research, as they unveil the approximations of the spatial decomposition of the GHG inventory. The variance in emissions across the ZPUs, attributed to distinct economic activities and lifestyle patterns, is thoroughly analyzed, confronting the results with the evaluation of other previously assessed spatial indicators for urban sustainability [86], showcasing the impact of incorporating income levels and socioeconomic strata as adjusting factors.

Furthermore, the section delves into the implications of these findings for urban planning and policymaking. A discussion on the socioeconomic factors driving these CO2 emission patterns emerged through the analysis of emissions hotspots and spatial indicators for urban sustainability.

The city's climate action plan depicts a totalized business as usual (BAU) scenario as the baseline for the compromises on climate action, taking as the base the year 2017. The projected BAU, as well as the alternatives for GHG mitigation, comply with the goal of decarbonization of the city by 2050 [37].

This section shows the results of the evaluation of the baseline scenario, applying the data disaggregation with the three described approaches to the Kaya identity. In the results, "Kaya 1″ refers to the data estimated with the Kaya identity that considers no expansion of any of its defining factors. "Kaya 2″ shows the results obtained by the application of the expansion of the factor of economic activity with an adjustment coefficient relative to the monthly income of the inhabitants in each spatial unit of the city (ZPUs). Such an adjustment coefficient was defined from the results of the Multipurpose surveys of Bogota for 2017 and 2021 [54,55]. Finally, "Kaya 3" portrays the results of the disaggregation performed with the expansion of the economic factor by a compound adjustment coefficient calibrated based on the spatial distribution and area availability of the socioeconomic strata within each ZPU and the respective mean household income within each of these areas.

Fig. 4 illustrates the trajectory of total carbon emissions for the city according to the estimation effectuated by each of the three Kaya equations proposed in this methodology, along with the reference series of the climate action plan. Compared with the series of total GHG emissions of the climate action plan, the three implementations of the Kaya Identity present a multiannual relative error between 0.5 % and 10 %.

The Kaya 1 aggregated trajectory of GHG emission fits within a 0.5 % multiannual error relative to the series reported in the climate action plan. The spatial disaggregation of the GHG emissions in the ZPU scale follows a spatial pattern linked to the distribution of the population in the city. Fig. 5 illustrates the maps with the spatial disaggregation of the GHG emissions for the years 2017 (the base year of the inventory), 2022, 2035, and 2050.

For this particular arrangement, the terms of the Kaya identity are sharply adjusted to the magnitude of the inventory of GHG emissions. However, since the spatial characterization of this approach is based solely on population, it fails to capture the complexity of the socioeconomic structure of the city and its relationship with GHG emissions.

The Kaya 2 aggregated trajectory of GHG emission is the series with the highest deviation relative to the series of the climate action plan. Fig. 4 shows that the mean adjustment presents an overestimation of the GHG emissions from the years 2017 to 2020, where the model uses the income adjustment factor based on the households' level of income reported in the survey of 2017 [55,56]. Later, the results show an inflection point in the year 2021, where the magnitude of the estimation of mean GHG emissions drops and turns into an underestimation compared with the reference series. This sudden drop in magnitude comes from the change in the data of the households' level of income used for the adjustment factor. From 2021 on, the adjustment factor was estimated with the data from the 2021 multipurpose survey [54,55]. This survey was applied after the COVID-19 pandemic, and the decrease in the level of household income is attributed to the effects of the pandemic on the economic conditions of the people [52,74].

The inclusion of this adjustment factor allows us to account for the city's economic structure and captures how the magnitude of carbon emissions changed due to the pandemic's economic effects. This reflects the approach's sensitivity to the city's socioeconomic complexity. Even if the trajectory of the emissions has an average offset of 10 % to the reference series, it is still within the margin of confidence of these inventories. In addition, the spatial pattern retrieved in the disaggregation of the emissions for each ZPU accounts for a better representation of the economic structure of the city. The maps presented in Fig. 6 portray a territorial distribution that differs from the distribution retrieved from Kaya 1 (Fig. 5). The territorial pattern retrieved with this approach follows a similar distribution to the socioeconomic strata presented in Fig. 3, even if that variable is not included in the calibration of the adjustment factor for the expansion of the Kaya.

The Kaya 3 aggregated trajectory depicted in Fig. 4 shows an approximation with an average offset of 2 % to the series of the climate action plan. The expansion performed in this identity included the terms of the level of income and the spatial distribution of the socioeconomic strata as the drivers of the adjustment factor. The combination of these factors, as disclosed in the methodological section, allows for the integration of another level of granularity into the GDP distribution within the city's territory. Moreover, given that it still includes the variables of the monthly income, the series shown in Fig. 4 preserves the shape of the series retrieved with the Kaya 2. This aspect accounts for the inclusion of the impact of the COVID-19 pandemic on the change of the economic structure of the city. However, the calibration of the adjustment factor with the available areas of the socioeconomic strata reduces the offset with the reference series and the difference in the magnitude between the results of the Kaya and the validation values.

Furthermore, the spatial disaggregation of the emissions, presented in the maps (Fig. 7), follows a similar territorial pattern to the maps of Kaya 2 (Fig. 6). The inclusion of the socioeconomic strata in the calibration of the expansion of the Kaya identity concerning the previous expression allowed a good approximation of the socioeconomic structure of the city, balanced between the distribution of the population and the wealth, with the extra value of an improvement of the aggregated estimation of the magnitude of the carbon emissions.

5. Discussion

The objective to delve into the spatial disaggregation of the inventory of GHG emissions in Bogota, approached with an expanded Kaya identity, marks a significant step forward in understanding urban emissions territorial dynamics with an open data-based approach. By contrasting the results of the three evaluated Kaya models, this research not only sought to align the results with the theoretical baseline inventory of the city but mainly sought to explore a granular analysis of GHG emissions across the ZPUs, proposing a term for the evaluation of the territorial nature of this aspect based on the socioeconomic patterns of the city.

5.1. Comparison with existing spatialization models and theoretical implications

The proposed methodology provides a framework for spatially disaggregating urban GHG emission scenarios, offering advantages when confronted with established urban emissions modeling approaches. As discussed in the introduction, these include methods such as LUR, RS applications (e.g., NTL data), ML models, and data fusion techniques integrating these methods.

Existing empirical and observational methods outperform the application of the expanded Kaya identity to estimate current and historical high-resolution urban emissions. LUR models, for instance, are crucial in establishing statistical relationships between specific land-use characteristics and observed emissions [22,23,32,87]. Likewise, NTL methods, often enhanced by ML algorithms, are powerful for widespread and rapid estimation of urban CO2 emissions at various spatial scales by correlating light intensity with economic activity and energy consumption [18,25,88,89].

However, a core distinction and the key contribution of our work lie in its capacity for forward-looking scenario development. While these models are highly effective for retrospective analysis, projecting how the emissions would evolve under future scenarios of population growth, economic development, or specific policy interventions remains a significant challenge [24–26]. The expanded Kaya framework, by explicitly linking macro-level drivers to spatially disaggregated outcomes, offers a transparent and interpretable pathway to propose 'what-if' policy interventions.

The expanded Kaya approach also addresses the practical limitations of data acquisition and availability often faced in developing countries. While highly accurate, many LUR and ML models rely on extensive, high-resolution geospatial big data (e.g., LIDAR, real-time traffic data) that are often costly or not available consistently [23,24]. Furthermore, while NTL data is typically publicly accessible in RS sources, it has the limitation of being limited to the time-periods with valid observations, and computationally demanding processes for the right calibration and correction of the satellite data, as well as being difficult to simulate reliable future NTL data to create scenarios. In contrast, the proposed methodology is built upon open data, such as population distribution, income levels, and economic activity perspectives, that are commonly collected and publicly accessible. This makes our framework less reliant on expensive, often proprietary, big data sources, thereby enhancing its applicability and replicability in a wider range of urban contexts.

Beyond its methodological contributions, this article offers a significant theoretical insight into urban GHG emission dynamics. By spatially expanding the traditionally aggregate Kaya Identity with socioeconomic factors, it is proposed that urban emission patterns are not merely the sum of city-wide average drivers, but are profoundly shaped by the

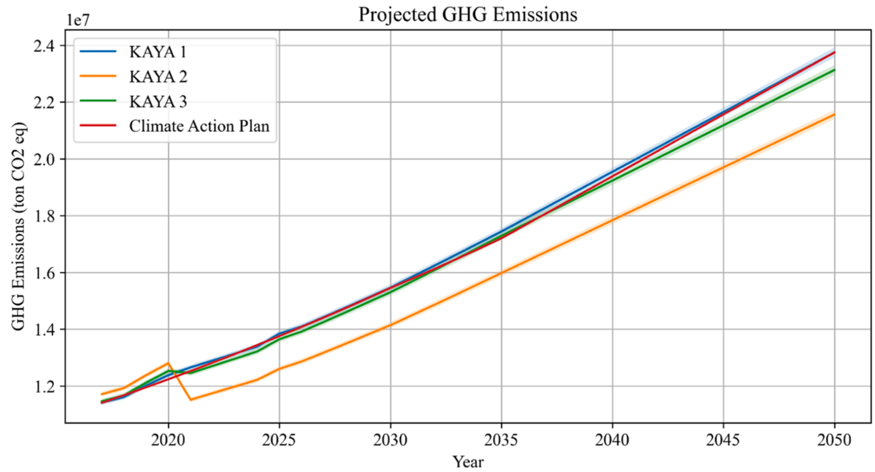

Fig. 4. Comparison between BAU Kaya Desegregation Approaches.

spatial heterogeneity of socioeconomic characteristics that mediate localized consumption behaviors, energy demand, and mobility choices within a city. This extends the classic Kaya framework by integrating the socio-spatial dimension of urban development into emission analysis, providing a new lens for understanding urban climate justice and informing the development of spatially differentiated policies.

5.2. *Insights from Kaya models and spatial patterns in Bogota*

According to the analysis presented by Lin et al. [29] in contexts like Colombia (upper-middle-income countries), population, GDP per capita, carbon intensity, and energy intensity are the most influential factors in the rise of GHG emissions. This analysis used data from 53 non-high-income countries to identify the impacts of urbanization and economic development on CO2 emissions at the national level. However, due to the scale of analysis, this study does not capture the level of granularity of the impact factors of GHG emissions on the cities.

Moreover, Yuan et al. [90] performed a subnational decomposition analysis of the driving factors of household carbon emissions in China. This work analyzes the relevance of population, income per capita, carbon intensity, energy intensity, and consumption patterns in the household carbon emissions of 30 provinces in the country. The factors of population and income per capita were segmented as scaling terms, and the remaining factors related to technological and political efforts. The findings show income and population as the major drivers of differentiation in household carbon emissions across the different provinces. Likewise, Wang et al. [64] depicted the spatial effects of different factors affecting household CO2 emissions in China at the provincial level. To do so, this study shows a multiannual spatial analysis of five determining factors. The findings show that the household income is a powerful explanatory variable with a positive impact on the carbon emissions throughout the analyzed year. These insights are aligned with the introduction of an adjustment coefficient based on household income levels presented in this study to differentiate the emissions across the ZPUs in Bogotá.

Given that these studies highlight the relevance of income as a driver in the analysis on a provincial scale [64,90], extending the analysis to an urban planning scale was included as an extra factor in the expansion of the Kaya identity. Furthermore, including socioeconomic strata enriched our study's analytical depth. This dual-factor approach not only accounted for the direct economic drivers behind GHG emissions but also reflected the broader socioeconomic structure's influence on urban emissions patterns.

The Kaya 1 model illustrates a spatialization of the emissions defined exclusively by the distribution of the population in the city. The Kaya 2 model's sensitivity to changes in household income levels, especially in light of the COVID-19 pandemic's economic repercussions, showcases the dynamic relationship between a city's economic health and its environmental footprint. Moreover, the Kaya 3 model, integrating both income levels and the spatial distribution of socioeconomic strata, illustrated an even approximation for delving into the spatial pattern of emissions. This model not only preserved the shape of the emissions trajectory, highlighting the impact of economic shifts such as those induced by the pandemic, but also improved the alignment with the city's climate action plan reference data.

Furthermore, it is beneficial to compare the results of the three Kaya models with previous research that provided a spatial assessment of 16 urban sustainability indicators in Bogota[1] [35]. Linking these indicators with the spatial distributions identified in the Kaya 1 model portrays a relation between the highest concentration of greenhouse gas (GHG) emissions, attributed to dense population areas, and the ZPUs with the highest concentration of social housing. These areas are also characterized by a lower quality of life, manifesting through poor accessibility to urban services and green spaces, and low-income levels. Moreover, these areas experience adverse environmental conditions, evidenced by elevated levels of urban air pollution and a larger proportion of the population being at a high risk of natural hazards [35]. Consequently, employing the Kaya 1 in this context would be inappropriate, as it fails to capture the complexity of the city's socioeconomic structure and its environmental impacts. Furthermore, its use for decision-making could worsen issues of climate justice by perpetuating the inequity of attributing the highest GHG emissions to the urban poor and the city's most vulnerable communities, thereby overlooking the complex contributors to urban emissions and the differential impact on various social groups.

In contrast, the Kaya 3 model's spatial distribution of GHG emissions aligns more closely with the living conditions, as it considers the socioeconomic variables of the city. Comparing these results with sustainability indicators [35] reveals that areas with fewer employment opportunities and a higher prevalence of social housing are associated with lower GHG emissions accountability. This variance in emissions across ZPUs reflects the intricate relationship between socioeconomic frameworks and environmental impacts. It underscores the importance of integrating socioeconomic strata to refine the estimation of the spatial distribution of GHG emissions.

The spatial distribution of GHG emissions exhibits distinct patterns when it is confronted with various urban indicators. The northern ZPUs, particularly in the northeast, are characterized by high emissions due to

[1] The maps portraying the assessment of the indicators of the referenced study are available for consultation in the following web-GIS application: https://arcg.is/0OX9Tb1

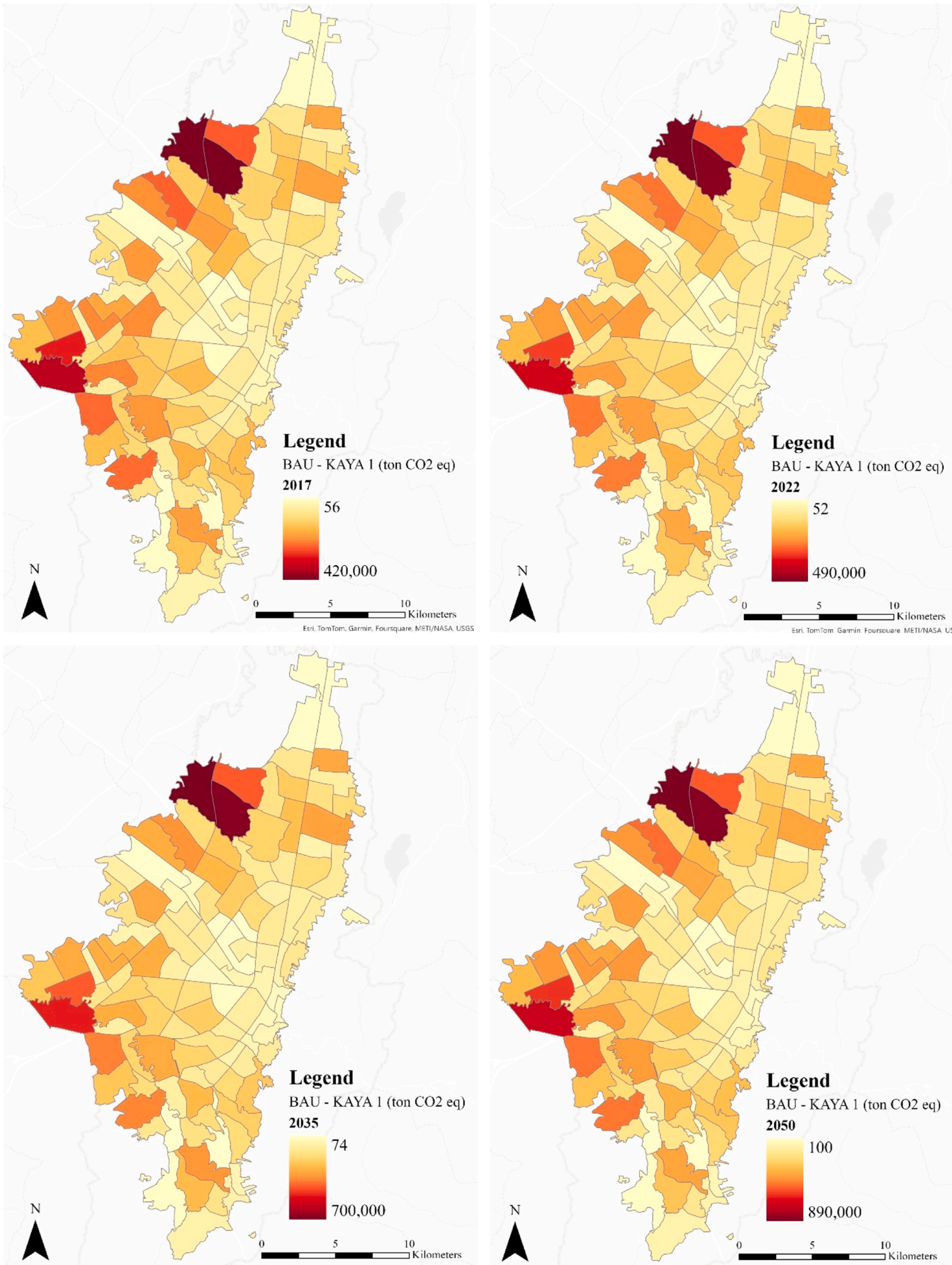

Fig. 5. Spatial distribution of GHG emissions of the KAYA 1.

their middle-high population and high socioeconomic activity. Notably, these areas contain <5 % social housing and offer the best access to urban services. Perceptions of safety are more favorable here compared with the overall conditions of the city, as well as environmental conditions that are superior, with lower air pollution and low exposure to natural hazards. These areas exhibit a lower proportion of residents working within the same ZPU of residence, requiring longer commutes for employment or education, and a poor level of service of the public transport system. These ZPUs are predominantly inhabited by high and middle-income households.

In contrast, the western and southwestern ZPUs show moderate emission levels and are notable for a high proportion of social housing, accounting for at least 75 % of the residential stock of these areas. Socioeconomic conditions here are more heterogeneous, hosting middle and

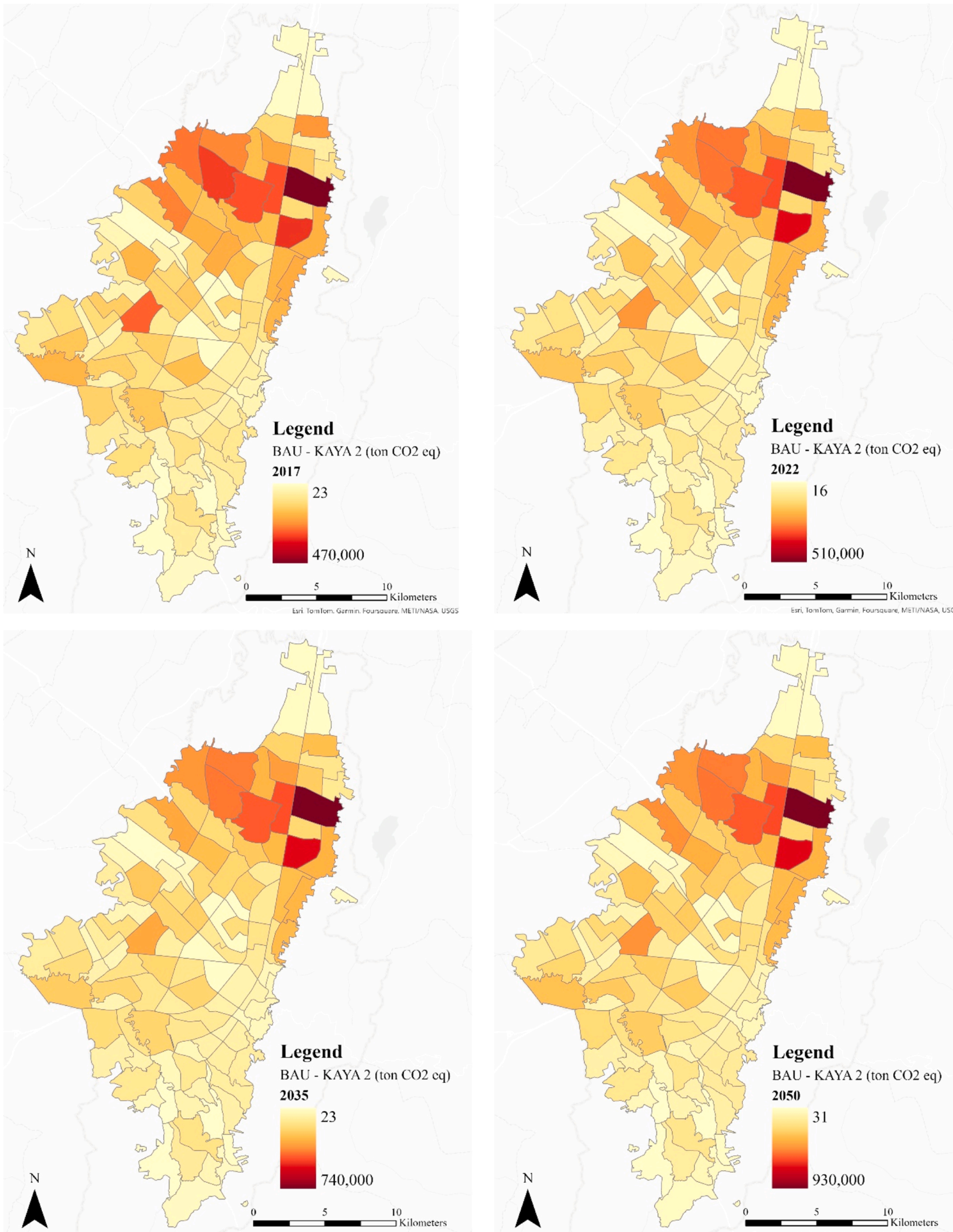

Fig. 6. Spatial distribution of GHG emissions of the KAYA 2.

low-income households, with less favorable environmental quality and higher exposure to natural hazards. While public space is abundant, there is a lack of green areas and an increased perception of insecurity. At the lower end of the range of GHG emissions, the central ZPUs exhibit a moderate presence of social housing, with a substantial increase in the ZPUs in the southeast hills. These regions have lower population density but boast significant natural spaces and form key parts of the city's ecological structure. Air quality is generally good, with balanced security perceptions. Service accessibility is varied; central areas benefit from good service provision, whereas southeastern zones face the city's worst service access and the longest public transport commutes. Overall, the spatial distribution of GHG emissions in Bogotá underscores the complex interrelations between urban development, socio-economic factors, and environmental impacts.

5.3. Limitations and challenges

It is important to acknowledge several limitations of this study.

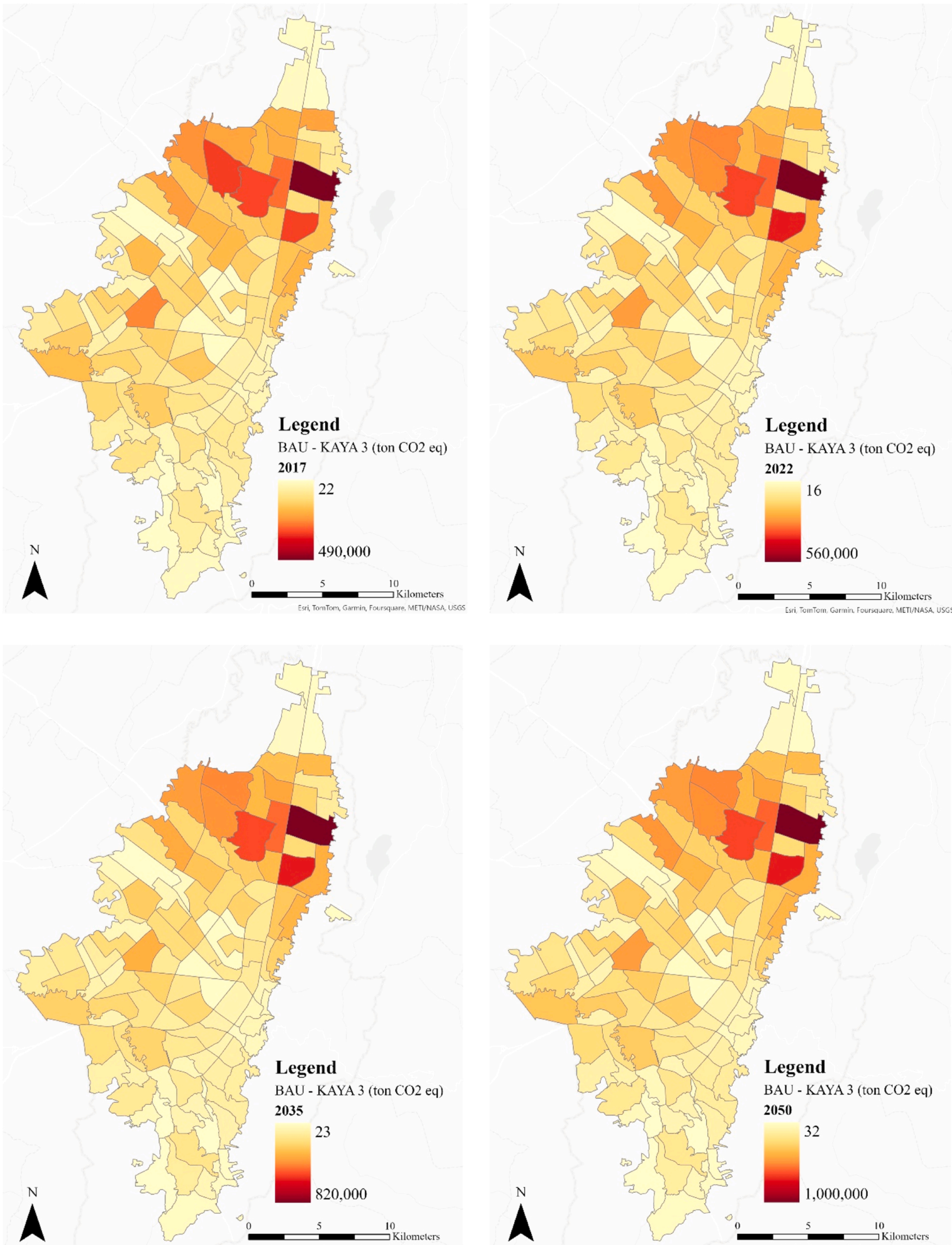

Fig. 7. Spatial distribution of GHG emissions of the KAYA 3.

While multiple secondary data sources were utilized, potential issues of time lags and statistical errors may affect the model accuracy. Some datasets (e.g., income levels and socioeconomic strata) may not perfectly reflect the rapid shifts induced by the COVID-19 pandemic. Post-COVID-19 income data shows significant shifts, which might have introduced biases in the model and impact the precision of the model's reflection of the city's socioeconomic dynamics. As these data sources produced by the city are not updated every year, the base values for the projection of these variables in the future were affected by the effects of the pandemic. Furthermore, the harmonization of multiple datasets across different temporal coverages and spatial resolutions required careful pre-processing, which can introduce its own set of uncertainties. Future research is recommended to focus on collecting and integrating more current and harmonized datasets to improve model accuracy.

From a critical standpoint, it is also important to acknowledge the limitations of excluding Scope 3 emissions, particularly those embedded in the consumption of goods, services, and construction materials. These indirect emissions are often substantial and tend to be concentrated in higher-income districts, where resource-intensive lifestyles and higher purchasing power contribute to significantly larger consumption footprints. Including Scope 3 emissions could therefore amplify the spatial disparities observed, revealing an even greater share of emissions attributable to wealthier socioeconomic strata, not only from transportation and energy use, but also from consumption patterns and the embedded carbon in materials.

This limitation is also reflected in the city's Climate Action Plan [37], which currently excludes Scope 3 emissions from both its inventory and mitigation strategy framework. This gap underlines the need for more comprehensive accounting and planning tools that integrate indirect emissions into local climate strategies.

Furthermore, this particular aspect presents a significant challenge for the city administration, which needs to harmonize its accounting and mitigation efforts on a broader, regional scale. The recently defined metropolitan region, encompassing Bogotá and its neighbouring cities, necessitates a coordinated approach to emissions accounting. Integrating the emissions of the metropolitan region in a coordinated way would increase the comprehensiveness of the emissions inventory, allowing for a more complete picture of complex mechanisms of emissions and urban metabolism. This would ultimately lead to a more effective and equitable climate action plan for the entire region. Such an approach, contingent upon overcoming the associated data challenges, would also enable the development of a spatial emissions model that encompasses the entire metropolitan area.

This study provides a methodology replicable for other cities, especially those in developing countries. However, adapting the model to different urban contexts presents challenges due to varying data governance and the potential absence of a detailed socioeconomic stratification system like that in Colombian cities. The replicability of the approach, therefore, centres on the availability of reliable, publicly accessible data that can serve as a proxy for key variables such as population, income distribution, energy consumption, and socioeconomic equity. While Bogotá's system of socioeconomic strata provided a robust framework for spatial disaggregation, adapting the model would require developing alternative proxies based on local data, such as property values, census-based income brackets, or detailed land use classifications. Furthermore, enhancing these data collection practices would sustain initiatives that facilitate a city's progression towards sustainability.

Future research should focus on two key areas. First, on developing and testing alternative proxies to ensure the methodology remains scalable and applicable to a wide range of urban contexts. Second, on expanding the Kaya identity with new factors, such as integrating models for land use changes in long-term urban evolution. This would enable the proposal of interesting "what-if" scenarios of emissions linked to possible territorialized land-use developments.

5.4. Policy implications and recommendations

The spatialized results of this study provide actionable insights for policymakers to design more effective GHG reduction strategies for Bogotá. The findings support a shift from city-wide, one-size-fits-all policies to a spatially differentiated approach considering the particular socioeconomic structure of the city. A notable deficiency in the current climate action plan is its lack of a spatial dimension within its GHG emission inventory. Such analysis proves indispensable for evaluating the spatial relevance of climate actions, encompassing both mitigation and adaptation strategies to combat the impacts of climate change. This identified gap presents a compelling opportunity to integrate spatially explicit data, thereby more accurately aligning climate actions with the geographic sources of emissions and areas of vulnerability.

Specific recommendations based on the analysis include: targeted transport policies given that the high emissions in northern ZPUs are strongly linked to high-income households' reliance on private vehicles for long commutes. Policies should focus on improving public transport service quality and frequency in these areas, or the facilitation of safe infrastructure for active mobility, which promotes modal shift to more sustainable modes, coupled with mechanisms of disincentives for private car use (e.g., congestion pricing, extended car-sharing services). Also, it is recommended the promote people-centric development in low-emission zones like the central and southeastern ZPUs, characterized by lower emissions and significant natural spaces. These present an opportunity to articulate existing policies like the project of interventions in urban areas for a better air quality (*ZUMAS*), or the Vital Neighborhoods for urban regeneration, promotion of active mobility, and citizen engagement [91]. Furthermore, policies for equitable resource allocation are informed by the finding that lower-income ZPUs have lower emissions, and highlight a potential misalignment between emissions and resource allocation. Policymakers should avoid a climate action framework that disproportionately burdens lower-income communities that might already be under conditions of energy and mobility poverty, as well as under deprived living conditions. Instead, they should invest in improving public transport and urban services in these areas to maintain sustainable mobility patterns and enhance quality of life without increasing GHG intensity in these areas.

This study emphasizes the critical role of socioeconomic factors in spatial GHG emissions analysis. The understanding gained from integrating income levels and socioeconomic strata not only enhances the precision of emissions mapping but also furnishes policymakers with a more detailed framework for targeted interventions. As cities worldwide strive towards sustainable urban development, the findings from this study underscore the need for a holistic approach that encompasses both economic and social dimensions in focalized urban climate action.

6. Conclusions

This study illustrates the spatial distribution of GHG emissions across Bogota by applying an expanded Kaya identity that is both simplified and replicable. The integration of scaling variables into the analysis based on population, level of income, and socioeconomic strata for each ZPU in Bogota allows for a detailed spatialization of the city's GHG emissions. This article evaluates annual emissions by ZPU, based on socioeconomic conditions, to define the spatial distribution pattern. Higher emissions are predominantly in the north and north-western ZPUs of the city, whereas the south-western ZPUs exhibit the lowest emission levels of the city.

Despite facing limitations due to data availability and the inherent uncertainties within model assumptions, the proposed methodology holds substantial value. Through appropriate calibration and refinement, it allows for the improvement of future iterations of the city's climate action plan, leveraging data sources that are promptly accessible and replicable to local authorities. A notable deficiency in the current climate action plan is its lack of a spatial dimension within its GHG emission inventory. Such analysis proves indispensable for evaluating the spatial relevance of climate actions, encompassing both mitigation and adaptation strategies to combat the impacts of climate change. This identified gap presents a compelling opportunity to integrate spatially explicit data, thereby more accurately aligning climate actions with the geographic sources of emissions and areas of vulnerability. This alignment is expected to improve the efficacy and precision of climate policies. Furthermore, this situation highlights the necessity for public entities to embrace more sophisticated and standardized practices in information management. Enhancing these practices would sustain the initiatives, facilitating the city's progression towards sustainability, thereby providing improved resources for analyses of this nature.

The implemented methodology provides a framework to refine traditional urban GHG inventories through a spatialization of the GHG in smaller spatial units. Although the study includes variables to improve the classical factors of the Kaya identity, there is still the chance to refine the implementation of the socioeconomic structure of the city with a higher level of detail. In future work, it is desired to integrate into this approach detailed data of land use classification in the city and the detailed emissions data for each typology. This inclusion could allow for to retrieval of an approximation with higher granularity into the spatialization of the GHG emissions of the city. Likewise, the inclusion of additional variables like land use, complemented with scenario modeling, could allow for evaluating the effects of territorial development plans on the GHG emissions of the city, by simulating the changes in land use and its effects through time.

This article lays the groundwork for a scalable methodology to incorporate a territorial dimension into the analysis of emission inventories, mitigation and adaptation measures, and climate justice considerations. By accounting for the vulnerability of populations and the specific needs of each contextual area within the city, in alignment with the Sustainable Development Goals, this approach aims to promote equitable and contextually relevant climate action initiatives not just in the context of Bogota or the Colombian cities, but to any emerging city or developing country in need of tools to support the targeted development of climate actions.

7. Abbreviations

- BAU: Business-as-usual
- GDP: Gross Domestic Product
- GHG: Greenhouse gas
- GIS: Geographic Information Systems
- GPS: Global Positioning System
- IAF: Income level adjustment factor
- IPAT: Impact = Population x Affluence x Technology
- LIDAR: Light Detection and Ranging
- LPU: Local planning units
- LUR: Land-Use Regression
- ML: Machine Learning
- NDCs: Nationally Determined Contributions
- NTL: Night-Time Light
- POT: Plan de Ordenamiento Territorial (Ordinance territorial plan)
- RS: Remote sensing
- STIRPAT: Stochastic Impacts by Regression on Population, Affluence, and Technology
- ZPU: Zonal Planning Units
- ZUMAS: Zonas Urbanas por un Mejor Aire (Urban areas for a better air)
- CO2: Carbon dioxide
- CO2e: Carbon dioxide equivalent
- ESAF: Economic structure adjustment factor

8. Equation terms

- A: Affluence (usually measured as GDP per capita)
- AZPU: Total area categorized on the ZPU
- ASESkZPUJ: Area of each socioeconomic strata k within ZPU J
- CIC: Carbon Intensity of the city
- CIi: Carbon intensity in year i relative to GDP
- CIE: Carbon intensity of energy
- E: Energy consumption (in TOE)
- Ei: Total GHG emissions of the city in year i
- Ej,i: Local emissions in ZPU j in year i
- EZPUi: GHG emissions in the ZPU in year i
- IAFZPU: Income level adjustment factor for each ZPU
- I: Environmental impact
- IC: Mean income per capita of the city
- IZPUj: Mean income per capita of ZPU j
- P: Population
- Pi: Population of the city in year i
- PZPUi: Population of the ZPU in year i
- T: Technology (often measured as impact per unit of GDP)
- EAi: Economic activity of the city in year i
- EAZPUi: Economic activity in the ZPU in year i
- ESAFZPU: Economic structure adjustment factor for each ZPU

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used GPT-4 and Paperpal, AI-assisted tools to make style corrections and improve the readability of the document. After using these tools, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

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CRediT authorship contribution statement

Jhon Ricardo Escorcia Hernández: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ayyoob Sharifi:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Sara Torabi Moghadam:** Writing – review & editing, Validation, Supervision, Conceptualization. **Patrizia Lombardi:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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