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Urban climate actions: connecting city characteristics to planning responses

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ABSTRACT

Cities, recognized as complex adaptive systems and epicentres of both climate vulnerability and innovative solutions, are increasingly adopting Climate Action Plans (CAPs) to navigate climate change. While considerable literature explores how various urban characteristics (climatic, physical, socio-anthropological, environmental) influence climate vulnerability, exposure, adaptation and mitigation responses, there is a gap in empirically understanding which of these distinct characteristics most powerfully drive the selection and prioritization of specific climate actions and interventions. This research aims to address this issue by systematically analysing the planned actions within the CAPs of twenty diverse global cities in relation to their unique urban fingerprints. Using multivariate statistical analysis to cluster cities by their characteristics and natural language processing to classify CAP actions, we empirically investigate the relationships between distinct urban profiles and the resulting climate action choices. Our analysis reveals that while cities facing severe, immediate climate pressures often prioritize community-level adaptation, mitigation and hazard awareness measures, cities with higher economic development tend to integrate climate action more broadly within economic restructuring and advanced policy frameworks. This study offers an in-depth understanding of how urban context translates into tangible climate actions, from a global perspective, aiming to inform more effective and tailored climate strategies for urban resilience.

1. Introduction

Urban areas are significantly susceptible to the severe impacts of climate change (Jiang et al., 2017). This phenomenon carries with it two implications. Firstly, it highlights the vulnerability of the global population (Kumar, 2021), given that over 55% of the world's population lives in urban areas (Ritchie & Rodés-Guirao, 2024). Secondly, it underscores the necessity for urban planning to adapt, with its primary objective of enhancing quality of life, in order to effectively address the challenges posed by climate change (Khalil, 2012; Papa, 2025a, 2025b). Since climate change has entered urban agendas worldwide, cities have mainly focused on the mitigation of its causes (Cohen et al., 2025; Debbage et al., 2025)., but as the limitations of such approaches become apparent, mainly due to the irreversible effects on the Earth's climate-regulating systems, urban planning is increasingly adding to strategies of adaptation that aim at responding to short and medium-term realities (Laukkonen et al., 2009; Wamsler et al., 2013; Carter et al., 2015; Hurlimann et al., 2021; Scorza & Santopietro, 2024; Gargiulo & Zucaro, 2025). Given the interconnected nature of urban systems, actions to enhance climate resilience generate co-benefits across sectors, improving public health, enhancing biodiversity, fostering economic development and reducing inequality (Sharifi, 2021, 2022). This narrative shifts the perspective on urban areas, highlighting them not only as vulnerable to disruptive events but also as unique opportunities for enhancing climate mitigation and adaptation (Batty, 2016; Gargiulo & Papa, 2021; Portugali, 2021). In this scenario, Climate Action Plans (CAPs) offer a strategic framework to guide cities towards a climate-proof future (Aboagye & Sharifi, 2024; OECD, 2023; Stone et al., 2012; UN-Habitat, 2016, 2024; Yılmaz & Işınkaralar, 2021).

CAPs are informed by both international and national strategies, while, as city-level tools, they are also designed to align with specific local contexts (MASE, 2022). Such *glocal* approach is essential to bridge climate goals with the unique complexities of local urban fabrics, governance structures, and socioeconomic realities. While research acknowledges the importance of context, few studies have systematically established and quantitatively modelled the multifaceted relationships between a comprehensive suite of urban characteristics, beyond purely geographical factors, and the specific action priorities within CAPs (Bery & Haddad, 2023; Cohen et al., 2025; Debbage et al., 2025; Otto et al., 2021). This gap highlights a disconnect between the aspirational goal

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of context-sensitive urban planning and a precise empirical grasp of the complex interplay between a city's multifaceted profile and its strategic climate action choices.

This study aims to address this gap by systematically investigating the relationships between planned climate actions and the defining characteristics of a diverse set of global cities. Taking CAPs developed by twenty major global cities as empirically grounded benchmarks of context-informed strategy, our research seeks to empirically identify how distinct clusters of urban characteristics, encompassing climatic, physical, socio-anthropological, and environmental dimensions, and crucially, their complex interplay, statistically correlate with and potentially drive the prioritization of specific climate action strategies within CAPs. By analysing CAP content through the lens of distinct urban typologies derived from a comprehensive characteristic profile, we aim to shed light on the empirical drivers of strategic choice in urban climate action. This approach serves to empirically validate the context-sensitivity principle and lays the groundwork for developing a "glocal" decision-support tool that facilitates the design of climate actions truly tailored to specific urban profiles and concordant with global sustainability aims.

The methodology involves three core steps: (1) identifying distinct city clusters based on their intrinsic characteristics using multivariate statistical analysis (PCA and hierarchical clustering); (2) classifying the actions within the CAPs of these cities using natural language processing and topic modelling; and (3) a comparative analysis to empirically link the city typologies with their prioritized climate actions, thereby revealing how specific urban contexts shape strategic planning responses.

Following this introductory section, the article is organised as follows. The next section provides a theoretical and practical framework. The third section explains the developed three-step methodology. The fourth section illustrates the application of the proposed methodology to a sample of twenty cities, followed by a detailed discussion of the results and their implications for urban climate adaptation. The concluding section summarizes the findings and their implications.

2. Theoretical framework

Drawing on theories of urban resilience (Batty, 2016), governance (Jacobs et al., 2024) and decision-making under complexity (Moroni & Chiffi, 2022; Shi et al., 2021), we acknowledge that the development of CAPs is a complex, negotiated process. Specifically, we adopt a multi-dimensional view of urban resilience, assuming that inherent capacities across ecological, social, economic, and institutional domains are shaped by a city's unique fingerprint (Bedinger et al., 2023). These capacities are not uniform but are fundamentally shaped by a city's "urban fingerprint": a unique, multidimensional configuration of characteristics that defines its vulnerabilities, resources, and transformation potential (Bedinger et al., 2023). This concept builds on place-based theory (Cutter et al., 2008) and systems thinking (Portugali, 2021), recognizing that urban systems exhibit emergent properties where the interaction between characteristics generates outcomes not predictable from individual components alone.

As for any decision-making processes that impact the governance of urban and territorial transformation, institutional capacities and established policy frameworks act as mediators in translating the inherent characteristics of cities into action (Gold & Tregenna, 2025; Page et al., 2024). Given their strategic role in limiting the impacts of climate change, CAPs are understood not as purely technical documents, but as reflections of multifaceted urban realities (Debbage et al., 2025; Jadidi et al., 2025; Swanson, 2025). Theories of decision-making under complexity suggest that the salience of certain characteristics or perceived or experienced risks may influence which climate interventions are prioritized by decision-makers operating with limited information and resources (Müller et al., 2020).

Over the past decade, a significant consensus has emerged in scientific literature regarding the deep influence of these intrinsic urban characteristics on how cities respond to the escalating climate crisis (García Díaz et al., 2024; Sera et al., 2019; Yari et al., 2024). However, a critical challenge remains: the need to empirically identify which specific urban characteristics, and crucially, how their interplay, most effectively drive the selection and prioritization of concrete climate interventions within city planning processes. The current research builds upon this understanding by aiming to investigate the relationships between planned climate actions and the distinctive urban fingerprints of a diverse set of global cities.

This study directly addresses this pivotal gap. Building upon the recognized importance of a city's distinct "fingerprint", a unique combination of these factors, and the growing body of evidence suggesting these characteristics significantly shape urban responses (Shi et al., 2021), we aim to delineate the key characteristics most influential in shaping cities' climate action choices. We hypothesize that the collective and interacting influence of these characteristics, forming a city's distinct 'urban fingerprint,' is a more powerful determinant of CAP vision and content than any single domain in isolation. This combined influence shapes both the spectrum of feasible climate actions and the prioritized pathways for their adoption (C40 & McKinsey Sustainability, 2021; Graham, 2025). To be more specific, we claim that certain configurations of urban characteristics will differentially predict the preference for nature-based versus grey solutions, higher socio-anthropological vulnerability will drive the selection of community-level resilience-building and hazard awareness initiatives, or a strong interplay between economic development and institutional capacity will favour the integration of climate action within broader economic restructuring and advanced policy frameworks.

To operationalise the urban fingerprint concept, we synthesise literature across four interconnected domains. This review serves two purposes: identifying measurable characteristics within each domain and establishing theoretical expectations for how these characteristics might influence climate action priorities.

The climatic domain, characterized by variables such as average annual temperature, maximum wind speed, and precipitation patterns, directly dictates the severity and frequency of extreme weather events (IPCC, 2007; IPCC, 2014; IPCC, 2022b; Isinkaralar et al., 2024). For instance, while higher temperatures and days with low humidity may increase forest fire risk (Torres et al., 2021), the efficacy and design of necessary cooling measures are heavily dependent on local meteorological characteristics, not solely on broader physical factors. However, climatic characteristics alone provide insufficient explanation for action choices. As Huang et al. (2025) demonstrate, identical climatic conditions can produce vastly different heat exposure outcomes depending on urban form and socioeconomic context. This observation reinforces our hypothesis that climate characteristics interact with other domains to shape responses. While climatic severity may establish baseline need for certain interventions, the specific prioritization of action types will be modulated by characteristics in other domains, particularly physical infrastructure and socio-anthropological vulnerability.

The physical domain encompasses factors such as population density, the extent of green spaces, and the prevalence of impervious surfaces. These are demonstrably correlated with phenomena such as urban heat islands and flood risk (Wu, 2021). Cities with extensive green spaces, for example, may exhibit greater preparedness for extreme weather (IPCC, 2023). Conversely, however, high population densities can complicate adaptation efforts, and while greater density can promote service efficiency (An & Dedekorkut-Howes, 2025; He & Weng, 2025; Isola et al., 2023), densification without complementary green planning can paradoxically worsen heatwave vulnerability. Impervious surfaces, such as concrete and asphalt, further augment heat and flooding risks by obstructing water drainage systems (IPCC, 2022b). Notably, cities characterized by decreasing population density and rapid urban expansion might present different heat exposure trajectories compared to static, highly dense urban areas (Huang et al., 2025), suggesting that urban form's relationship with heat exposure is complex and dynamic. Physical characteristics will influence the technical feasibility and preference for particular intervention types.

The socio-anthropological domain captures the social fabric of a city, its economic disparities, the proportion of elderly residents, poverty, inadequate social networks, and language barriers, factors which critically influence a community's capacity to withstand climate-related hazards and benefit from interventions (Ramli et al., 2023; Sun et al., 2022; Leichenko & Silva, 2014; IPCC, 2022a). For example, low-income communities often face heightened Urban Heat Islands (UHIs) with a paucity of resources for cooling (Huang et al., 2025). This underscores that even technically sound adaptation projects may have minimal impact if socio-economic and cultural factors are not adequately addressed. While studies widely highlight the vulnerabilities associated with these factors (Gargiulo & Guida, 2026), the existing literature does not extensively explore whether a younger population would inherently be less vulnerable, representing a potential area for contextual exploration or future research.

The environmental domain encompasses crucial variables for mitigating climate impacts and enhancing urban resilience, including the production of energy from renewable sources, the reduction of energy consumption for transportation, and the integration of sustainable mobility solutions (Chapman, 2007; Mashayekh et al., 2012; Olabi & Abdelkareem, 2022). There is an emerging discourse that equates "green" approaches with success in urban adaptation, advocating for the pivotal role of nature-based solutions (Turner et al., 2022). However, a critical counterpoint is the observed paucity of studies detailing methodologies for effectively measuring the success of these initiatives (Goodwin et al., 2025). This ambiguity surrounding the universal effectiveness and measurement of nature-based solutions, and their interaction with socio-economic factors (Ramli et al., 2023), highlights the need to empirically map which specific characteristics truly drive the prioritization of such initiatives and how they are contextually applied, rather than assuming a universally "better" approach based on broad categories like "greening".

It is through the formal articulation and prioritization of climate interventions within their CAPs that these multifaceted urban characteristics become empirically observable and amenable to systematic analysis. Climate Action Plans serve as formalised manifestations of how cities translate their unique fingerprints into strategic responses. As policy documents, CAPs crystallise the outcomes of complex negotiation processes involving technical assessments, stakeholder consultations, political deliberations, and resource constraints (Reckien et al., 2018; Salvia et al., 2021).

It is worth emphasising that CAPs are policy instruments and do not guarantee the effective implementation of the policies they contain. For the planned measures to translate into concrete actions, the plan should be underpinned by three fundamental enabling conditions: (i) robust and well-structured governance, often spanning multiple institutional levels from local to national; (ii) financial resources adequate to both the scale and complexity of the interventions (Melica et al., 2018); (iii) a robust monitoring system, which also includes the systematic tracking of greenhouse gas emissions over time (Rivas, Urraca, & Bertoldi, 2022).

Since many global cities are signatories of the Global Covenant of Mayors (GCoM), their CAPs are governed by a well-organised structure that mandates achieving climate neutrality by 2050 or 2030, the mitigation of energy poverty and access to sustainable energy (GCoM, 2025). These mandatory targets dictate a significant portion of the mitigation strategy. Within this framework, as Rivas, Urraca, Palermo, and Bertoldi (2022) highlighted, mitigation actions are often prioritized in sectors where GHG emissions are easier to abate or cost-effective to address, such as mobility and building efficiency, frequently involving private stakeholders and public-private partnerships. As for adaptation policies, they are not bound by predetermined targets at the global level. It follows that it is up to each city, based on its own risk profile, institutional capacities and local priorities, to identify and select the actions it deems most appropriate. Even in this case, however, the quality of governance, the availability of resources and the effectiveness of monitoring remain essential conditions for transforming planning intentions into measurable results.

CAPs typically articulate: (1) identified climate risks and vulnerabilities specific to the city, (2) prioritized action areas and intervention types, (3) implementation mechanisms and governance arrangements, and (4) resource allocation strategies.

By systematically analysing CAP content, specifically, the types of actions prioritized and their thematic focus, we can empirically trace how urban characteristics manifest in strategic choices.

This approach offers methodological advantages over surveys or case studies. CAPs represent revealed preferences: cities commit resources and political capital to these strategies, making them credible indicators of perceived priorities. The textual nature of CAPs enables systematic, comparable analysis across diverse cities using natural language processing. Finally, CAPs' structured format allows identification of both explicit priorities (frequently mentioned actions) and implicit emphasis (resource allocation, sequencing).

By linking systematically derived urban typologies to systematically classified CAP content, this study provides empirical grounding for the theoretical proposition that urban context shapes climate strategy. This evidence-based approach moves urban climate adaptation research from recognizing context matters to specifying how and why it matters, offering a foundation for developing generalizable yet context-sensitive planning frameworks.

3. Methodology

This section details the methodological framework designed to identify the potential relationships between the climate initiatives advanced in CAPs and the characteristics of the relative urban systems. A comprehensive understanding of these relationships is imperative to ensure that CAPs go beyond the mechanical identification of climate risks and formulation of general strategies, instead serving as tailored approaches addressing the unique vulnerabilities and capacities of each urban system. As summarized in the previous section, distinct urban characteristics determine how cities respond to climate change and the effectiveness of climate-related actions.

The methodology (Fig. 1) comprises three steps following the initial sample selection, in which twenty global cities are selected and their urban characteristic data are observed:

- City Clustering, where cities are grouped based on shared urban characteristics;
- Climate Action Classification, where actions from CAPs are analyzed and categorized;
- The Comparative-Analytical Analysis integrates these outputs, enabling a systematic comparison between the statistical CAP actions to identify how specific urban profiles are associated with particular planning strategies and priorities.

The following subsections describe each of the steps in detail.

3.1. Sample selection

The selection of cities follows multiple criteria, ensuring a diverse and representative dataset. For a comprehensive perspective, at least two cities are chosen from each inhabited continent. The sample reflects global heterogeneity in terms of population size, density, urban morphology and socio-economic conditions. As de Oliveira (2009) notes, the heterogeneity of contexts is critical in the varying capacities of cities to implement climate measures. Differences in economic development, governance structures and institutional capacities influence how cities respond to climate risks. By selecting cities with characteristics varying across these dimensions, the analysis can better reveal the

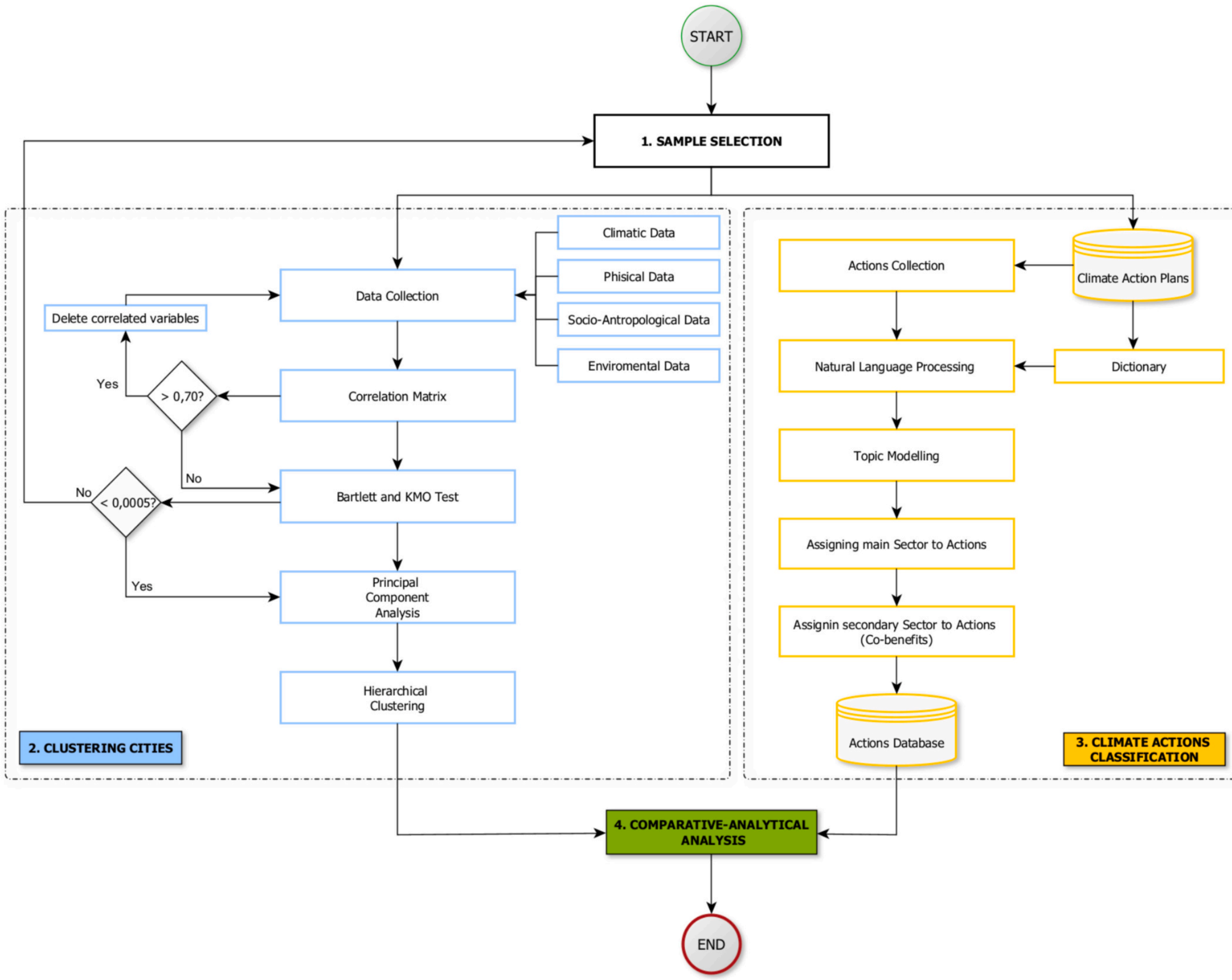

Fig. 1. Methodology workflow.

different pathways of planning and implementing measures of mitigation and adaptation. Another key criterion is the selection of cities exposed to different climate hazards, such as those of rising sea-levels, extreme heat waves, heavy precipitation, desertification and drought. The selection also choosers cities of strategic functional relevance, serving as economic, financial, social and cultural hubs at the national and global levels.

Finally, all the cities selected are part of the C40 network, demonstrating a formal commitment to climate change mitigation and adaptation through dedicated policies and allocation of resources (C40, 2023).

3.2. Clustering of cities

The second methodological step serves to group the selected cities based on shared urban characteristics, prior to analysis in terms of their relationships with climate actions. The classification of the cities is based on data collection on four domains, identified pursuant to the literature review: climatic, physical, socio-anthropic and environmental (Table 1).

Once the data collection is completed, the cleaning process follows with computation of a correlation matrix. In keeping with Schober et al. (2018) and Friendly (2002), variables exhibiting strong correlation (>0.80) are removed from the dataset. The process begins with identification of pairs of variables that demonstrate a correlation in excess of the identified threshold. Subsequently, the variables deemed less central to the study's aims are eliminated. This step mitigates potential issues related to multicollinearity, ensuring a more stable and interpretable dataset for the subsequent analysis.

After the data cleaning process, the Bartlett test of sphericity assesses the suitability of the data for Principal Component Analysis (PCA). A *p*-value below 0.001 indicates a significant result, confirming sufficient variable correlation for PCA (Doyle et al., 2017).

To better understand the intricate relationships between a city's unique characteristics and its strategic climate action planning, we employed Principal Component Analysis (PCA) as an initial step in characterizing the complex, multi-dimensional nature of urban environments. PCA is a robust statistical technique employed to reduce data complexity and dimensionality while retaining a significant portion of the variance present in the original, potentially inter-correlated, variables (Ringnér, 2008). By statistically reordering the original urban features into a new set of uncorrelated variables known as Principal Components (PCs), ordered by the variance they explain, PCA helps identify latent underlying structures. The sign and magnitude of component loadings illustrate the direction and strength of association between original variables and these emergent dimensions, offering a condensed yet informative profile of urban contexts (Abdi & Williams, 2010). This process is crucial for moving beyond a simple

Table 1
Set of significant urban characteristics that contribute to cities' responses to climate change, identified in the literature.

	Variable	Units	Description	Data source and methodology	References
Climate system	Average annual temperature **AvTy**	°C	The arithmetic mean of daily average temperatures calculated over 2024	Meteorological data was sourced Weather Spark. For each city, the weather data from stations are interpolated. A temporal average of daily mean temperatures was then computed over the specified reference period to derive the annual mean.	IPCC, 2021a; Ferranti et al., 2023
	Maximum annual temperature **Max TY**	°C	The highest recorded average daily temperature within a calendar year for a given city.	Extracted from annual maximum daily temperature records from Weather Spark, meteorological data provider.	
	Cooling degrees days **CDD**	degree-days	The sum, over 2024, of the daily temperature differences where the average daily temperature exceeds a thermal comfort threshold of 25 °C.	$\sum_{year} max\left(0, Average\_Daily\_Temperature - 25\right)$	IPCC, 2022b;
	Maximum wind speed **MaxWindSpeed**	Km/h	The highest recorded daily average wind speed within 2024.	Extracted from annual peak wind speed records from Weather Spark.	IPCC, Isinkaralar et al., 2024
	Average wind speed **AvWindSpeed**	Km/h	The arithmetic mean of daily average wind speeds over 2024	Calculated from daily average wind speed data obtained from Weather Spark.	
	Maximum of average monthly precipitation **MaxPrecipIntensity**	mm	The highest average monthly precipitation total recorded within 2024 for a given city.	Derived from daily precipitation records. Monthly precipitation totals were calculated, and the maximum among these 12 monthly values was identified.	Ramli et al., 2023
	Average of number of days per month with precipitation **AvPrecipFreq**	dd	The average count of days per month that experienced precipitation (defined as >0 mm) across 2024.	Derived from daily precipitation records. The number of days with precipitation was counted for each month. The average of these 12 monthly counts was then computed.	
	Standard deviation of days per month with precipitation **DevStdPrecFreq**	dd	Measure of the temporal variability in the monthly frequency of precipitation days across 2024.	Calculated as the standard deviation of the 12 monthly counts of precipitation days.	
Physical system	Range of elevation **HeightRange**	m	The difference between the highest and lowest elevation points within a city's defined administrative boundary.	Calculated using GIS software (QGIS). Elevation data from national DEMs were processed using city administrative boundaries to extract minimum and maximum elevations, and their difference computed.	Ahmadi et al., 2023
	Linear extension of the coast **CoastlineLength**	Km	The linear measurement of a city's interface with a significant water body (ocean, sea, large lake).	Extracted and calculated from GIS data. Primarily used OpenStreetMap (OSM) administrative boundary and coastline features. Length was measured using GIS tools.	Wu, 2021
	Altitude **Alt**	m	The weighted average altitude of the city's territory relative to sea level.	Calculated in GIS by using the city's administrative boundary polygon intersected with DEM. The average elevation value across the entire area of the polygon was computed.	Ahmadi et al., 2023
	Percentage of green space **GreenSup**	%	The proportion of land within a city's administrative boundaries classified as green space. This includes areas designated as parks, public gardens, urban forests, natural reserves, and vegetated community areas accessible to the public.	The data was sourced from the HUGSI (Human Geography, Urban Studies and Spatial Intelligence) platform, specifically their Green Space Index. HUGSI quantifies urban green space by analysing high-resolution satellite imagery (e.g., Sentinel-2) and applying advanced land cover classification algorithms. For each city's administrative boundary polygon, the total area classified as green space was calculated, and this was then divided by the total urban administrative area. The result was multiplied by 100 to yield the percentage.	Ferranti et al., 2023; Sun et al., 2022
	Extension of urban surface **UrbanSup**	Kmq	The total land area classified as the urbanized or built-up zone of a city.	Defined using GIS-processed datasets such as the Global Human Settlement Layer (GHSL) GHS-BUILT. Total area of these urban classifications within administrative boundaries was calculated.	Sun et al., 2022
Socio-anthropic system	Population **Pop**	N° of habitants	The total resident population of the city.	Obtained from official census data or the most recent demographic estimates from national statistical offices.	Ramli et al., 2023; Sun et al., 2022
	Population density **Pdensity**	Inhabitants/ kmq	The total resident population divided by the city's urban surface area (UrbanSup).	Calculated by dividing the total population count by the UrbanSup derived from land-use data.	Sun et al., 2022
	Percentage of elderly population **POver65**	%	The proportion of the total resident population aged 65 years or older.	Extracted from official national census data or demographic statistics from statistical.	Ramli et al., 2023
Environmental system	Average monthly salary **AvMonSalary**	€	The average net monthly income per resident after the deduction of taxes and social contributions.	Compiled from official national statistical offices, Eurostat, or other authoritative economic data providers for consistency in definition and currency. Crowdsourced data (e.g., Numbeo) was used supplementarily where official granular data was absent. Data were converted to EUR using exchange rates from 2024.	Leichenko & Silva, 2014; Sun et al., 2022

(continued on next page)

Table 1 (*continued*)

	Variable	Units	Description	Data source and methodology	References
	Percentage of use of sustainable modes of transport **PercetSustMob**	%	The proportion of total commuter journeys or daily mobility within a city made using sustainable modes: walking, cycling, and public transportation.	Derived from Google Sustainability Insights, modal split analyses from transport authorities, or household travel surveys, often involving questionnaires and data on mode of travel to work/study.	IPCC, 2022b; Mashayekh et al., 2012
	Percentage of current CO_2 emission **CO_2Em**	Tonnes of CO_2 equivalent per capita (tCO_2e/capita)	Total annual greenhouse gas emissions for the city, divided by the total resident population. Serves as a proxy for direct place-based emissions and climate impact.	Compiled from C40 Knowledge Hub. This involved summing emissions from energy supply, buildings, transport, and waste within city boundaries, then dividing by the corresponding year's population.	IPCC, 2022b; Hansen et al., 2013

enumeration of urban features towards an understanding of how various characteristics organize themselves to form a city's distinctive urban fingerprint.

Subsequently, we utilized Hierarchical Clustering (HC) on the individual urban characteristics to group cities based on similarities in these profiles (Cesario et al., 2020). The optimal number of clusters was determined through dendrogram inspection, a method that iteratively merges similar cities to reveal a hierarchical structure allowing for various levels of aggregation (Murtagh & Contreras, 2012).

It should be emphasised that the decision to use HC rather than other clustering methods, such as K-means, was deliberate and motivated by the aim of identifying similarities among groups of identified cases. Unlike K-means, which forcibly assigns cities to a predefined number of groups, HC allows for the identification of groups of cities that naturally cluster together based on the variables used (Ran et al., 2022). Whilst city groupings allow similarities to be identified through their "urban fingerprint", based on common characteristics (urban, climatic, social, etc.), it is precisely these characteristics that enable the definition of transformation and adaptation strategies that are more effective in addressing the effects of climate change. Finally, comparing the clusters of cities with the governance transformation strategies already in place allowed us to assess whether these strategies were responsive to the urban characteristics and the geoclimatic and social context, or whether, conversely, they were idiosyncratic. This latter methodological step is explained in detail in the following section.

3.3. *Classification of climate actions*

The third methodological step is to develop a detailed database of the actions reported in the CAPs of the selected cities, leading to systematic classification in relevant sectors, and to the identification of co-benefits.

The classification of actions into sectors is conducted through a textual analysis based on topic modelling, using Latent Dirichlet Allocation (LDA). The optimal number of topics is determined by evaluating coherence and interpretability. Each action is assigned to the most pertinent thematic category on the basis of the keywords extracted by the model (Jelodar et al., 2019).

To ensure accurate text processing and thematic attribution tailored to urban climate action discourse, a specialized dictionary was developed. This dictionary was informed by an iterative analysis of action descriptions within the analyzed CAPs, cross-referenced with keywords identified through extensive review of relevant academic literature on climate action and urban planning. Following the approach proposed by Franco et al. (2025) for the action plans of over 700 cities that are signatories to the Covenant of Mayors, and by Jin et al. (2023) for analysing the alignment between urban climate adaptation and sustainable development, the domain vocabulary used to feed and validate the model was constructed by integrating the terminological frameworks developed in both studies. This methodological choice allows the results of the LDA to be linked to established terminologies of urban climate action, whilst ensuring comparability with the results of the existing literature. The thematic structure that emerged reflects both the mitigation and adaptation dimensions of the plans, confirming the integrated nature of the CAP framework within the GCoM (Franco et al., 2025; Jin et al., 2023). This custom approach allows for a more context-specific and refined classification than generic language processing dictionaries. The choice of LDA is driven by its established effectiveness in identifying latent thematic structures within large text corpora, making it well-suited for extracting common themes and categories from diverse policy documents such as CAPs (Jelodar et al., 2019).

Complementary Natural Language Processing (NLP) techniques further enhance the objectivity and systematicity of this process by minimizing potential biases, distortions, and omissions inherent in manual content analysis. The NLP process involved standard preprocessing steps: firstly, text segmentation into tokens for unitized analysis, followed by the removal of common stop words and lemmatization to reduce terms to their base form, thereby ensuring consistency and enabling the model to focus on semantically informative words (Sun et al., 2017).

To objectively determine the optimal number of sectors (topics), the analysis followed a grid-search procedure (Franco et al., 2025; Jin et al., 2023), based on human interpretability optimisation, using the R package *ldatuning* (Nikita & Nikita, 2020). In particular, the optimal number of k was the output of balancing two contraposed information-theoretic metrics: the maximisation of the Jensen-Shannon Divergence (Deveaud et al., 2014) and the minimisation of average inter-topic similarity (Cao et al., 2009). The first metric ensures that each sector is distinct and informative, while the second identifies and penalises semantic redundancy. This mathematical framework allows the model to transition from a purely descriptive clustering to an empirically validated taxonomy of urban climate actions. As for our research, this approach ensures that the extracted sectors are as distinct as possible from one another, minimizing conceptual overlap. Moreover, this procedure guarantees the reproducibility of the study, anchoring the choice of *k* to statistical criteria of thematic separation rather than manual selection (O'Callaghan et al., 2015).

By employing a combination of topic modelling and tailored NLP pre-processing, this methodology allows for a systematic and empirically grounded classification of planned actions, moving beyond mere enumeration to discern the thematic emphases within CAPs. This provides the foundational data required to empirically investigate the links between diverse urban characteristics and their translation into tangible climate actions, directly addressing the gap in understanding which specific interventions are prioritized in response to varying urban contexts.

3.4. *Comparative-analytical analysis*

Following the steps of city clustering (Section 3.2) and classification of climate actions (Section 3.3), a comparative and analytical approach is used to compare and interpret the results. This final step leverages the outputs from city clustering and action classification to empirically investigate the relationships between urban characteristics and planned climate actions. By systematically comparing the clusters against the classified actions, we aim to identify patterns and test hypotheses regarding the extent to which distinct urban fingerprints align with particular climate strategies and interventions.

To support the interpretation of results, radar diagrams are used to highlight similarities and differences among cities and their planned climate actions. These visualization tools are employed not only to highlight patterns but also to provide an empirical basis for discussing observed associations and formulating interpretations regarding the likelihood of certain urban profiles adopting specific climate strategies, while being mindful of statistical significance. Furthermore, this comparative analysis serves in exploring whether some urban profiles are more likely to adopt specific climate strategies, and to assess the role of co-benefits in shaping multi-sectoral approaches. This structured analysis provides a comprehensive framework for understanding the relationship between CAPs and urban characteristics, thereby informing the development of the proposed decision-support tool. In order to assess the associations between the clusters and the sectoral priorities for climate action pursued by individual cities, not only descriptively but also quantitatively, a statistical analysis known as the effect size was conducted. The η^2 value was therefore calculated for each of the ten sectors of action identified through the LDA analysis of topic modelling. η^2 is a measure of effect size that represents the 'proportion of variance' (PV) of a dependent variable explained by membership of different groups (Cohen, 1988; Sullivan & Feinn, 2012). In this case measures the degree to which belonging to a particular cluster (from 1 to 5) explains the differences in the proportions of actions taken by cities in each sector. Following the conventional thresholds of Cohen (1988), η^2 values are interpreted as: $0.01 < \eta^2 < 0.06$ Small effect size, $0.06 \leq \eta^2 < 0.14$ Medium effect size, $\eta^2 \geq 0.14$ Large effect size.

3.5. Data acquisition

The selected sample consists of twenty cities from the C40 network, chosen based on the multiple criteria described in the previous section. The sampled cities provide a statistically robust dataset for identifying distinct urban fingerprints and analysing, thought this lens, their climate action priorities, without diluting the focus required for in-depth qualitative insight into planning processes. It is worth noting that, in order to ensure the quality of open-data available for each city, the sample is smaller than all cities in C40 network. Fig. 2 below shows the cities included in the study.

North America is represented by New York, New Orleans, Los Angeles and San Francisco, providing insight into climate strategies in highly urbanized and economically powerful cities. From South America, Buenos Aires and Rio de Janeiro are included, representing major urban centers where factors such as social inequality significantly influence climate resilience strategies (Vásquez et al., 2019). In Africa, Accra and Cape Town face climate challenges in contexts of rapid urbanization (Danso et al., 2021; Rebelo et al., 2011). Europe is represented by Milan, Paris, Barcelona, Copenhagen, Rotterdam and Istanbul, demonstrating different urban contexts and measures for climate adaptation and response. From South Asia, Mumbai and Ahmedabad are important cities facing significant climate challenges (Sivakumar & Stefanski, 2010), while Wuhan and Seoul provide perspectives on East Asia. Finally, the coastal cities of Sydney and Auckland represent the urban systems of Oceania (Hebert & Taplin, 2006).

The selected sample shows a high degree of heterogeneity. Population densities range from 875 inhabitants/km^2 in New Orleans to 31,951 inhabitants/km^2 in Mumbai. Other densely populated cities include Paris, Ahmedabad, Seoul, Barcelona and Istanbul. These variations are expected to influence their climate-response needs and policies of the respective cities. Furthermore, the sample reflects the exposure of cities to different climate hazards, with cities such as Rotterdam, Cape Town and New Orleans facing rising sea levels, while others, including Milan, Ahmedabad and Paris, experience extreme heat waves. Cities such as Mumbai, New York and Rio de Janeiro are prone to extreme precipitation, while Accra and Los Angeles are particularly affected by desertification and drought.

The selected cities are also strategically relevant: most are national capitals, and all are important economic, social and cultural hubs at the regional and global levels.

4. Results

This section outlines the results of three methodological steps: first, clustering cities according to their urban features; second, analysing the CAPs and categorizing climate actions by sector; third, exploring the links between urban characteristics and both planned and implemented climate actions.

4.1. Urban fingerprints clustering

Fig. 3 presents the results of the correlation analysis. To avoid

Fig. 2. Cities map.

	Av Ty	Max TY	CDD	MaxWindSpeed	AvWindSpeed	MaxPrecipIntensity	DevStdPrecFreq	HeightRange	Altitude	GreenSup	UrbanSup	Population	Pdensity	POver65	AvMonSalary	CO2Empp	PercetSustMob	CoastlineLength
AvTy	1,00	0,54	0,56	0,38	0,06	-0,07	0,18	-0,19	-0,01	0,23	-0,43	-0,16	0,15	0,00	-0,30	-0,17	-0,35	-0,07
MaxTY	0,54	1,00	0,82	0,44	0,33	0,06	0,25	-0,18	-0,24	0,10	-0,36	-0,08	0,25	-0,32	-0,34	-0,09	-0,55	0,16
CDD	0,56	**0,82**	1,00	0,41	0,11	0,00	0,24	-0,12	0,02	0,11	-0,19	-0,08	0,21	-0,38	-0,40	-0,37	-0,46	0,07
MaxWindSpeed	0,38	0,44	0,41	1,00	0,06	0,00	0,06	-0,27	-0,11	-0,10	-0,21	-0,10	0,21	0,12	-0,33	-0,12	-0,33	-0,19
AvWindSpeed	0,06	0,33	0,11	0,06	1,00	-0,21	-0,18	-0,13	-0,55	-0,08	-0,15	-0,10	-0,14	-0,18	0,09	0,22	-0,13	0,41
MaxPrecipIntensity	-0,07	0,06	0,00	0,00	-0,21	1,00	0,84	-0,02	-0,18	0,30	0,15	0,58	0,62	-0,43	-0,38	-0,25	-0,10	-0,18
DevStdPrecFreq	0,18	0,25	0,24	0,06	-0,18	**0,84**	1,00	0,00	-0,22	0,24	-0,02	0,45	0,53	-0,59	-0,42	-0,33	-0,38	-0,11
HeightRange	-0,19	-0,18	-0,12	-0,27	-0,13	-0,02	0,00	1,00	0,16	0,50	0,00	0,06	-0,22	-0,10	0,19	-0,13	-0,38	0,15
Altitude	-0,01	-0,24	0,02	-0,11	-0,55	-0,18	-0,22	0,16	1,00	0,08	0,01	0,15	0,05	0,14	-0,17	-0,25	0,14	-0,09
GreenSup	0,23	0,10	0,11	-0,10	-0,08	0,30	0,24	0,50	0,08	1,00	0,24	0,37	-0,17	-0,31	-0,21	-0,11	-0,42	0,15
UrbanSup	-0,43	-0,36	-0,19	-0,21	-0,15	0,15	-0,02	0,00	0,01	0,24	1,00	0,39	-0,32	-0,14	-0,23	-0,06	0,27	-0,04
Population	-0,16	-0,08	-0,08	-0,10	-0,10	0,58	0,45	0,06	0,15	0,37	0,39	1,00	0,43	-0,47	-0,45	-0,33	0,03	0,32
Pdensity	0,15	0,25	0,21	0,21	-0,14	0,62	0,53	-0,22	0,05	-0,17	-0,32	0,43	1,00	-0,23	-0,36	-0,42	0,10	-0,17
POver65	0,00	-0,32	-0,38	0,12	-0,18	-0,43	-0,59	-0,10	0,14	-0,31	-0,14	-0,47	-0,23	1,00	0,40	0,12	0,28	-0,14
AvMonSalary	-0,30	-0,34	-0,40	-0,33	0,09	-0,38	-0,42	0,19	-0,17	-0,21	-0,23	-0,45	-0,36	0,40	1,00	0,34	-0,02	0,12
CO2Empp	-0,17	-0,09	-0,37	-0,12	0,22	-0,25	-0,33	-0,13	-0,25	-0,11	-0,06	-0,33	-0,42	0,12	0,34	1,00	0,10	-0,11
PercetSustMob	-0,35	-0,55	-0,46	-0,33	-0,13	-0,10	-0,38	-0,38	0,14	-0,42	0,27	0,03	0,10	0,28	-0,02	0,10	1,00	-0,14
CoastlineLength	-0,07	0,16	0,07	-0,19	0,41	-0,18	-0,11	0,15	-0,09	0,15	-0,04	0,32	-0,17	-0,14	0,12	-0,11	-0,14	1,00

Fig. 3. Correlation matrix.

multicollinearity issues, variables with high correlation are removed from the dataset, in particular Maximum annual temperature (Max TY) and Maximum of average monthly precipitation (MaxPrecipIntensity). Max TY was excluded because the variable Cooling degree days (CDD) provides more comprehensive information, reflecting not only the values of peak temperature but also the overall demand for cooling. Similarly, MaxPrecipIntensity was removed in favour of the Standard deviation of days per month with precipitation (DevStdPrecFreq), which is more central to the aims of the current study.

After reducing the number of variables, the Bartlett test was performed. The p-value is $1.0*10^{-4}$, which is below the threshold of 0.001 and indicates sufficient variable correlation for PCA. Hence, as shown in Table 2 the PCA was performed: the first five principal components explain more than 70% of total variance. PC1 (explaining 22.2% of variance) is characterized by strong positive loadings from climatic variables and strong negative loadings from socio-anthropic ones. For instance, higher Cooling degree days and Standard deviation of precipitation frequency load positively on PC1, while CO_2 emissions show a strong negative loading on PC1. PC2 (explaining 15.9% of variance) is characterized by strong positive loadings from socio-anthropic and physical variables and strong negative loadings from socio-anthropic ones. For instance, higher Population and Extension of urban surface load positively on PC2, while Maximum wind speed shows a strong negative loading on PC2.

PC3 (explaining 13.8% of variance) is characterized by strong positive loadings from climatic and physical variables and strong negative loadings from socio-anthropic and environmental. For instance, higher Linear extension of coast and Average wind speed load positively on PC3, while Percentage use of sustainable modes of transport shows strong negative loading on PC3. PC4 (explaining 11.0% of variance) is characterized by strong positive loadings from physical variables and strong negative loadings from climate variables. For instance, higher Altitude and Range of elevation load positively on PC4, while Average wind speed shows strong negative loading on PC4. PC5 (explaining 7.7% of variance) is characterized by strong positive loadings from physical and environmental variables and strong negative loadings from socio-anthropic ones. For instance, higher Extension of urban surface and CO_2 emissions load positively on PC5, while Population density shows a strong negative loading on PC5.

The loadings indicate that a wide range of the identified variables contribute to these first five components, with climatic, urban, socio-anthropic and environmental features all represented, indicating their collective utility in characterizing the cities.

The output of the PCA provided the multi-dimensional coordinates for the subsequent HC. The selection of five clusters was confirmed by evaluating the linkage distance (fusion height) in Fig. 4. A significant

Table 2
PC variance.

PC1		PC2		PC3		PC4		PC5	
22,2%		15,9%		13,8%		11,0%		7,7%	
DevStdPrecFreq	0,40053	UrbanSup	0,41935	CoastlineLength	0,36421	Altitude	0,47694	UrbanSup	0,55719
CDD	0,34378	Population	0,41177	AvWindSpeed	0,36330	HeightRange	0,40095	CO2Empp	0,24995
Pdensity	0,29968	HeightRange	0,24900	HeightRange	0,34920	GreenSup	0,27269	MaxWindSpeed	0,24984
Population	0,28322	GreenSup	0,23911	GreenSup	0,33563	POver65	0,26470	GreenSup	0,23921
Av Ty	0,25085	Altitude	0,18074	AvMonSalary	0,21678	Av Ty	0,19416	CDD	0,12656
GreenSup	0,21881	PercetSustMob	0,17046	CO2Empp	0,15094	AvMonSalary	0,08128	Av Ty	0,11431
MaxWindSpeed	0,18123	CoastlineLength	0,10790	CDD	0,07373	CDD	0,08118	PercetSustMob	0,01245
CoastlineLength	0,02248	DevStdPrecFreq	0,08176	Av Ty	0,03540	MaxWindSpeed	0,03498	AvWindSpeed	−0,00472
Altitude	0,02015	Pdensity	−0,04201	DevStdPrecFreq	−0,01732	UrbanSup	−0,12102	POver65	−0,03023
HeightRange	0,01253	AvMonSalary	−0,06001	UrbanSup	−0,04797	DevStdPrecFreq	−0,13883	Altitude	−0,07480
UrbanSup	−0,02487	CO2Empp	−0,09069	Population	−0,04945	CO2Empp	−0,16071	Population	−0,08178
AvWindSpeed	−0,04034	POver65	−0,17615	MaxWindSpeed	−0,11121	Pdensity	−0,16673	DevStdPrecFreq	−0,13254
PercetSustMob	−0,25010	AvWindSpeed	−0,20263	POver65	−0,19139	CoastlineLength	−0,17916	HeightRange	−0,21248
CO2Empp	−0,30187	CDD	−0,28642	Altitude	−0,26832	Population	−0,19831	CoastlineLength	−0,28652
POver65	−0,33591	Av Ty	−0,37800	Pdensity	−0,34695	PercetSustMob	−0,23161	AvMonSalary	−0,35393
AvMonSalary	−0,37135	MaxWindSpeed	−0,38047	PercetSustMob	−0,42177	AvWindSpeed	−0,45013	Pdensity	−0,44147

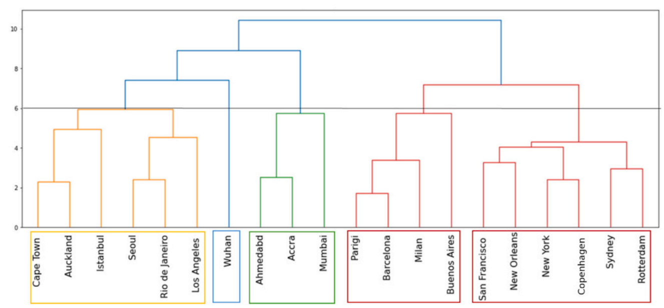

Fig. 4. Hierarchical cluster analysis dendrogram.

increase in the linkage distance occurred when attempting to merge beyond five groups, indicating that a 5-cluster solution represents the optimum for cluster consistency, while preserving meaningful differences between urban fingerprints.

To interpret and describe the clusters, percentage deviations from the overall sample mean were calculated for each cluster, using the variables showing the strongest loadings on the differentiating Principal Components. These deviations reveal how cities within a cluster differ from both the overall dataset and from other groupings in terms of distinctive characteristics, providing a robust foundation for interpretation of results.

4.1.1. Cluster 1: Cape Town, Auckland, Istanbul, Seoul, Rio de Janeiro, Los Angeles

The cities in this group show a value very close to the sample mean (−5.57%) in terms of Cooling degree days (CDD), indicating a moderate demand for cooling. The standard deviation of precipitation frequency is also lower (−9.17%), suggesting a climate with stable precipitation patterns. The data related to territorial morphology are particularly noteworthy: Linear extension of coast and Range of elevation are the highest among the selected cities, exceeding the mean by 176% and 192%, respectively. This indicates that the cities in cluster 1 are coastal and characterized by the presence of elevated terrain. Percentage of green space is also 30.41% above the sample average. Percentage use of sustainable mobility is −38%, reflecting a relatively low use of more sustainable transportation modes. CO_2 emissions average 4 tons per capita per year, which is slightly below the sample mean. Population density is 7874 inhabitants/km^2, indicating densely populated urban areas. The average Extension of urban surface for these cities is 957 km^2, reflecting a substantial but not exceptional urban size relative to the overall sample (−53.26% compared to the mean Extension of urban surface for the entire sample).

4.1.2. Cluster 2: Wuhan

This cluster consists solely of Wuhan, a city characterized by a significantly lower value of Cooling degree days (CDD) compared to the sample average (−99.36%) and a moderately low Standard deviation of precipitation frequency, 18.12% below the mean. These data suggest a climate with relatively limited seasonal variability in terms of precipitation. The Average monthly salary is particularly low, amounting to €812.03, which is 58.28% below the sample average. Concerning urban mobility, 58.36% of trips are made using sustainable modes, the highest percentage in the sample. Population density is extremely low (−88.18% compared to the mean), with 10,494,879 inhabitants distributed over an area that exceeds the sample average by 314.87%. In terms of demographic structure, the Percentage of elderly population is 11.20% lower than the sample mean.

4.1.3. Cluster 3: Accra, Ahmedabad, Mumbai

Cluster 3 is characterized by a very high Cooling degree days (CDD) value (+182.73%), indicating a hot climate with a high cooling demand. Standard deviation of precipitation frequency is also high (+119.71%), suggesting significant climatic variability. CO_2 emissions are relatively low (−24.81%) compared to the average of annual emissions for the overall sample. Population density is extremely high (+112.82%), with 70.12 million inhabitants, while Extension of urban surface is significantly lower (−82.73%), averaging 353.67 km^2. From a demographic perspective, the cities in this cluster show the lowest percentage of elderly residents: only 5% of are over age 65, representing a 60.98% lower proportion compared to the overall sample. The cities in this group are highly urbanized, with a predominantly young population and high population density.

4.1.4. Cluster 4: Barcelona, Buenos Aires, Milan, Paris

The cities in this cluster show Cooling degree days (CDD) close to the sample average (−2.03%) and an Average monthly salary of €1841.58, in line with the mean of the other clusters (−5.39%). The Standard deviation of precipitation frequency is low (−57.40%), indicating relatively stable precipitation patterns. The Percentage of sustainable mobility is among the highest in the sample, reaching 28.77%, while CO_2 emissions are relatively low (−42.32%), with annual per capita emission of 2.74 tons. Total population averages 2,059,273 and population density is moderate, although Extension or urban surface is relatively small (−65.59%), averaging 148 km^2. Regarding demographic structure, the cities in this group have a relatively high percentage of elderly residents, accounting for 20% of the total population, which exceeds the sample average by 65.36%. From a topographical perspective, not all cities in this cluster are located along the coast, as seen in the average Linear extension at 76.36% lower than the overall sample average.

4.1.5. Cluster 5: San Francisco, New Orleans, New York, Copenhagen, Sydney, Rotterdam

Cluster 5 is characterized by a significantly lower value of Cooling degree days (CDD), the lowest after Wuhan (−75.77%). The Standard deviation of precipitation frequency is also low (−35.02%), indicating a temperate climate. CO_2 emissions are the highest (+124.06%) compared to the average emissions across the entire sample. The average monthly income is also the highest (+128.92%), suggesting a potential relationship between economic activities in these cities and CO_2 emissions. From a morphological perspective, this cluster has a very low altitude (13 m above sea level), deviating from the sample average by −63.52%.

4.2. Classification of climate actions

The primary result from the classification of climate actions is the dictionary presented in Table 3, which refines the NLP and Topic modelling process. Keywords for each topic were initially identified from the topic modelling output (highest probability words per topic) and subsequently refined by cross-referencing with the content of the analyzed CAPs and the relevant literature (e.g., Jin et al., 2023).

The selection of 10 topics was empirically validated through an optimisation process using the ldatuning package. The Deveaud curve (maximising distance) shows a sharp increase until k = 10 followed by a clear plateau indicating diminishing marginal returns in information gain. Simultaneously, the Cao curve (minimizing similarity) reaches a state of stability between k = 8 and k = 12. Selecting k = 10 thus avoids both too few broad sectors and semantic over-fragmentation.

The first thematic area, Urban Planning and Policies, covers all the actions concerning territorial planning. The second, Energy and Buildings includes actions focused on use of renewable energy and energy efficiency of buildings. In the Mobility and Transport sector, the aim of actions is to implement solutions of sustainable mobility. The fourth sector, Waste Management and Resource Management, includes actions concerning waste recycling and resource efficiency. The fifth sector, Green Space and Biodiversity, includes actions for urban greening and conservation of biodiversity. The actions of the Climate Emergency sector are preparedness measures for extreme events, as well as those

Table 3
Topic dictionary.

Topic	Key words
Urban Planning and Policies	"Planning", "territorial", "urban", "regulations", "policies", "guidelines", "urban development", "governance", "strategic framework", "instruments", "directives", "resilience", "land", "zones"
Energy and Buildings	"energy", "renewable", "solar", "photovoltaic", "thermal", "efficiency", "buildings", "heating", "cooling", "consumption", "electric", "gas", "decarbonization", "ZEB", "lighting", "network", "production"
Mobility and Transport	"Mobility", "transport", "public", "bicycles", "cycling", "vehicles", "electric", "hybrid", "parking", "roads", "traffic", "infrastructure", "tram", "bus", "interchange", "pedestrian", "taxi"
Waste and Resource Management	"Waste", "recycling", "reuse", "collection", "disposal", "water", "hydric", "purification", "soil", "permeable", "drainage", "resources", "circular", "composting", "packaging", "discharges", "recovery"
Green Spaces and Biodiversity	"Green", "trees", "parks", "gardens", "forests", "biodiversity", "nature", "ecosystems", "species", "vegetation", "restoration", "woods", "greening", "protected areas", "sea"
Climate Emergency	"Climate", "climate change", "resilience", "adaptation", "drought", "floods", "heat waves", "risks", "vulnerability", "emergency", "forecasting", "protection", "waves", "heat", "health", "shelter"
Community Engagement and Communication	"Participation", "engagement", "community", "awareness", "information", "training", "education", "public", "networks", "communication", "citizens"
Sustainable Economy and Finance	"Economy", "finance", "sustainable", "incentives", "funds", "procurement", "taxes", "market", "labor", "training", "companies", "circular", "investments", "green", "fiscal", "ethics", "value", "innovation", "social", "work", "employment", "credit", "purchase
Responsible Consumption and Sustainable Lifestyles	"Consumption", "responsible", "waste", "repair", "second hand", "ethics", "food", "vegetarian", "vegan", "agriculture", "organic", "local", "zero kilometer", "barter", "reduction", "reuse", "food"
Monitoring and Evaluation	"Monitoring", "indicators", "evaluation", "data", "analysis", "verification", "reporting", "budget", "report", "measurement", "control

concerning public health and safety. The sector of Community Engagement and Communications gathers actions for community involvement in climate planning processes and for public awareness on climate issues. The Sustainable Economy and Finance sector gathers measures in favour of a circular economy, while Responsible Consumption and Sustainable lifestyles includes actions in favour of more sustainable ways of living. Finally, the Monitoring and evaluations sector includes actions for measuring the effectiveness of adaptation and mitigation interventions.

The actions classified within each sector can also generate positive impacts in other sectors. Such co-benefits were identified by assigning each action to a secondary sector, based on the modelling results for the sector with the second-highest probability for the specific action.

A total of 1264 climate actions were extracted and classified from the CAPs. Overall, the most prevalent primary sectors were Community Engagement and Communications (17% of actions) and Energy and Buildings and Waste and Resource Management (13% of actions), while Monitoring and Evaluation was the least represented (3%). The database facilitates comparative analysis and enhances the understanding of how cities integrate climate strategies in their urban planning.

4.3. Results from comparative-analytical analysis

The purpose of this step is to investigate the relationships between urban characteristics and the climate actions in the CAPs planned by cities. Comparing the results from the statistical city clustering and classification of actions classification allows analysis of how different types of cities develop strategies for climate mitigation and adaptation.

The relationships are represented using radar charts of the distribution of climate actions by primary and secondary sector for each city cluster, thereby revealing the predominant topics of climate actions. In the radar charts below, for each cluster, actions are grouped according to their primary sector. Furthermore, the figures also reveal the multi-sectoral nature of actions by charting, for each one, the secondary sector of classification, as visualized in the light grey Co-benefits polygon. The data presented have been normalized to account for the different number of cities and actions across clusters.

The profile of actions for Cluster 1 appears largely reactive to the characteristics of the relative cities. The high proportion of primary actions in Mobility and Transport (33%) directly corresponds with the low share of sustainable mobility (−38%) for the cities of this cluster. This suggests a strategic focus on addressing existing deficiencies, with initiatives like bus fleet electrification, low-emission zones and micromobility incentives aimed at transitioning away from car-dependent systems. The prominence of Waste and Resource Management (30%) and Green Spaces and Biodiversity (29%) aligns with the profile of large coastal cities (highest Extension of coastline and Range of elevation, +176% and + 192% respectively), which often grapple with waste from dense populations and the need for nature-based solutions for coastal resilience and urban heat mitigation (evidenced by Percentage of green space that is 30% above average). Climate Emergency (29%) actions, such as early warning systems, are logical for cities facing diverse hazards.

The relatively low focus on Community Engagement & Communication (9%) as a primary sector is notable. For these globally significant and diverse cities, this could represent a missed opportunity to leverage social capital and ensure equitable adaptation. However, this underemphasis is reduced significantly when co-benefits are considered. Here, Energy & Buildings actions contribute 56% (vs. 24% primary), Mobility & Transport 57% (vs. 33%) Green Spaces 55% (vs. 29%). Crucially, Community Engagement jumps to 35% via co-benefits, indicating that many infrastructural projects are likely designed with embedded participatory elements or aim for public awareness, such as advocacy campaigns for sustainable mobility or public climate risk education. This suggests an implicit rather than explicit prioritization of community aspects in some core interventions.

The CAPs of Cluster 3 cities show a strong reliance on “soft” and participatory measures, a strategy highly congruent with their sociodemographic profile: extremely high Population density (+112%), a predominantly young population (lowest Percentage of elderly, −60%), and likely limited financial resources for large-scale hard infrastructure, as often seen in cities in the global South. This is clearly reflected in the predominance of Community Engagement and Communication (52%) as a primary sector, alongside Responsible Consumption and Sustainable Lifestyles (41%). Actions such as distribution of emergency ice packs, provision of misting systems and campaigns for awareness of heat sickness serve as low-cost responses to this cluster's exceptionally high Cooling degree days (+182%) and climate variability (+119% Standard deviation of precipitation). This emphasis on community-based adaptation and social learning aligns with literature suggesting such approaches are critical in contexts with resource constraints and high social vulnerability (e.g., Dodman & Mitlin, 2013; Pelling & High, 2005). The transformative role of co-benefits is obvious for this cluster of cities: Community Engagement rises to 85%, Climate Emergency to 72%, and crucially, Monitoring and Evaluation to 74%. This last point is significant, suggesting that even if direct actions are community-focused, there is an understanding of the need to track progress and adapt strategies through participatory Monitoring and Evaluation, such as community risk mapping and local observatories.

The co-benefit analysis also reveals that essential sectors like Energy and Buildings (43%) and Mobility and Transport (52%) gain presence through socially-oriented projects like school shading and pedestrianization in low-income areas, demonstrating how infrastructural needs are addressed through an equity and co-benefit approach.

Cluster 4 shows a more diversified and arguably more mature approach to climate action. The strong emphasis on Responsible Consumption and Sustainable Lifestyles (40% primary, 78% with co-benefits) and Sustainable Economy and Finance (35% primary, 73% co-benefits) suggests these cities (largely European, plus Buenos Aires) are moving beyond foundational climate actions towards deeper integration of sustainability into economic and social fabrics. This may reflect a later stage of climate policy development where basic mitigation and adaptation infrastructures are more established, allowing for an increasing focus on systemic change. Indicative initiatives would be those promoting the circular economy, local ecological food, and sustainable business models.

The breadth of action is notable: even sectors less central as primary targets show high engagement through co-benefits, including Energy and Buildings (60%), Green Spaces (59%) Mobility and Transport (55%). Critically, Monitoring and Evaluation (47%) and Urban Planning and Policies (47%) are well-represented even as primary sectors, with actions like integrating climate risk into land-use plans and establishing city-specific climate indicators. Such commitment to policy integration and robust Monitoring and Evaluation is a hallmark of advanced climate governance and contrasts with some other clusters, suggesting a capacity for strategic, evidence-based adaptive management of climate actions.

Cluster 5, characterized by the highest CO_2 emissions (+124%) and highest Average income (+128%), presents a somewhat perplexing profile of actions. Primary actions are notably concentrated in Urban Planning and Policies (18%), implementing strategies such as in the design of public space and implementation of climate-resilient building codes. Alongside this are moderate efforts in Mobility and Transport (14%) and Sustainable Economy and Finance (14%), however several key sectors appear underdeveloped as primary targets, including Energy and Buildings (7%), Waste and Resource Management (8%) Green Spaces (9%). This shortcoming is notable, given the relevance of such actions to mitigating high emissions and adapting to climate risks, and the inclusion in this cluster of low-lying coastal cities.

This concentration on planning approaches, with limited primary attention to social dimensions (e.g., Responsible Consumption at 4%) and critical mitigation sectors (Energy & Buildings), raises concerns. While these cities are innovation hubs of the global North, the sectoral analysis shows that their CAPs are less comprehensively engaged than those of the cities of Cluster 4, for example. The lower overall number of distinct actions compared to Cluster 1 suggests a less urgent or less broad-based engagement. There is a pertinent risk of “maladaptation” (Barnett & O'Neill, 2010) for these cities, with exacerbation of existing vulnerabilities or creation of new ones, if strategies heavily favour technological, infrastructural solutions without sufficient multisectoral integration and attention to social equity and governance. In terms of mitigation, with the high CO_2 emissions profile of this cluster, the low primary focus on energy and buildings is particularly concerning.

Cluster 2 is composed solely of the outlier city of Wuhan and so is not reported here in radar charting. The total number of climate actions for this cluster is very low (18 actions). The Energy and Buildings sector accounts for the highest share of actions (19%). No actions were observed in the sectors of Climate Emergency, Responsible Consumption and Sustainable Lifestyles, Urban Planning and Policies, or Waste and Resource Management. However, in examining co-benefits, some actions are found to contribute to Climate Emergency (6%), Responsible Consumption and Sustainable Lifestyles (8%), Urban Planning and Policies (13%) Waste and Resource Management (7%). Moreover, the co-benefits analysis shows that the percentage of actions remains unchanged for the sectors Community Engagement and Communication, Green Spaces and Biodiversity, Mobility and Transport, and Sustainable Economy and Finance.

The above comparative analysis directly addresses the primary research question, showing distinct sectoral emphases across the five city clusters and providing strong evidence that urban characteristics significantly shape CAP priorities. For example, the resource constraints and demographic profiles of Cluster 3 cities evidently steer them towards community-based, low-cost adaptation measures, while the mature governance and diversified economies of Cluster 4 cities allow for broader integration of sustainability principles. The focus of Cluster 1 on transport and coastal adaptation reflects the physical and infrastructural realities of these cities. Conversely, the very strong concentration of Cluster 5 on planning approaches, despite the high emissions and resources of these cities, suggests that urban characteristics alone do not guarantee comprehensive action. Further qualitative investigation would be justified into issues such as possible complacency, greater or lesser political will, and the reasons for lack of policy priorities.

The analysis of co-benefits reveals a critical, often hidden, dimension of climate action. Many actions primarily categorized under one sector (e.g., infrastructure) generate substantial impacts in others (e.g., community engagement, public health). This underscores the interconnectedness of urban systems and the potential for integrated planning to maximize positive outcomes. It also suggests that cities may be achieving broader goals implicitly, which warrants explicit recognition and strategic leveraging.

To complete the visual analysis of the radar charts, the η^2 effect sizes were calculated for each of the ten areas of action identified through LDA topic modelling. The effect size value presented in Table 4 measures the proportion of variance in cities' behaviour that is directly attributable to being in one cluster rather than another. A larger effect size indicates that the cluster means are much further apart from one another than the variation between individual cities within the same cluster. The results are interpreted according to Cohen's (1988) conventional thresholds.

The effect size analysis reveals varying degrees of association between the clusters and the allocation of sectoral climate actions. Eight sectors show an effect size classified as ‘large’ according to Cohen's (1988) thresholds ($\eta^2 > 0.14$). Three of these achieve particularly high values: Energy and Buildings ($\eta^2 = 0.35$), Waste and Resource Management ($\eta^2 = 0.34$) and Community Engagement and Communication ($\eta^2 = 0.33$). In these sectors, knowing which cluster a city belongs to allows one to predict with a good degree of accuracy the percentage of actions it will dedicate to that domain. The differences between the clusters are substantial. For example, in the Energy and Buildings sector, cities in Cluster 4 (Barcelona, Buenos Aires, Milan, Paris) record an average of 10%, compared to 2% for Cluster 5 (Copenhagen, Rotterdam, San Francisco, Sydney, New Orleans, New York). This difference confirms that the various structural and socio-demographic characteristics captured by the different clusters provide a strong basis for orienting climate action. While the Monitoring and Evaluation sector shows a

Table 4
Effect size (η^2) by action sectors.

Sectors	η^2 value	Effect size
Energy and Buildings	0.35	Large
Waste and Resource Management	0.34	Large
Community Engagement and Communication	0.33	Large
Climate Emergency	0.24	Large
Responsible Consumption and Sustainable Lifestyles	0.23	Large
Mobility and Transport	0.19	Large
Green Spaces and Biodiversity	0.16	Large
Urban Planning and Policies	0.15	Large
Monitoring and Evaluation	0.09	Medium
Sustainable Economy and Finance	0.01	Small

medium effect size ($\eta^2 = 0.09$), indicating that cluster membership still allows for a distinction, albeit partial, between the groups' priorities for action, the Sustainable Economy and Finance sector records a small effect size ($\eta^2 = 0.01$), indicating that cluster membership does not explain the differences observed between cities. Cities within the same cluster, in fact, show allocations that are very different from one another. For example, in Cluster 4, Barcelona dedicates 26% of its actions to this domain, compared to 0% in Buenos Aires, 1% in Milan and 3% in Paris. However, this result should not be interpreted as a methodological anomaly, but rather as a tendency to incorporate economic dimensions into the CAPs that directly reflect administrative capacity and local political-institutional dynamics which transcend the urban characteristics under consideration.

The visual variations observed in the radar charts (Figs. 5–8) are corroborated by the high effect sizes reported in Table 4. Notably, the Energy and Buildings sector ($\eta^2 = 0.35$) and Community Engagement ($\eta^2 = 0.33$) exhibit the strongest associations with cluster membership. This indicates that the prioritization of these sectors is not an artifact of specific cities but a robust feature of the identified urban typologies, where geographical and economic characteristics explain more than 30% of the variance in planning allocation.

The results indicate that the clustering is not merely a statistical grouping but represents a meaningful typology for action. The high degree of internal consistency within Cluster 3 (resource-constrained cities) or Cluster 4 (cities with advanced climate governance), for instance, proves that urban characteristics are not passive traits but active determinants of planning priorities. The fact that cities within the same cluster, despite being on different continents, chose similar primary and secondary action sectors (as shown in the radar charts) provides empirical validation that the “urban fingerprint” is a significant predictor of climate action.

5. Discussion

This section discusses the results from the comparative analysis between the city clustering and classification of climate actions, offering insights into the relationship between urban characteristics and the actions implemented in the Climate Action Plans (CAPs).

The primary finding validates the central premise of the research: urban context is the decisive determinant of strategic climate action. The identification of five distinct city clusters, defined by the interplay of climatic, physical, socio-anthropological, and environmental attributes, namely the “urban fingerprint”, provides strong validation for this hypothesis. This heterogeneity underscores the inadequacy of generic, “one-size-fits-all” climate solutions and empirically grounds the recognized necessity for context-sensitive urban planning (Khalil, 2012; Papa, 2025a, 2025b). The classification of actions and the inclusion of co-benefits further reveal the complex, multisectoral nature of urban policy preferences.

The comparative analysis shows how differing global urban realities shape strategic choices in alignment with decision-making under complexity. For instance, the strategy adopted by Cluster 3 cities (Accra, Ahmedabad, Mumbai) is a clear case of resource-constrained adaptation. Characterized by extremely high cooling demand and density, their CAPs rationally prioritize Community Engagement and Communication and Responsible Consumption measures. Actions like early-warning systems, distributing health advisories, or adjusting labor hours are low-cost, high-impact social-learning interventions that maximize existing social capital, aligning with literature on effective community-based adaptation in resource-poor contexts, thus demonstrating how socio-anthropological characteristics can logically override investments in hard infrastructure (Larsen & Gunnarsson-Östling, 2009; Torabi et al., 2025). The results from this cluster also raise further questions: although its cities are not strictly representative of the wider Global South, their strong reliance on community responsibility and behavioral awareness as adaptive mechanisms highlights a recurring governance pattern in resource-limited contexts. This reliance can hide a structural imbalance, where the burden of adaptation is informally shifted from institutions to citizens. Such a pattern underscores the need for institutional strengthening and capacity-building to ensure that participatory adaptation complements, rather than substitutes for, formal public investment. Such insights will guide future research to investigate if this adaptation model is a transitional phase towards more institutionalized resilience or a persistent feature of low-capacity governance systems.

Conversely, the strategic profile of Cluster 1 (e.g., Cape Town, Seoul) is more reactive. Their high focus on Mobility and Transport directly addresses a recorded deficit, signifying a strategy of corrective catch-up. Simultaneously, their high scores in Green Spaces and Biodiversity

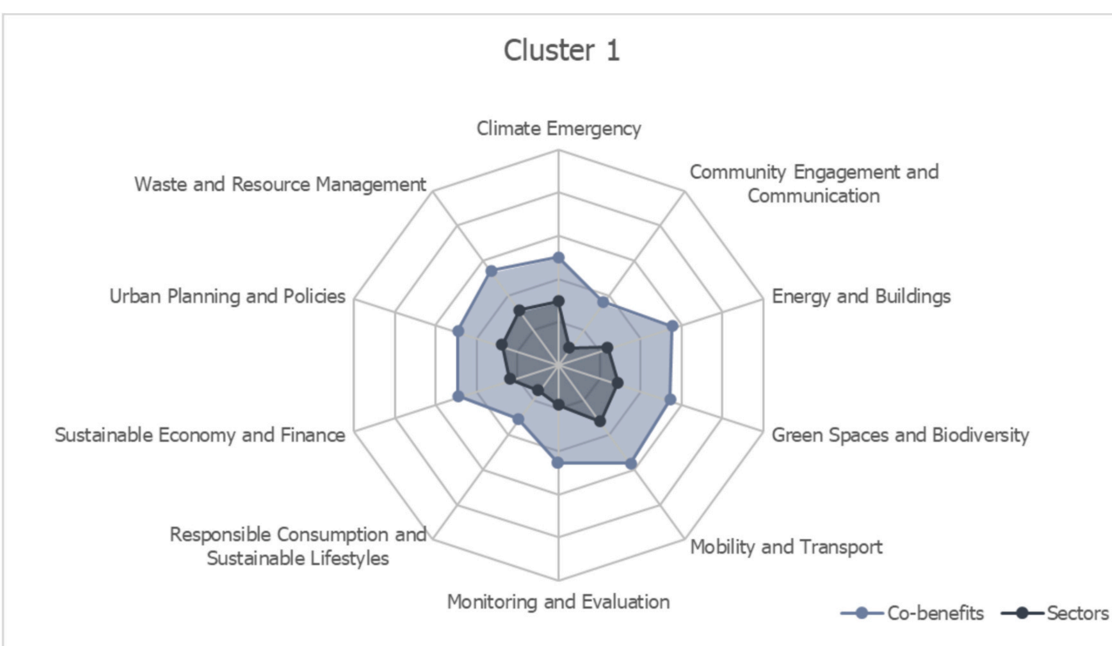

Fig. 5. Distribution of climate actions by primary sectors (dark line) and co-benefits (light line) for Cluster 1.

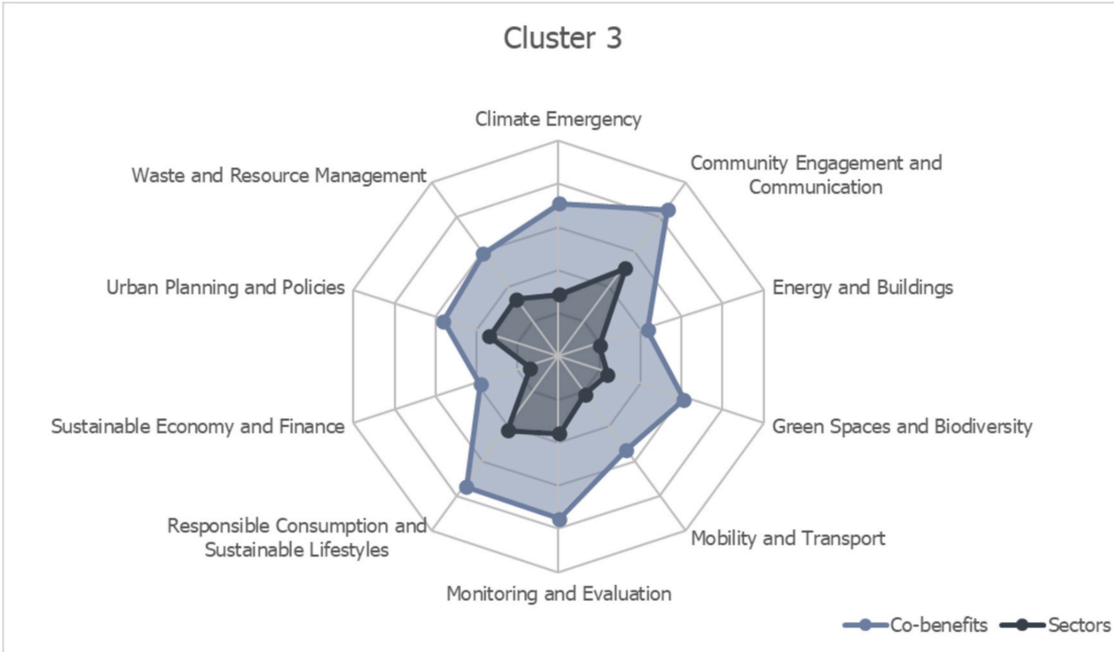

Fig. 6. Distribution of climate actions by primary sectors (dark line) and co-benefits (light line) for Cluster 3.

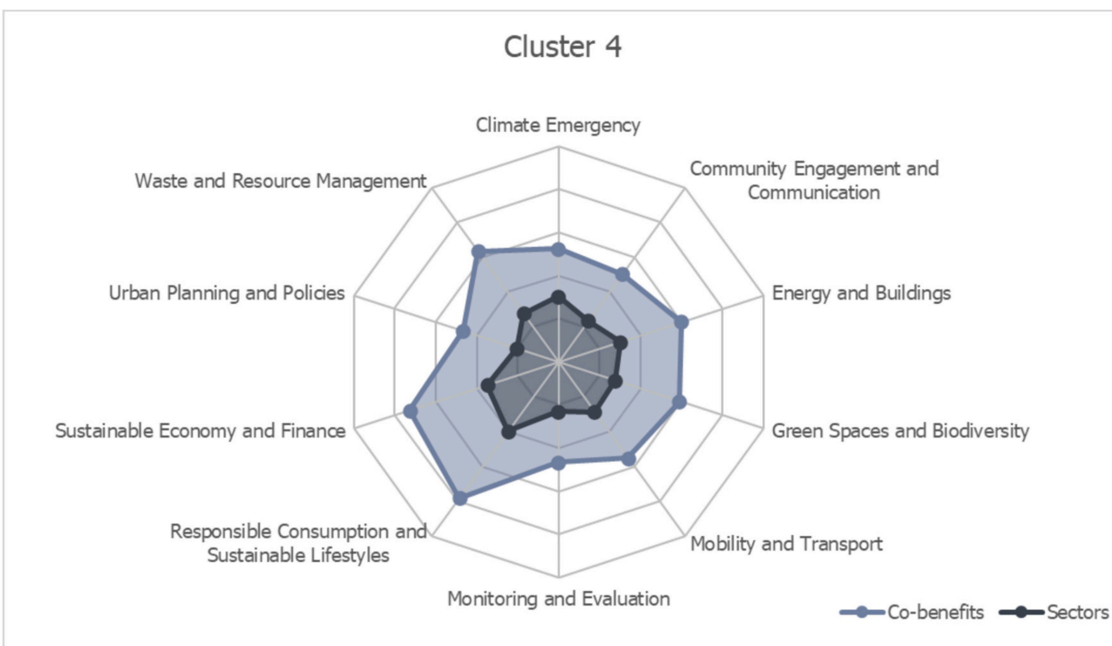

Fig. 7. Distribution of climate actions by primary sectors (dark line) and co-benefits (light line) for Cluster 4.

indicate a rational choice to leverage existing natural assets for adaptation benefits like coastal protection and urban heat mitigation, a decision which their coastal and elevated terrain features may have guided.

The climate action profile of Cluster 4 cities (Barcelona, Paris, Milan) reflects an advanced stage of climate governance. With foundational mitigation and adaptation infrastructure largely addressed, their strategies shift towards deeper systemic integration, prioritizing sectors like Sustainable Economy and Finance and Responsible Consumption. This focus on promoting the circular economy and sustainable business models suggests a move beyond foundational climate action towards embedding resilience within the economic and social fabric, characteristic of mature policy frameworks. However, the findings for Cluster 5 (San Francisco, New York, Copenhagen), characterized by the highest income and highest CO_2 emissions, present a critical policy concern. Despite possessing vast financial resources along with high risk profiles, this cluster shows a disproportionate concentration on Urban Planning and Policies and grey/hard infrastructure (Mobility), while key mitigation sectors like Energy and Buildings are significantly underdeveloped as primary actions (Gargiulo & Lombardi, 2016). This lack of sector-specific focus (e.g., in Energy and Buildings) is particularly striking given that most cities in Cluster 5 are prominent GCoM

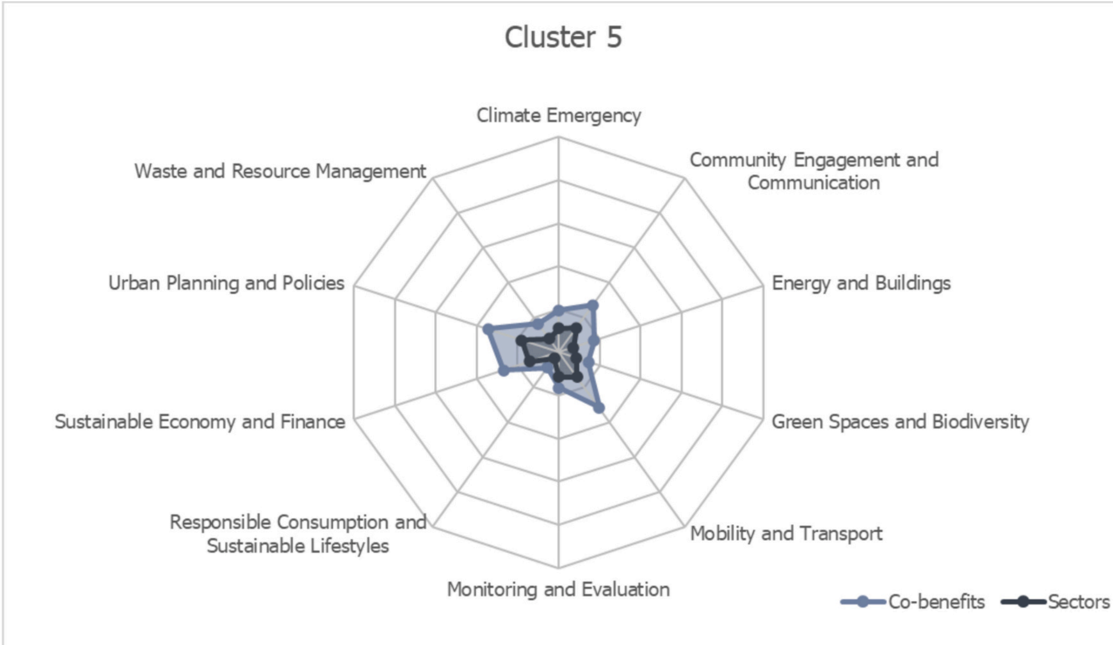

Fig. 8. Distribution of climate actions by primary sectors (dark line) and co-benefits (light line) for Cluster 5.

signatories. While their plans excel in governance frameworks, they risk falling short of mandatory 2030 and 2050 mitigation targets if administrative 'greening' of policies is not translated into immediate technological abetment strategies. Moreover, the reliance on technological and managerial solutions, rather than comprehensive sectoral engagement, raises the serious risk of maladaptation (Barnett & O'Neill, 2010). Such an approach may fail to address the root causes of high emissions or may exacerbate social vulnerability by prioritizing expensive grey fixes over equitable energy transitions, a critical point for high-resource settings.

Furthermore, the analysis of co-benefit provides an additional layer of insight, revealing the implicit priorities within urban systems. The fact that many infrastructural or transport projects often produce substantial co-benefits in Community Engagement or Public Health underscores that actions are inherently multisectoral. This finding is essential for integrated planning, confirming that cities achieve broader goals through their core interventions and allowing planners to strategically leverage these positive externalities to maximize outcomes across public health, equity, and biodiversity. Consequently, outcomes will be optimised not only across different sectors but also between adaptation and mitigation strategies, ensuring that the chosen solution meets both global objectives and local needs. One example is nature-based solutions (NBS), which tackle many urban challenges at the same time (IPCC, 2022b). They mitigate the urban heat island effect, managing stormwater, increasing biodiversity and reducing energy use through passive cooling and shading (Ascione et al., 2025a, 2025b; Gargiulo et al., 2025; Isola et al., 2025, Wamsler, 2015; Lai & Zoppi, 2025). In this study, this kind of measure is included in the category of green spaces and biodiversity and encompasses urban greening initiatives and actions aimed at preserving biodiversity. Examples found in the twenty selected cities include tree-planting campaigns in Milan and Los Angeles, as well as the creation and connection of blue-green corridors in Rotterdam and San Francisco. In Ahmedabad, on the other hand, the fundamental role of green spaces during heatwaves is highlighted, with the extension of opening hours for parks and gardens.

In conclusion, by providing a global and empirically grounded framework for linking urban typologies to climate action priorities, this research represents a vital first step towards the development of "glocal" decision-support tools. In fact, the empirical evidence arising from this work proves that cluster profiles serve as an immediate benchmarking tool to assess whether their current CAPs align with the strategies empirically proven to be most logical for their specific "urban fingerprint".

6. Conclusion

This contribution presents the foundational phase of a broader research endeavor aimed at developing a decision-support tool for policymakers and urban planners. The ultimate goal is to facilitate the design of climate action strategies tailored to specific urban characteristics, thereby enhancing urban resilience and minimizing risks of maladaptation.

This initial work provides an updated framework for understanding how global cities are addressing climate change through their Climate Action Plans (CAPs), by identifying the presence of strategies and interventions across the different plans and adopted more or less in relation to the characteristics of specific cities. A comprehensive literature review identified potential links between effective climate actions and diverse urban features (physical, functional, environmental, climatic). The research proceeded in three methodological steps. The first employed multivariate statistical analysis to cluster a sample of twenty C40 cities. Principal Component Analysis (PCA) was utilized to reduce dimensionality and characterise the cities, followed by hierarchical clustering, which grouped them into five distinct clusters. These clusters represent different urban contexts: Cluster 1 (coastal, elevated cities with moderate climates and low sustainable mobility adoption); Cluster 2 (a unique, low-density megacity with high sustainable mobility and limited climate variability); Cluster 3 (densely populated cities with young populations and compact urban forms, subject to extreme heat); Cluster 4 (cities with stable climates, aging populations lower emissions); and Cluster 5 (cities with temperate climates but notably high CO_2 emissions and average incomes).

The second step involved topic modelling to classify actions within the CAPs of the selected cities into ten macro-sectors. Each action was assigned to both a primary sector of intervention and a secondary "co-benefit" sector, highlighting the synergistic potential of climate initiatives. The final step was the comparative analysis of the city clusters in relation to their prioritized climate actions. This revealed a general tendency for cities to focus actions in sectors corresponding with their most evident challenges and characteristics. For instance, cities with low sustainable mobility emphasised transport improvements, while highly exposed coastal cities prioritized emergency planning and urban greening. Overall, these findings empirically validate the importance of aligning climate planning with specific urban contexts and offer a replicable analytical framework for assessing the coherence between declared city vulnerabilities and proposed policy measures.

The insights and classified actions collated in this study constitute a valuable resource and a crucial step towards the overarching research goal. This work provides a structured understanding of current practices and informs the development of tools offering clear, context-specific recommendations for urban planners and policymakers.

While this study yields reliable insights, several limitations must be acknowledged. Open data were not always available for all variables of urban classification, necessitating the use of proxies. The topic modelling approach, though systematic, could oversimplify the nuanced language of CAPs, overlooking certain details. In particular, the LDA approach is based on a bag-of-words representation of the text. That is to say, it disregards word order and the syntactic structure of sentences. Consequently, causal, conditional or negation relationships present in the original text of the CAPs may be invisible to the model, which treats identical tokens as semantically equivalent regardless of the context in which they appear (Benites-Lazaro et al., 2018; Blei et al., 2003; Franco et al., 2025). We recognize that these steps may oversimplify policy documents; however, these methodologies remain valid and appropriate for our research objectives.

The categorisation into primary and secondary sectors, while revealing co-benefits, could fail to detect complex interdependencies between actions because it loses the argumentative complexity that characterises integrated climate planning. It should be acknowledged that the twenty cities selected are all major global urban centres, which constitutes an explicit limitation of the study. The results may not be representative of smaller-scale urban contexts, characterized by different economic, housing and geographical structures. However, this choice reflects a specific objective of the study, which is to construct a global framework capable of identifying the most commonly implemented climate actions and of detecting recurring patterns among cities recognized as being engaged in climate governance. Future studies, building on the results presented here, may apply this perspective to different territorial scales, including smaller urban centres and more specific regional contexts (Rivas et al., 2021).Future research will aim to address these limitations by expanding the city sample to encompass a wider range of urban settings and socio-economic contexts. Methodological refinements will enhance data collection protocols for greater consistency and will integrate qualitative data, such as stakeholder interviews and in-depth case studies, gaining richer insights into the decision-making processes in development of CAPs. These advancements will further strengthen the evidence base of the decision-support tool, ultimately contributing to more effective and equitable urban climate action worldwide.

CRediT authorship contribution statement

Laura Ascione: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Carmela Gargiulo:** Writing – review & editing, Supervision. **Carmen Guida:** Writing – original draft, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Carmen Guida reports article publishing charges was provided by University of Naples Federico II. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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