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Identificación de indicadores discriminantes y criterios de sustentabilidad, resiliencia, y habitabilidad en metrópolis de Latinoamérica y del Caribe.

Identification of discriminating indicators and criteria for sustainability, resilience, and liveability in Latin American and Caribbean metropolises.

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Resumen

*El propósito de esta investigación fue seleccionar 25 indicadores bioclimáticos, urbanos, geográficos, socioeconómicos y sociopoliticos para identificar condiciones socio ambientales- climáticas, indicadores discriminantes y aspectos de sostenibilidad, resiliencia y habitabilidad de 70 metrópolis Latinoamericanas (periodo 2014-2018). Para organizar la información se propusieron datos de metrópolis e indicadores según tres variables dependientes (VD): VD-Zona climática Köppen Geiger, VD-Estratificación poblacional y VD-Localización geográfica. Cada VD se dividió en dos grupos, el primero en función de la altitud promedio de las metrópolis (sin prefijo altitudinal) y el segundo grupo reclasificando la altitud en 3 niveles (1 para cotas bajas, 3 para cotas medias y 5 para cotas altas). Posteriormente, se aplicaron dos modelos discriminantes, el primero de Conglomerados (MC), para graficar los clústeres (herramienta heatmap) y el segundo modelo de tipo Discriminante (MD) para validar errores por mala clasificación de los clústeres. La aplicación del MD corroboró que la VD-Localización geográfica (sin prefijo) obtuvo el menor error (4.7%) y el indicador discriminante de tipo urbano (Isla de calor) explicó el 61% de los datos, y en el segundo caso la VD-Zona climàtica (error de 8,5%) identificó los indicadores discriminantes socioeconómicos: índice de desarrollo humano (HDI), huella de carbono per cápita (Cf) y el índice de pobreza multidimensional (MPI) que explican el 100 % de los datos de un minoritario grupo (6%) de climas desérticos, tropicales y subtropicales. **La validación estadística permitió reconocer** indicadores influyentes y establecer las características socio ambientales-climáticas metropolitanas regionales, a su vez estas caracterizaciones permitieron verificar el desempeño de las metrópolis en función a la sustentabilidad, resiliencia y habitabilidad propuestos por organizaciones internacionales. Se concluye que para aplicar políticas climáticas realistas en Latinoamérica, se deben establecer primero las caracterizaciones metropolitanas de acuerdo a los indicadores aportados por el estudio, los cuales son coincidentes con las prioridades de los expertos internacionales.*

Palabras clave: *Metrópolis regionales, Latinoamérica y el Caribe, Variables dependientes, Modelos multivariantes, Indicadores discriminantes, Políticas climáticas.*

Abstract

The purpose of this research was to select 25 bioclimatic, urban, geographic, socioeconomic and socio-political indicators to identify socio-environmental-climatic conditions, discriminant indicators and aspects of sustainability, resilience and habitability of 70 Latin American metropolises (period 2014-2018). To organize the information, metropolis data and indicators were proposed according to three dependent variables (DV): DV-Köppen Geiger climate zone, DV-population stratification and DV-geographical location. Each DV was divided into two groups, the first according to the average *altitude of the metropolises (without altitudinal prefix) and the second group reclassifying altitude into 3 levels (1 for low altitudes, 3 for medium altitudes and 5 for high altitudes). Subsequently, two discriminant models were applied, the first Clustering Model (CM), to plot the clusters (heatmap tool), and the second Discriminant Model (DM) to validate errors due to misclassification of the clusters. The application of the DM corroborated that the DV-Geographic location (without prefix) obtained the lowest error (4.7%) and the urban-type discriminant indicator (Heat Island) explained 61% of the data, and in the second case the DV-Climate Zone (8.5% error) identified the socio-economic discriminant indicators: human development index (HDI), carbon footprint per capita (Cf) and the multidimensional poverty index (MPI) explaining 100% of the data for a minority group (6%) of desert, tropical and subtropical climates.* ***Statistical validation made it possible to recognize*** *influential indicators and to establish regional metropolitan socio-environmental-climatic characteristics, while these characterizations made it possible to verify the performance of metropolises in terms of sustainability, resilience and habitability as proposed by international organisations. It is concluded that in order to apply realistic climate policies in Latin America, metropolitan characterizations must first be established according to the indicators provided by the study, which coincide with the priorities of international experts.*

Keywords: Regional metropolises; Latin America and the Caribbean; Dependent variables; Multivariate models; Discriminant indicators - Climate policies.

1 Introduction

The world population reached 8 billion people in 2022, of which more than half (55%) live in urban areas, however this growth will continue on an upward trend towards 2050 (70% of the population) in urban areas according to the Sustainable Development Goals Report proposed by the United Nations (2023). This trend is much more marked in Latin America and the Caribbean (LAC), according to data from the United Nations Habitat Organization (UN-HABITAT, 2016), which shows an urban population of eighty percent (80%) of the region's total population and only thirteen percent (13%) of the global urban population. These heterogeneous population conditions added to the climatic and geographic variability of the region's metropolitan areas affect the social and economic vulnerability of more than 50% of the regional population, which already resides in areas with extreme climate risks according to the Development Bank of Latin America (CAF,2014) and has a significant deficit of physical infrastructure.

According to international scientific consensus, this role and impact of metropolises on climate is undeniable according to Intergovernmental Panel on Climate Change (IPCC, 2021). The impact of these climate dynamics can be assessed according to various indicators based on the population, climate, geographic, and urban characteristics of metropolises. Historically, in recent decades, many reports have analyzed the differences in urban temperatures between rural and urban environments and their surroundings, known as Urban Heat Islands. These studies have been the forerunners in the climate assessment of clusters of regional metropolises (Casadei et al., 2021).

Another indicator that reflects the relevant role in the climate of the social and environmental dynamics of metropolises is urbanization and its progressive expansion, which is a factor that generates an environmental impact through changes in land use and carbon release (Grimm et al., 2008). Under this approach, regional studies relating urbanization, urban land expansion and temperature can be identified in 43 cities of Chile (Henríquez et al., 2017) and megacities such as Sao Paulo (Pacifici et al., 2019).

Recent approaches to climate studies, in turn, include socio-economic and socio-political indicators, which allow capturing the structure and nature of city growth. It is necessary to identify these anthropogenic socio-economic indicators such as carbon dioxide (CO_2) emissions and pollution (PM2.5, PM10) as climate-influencing aspects (Creutzig et al.,2015) the Gross Domestic Product (GDP) of each country and energy consumption. Aware of this situation, regional researchers have estimated per capita carbon footprint (Morán et al., 2018) and particulate matter measurements in several South American metropolises and megacities in Brazil according to Andrade et al. (2012). These anthropogenic factors have a high environmental impact, as do the socio-economic indicators that measure the influence of the population in metropolises, such as the Human Development Index (HDI), the income of these populations (GDP), and the GINI, which evaluates data on the social evolution of a population (Lipset, 2007).

As the impact of climate change at the regional level and specifically in large metropolises is a scientific concern concerning the development of cities, socio-political indicators have been proposed within urban planning, including climate governance and adaptation-mitigation strategies. Specifically, let's talk about governance and its influence on climate policy development. We only let's talk about governance and its influence on climate policy development. We proceed to analyze current democratic trends, which indicate that 55% of the world's population lives in authoritarian and hybrid regimes. Only 12% are optimal democracies according to the Economist Intelligence Unit Democracy Index (EIU, 2018). Although there are shortcomings in the estimation of these socio-political indicators in the LAC region, it is recognized that efforts have been made to report sustainability studies in 100 cities in Mexico (Estrada et al., 2020) and broader studies geographically referring to ecosystem services, habitat, democracy, and human development in 21 metropolises in the region (Dobbs et al., 2014).

However, it is worth mentioning that when reviewing other types of socio-political indicators, not included in these studies, some assess climate risk, which is particularly high in the Latin American region according the Global Climate Risk Index (GERMANWATCH, 2021), which involve assessing the rule of law of the population, which in the case of LAC is deficient according to Global Justice Project (WJP) and those that structure social gaps (multidimensional poverty), which is particularly marked in the region, according to the Oxford Poverty and Human Development Initiative (OPHI, 2023).

The current state of the art indicates that, although socio-environmental and climate studies on the region's metropolises can be found in the literature, there are no proposals that integrate this type of situation using various indicators weighted according to the different groups of metropolises. Therefore, this study aims to establish and validate with multivariate models (Clusters and discriminant) organisations of different clusters of ‘Köppen Geiger climate-indicators’ according to dependent variables such as population, climate or geographical location and to obtain the most discriminant indicators within the data sets.

These differences between the climate groups (Clusters) according to the dependent variables will be visualized in a thematic cartography elaborated in a Geographic Information System (GIS). Subsequently, after recognizing the socio-environmental and climatic characteristics of the clusters and their discriminating indicators, reports on climate policies aimed at sustainability, resilience and liveability proposed by international organizations such as the 100 Resilient Cities project will be evaluated: 100 Resilient Cities project (100RC, 2013), cited by Hofmann (2021), Sustainable cities index (ARCADIS , 2015) on the 100 most sustainable cities in the world, Resilient Cities Index proposed by Economist Impact (2023) and the Global Liveability Index proposed by the Economist Intelligence Unit (EIU, 2024) which includes 173 global metropolises. This research on indicators that support international climate policies will enable the performance of regional metropolises in terms of sustainability, resilience and liveability to be assessed.

2. Methodology

The Latin America and Caribbean (LAC) region comprises 33 states, located in three sub-regions: South America, Mesoamerica, and the Caribbean (Figure 1). This geographic region represents a relatively large and highly vulnerable area to extreme weather events according to reports made by the Development Bank of Latin America (CAF, 2014), which also reported that at the regional level 48% of the capitals present a situation of high risk to climate change scenarios.

In addition to this risk condition, the Latin American region is characterized by significant climate variability according to the Köppen-Geiger classification, which has served as a reference in regional climate studies (Wu et al., 2019). These updated Köppen-Geiger climates in the region (Beck et al., 2018), are made up of the following climatic zones: steppes (warm and cold), arid (warm and cold), subtropical, tropical and temperate (Table 1). About population aspects, it should be noted that there is an important stratification of the regional population according to the number of inhabitants (UN-Habitat, 2016), which leads to an important urban dynamic, therefore, based on these climatic, population and geographic criteria, the study proposed to include seventy (70) metropolises which represent an important percentage sample (44%) within the regional urban population estimated at 625.806.000 inhabitants, according to the Economic Commission for Latin America and the Caribbean (CEPAL, 2017).

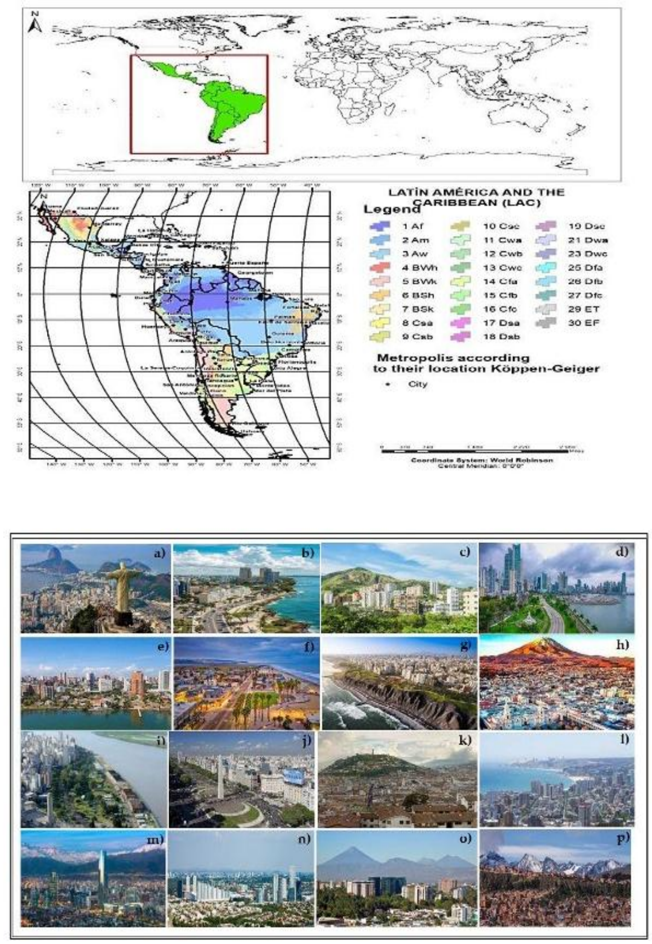


Fig.1. Location of metropolises. Some illustrative examples of the metropolises in LAC: (a) Rio de Janeiro ; (b) Santo Domingo , (c) Cali ; (d) Panama City ; (e) Maracaibo ; (f) Tijuana ; (g) Lima ; (h) Arequipa ; i) Rosario ; j) Buenos Aires ; k) Quito ; l) Gran Valparaíso ; m) Santiago de Chile , n) Guadalajara ; o) Guatemala City ; p) La Paz .

Table 1. Metropolis according to their location Köppen-Geiger

Climate	Köppen-Geiger	Sub-group	Metropolises
	Af	Ecuatorial	Salvador, Manaos, Belem, Rio de janeiro, Santos
Tropical	Am	Monsoon	Joao Pessoa, Managua, Santo Domingo, San Juan, Sao Luis, Recife, San Pedro Sula Bucaramanga, Cali, Medellin
	As (Aw)	Tropical savanah	Caracas, Ciudad de Panamá, Fortaleza, La Habana, Natal, Brasilia, Santa-Cruz, Barranquilla, Guayaquil, Mérida, Goiania, Maracay, San Salvador, Tegucigalpa, Valencia, Vitoria.
Sub tropical	Cwa	Subtropical with dry winters	Belo horizonte, Campinas, Córdoba, Guadalajara, San Miguel de Tucumán, Cuernavaca, San José.
	Cfa	Humid subtropical	Asunción, Puerto Alegre, Rosario, Sao Paulo.
Arid	Bsh	Steppes (hot)	Maracaibo, Monterrey, León, Querétaro,Cartagena, Cochabamba, Tijuana,
	Bsk	Steppes (cold)	San Luis Potosí.
Desert	Bwh	Desertic (hot)	Lima, Torreon, Mexicali
	Bwk	Desertic (cold)	Ciudad Juarez, Mendoza, Arequipa
Temperate	Csb	Mediterraneam with fresh summers	Concepción, Valparaíso
	Csc	Cold-summer Mediterranean	Santiago de Chile.
	Cwc	Cold subtropical highland	La Paz
	Cfb	West coast maritime (oceanic)	Buenos Aires, Curitiba, Montevideo, Bogotá, Quito,
	Cwb	Temperate with dry winters	Toluca, C.D México, Morelia, Puebla, C.D Guatemala

2.1 Period of analysis and selection of indicators

Five-year period (2014 to 2018) was selected for the analyses, for which it was possible to use and generate robust data on metropolitan climates and their urban, climatic, socio-economic and socio-political conditions. The information is widely reported in international articles and publications on climate and population inhuman settlements of the Intergovernmental Panel on Climate Change (IPCC, 2021). The temporal sequence underpinning the choice of the period was based on the following criteria: 1) during the years 2014-2018, there was a significant contribution of publications related to climate and urban dynamics of human settlements at the regional level, 2) from 2014 onwards, the annual reports are consistent in terms of generating socio-political indices related to democracy, rule of law, global risks, climate risks and social gaps, in addition there was also significant information regarding socioeconomic indices involving carbon emissions, particulate matter, human development, social inequalities and population trends.

The data for the indicators proposed for this study (Table2) were extracted from official websites of international and non-governmental organizations, scientific articles and global platforms. In the first case, when referring to bioclimatic indicators (temperature, precipitation, humidity-urban aridity) were taken from portals and publications of the World Meteorological Organization (OMM, 2018),the geographic-urban indicators (altitude, urban area, heat islands, population density and urban sprawl) were extracted from official reports of Demography of World Urban Areas (2018) and reports of climate behavior of South American metropolises (Wu et al.,2019), as for socio-economic indicators data such as population (Pob), energy (E), carbon emissions (Cf,CO2), pollution (PM2.5-PM10), social inequality (GINI) and human development (HDI), were extracted from scientific articles (Morán et al., 2018) , international agencies such as the World Health Organization (OMS, 2018) and the United Nations Development Programme (PNUD, 2018).

Finally, the selected socio-political indicators such as the democracy index (DI), rule of law (WJP), global risks (WR), Global climate risks (CRI) and multidimensional poverty index (MPI), were obtained from annual reports of organisations such as the Economic Intelligence Unit (better known by its acronym EIU,2018), the Global Justice Project (WJP, 2021) of the Germanwatch Organization, the Global Climate Risk Index (Germanwatch, 2021), the Oxford Poverty and Human Development Initiative (OPHI, 2023), and the Global Risk Index (World Economic Forum, 2021). The indicators selected by the study and the respective source are shown in Table 2.

Table 2. Indicators and their respective data sources

Indicator	Unit	Data
Altitude (Alt)	(m.a.s.l)	Wu et al.(2019)
Urban area (UA)	Square kilometers (SK)	Demographia World Urban Áreas (2018).
Population density (Pd)	Inhabitant /km2	Demographia World Urban Áreas (2018).
Urban Growth (UG)	% urban growth/year	Urban Áreas (2015-2018)
Urban Heat Islands (UHI)	Temperature (◦C)	Wu et al.(2019).
Temperature (Tm)	(◦C)	World Meteorological Organization (2021)
Precipitation (Pp)	(mm/year)	World Meteorological Organization (2021)
Humidity (H)	%/year	World Meteorological Organization (2021)
Aridity index (AI)	% Water availability	World Meteorological Organization (2021)
Population (Pob)	Millions of inhabitants	Demographia World Urban Areas (2018).
Carbon footprint per capita (Cf)	Tons/year	Morán et al. (2018).
Carbon emissions year (CO2)	Tons/year	Morán et al. (2018).
Fine Particulate Matter (PM2.5)	Micrometer - diameter	World Health Organization (2018)
Coarse Particulate Matter (PM10)	Micrometer - diameter	World Health Organization (2018)
Energy (E)	Kilowatt hours-year (Kwh/year)	World Bank 2021
Energy intensity (EI)	Cost-energy/GDP	World Bank 2021
Gross domestic product (GDP)	Thousands ($) Millions (year)	World Bank 2021.
Economy per year (Economy)	Thousands ($) Millions (year)	World Bank 2021.
Social inequality index	Social inequality hab /año	World Bank 2021.
Human Development Index	Human Development	(PNUD, 2018).
Democracy index (DI)	Democracy	The Economist Intelligence (2018)
Multidimensional poverty index	Multidimensional poverty	Oxford Poverty & Human (2023)
Global Climate Risk Index (CRI)	Loss of human life (GDP).	Germanwatch (2021)
Global risks Index (WR)	Resilience	Wolrd Economic Forum (2021)
Global Justice Project index(WJP)	Rule of law	Global Justice Project (2021)

2.2 Dependent variables and metropolises categorization

In this study it was proposed to recognize metropolitan clusters of various types of indicators (mentioned in 2.1), which will be organized in databases according to three dependent variables (DV), namely the regional Köppen-Geiger climate zone (hereafter DV-Climate zone), regional population stratification (hereafter DV-Population stratification), and regional geographical location (hereafter DV-Geographical location).

In order to organize the work it was necessary to establish the different categories of the 70 regional metropolises, therefore, a respective coding was assigned to the metropolises according to the DV based on, 1) the Köppen Geiger climate (Beck et al.,2018), the population stratum (UN-Habitat, 2016) and the geographic coordinates (Geographic Coordinate System), defined as follows according to Köppen-Geiger (Af, Am, Aw, As, Bsh, Bsk, Bwh, Bwk, Cfb, Cfa, Csc, Csb, Cwc, Cfa, Cwa: Cwb), 2) according to population ranges (500 thousand - 999 thousand are Intermediate metropolises (IM), 1 million to less than 5 million are Medium metropolises (MM), 5 million to less than 10 million are Large metropolises (MG) and finally more than 10 million inhabitants, are Megacities (MC), 3) according to their geographical parallels such as the Northern Temperate Zone (NTZ) Arctic Circle (Latitude 66.33)- Tropic of Cancer (Latitude 23.5 N); Intertropical Zone (IZ) Tropic of Cancer GCS (Latitude 23.5 N)-Tropic of Capricorn (Latitude -23.5) and Southern Temperate Zone (STZ) Tropic of Capricorn GSC (Latitude -23.5)-Antarctic Circle (Latitude -66.33). In addition to these codifications and to differentiate the analyses in each DV, an altitudinal prefix was added or excluded from the metropolis (adding P to the DVs), according to: a) low altitudes or altitudes with prefix 1 (0 m.a.s.l - 200 m.a.s.l), b) medium altitudes with prefix 3 (300 m.a.s.l - 800 m.a.s.l) and high altitudes, with prefix 5 (900 m.a.s.l). Therefore, the final coding was established with the following components: (a) DV-Climate zone (Bsh, Bsk, Cwb; (a1) DVClimate zoneP (1Bsh, 3Bsk, 5Cwb). (b) DV-Population stratification (BskMI, CscMM, BwkMG,AwMC);(b1)DVPopulationstratificationP(1BskMI ,3CscMM,5BwkMG,1AwMC);(c)DV-Geographicallocation (CwaGCS (ZTN), AmGCS (ZI), BwhGCS(ZTS)(c1)DV-Geographical locationP(1CwaGCS (ZTN), 3AmGCS (ZI), 5BwhGCS (ZTS).

2.3 Exploratory data analysis

After recording each metropolises according to the components of each DV, statistical analysis was performed using R software version 4.0.2 (R Development Core Team, 2023) and the cluster libraries factoextra, NbClust, pheatmap and clustertend. Three analyses were performed: exploratory and general frequency of indicators, Pearson correlations and validation of statistical hypotheses.

The hypotheses were based on the Hopkins statistic (Kassambara, 2017), which assesses the clustering tendency of a dataset by calculating the probability that the data come from a uniform distribution. If they come from a uniform distribution, the information is random. According to these criteria, hypothesis testing was defined as the null hypothesis that a dataset has uniform behaviour, and the alternative hypothesis that some kind of clustering exists in the dataset. The decision criterion was defined as follows: if the statistic obtained is in the interval $0.0 < H < 0.5$ the null hypothesis is not rejected, but if on the contrary the value of H is greater than 0.5 it can be concluded that in the data set there is evidence to use multivariate clustering methods, accepting the alternative hypothesis. A cluster model (CM) was then applied to rank and organize indicators contributing to each cluster, and a statistical significance assessment (Hopkins statistic) was performed to select clusters according to the methods: Elbow, (compactness), Silhouette (quality), Gap statistic, (variation) and Nablus, and finally, with the graphic tool heatmap, the clusters of Köppen-Geiger-indicator climates were selected in heterogeneous groups and which are most associated with the indicators visualized in the heatmap according to the intensity of the traffic light (red, high association, blue, low association and white very low association).

2.4 Validation of clusters obtained in the CM

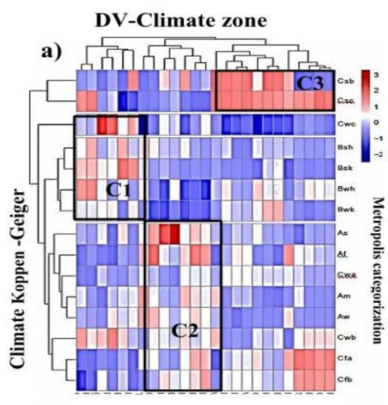
A multivariate discriminant model (DM) was used to evaluate the presence of statistically significant differences in the DV clusters defined with the CM, including or excluding the altitudinal prefix, and the univariate variance (ANOVA) was calculated, to validate key indicators that have a greater discriminant capacity within the dataset ($p<0.0001$). Then, to assess the membership of the data (clusters), a random partitioning of the information from the databases was performed, using a selection of 70% of the data for the training group and the remaining 30% of the data as the test (validation) group. After validating the clusters and indicators with the discriminant models, the socio-environmental and climatic characterization of the different clusters (according to the DVs) was carried out, which made it possible to describe the characteristics of each metropolitan group in a Köppen Geiger base cartography (cartographic layers updated by Beck et al., 2018), within a Geographic Information System (GIS).

Subsequently, twenty (20) regional metropolises were taken, located in different clusters according to the DVs with the lowest classification error and with the following influential indicator requirements: per capita carbon rates, Köppen Geiger climate conditions, energy consumption-management/year, pollution levels, incidence of Urban Heat Islands, socio-economic dynamism, social inequality, population size, democratic and rule of law levels, and climate and global risk conditions. In this selection of metropolises, the overall performance (deficits and strengths) of climate policies provided by international organisations in terms of sustainability, resilience and liveability will be verified. To identify these indicators (sustainability, resilience and liveability) that are the basis of global climate policies, the following initiatives were reviewed: the 100 Resilient Cities project 100RC, 2013 proposed by the Rockefeller Foundation (Hofmann, 2021), which considers climate risks and vulnerability, governance, human development, resilience and the Köppen-Geiger climate classification of metropolises. The second case considered the ARCADIS index (2015) of 100 sustainable city indices measuring energy consumption, waste, pollution, GHG emissions, economy, income and energy efficiency. The third proposal evaluated was the Resilient Cities Index (Economist Impact, 2023) which measures mitigation, heat events, social integration and resilient economy, and finally the fourth report considered included the livability index, known as The Global Liveability Index (EIU,2024), which includes 173 metropolises and 30 indicators divided into five categories: political stability, quality of life, environment and culture, health, education and infrastructure.

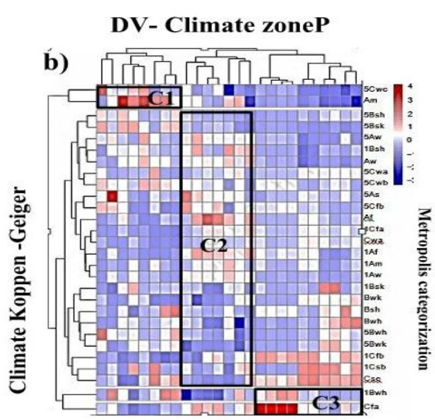
3. Discussion and Results

The statistical validity of the analyses yielded a value of $H= 0.1854$, considering that the R software at the time of the calculation estimated **(1-H)**, the comparison will be as follows: $(1\text{-}H) = 0.8146 > 0.5$ and therefore the null hypothesis is rejected. The data do not follow a uniform distribution and it is valid to assume that there is a clustering tendency. When performing the categorization over a period of 5 years (2014-2018), a total of 350 metropolises frequencies were obtained in each of the DVs, subsequently, when performing an analysis of the 70 categorized metropolises, it was mainly noticed that when altitudinal discrimination (prefix, denoted with the letter P) is performed, new metropolises types are generated according to their altitude, climate, population and geographical location if we compare it with the metropolises types where P was not applied. This new coding implies a greater heterogeneity of metropolises to the already existing in the Latin American region. As examples of this variability (application or exclusion of P), for each DV we obtained the following numbering: DV-Climate zone (15); DV-Climate zoneP (28); DV-Population stratification (26); DV-Population stratificationP (37); DV-Geographic location (23) and DV-Geographic locationP (32).

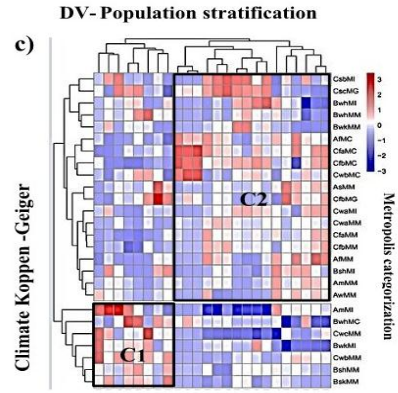
The Elbow, Gap and NbClust methods (Figure 2) generally suggest an average total of four (4) climate clusters for the DVs, and Silhouette recommends an average of eight (8).Regarding the indicator clusters, the cluster model (CM) and the heatmap graphical tool suggest between three and four clusters in general (for the three DVs), however in each group of dendrograms a quite differentiated Euclidean distance is presented according to the types of indicators (Figures 3a,3b.3c,3d,3e,3f), as an example of these trends, we have the clusters of indicators with a lower Euclidean distance, which are mainly socio-political and socio-economic indicators such as democracy (DI), carbon footprint (Cf), rule of law of the population (WJP), size of the economy (Economy) and income (GDP) to name a few, and other examples of clusters with a high Euclidean distance for socio-economic indicators such as urban pollution (PM2.5-PM10), and multi-dimensional poverty (MPI) and bioclimatic ones including urban temperature (T), precipitation (P) and humidity (H). According to the criteria of the analyses that seek to form heterogeneous and correlated groups of climate-indicators, several clusters were selected with a lower range than the average recommended by the methods, so the following number of clusters was considered excluding and including P: VD-Climate zone (3); VD-Climate zoneP (3); VD-Population stratification (2); VD-Population stratificationP (2); VD-Geographic location (4) and VD-Geographic locationP with 3 respective clusters.



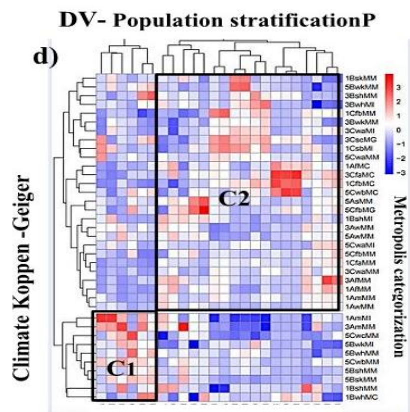
INDICATOR												
C1	PM2.5	PM10	Alt	MPI	UG	EI	T					
C2	GINI	UHI	Pd	H	P	AI	WR					
C3	DHI	DI	WJP	GDP	Cf	E	CRI	UA	Pob	CO2	Economy	



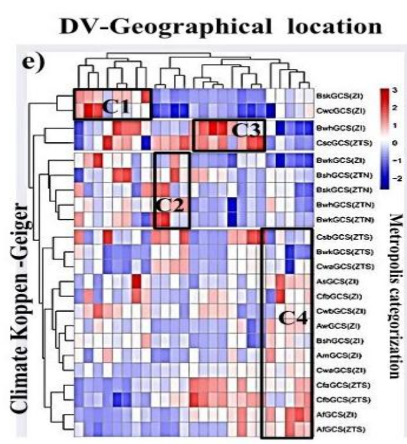
INDICATOR										
C1	Alt	Pd	UG	EI	MPI	WR	PM2.5	PM10		
C2	UHI	GINI	P	AI	T	H	CRI			
C3	UA	Economy	Pob	CO2	DI	WJP	Cf	E	GDP	DHI



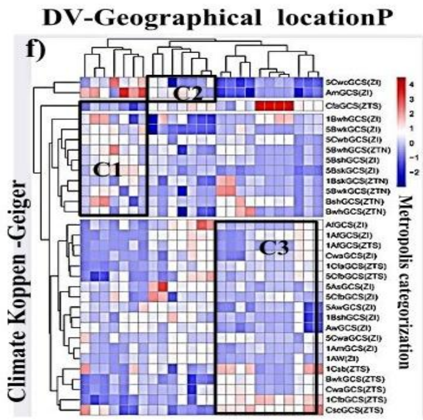
INDICATOR												
C1	MPI	EI	WR	PM2.5	PM10	Alt	Pd	UG				
C2	UA	CO2	Economy	CRI	DI	WJP	Cf	E	GDP	DHI	T	
	UHI	GINI	H	P	AI							



INDICATOR											
C1	WR	EI	MPI	Alt	PM2.5	PM10					
C2	T	GINI	UG	UHI	Pd	DI	WJP	Cf	E	GDP	DHI
	UA	CO2	Economy	CRI	H	P	AI				



INDICATOR								
C1	EI	Alt	MPI	WR	PM2.5	PM10	Pd	UG
C2	Cf	E	GDP	DHI				
C3	UA	Economy	Pob	CO2	H	CRI	DI	WJP
C4	T	UHI	GINI	P	AI			



INDICATOR							
C1	WR	PM2.5	PM10	Alt	UG	EI	MPI	
C2	UHI	Pd	T	H	GINI	P	AI	
C3	Cf	E	GDP	DHI	UA	Economy	Pob	CO2
	CRI	DI	WJP					

Fig.2. Clusters with climate heterogeneity criteria. In heatmap a) (VD-Climatic zone), b) (VD-Climatic zoneP), c) (VD-Population stratification), d) (VD-Population stratification), e) (VD-Geographic location),f) (VD-Geographic location). Colour of the indicators organised in the heatmap**: Bioclimatic (green), urban-geographical (brown), socio-economic (grey), socio-political (purple).** Own elaboration

3.1 Cluster validation with MD

The percentage of misclassification was acceptable in the analyses, particularly when P is not included, according to this point the lowest errors (30% of the validation), were DV-Geographic location (4.7%) and DV-Climate zone (6.6%), so in these DVs a lower dispersion in the point cloud is observed (Figure 3). Other cases that attracted attention were the high errors in DV-Population stratification (14%) and DV-Population stratification-P (11.3%), which were expected to have lower errors, but an overlap of not highly correlated indicators may have influenced the results. Percentage data for discriminant functions (hereafter LD) and misclassification errors are explained below.

DV-Climate zone:

The proportion explained in the LDs were, first in LD1 54.66 % of the total variability for the first eigenvalue, and the second LD2 explains 45.34 % of the same total variability, implying that between them they explain 100.0 %. In the 70% training data of the cluster observations (hereafter C), the first Cluster 1 was made up of 52 observations and 42 (80.7%) were correctly classified. In cluster 2 out of the 182 observations in the group 179 were correctly classified (98.4%) and for cluster 3, out of 10 observations all were classified correctly (100.0%). Therefore, the probability of being correct using this model is 94.7% (overall error of 5.3%). In the test data (30%), out of 23 observations in Cluster 1, 16 (69.6%) were correctly classified, in cluster 2 out of 78 observations all (100%) were correctly classified, and in Cluster 3 out of 5 observations also 100.0%. Therefore, this result implies that the probability of being correct using this model is 93.4% (overall error of 6.6%).

DV-Climate zoneP

The proportion explained by LD1 is 75.07% of the total variability for the first eigenvalue, and LD2 is 24.93% of the same total variability. The 70% training data explained a proportion in LD1 of 69.43%, and LD2 of 30.57% of the total variability. In the Clusters the hits were, in Cluster 1 with 7 (100.0%), in cluster 2 with 219 (92.2%), and in Cluster 3 with 7 (100%), with a hit probability of 95.5% (overall error 4.5%). In the test data (30%), the probability of hits on observations in Cluster 1 was 3 (100%), Cluster 2, with 91 (90.0%) and Cluster 3, with 3 (100%), giving a probability of 91.5% hits (overall error of 8.5%).

DV-Population stratification

The overall proportion explained in LD1 (88.6%) of the total variability (overall error of 11.4%). In the 70% training data the hits were 52 observations in Cluster 1, where 37 (71.2%) were correctly classified, and in Cluster 2 with 179 (93.2%). Therefore, this result implies that the probability of being correct using this model is equal to 88.5% (overall error of 11.5%). In the test data (30%), the 23 observations in Cluster 1 were correctly classified 13 (56.5%), in cluster 2 out of 83 78 (94.0%), and misclassified 5 (6.0%). Furthermore, the probability of being correct using this model for the two groups is equal to 88.8% (overall error of 14.2%).

DV-Population stratificationP

The proportion explained by the LD1 function is 54.66% of the total variability for the first eigenvalue, and LD2 is 45.34% of the same total variability. In the training data, (70%), the proportion explained by LD1 is 88.0% of the total variability, (overall error of 12.0%). In cluster 1 the hit probability was 37 hits (71.2%) and in Cluster 2 with 181 hits (94.3%), with the group's hit probability being 89.3% (error 10.7%). For the other 30%, the observations were in Cluster 1 with 37 hits (60.8%) and cluster 2 with 181 hits (96.4%), with a group probability of 88.7% (overall error 11.3%).

DV-Geographical location

The overall proportion explained were as follows; in LD1 (63.9%), LD2 (25.51%) and LD3 (10.59%), which explain 100% of the total variability. In the 70% training data LD1 was 61.77% of the total variability for the first eigenvalue, the second LD2 26.02% of the same total variability, and LD3 (12%), which implies that between LD1 and LD2 they explain 87.79% of the total variability. Of the 10 observations in Cluster 1, 7 (70.0%) were correctly classified, in Cluster 2, 17 (80.95%) out of 21 were observed, and in Cluster 3, all 7 observations were correct (100.0%), and in Cluster 3, all 7 were correct (100.0%). Consequently, the probability of correctness of the observations by Cluster 1, cluster 2 and Cluster 3 are 70.0%, 80.9% and 100% respectively, and for cluster 4 98.5%. This result verifies that the probability of being correct using this model is equal to 96.9% (overall error of 4.1%). In the test data (30%), out of 5 observations in Cluster 1, 2 (40.0%) were correctly classified, in Cluster 2, out of 9 observations 8 (88.9%) were correctly classified, in Cluster 3 out of 3 observations were correctly classified (100.0%), and finally in Cluster 4, out of 89 observations 88 (98.9%) were correctly classified. Therefore, the result suggests a probability of being correct of 95.3% (overall error of 4.7%).

DV-Geographical locationP

The proportion explained by LD1 is 86.73% of the total variability for the first eigenvalue, and LD2 explains 13.27% of the same total variability. In the 70% training data, the proportion explained by LD1 was 85.93% of the total variability and LD2 14.07% (of the total variability). Forty-eight (48) observations were correctly classified in Cluster 1 (81.4%), cluster 2 with 5 (71.4%), and Cluster 3 with 170 observations (95.5%), with a hit probability of 90.9% (overall error of 9.1%). In the 30% Cluster 1, 21 observations were correctly classified (80.8%), cluster 2 with 3 (100.0%), and Cluster 3 with 72 observations (93.5%). This result implies a hit probability of 90.6% (overall error of 9.4%). In Figure 3 shows the scatter plots of the DVs and shows in Figure 3a (DV-Climatic zone) and Figure 3e (DV-Geographical location) the lowest scatter in the point clouds, according to the lowest classification errors obtained. Note that in Clusters 2 and 4 (Figure 3a-e*)* the highly correlated groupings of metropolises are heterogeneous in Köppen-Geiger climates.

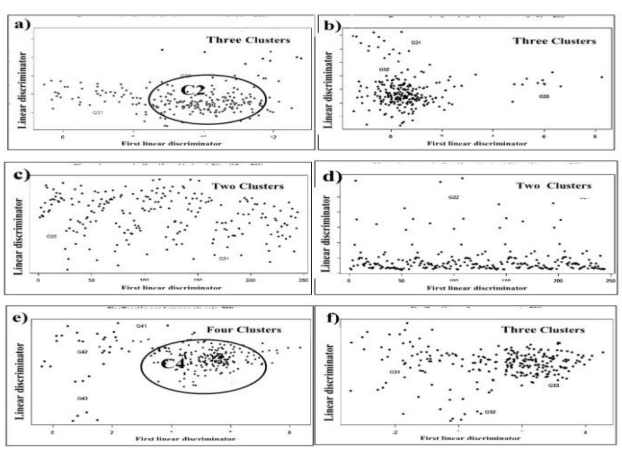


Fig.3. Dipover plots evaluated with the MD. In the Heatmaps: a) (DV-Climate Zone),b)(DV-Climate Zone P), c) (DV-Population stratification), d)(DV-Population stratificationP), e) (DV-Geographical location), f) (DV-Geographical locationP).

In black circle; the DV where the smallest classification error.

3.2 Recognized discriminant indicators

With the above results, the DVs with the lowest misclassification errors in the dataset were obtained to select the clusters and discriminant indicators characterizing the different Köppen Geiger metropolis groups (Table 3). In the first case the DV-Geographic location with 4.7% misclassification error (at 30% of data validation), and in the second case DV-Climate zone with 6.6% mis classification error (at 30% of data validation) was recognized. Discriminant indicators of DV-Geographic location (**in bold** Table 3-4), according to Fischer linear functions, determined in LD1 urban and socio-political type indicators, such as Urban Heat Island (UHI) and the state of the law of the population (WJP), both were able to explain 61% of the data, for LD2, the socio-political indicator found that the democracy index (DI) could explain 26% (contribution to the data), and with LD3 the rule of law of the population (WJP) explained 12% of the data. It was noted that the discriminants characterize different clusters, as in the case of Cluster 3, where DI and WJP characterize dynamics of 3% of the metropolises and in the case of Cluster 4, the Urban Heat Island (UHI) characterizes 84% of metropolises. For the DV-Climate Zone, the socio-political indicator population's rule of law (WJP), is the most discriminating (56% in LD1 and 43% in LD2), which characterizes Cluster 2 that groups a minority group the metropolises (4%).

Table 3. Discriminant indicators

Highlighted in bold: UHI (Urban Heat Islands; DI (Democracy Index), WJP (Rule of Law Index),DI (democracy index).

DV- Climate-zone							
Indicators	LD1	LD2		LD1	LD2		
T	9.29E-02	-1.44E-01	PM10	-4.82E-02	4.62E-02		
UHI	5.18E-01	1.68E-01	E	-5.88E-05	-1.80E-04		
PM25	-2.32E-03	8.50E-04	GDP	3.86E-05	-9.44E-05		
H	5.44E-02	4.11E-03	DHI	-2.17E+00	6.95E+00		
AI	1.14E-01	-4.15E-02	GINI	7.81E-03	-3.64E-02		
AU	1.26E-04	-3.75E-04	DI	-5.84E-01	-1.08E+00		
UG	-2.29E-01	1.63E-01	CRI	6.03E-03	1.12E-02		
Cf	3.16E-01	1.18E+00	WR	5.88E-02	1.26E-01		
PM25	6.92E-02	-4.80E-02	**WJP**	**1.17E+01**	**1.78E+01**		
DV-Geographical location							
Indicators	LD1	LD2	LD3		LD1	LD2	LD3
T	1.30E-01	9.16E-02	2.02E-01	PM25	-7.04E-03	-5.07E-02	2.49E-02
UHI	**5.33E-01**	3.05E-01	5.28E-02	PM10	-3.73E-02	2.08E-03	-2.48E-02
P	-4.39E-03	-4.02E-03	-1.21E-03	E	9.14E-05	-1.39E-04	2.20E-04
H	7.76E-02	-5.85E-02	-1.63E-02	GDP	-1.04E-05	-1.03E-04	1.90E-04
AI	1.74E-01	1.47E-01	2.63E-02	Economy	7.46E-12	4.83E-11	-6.68E-12
AU	1.87E-05	-4.84E-04	-3.44E-04	DHI	-3.10E+00	-3.03E+00	-1.70E+00
Pd	-8.80E-05	-6.59E-05	-3.51E-05	GINI	1.63E-03	9.77E-03	7.62E-02
UG	-1.84E-01	-2.44E-02	-2.69E-01	**DI**	-5.37E-02	**1.10E+00**	-2.44E-01
Pob	-7.13E-08	-5.93E-07	2.72E-07	CRI	2.87E-05	-6.71E-03	-3.91E-03
Cf	-5.23E-01	6.86E-01	-2.61E-01	**WJP**	**8.57E-01**	-1.57E+01	**1.92E+00**
CO2	-2.29E-08	-6.67E-08	-3.45E-08				

Table 4 . Classification errors and percentage of explanation of the discriminant indicators for each DV. **Highlighted in bold**

Dependent variable (DV)	Error (30%)
DV- Climate Zone P	8.5
DV-Population stratification	14.2
DV-Population stratificationP	11.3
DV-Geographical location	**4.7**
DV-Geographical locationP	9.4
Percentage of explanation of the discriminant indicators	
DV-Climate Zone **: LD1 (56) (WJP) , LD2 (43) (WJP)** (Cluster 3 (WJP) 4% of metropolises)	
DV- Climate Zone P : LD1 (69) (HDI), LD2 (30) (Cf) (Cluster 3 (Cf-DHI) 3% of metropolises)	
DV-Population stratification : LD1 (89) (MPI, WJP) (Cluster 2 (WJP) 90 % of metropolises)	
DV-Population stratificationP : LDI (89.3) (WJP, UHI, Cf) (Cluster 2 (WJP, UHI, Cf) 90 % of metropolises)	
DV-Geographical location,*:* **LD1 (61) (UHI,WJP), LD2 (26) (DI), LD3 (12) WJP** **(**Cluster 4 (UHI) 84 % of metropolises)	
DV-Geographical locationP: LD1 (85) (Cf, HDI,WJP) LD2 (14) (HDI,WJP) LD3 (12) (WJP) **(**Cluster 3 (Cf,HDI,WJP) 84 % of metropolises)	

4. Socio-environmental and climatic conditions

The results of this study describe a very varied socio-environmental and climatic characterization of Latin American metropolises according to the most discriminating DVs and indicators.

In the Table 4 and Figure 4a and 4b the conformation of the metropolitan Clusters is detailed, note that the main spots in both DV are conformed by a majority group of very heterogeneous metropolises in Köppen Geiger climates, particularly in Cluster 2 (DV-Climate zone) is conformed by 74% of the total metropolitan in study, and in the DV-Geographic location by 84% of metropolitan groupings. In other cases, when talking about smaller groups, in Cluster 1 of the DV-Climate zone, 22% of arid and desert climates are grouped mainly (Bsh, Bsk, Bwh, Bwk) and in Clusters 1 of the DV-Climate zone, 22% of arid and desert climates are grouped mainly (Bsh, Bsk, Bwh, Bwk) and in Cluster 2 of VD-Geographical location we find 9% of metropolitan areas belonging to arid and desert Köppen Geiger zones (Bsh,Bsk,Bwh,Bwk), distributed from the intertropical zone (IZ) to the North Temperate Zone (NTZ), where the metropolises of Mexico are particularly appreciated.

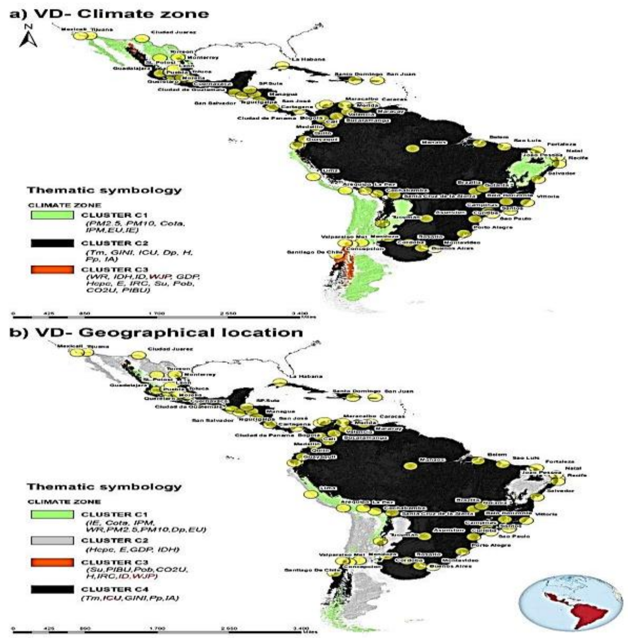


Fig.4. Socio-environmental and climatic characteristics of clusters (C) including twenty (20) selected metropolises a) clusters in VD-Climatic zone, b) clusters in VD-Geographical location.

4.1Discriminant-indicators associated with sustainability ,resilience, and liveability

To assess the relationships between socio-environmental and climatic dynamics of metropolises and performances on sustainability, resilience and liveability, 20 regional metropolises of various Koppen Geiger-indicator climates were taken as a reference in this study, within the DVs with the lowest percentage of error (named in 2.4 and 3.2). The selection criteria of the metropolises were based on urban environments with the following characteristics:
(a) Democratic levels, human development, rule of law and low climate risks (Concepción M, Buenos Aires, Lima, Montevideo, Santiago de Chile,), b) Levels of pollution, carbon emissions, inequality and hot spots (Bogotá, Mexico City, Ciudad Juárez, Medellin, S. Paulo, Tijuana).
c) Significant climate risks and low global resilience (Cartagena, Ciudad Juarez, Tijuana).d) Urban pollution and carbon footprint (Cali, Curitiba, Panama City, Mendoza, P Alegre, Quito, Rio de Janeiro).e) Large metropolises and megacities with high population rates and urban areas (Mexico City, Bogota, Buenos Aires, Lima, Rio de Janeiro and Santiago de Chile), and finally we have the metropolises group with the following characteristics, f) Economic dynamism (Buenos Aires, Bogota, Mexico City, Lima, Monterrey, Santiago de Chile and Sao Paulo).

On the other hand, the performance of the metropolises concerning sustainability, resilience and liveability was evaluated with the indices proposed in the four international reports (see Table 5), which define the following parameters: firstly, the 100 Resilient Cities (Hofmann, (2021). project initiatives proposed by the Rockefeller Foundation, which considers climate risks and vulnerability, governance, human development, resilience and the Köppen-Geiger climate classification of the metropolises. Secondly, the ARCADIS (2015) index of 100 sustainable city indicators measuring energy consumption, waste, pollution, GHG emissions, economy, income and energy efficiency was taken. A third proposal was also considered, the Resilient Cities Index (Economist Impact, 2023), which measures mitigation, heat events, social integration and resilient economy, and finally the Global Liveability Index (EIU, 2024), which includes 173 metropolises and 30 indicators divided into five categories: political stability, environment and culture, health, education, infrastructure and quality of life.

Table 5. Sustainability, resilience and liveability criteria from international reports.

Metropolises assessment criteria by indicator	
ARCADIS (Sustainability)	Social Performance, Quality of Life, CO2 capture-Carbon Footprint, Energy, Pollution, Economic Performance).
100RC (Resilience)	Vulnerability and Risk, Governance, Rule of Law, Resilience, Human Development, Social Equity, Koppen Geiger Climates)
Resilient Cities Index (2023) (Resilience)	Energy, water availability, , flooding, heat stress, pollution, disaster management, decarbonization, waste management, urban resilience, social inclusion, access and trust in government, quality of life, safety, income inequality, social protection, economic strength, economic exposure and risk, innovation and entrepreneurship, and human capital).
Global Liveability Index (Liveability)	Political stability, environmental conditions, climate and educational attainment)

4.2 Socio-environmental-climatic characterizations and sustainability, resilience and habitability performance

In the description of the climatic groups we have in the first place the metropolitan conglomerate belonging to the VD-Climate Zone, where particularly in Cluster 1 are located metropolises with arid climates such as Cartagena, Tijuana and Monterrey (Bsh, Bsk), and desert climates such as C. Juárez and Mendoza (Bwk). These urban environments with dry climates (arid-desert) are characterized in their socio-environmental and climatic dynamics by social gaps, altitudinal conditions, urban sprawl, pollution and the energy intensity of their economy (PM2.5, PM10, Alt, MPI, UG, EI). Now if we evaluate their performance in sustainability, resilience and habitability, we note that they can be characterized according to aspects of socio-economic evolution and social equity, which are important parameters in sustainability; however, their high rates of pollution, which is characteristic of areas in transition towards greater aridity according to Georgescu et al. (2013), could influence resilience; however, despite the impacts of pollution, the marked metropolitan energy efficiency is noteworthy, which allows the reduction of particulate matter. On the other hand, in terms of habitability, the socio-political deficit (rule of law and political instability), increase habitat weaknesses, so it is important to work on reducing existing social gaps and improving the level of governance, which can plan more habitable urban spaces.

The case of Cluster 2, it includes a majority group of metropolises with subtropical climates such as S. Paulo and P. Alegre (Cfa), tropical ones such as C. Panama, R. Janeiro, Cali and Medellin (Aw, Af, As) and temperate ones such as Bogotá, B.Aires, C.D., C.D., Mexico, Curitiba, Montevideo and Quito (Cfb, Cwb, Cfb, Cfb, Cfb respectively). Mexico, Curitiba, Montevideo and Quito (Cfb, Cwb, Cfb, Cfb, Cfb respectively), which present dynamics due to bioclimatic interactions and urban aridity, as well as having an important incidence of Urban Heat Island (UHI), which are generally associated with high population density and social inequality (T, GINI, UHI, Pd, H, P, AI). These metropolises are also characterized by high pollution rates as was found in Mexico City and Sao Paulo, as well as a general lack of democratic deficits (EIU, 2018), but the most influential aspects that explain urban dynamics are the marked social inequalities, which affect the deficit in sustainable concepts (social performance/equity). In terms of resilience, it is noted that these metropolises need to monitor heat incidence (UHI), review bioclimatic patterns (geographical zones of high climate risks) and improve inadequate political management (democratic deficits), according to EIU (2018), which are factors that can increase extreme events and weaken the resilient support of metropolitan space, comfort and habitat.

Cluster 3 includes a group of two metropolises in Chile, with temperate climates such as Concepción and Santiago (Csb, Csc respective), and where socio-environmental and climatic conditions are recognized due to a high rule of law of the population and democratic standards above the regional average (EIU, 2018), further characterized by low carbon footprint rates, and high standards of human development, resilience, income, and economic, and energy dynamism (WR, HDI, DI, WJP, CO2, GDP, Economy, Cf, E). Therefore, according to the indicators proposed by the reviewed reports, these metropolises are more resilient by incorporating socio-political aspects (democracy, governance and rule of law), more sustainable by their socio-economic conditions (carbon, energy and pollution management) and liveable by possessing high human development, political stability and acceptable environmental conditions.

Regarding the DV-Geographical location, it contains 4 clusters, however the selected metropolises are present in only three (C2, C3, C4), as examples, we have in Cluster 2 the metropolitan group of Mexico, which are located in the North Temperate Zone (NTZ), and which are belong to arid climates like Monterrey (Bsh) and Tijuana (Bsk), and desert ones like Ciudad Juarez (Bwk). The socio-environmental and climatic dynamics of this group are characterized by human development, energy and carbon impact (Cf, E, GDP, HDI). Now within international climate policy performance, we can affirm that the populations in this group have adequate economic and human development within sustainable standards, and in terms of their resilient aspects, the socioeconomic aspects (human and economic development) stand out, which contribute to the quality of life of the population. However, deficits are observed in the management of carbon, energy and pollution, which in dry climates (arid and desert) are associated with environmental conditions, energy, and emissions (Guttikunda et al., 2019). For habitat conditions, we note that extreme (arid) climatic conditions, governance deficiencies and low human development (HDI), hinder the implementation of climate policies to improve urban living space.

In the case of Cluster 3, we have two metropolises (low and medium altitude), one with a desert climate such as Lima (Bwh) located in the Intertropical Zone (IZ) and the other with a Mediterranean climate and dry summer such as Santiago de Chile (CSC), located in the Southern Temperate Zone (STZ), both characterized by the democratic level (DI) and the rule of law of the population (WJP), as well as having characteristics associated with large urban areas, economic dynamics, relative climate risks and low carbon rates (AU,GDP,Pob,CO2,H,CRI,DI,WJP), which position them as highly sustainable, resilient and liveable urban environments, and their urban and environmental, socio-economic and political infrastructures allow for strategies that can optimize governance in a city (Mees, 2016).

Finally, in Cluster 4, 84% of the metropolises under study (15% of the sample to assess sustainability, resilience and habitability) were organized, and which, due to their geographical conditions, are distributed in the intertropical zone (IZ) and in the southern temperate zone (STZ). These metropolises (varied climate and altitudes) are characterized by marked bioclimatic patterns (T, P, AI), heat incidence IU), and social inequality (GINI), so this result clearly explains the relationships between the social vulnerability of the population and the effects of heat (Rosenthal et al., 2014). On the other hand, this important climate group presents few sustainable and livable conditions, due to low democratic and human development performances, and their resilience can be affected by climatic fluctuations (heat stress) in urban areas with high social risk and significant socio-economic inequalities as evidenced in metropolises with tropical climates. Tables 6 and Table 6.1 define the deficits and strengths, which allow for verifying the performance of the selected metropolises according to climate policies (sustainability, resilience, and Liveability).

Table 6. Sustainability, resilience and liveability characteristics of the selected metropolises according to VD-Climate zone.
Köppen Geiger colours are determined according to the update proposed by Beck, et al., 2018. Cluster (C). **Highlighted in bold**

DV-Climate zone			
Climate-Indicators	Sustainability	Resilience	Liveability
Bsh- Bsk Bwk C1-(PM2.5, PM10, Alt, MPI,UG, EI)	Sustainability Deficit, Social Gaps, Pollution **Strengths Energy management** **Strengths Energy management**	Resilience Deficit, Social gaps Pollution, Wastemanagement, Urban sprawl **Strengths Energy management**	Habitability Deficit, Environmental conditions Environmental impact urban atmosphere
Cfb, Csb,Cwb Cfa,Af,As ,Aw C2: (T, GINI, UHI, Pd, H, P,AI).	Deficit Social performance	Deficit Vulnerability Heat stress, Floods Social inclusion, Water availability, Resilience (population density)	Deficits Environmental conditions Fluctuations-climate
Csc, Csb C3: (WR,HDI DI,**WJP,** CO2, Economy, ,GDP, IRC, Cf, E).	**Strengths Quality of life, Socio economic performance** **Carbon management, Human development**	Deficit Risks – vulnerability **Strengths Urban resilience** **Governance, Rule of law, Economic strength**	Deficit environmental conditions **Strengths Political stability** **Human development Governance**

Table 6.1. Sustainability, resilience and liveability characteristics of the selected metropolises according to DV-Geographical location.
Köppen Geiger colours are determined according to the update proposed by Beck, et al, 2018. Cluster (C). **Highlighted in bold**

DV-Geographical Location			
Climate-Indicators	Sustainability	Resilience	Liveability
Bsh-Bsk Bwk	Deficit Carbon-energy management	Deficit Carbon-energy management	Deficit Climate impact (emissions)
C2: (Cf, E, GDP,HDI)	**Strengths Economic performance**	**Strengths Human development Economic strength**	**Strengths Education, level-human development**
Csc **Bwh**	Deficit Urban emissions	Deficit Vulnerability -climate risks and risk	Deficit Environmental conditions climate
C3: (AU, Economy,Pob, CO2,H,CRI,**DI ,WJP)**	**Strengths Economic performance**	**Strengths Urban resilience, Governance, Rule of law, Economic strength**	**Strengths Political, Stability, Governance**
Bwk Cfa, As, Af C4: (T,**UHI**,GINI,P ,AI)	Deficit Social performance	Deficit Vulnerability Heat stress Flooding, Social inclusion, Water availability	Deficits Environmental conditions Fluctuations-climate

5. Conclusions

According to the results and considering the main clusters of the metropolises according to the DV with the lowest classification error, we have that the socio-environmental and climatic dynamics of 74% of the metropolises in the DV-Climate zone (Cluster 2), are heterogeneous due to the influence of multiple bioclimatic patterns, urban aridity, population density, social inequality and presence of Heat Islands (Tm, GINI, UHI, Pd, H, P, AI). In turn, when evaluating 84% of the metropolises in Cluster 4 (DV-Geographic location) we identified homogeneity dynamics according to the Urban Heat Islands (UHI) discriminant indicator, which explains that urban-climatic factors are those that exert the greatest influence on metropolitan socio environmental and climatic characteristics in Latin America and the Caribbean, when geographic distribution criteria are selected.

With these findings and reviewing the different indicators proposed by international reports recommending sustainability, resilience and liveability, we can point out that the largest groups of metropolises located in tropical, subtropical and temperate climates (which include megacities such as Bogotá, Buenos Aires, Mexico City, Rio de Janeiro and Sao Paulo), as observed in Cluster 2 (VD-climatic zone) and Cluster 4 (VD-Geographical location), present deficits in societal aspects. C.D Mexico, Rio de Janeiro and Sao Paulo) as observed in Cluster 2 (VD-climate zone) and Cluster 4 (VD-Geographical location), show deficits in sociopolitical aspects (governance, rule of law), bioclimatic urban risks (heat stress due to UHI incidence), and low social performance to develop sustainability, resilience and liveability as recommended by international organizations. However, it can also be concluded that the discriminating factor of UHI in the DV - Geographical location, could influence greater resilience and adaptation of urban environments to heat stress. On the other hand, small groups of metropolises with dry temperate Mediterranean-type climates (Santiago, Concepción M), hot desert (Lima) and cold desert (Juarez), hot steppes (Monterrey) and cold steppes (Tijuana), show a better performance in resilient requirements, related in the first three metropolises to democratic development, rule of law, social and economic dynamics, and in the case of the Mexican metropolises to economic performance and human development. These results explain that the specific urban structures, and political, socioeconomic and climatic conditions of these metropolises are conducive to greater sustainability and resilience within the objectives of global climate planners.

The results of the study demonstrated the influence of urban, socio-economic and socio-political indicators to characterize different groups of Latin American metropolises, and when reviewing the indicators recommended by the reports, we observed that they are very much aligned with those proposed by this study, mainly those of a socio-economic (social inclusion/inequality, human development, and carbon management), socio-political (governance, political stability, rule of law, risk management),and urban-climatic nature such as the presence of metropolitan heat stress. These findings validate the analyses carried out by the study and demonstrate that the transformation towards resilient, sustainable and habitat-friendly metropolises depends to a greater extent on the urban, political and socio-economic management of governments and planners. However if improvements in democracy, human development, multidimensional poverty or social inequalities, which are very marked in the Latin American region, are not observed, this will imply greater efforts and resources to position these metropolises within these global climate initiatives. It should be noted that the socio-environmental and climatic characteristics of the different metropolitan groups are not definitive, and are subject to two conditioning factors: firstly, to the socio-economic and socio-political decision-making of governments, scientists and planners, and secondly, to the uncertainty of extreme climate change in the medium term, which can have a significant impact on the bioclimatic patterns of the region, and thus increase uncertainties in the evolution of regional metropolises towards more sustainable, resilient and liveable concepts.

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