Geospatial Health 2024; volume 19:1249

Spatial pattern analysis of the impact of community food environments on foetal macrosomia, preterm births and low birth weight

Micaela Natalia Campero,[1,2,3] Carlos Matías Scavuzzo,[1,2,3] Carlos Marcelo Scavuzzo,[1] María Dolores Román[2]

[1]Mario Gulich Institute for Higher Space Studies, National University of Córdoba, National Commission of Space Activities, Falda del Cañete, Córdoba; [2]Human Nutrition Research Center, School of Nutrition, Faculty of Medical Sciences, National University of Córdoba, Córdoba; [3]National Council for Scientific and Technical Research, Buenos Aires, Argentina

Abstract

Community food environments (CFEs) have a strong impact on child health and nutrition and this impact is currently negative in many areas. In the Republic of Argentina, there is a lack of research evaluating CFEs regionally and comprehensively by tools based on geographic information systems (GIS). This study aimed to characterize the spatial patterns of CFEs, through variables associated with its three dimensions (political, individual and environmental), and their association with the spatial distribution in urban localities in Argentina. CFEs were assessed in 657 localities with ≥5,000 inhabitants. Data on births and CFEs were obtained from nationally available open-source data and through remote sensing. The spatial distribution and presence of clusters were assessed using hotspot analysis, purely spatial analysis (SaTScan), Moran's Index, semivariograms and spatially restrained multivariate clustering. Clusters of low risk for LBW, macrosomia, and preterm births were observed in the central-east part of the country, while high-risk clusters identified in the North, Centre and South. In the central-eastern region, low-risk clusters were found coinciding with hotspots of public policy coverage, high night-time light, social security coverage and complete secondary education of the household head in areas with low risk for negative outcomes of the birth variables studied, with the opposite with regard to households with unsatisfied basic needs and predominant land use classes in peri-urban areas of crops and herbaceous cover. These results show that the exploration of spatial patterns of CFEs is a necessary preliminary step before developing explanatory models and generating novel findings valuable for decision-making.

Correspondence: Micaela Natalia Campero, Mario Gulich Institute for Higher Space Studies, National University of Córdoba, National Commission of Space Activities, Falda del Cañete, Ruta C45 Km 8, Falda del Cañete, Córdoba, ArgentinaCórdoba, Argentina.
Tel: +54.9.351.35350974
E-mail: mncampero@fcm.unc.edu.ar

Key words: spatial analysis, food environment, birth weight, preterm births, Argentina.

Conflict of interest: the authors declare no potential conflict of interest, and all authors confirm accuracy.

Availability of data and materials: all data generated or analyzed during this study are included in this published article.

Received: 25 October 2023.
Accepted: 13 Marchn 2024

Geospatial Health 2024; 19:1249
doi:10.4081/gh.2024.1249

Introduction

The characteristics of current food systems contribute to the creation of food environments that influence the adoption of unhealthy diets, thereby affecting nutrition and health. Improving these environments is a global challenge, requiring actions tailored to the socio-demographic, economic, political and environmental characteristics of each territory (PAHO, 2021). In response to the need to assess food contexts, the Community Food Environments (CFE) model (Glanz *et al.*, 2005) proposed a comprehensive approach to understanding food reality through three dimensions (political, individual, and environmental) that collectively shape the dietary behaviour. The first dimension involves public policies, the second the socio-demographic and economic characteristics and the third the availability, accessibility and information related to food (Glanz *et al.*, 2005). Although the latter dimension did not initially involve physical and climatic environment, it is fundamental in the context of climate change and food production (WHO, 2008). The versatility of this model allows for the addition of characteristics not originally included in the original model (such as the environmental conditions at each location). Furthermore, the study of CFE can be conducted at various scales, both comprehensively through the three dimensions (Campero *et al.*, 2022) and in a disaggregated manner, prioritizing specific aspects or variables based on the needs of each territory (Lytle & Sokol, 2017).

Globally, the majority of research on CFE has been conducted in developed English-speaking countries (Lytle & Sokol, 2017; Turner *et al.*, 2018). In Latin America, particularly in Argentina, research is still scarce. The topics most addressed in Latin America from this approach are food availability and accessibility as well as diet affordability and nutritional characteristics (Pérez-Ferrer *et al.*, 2019; Gutierrez *et al.*, 2021). In Argentina, the study of CFEs not only aligns with the aforementioned themes but is also conducted at a local scale, complicating the comprehensive understanding of the food reality on the national level (Elorriaga *et al.*, 2021; Seijo *et al.*, 2021). In 2012, the World Health Organization (WHO) formulated six global goals to be achieved by 2025 that are related to improving the nutrition of children and pregnant mothers, while the United Nations, in its Global Nutrition Report (2021), emphasizes the need to continue working on food during childhood (UN, 2021). Thus, one of the research priorities in this context is maternal and child health.

The health of the newborn child (especially its weight) is a significant indicator of population health and development (Ramírez-López *et al.*, 2015). The literature indicates that part of the current epidemic of chronic diseases originates before birth and can thus be prevented (Safi-Stibler & Gabory, 2020). Moreover, through nutritional, toxicological, endocrine and environmental factors induce changes in foetal development (Castro, 2020). The most evaluated indicator related to this is low birth weight (LBW), defined as <2,500g, a primary risk factor for infant and neonatal mortality. While its main causes are gestational, it has been associated with socio-demographic factors (such as social class, ethnic group, maternal education level, socioeconomic status and place of residence) and environmental variables (such as season, altitude, air pollution, agricultural contamination of groundwater, and greenery; Momeni *et al.*, 2017; Lu *et al.*, 2020). In addition, LBW is closely linked to preterm births (<37 weeks of gestation). The main causes include gestational factors related to maternal age and health, which has been studied in association with a multitude of factors (Ncube *et al.*, 2016). In fact, studies are increasingly linking birth weight and preterm births to factors derived from climate change, such as extreme temperatures, decreased precipitation and increases in greenhouse gases (Teixidó Trujillo, 2015; Piña Borrego, 2020). Moreover, foetal macrosomia, a condition in which the fetus is larger than average (>4,000g), is frequently associated with factors, such as inadequate physical activity, excess weight, gestational/ pregestational diabetes mellitus and inappropriate diets. Other factors include the mother's ethnic group, multiparity, history of foetal macrosomia, and maternal age and height (García de la Torre, *et al.*, 2016; Júnior *et al.*, 2017). Today's literature highlights the need to further delve into the study of the socioeconomic and environmental determinants and their influence on the indicators mentioned (Momeni *et al.*, 2017; Uwiringiyimana *et al.*, 2019). In this context, addressing newborn health indicators from the CFE approach has great potential.

Advancements in tools based on geographic information systems (GIS) and the availability of health and environmental data have facilitated the complementarity between spatial analysis and classical methodologies for studying the aetiology of diseases (Àlvarez Di Fino, 2020). Among methods applied to the study of food environments, GIS are frequently employed, with distance calculation being the most used (Caspi *et al.*, 2012). However, there are other spatial analysis tools, such as detection of clusters and other spatial patterns, which allows for a deeper understanding of health processes in conjunction with mapping (Mena *et al.*, 2018). Pattern analysis focuses on studying how points are distributed in the territory and the demonstration the of the patterns and their association to specific variables is of great importance in researching the mechanisms involved in the aetiology of diseases and in identifying areas of higher vulnerability. In developing countries, these geospatial tools are useful for decision-making, enabling the planning of prevention strategies and the efficient allocation of resources (Amarasinghe *et al.*, 2022; Suerungruang *et al.*, 2023).

Despite the importance of addressing the multifactorial aetiology of health and birth processes, no evidence has been found globally of the assessment of CFE in an integrated manner in its three dimensions and on a regional scale. Argentina, in particular, lacks studies addressing health responses in general from an integrated CFE approach. Considering the context described above, this work aimed to characterize the distribution and spatial patterns of the prevalence of LBW, macrosomic and preterm newborns and their relationship with the spatial behaviour of political, individual, and environmental CFE determinants in urban localities of more than 5,000 inhabitants.

Materials and Methods

Locations and data

A total of 657 urban localities with a population of 5,000 or more inhabitants according to the National Census of Households and Dwellings (Spanish abbreviation=INDEC) in Argentina (INDEC, 2010) were included. The birth variables studied were the prevalence of LBW infants, the prevalence of macrosomic infants (>4,000 g), and the proportion of infants born preterm (<37 gestational weeks). The variables concerning CFE were selected according to the multi-causal aetiology of feeding behaviour and the socio-environmental factors linked to the chosen birth indicators and their availability as shown in Table 1 (for the data sources used for the construction of the CFE variables, see the Supplementary information). The data collection timeframes for some variables differ from the years of data collection for the dependent variables, a disparity that enabled us to elucidate the enduring characteristics individuals were exposed to, which may exert an influence on the selected response variables

The birth weight data were derived from the comprehensive live birth records spanning 2018-2019, encompassing the entirety of the national territory. These compiled records are maintained by the Health Statistics and Information Department of the Ministry of Health (Secretaría de Gobierno de Salud, 2019). This dataset includes information about the frequency of live births by jurisdiction, their corresponding birth weights, gestational ages and various other data points.

Data analysis

A database was crafted at the location scale to effectively aggregate the pertinent information. From the dataset encompassing live births recorded during 2018-2019, dependent prevalence variables were constructed for: LBW, macrosomic births and preterm births. Initially, the total number of live births occurring during the years 2018 and 2019 was summed, then the prevalence rates were computed using the following formula: e.g., number of LBW children in city XX * 100/the number of live births in the city XX. The variable including the percentage of individuals holding both the Alimentar Card, a health policy linked to the basic food basket, and being enrolled in the Empowering Work programme, a policy to improve the income of financially vulnerable people, underwent the following process: Firstly, the number of beneficiaries was averaged across the reported period, then the proportion of beneficiaries in relation to the total population of each jurisdiction was computed drawing upon the data from the latest available National Census of 2022 (for the moment, this Census provides only population data and certain socio-economic indicators not utilized in this study) (De Grande & Rodriguez, 2023).

The infant mortality rate (IMR) variable and those characterizing the individual dimension were ascertained through the calculation of means for the attributes extracted at the level of census radius (a territorial space in each locality with a certain number of housing units to be surveyed) for each locality examined. Similarly, the environmental variables were formulated using raster-format data pertaining to the aforementioned attributes. For attributes, such as altitude, the normalized difference vegetation index (NDVI), night-time light and precipitation, the averages were computed within the polygon delineating the urban area of each locality. The demarcation of the urban area was based on urban census units. The variable denoting the predominant land cover class in the peri-urban area was determined as the mode of land cover categories found within a 5-km buffer surrounding the urban area of each locality. Initially, a series of distribution maps were generated for each attribute/variable. To discern spatial patterns of significance, an optimized hotspot analysis was conducted, distinguishing high values (hotspots) from low values (coldspots). Statistical significance in this analysis was conferred through the application of spatial associations statistics. A purely spatial analysis was undertaken to pinpoint statistically significant clusters and a normal distribution model was employed to evaluate all variables, with the exception of land use cover, for which a multinomial model suited for categorical data was applied (Kulldorff, 2022). To gauge the pattern detected for each attribute, Moran's *I* was employed, categorizing it as sparse (values between -1 and 0), clustered (values between 0 and 1) or random (=0). The level of significance was set as $p<0.05$ (ESRI, 2023). Structural analysis was conducted by calculating the experimental variogram and fitting it to a suitable theoretical model (Santamaría & Malla, 2006). For this study, the theoretical models considered for adjustment included the exponential, spherical and Gaussian models, with the most appropriate one selected for each attribute. A spatially constrained multivariate cluster analysis was undertaken to characterize each dimension based on the encompassed variables. This analysis identified spatially contiguous clusters based on the attributes of interest (ESRI, 2022). The study specified a minimum of 33 localities (5% of the total) and a maximum of 197 (30% of the total) for this purpose. To affirm that the analyses were anchored in the values of the attributes of interest, parallel analyses were performed using a random variable and a single-valued variable (see the Supplementary information). This approach mitigated the potential confounding effects of location. The random variable was generated by assigning a random value between 0 and 1 to each observation (utilizing the Excel function = RANDOM()), while the single-valued variable was created by assigning a consistent value of 0.5 to every observation. All of these analyses were executed employing software tools including ArcGIS Pro 3.1 (https://www.esri.com/es-es/arcgis/products/ arcgis-pro/overview), SatScan 10.1 (https://www.satscan.org/), QGIS 3.22 (https://qgis.org/es/site/), and R Studio 2023.06.0 (https://www.r-studio.com/).

Table 1. Variables of the tree dimensions investigated.

Dimension	Current community food environments (CFE) variables				
Political	Alimentar Card holders* (%)	Individuals enrolled in the Empowering Work programme** (%)	Infant mortality rate		
Environmental	Mean altitude above sea level (m)	Predominant land use/land cover class in the peri-urban area	The normalized difference vegetation index (NDVI)	Night-time light data	Annual average precipitation
Individual	Households led by females	Households led by heads with complete secondary education (%)	Households with unsatisfied basic needs (%)	Individuals covered by social security (%)	Children of 5-17 years age not attending formal education (%)

**health policy linked to access to the basic food basket; **social policy aimed at improving the income of people in vulnerable situation.*

Results

There were 547,966 live births in Argentina during 2018-2019. On average, 15.4% had LBW (84,417), 10.3% macrosomia (56,541) and 17.2% were preterm births (94,076). However, the prevalence rates varied throughout the national territory. Figure 1 illustrates the spatial distribution of CFE and the birth weight attributes. Map A reveals the elevated prevalence rates of LBW in the central regions of the country, with isolated prevalence rates in the northern and southern areas; Map B the macrosomia distribu-

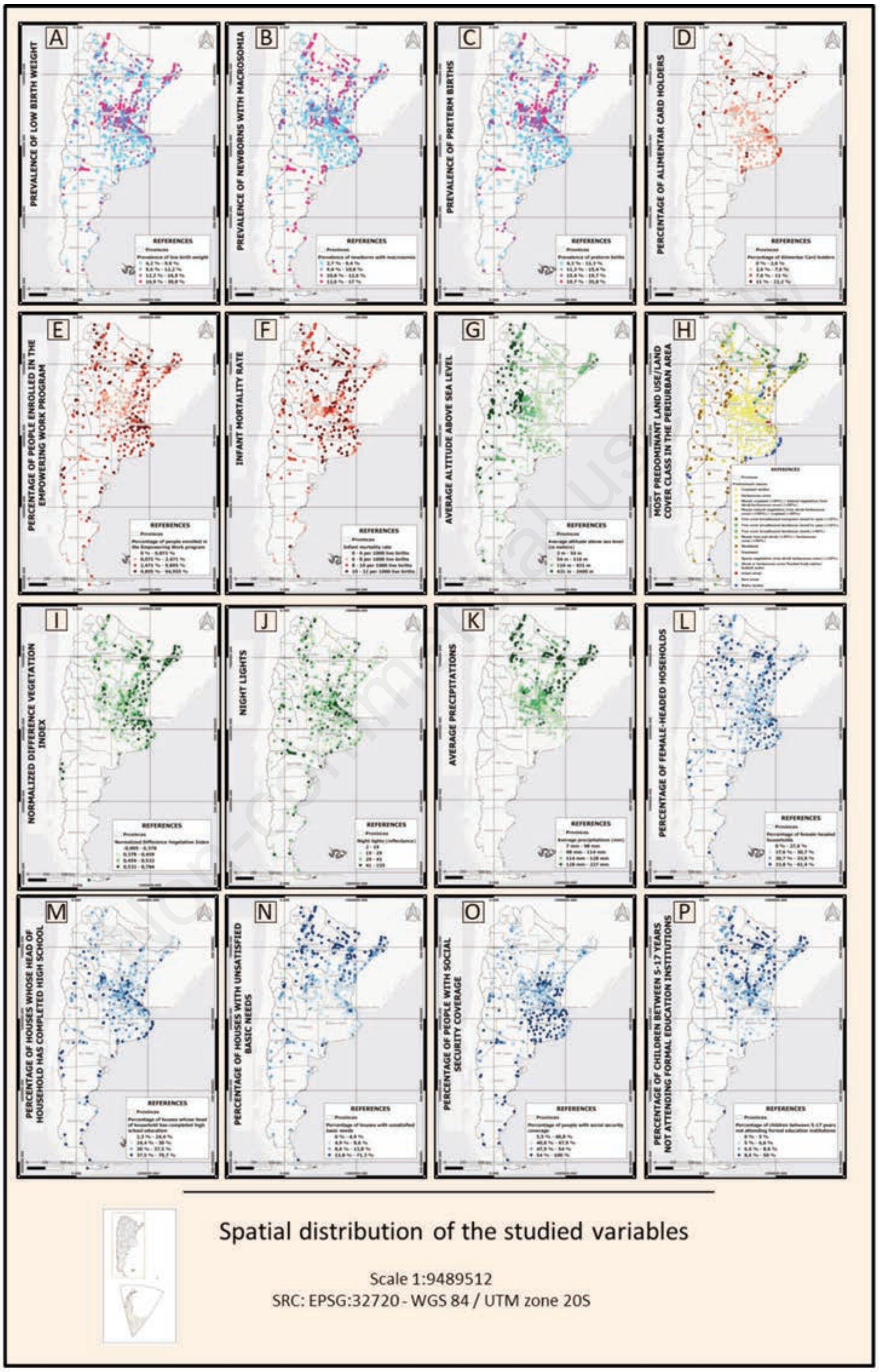

Figure 1. Dependant and CFE variables spatial distribution. The spatial distribution of variables associated with the political dimension are depicted in red; those associated with the environmental dimension variables in green; and those associated with the individual dimension in blue.

tion, with higher prevalence rates concentrated in the northern and southern regions; and Map C the high rates of preterm births in the central and northern regions. In contrast, all these three variables exhibited lower prevalence rates in the central-eastern part of the nation.

Map D illustrates that less than 2.6% of the populations the majority of the cities possessed the Alimentar Card. While the highest values were distributed in the northern and western regions of the country, elevated values were also clustered in the central-eastern zone. Map E concerns the Empowering Work programme and shows lower percentages in the central regions, with higher percentages in the central-eastern areas. Map F, depicting the IMR, shows the highest rates in the northern and eastern parts of the country.

Map G displays increased altitudes in the east-west direction, with some exceptions in the northeast, and Map H highlights shrub-lands in the peri-urban zones in the West and South that changes into various crop-lands and herbaceous covers towards the central-eastern regions, with coastal cities and water bodies in the East and increased prevalence of tree cover in the Northeast. Maps I-K portray a higher NDVI in the central-eastern regions, elevated night-time light in the central-eastern territories and increased average rainfall in the southwest-northeast direction.

Map L shows higher values of the percentage of female-headed households in the northern and eastern regions, which are lower in the central areas, and Map M displays household heads with completed secondary education notably elevated in the central-eastern and southern regions, whereas the northern regions display lower proportions. Map N shows higher percentages of households with unsatisfied basic needs (UBN) in the North compared to the central-eastern areas. Map O exhibits higher coverage of people with social security coverage in the central-eastern regions with diminished coverage in the northern parts of the country, while Map P depicts a lower percentage of school absenteeism in the central-eastern and southern territories (Figure 1).

Figure 2 provides an insight into the outcome of the optimized hotspot analysis and indicates that the point concentrations are not random but evidence of a genuine pattern. Maps A-C depict the three birth-related variables, each showing a coldspot in the central-eastern part of the country, while LBW exhibits hotspots in the central, north-eastern and southern regions of the country. Both macrosomia and preterm births display hotspots in the South, while there are also hotspots of the former in the North and of the latter in central Argentina.

Maps D and E show hotspots in the central-eastern region that align with the coldspots of the birth-related variables; some of them distributed in the North but of low statistical significance, and Map F reveal coldspots of high statistical significance with regard to the Empowering Work program, and there is a IMR coldspot in the central region and hotspots in the North and in the central-southern regions with lower statistical significance. The IMR coldspots and the percentage of individuals enrolled in the Empowering Work programme at the centre coincide with the hotspots of LBW and preterm births.

Map G displays a coldspot for altitude in the eastern part of the country and a hotspot in the central and western regions, both with 99% statistical significance. Map H shows the most frequent land use cover in peri-urban areas, with clusters in the central-eastern part of the country that mainly corresponds to crop-land. This also the case where urban areas and water bodies along the coast predominate and in the Northeast where the land is characterized by tree cover. Map I concerns NDVI, for which there is a 99% statistical significance hotspot in the Northeast, with coldspots located in the West and South. Map J indicates high night-time light in the central-eastern north-eastern, southern and central territories localities, with concentrations of relatively low values in the North. Map K demonstrates a precipitation hotspot in the North and East (the latter with only lower statistical significance) and coldspots in the West and South. Notably, coldspots in the birth-related variables (central-eastern localities) align with low-altitude values and high NDVI and night-time light. In the central part of the country, where there are elevated prevalence rates of LBW and preterm

Table 2. Moran's spatial autocorrelation index of the variables under study.

Variable	Moran's *I*	Z-score	p
Prevalence of low birth weight	0.353916	22.000120	<0.001
Prevalence of newborns with macrosomia	0.364855	22.682850	<0.001
Prevalence of preterm births	0.387336	24.071131	<0.001
CFE variables: political dimension			
Percentage of Alimentar Card holders	0.282282	17.567762	<0.001
Percentage of people enrolled in the Empowering Work program	0.356116	22.272765	<0.001
Infant mortality rate	0.064857	4.123359	0.000037
CFE variables: environmental dimension			
Average altitude above sea level	0.669862	42.164391	<0.001
Most predominant land use/land cover class in the peri-urban area	0.371800	23.087518	<0.001
Normalized difference vegetation index	0.563041	34.944262	<0.001
Night-time light	0.291246	18.185499	<0.001
Average precipitation	0.879655	54.551843	<0.001
CFE variables: individual dimension			
Percentage of female-headed households	0.209029	13.102543	<0.001
Percentage of houses whose head of household has completed high school education	0.286292	17.824412	<0.001
Percentage of houses with unsatisfied basic needs	0.663300	41.380010	<0.001
Percentage of people with social security coverage	0.525354	32.646530	<0.001
Percentage of children between 5-17 years not attending formal education institutions	0.352641	22.586415	<0.001

births, peri-urban areas are characterized by cropland and herbaceous cover. Additionally, in the northern regions of the country (where higher proportions of macrosomia are concentrated), there are less night-time light, increased precipitation and higher NDVI.

Map L displays cold spots in the central region and some localities in the Northwest. However, higher percentages of households with female heads of household are observed in the East. Map M (showing percentage of households with heads of household who have completed secondary education) illustrates a coldspot zone in the northern region, with hotspots in the central and central-eastern

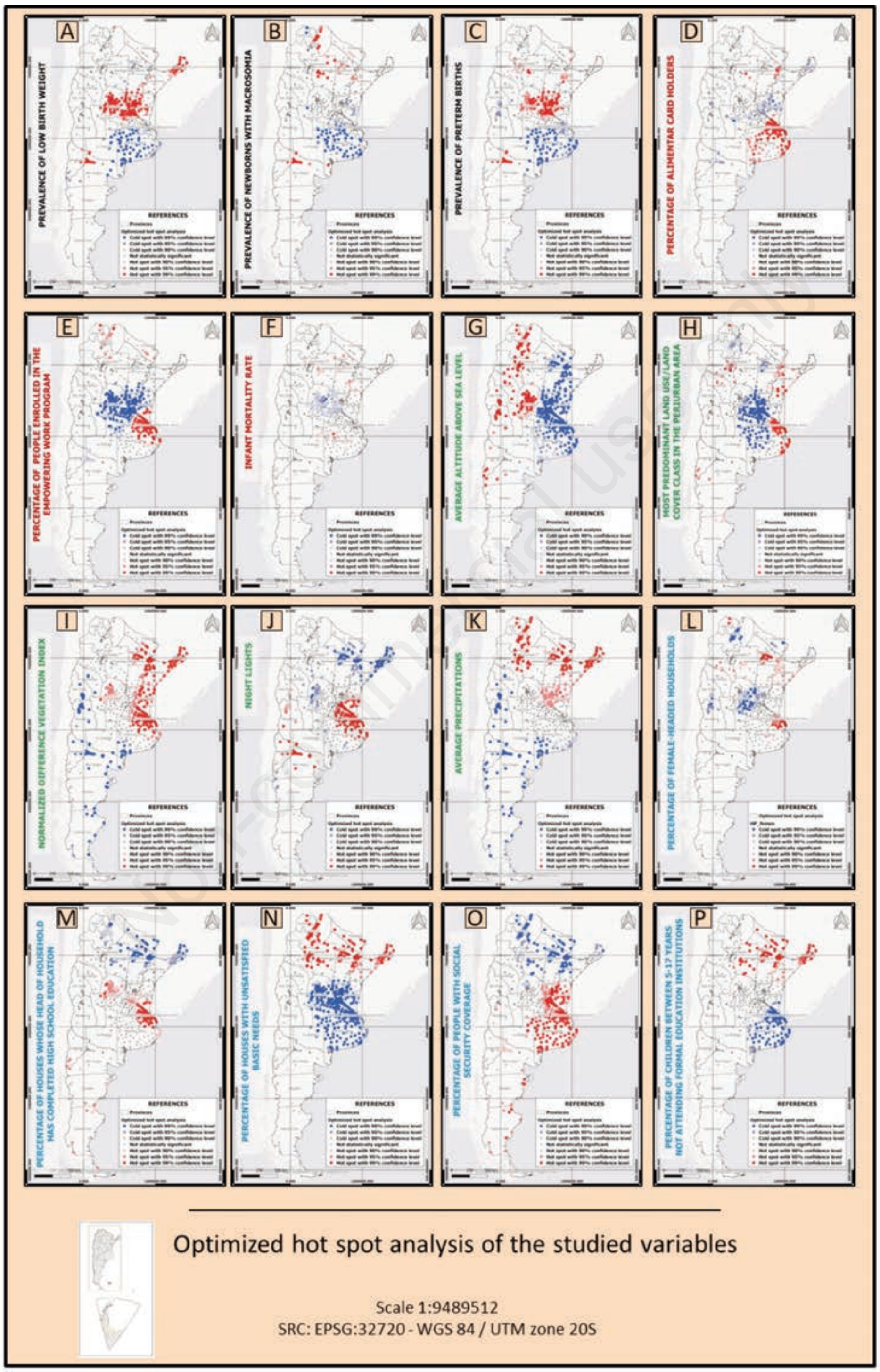

Figure 2. Dependant and CFE variables optimized hotspot analysis. Coldspots are depicted in blue and hotspots in red. More intense colours are associated with higher statistical significance.

areas. Map N, which concerns households with UBN, shows a concentration of high percentages in the North with 99% statistical significance. Map O (related to the percentage of individuals with social security coverage) exhibits an inverse pattern to the previous attribute, while Map P (school absenteeism of children aged 5-17 years) shows a similar distribution to households with UBN, with higher values in the North and lower values in the central-eastern region. Areas with lower percentages of households with UBN, higher social security coverage, lower school absenteeism coincide with the coldspots of all the birth-related variables. Additionally,

Figure 3. Dependant and CFE variables by purely spatial analysis. Significant positive clusters in red; and significant negative clusters in blue.

concentrations of localities with higher prevalence of macrosomia in the North align with areas with higher UBN, lower social security coverage, higher school absenteeism and a lower percentage of household heads with completed secondary education.

Table 2 presents the results of the autocorrelation analysis conducted. As can be observed, all Moran's *I* values for the evaluated attributes are positive, indicating a clustered pattern in the variables. Regarding the analyzed CFE dimensions, the IMR exhibits the lowest index value for the political dimension (Moran's I = 0.06). Additionally, the average precipitation, altitude, and NDVI have the highest values of the index in the environmental dimension (Moran's I = 0.87, 0.66 and 0.56 respectively). Concerning the individual dimension, the percentage of houses with UBN and the percentage of people with social security coverage showed higher index values compared to the other variables in this dimension (Moran's I = 0.66 and 0.52 respectively). Furthermore, based on the conducted analysis, Z-score ≥2.50 and p-value <0.05 indicate that the detected pattern is not significantly different from random.

Figure 3 and Tables 3 and 4 illustrate the results of the purely spatial analysis. It can be observed that the low-risk clusters of birth-related variables are located in the same region as the low-altitude cluster and include the high night-time light cluster. The high-risk cluster 2 of LBW in the central part of the country is situated in the same region as the crop-dominated clusters and includes the high NDVI cluster 3. Furthermore, the third high-risk cluster of all three birth-related variables coincides with a high night-time light cluster. Finally, it can be observed that the high-risk clusters of macrosomia and preterm births in the North and Northeast are located in areas with a predominant mosaic of cropland and natural vegetation, high NDVI, precipitation and a lower level of night-time light.

The location of the low-risk clusters of the birth-related variables (in the central-eastern part of the country) coincides with clusters of a lower percentage of households with UBN (cluster 2) and is included in those with a higher percentage of household heads with completed secondary education (cluster 2) and higher health insurance coverage (cluster 2). Furthermore, the high-risk clusters of macrosomia and preterm births in the north of the country share a geographical location with the school absenteeism cluster, which has lower health insurance coverage, a higher percentage of UBN, and a lower percentage of household heads with completed secondary education.

Figure 4 illustrates the results of the conducted experimental and fitted variograms of the various variables with outcomes summarized in Tables 5 and 6.

Figure 5 shows spatially constrained multivariate clustering in three maps, one for each dimension, The results of integrating the variables studied are summarized in Tables 7, 8, and 9.

Discussion

From the perspective of landscape epidemiology, the usefulness of geospatial approaches for the analysis of spatial distribution patterns are indispensable to infer and reveal new hypotheses not detected without this spatial vision. This work is a preliminary and indispensable first step before generating different explanatory models. The extensive spatial variability in the attributes of interest detected across the entire national territory should be seen in the light of the response to a historical phenomenon that took place in Argentina before and after 2000, where territories in the North experienced lower socioeconomic growth compared to central or southern regions of the country (Niembro *et al.*, 2016), with inequalities linked to health disparities, largely associated with the availability and access to health resources and services (Niembro *et al.*, 2016).

We noted clusters and hotspots of the three birth variables investigated towards the South as well as coldspots and clusters of low NDVI and precipitation. In the same locations, hotspots and clusters of high levels of night-time light and significant groupings of low altitudes were found together with clusters of high social security coverage and households headed by individuals with complete secondary education. This was interpreted as due to the fact that southern Argentina does not exhibit the same socioeconomic vulnerability as seen in the North or even in major urban areas at the expense of regional development. These findings are in line with the sparsely populated territory with greater socioeconomic and environmental resilience here pointed out by Mikkelsen et al. (2016).

To the North of the country, hotspots and clusters of macrosomia were observed together with hotspots and clusters of high NDVI and precipitation values were evident along with coldspots and groups of low night-time light. In these locations, coldspots and groups of low percentages of household heads with secondary education and social security coverage were observed, as well as significant hotspots and clusters characterized by a higher proportion of households with UBN and high rates of school absenteeism. This sociopolitical scenario places this North as the most vulnerable in the country and the literature reinforces this fact and that it requires urgent intervention (Andrada, 2014). Thus, it is crucial to redirect strategic resource investment to address and prevent the most urgent issues in a prioritized order.

In the central region of the country, where there are clusters of high prevalence of LBW and preterm births, coldspots and clusters of low coverage of the Empowering Work program and coldspots of IMR (both related to the political dimension) were observed. We also noted coldspots and groupings of a lower proportion of households led by women and a lower percentage of households with UBN in these areas. Hotspots and clusters were observed for household heads with completed secondary education as well as hotspots of average altitude, predominance and clustered crop production. Likewise, the multivariate clustering analysis in this area revealed a political cluster, an environmental cluster and two linked to the individual dimension. Importantly, contrary to what literature suggests for this region, we observed indicators of unfavourable birth outcomes, with evidence of increased levels of LBW and infant mortality. However, the strength of the association between them has declined in developed and developing territories (Kramer *et al.*, 2005). In fact, this region of the country has currently the lowest infant mortality, which may suggest that favourable sociodemographic conditions contribute to the reduction of this vital statistic. It is crucial to monitor indicators that begin to show variations, which could represent the onset of health spatial patterns already observed in the North.

Coldspots and clusters of the three birth variables studied were found in the central-eastern area of the country, which corresponds to significant hotspots and clusters of high Alimentar Card coverage and enrolment in the Empowering Work program. Peculiarly, hotspots and clusters of high night-time light were detected in the same location together with coldspots, groups of high altitude and predominant classes in the peri-urban area of crops and herbaceous coverage. Furthermore, the individual dimension showed

Table 3. Cluster analysis of the three birth outcomes under study.

Outcome	Cluster and risk	Part of the country	Radius (km)	Locality (no.)	Inside (%)	Outside (%)	p
LBW*	1-low	Centre East	429.03	105	9.4	14.2	0.001
LBW*	2-high	Centre	255.70	158	16.6	12.5	0.001
LBW*	3-high	South	109.68	15	20.6	13.3	0.001
Macrosomia	1-low	Centre East	388.04	109	8.7	11.2	0.001
Macrosomia	2-high	North	524.85	113	12.6	10.5	0.001
Macrosomia	3-high	South	109.68	15	15.4	10.7	0.001
Preterm birth	1- low	Southeast	500.26	111	11.1	17.2	0.001
Preterm birth	2- high	North	632.83	324	18.3	14.1	0.001
Preterm birth	3- high	South	109.68	15	27.7	15.9	0.001

**Low birth weight.*

Table 4. Cluster analysis of the different variables under study

Outcome	Cluster and risk	Part of the country	Radius (km)	Locality (no.)	Inside (%)	Outside (%)	p
D-Alimentar[a]	1	Centel East	549.19	143	6.0%	2.1%	0.001
D-Alimentar[a]	2	North	39.47	3	15.2%	2.9%	0.031
E-Work prog.[b]	1	East	70.43	41	35.4%	6.3%	0.001
E-Work prog.[b]	2	Centre 417.41	232	2.2%	11.4%	0.005	
IMR[c]	None						
F-Altitude[d]	1	Northwest	622.93	198	623.06m	146.72 m	0.001
F-Altitude[d]	2	East South	732.24	256	105.81m	408.03 m	0.008
G-LULC[e]	1	Centre East	413.49	248	46.4A		0.001
G-LULC[e]	2	Northeast	475.32	56	48.2B		0.001
G-LULC[e]	3	Northwest	589.11	193	38.9A		0.001
H-NDVI[f]	1	West South	1,067.11	141	0.33	0.48	0.001
H-NDVI[f]	2	Northeast	1,135.93	328	0.50	0.40	0.001
H-NDVI[f]	3	Centre	28.84	16	0.60	0.44	0.009
I-Night-light[g]	1	East	30.37	22	75.25	31.24	0.001
I-Night-light[g]	2	South	97.19	14	70.35	31.89	0.003
I-Night-light[g]	3	Centre North	1,132.23	320	27.29	37.86	0.007
J-rainfall[h]	1	West South	1,067.83	115	47.21mm	122.37mm	0.001
J-rainfall[h]	2	Centre North	675.27	328	135.86mm	82.65 mm	0.001
K-home/fem[i]	1	North	67.98	11	17.5%	30.7%	0.001
K-home/fem[i]	2	North	69.22	3	53.4%	30.4%	0.001
K-home/fem[i]	3	Centre West	416.29	199	28.6%	31.3%	0.019
L-home/edu[j]	1	Northeast	718.58	176	24.0%	34.1%	0.001
L-home/edu[j]	2	Centre South	1,757.61	325	34.4%	28.6%	0.001
L-home/edu[j]	3	Centre	39.22	19	45.3%	31.0%	0.009
M- UBN[k]	1	North	462.96	85	24.5%	8.6%	0.001
M- UBN[k]	2	Centre East	491.85	328	6.1%	15.2%	0.001
N-security[l]	1	North	492.37	99	32.1%	49.3%	0.001
N-security[l]	2	Centre South	2,070.17	208	53.9%	43.4%	0.001
O-school[m]	1	Northeast	727.66	155	10.0%	6.2%	0.001

[a]percentage of Alimentar Card holders; [b]percentage of citizens enrolled in the Empowering Work program; [c]Infant mortality rate; [d]average altitude above the sea level; [e]Land use/land class; [f]normalized difference vegetation index; [g]average night-time light; [h]average, annual precipitation; [i]percentage of female-led households; [j]percentage of households led by somebody with complete secondary education; [k]percentage of households with unsatisfied basic needs; [l]percentage of individuals covered by health insurance; [m]percentage of children aged 5-17 years not attending formal educational institutions; Ashrub-land; Bclose to open broad-leaved deciduous tree cover.

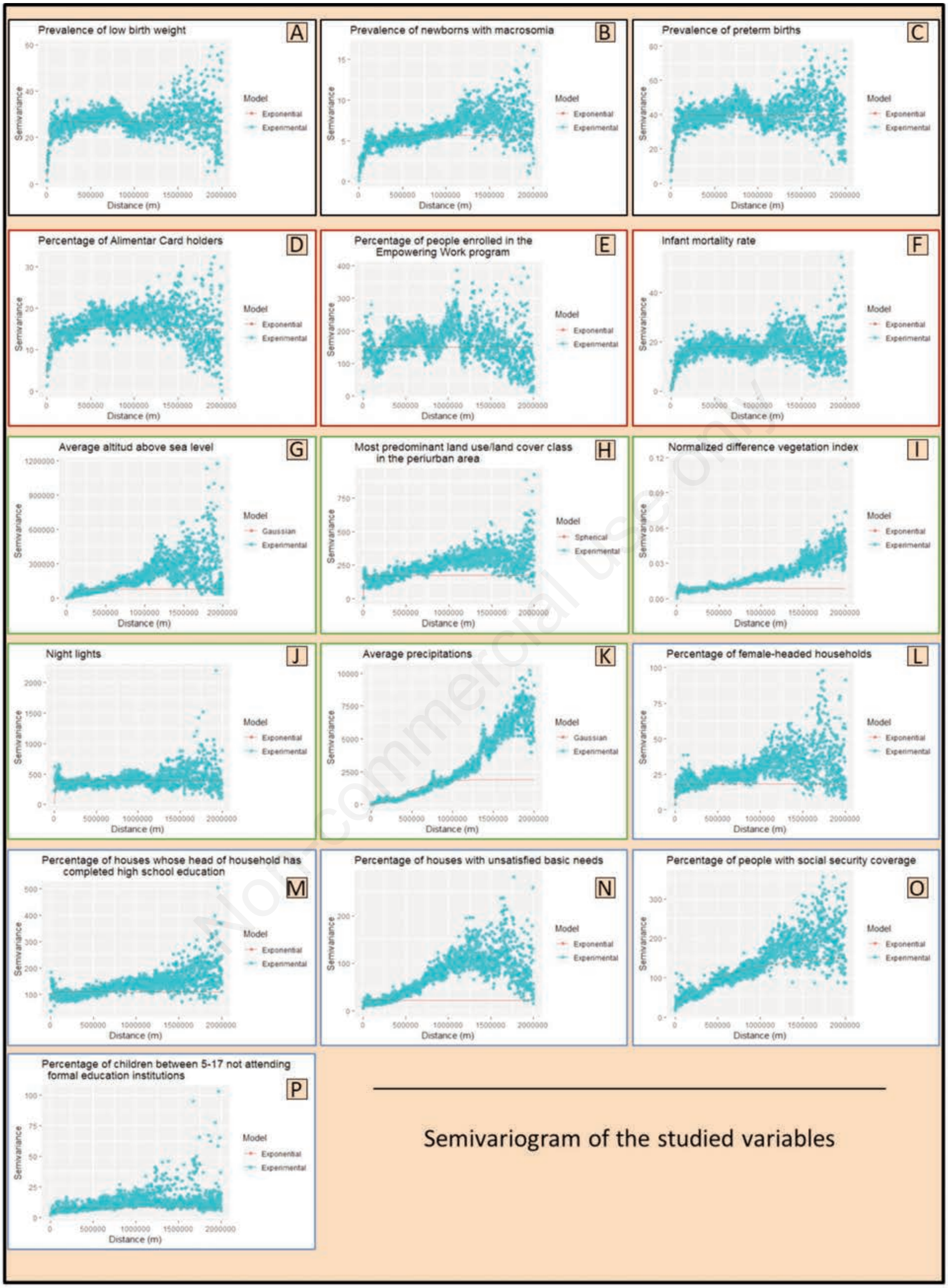

Figure 4. The dependant and CFE variable semivariograms.

coldspots and clusters of a lower proportion of households with UBN. There were also hotspots and significant clusters of a higher proportion of household heads with completed secondary education and social security coverage. The semivariograms corresponding to the prevalence of LBW and preterm births presented a similar spatial variability to each other and with infant mortality and the percentage of households led by women. This is in accordance with the association between LBW, preterm births and infant mortality on the one hand, and the overall higher mortality observed in the presence of a greater prevalence of birth events observed by Almli *et al.* (2020). Additionally, the direct relationship between infant mortality and the percentage of households headed by women has also been discussed (albeit to a lesser extent), indicating increased vulnerability (and therefore a priority) in households led by women (Mogollón-Pastran *et al.*, 2020 MISSING FROM THE LIST). While the application of variograms to the study of birth weight has been documented, no studies have been found applying these methodologies in Latin America.

Table 5. Values associated to semivariogram for all birth outcomes.

Graph	Disorder	Nugget	Sill	Range
A	LBW	2.83	23.73	27,886.95
B	Macrosomia	1.32	4.28	405,062.50
C	Premature birth	7.03	32.89	42,245.68

Table 6. Values associated to semivariogram for all community food environment variables.

Graph	Variable	Nugget	Sill	Range
The political dimension				
D	Alimentar[a]	3.47	11.58	40876.91
E	Work prog.[b]	78.86	70.30	5823.22
F	IMR[c]	0	17.78	6,7669.88
The environmental dimension				
G	Altitude[d]	2,097.66	79,454.56	11,8688.70
H	LULC[e]	52.94	174.72	8969.47
I	NDVI[f]	0.00021	0.0084	9179.96
J	Night-light[g]	0	391.02	846.16
K	Precipitation[h]	31.26	1,852.87	554,684.80
The induvidual dimension				
L	House/female[i]	3.66	14.43	6979.80
M	House/edu[j]	96.80	10.51	17,506.72
O	House/UBN[k]	0	21.52	7,018.84
P	Insurance[l]	31.82	124.13	659,703.40
Q	Schooling[m]	1.84	6.50	53,179.43

[a]percentage of Alimentar Card holders; [b]percentage of citizens enrolled in the empowering work program; [c]Infant mortality rate; [d]average altitude above the sea level; [e]Land use/land class; [f]normalized difference vegetation index; [g]average night-time light; [h]average, annual precipitation; [i]percentage of female-led households; jpercentage of households led by somebody with complete secondary education; [k]percentage of households with unsatisfied basic needs; [l]percentage of individuals covered by health insurance; [m]percentage of children aged 5-17 years not attending formal educational institutions.

Table 7. Results of multivariate clustering revealing integration of the variables in the political dimension.

Clusters in map A	Part of the country	Locality (no.)	Alimentar Card[a] (%)	Work program[b] (%)	IMR (average no. of deaths per 1,000 live births)
1	Central East	72	5.5	10.3	10.52
2	South	2	0	7.4	7.00
3	Central South	163	0.9	3.5	7.97
4	Northwest	85	1.6	13.3	9.85
5	Centre	77	4.9	1.1	7.44
6	Central East	70	6.9	20.2	8.74
7	Northeast	188	2.1	7.4	9.32

[a]Alimentar Card holders; [b]citizens enrolled in the empowering work program.

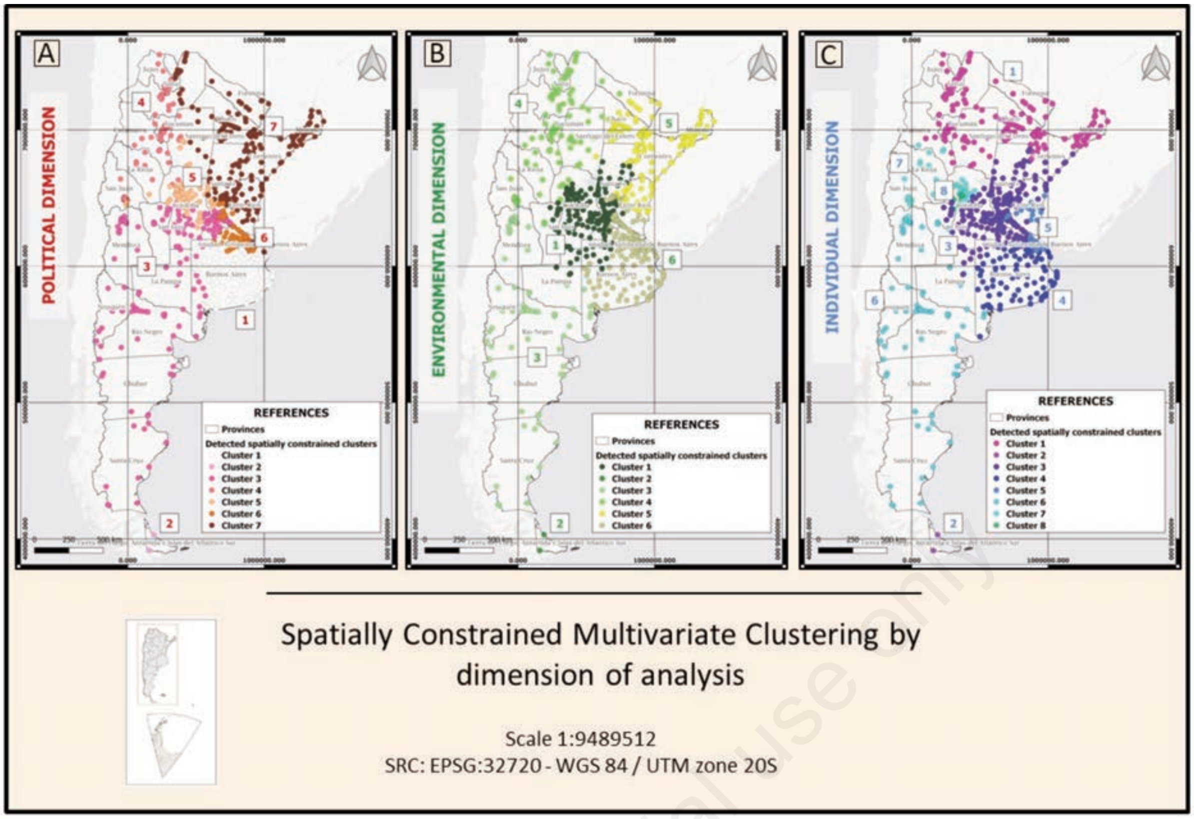

Figure 5. Spatially constrained multivariate clustering of the dependant and the three CFE dimensions.

Table 8. Results of multivariate clustering revealing integration of the variables in the environmental dimension.

Clusters in map B	Part of the country	Locality (no.)	Altitude (m above the sea)	LULC[e] (main land cover)	NVDI	Night- light[g]	Rainfall[h] (mm)
1	Centre	161	284	Cropland & herbaceous	0.47	29.69	116
2	South	2	46	Trees & shrub-land	0.40	33.93	37
3	Southwest	83	452	Peri-urban shrub-land	0.26	42.45	30
4	Northwest	126	672	Peri-urban herbaceous	0.41	29.61	134
5	Northwest	123	117	Trees & water bodies	0.53	23.40	137
6	Central East	162	51	Peri-urban herbaceous	0.46	21.54	104

[d]average altitude above the sea level; [e]Land use/land class; [f]normalized difference vegetation index; [g]average night-time light; [h]average, annual precipitation.

Table 9. Results of multivariate clustering revealing integration of the variables in the individual dimension.

Clusters in map B	Part of the country	Locality (no.)	Home/fem[i] (%)	Home/edu[j] (%) (%)	UBN[k] (%)	Security[l] (%)	School[m] (%)
1	North	179	30.8	24.4	19.7	37.1	9.4
2	South	2	30.9	54.9	14.1	62.7	2.4
3	Central East	184	29.2	30.7	6.3	48.7	7.2
4	East	83	32.0	33.4	4.7	57.5	4.8
5	East	63	32.4	39.5	8.3	48.0	5.6
6	West South	78	30.2	36.5	8.7	53.3	5.5
7	West	54	29.6	32.5	10.8	43.7	7.3
8	Centre	14	31.2	47.1	7.2	44.6	5.6

[i]percentage of female-led households; [j]percentage of households led by somebody with complete secondary education; [k]percentage of households with unsatisfied basic needs; [l]percentage of individuals covered by health insurance; [m]percentage of children aged 5-17 years not attending formal educational institutions.

Regarding the limitations of this study, the lack of availability of sociodemographic data from the latest National Census (2022, De Grande & Rodriguez, 2023) at the locality level represented a difficulty. However, the use of information from the previous Census (INDEC, 2010) allowed for an assessment of the sociodemographic situation to which the populations of the studied localities were exposed. In Argentina, one of the goals of the National Spatial Plan is the observation of the Earth for the efficient use of spatial information by developing applications required by society, giving value to primary information for its use and distribution (Álvarez Di Fino, 2020). Thus, this research is pioneering in the evaluation of CFE, like other works that apply spatial statistics to different objects of study and at different scales in the country and the region (Celemín *et al.*, 2015; Celemín & Velázquez, 2017).

Conclusions

This study identified clusters of high prevalence of LBW and preterm births, which has not been previously documented in the literature. Moreover, the employed methodologies facilitated a comprehensive characterization of each attribute, with a particular emphasis on spatial behaviour allowing for explanatory analyses of the data considering the significance of each attribute. The spatial variability identified in this study proposes new study hypotheses that highlight the importance of space as an epidemiological variable. From the CFE perspective, this research enabled a re-examination of health and environmental data, providing valuable insights for national-level and provincial-level decision-making considering the particularities of the territories making efficient and strategic use of public policy resources. From the spatial analysis perspective, these results showed the convenience of using several tools that highlight different aspects that could be complementary in an alternative way to the adoption of a single tool. Importantly, the remote sensing results highlight the potential of satellite-generated data in the realm of healthcare research and encourage further investigation into environmental and climatic factors as they play a role in the health-disease process with special reference to climate change.

Credit author statement

Campero, Micaela Natalia: Conceptualization, Data Curation, Software, Formal analysis,

Investigation, Methodology, Writing - Review and Editing, Visualization.

Scavuzzo, Carlos Matías: Investigation, Methodology, Writing - Review and Editing, Visualization.

Scavuzzo, Carlos Marcelo: Conceptualization, Investigation, Methodology, Writing - Review and

Editing, Visualization.

Román, María Dolores: Conceptualization, Investigation, Methodology, Writing - Review and

Editing, Visualizati Spatial pattern analysis of community food environments variables determinants.

References

Almli LM, Ely DM, Ailes EC, Abouk R, Grosse SD et al., 2020. Infant mortality attributable to birth defects – United States, 2003-2017. Morb Mortal Wkly Rep 69:25.

Alvarez Di Fino EM, 2020. Aplicación de tecnologías geoespaciales para el análisis de la seguridad alimentaria y nutricional en la ciudad de Córdoba, Argentina. Master Thesis, National University of Córdoba, Córdoba, Argentina.

Amarasinghe GS, Agampodi TC, Mendis V, Agampodi SB, 2022. The geo-spatial perspective of biological, social and environmental determinants of early pregnancy anaemia in rural Sri Lanka: Need for context-specific approaches on prevention. Geospat Health 17:1110.

Andrada MJ, 2014. Niveles de mortalidad y vulnerabilidad social en el noroeste argentino. 2001-2010.

Campero MN, Marinelli MV, Scavuzzo CM, Roman MD, 2022. Community Food Environments, exploring a geomatic vision of regional scale. In 2022 IEEE Biennial Congress of Argentina (ARGENCON) (pp. 1-8). IEEE

Caspi CE, Sorensen G, Subramanian SV, Kawachi I, 2012. The local food environment and diet: a systematic review. Health Place 18:1172-87.

Castro MJ, 2020. Programación fetal. Rev Digit Postgrado 9:e214.

Celemín JP, Mikkelsen C, Velázquez G, 2015. La calidad de vida desde una perspectiva geográfica: Integración de indicadores objetivos y subjetivos. Rev Univ Geogr 24:63-84.

Celemín JP, Velázquez GA, 2017. Spatial Analysis of the Relationship Between a Life Quality Index, HDI and Poverty in the Province of Buenos Aires and the Autonomous City of Buenos Aires, Argentina. Soc Indic Res 134:1-21.

De Grande P, Rodriguez G, 2023. Censo Nacional de Población, Hogares y Viviendas 2022 - Resultados provisionales. Retrieved 11 August, 2023. Available from: https://mapa.poblaciones.org/map/151701

Elorriaga N, Moyano DL, López MV, Cavallo AS, Gutierrez L, et al., 2021. Urban Retail Food Environments: Relative Availability and Prominence of Exhibition of Healthy vs. Unhealthy Foods at Supermarkets in Buenos Aires, Argentina. Int J Environ Res Public Health 18:944.

Esri, 2022. Clustering multivariante restringido espacialmente (Estadística espacial). Available from: https://pro.arcgis.com/en/pro-app/3.0/tool-reference/spatial-statistics/spatially-constrained-multivariate-clustering.htm

García-De la Torre JI, Rodríguez-Valdez A, Delgado-Rosas A, 2016. Factores de riesgo de macrosomía fetal en pacientes sin diabetes mellitus gestacional. Ginecol Obstet Mex 84:164-171.

Glanz K, Sallis JF, Saelens BE, Frank LD, 2005. Healthy nutrition environments: concepts and measures. Am J Health Promot 19:330-3.

Gutierrez LE, Elorriaga N, Gibbons L, Melendi S, Chaparro M, Calandrelli M, Lanas F, Mores N, Ponzo J, Poggio R, Berrueta M, Irazola V, 2021. Attributes of the food and physical activity built environments from the Southern Cone of Latin America. Sci Data 8:291.

Instituto Nacional de Estadísticas y Censos (INDEC), 2010. Censo 2010. Disponible en: https://www.indec.gob.ar/indec/web/Nivel4-Tema-2-41-135.

Júnior EA, Peixoto AB, Zamarian ACP, Júnior JE, Tonni G, 2017. Macrosomia. Best Pract Res Clin Obstet Gynaecol 38:83-96.

Kramer MS, Barros FC, Demissie K, Liu S, Kiely J, Joseph KS, 2005. Does reducing infant mortality depend on preventing low birthweight? An analysis of temporal trends in the Americas. Paediatr Perinat Epidemiol 19:445-51.

Kulldorff M, 2022. SaTScan™ User Guide for version 10.1. Available from: https://www.satscan.org/techdoc.html

Lu C, Zhang W, Zheng X, Sun J, Chen L, et al., 2020. Combined effects of ambient air pollution and home environmental factors on low birth weight. Chemosphere 240:124836.

Lytle LA, Sokol RL, 2017. Measures of the food environment: A systematic review of the field, 2007–2015. Health Place 44:18-34.

Mena C, Sepúlveda C, Fuentes E, Ormazábal Y, Palomo I, 2018. Spatial analysis for the epidemiological study of cardiovascular diseases: A systematic literature search. Geospat Health 13:587.

Mikkelsen C, Ares S, Gordziejczuk M, 2016. Dinámica socioterritorial del espacio rural en Argentina. En: Velázquez G. (dir.) Geografía y calidad de vida en Argentina. Análisis regional y departamental (2010). Tandil: IGEHCS/CIG.

Mogollón-Pastrán SC, García-Ubaque JC, Martínez-Martínez, S, 2020. Determinantes sociales de la mortalidad infantil en municipios de frontera en Colombia, 2005-2011. Rev Fac Med, 68(2), 269-278.

Momeni M, Danaei M, Kermani AJ, Bakhshandeh M, Foroodnia S, Mahmoudabadi Z, Amirzadeh R, Safizadeh H, 2017. Prevalence and Risk Factors of Low Birth Weight in the Southeast of Iran. Int J Prev Med 8:12.

Ncube CN, Enquobahrie DA, Albert SM, Herrick AL, Burke JG, 2016. Association of neighborhood context with offspring risk of preterm birth and low birthweight: A systematic review and meta-analysis of population-based studies. Soc Sci Med 153:156-64.

Niembro A, Dondo M, Civitaresi HM, 2016. La manifestación territorial de las desigualdades socioeconómicas en Argentina: del diagnóstico a las políticas públicas. Población y sociedad 23:79-123.

Pan American Health Organization (PAHO), 2021. Sistemas Alimentarios para la salud: Resumen informativo. Disponible en: https://iris.paho.org/bitstream/handle/10665.2/56525/9789275325520_spa.pdf?sequence=1&isAllowed=y.

Pérez-Ferrer C, Auchincloss AH, de Menezes MC, Kroker-Lobos MF, Cardoso LO, Barrientos-Gutierrez T, 2019. The food environment in Latin America: a systematic review with a focus on environments relevant to obesity and related chronic diseases. Public Health Nutr 22:3447-64.

Piña Borrego CE, 2020. Cambio climático, inseguridad alimentaria y obesidad infantil. Rev Cubana Salud Pública 45:e1964.

Ramírez-López MT, Vázquez Berrios M, Arco González R, Blanco Velilla RN, Decara del Olmo J, et al., 2015. El papel de la dieta materna en la programación metabólica y conductual: Revisión de los mecanismos biológicos implicados. Nutr Hosp 32:2433-45.

Santamaría MS, Malla MS, 2006. Notas sobre el manejo del software geoestadístico Variowin. Parte I: Cálculo del variograma. Rev Inst Investig Fac Minas Metal Cienc Geogr 9(18):82-90.

Safi-Stibler S, Gabory A, 2020. Epigenetics and the Developmental Origins of Health and Disease: Parental environment signalling to the epigenome, critical time windows and sculpting the adult phenotype. Semin Cell Dev Biol 97:172-180.

Secretaría de Gobierno de Salud [Government Secretariat of Health], 2019. 2da Encuesta Nacional de Nutrición y Salud (ENNyS 2). Resumen Ejecutivo. [2nd National Nutrition and Health Survey (ENNyS 2). Executive Summary.] Available from: https://cesni-biblioteca.org/wp-content/uploads/2019/10/0000001565cnt-ennys2_resumen-ejecutivo-20191.pdf.

Seijo M, Spira C, Chaparro M, Elorriaga N, Rubinstein A, García-Elorrio E, Irazola V, 2021. Development of physical activity and food built environment quality indicators for chronic diseases in Argentina. Health Promot Int 36:1554-1565.

Suerungruang S, Sornlorm K, Laohasiriwong W, Mahato RK, 2023. Spatial association and modelling of under-5 mortality in Thailand, 2020. Geospat Health 18:1220.

Teixidó Trujillo D, 2015. Meteorología y salud infantil: una aplicaciónal caso de Nigeria. Degree Thesis. University of La Laguna, España.

Turner C, Aggarwal A, Walls H, Herforth A, Drewnowski A, et al., 2018. Concepts and critical perspectives for food environment research: a global framework with implications for action in low-and middle-income countries. Global Food Sec 18:93-101.

United Nations, 2021. Global Nutrition Report. The state of global nutrition. Disponible en: https://www.un.org/nutrition/sites/www.un.org.nutrition/files/global_nutrition_report_2021.pdf

Uwiringiyimana V, Veldkamp A, Amer S, 2019. Stunting spatial pattern in Rwanda: An examination of the demographic, socio-economic and environmental determinants. Geospat Health 14:820.

World Health Organization (WHO), 2008. Climate change and health. Available from: https://iris.who.int/handle/10665/126809

Online supplementary materials

Data sources

References about the analysis

Analysis performed on random and single value variables

Purely spatial analysis