# A geospatial analysis of cardiometabolic diseases and their risk factors considering environmental features in a midsized city in Argentina

**Micaela Natalia Campero,[1,2,3] Carlos Matías Scavuzzo,[1,2] Verónica Andreo,[2,3] María Sol Mileo,[1] Micaela Belén Franzois,[1] María Georgina Oberto,[1] Carla Gonzalez Rodriguez,[2,3] María Daniela Defagó[1,2,4]**

***[1]Centre for Research in Human Nutrition School of Nutrition, Faculty of Medical Sciences, National University of Cordoba, Ciudad de Córdoba, Córdoba; [2]Mario Gulich Institute for Advanced Space Studies, National University of Cordoba, National Commission for Space Activities, Falda del Cañete, Córdoba; [3]National Council for Scientific and Technical Research, Buenos Aires; [4]Health Sciences Research Institute, Ciudad de Córdoba, Córdoba, Argentina***

Correspondence: Verónica Andreo, Mario Gulich Institute for Advanced Space Studies, National University of Cordoba, National Commission for Space Activities, Falda del Cañete, Córdoba, Argentina. Tel: +54.9358417-6725.
E-mail:veronica.andreo@ig.edu.ar

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## Abstract

New approaches to the study of cardiometabolic disease (CMD) distribution include analysis of built environment (BE), with spatial tools as suitable instruments. We aimed to characterize the spatial dissemination of CMDs and the associated risk factors considering the BE for people attending the Non-Invasive Cardiology Service of Hospital Nacional de Clinicas in Córdoba City, Argentina during the period 2015-2020. We carried out an observational, descriptive, cross-sectional study performing non-probabilistic convenience sampling. The final sample included 345 people of both sexes older than 35 years. The CMD data were collected from medical records and validated techniques and BE information was extracted from Landsat-8 satellite products. A geographic information system (GIS) was constructed to assess the distribution of CMDs and its risk factors in the area. Out of the people sampled, 41% showed the full metabolic syndrome and 22.6% only type-2 diabetes mellitus (DM2), a cluster of which was evidenced in north-western Córdoba. The risk of DM2 showed an association with high values of the normalized difference vegetation index (NDVI) (OR= 0.81; 95% CI: -0.30 to 1.66; p=0.05) and low normalized difference built index (NDBI) values that reduced the probability of occurrence of DM2 (OR= -1.39; 95% CI: -2.62 to -0.17; p=0.03). Considering that the results were found to be linked to the environmental indexes, the study of BE should include investigation of physical space as a fundamental part of the context in which people develop medically within society. The novel collection of satellite-generated information on BE proved efficient.

## Introduction

Since the beginning of the $20^{th}$ century, Latin America, including the Caribbean region, faces socioeconomic and demographic changes generating profound transformations in the dietary patterns and physical activity of the population (Popkin & Reardon, 2018). The modern food systems is undergoing growing industrialization, urbanization and mass consumption that have created adverse environments promoting unhealthy diets characterized by high contents of fats, simple sugars and animal protein with little fibre and complex carbohydrates. Besides, lifestyles have become increasingly sedentary with consumption of harmful substances, such as tobacco, alcohol and other drugs (Popkin & Reardon, 2018). These changes have triggered acute malnutrition processes associated with primary deficiencies giving rise to excess malnutrition as precursor to the increased prevalence of non-communicable diseases (NCDs), e.g., certain types of cancer, cardiometabolic diseases (CMDs) including the combination of diabetes, hypertension and obesity, which is referred to as the metabolic syndrome (MS) (Alvarez Di Fino, 2020). Consequently, population morbidity has increased but, counter-intuitively, mortality patterns have decreased. These transformations have been called "the epidemiological nutritional transition" (Popkin *et al.*, 2012; Pou *et al.*, 2020). According to the World Health Organization (WHO), 74% of reported deaths worldwide are instigated by NCDs (WHO, 2022). Similarly, the Pan American Health Organization (PAHO), research asserts that Argentina follows global trends with cardiovascular diseases (CVDs) accounting for 28.5% of all mortality (Organización Panamericana de la Salud, 2021). In Argentina, 80% of morbidity and mortality is caused by NCDs (Arrieta *et al.*, 2022).

In this epidemiological context, it is relevant to highlight the importance of built environment (BE), which is defined as the spaces, buildings and structures created, or modified, by humans for everyday life. This includes urban design projects, workplaces, parks, recreation areas, transportation routes and land use (Booth *et al.*, 2005). BE may affect physical (such as climatic conditions) and social (such as civic participation and investments) environments and thus influence health and quality of life in general, in particular the genesis of NCDs (Álvarez Di Fino, 2020). Given the complex nature of NCDs involvement, study approaches require geospatial tools, such as geographic information systems (GIS), which allow compilation of relevant information through the combination of informative layers at desired scales of analysis (Mohammad Ebrahimi *et al.*, 2022).

Recent research in Latin America has used geospatial tools to study the distribution of different variables associated with NCDs (Álvarez Di Fino *et al.*, 2019; Mena *et al.*, 2018; Scarlatta & Defagó, 2020). Remote sensing and GIS allow the visualization and analysis of the relationships between BE, risk factors and disease clustering (Álvarez Di Fino *et al.*, 2019; Drewnowski *et al.*, 2019; Xu & Wang, 2015) The integration of GIS, remote sensing and health data offers expanded potential when coupled with primary data acquired through surveys and interviews. In diabetes research, specifically, these datasets can be applied to smaller geographical units. For example, they have been used to scrutinize the effectiveness of health interventions (Tang *et al.*, 2011), to analyze the well-being of communities considering CMDs (Curtis & Lee, 2010; Gesler *et al.*, 2004), to explore the correlation between socio-environmental factors and health outcomes like diabetes (Schlundt *et al.*, 2006) as well as to investigate the interplay between social networks and health knowledge in terms of CMDs (Cravey *et al.,* 2001). To the best of our knowledge, there are no citywide studies in Argentina addressing the risk factors of BE in relation to CMD. Moreover, the use of information from remote sensing for characterizing BE is still an unexplored area in the metropolitan area of Córdoba. Based on the above, we aimed to analyze the spatial distribution of CMDs and their risk factors considering the BE in relation to people attending the Non Invasive Cardiology Service of the Hospital Nacional de Clínicas Prof. Dr. Pedro Vella (HNC) in this city in the period 2015-2020.

## Materials and Methods

This study is part of a larger project called "Clinical epidemiological approach to arterial hypertension based on biomarkers and food environment", approved and funded by the Secretaria de Ciencia y Tecnología, *i.e.* the Science and Technology Authority (SeCyT-UNC, Res. No. 313/16) in Argentina. An observational, analytical and cross-sectional study was conducted involving patients at the HNC, a referral health centre with a high demand for care (Oberto et al., 2020). However, a probabilistic sample could not be accessed due to the absence of official patient care statistics at the Non-invasive Cardiology Service.

### Study area

The study area was defined by the self-reported addresses of the study participants. Thus, as shown in Figure 1, the area in question consisted mostly of the area of Great Córdoba, which is situated in central Argentina. According to the Statistics and Censuses Institute (Instituto Nacional de Estadística y Censos de la República, INDEC), this total area covers a surface of 608 $km^2$ and includes the city of Córdoba and the municipalities and communes of Colón, Santa María, Punilla, Río Primero, and Río Segundo departments (INDEC, 2010). The latest National Population, Households, and Housing Census carried out in 2022 is yet to be finalized, so the population of Great Cordoba cannot be known with accuracy, but the 2010 Census gives a count of 1,981,737 inhabitants (INDEC, 2010). Currently, it is the second-largest urban agglomeration in Argentina in terms of population and area. Figure 1 presents the spatial distribution of individuals based on the geolocation of their residences. Cordoba City has the highest percentage of participants, with fewer in the rest of the metropolitan area (La Falda, La Calera, Villa Carlos Paz, and Villa Allende).

### Study population

Using non-probabilistic convenience sampling, the data collection included volunteers, who agreed to participate and to whom the measurements to be evaluated applied. The inclusion criteria were people of both sexes over 35 years of age with a CMD diagnosis without distinction of ethnicity. The exclusion criteria included patients with special diets, neuropsychological problems (dementia or depression), pregnant women, those with chronic renal or hepatic insufficiency, severe septic states, a HIV/AIDS diagnosis, diagnosis of any NCD in the most recent six months, disability or those domiciled outside the province of Cordoba. The final sample consisted of 345 people ≥35 years old of both sexes (female/male ratio = 1.25:1).

### Health data

From the medical records, we extracted information on patients, such as biometrics, hereditary-family history of NCDs, current diseases and toxic habits (intake of tobacco, alcohol or other substances). Blood samples were obtained by venipuncture following a 12-h overnight fasting. Inflammatory afflictions evidenced by high-sensitivity C-reactive protein (hs-CRP) serum measurements were obtained using the turbidimetric hs-CRP test by Wiener Lab® (https://www.wiener-lab.com.ar/en-OT/). Lipid serum concentrations were determined using enzymatic assays with reagents from Roche® (Buenos Aires, Argentina) and processed by standard methodologies using a Cobas 6000 (c501) analyzer (Roche Diagnostics® (Buenos Aires, Argentina).

Training and certified staff obtained biometric measurements using standard protocols and techniques. Body weight and height were measured twice during the clinical examination and the average of two measurements was used in all analyses. Weight was measured in kilograms to one decimal place using standing scales with patients in light indoor clothing without shoes. Height was measured in centimeters to one decimal place without shoes using a wall-mounted stadiometer. The body mass index (BMI) was calculated as weight divided by height (kg/m$^2$) and classified according to WHO guidelines. Waist circumference (WC) was measured at the middle point between the bottom of the rib cage and the uppermost border of the iliac crests at the end of exhalation in a standing position with an inelastic tape. The cut-off points for abdominal obesity were WC measurements of ≥94 cm for men and of ≥80 cm for women (WHO, 2011).

Hypertension, defined as systolic blood pressure ≥140 mmHg and/or diastolic blood pressure ≥90 mmHg and/or use of antihypertensive medication, was diagnosed by pressure measurements according to the guidelines of the American Heart Association, with the participant seated after 5 min of rest using a standardized automatic device (Japanese Omron M7 Intelli IT, model HEM123 7322T-E). Besides, the measurements were done with the participants having no previous consumption of tea, coffee, mate or tobacco (Flack & Adekola, 2020). For the assessment of the type, intensity and frequency of physical activity, the international physical activity questionnaire (IPAQ) was applied, which classifies physical activity as low, moderate or high (Barrera, 2017).

Food intake was obtained by a validated food consumption frequency questionnaire (Perovic *et al.*, 2015). A healthy diet was assessed based on four food components: 1) ≥400 g/day of fresh, whole vegetables and fruits, excluding starchy vegetables); 2) ≥200 g/week of fresh fish and seafood, excluding canned products; 3) ≤1500 mg of sodium/day estimated according to nutrient intake (salt added at the table or during cooking not included); and 4) ≤1.5 l/week of sugar-sweetened beverages, including soft drinks, fruit juices, reconstituted juices, and sugar-flavoured water. A healthy diet was classified as "ideal" when adhering to all four components; "intermediate", when adhering to two or three components and "poor" when complied with one or zero components (Seron *et al.*, 2018). The dietary-nutritional information analysis was performed using the Interfood v.1.3 software, which reports the amount of beverages (in milliliters) and food (in grams) consumed per day (Defagó *et al.*, 2009).

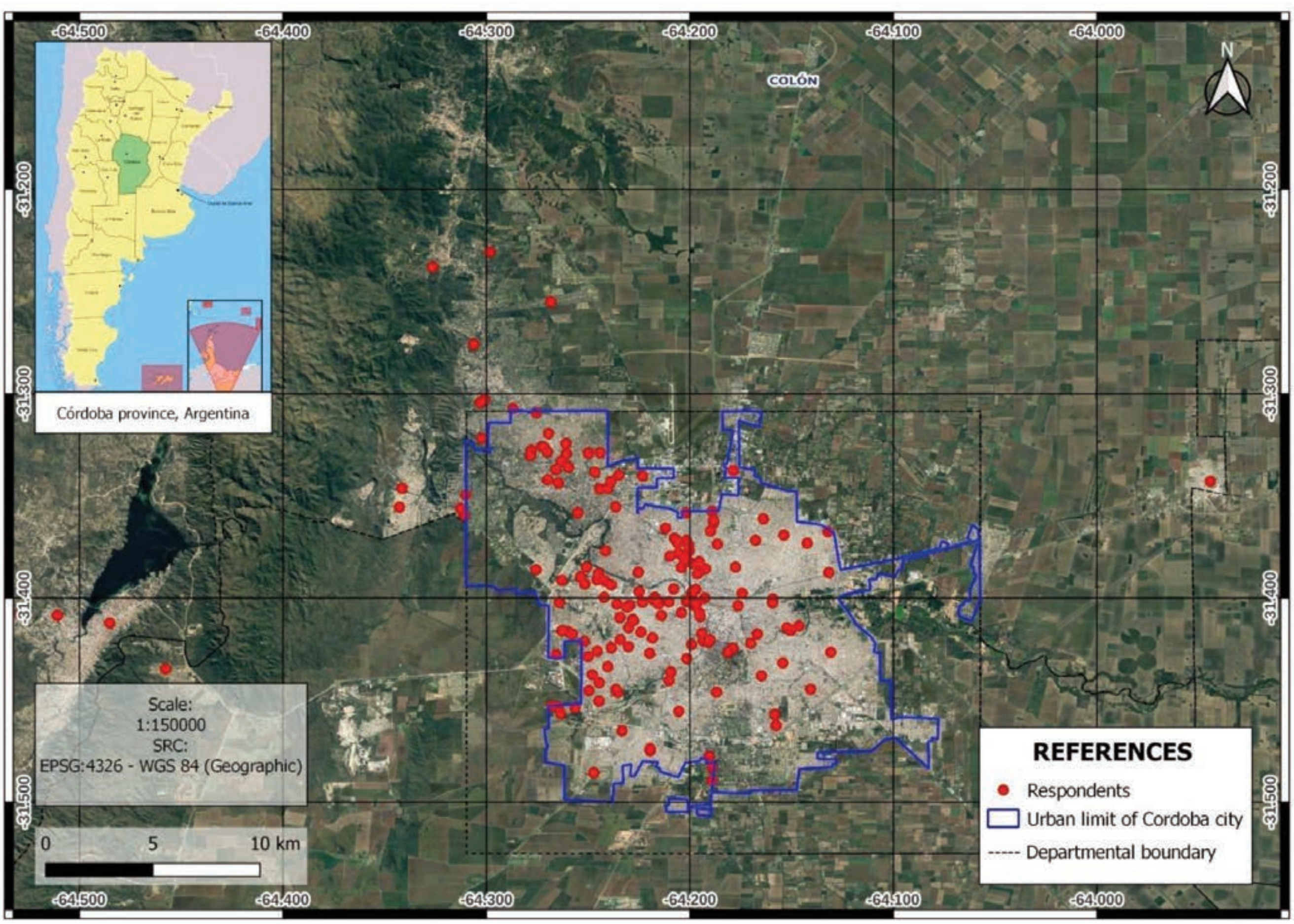


**Figure 1. Geospatial distribution of the residences of the study subjects. The area corresponds to the city of Córdoba and its metropolitan area. Map data© 2020 Google. Base map obtained through Quick Map Services QGIS plugin, Open Source Geospatial Foundation project (http://qgis.osgeo.org).**

### Environmental data

The BE variables were categorized as follows: The normalized difference vegetation index (NDVI) was categorized as "Soil without vegetation" <0.2, "Sparse vegetation" 0.2 and 0.6, "Medium vegetation" 0.6 and 0.8, "Thick vegetation" >0.8 adapted from Chuvieco *et al.* (2004). The normalized difference water index (NDWI) was categorized as "Surface with water" 0.2 and 1, "Moist soil'' 0.0 and 0.2, "Moderate drought" -0.3 and 0.0, "Drought" -1 and -0.3 according to the Earth Observing System (2022), while the normalized difference built-up index (NDBI) was categorized as "Mostly vegetative cover" <0, "Mostly built-up land" >0 as used by Gómez Vicario (2014). For each of these indices, the mean value was calculated in a circular buffer of 50 m radius from the residence of each patient (Zapata Bedoya *et al.*, 2023). The relevant mapping was produced using QGis 3.22 software (http://qgis.osgeo.org).

### Data collection

Patients were geocoded according to the residential address reported in the medical records. Two environmental indices were obtained from the mean annual top of atmosphere reflectance product at the 30-m spatial resolution estimated by the Landsat-8 satellite (https://www.usgs.gov/landsat-missions/landsat-8) based on Tier 1 scenes from 2020 by open access courtesy of the U.S. Geological Survey (USGS). The NDVI, generated from the near-infrared (IR) B5 band and the red (B4) bands and calculated as: (B5 - B4) / (B5 + B4), together with the NDWI, derived from the near-IR band and a shortwave-IR band (B6) when available (otherwise the nearest available IR band) and calculated as: (B5 - B6) / (B5 + B6) were estimated and downloaded from the Google Earth Engine platform. Both the NDVI and NDWI value range between +1.0 and -1.0. NDWI, with positive values of the former indicating dense vegetation and negative barren areas, while positive values of the latter indicating is water features and negative ones for soil and terrestrial vegetation. We also estimated the NDBI [that also ranges from +1 to -1 and is calculated as: (B6 - B5) / (B6 + B5)] based on a Landsat-8 OLI/TIRS Collection 2 Level-2 image corresponding to December 2020 (path 229-row 82, cloud percent cover <1%) that was downloaded from the USGS platform (Picone, 2017).

### Statistical and spatial analysis

A descriptive analysis of the study population was performed including information on age and sex, biometricy, biochemicstry, dietary-nutritional status and risk factors associated with CMDs. Summary measures of dispersion and position and of absolute and relative frequencies were calculated, including a T-test for comparison of means (age by sex) with proportions adjusted for sex and pathologies. For the purely spatial analysis, a cluster analysis of the diabetes-positive cases was performed with Satscan software (https://www.satscan.org/) using the nearest neighbour model (Kuldorff *et al.*, 2005). Moreover, to explore clusters of high disease prevalence, a hotspot analysis was performed with QGIS 3.22 software (https://www.qgis.org) (Quantum, 2015). To improve our understanding of risk factors as obtained from BE variables, we predicted DM2 and MS utilizing a logistic regression model adjusted by sex, age, physical activity, caloric intake and a healthy diet index. We used Stata v.15 (https://www.stata.com/stata15/) for all statistical analyses.

## Results

The sample under study was 52.9% (n=181) women and 47.1% (n=161) men aged between 35 and 80 years with an average age of 56.01±9.69 years. The average age for the men was significantly higher than that for the women (p=0.02). As shown in Table 1, most of the subjects (84.6%) were from Córdoba City, with the remaining 15.4% from townships nearby. Regarding main occupation, 31.8% were domestic employees, out of which only 0.7% (n=2) were men. Concerning the hereditary-family history of NCDs, 84.2% of the participants gave positive answers.

22.6% of the subjects presented with DM2. The prevalence of DM2 was 21.5% and 23.8% in women and men, respectively. Likewise, 41.0% of the population under study presented with MS, out of which 53.8% were women and 46.2% men. Table 2 presents the analysis of risk factors concerning the occurrence of DM2 and MS. We observed a diminished percentage of individuals engaging in high physical activity, adhering to an ideal dietary quality and exhibiting lower levels of chronic vascular inflammation in contrast to the remaining categories with these variables. Statistical analyses did not show a significant augmented proportion of indi-

**Table 1. Main characteristics of the study population.**

| Variable | Total | Men | Women | p* |
|---|---|---|---|---|
| Age (in years): given by mean age and (SD) | 56.01 (9.69) | 57.29 (9.79) | 54.87(9.49) | 0.02 |
| Residency**: given by no. and (%) | 248 (84.6) | 114 (38.9) | 134 (45.7) | 0.27 |
| Cordoba City | 45 (15.4) | 16 (5.5) | 29 (9.9) | 0.49 |
| Other | | | | |
| Occupation: given by no. and (%) | 18 (6.4) | 11 (3. 9) | 7 (2.5) | 0.87 |
| Unoccupied | 56 (19.8) | 35 (12.4) | 21 (7.4) | 0.55 |
| Retiree | 30 (10.6) | 22 (7.8) | 8 (2.8) | 0.62 |
| Merchant | 90 (31.8) | 2 (0.7) | 88 (31.1) | 0.35 |
| Domestic employee | 65 (23.0) | 49 (17.3) | 16 (5.7) | 0.24 |
| Trade (office), professional | 24 (8.5) | 11 (3.9) | 13 (4.6) | 0.93 |
| NCD family history: given by no. and (%) | | | | |
| Presence | 245 (84.2) | 112 (38.5) | 133 (45.7) | 0.25 |
| Absence | 46 (15.8) | 18 (6.2) | 28 (9.6) | 0.30 |

*obtained from the T-test of the difference between means and proportions according to sex; **shows the division between city and rural living; SD, standard deviation; NCD, non-communicable disease.

viduals with diabetes displaying the targeted risk factors. Nevertheless, within the cohort diagnosed with hypertension, the proportion of MS was significantly higher.

Given the above significance values, Figure 2 shows the spatial distribution of the participants with DM2 diagnosis. There was a marked pattern of participants with DM2 towards the Northwest of the study area. In contrast, a pattern of lower density of positive cases was observed in the Southeast. The distribution of negative cases showed a relative spatial homogeneity.

In Table 3, it can be observed that the surroundings of the homes of patients with DM2, had significantly less sparse vegetation (p=0.01), less moist soil (p=<0.00001) and less vegetation cover (p=0.004). The same analysis performed for the presence and absence of MS, showed insignificant differences except with

**Table 2. Characterization of the presence of type-2 diabetes and the full metabolic syndrome in relation to modifiable risk factors in the study population.**

| Variable | Subjects with DM2 | Subjects without DM2 | p (DM2)* | Subjects with MS | Subjects without MS | p (MS)** |
|---|---|---|---|---|---|---|
| Body volume (BMI): given by mean and (SD) | | | | | | |
| Obese | 39 (12.58) | 99 (31.94) | 0.02 | 80 (27.59) | 47 (16.21) | 0.14 |
| Non-obese | 31 (10.00) | 141 (45.48) | 0.0002 | 39 (13.45) | 124 (42.76) | 0.0009 |
| Waist circumference: given by mean and (SD) | | | | | | |
| Desirable | 3 (1.00) | 14 (4.65) | 0.76 | 2 (0.71) | 61 (21.55) | 0.47 |
| Increbyed risk | 1 (0.33) | 5 (1.66) | - | 10 (3.53) | 33 (11.66) | 0.44 |
| Very high risk | 65 (21.59) | 213 (70.76) | <0.001 | 107 (37.81) | 70 (24.73) | 0.06 |
| Physical activity: given by mean and (SD) | | | | | | |
| High | 10 (3.31) | 40 (13.25) | 0.37 | 13 (4.64) | 30 (10.71) | 0.52 |
| Moderate | 28 (9.27) | 91 (30.13) | 0.02 | 41 (14.,64) | 70 (25.00) | 0.19 |
| Low | 32 (10.60) | 101 (33.44) | 0.01 | 63 (22.50) | 63 (22.50) | 1.00 |
| Smoking habit: given by mean and (SD) | | | | | | |
| Presence | 13 (4.30) | 43 (14.24) | 0.33 | 23 (8.19) | 27 (9.61) | 0.86 |
| Absence | 56 (18.54) | 190 (62.91) | <0.001 | 94 (33.45) | 137 (48.75) | 0.02 |
| Healthy diet: given by mean and (SD) | | | | | | |
| Ideal | 1 (0.33) | 2 (0.66) | - | 1 (0.35) | 2 (0.71) | - |
| Medium | 40 (13.11) | 130 (42.62) | 0.0007 | 61 (21.55) | 99 (34.98) | 0.07 |
| Poor | 28 (9.18) | 104 (34.10) | 0.009 | 56 (19.79) | 64 (22.61) | 0.70 |
| Chronic inflammation: given by mean and (SD) | | | | | | |
| Low | 0 (0.00) | 12 (9.45) | - | 2 (1.59) | 11 ( 8.73) | 0.72 |
| Medium | 8 (6.30) | 33 (25.98) | 0.22 | 21 (16.67) | 22 (17.46) | 0.94 |
| High | 14 (11.02) | 60 (47.24) | 0.01 | 29 (23.02) | 41 (32.54) | 0.38 |
| Hypertension: given by mean and (SD) | | | | | | |
| Presence | 51 (16.50) | 136 (44.01) | 0.0005 | 114 (39.45) | 51 (17.65) | 0.005 |
| Absence | 18 (5.83) | 104 (33.60) | 0.01 | 5 (1.73) | 119 (41.18) | 0.07 |
| Dyslipidemia: given by mean and (SD) | | | | | | |
| Presence | 30 (11.86) | 142 (56.13) | <0.001 | 95 (37.25 ) | 78 (30.59) | 0.35 |
| Absence | 19 (7.51) | 62 (24.51) | 0.01 | 12 (4.71) | 70 (27.45) | 0.08 |

*obtained from the T-test for the difference of proportions according to the presence of diabetes; **obtained from the T-test for the difference of proportions according to the presence of metabolic syndrome; BMI, body mass index; DM2, diabetes mellitus type-2; MS, metabolic syndrome.

**Table 3. Characterization of the built environment surrounding homes of patients with DM2 diagnosis.**

| Variable | Subjects without DM2 | Subjects with DM2 | p* |
|---|---|---|---|
| NDVI: given by number and (%) | | | |
| Soil without vegetation | 30 (19,2) | 5 (3,2) | 0,37 |
| Sparse vegetation | 73 (46,8) | 33 (21,2) | 0,01 |
| Medium vegetation | 10 (6,4) | 4 (2, 6) | 0,77 |
| Thick vegetation | 1 (0,6) | NP | NA |
| NDWI: given by umber and (%) | | | |
| Drought | NP | NP | NA |
| Moderate drought | 4 (2,6) | NP | NA |
| Moist soil | 107 (68,6) | 42 (26,9) | <0,00001 |
| Water surface | 3 (1,92) | NP | NA |
| NDBI: given by number and (%) | | | |
| Mostly built-up land | 34 (21,8) | 6 (3,85) | 0,3 |
| Mostly vegetative cover | 80 (51,3) | 36 (23,1) | 0,004 |

*obtained from the T-test for the difference of proportions according to the presence of diabetes; DM2, diabetes mellitus type-2; NDVI, normalized difference vegetation index; NDWI, normalized difference water index; NDBI, normalized difference building index; NP, not present; NA, not applicable.

respect to the NDWI index. Hence, there was significantly higher moist soil in the surroundings of houses where there were no MS cases compared to houses with MS patients (57.0% *vs* 38.7%, respectively; p=0.03).

Concerning purely spatial analysis, Figure 3 shows the output of the nearest neighbour model, which yielded a statistically significant spatial clustering of the DM2 variable (p=0.02). The observed cluster had a radius of 13.7 km and an area of 592.8 km$^2$ (70% of which corresponded to urban plots of the land). There were 78 study subjects living within the cluster limits, out of which number 31 presented with DM2. This yielded a spatial prevalence of 39.7%, whereas the expected number of cases according to the mean and dispersion of data was 19.9%. The relative risk of the cluster was 3.49, which indicated that people whose homes were distributed within the cluster had a 3.5 higher chance of being positive for DM2 than those located outside the cluster. The MS hotspot map in Figure 3 shows that the purple colours (which indicate a higher prevalence of MS) were found within the detected diabetes cluster. Moreover, the same purely spatial analysis was performed for the presence/absence of MS, but no significant clustering was observed.

The logistic multivariate analysis showed a risk association between NDVI and positive DM2 diagnosis (Table 4). It was observed that in contrast to compared to the low NDVI values, the high NDVI values were associated with a lower probability of DM2 diagnosis (OR= 0.81, 95% CI -0.30 to 1.66, p=0.05) adjusted for age, sex, BMI, caloric intake, diet quality and physical activity. In this sense, although the p-value equals the 0.05 significance level, it is interesting that the result found was close to the threshold. Similarly, low NDBI values (*i.e.* mostly vegetative cover), compared to the presence of BE cover, decreased the odds of having a diabetes diagnosis (OR= -1.39, 95% CI -2.62 to -0.17, p=0.03) and adjusted by the same variables. No significant associations were detected between the BE variables and MS.

## Discussion

Exploration of the presence of CMDs and risk factors related to subjects attending the HNC in Córdoba City, informed us that obesity was associated with a lower prevalence of CMD (this can be explained in case the subjects are under treatment), while subjects with increased WC values showed a higher proportion of CMDs. The literature amply demonstrates that both WC and obesity correlate positively with CMD risk (Ferreira *et al.*, 2018; Goossens, 2017). Moreover, the former is a good predictor of DM2, so it is relevant to include this indicator in the surveillance of global obesity (Ross *et al.*, 2020). Positive correlation of increased blood lipid values with the presence of CMDs has been demonstrated (Ramirez & Agredo, 2012; Wang *et al.*, 2013), which

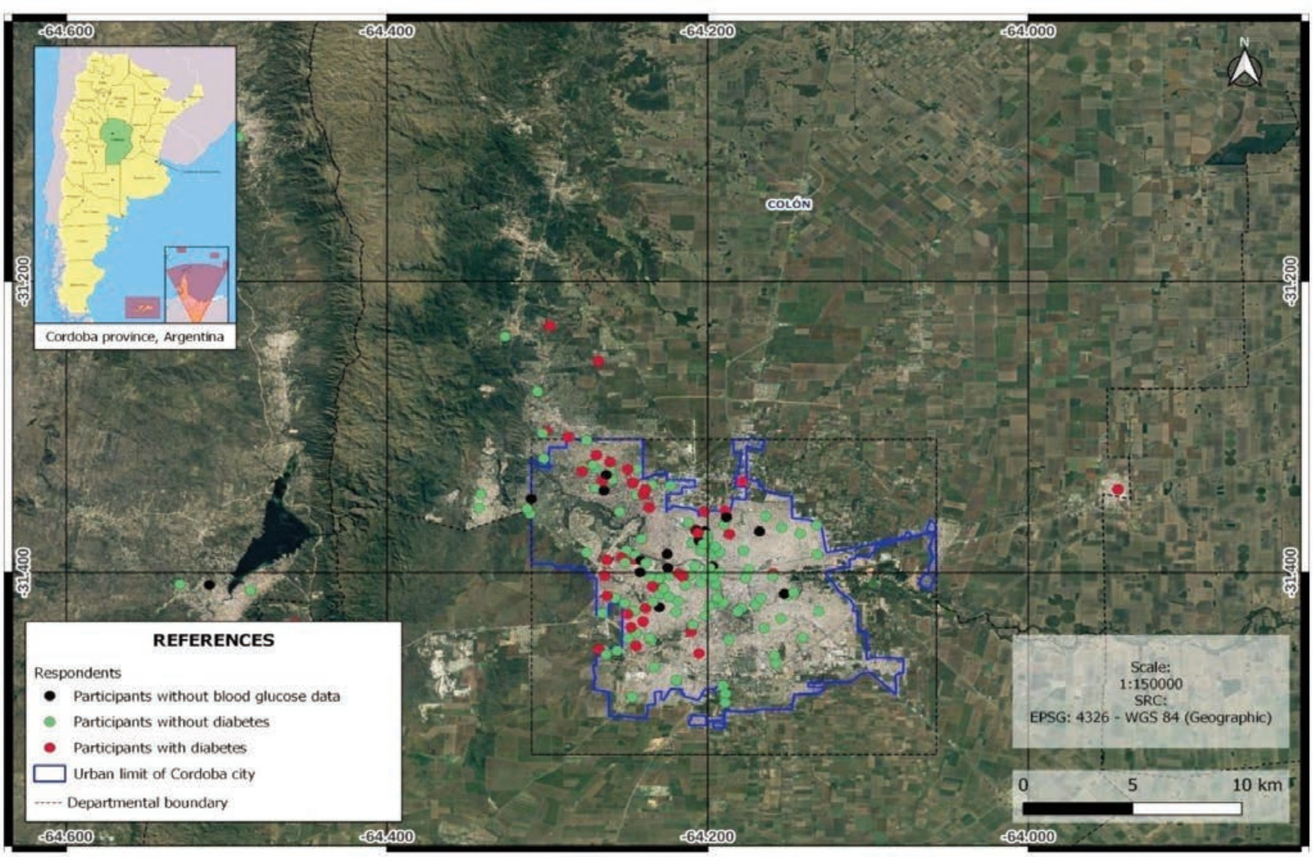


**Figure 2. Map of DM2 cases Map data© 2020 Google. Base map obtained from Quick Map Services QGIS plugin- Open Source Geospatial Foundation Project (http://qgis.osgeo.org)**

is in line with the elevated serum lipid and hs-CRP values found in this study. It was additionally found that the ideal healthy diet was the least representative in relation to food intake (only 3 people in this category), and there was a lower proportion of people with DM2 and MS among people with diets at the intermediate and poor level. That the quality of the diet did not correspond significantly to a lower CMD prevalence may be due to ongoing nutritional and drug treatment; in fact, several investigations in Latin America, report that a healthy diet is the least prevalent category, with a range between 0.2% and 23.6% (Benzinger *et al.*, 2018; Matozinhos *et al.*, 2017). A more healthy diet is related to the higher local consumption of fruits, vegetables, and fish as well as the

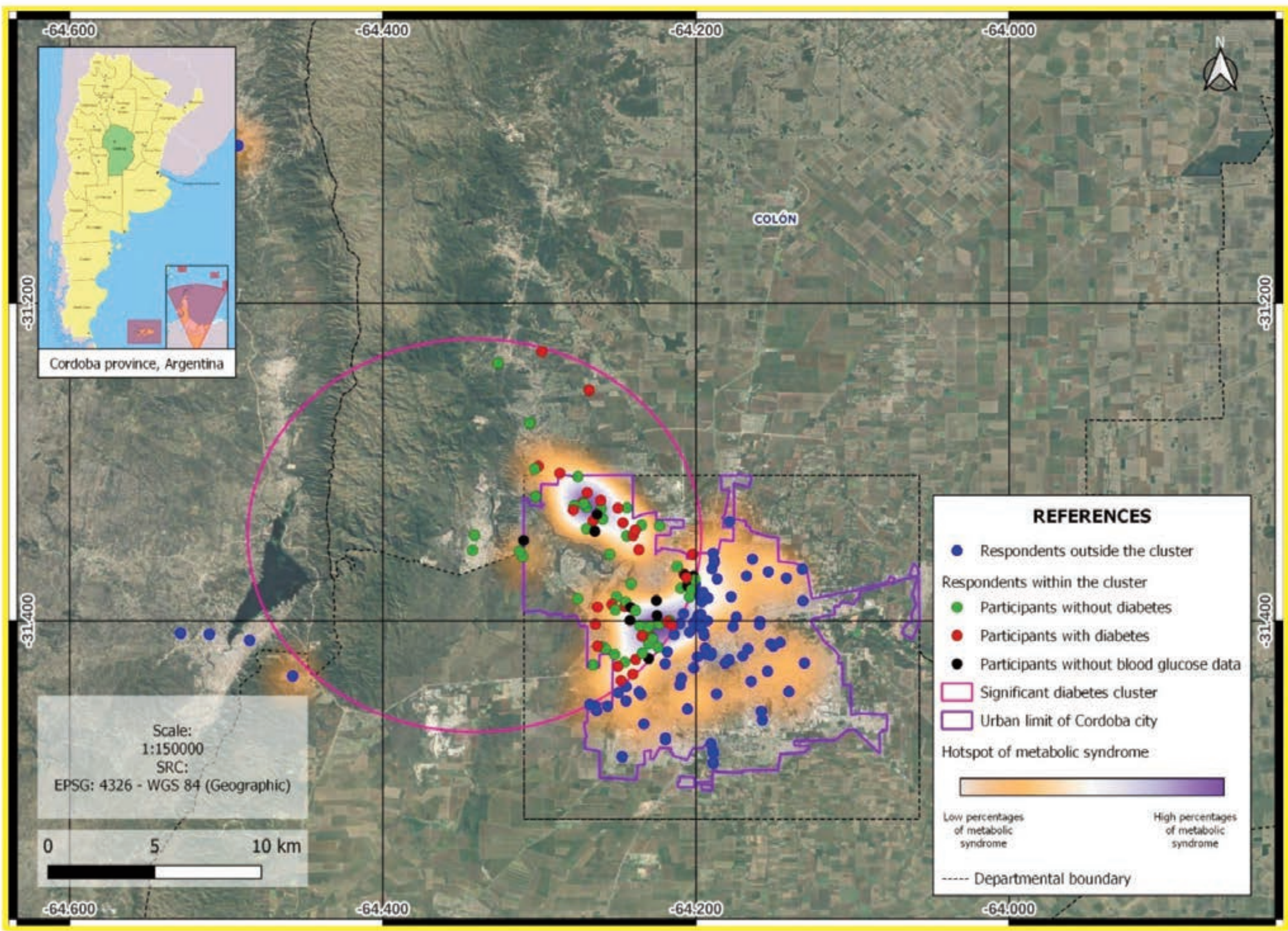


**Figure 3. Cluster map of diabetes-positive cases in superposition of a MS hotspot, obtained by purely spatial analysis. Map data© 2020 Google. Base map obtained from Quick Map Services QGIS plugin - Open Source Geospatial Foundation Project (http://qgis.osgeo.org).**

**Table 4. Multivariate logistic regression of the presence of diabetes.**

| Variable | Multi-variable OR | 95% CI | p* |
|---|---|---|---|
| NDVI** | 0,81 | (- 0,03 - 1,66) | 0,05 |
| NDBI** | -1,39 | (- 2.62 - -0.17) | 0,03 |
| Sex | 0,32 | (- 0,60 -1,26) | 0,49 |
| Age** | -0,04 | (-0,09 - 0,002) | 0,06 |
| BMI** | 0,98 | (- 0,27 - 2,24) | 0,12 |
| Total energetic value** | -0,0002 | (- 0,0006 - 0,00008) | 0,13 |
| Healthy diet** | 0,42 | (-0,43 - 1,29) | 0,33 |
| Physical activity** | -0,008 | (-0,72 - 0,70) | 0,98 |

OR, odds ratio; CI, confidence interval; NDVI, normalized difference vegetation index; NDBI, normalized difference building index; BMI, body mass index *resulting from multivariate logistic regression; **treated as continuous variable.

implementation of nutritional food education programmes aimed at the consumption of these types of food (Matozinhos *et al.*, 2017). In turn, other authors argue that the comparatively low level of availability and affordability of healthy foods may be an important factor in low adherence to a healthy diet. Thus, less availability and elevated costs of healthy foods may be hindering adequate consumption (Schwingshackl & Hoffmann, 2014; Seron *et al.*, 2018; Tobias *et al.*, 2015).

This work evidenced a lower proportion of people with hypertension among those with DM2; compared to those with MS. In this regard, the literature agrees that hypertension plays a central role for CMDs due to its association with several metabolic disorders, such as insulin resistance, hyperinsulinemia, abdominal obesity and dyslipidemia (Tasic & Lovic, 2018). Considering the spatial distribution of CMDs, the presence of MS and DM2 was higher in Cordoba compared to the rest of the localities included in the study area. Although urbanization has been commonly related to a higher number of NCDs since it promotes lifestyles characterized by less physical activity and often unhealthy diets, results are still inconsistent (Den Braver *et al.,* 2018). Several authors claim that urbanization and well-organized neighbourhoods allow mobility alternatives, better street connectivity and higher density of shops etc., which improves walkability, resulting in less sedentary and more active behaviour (Chandrabose *et al.*, 2019; Den Braver *et al.*, 2018; Malambo *et al.*, 2016; Paquet *et al.*, 2014). However city designs are very heterogeneous, and walkability is not the only aspect of BE, with an influence on the development of CMDs. Even in one and the same city, there may be different walkability levels. Thus, in relation to the environmental variables studied to characterize BE, evidence shows that higher levels of green spaces (or greenery in general) are associated with a lower prevalence of CMDs. The reason may be that these spaces stimulate outdoor physical activities with the consequent reduction of adiposity (Yang *et al.*, 2020; Voss *et al.*, 2021). In this regard, it has been reported that physically active people in parks are more likely to continue exercising (Muller Riemenschneider *et al.*, 2020). In other words, a BE with greener areas promotes better levels of physical activity and outdoor recreation. Our results are in agreement with previous evidence, as the presence of DM2 showed a reduction in the risk at high NDVI levels and low NDBI ones. It should be clarified that studies suggesting that exposure to vegetation reduces the risk of, and mortality from, CMDs are mostly cross-sectional and limited in their attribution of causality (Dadvand *et al.*, 2016; Pereira *et al.*, 2012). However, a prospective study in the northern USA determined that the loss of trees indeed increased CMDs (Donovan *et al.*, 2013).

The MS heat map shows that the hotspots identified lay mostly within the DM2 cluster identified in the north-western area of Córdoba City towards what is called greater Cordoba. In a study by Alvarez Di Fino *et al.* (2019), a higher variability in WC and obesity prevalence between the eastern and western parts of Córdoba was reported. This study validates our findings and the relationship between WC and obesity with MS and DM2 has been commonly reported in the literature (Hirschler *et al.*, 2010; Liu *et al.*, 2010).

Data on the sociodemographic characteristics of Córdoba city and greater Córdoba that was obtained in the 2010 census show a higher percentage of households with unsatisfied basic needs towards the periphery of the city and towards the north-western periphery of the metropolitan area (which coincides with the points indicated as DM2 positive in the cluster obtained). Evidence shows that people living in geographical areas with low socioeconomic status are significantly associated with a higher risk of developing DM2 and with higher morbidity and mortality related to this disease (Emadi et al., 2019; Hipp & Chalise, 2015; Gassasse *et al.*, 2017; Lago-Peñas *et al.*, 2020). In lower socioeconomic conditions, access to fresh food decreases, while processed products (which are high in fats and sugars, *i.e.* "empty" calories) are more economically accessible (Popkin *et al.*, 2012). This trend is mostly observed in developing countries (as in this case), where poor and peri-urban populations have a higher consumption of what is called "obesogenic" food, with lower consumption of fresh vegetables and grains (Popkin *et al.*, 2012). Without a doubt, the increase in the production of processed and ultra-processed foods, rapid urbanization, and changing lifestyles have led to a change in eating habits (Scarlatta & Defagó, 2020). Indeed, the Latin American Nutrition and Health Study reported that populations aged 15-65 years in Argentina and Peru were the main consumers of sugar-sweetened beverages (Kovalskys *et al.*, 2019). This is in line with this work, where a high consumption of sugary drinks and sodium was observed.

This work is pioneering at the local level but some limitations could not be avoided, e.g., the reduced sample size and the lack of high spatial resolution images. In addition, the household-centred analysis captures the characteristics and resources within an individual's neighbourhood; however, proximity does not always allow inferences on household use. Therefore, it would be useful to also take into account variables where the physical activity takes place and where food is acquired and/or consumed. Finally, the inaccessibility of socioeconomic and demographic information from the latest (2022) National Census at the local scale necessitated the use of the 2010 Census data, the only source of reliable, official data available on socio-demographic aspects.

## Conclusions

The present manuscript represents an innovative approach to understand the relationship between health and BE. The fact that environmental variables such as NDVI and NDBI can explain part of the variability of the NCDs under study reinforces the idea that environmental studies should include the investigation of the physical space as a fundamental part of the context in which people develop in society. The DM2 cluster detected opens the door to a larger study of NCDs in the area. In this context, the use of satellite imagery applied to collect information on people and populations' environment is novel and efficient.

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