

A New Approach to Studying the Cardiovascular Health Index Using Satellite Tools and Machine Learning

Un nuevo enfoque para estudiar el Índice de Salud Cardiovascular utilizando herramientas satelitales y aprendizaje automático

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Declaration of interests

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Abstract

Introduction. Cardiovascular diseases are the leading cause of morbidity and mortality worldwide, and their occurrence is linked to behavioral and modifiable risk factors, such as the built environment (BEs). The objective of this study was to characterize the spatial distribution of the Ideal Cardiovascular Health Index (ICHI) and its association with BEs among individuals attending the Non-Invasive Cardiology Service at the Hospital Nacional de Clínicas in Córdoba, Argentina, during the period 2018-2020.

Methods. An observational, correlational, and cross-sectional study was conducted. Clinical, anthropometric, and lifestyle variables used to determine ICHI were collected through validated instruments. A spatial XGBoost was used for modelling the possibility of having poor ICHI. The associations between variables were evaluated by multivariate logistic regression analyses ($p < 0.05$).

Results. Overall, 91.36% of participants had a “poor” ICHI, and no participants were classified as “ideal.” A spatial pattern emerged showing participants with a “poor” ICHI towards the northwest of the study area. The distribution of “intermediate” ICHI cases showed relative spatial homogeneity. Lower educational levels and certain occupations were associated with an increased likelihood of having a “poor” ICHI. An $F1 = 0.75$ was obtained with the XGBoost model.

Ethics statement

This study was approved by the Ethics Committee of the National Clinical Hospital (Hospital Nacional de Clínicas, HNC), affiliated with the National University of Córdoba (UNC), Argentina. The approval was recorded in Minutes Book II, entry No. 177. All participants provided written informed consent before participation.

Data availability

All data supporting the findings of this study are available within the article. For additional details, please contact the corresponding author.

Author Contributions

Micaela Natalia Campero: conceptualization, formal analysis, investigation, methodology, supervision, writing – original draft.

Carlos Matías Scavuzzo: conceptualization, formal analysis, investigation, methodology, supervision, writing – original draft.

Mauro Gómez: formal analysis, investigation, writing – review & editing.

Maria Georgina Oberto: formal analysis, investigation, writing – review & editing.

María Lucía Baraquet: formal analysis, investigation, writing – review & editing.

Maria Daniela Defagó: conceptualization, methodology, project administration, writing – review & editing.

Generative AI declaration

The authors declare that no generative AI tools were used in the writing, editing, data analysis, or any other part of the preparation of this manuscript.

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Conclusions. There is a need for multifaceted interventions addressing both individual and contextual determinants of cardiovascular health. Machine learning tools are novel, useful approaches for detecting ICHI in cardiovascular health.

Keywords

Cardiovascular diseases; built environments; landscape epidemiology; machine learning.

Resumen

Introducción. Las enfermedades cardiovasculares son la principal causa de morbilidad y mortalidad a nivel mundial, y su incidencia está vinculada a factores de riesgo conductuales y evitables, como el entorno construido. El objetivo de este estudio fue caracterizar la distribución espacial del Índice Ideal de Salud Cardiovascular (ICHI) y su asociación con los entornos construidos (EC) de las personas que acudieron al Servicio de Cardiología No Invasiva del Hospital Nacional de Clínicas de Córdoba, Argentina, durante el período 2018-2020.

Métodos. Se realizó un estudio observacional, correlacional y transversal. Se recolectaron variables clínicas, antropométricas y de estilo de vida empleadas para determinar el ICHI mediante instrumentos validados. Se utilizó un XGBoost espacial para modelar la posibilidad de tener un ICHI deficiente. La asociación entre las variables se evaluó mediante análisis de regresión logística multivariada ($p < 0,05$).

Resultados. El 91,36 % de los participantes presentó un ICHI deficiente y ningún participante fue clasificado como ideal. Se observó un patrón espacial que mostraba a los participantes con un ICHI “bajo” hacia el noroeste del área de estudio. La distribución de los casos de ICHI “intermedio” mostró una relativa homogeneidad espacial. Un menor nivel educativo y ciertas ocupaciones se asociaron con una mayor probabilidad de tener un ICHI deficiente. Se obtuvo un puntaje F1 de 0,75 con el modelo XGBoost.

Conclusiones. Se necesitan intervenciones multifacéticas que aborden los determinantes individuales y contextuales de la salud cardiovascular. Las herramientas de aprendizaje automático son enfoques novedosos y útiles para detectar patrones asociados al ICHI en la salud cardiovascular.

Palabras clave

Enfermedades cardiovasculares; entornos construidos; epidemiología panorámica; aprendizaje automático.

Introduction

Non-communicable chronic diseases (NCDs) are the leading cause of death and disability worldwide. Each year, 41 million people die from NCDs, accounting for approximately 71% of global mortality [1]. These diseases represent one of the greatest challenges to health and human development, particularly in developing countries, due to their profound health, economic, and social consequences. The main risk factors for NCDs include unhealthy diets, tobacco use, harmful alcohol consumption, and physical inactivity [2].

The global relevance of NCDs and their determinants is highlighted in major international frameworks, including the United Nations 2030 Sustainable Development Goals (SDGs). Specifically, SDG 3 aims to reduce premature mortality from NCDs by one third through prevention, treatment, and the promotion of mental health and well-being. Likewise, the World Health Organization (WHO) recognizes NCDs as a global priority because of their substantial public health and economic burden [3].

Among NCDs, cardiovascular diseases (CVDs) constitute the leading cause of morbidity and mortality worldwide. According to the Pan American Health Organization (PAHO, 2023), CVDs account for 38% of all NCD-related deaths. Therefore, improving cardiovascular health through the promotion of healthy lifestyles and preventive strategies is essential [1]. In this context, the American Heart Association proposed the concept of the Ideal Cardiovascular Health Index (ICHI) to emphasize the importance of primary prevention. The ICHI is defined by the presence of four ideal health behaviors (non-smoking, body mass index-BMI <25 kg/m², regular physical activity, and a healthy diet) and three ideal health factors (untreated total cholesterol <200 mg/dL, untreated blood pressure <120/<80 mmHg, and untreated fasting glucose <100 mg/dL) [4]. Based on these criteria, individuals are classified into three categories—poor, intermediate, or ideal cardiovascular health—depending on their adherence to the defined behaviors and factors [5]. A population-based study conducted in the Southern Cone of Latin America reported a low prevalence of adherence to the ICHI, with only 0.1% of participants meeting all seven criteria [5]. Similar findings were observed in Argentina, where the prevalence of adherence to the ICHI among adults aged over 40 years was also low [6].

Despite global efforts, most NCDs and their risk factors are preventable and often occur prematurely due to suboptimal lifestyles and environmental conditions that promote disease development. Built environments (BEs), defined as the man-made surroundings where people live, work, and engage in daily activities, play a crucial role in the adoption of health behaviors. According to the American Heart Association, the factors that contribute the most to rising mortality and NCDs in developing countries (obesity, hypertension, type 2 diabetes, and major CVD), are the rapid urbanization and technological advancement, walkability, urban exposure, transit accessibility, and access to green spaces, along with socioeconomic factors that indicate greater vulnerability [7].

In recent years, Geographic Information Systems (GIS) and remote sensing data have become essential tools for studying the relationship between BEs and NCDs. These systems allow for the spatial analysis of various health-related variables, facilitating the identification of risk areas and the planning of effective interventions [8]. In Latin America, the application of GIS has enhanced the understanding of the interactions between BEs and health, highlighting their potential to improve the prevention and management of NCDs [9,10]. Additionally, the use of machine learning (ML) models in addressing CVDs has revolutionized the ability of researchers to predict and manage these conditions. ML algorithms are commonly used for risk stratification of patients, enabling more personalized and precise interventions. These technologies enable spatial analysis of health-related variables, facilitating the identification of high-risk areas and the design of effective public health interventions. However, their use in Latin America, particularly in Argentina, remains limited [11,12].

The aim of this study was to design and implement a combined methodological approach to address CVDs through the analysis of the geospatial characterization of the ICHI and its relationship with the built environment in an urban midsize city in Argentina and its metropolitan area. By utilizing spatial analysis tools and a spatial machine learning model, this research seeks not only to identify risk areas but also to provide valuable information for the

promotion of healthy environments and the prevention of CVDs. We hypothesized that the characteristics of the BEs are significantly associated with adherence to the ICHI in the population under study.

Methods

This work is part of the “Clinical-epidemiological approach to hypertension based on biomarkers and the food environment” project (Resolution of the Secretariat of Science and Technology of the National University of Córdoba (UNC) No. 411/18), which was also approved by the Ethics Committee of the National Clinical Hospital (Hospital Nacional de Clínicas, HNC), affiliated with the National University of Córdoba (UNC), Argentina. The approval was recorded in Minutes Book II, entry No. 177, dated September 13, 2018. All methods were conducted in accordance with the Declaration of Helsinki for research on human subjects. Córdoba city is considered the third largest urban center in Argentina and it is located in the center of the country, with approximately 1,500,000 inhabitants.

Participation was voluntary, considering the following inclusion criteria: adults of both sexes, of any ethnicity, over 30 years old, diagnosed with CVDs and/or associated risk factors (i.e. diabetes, dyslipidemia, hypertension), with signed informed consent. Exclusion criteria included adults on special diets or with extreme energy intake (≤ 800 and ≥ 7000 kcal/d), pregnant or breastfeeding women, individuals with cognitive impairment, chronic renal or hepatic failure, severe septic state, and those diagnosed with HIV/AIDS.

Clinical-pathological aspects were obtained from each patient’s medical records, extracting personal data, address records, family history of NCDs, and current diseases. Information on smoking habits, alcohol consumption, and other toxic substances was collected by trained interviewers [13]. Blood samples were obtained from each patient via venipuncture by the hospital Central Laboratory and biochemical values (glycemia, lipid profile, high-sensitivity C-reactive protein among others) were determined by standardized techniques. Anthropometric measurements (weight, height and waist circumference (WC)) were taken according to WHO guidelines (1995) and blood pressure measurements by American Heart Association guidelines (2020) [14,15]. Physical activity was assessed using the International Physical Activity Questionnaire (IPAQ), evaluating the type, intensity, and frequency of activity [16]. Food intake was evaluated by trained nutritionists and nutrition students from the research team using a validated food frequency questionnaire (FFQ). FFQ requests information concerning food choices, portion size, quantity, and frequency intake [17]. Food data was processed using a software package called Interfood v.1.3, to produce information in grams/day of each food item consumed and also about nutrient intake [18].

Based on obtained information, the level of adherence to ICHI was calculated [5,19]. As mentioned above, the ICHI is determined by evaluating whether an individual meets the seven ideal cardiovascular health metrics: smoking status, diet quality, physical activity, BMI, blood pressure, total cholesterol, and fasting glucose. Each metric is scored as 0 (unhealthy) or 1 (healthy), and the total ICHI is calculated as the sum of these scores, ranging from 0 to 7. A total score of 7 represents ideal cardiovascular health, whereas a score of 0 reflects poor cardiovascular health.

Regarding BEs measurements, environmental indices linked to the structure of cities (vegetation, soil moisture and urbanization, as described below) were obtained by calculating bands from a collection of Sentinel 2 satellite images from the study period. Index calculations were performed on the Google Earth Engine platform based on a collection of images with less than 10% cloud cover (Figure 1).

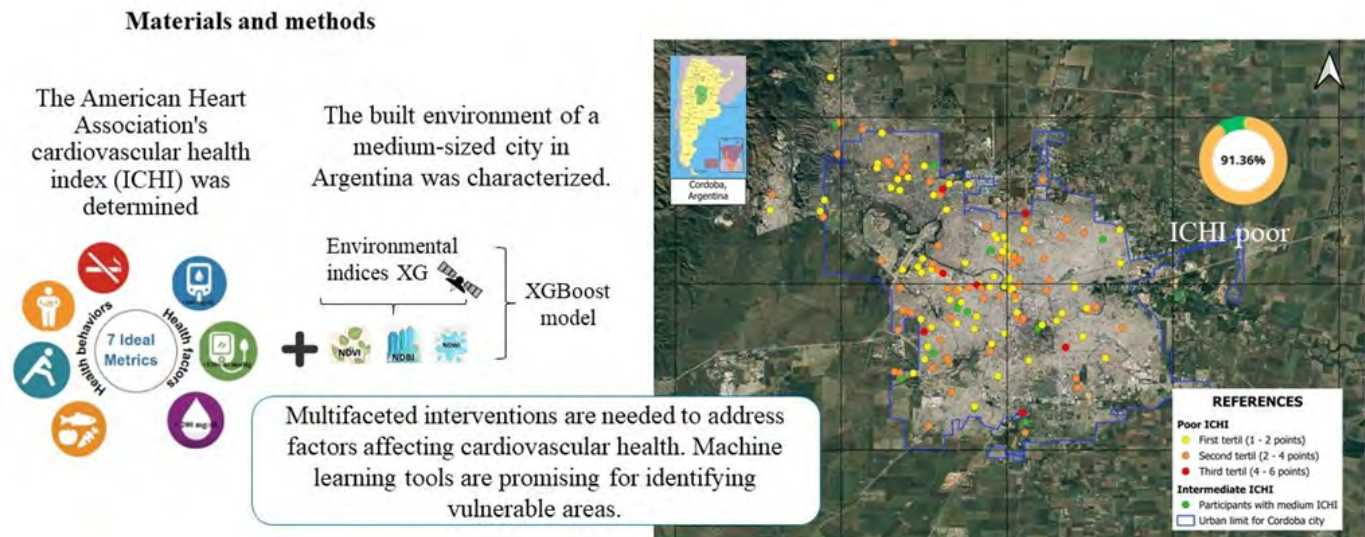


Figure 1. Central illustration. Summary of the main results of the study.

Data Analysis

Clinical and environmental information was analyzed to identify health factors and behaviors, and to determine the level of adherence to ICHI. An exploratory analysis of sociodemographic and BEs variables was conducted by summary and frequency measures (t-test). Associations between qualitative variables were evaluated using Pearson's Chi-square test or Fisher's exact test ($p < 0.05$).

For obtaining BEs variables, a vector layer of points with the geographic location of each household (from latitude and longitude coordinates obtained via Google Maps through medical records) was created; an environmental layer corresponding to the 2020 annual averages of Normalized Difference Vegetation Index (NDVI) (vegetation), Normalized Difference Water Index (NDWI) (soil moisture), and Normalized Difference Built-up Index (NDBI) (urbanization) was added to the point layer (characteristics of BEs whereas they reflect the environment modified by humans). The mean values of these indexes were calculated in the peridomicile represented by a 50 m buffer for each household.

A GIS was constructed by overlaying information layers based on the geospatial distribution of ICHI categories. The relevant cartography was prepared using QGIS 3.28 software.

Two classification models were instantiated in order to evaluate the association of BEs characteristics with poor ICHI: Logistic Regression (scikit-learn) and XGBoostClassifier. In both models, the components of the index were used independently as features (prior to classification for the calculation of the index), as well as individual adjustment variables (gender, age, occupation, and educational level) and BEs variables (indices obtained from remote sensing). Both models used the same training and testing data and were subjected to the same evaluation criteria. All details of the routine used for statistical analysis can be found at <https://n9.cl/v0coln>

Results

Table 1 shows the basic characteristics of the study subjects. A total of 45.32% were obese and 26.06% were smokers. No significant differences were observed according to sex in total cholesterol, but values higher than desirable were observed in the group of women. Significant differences were found according to gender for blood pressure and blood glucose parameters. In addition, SBP levels were found to be above the recommended limit.

Table 1: Anthropometric and clinical characteristics of the study participants.

	All (n=342)	Women (n=181)	Men (n=161)	p
BMI (Kg/m²), mean (± SD)	30.57 ± 6.82	30.54 ± 7.39	30.60 ± 6.12	0.94
Low weight, n (%)	4 (1.17)	3 (1.66)	1 (0.62)	0.02**
Normal weight, n (%)	61 (17.83)	40 (22.09)	21 (13.04)	
Overweight, n (%)	122 (35.67)	54 (29.83)	68 (42.23)	
Obesity, n (%)	155 (45.32)	84 (46.40)	71 (44.09)	
Current smoker, n (%)	61 (26.06)	32 (12.15)	29 (18.02)	0.90
Physical activity (METs), mean (± SD)	1759.88 (2709.78)	1531.45 (2027.88)	2020.94 (3310)	0.11
Total cholesterol (m/dL), mean (SD)	197.55 ± 44.63	207.30 ± 43.98	186.33 ± 42.88	0.94
SBP (mmHg), mean (± SD)	133.21 ± 21.03	130.02 ± 21.08	136.84 ± 20.44	0.003*
DBP (mmHg), mean (± SD)	79.79 ± 12.04	77.42 ± 11.56	82.49 ± 12.04	0.0001*
Blood glucose (mg/dL), mean (± SD)	108.62 ± 33.45	104.66 ± 24.96	113 ± 40.94	0.04*

Notes. Values are presented as means and standard deviations (SD) for continuous variables and frequencies (percentages) for categorical variables. T-test and Wilcoxon test (*) were used to evaluate statistical differences in continuous variables, and Fisher test (**) to analyze statistical associations in categorical variables.

Regarding the ICHI, 91.36% had a “poor” ICHI, 9.09% of the total sample had an “intermediate” ICHI, and no subjects met all 7 ideal metrics to be classified as “ideal”. For “poor” ICHI 51.69% were women and 48.31% men. Also, in the “poor” category, 85.60% resided in the city of Córdoba and 14.40% in the interior of Córdoba, a difference that was not statistically significant but may have clinical relevance ($p = 0.074$).

Figure 2 shows the spatial distribution of the individuals in the sample based on the geolocation of their residences. Córdoba city showed the highest percentage of participants (84.64%), with less presence in the rest of the metropolitan area (15.36%).

For the “poor” category of the index, the number of ICHI components that obtained this value was summed and divided into tertiles, according to the amount: yellow, 1 to 2 components with a poor value; orange, 2 to 4 components with a poor value; red, 4 to 6 components with a poor value. The high adherence to the poor index is shown on the map, where a distribution of people with more components that make up a poor index (red dots) can be seen in a west-north direction. The distribution of “intermediate” cases (green) showed relative spatial heterogeneity.

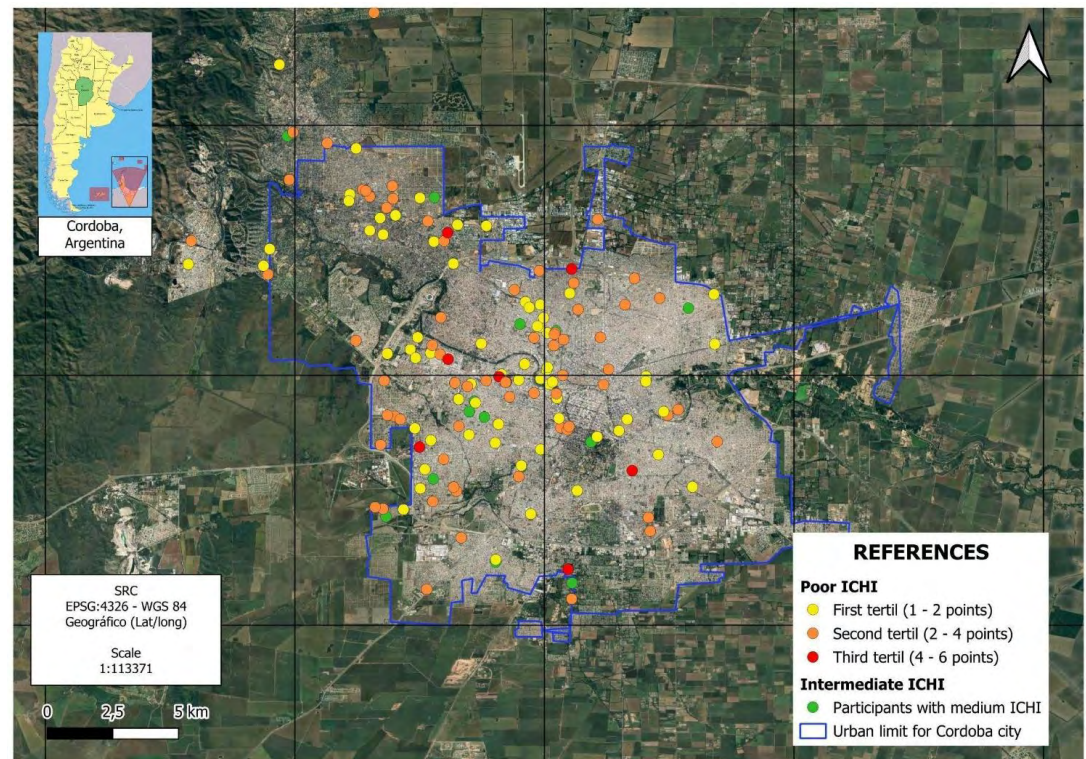


Figure 2. Geospatial distribution of the ICHI in the study sample.

Note. The area included in this study corresponds to Córdoba city and surroundings. Map data © 2020 Google. Base map obtained through Quick Map Services QGIS plugin - QGIS Geographic Information System. Open source: Geospatial Foundation Project. <http://qgis.osgeo.org>.

Regarding BEs variables, the main NDVI value was 0.284 (SD 0.998) (corresponding to the *little vegetation* category). As can be seen, (Table 2), 69.09% of the households in the total sample had a surface with *little vegetation*, 20% had *no vegetation*, 10.3% had “medium vegetation,” and only one household had a surface with “dense vegetation.”

Table 2. Characterization of the built environment of the sample differentiated by ICHI.

Environmental Variables	ISCI [No. (%)]		TOTAL	*p-value
	Intermediate	Poor		
NDVI (n = 164)				0,82
Soil without vegetation	5 (25)	30 (20,83)	35 (21,34)	
Little vegetation	13 (65)	100 (69,44)	113 (68,90)	
Dense vegetation	s/d	1 (0,69)	1 (0,61)	
Medium vegetation	2 (10)	13 (9,03)	15 (9,15)	
Total	20 (100)	144 (100)	164 (100)	

NDWI (n = 164)				0,6
Drought	s/d	s/d	s/d	
Moderate drought	1 (5)	3 (2,08)	4 (2,44)	
Moisture	19 (95)	138 (95,83)	157 (95,73)	
Surface with water	s/d	3 (2,08)	3 (1,83)	
Total	20 (100)	144 (100)	164 (100)	
NDBI (n = 164)				0,59
Built-up cover	6 (30)	35 (24,31)	41 (25)	
Vegetation cover	14 (70)	109 (75,69)	123 (73)	
Total	20 (100)	144 (100)	164 (100)	

Note. n: sample, No: absolute frequency; %: relative frequency, s/d: no data.

As for NDWI, the mean value was 0.058 (SD 0.050), in the *moisture* category. No household had a surface determined by *drought*, only three had a surface with *moderate drought*, and almost all (96.36%) had a surface with *moisture*.

Concerning, NDBI mean value was -0.022 (SD 0.029), in the *vegetation cover* category. Only two categories differentiated this variable, with households having *built-up cover* accounting for 24.85% of the sample, and the rest (75.15%) having more *vegetation cover* than *built-up cover*.

Referring to the values found in the “poor” ICHI category, it is observed that for NDVI, 69.44% of subjects live on a surface with *little vegetation*. For NDWI, almost all live on a surface with *moisture*. Regarding NDBI, 75.69% have a surface with *vegetation cover*. No significant association values were found between environmental variables and ICHI.

Both models proved robust in predicting “poor” ICHI values for patients, with a very low rate of erroneous predictions (accuracy and sensitivity above 90%, area under the ROC curve above 0.9, and optimal classification reports).

Upon investigating the most relevant characteristics for the models’ predictions, we found that both “TBQ_cod” (tobacco consumption) and “IMC_Kg/m2” had a greater influence in predicting class 1 (ICHI == ‘Poor’), and that for Logistic Regression, “NDVI_clasif_Poca Vegetacion” gives meaning to the prediction of class 0 “ICHI == “Intermediate” (Figure 3).

The XGBoost model effectively predicted poor ICHI by integrating social variables (education, occupation) and remotely sensed environmental indices (NDWI, NDVI, NDBI), adjusted by age. Age was the most influential predictor (23% gain), followed by NDBI (20%), NDVI (19%), NDWI (17%), education (11%), and occupation (10%), aligning with known cardiovascular risk factors. While model performance was perfect on training data (F1, MCC, sensitivity, and precision = 1.00), validation showed reduced generalization: F1 scores of 0.75 (category 3), 0.40 (category 2), and 0.25 overall; MCCs of 0.42, 0.17, and 0.13; with lower sensitivity and precision for certain classes, particularly category 2. These gaps reflect challenges with class imbalance and limited generalization. The classification map (Figure 4) shows correct predictions (blue points) in central, southern, and eastern areas, while misclassifications (orange points) tend to be distributed in west-north zones (such as poor ICHI). Overall, the model captures key determinants of cardiovascular health in dense urban areas, but requires additional data to enhance performance in peripheral regions.

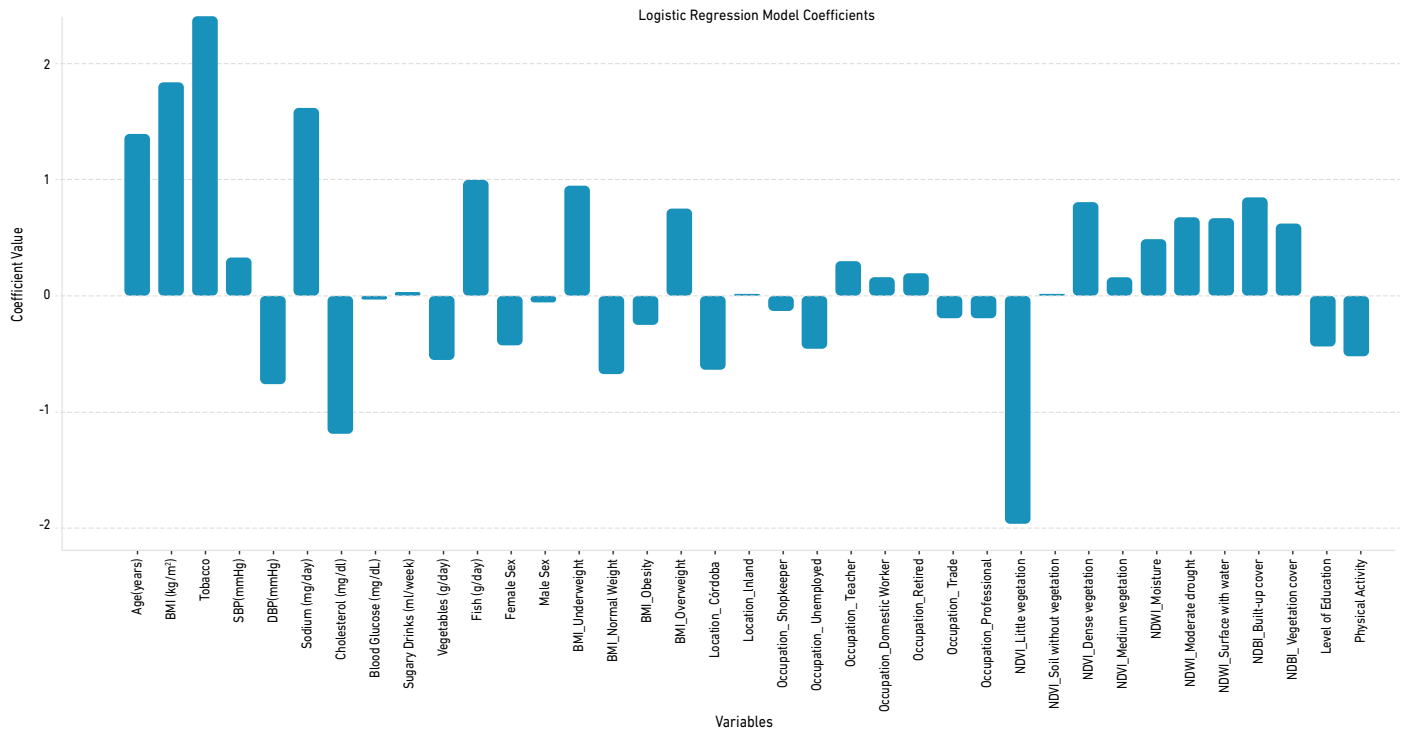


Figure 3: Logistic regression model coefficients.

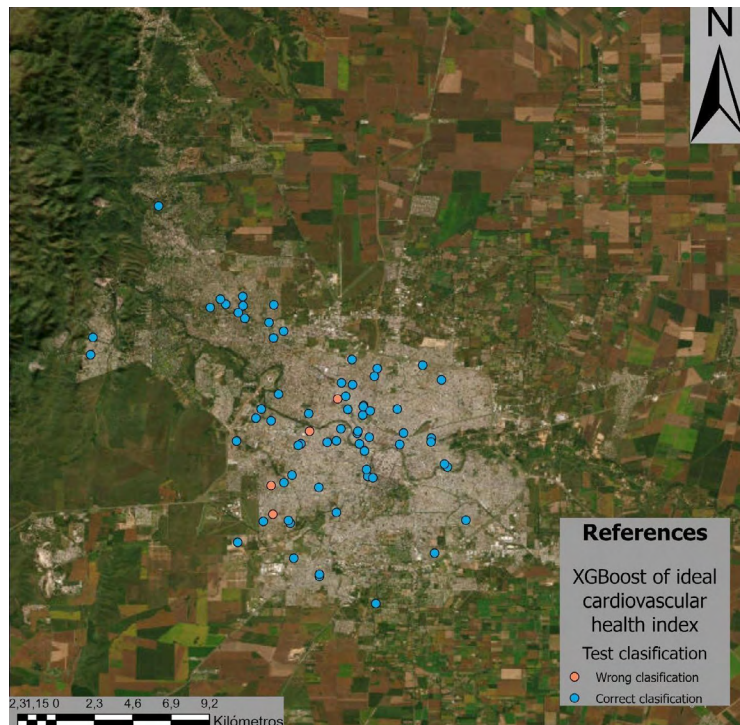


Figure 4: XGBoost classification of cardiovascular health index.

Note. The area included in this study corresponds to the City of Córdoba and its surroundings. Map data © 2020 Google. Base map obtained through Quick Map Services QGIS plugin - QGIS Geographic Information System. Open source: Geospatial Foundation Project. <http://qgis.osgeo.org>.

Discussion

The aim of this study was to design and implement a combined methodological approach to address CVDs through the analysis of the geospatial characterization of the ICHI and its relationship with the BEs in an urban midsize city in Argentina.

Several studies have reported on ICH in adult populations, but there are few reports from South America [5,6,20]. While maintaining ICH throughout life is crucial for preventing CVDs, the prevalence of ICH in adults is generally low. Systematic reviews have shown that the global prevalence of an “ideal” state is unsatisfactory, with only 19.6% achieving “ideal” ICH compared to 32.2% having “poor” ICH [20,21]. Our findings support this information, as 91.36% of the subjects had a “poor” score, and none met the 7 metrics to be categorized as “ideal.”

In Argentina, demographic, epidemiological, and nutritional transitions have led to a significant increase in the prevalence of NCDs. The Cordoba province has experienced exponential growth in its urbanized areas, highlighting the importance of analyzing city structure (BEs) related to cardiovascular health [22]. BEs, through their physical and social characteristics, significantly influence the health and quality of life of populations. Recent studies have shown that environments with access to green spaces, facilities for physical activity, and availability of healthy foods are associated with better health outcomes [23,24]. One study that investigates the availability of foods in stores according to DASH guidelines (Dietary Approaches to Stop Hypertension) in Córdoba, Argentina, using geospatial tools reaches similar conclusions regarding the influence of the environment [25].

The relationship between the BE and how it influences CVD aims to investigate the risk factors that predispose individuals to these diseases. A study in Spain suggests that areas with more vegetation, higher building density, lower population density, and absence of main roads are associated with better health behaviors [26]. Another study from Australia found that the combination of land use, neighborhood aesthetics, and pedestrian infrastructure correlates with a lower risk of metabolic syndrome among adults [27]. Researchers in Canada reported that land use, specifically higher density of commercial destinations and street integration (connectivity between pedestrian pathways, streets, and bike lanes), was associated with lower BMI or reduced likelihood of being overweight, as it promotes movement among people [28].

Our findings are consistent with most studies supporting the link between land use and NCDs. It was observed that for the NDVI, the majority of subjects with a “poor” score (69.44%) lived in areas with “little vegetation,” and for the NDBI, 75.69% had a “vegetation cover.” Several authors affirm that living in densely built and well-organized neighborhoods allows for mobility alternatives, better street connectivity, and higher store density, improving walkability and resulting in less sedentary behavior [29-32].

Regarding the environmental variables studied to characterize the BE, evidence shows that higher levels of green spaces are associated with lower prevalence of CVD. The reason could be that these spaces encourage outdoor physical activities, consequently reducing adiposity [8,32]. In other words, a BE with more green areas promotes better levels of physical activity and outdoor recreation. Contrary to the literature presented above, and although we observed differences in terms of vegetation and built cover, we found that the “soil without vegetation” category was associated with a decreased likelihood of having a “poor” ICHI. This suggests that while the BE can indirectly influence cardiovascular health, other factors may be more determinant in the presence of a “poor” ICHI.

In summary, the map provides a visual representation of the model's predictions, emphasizing areas with varying cardiovascular health indexes. The distribution of categories suggests that the model effectively captures the spatial variation in cardiovascular health risks, although further refinement may be needed to improve accuracy in predicting higher-risk categories. The integration of geospatial analysis and geographic information systems in this study has enabled a deeper understanding of how physical space influences health. This methodological approach underscores the importance of applying geospatial technologies to the design and implementation of more precise and effective public policies in promoting healthy food environments.

A limitation of this study lies precisely in its methodological design, which was intentionally constructed, not to draw definitive conclusions about the epidemiological phenomenon per se, but rather to validate and propose a novel geospatially-enabled analytical framework for index-based assessment. Given this instrumental and exploratory orientation, the findings must be interpreted with caution. The outcomes presented herein should not be extrapolated as conclusive evidence regarding the object of study itself; instead, they serve as internal validation of the index structure and its operational potential. In this sense, the correlations found do not necessarily indicate cause-effect. As such, the study advances methodological innovation rather than empirical generalization, and its contributions reside in refining the tools through which domain-specific knowledge can later be more robustly interrogated.

Conclusions

The integration of ML models and geomatics in healthcare offers a powerful approach to addressing complex health problems. Together, these technologies can lead to more precise, personalized interventions and more effective public health strategies. Expanding their use could significantly improve cardiovascular health outcomes and advance epidemiological research in the region.

Glossary of Acronyms

BE:	Built environments
BMI:	Body mass index
CVD:	Cardiovascular diseases
DASH:	Dietary Approaches to Stop Hypertension
FFQ:	Food frequency questionnaire
GIS:	Geographic information systems
ICHI:	Ideal Cardiovascular Health Index
IPAQ:	International Physical Activity Questionnaire
ML:	Machine learning
NCD:	Non-communicable chronic diseases
NDBI:	Normalized Difference Built-up Index
NDVI:	Normalized Difference Vegetation Index
NDWI:	Normalized Difference Water Index
SDG:	Sustainable Development Goals
WC:	Waist circumference

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