Original article

Compulsorily notifiable diseases and health problems and socio-environmental conditions: an ecological study, Espírito Santo, Brazil, 2011-2015*

doi: 10.1590/S1679-49742021000200019

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Abstract

Objective: To analyze association between climatic-environmental conditions and occurrence of compulsorily notifiable diseases and health problems, in the state of Espírito Santo, Brazil, 2011-2015. **Methods:** This was an ecological study of municipality clusters calculated based on cases confirmed on the Notifiable Health Conditions Information System for the period 2011-2015. **Results:** Notifications were more frequent among females (51.1%); people of brown race/skin color (31.7%); in the 20-49 year age group (48.1%) and in the Metropolitan Health Region (60.3%). The factors associated with health problems were ambulatory care sensitive conditions (p-value<0.001); education development index (p-value<0.001); temperature (p-value=0.019) and degree of urbanization (p-value=0.004). Diseases were associated with population density (p-value<0.001); temperature (p-value<0.001), humidity (p-value<0.001) and altitude (p-value=0.005). **Conclusion:** Health problems were positively associated with ambulatory care sensitive conditions, the education development index and temperature; but negatively associated with degree of urbanization. Diseases were positively associated with the factors mentioned.

Keywords: Incidence; Disease Notification; Socioeconomic Factors; Spatial Analysis; Environment.

*This research received support from the Espírito Santo State Health Department, via the Espírito Santo State Research and Innovation Support Foundation.

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Introduction

Understanding the relationship between health and environment is in the spotlight, especially in view of the climate changes underway and their impact on illness among the population. Records of environmental influences on the distribution of the health-illness process date from the 5th Century BC, having been described by Hippocrates.[1] In the present day, the Intergovernmental Panel on Climate Change has brought to the fore reflections of reconsideration about the impact of environmental conditions on the occurrence of diseases, suggesting that the harmful effects of climate change on the planet should be mitigated for the sake of protecting and promoting human health, by means of so-called 'environmental health'.[2,3] As such, increased understanding of the interrelationship between 'environment' and 'health' resignifies places as conditioning factors of becoming ill, driving forward analyses of the impacts of socio-environmental changes and their consequences for both the local and the global health scenario.[4,5]

> ***Increased understanding of the interrelationship between 'environment' and 'health' resignifies places as conditioning factors of becoming ill.***

National studies into incidence of compulsorily notifiable diseases and health problems (CNDHP) employ spatial distribution techniques with the purpose of identifying risk areas, as well as providing information for prioritizing financial resources aimed at addressing them.[6-8] In the state of Espírito Santo, spatial distribution studies address specific types of diseases or health problems, although from an individualized approach.[9,10]

Differently, this study seeks to achieve an holistic approach, considering CNDHP and their common transmission routes. It is the case of arbovirus infections, zoonoses, sexually transmitted infections or characteristics common to their occurrence, such as occupational diseases, as well as prevention methods common for vaccine-preventable diseases.

The National Epidemiological Surveillance System was officially created in 1975, following the recommendation of the 8th National Health Conference, establishing responsibilities for identifying and recording compulsorily notifiable events within Public Health.[11] A 'notifiable event' is considered to be any case which

> "shows risks of disease propagation or dissemination to more than one Federative Unit, with priority for immediately notifiable diseases and other public health events, regardless of their nature or origin, which may need an immediate national response."[12]

The National Compulsory Notification List is updated periodically. At the time of writing this publication, the list is currently in force in the form of Ministerial Consolidation Ordinance No. 4, dated September 28th 2017, Appendix V of Ordinance MS/GM No. 204, dated February 17th 2016, updated recently by Ordinance GM/MS No. 1061, dated May 18th 2020. Records of compulsorily notifiable diseases and health problems are kept on the Notifiable Health Conditions Information System (Sinan).[13] In 1993 the first version of Sinan ran on the Disk Operating System-DOS. It was updated to Sinan-Windows in 1998 and then to the online Sinan-NET version in 2006. Data is input to the Sinan system at municipal level based on data that are filled in locally on Individual Notification Forms. This form has field for recording geographical coordinates of latitude (ID_GEO1) and longitude (ID_GEO2); however, they are not available for retrieval on the online tabulation systems (TABNET).

The approach taken by the present study intends to demonstrate the effects of conditions of health iniquity associated with climate and environmental variables and with the occurrence of CNDHP, by employing geoprocessing techniques; with the purpose of investigating possible associated conditions, according to the ecosocial model involved in the determination of their occurrence.[14] The objective of this report on the investigation undertaken was to analyze the relationship between social iniquities, (i) climate and environmental conditions and (ii) occurrence of CNDHP in Espírito Santo between 2011 and 2015.

Methods

This was a longitudinal ecological study using municipality clusters, according to definition criteria of confirmed CNDHP cases in people resident in the state of Espírito Santo between 2011 and 2015. The participating cases were retrieved from the Sinan system and tabulated on May 29th 2019, via a standard Nindinet.dbf file, provided by the Espírito Santo State Health Department Health Vigilance Administration Special Information Systems Group. The file initially retrieved had 511,912 records, which were then filtered according to the following fields: <notification number>, <name of notified person>, <mother's name>, <date of notification> and <name of health condition> and place of residence, to identify duplicated records (54,449 cases), resulting in 347,789 cases with complete and consistent records.

Espírito Santo is located on the Southeast Brazilian coast and borders the states of Bahia to the north, Minas Gerais to the west and northwest, and Rio de Janeiro to the south. The state's inhabitants (known as '*capixabas*' in Portuguese) live in a territory covering 46,095.583km², with population density of 76.25 inhabitants/km² spread over 78 municipalities, distributed within the state's four health regions.[20,21]

The confirmed cases were included and clustered according to common etiological characteristics, as identified according to the Tenth Revision of the International Classification of Diseases and Related Health Problems (ICD-10):

a) Arbovirus infections: A90; A92.0; A92.8; A95.9;

b) Vaccine-preventable diseases: A35; A36.9; A37.9; A80.9; D01.9; B019; G03.9; J09; J11; J18.9; P35.0; Y59; B19 (hepatitis B);

c) External causes: T65.9; X29; Y09; Y96; Z20.9;

d) Neglected diseases: A19.6; A30.9; B54; B55.0; B55.1; B57.1; B65.9;

e) Sexually transmitted infections (STI): A50.9; A53.9; B24; B19 (hepatitis C); B54; O98.1; R36; Z20.6; Z21;

f) Zoonoses: A23; A27.9; A77.9; A82.9; A98.8; B58; O98.6; P36.1; W64,

g) Waterborne and foodborne diseases: A00.9; A01.0; A05.1; A08.0; B19 (hepatitis A);

h) Occupational diseases: C80; F99; H83.3; J64; L98.9; Z57.9;

i) Hepatitis without etiological confirmation;

j) Residual group: A05.9; A22.9; A69.2; A81.0; R17;

The study was carried out in the following stages:

1) Acquisition of the data in files retrieved from the Sinan/ES system, subsequently analyzed using Stata version 16 MP.

2) Critical analysis of the database, in order to exclude duplicated records and inconsistencies.

3) Retrieval of geographic coordinates, using the addresses on the notification forms, with the aid and development of automated online search tools. Address validation used eight addressing combinations, whereby the 'complete address' combination was comprised of the following data: street; number; neighborhood; municipality; state; and country.

4) Exploratory data analysis

Summary statistics were obtained for the biological variables (sex [female; male]; race/skin color variables [yellow; white; indigenous; brown; black], age group variables [in years: under 1; 1-4; 5-9; 10-19; 20-49; 50-79; 80 or over]; geographical variables (health regions); and etiological variables (ICD-10).

5) The factor analysis technique was then applied, taking the incidence rates of the 30 diseases and health problems with the largest number of cases (resulting in 347,000 cases, 99.8% of the total), with the aim of identifying spatial distribution patterns.

6) Socio-environmental modeling

Poisson regression models and negative binomial regression models were applied to health problems (codes: W64; X29; T659; Y09; Z209; Y96; Z579 and Y59) and to diseases (the remaining codes). When adjusting to choose the model, we used the Akaike information criteria and the statistical significance of the negative binomial regression dispersion parameter. The results of the regression models highlight significant relationships, expressed as: β; p-value. In order to assess the longitudinal effect over the five-year study period, we checked for the presence of temporal correlation, by using the Gaussian copula marginal approach.[16]

7) Multivariate analysis

The exploratory factor analysis technique was used, taking municipal incidence rates, to identify common factors and their relationship with CNDHP burden. The estimates for the factor analysis models and regression models were obtaining using R software, taking a 10% significance level for the hypotheses tests.

The relational construct used involves three hierarchical levels of exposure associated with the outcome of CNDHP incidence, which was used as the reference for the application of the regression models for longitudinal data, described as follows.

First exposure level

This first level is comprised of the population density of the municipal units and of indicators that express municipal development status, such as labor, income and education conditions, as per the Firjan Municipal Development Index (IFDM).[17] Also added to this level of determination were SUS indicators contained in Tripartite Intermanagerial Commission Resolution No. 5, dated June 19th 2013, on municipal indicators for the 2013-2015 Guidelines, Objectives, Targets and Indicators, namely: (i) proportion of hospitalizations due to ambulatory care sensitive conditions, as described in Ordinance GM/MS No. 221, dated April 17th 2008; (ii) coverage of Bolsa Família Program healthcare requirements compliance monitoring, as established by Interministerial Ordinance MS/MDS No. 2.509, dated November 18th 2004;[15,16] and (iii) municipal Primary Care team coverage, expressed as percentage population coverage achieved by Primary Care in accordance with the Public Health Action Organizational Agreement.[18]

Second exposure level

This level incorporated specific environmental conditions for climate variables: average annual temperature, expressed as percentiles 10 and 90°C of annual temperatures in degrees Celsius (unit: °C); cumulative annual rainfall, estimated in square millimeters (mm^2); relative humidity, expressed as percentiles 10 and 90 of the units; and municipal benchmark altitude, in meters (m). Coastal exposure and vegetation coverage indices were also included. These were retrieved from the Climate Vulnerability System (SisVuClima).[19]

Third exposure level

This level considered local sociodemographic aspects: proportion of females in the population; race/skin color, expressed by the percentage of individuals stating they were White; and age group, represented by percentages for 0-14 years ('Menor15'), 15-64 years ('Adultos') and 65 years or over ('Maior65'). Social vulnerability conditions on the municipal level were also added: expected years of study; proportion of poor citizens; proportion of the population living in urban areas; percentage of households with mains water supply; and percentage of households with garbage collection.

With the aim of avoiding multicollinearity effects, once the correlation matrix had been analyzed, one model was prepared using average annual temperature while a second model considered percentiles 10 and 90. The same procedure was applied to the remaining climate parameters for humidity, as well as to the up to 15 years, adult and over 65 years old age ranges. With regard to race/skin color, use of the proportions of two or more categories would imply multicollinearity, so that we opted to only consider the proportion of White people.

In order to validate the use of Google Maps via the search engine, we checked agreement with the Bing Maps system using a random sample, proportionally representative of the municipalities, comprised of 1123 addresses. Quadratic weighted Kappa index agreement was measured as being 0.42 (p-value<0.001). Finally we used multivariate analysis by applying the factor analysis technique, estimating the main components and the varimax orthogonal rotation of the 30 diseases/health problems with the largest volume of cases: arbovirus infections; vaccine-preventable diseases; hepatitis B; external causes; neglected diseases: STI; hepatitis C; zoonoses; and occupational diseases.

The study project was approved by the Federal University of Espírito Santo Health Sciences Center Research Ethics Committee: Opinion No. 2.991.488, issued on October 30th 2018. In order to ensure confidentiality in the handling of health data, the team members signed a document committing to guaranteeing the privacy of the data they worked with.

Results

The study included 347,789 records of confirmed cases, out of a total of 457,463 notified cases. Confirmed cases were more frequent among females (51.1%), those of brown skin color (31.7%), those in the 20-49 year age range (48.1%) and those living in the Metropolitan Health Region (60.3%); 46% of investigated cases were confirmed dengue cases (46.3%) (Table 1).

The automated geographic coordinate retrieval process showed 74.4% sensitivity, as it located 258,910 retrieved coordinates. Of these, 235,456 (90.9%) were true to the corresponding municipality. Sensitivity showed slight variation in the five-year study period, ranging from 71.7% in 2011 to 79.3% in 2012. Validation used eight address combinations. The 'complete address' combination, comprised of street, number, neighborhood, municipality, state and country, achieved the greatest sensitivity, i.e. 71,2% for the period as a whole, varying between 65.2% in 2012

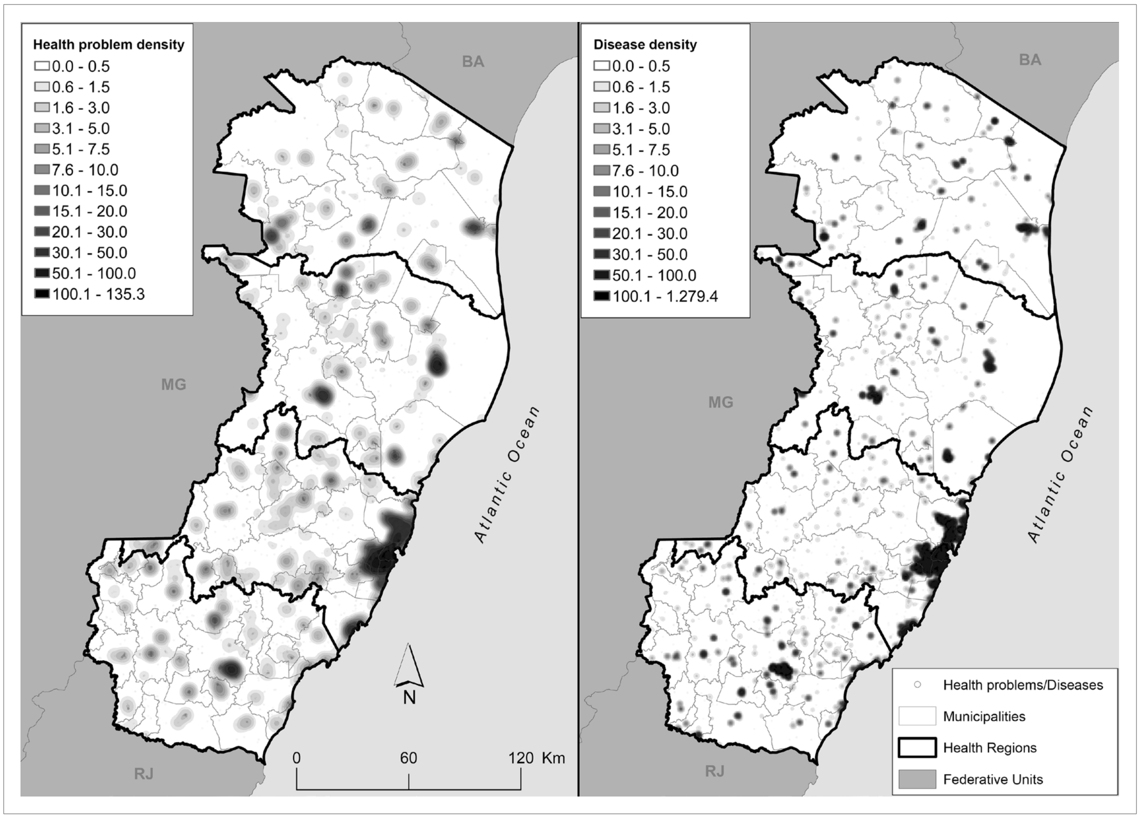

Figure 1 – Estimated distribution of notifiable diseases and health problems in the state of Espírito Santo, 2011-2015

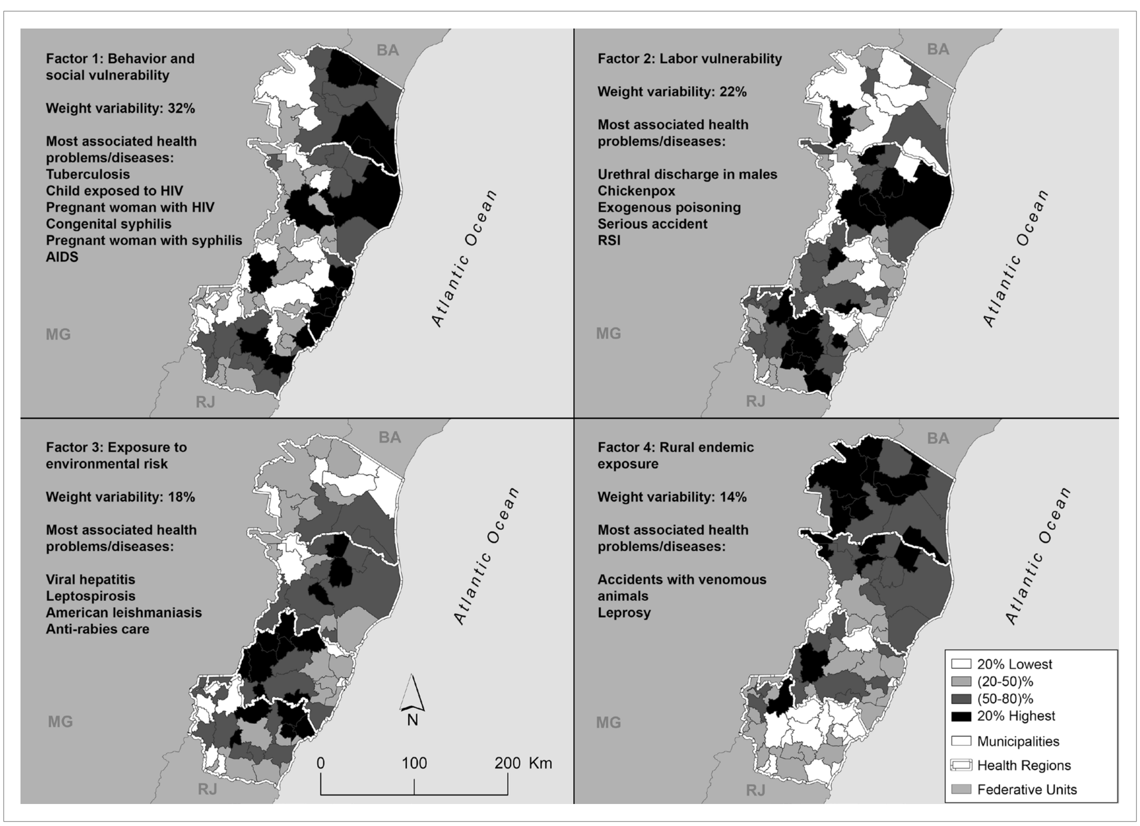

Figure 2 – Distribution of factor scores for notifiable disease and health problem incidence rates in the state of Espírito Santo, 2011-2015

Table 1 – Biological, geographic and etiological category variables of compulsorily notifiable diseases conformed in people resident in the state of Espírito Santo, 2011-2015

Variables	N (347,789)	%
Sex		
Female	177,722	51.1
Male	169,721	48.8
Not defined	346	0.1
Race/skin color		
White	91,913	26.4
Black	20,744	6.0
Yellow	1,813	0.5
Brown	110,364	31.7
Indigenous	781	0.2
Unknown	122,174	35.1
Age group (years)		
<1	8,719	2.5
01-04	17,778	5.1
05-09	22,446	6.5
10-19	56,996	16.4
20-49	167,439	48.1
50-79	60,724	17.5
≥80	3,141	0.9
Unknown	10,546	3.0
Geographical region		
North	33,771	9.7
Central	49,526	14.2
Metropolitan	209,824	60.3
South	54,668	15.7
Etiological groups		
Arbovirus infections	161,176	46.3
External causes	54,789	15.8
Occupational diseases	821	0.2
Waterborne and foodborne diseases	122	0.0
Hepatitis without etiological confirmation	177	0.1
Vaccine-preventable diseases	21,010	6.0
Sexually transmitted infections (STI)	22,485	6.5
Neglected diseases	14,885	4.3
Zoonoses	72,301	20.8
Residual (other)	23	0.0

Table 2 – Regression model for conditions of iniquity and environmental conditions associated with notifiable health problems

Hierarchical model	Variables	1st Stage – Level 1		2nd Stage – Level 2		3rd Stage – Level 3		4th Stage – Final model	
		Coef (β)	p-value	Coef (β)	p-value	Coef (β)	p-value	Coef (β)	p-value
Level 1	IntCdAtBca	0,009	<0,001	0,003	0,154	0,004	0,072	0,005	0,033
	CobCondSaud	0,001	0,773						
	CobAtencBsca	-0,001	0,707						
	ifdm_edu	0,034	<0,001	0,019	0,003	0,010	0,100	0,015	0,013
	ifdm_emprend	-0,003	0,130						
	Dens	<0,001	0,563						
Level 2	Temp			–	–				
	Temp_p10			0,079	0,019	0,051	0,040	0,040	0,086
	Temp_p90			-0,041	0,159				
	log(Precip)			0,009	0,904				
	Umid			–	–				
	Umid_p10			0,006	0,376				
	Umid_p90			-0,017	0,196				
	log(Alt)			0,123	0,001	0,101	0,013	0,084	0,029
	Cobveg			0,001	0,354				
	ExpCosteira			0,002	0,286				
Level 3	Urb					–	0,004	-0,010	0,001
	Menor15					–	–		
	Adultos					–	0,842		
	Maior65					–	–		
	Branc					–	0,744		
	Mulh					0,045	0,364		
	ExpAnosEstud					–	0,079	-0.116	0,163
	AguEncan					0,022	0,059	0,028	0,013
	ColetLixo					0,016	0,441		
	Pobr					-0,014	0,225		

Legend:
IntCdAtBca: proportion of hospitalizations due to ambulatory care sensitive conditions.
CobCondSaud: coverage of Bolsa Família Program healthcare requirements compliance monitoring.
CobAtencBsca: municipal Primary Care team coverage expressed as percentage population coverage achieved.
ifdm_edu: Firjan Municipal Development Index (IFDM) for education.
ifdm_emprend: IFDM for labor and income conditions.
Dens: population density.
Temp: average annual temperature.
Temp_p10: temperature percentile 10.
Temp_p90: temperature percentile 90.
log(Precip): cumulative annual rainfall in logarithmic scale.
Umid: average annual relative humidity.
Umid_p10: relative humidity percentile 10.
Umid_p90: relative humidity percentile 90.
log(Alt): altitude of municipal benchmark in logarithmic scale.
Cobveg: vegetation coverage index.
ExpCosteira: coastal exposure index.
Urb: proportion of the population that lives in urban areas.
Menor15: proportion of the population aged 0 to 14 years old.
Adultos: proportion of the population aged 15 to 64 years old.
Maior65: proportion of the population aged 65 or over.
Branc: percentage of individuals stating they are White.
Mulh: percentage of females.
ExpAnosEstud: expected years of study.
AguEncan: percentage of households with mains water supply.
ColetLixo: percentage of households with garbage collection.
Pobr: proportion of poor people.

Table 3 – Regression model for conditions of iniquity and environmental conditions associated with notifiable diseases

Hierarchical model	Variables	1st Stage – Level 1		2nd Stage – Level 2		3rd Stage – Level 3		4th Stage – Final model	
		Coef (β)	p-value	Coef (β)	p-value	Coef (β)	p-value	Coef (β)	p-value
Level 1	IntCdAtBca	0,002	0,648						
	CobCondSaud	-0,003	0,507						
	CobAtencBsca	-0,004	0,186						
	ifdm_edu	0,015	0,190						
	ifdm_emprend	0,005	0,193						
	Dens	0,001	<0,001	0,000	0,082	<0,001	0,678	<0,001	0,107
Level 2	Temp			0,398	<0,001	0,105	0,114	0,224	<0,001
	Temp_p10			–	–				
	Temp_p90			–	–				
	log(Precip)			0,624	0,083	-0,060	0,812	0,155	0,549
	Umid			–	–				
	Umid_p10			-0,097	<0,001	-0,133	<0,001	-0,144	<0,001
	Umid_p90			0,246	<0,001	0,317	<0,001	0,326	<0,001
	log(Alt)			0,155	0,005	0,027	0,622	0,062	0,224
	Cobveg			-0,001	0,656				
	ExpCosteira			-0,007	<0,001	0,003	0,259	0,006	0,035
Level 3	Urb					0,005	0,387		
	Menor15					–	–		
	Adultos					0,221	<0,001	0,165	<0,001
	Maior65					–	–		
	Branc					-0,024	0,001	-0,024	<0,001
	Mulh					0,088	0,110		
	ExpAnosEstud					0,080	0,397		
	AguEncan					0,018	0,191		
	ColetLixo					0,022	0,309		
	Pobr					0,043	0,001	0,020	0,054

Legend:
IntCdAtBca: proportion of hospitalizations due to ambulatory care sensitive conditions.
CobCondSaud: coverage of Bolsa Família Program healthcare requirements compliance monitoring.
CobAtencBsca: municipal Primary Care team coverage expressed as percentage population coverage achieved.
ifdm_edu: Firjan Municipal Development Index (IFDM) for education.
ifdm_emprend: IFDM for labor and income conditions.
Dens: population density.
Temp: average annual temperature.
Temp_p10: temperature percentile 10.
Temp_p90: temperature percentile 90.
log(Precip): cumulative annual rainfall in logarithmic scale.
Umid: average annual relative humidity.
Umid_p10: relative humidity percentile 10.
Umid_p90: relative humidity percentile 90.
log(Alt): altitude of municipal benchmark in logarithmic scale.
Cobveg: vegetation coverage index.
ExpCosteira: coastal exposure index.
Urb: proportion of the population that lives in urban areas.
Menor15: proportion of the population aged 0 to 14 years old.
Adultos: proportion of the population aged 15 to 64 years old.
Maior65: proportion of the population aged 65 or over.
Branc: percentage of individuals stating they are White.
Mulh: percentage of females.
ExpAnosEstud: expected years of study.
AguEncan: percentage of households with mains water supply.
ColetLixo: percentage of households with garbage collection.
Pobr: proportion of poor people.

and 75.3% in 2011. In relation to notification type, 82,054 (34.9%) referred to the occurrence of health problems and 153,402 (65.2%) referred to diseases, the distribution densities of which can be visualized in Figure 1: health problems were scattered over urban and rural areas, while diseases were concentrated in urban areas.

With regard to the comparative analysis between the Google Maps and Bing Maps systems, it is noteworthy that 60% of the distances were between 0 and 400 metros. The values measured were distributed in distance classes over a bimodal curve, where the first class was between 0 and 50 meters and accounted for 32.1% of the georeferenced points. The second mode was between 1km and 1.5km, accounting for 14.1% of the georeferenced cases. These findings denote systematic disagreements between the search engines.

With regard to the results of the regression analysis of the occurrences of health problems (Table 2), on exposure level 1 the proportion of hospitalizations due to ambulatory care sensitive conditions (β=0.009; p-value<0.001) and the IFDM education component (β=0.034; p-value<0.001) remained associated. On the second exposure level, the variables showing association were temperature percentile 10 (β=0.079; p-value=0.019) municipal benchmark altitude in logarithmic scale (β=0.123; p-value=0.001). On the third level, percentage urbanization (β=-0.013; p-value=0.004), expected years of study (β=-0,152; p-value=0,079) and access to mains water (β=0.022; p-value=0.059) were associated with incidence of health problems. The value of the temporal dependence parameter was estimated (porρ=0.843; p-value <0.001), indicating that the number of occurrences of health problems in a given year was strongly correlated to their incidence in the preceding year.

According to the results obtained for disease occurrence modeling, 31% of variance was explained by the model (Table 3). Positive association was found with population density (β=0.001; p-value<0.001). On the second exposure level, temperature (β=0.398; p-value<0.001), annual rainfall (β=0.624; p-value=0.083) and altitude (β=0.155; p-value=0.005) (both in logarithmic scale), relative humidity percentile 10 (β=-0.097; p-value<0.001), relative humidity percentile 90 (β=0.246; p-value<0.001) and coastal exposure index (β=-0.007; p-value<0.001) remained associated with disease incidence. On the third exposure level, association was found between disease occurrence and adult individuals (β=0.221; p-value<0.001), proportion of White people (β=-0.024; p-value=0.001) and proportion of poor people (β=0.043; p-value=0.001). Following inclusion of variables on a new exposure level, some determinants lost significance in the final model.

The factor analysis technique was applied to the incidence rates of the 30 diseases and health problems with the largest number of cases among all 78 municipalities, the adequacy of which was checked using Bartlett tests (p-value<0.001) and the Kaiser-Meyer-Olkin statistic (0.65). The factor analysis resulted in four factors, which accounted for 86% of data variance. These factors were typified as: Factor 1, Behavior and social vulnerability; Factor 2, Labor vulnerability; Factor 3, Exposure to environmental risk; and Factor 4, Rural endemic exposure. In this way, it was possible to group municipalities together in four categories, as represented in Figure 2.

Discussion

Association was found between compulsorily notifiable health problems and ambulatory care sensitive conditions, municipal development index for education, temperature, relative humidity, altitude and municipal urbanization rate, expected years of study and mains water supply. Occurrence of diseases was associated with population density, temperature, rainfall, relative humidity, altitude and coastal exposure index, as well as the proportions of adults, White people and poor people in the population, suggesting that association with socio-environmental condition and iniquities corroborate CNDHP incidence.[21]

A limitation of this study relates to the low explanatory power of the health problem model. They are occurrences/notifications of a quite distinct nature, such as serious accidents at work, post-vaccination adverse events and accidents caused by venomous animals, so that specific risk of each of these conditions needs to be detailed on the proximal level. In the case of the model used for diseases, a greater determination coefficient was obtained, given that the health conditions of the population of a region are characterized by relationships between territory and disease, in an unequivocal, intrinsic and socially determined manner.

The impacts of climate change can be reflected in diverse scenarios, such as mass migrations and economic relations, affecting segments of the population which, in turn, overburden health systems. Knowledge of these impacts on CNDHPs can contribute to their mitigation and enable public authorities to address affected populations.[22-24]

Barcellos et al.[25] indicate that municipal experiences in approaching health data require improvement to data quality in order for geoprocessing techniques to be employed. It stands out that such experience reports were limited to municipalities, thus drawing attention to the originality of the present study in its statewide approach to the territory of Espírito Santo. Other findings, such as those of Bando et al.,[26] indicate that unemployment in Brazil is positively correlated to homicide, and that suicide may be related to high socioeconomic level. Analyses indicating possible conditions for generalization motivated the factor analysis estimates, which enabled identification of factors common to the etiological groups, thus favoring generalized interpretations of their occurrences. Standing out are (i) 'Behavior and social vulnerability', represented by Sexually transmitted infection health problems, and which were located along the coastal area, as well as tuberculosis in larger municipalities in the interior region of the state; (ii) 'Labor vulnerability', regarding work-related diseases, associated with potential risk activities in the workplace; (iii) 'Exposure to environmental risk', owing to the presence of biotic, physical and geographical agents in its composition, characterized by conditions intrinsically associated with the rural environment; and finally, (iv) 'Rural endemic exposure', represented by health problems closely linked to rural areas, such as accidents involving venomous animals and leprosy, which had high incidence rates in municipalities in Northwest Espírito Santo. It is also appropriate to mention the region on the border with the state of Minas Gerais, specifically the Caparaó subregion comprised of 11 small municipalities in Southwest Espírito Santo, close to Minas Gerais, where a cluster of diseases typified by 'Behavior and social vulnerability' factors and 'Exposure to environmental risk' factors can be identified. Similarly, another cluster can be identified in the northern region of the state of conditions typified as 'Labor vulnerability' as well as 'Rural endemic exposure' to a lesser extent.

According to Freiler,[27] in her study of "poor" neighborhoods in the city of Toronto in 2004, social networks act as a building block where there are concentrations of poverty and unfavorable environmental conditions with regard to people's well-being, in search of their own solutions to local problems, including those related to health. As such, our intention is that the methodology used in this study be replicated in the specific etiological groups on a municipal scale so as to contribute to the formulation of public health policies.

The geographic coordination retrieval tool suggests that the development of local systems can contribute to improvements in the validation of the compulsorily notifiable morbidity database. Evidence is added as to explanatory environmental conditions of greater amplitude about possible causal relationships of the health-illness process associated with CNDHP. The moderate agreement we found points to weakness in the use of the tool, among the diverse components of addresses held on health information systems. This situation is well-known within Public Health, in view of the quality of data input to information systems and the precarious nature of the address database available in Brazilian cities.[28,29] However, these phenomena are not directly observable due to different limitations, such as underreporting, difficulties in accessing health services, gaps in processes following notification, laboratory confirmation and discarding of cases. It is therefore relevant to use multivariate techniques which contribute to the understanding of the interrelations between environmental and social conditions for determining incidence in the case of CNDHP. Multivariate techniques favor understanding of the territory, existing living conditions, resignification of the complexities of adaptation processes, confirming that the field of Health, on its own, is not able to ensure decent quality of life and health for the population. As the results of this study suggest, climate and environmental conditions and social iniquities are associated with the occurrence of CNDHP in Espírito Santo.

We conclude that there was association between notifiable health problems and environmental conditions of temperature, rainfall, relative humidity, municipal benchmark altitude; as well as with social indicators of ambulatory care sensitive conditions, municipal development index for education, proportion of people living in urban areas, years of formal education and percentage of households with mains water supply.

Diseases were associated with population density, climate/environmental conditions of temperature, rainfall, relative humidity, municipal benchmark altitude and coastal exposure index; as well as with sociodemographic groups of White race/skin color, those in the 15-65 year age group and proportion of poor people. These findings identify the spatial determinants involved in the distribution of CNDHP in the state of Espírito Santo.

Authors' contributions

Andrade RLM, Bertolde AI and Dantas A contributed to the concept and design of the article, data analysis and interpretation and drafting the first version of the manuscript. Spala MR, Silva G and Ribeiro FAS contributed to data analysis and interpretation, drafting and critically reviewing the contents of the manuscript. Silva RC, Morellato SA and Ramalho WM contributed to the concept of the article, analysis and interpretation of the results, drafting and critically reviewing the contents of the manuscript. All the authors have approved the final version of the manuscript and are responsible for all aspects thereof, including the guarantee of its accuracy and integrity.

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Received on 25/06/2020
Approved on 06/01/2021

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