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Spatial Patterns in the Association between the Prevalence of Asthma and Determinants of Health

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The World Health Organization endorses the study of diseases from the perspective of the Determinants of Health (DH), that is, the circumstances in which people are born and raised, the environment in which they grow up and age and their lifestyle. The aim of this study is to analyze the spatial behavior of the prevalence of asthma in Aragon, a Mediterranean region in Spain, under the DH approach. The methodological process entailed building a spatial database collating asthma prevalence as dependent variable, and lifestyle, socioeconomic, and climate indicators as explanatory factors, and then evaluating the spatial variability of the relationships by combining the Principal Component Analysis (PCA), Multiscale Geographically Weighted Regression (MGWR) models and cartographic design techniques. MGWR evidenced spatially varying relationships operating at different scales. Lifestyles seem closely tied to the prevalence of asthma in most of the study area while urban functionality and local climate patterns seem to boost prevalence rates in some specific enclaves. Consequently, the social and environmental conditions that characterize the study area translate into several DH scenarios modulating the spatial distribution of asthma. This differential DH behavior detected by local regression models is relevant to guiding and refining public health decision-making.

Introduction

Goal 3.4 of the United Nations Sustainable Development Goals for 2030 aims to reduce premature mortality from noncommunicable diseases (e.g., chronic respiratory disease, cancer, cardiovascular disease, diabetes, and mental illness) by at least one-third. Achieving such a goal

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poses a tough challenge given the increasing incidence and prevalence of this kind of diseases worldwide (Harris, 2019). The scientific community recognizes that the Determinants of Health (DH) largely modulate the appearance and severity of these diseases (Truglio et al., 2012; Ferrer, 2023). DH, understood as the circumstances in which people are born, grow, live, work, and age (World Health Organization, 2008) – that is, the interactions between people and their environment – constitute the main framework for reducing inequalities in health (Marmot et al., 2008). Asthma is one of the most common major noncommunicable diseases and has a substantial impact on quality of life (Dharmage, Perret, and Custovic, 2019). With a universal geographical distribution and affecting all age groups, it has a great impact on the individual who presents it both in his social and work environment. The prevalence of asthma has increased worldwide from 1990 to 2015 by 12.6 percentage points. The Global Burden of Disease study 2016 estimated some 339 million people worldwide suffering from asthma, expecting a further 100 million likely affected by 2025 (Global Asthma Network, 2018). With an overall mean prevalence ranging from 1% and 18%, it incidence differs widely depending on the region and population studied. The clinical asthma rates in adults aged 18–45 years vary between 1% (Vietnam), 1.4% (China and Bosnia-Herzegovina), 20.2% (Sweden), and 21.5% (Australia) (To et al., 2012). The adult prevalence in Spain varies between 1.5% and 16.7% (Plaza Moral et al., 2016), with a remarkable geographical variability, varying, depending on the territory surveyed from 1 (Huelva) to 4.7 percentage points (Albacete) (Antó et al., 1996; Blanco-Aparicio et al., 2023).

The risk factors of asthma are complex as there is an interplay between genetic predisposition and environmental and social factors and it is also important to consider that some factors foster the appearance of asthma while others trigger symptoms or exacerbations (Toskala and Kennedy, 2015). Nevertheless, the rise in asthma prevalence is most likely caused by changes in the environment, since it is unlikely that the population's genetic background has recently changed (Koppelman, 2006; Jie et al., 2013). Unfavorable lifestyle habits (smoking, unhealthy diet, and sedentarism) (Polosa and Thomson, 2013; Alwarith et al., 2020) and frequently associated diseases, such as obesity and COPD contribute to the development of asthma (Gibson and McDonald, 2015; Maselli and Hanania, 2018; Klepaker et al., 2019; Miethe et al., 2020). Socio-economic deprivation, as expressed through educational level, employment status, income, and household quality, has been also associated with increased vulnerability to asthma manifestations (Singh et al., 2020; Vowles et al., 2020; Redmond et al., 2022). From the point of view of the physical environment, the geographical distribution of species and climatic conditions implies a spatial variability of exposure to allergens, air quality, and weather-related events – heat waves, heavy rainfall, and strong winds – that may pose an increased risk for the development or exacerbations of asthma (Analitis et al., 2018; Eguiluz-Gracia et al., 2020; Chen et al., 2021). Previous studies claim that the high prevalence of asthma in more developed countries may be due to urbanization and westernized lifestyle, fostering higher rates of obesity, and/or pollution (Enilari and Sinha, 2019). However, protective and risk factors can be identified in rural areas as well (Rodriguez et al., 2019). In rural areas, disadvantaged economic backgrounds, barriers to health care access, and fewer health care services may be unfavorable for the diagnosis, control, and management of asthma (Valet, Perry, and Hartert, 2009; Estrada and Ownby, 2017; Lotfata and Hohl, 2022), despite the evidenced protective effect of farming environment.

Taken together, these pieces of evidence suggest the prevalence of asthma is likely to keep increasing in the future, at least in response to environmental changes resulting from human activity, which will pose a challenge for social and health strategies. Therefore, healthcare, policymaking, and management initiatives would strongly benefit from incorporating the DH perspective. However, neither DH nor the prevalence of disease are distributed homogeneously throughout the territory; they are linked to the living environment. Representing this variability in administrative spatial aggregations or stratified population groups, presenting results such as: rates, correlation results, or linear regression models, makes the dreaded ecological fallacy evident. This ecological fallacy "undermines" the results of these studies, which could lead to decisions being made by the politician/manager. To reduce biases in the selection of these stratified groups and to reduce "the ecological fallacy" by avoiding simplified results (Borja-Aburto, 2000) this study proposes a spatial-explicit modeling approach to assess the relationships between DHs and disease prevalence. The method is exemplified in Aragon (Spain) by leveraging the large data pool generated by the local, regional, and health administrations. We integrate this information into cartographic tools via Geographic Information Science and Technology (GIS&T) and Multiscale Geographically Weighted Regression (MGWR) as a methodological baseline to unravel spatially varying relationships and scale-dependent effects. GIS&T allows for complex spatial analysis procedures, thus guiding the solution of specific problems in several areas: health management and primary-care orientation, territorial planning with a "Health in All Policies" (HiAP) perspective focusing on health inequities or characterizing regions via health-related indicators (Cromley and McLafferty, 2011). We propose using spatially explicit models to analyze the spatial variability of associations between prevalence and DH indicators. The existence of multiscale relationships between disease prevalence and DH stresses the necessity of adopting a spatial-explicit perspective. Targeting the correct scale(s) toward the appropriate course of action improves effective decision-making in public health matters. Environmental and socioeconomic drivers operate at different spatial levels, demanding *ad hoc* responses. The proposed method was aimed at identifying such levels and outlining their spatial extent and relevance.

Materials and methods

In the present study, a methodological procedure was developed and applied to evaluate whether there is spatial variability in the statistical association between the prevalence of asthma and DH indicators. The methodology leverages Geographically Weigther Regression models (Fotheringham, Brunsdon, and Charlton, 2002) as they can identify spatially varying relationships, translated into a set of local regression outputs. These methods have been used recently in the field of health geography, and previous studies on asthma have demonstrated their suitability for studying the spatial behavior of their prevalence using a DH approach though scale-dependent effects and relationships – as the one we addressed – remain largely unexplored (Kumarihamy and Tripathi, 2019; Pala et al., 2019; Davies, Konings, and Lal, 2020).

Study design: Study area and prevalence data

The study area was established as the Autonomous Community of Aragon (Fig. 1). Aragon is a paradigmatic example of dissimilar population systems and environmental conditions. It encompasses a major metropolitan area (around the city of Zaragoza) gathering half the population, while low densely populated and rural settlements occupy the rest of the region (47.720 km^2). Aragon shows contrasting climate patterns, from wet and cool conditions in the two surrounding mountain ranges (north and south of the region) to warm and dry situations in the central corridor of the River Ebro Valley (central sector of the province of Zaragoza in a north-west-south-east direction). The observational unit of our study was the Basic Health Area (BHA), which is the territorial and administrative unit for primary healthcare in Aragon. The

Figure 1. Study area main characteristics: administrative limits and physical environment.

Aragon Health Sciences Institute of the University of Zaragoza provided prevalence indicators of asthma. Prevalence was measured in cases percent. Raw data consisted of diagnosed individuals from computerized records in primary care from 2005 to 2016. The data provided corresponded to patients over 16 years and were submitted to quality assurance control by the researchers to cleanse wrong records. Data were standardized into an adjusted prevalence rate to override potential bias among age or gender-related groups. Standardized rates were calculated and spatialized at BHA level, later used as dependent variable in the regression analyses.

DH indicators and explanatory variables

The core of the method lies in calibrating spatially explicit regression models. This calibration was performed by investigating the role of a series of indicators related to individual, social, and environmental DH domains (Whitehead and Dahlgren, 2006). On the basis of previous studies, we used a variety of variables potentially connected to asthma prevalence from all three domains (Table 1). The prevalence of Overweight-obesity and COPD were used as proxy variables of individual habits considered as risk factors for asthma such as smoking, unhealthy dietary patterns, and low physical activity (Anderson and Jackson, 2017; GEMA, 2021; Yawn et al., 2015). Within the socioeconomic domain, we included variables related to illustrate the rural–urban gradient – for example, Functionality, Accessibility, and Communications (Jie et al., 2013; Lawson et al., 2014; Elholm et al., 2015; Timm et al., 2016), the population structure by means of indicators such as Young and Elderly Dependency Indexes, Education attainment, Income, and Unemployment (Gong et al., 2014; Sahni et al., 2017; Grant, Croce, and Matsui, 2022) and the residential environment, through Household size, Building condition, Household equipment, and Quality of the landscape indicators (Corburn, Osleeb, and Porter, 2006; Bryant-Stephens, 2009;

Table 1. Explanatory Variables

Lifestyle domain		
Overweight-obesity prevalence		
COPD prevalence		
Socioeconomic domain		
Territorial Development Index	Population with first level studies	Households with 5 or more people
Territorial functionality	Population with second level studies	Building condition
Accessibility of primary care centers	Population with third level studies	Household equipment
Communications	Undereducated youth	Landscape Factor
Femininity Index	Undereducated foreign population	Landscape quality
Young Dependency Index	Deprivation Index	Social appreciation of the landscape
Elderly Dependency Index	Rate of unemployment	Approved tourist trails
Labor Force Structure Index	Median income	
Foreign population	Separation, divorce, or widowhood	
Uneducated population	Households with one person over 65	
Climate domain		
Maximum temperature	Number of days with minimum temperature below 0°C	Number of days with precipitation under 1 mm
Minimum temperature	Number of days with minimum temperature above 20°C (tropical nights)	Relative humidity
95th percentile of maximum daily temperature	Accumulated precipitation	Wind speed
Number of days with minimum temperature below 0°C	Number of days with precipitation over 20 mm	

Northridge et al., 2010). To illustrate climatic conditions, indicators on Maximum and Minimum temperature, Average and Accumulated precipitation, Relative humidity, and Wind speed were used (Taylor and Jonsson, 2004; Rorie and Poole, 2021; Makrufardi et al., 2023). DH indicator data are freely available, retrieved from the Spanish Statistics Institute, the Aragon Statistics Institute, the Aragon Geographic Institute and the Spanish State Meteorological Agency. The description and source of information of the variables is detailed in the Appendix A.

Model calibration and performance

The evaluation of spatial variability in the statistical association between the prevalence of disease and DHs was based on the combination of Principal Component Analysis (PCA) and Multiscale

Geographically Weighted Regression (MGWR). Variables from the Socioeconomic and climate domains were submitted to PCA to summarize the original dataset (37 variables, Table 1) into a smaller number of components (PCs). We applied PCA to variables in the socioeconomic and climate domains separately to preserve their intrinsic nature in the models and, thus, properly contextualize their effects. We selected those components with an eigenvalue greater than one, based on the Kaiser criteria (Kaiser, 1960). The selected PCs and the overweight-obesity and COPD prevalence were submitted to GWR models as predictors. GWR is a statistical technique for regression and exploratory analysis based on the spatial disaggregation of a global regression model into a set of spatially limited samples. GWR extends the traditional use of global regression models (e.g., Ordinary Least Squares), through the assessment of local regression parameters. Analyzing the spatial behavior of different diseases from the DH approach allows us to assess whether the relationships are local (i.e., spatially varying across the region) or global (homogenous over the entire region). The following equation describes a conventional GWR mathematically:

$$y_i = \sum_{j=0}^{m} \beta_j \left(u_i, v_i\right) x_{ij} + \varepsilon_i \tag{1}$$

where x_{ij} is the jth predictor variable, $\beta_j(u_i, v_i)$ is the jth coefficient, ε_i is the error term, and y_i is the response variable. In GWR, a region is described around each observation location i (with coordinates u_i,v_i) and all the data points within a given neighborhood window are used to calibrate a regression model. This process is repeated over all the candidate locations obtaining a set of local regression statistics as a result. GWR applies a distance weight pattern; hence, observations – neighbors – closer to the center of the window – kernel – are weighted more heavily. We applied an adaptive kernel window, which varies in size (bandwidth or radius) according to the number of neighboring closest observations to be included. The adaptive approach is recommended when dealing with spatially clustered or imbalanced patterns, as is the case of BHA distribution (Moran's Index = 0.124; P value: 0.001; z-score: 3.260). The number of neighbors was optimized by minimizing the Akaike Information Criterion (AIC), adapted for GWR by (Hurvich et al., 1998). A GWR model includes the usual outcomes of an ordinary least square regression model but grants an individual set per each location, in other words, it yields local regression parameters estimates instead of a unique set of global regression outputs (Brunsdon et al., 1996). This allows us to address the spatial pattern in beta coefficients or significance level of the predictors, or the percentage of variance captured by the model (R^2). Specifically, we used the Multiscale Geographically Weighted Regression approach (MGWR), which provides a more flexible and scalable framework in which to examine multiscale processes (Fotheringham, Yang, and Kang, 2017). In regular GWR all covariates are assumed to operate at the same scale, that is, sharing a common bandwidth to ascertain the spatial relationships, which is unlikely. MGWR overcomes this limitation by allowing the bandwidth size to vary across covariates and thus the conditional relationships between variables to act at different spatial scales (Yang, 2014).

$$y_i = \sum_{j=0}^{m} \beta_{bwj} \left(u_i, v_i\right) x_{ij} + \varepsilon_i \tag{2}$$

where bwj in β_{bwj} indicates the bandwidth used for calibration of the jth conditional relationship.

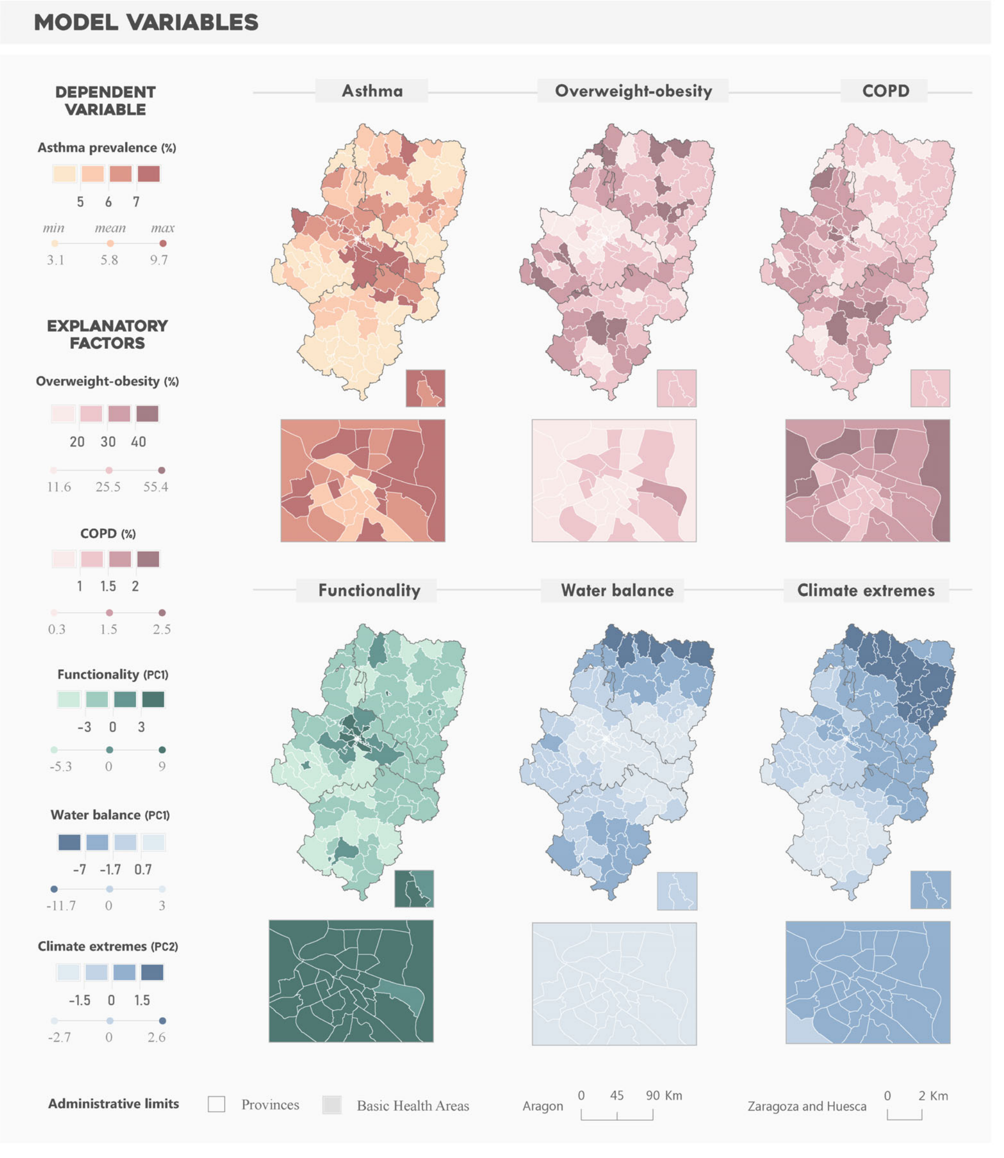

Figure 2. Spatial distribution of the model variables: asthma prevalence and explanatory factors.

Results

Asthma prevalence and key explanatory factors

The spatial distribution of model variables is presented in Fig. 2. The prevalence of asthma in Aragon ranged from 3.1 to 9.7 cases percent. Higher rates were observed in urban settlements such as the metropolitan area of Zaragoza and most densely populated areas of the Huesca province, and the central corridor along the River Ebro Valley. A contrasting spatial pattern emerges with respect to the prevalence of overweight-obesity: highest rates – between 30 and

40 cases percent – are observed in BHAs in the southeast of the region and around the borders between the provinces of Zaragoza and Huesca. In case of COPD, highest rates – between 1.5 and 2.5 cases percent – are observed in the province and city of Zaragoza as well as in some BHAs in the middle-north of the Teruel province. Regarding variables derived from PCA (Table 2), we initially retained the first component from the socioeconomic domain (hereafter "Functionality") and the first two from the climate domain ("Water balance" and "Climate extremes"). The "Functionality" PC gathers a 39% variance within the socionomic domain: it relates to the urban functional hierarchy in Aragon. High scores of the component appear in the metropolitan surroundings of the city of Zaragoza and in the main cities, denoting an urban profile and advantageous situations in terms of accessibility, communications, and services. Higher proportions of women, single young people, and higher education attainment are also positively associated with this component. The lower values indicate a predominantly rural profile, with lower population densities characterizing the southeast of the province of Zaragoza and a large part of Teruel. The first component of the climate domain "Water balance" gathers up to 78% of variance. High index scores indicate wet and cool conditions and vice versa, being negatively correlated with temperature and positively with rainfall-related variables. Spatially, it broadly shows the climatic distribution of the region, which is characterized by the gradient between mountain climates in the north and southeast of the region – in the surroundings of the Pyrenees and the Iberian System – and the continental Mediterranean climate that predominates in the center of the region along the Ebro valley. The second component of the climate domain, "Climate extremes" (11% variance) relates to unusual hazardous weather conditions and extreme events. The index scores draw a spatial pattern in a northwest-southeast direction, with highest scores corresponding to events related to strong winds and sudden temperature drops and the lower ones associated with outstanding rainfall episodes and heat waves.

Modeling outputs and spatial effects

Local models exhibited a better prediction capability than global models, showing a difference of 25% in the percentage of variance explained (R^2: 0.64 MGWR; 0.39 OLS) (Table 3). Thus, spatially varying relationships operating at different scales were evidenced. The bandwidth size – number of neighbors, BHAs – (optimized by minimizing the AIC) varied by 25 units. The widest bandwidth corresponded to the Functionality factor (88), followed by that of COPD and Climate extremes (76), Overweight-obesity (67), and Water balance (63). Regarding the direction of the associations with the prevalence, those of the Overweight-obesity, COPD, Functionality, and Water balance variables were positive, the opposite in case of the extreme weather factor. It means that asthma would be expected to increase in parallel with the increase of overweight-obesity and COPD and territorial functionality. Within the climatic domains, an increase would be associated with cold and wet conditions and episodes of strong winds. The explanatory capacity of all variables was significant in both models, but MGWR revealed contrasting patterns in the spatial representativeness of significance (Fig. 3). The Overweight-obesity and COPD factors showed a more regional pattern of significance: a total of 105 out of 123 BHAs with significant coefficients in the case of Overweight-obesity mostly located in the provinces of Huesca and Zaragoza. In the case of COPD and 101 BHAs spatially distributed around the province of Zaragoza and in BHAs bordering the provinces of Huesca and Teruel. The coefficients of the PCA-derived factors displayed a more local influence as evidenced by its smaller extent of significant BHAs. The Functionality factor largely operates in the province of Huesca (35 out of 123 BHAs with significant coefficients), while in the

Table 2. PCA Outputs

Domain	PC	Alias	%V	Variable	Sign	EigVal
Socieconomic	First	Functionality	39%	Population with first level studies	−	0.26
				Uneducated population	−	0.25
				Rate of unemployment	−	0.24
				Territorial functionality	+	0.27
				Communications	+	0.28
				Building condition	+	0.28
Climate	First	Water balance	78%	95th Percentile of maximum daily temperature	−	0.33
				Maximum temperature	−	0.33
				Number of days with precipitation under 1 mm	−	0.33
				Accumulated precipitation	+	0.32
				Number of days with minimum temperature below 0°C	+	0.32
				Relative humidity	+	0.32
	Second	Climate extremes	11%	Wind speed	−	0.46
				Number of days with minimum temperature below 0°C	−	0.20
				Number of days with minimum temperature above 20°C	+	0.41
				Accumulated precipitation	+	0.50

Note: Description of the selected PCs. %Var indicates the proportion of variance within the block gathered by the PC. Sign indicates the direction of the association between the original variables (only those with EigVal >0.2 were shown) and PCs. EigVal denotes the correlation value between the original variables and the PCs.

sector of the Ebro Valley and in the province of Teruel are the climate factors that show significant coefficient values (84 and 25 BHAs in case of Water balance and Climate extremes, respectively).

Discussion

In the present study, we built and exploited a cross-sectional spatial database including lifestyle, socioeconomic, and environmental factors to identify spatial-dependence associations with

Table 3. Summary Statistics of OLS and MGWR Models

OLS						
Variables (x)	Coefficients value	SE	T statistic	P value	VIF	Adj. R^2
Intercept	3.365	0.098	36.917	<0.001	-	0.397
Overweight-obesity	0.005	0.002	2.362	0.019	1.548	
COPD	0.016	0.005	3.171	0.001	1.316	
Functionality	0.031	0.007	4.344	<0.001	1.980	
Water balance	0.012	0.007	1.659	0.099	1.436	
Climate extremes	0.064	0.172	3.717	<0.001	1.185	

MGWR						
	Coefficient estimates					
Variables (x)	Minimum	Mean	Max	N° BHAs with significant coefficients (N = 123)	Bandwidth (N° BHAs)	Adj. R^2
Intercept	2.969	3.383	4.211	-	58	0.642
Overweight-obesity	−0.003	0.008	0.190	105	67	
COPD	−0.015	0.023	0.048	101	76	
Functionality	−0.007	0.006	0.067	35	88	
Water balance	−0.019	0.00	0.175	84	63	
Climate extremes	−0.126	−0.091	−0.028	25	76	

asthma prevalence. The prevalence of physician-diagnosed asthma in Aragon ranged from 3.1 to 9.7 cases per hundred, thus showing large differences over the study area. These differences were also observed in other studies in other geographical contexts (Antó et al., 1996; To et al., 2012; Blanco-Aparicio et al., 2023), supporting the existence of spatial differences in the impact of asthma and its underlying determinants. Spatially explicit analyses are therefore recommended, as we continue to demonstrate in this study.

Our results showed that the prevalence of overweight-obesity and COPD – used as proxy variables of individual behaviors related to diet, sedentarism, and smoking – have explanatory power for asthma prevalence in Aragon on a regional scale (Table 3 and Fig. 3). These results provide further evidence of interactions between individual DH and asthma (Polosa and Thomson, 2013; Rasmussen and Hancox, 2014; Alwarith et al., 2020) underlining the need to a disease management based on a multidimensional assessment (Gibson and McDonald, 2015; Klepaker et al., 2019). Furthermore, being aware of the spatially varying relationships could be useful when prioritizing areas in which to carry out lifestyle interventions to target improved asthma outcomes (Nyenhuis, Dixon, and Ma, 2018; Stoodley et al., 2019). Regarding the socioeconomic domain, the regression analysis revealed a significant positive association between the prevalence of asthma and the functionality factor, although spatially restricted to the province of Huesca (Fig. 3). An increase in risk could be inferred due to the industrial development in parallel to urban growth that has traditionally characterized this province, thus fostering the increase of air pollutants in suspension in the vicinity of industrial areas (Edwards, 2004; Huang et al., 2020; Paciência, Cavaleiro Rufo, et al., 2022). However, other regions in Aragon share

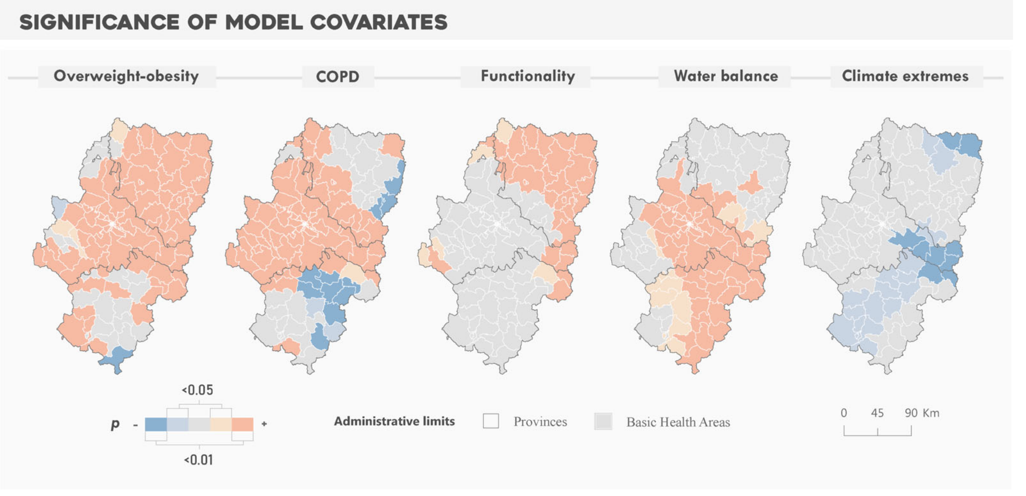

Figure 3. Spatial distribution of significance of model covariates.

this industrial heritage. We therefore consider preferable to reserve this hypothesis for future studies in which we incorporate variables related to the industrial activity, air quality, and land use (Eguiluz-Gracia et al., 2020; Paciência, Moreira, et al., 2022; Santika et al., 2023).

The analysis of climate factors revealed some interesting patterns with both "Water balance" and "Climate extremes" operating at the local scale (i.e., showing spatially-varying relationships; Table 3). The significant relationships observed in both climate indicators suggests an increase in prevalence promoted by sustained dry and warm conditions or sudden rain events. Such events are known to exacerbate chronic respiratory conditions (Analitis et al., 2018; Chen et al., 2021) but, as we illustrate here, these relationships do not necessarily hold elsewhere (Fig. 3). We believe the local association identified this eastern sector of the River Ebro valley concerns acute water deficit fostering parched conditions leading to breathing distress. Other studies suggest higher vulnerability to asthma with increasing temperatures and extreme weather events (George, Bruzzese, and Matura, 2017). The positive relationship with "climate extremes" we believe relates to sudden changes in weather conditions such as strong winds, heavy rains and heat waves. Nonetheless, the spatial arrangement of the zones under climate influence encompasses the main olive growing areas, peach trees, or cherry trees in the middle-eastern of the region. Hence, it might be the confluence of weather conditions prone to asthma and the presence of pollen dispersals what drives the observed pattern (Darrow et al., 2012; Kitinoja et al., 2020). Likewise, the aforementioned area locates downstream of the dominant winds (the so-called "Cierzo"), thus constraining the influence to this southeastern enclave by impeding pollen dispersal upwind. In any case, under the ongoing context of global change and climate warming the prevalence of asthma is expected to increase, especially in industrialized regions. One of the impacts on human health resulting from the increase in global temperature derives from mechanisms such as increased pollen dispersal and pollution rates, which increase vulnerability to respiratory disorders (D'Amato et al., 2015). In terms of prevention, it would be relevant to focus on these areas, informing the population of possible complications of the disease linked to extreme weather events, and health professionals of a possible greater use of health resources.

One of the study's limitations goes in line with the previously with the previously mentioned incorporation of new variables. Indicators on socioeconomic status are contemplated in the Functionality indicator derived from PCA. By the very nature of PCA and the characteristics of the study area, greater territorial functionality is accompanied – in general terms – by a better socioeconomic situation. However, this generalization could mask contrasting situations, for example, within cities: all the urban BHAs perform contrasting socioeconomic profiles. The same occurs in rural areas. We consider that this masking has hindered the ability of the regression analysis to identify, if it existed in our study area, the explanatory capacity of the socioeconomic dimension. Future studies will consider working either with a principal component derived from a set of socioeconomic variables or, alternatively, with individual indicators to explore whether widely studied associations between asthma and socioeconomic status are also relevant in Aragon (Singh et al., 2020; Vowles et al., 2020; Redmond et al., 2022).

Another limitation of the study is that data could not be obtained from children under 16 years of age, which excludes childhood asthma. The prevalence is calculated at the general population level and therefore the comparison with other epidemiological studies should be carried out carefully, as the methodology is slightly different. Also, a common drawback in epidemiological studies is the divergence of results depending on the diagnostic method used. Studies have reported that problems with diagnosis accuracy among primary-care health services caused under- (54 percent) or overdiagnosis (34%) (Piassi de São José et al., 2014). Under-diagnosis is more difficult to overcome; however, all primary care centers in the region have spirometry equipment, and the network of health centers covers the entire population of Aragon with sufficient proximity, which limits to some extent the under-diagnosis bias. In this line, one of the strengths of our study design is that it avoids participation biases that are inevitable in epidemiological studies and offers the possibility of examining health determinants in rural areas as well, thus leading to sound and solid findings.

Conclusion

In our study, the multiscale alternative to the traditional GWR (MGWR) enabled further insights into scale effects by differentiating the local character of the covariates, which are forced to be nonstationary (both temporally and spatially) in the aforementioned approaches. The MGWR approach seems particularly suitable for addressing regions with contrasting settings, for example, complex reliefs, contrasting patterns of population distribution, or local climate and weather conditions. The strength of the model lies in its capability to overcome the differential behavior of the disease prevalence and its determinants and their statistical association. Altogether, this contributes to improved decision-making in public health matters by adjusting the scale of the problem to that of the actions required. We successfully identified four major drivers of asthma prevalence operating at different spatial scales. Overweight-obesity and COPD controls exert a near-global influence over the region while climate factors highlight local clusters under weather influence. Climate influence depicts a pattern of influence that allows us to emphasize a local context of vulnerability that would remain hidden with traditional approaches. Altogether, coupling the DH framework with local regression approaches and mapping techniques enables the in-depth insights required to implement health-related policies in the current context of global change.

Appendix A

Variable	Description	Source
Overweight-obesity prevalence	Adjusted prevalence rate of overweight or obesity in population older than 14 years in 2014.	IGEAR
COPD prevalence	Tasa ajustada de prevalencia de al en 2017	IGEAR
Functionality and socioeconomic variables		
Territorial Development Index	Synthetic index of more than 90 variables related to economic, demographic, and settlement distribution factors, as well as factors related to accessibility to facilities, communications, and natural environment components: climate and landscape.	IGEAR
Territorial functionality	Synthetic index on the functional hierarchy of settlements in Aragon. It integrates variables on population growth, accessibility to facilities, and economic activities.	IGEAR
Accessibility of primary care centers	Average time (in minutes) to reach the nearest primary-care center.	IGEAR
Communications	Integrates indicators related to digital communication, namely the fiber optic and 4G mobile coverage, and access to fixed or wireless networks.	IGEAR
Femininity Index	Expresses the number of women per 100 men.	INE
Young Dependency Index	Expresses the ratio between the population aged 0–14 and the population aged 15–64.	INE
Elderly Dependency Index	Ratio between the sum of the population under 15 and over 65 and the working age population (16–64).	INE
Labor Force Structure Index	Ratio between the population aged 16–39 and the population aged 40–64.	INE
Foreign population	Ratio between the foreign population and the total population.	INE
Uneducated population	Ratio between the total number of persons aged 16 and over who cannot read or write in any language and the total population of this age group.	INE
Population with first level studies	Ratio between the total number of persons aged 16 and over who have not completed ESO, EGB, or elementary baccalaureate studies and the total population in this age group.	INE
Population with second level studies	Ratio between the total number of persons aged 16 and over who have completed ESO, EGB or elementary baccalaureate studies and the total population in this age group.	INE

Variable	Description	Source
Population with third level studies	Ratio between the total number of persons aged 16 and over who have completed university studies and the total population in this age group.	INE
Undereducated youth	Ratio between the number of people aged 16–30 who have not completed primary education and the total population in this age group.	IGEAR
Undereducated foreign population	Ratio of the foreign population that has not completed primary education and the total foreign population.	IGEAR
Deprivation Index	Synthetic index of the percentage of unemployment, temporary employees, and insufficient education.	IGEAR
Rate of unemployment	Ratio between the total unemployed population aged over 15 and the total employed and unemployed job seekers.	IGEAR
Median income	Expresses the average wage of each inhabitant (ratio between earnings and salaries), in thousands of euros.	IGEAR
Separation, divorce, or widowhood	Ratio between the number of separated, divorced, or widowed persons and the total number of persons aged over 16.	IGEAR
Households with one person over 65	Ratio between the number of households with one person aged over 65 and all households.	INE
Households with 5 or more people	Ratio between the number of households with 5 or more persons and the total number of households.	INE
Building condition	Weighted average of the percentage of buildings based on their condition in accordance with the 2011 Population and Housing Census.	IAEST
Household equipment	Weighted average of the percentage of dwellings based on their facilities according to the 2011 Population and Housing Census.	IAEST
Landscape factor	Integrates indicators relating to the quality of the landscape, the municipal area included in a Protected Natural Spaces category, and the presence of approved tourist trails.	IGEAR
Landscape quality	Weighted average value of the quality of landscape types.	IGEAR
Social appreciation of the landscape	Ratio between the area classified as outstanding (in hectares) in relation to the municipality surface area.	IGEAR

Variable	Description	Source
Approved tourist trails	Presence of approved tourist trails in the municipality (km).	IGEAR
Climate variables		
Maximum temperature	Monthly average value of maximum temperatures. Calculation based on dynamic methods for regionalization of climate models.	AEMET
Minimum temperature	Monthly average value of minimum temperatures. Calculation based on dynamic methods for regionalization of climate models.	AEMET
95th Percentile of maximum daily temperature	Annual 95th percentile of maximum daily temperature. Calculation based on dynamic methods for regionalization of climate models.	AEMET
Number of days with minimum temperature below 0°C	Annual cumulative number of days with minimum temperature below 0°C. Calculation based on dynamic methods for regionalization of climate models.	AEMET
Number of days with minimum temperature above 20°C (tropical nights)	Annual cumulative number of days with minimum temperature above 20°C. Calculation based on dynamic methods for regionalization of climate models.	AEMET
Accumulated precipitation	Monthly average cumulative precipitation. Calculation based on dynamic methods for regionalization of climate models.	AEMET
Number of days with precipitation over 20 mm	Monthly cumulative number of days with precipitation over 20 mm. Calculation based on dynamic methods for regionalization of climate models.	AEMET
Number of days with precipitation under 1 mm	Monthly cumulative number of days with precipitation under 1 mm. Calculation based on dynamic methods for regionalization of climate models.	AEMET
Relative humidity	Monthly average relative humidity. Calculation based on statistical methods for regionalization of climate models.	AEMET
Wind speed	Monthly average wind speed at 10 m	AEMET

IGEAR, Aragon Geographic Institute; INE, Spanish Statistics Institute; IAEST, Aragon Statistics Institute; AEMET, Spanish State Meteorological Agency.

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