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Geographical variability in the prevalence of dementia from the perspective of determinants of health: a case study of Aragon (Spain)

Variabilidad geográfica de la prevalencia de demencia desde el enfoque de los determinantes de la Salud: caso de estudio de Aragón (España)

Carmen Bentué-Martínez

cbentue@unizar.es

María Zúñiga-Antón

mz@unizar.es

Marcos Rodrigues Mimbrero

rmarcos@unizar.es

Department of Geography and Land Use Planning

Universidad de Zaragoza (Spain)

Abstract

Diseases linked to cognitive impairment, such as dementia, pose major challenges to health systems due to their high incidence, prevalence, and associated mortality. The World Health Organization (WHO) promotes studying diseases through the lens of health determinants (DH), encompassing social, environmental, and territorial factors. This study examines the spatial behaviour of dementia in Aragon (Spain) using a health determinants approach. Databases were

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built with dementia prevalence as the dependent variable (by sex) and DH indicators (sociodemographic, territorial development, and comorbidities) as explanatory factors. Principal component analysis (PCA) and geographically weighted regression (GWR) were applied to reduce variable dimensionality and assess spatial variability in associations. Results show higher prevalence in rural areas with ageing populations, low education, widowhood, and elevated rates of hypertension and diabetes. However, the explanatory power of DH varies across space, revealing particularly vulnerable areas. Understanding this local variability is essential to inform targeted prevention and management strategies tailored to each region's specific needs.

Key words: Geographically Weighted Regression (GWR); spatial analysis; mapping.

Resumen

Las enfermedades asociadas al deterioro cognitivo, como la demencia, representan un reto importante para los sistemas de salud por su alta incidencia, prevalencia y mortalidad. La Organización Mundial de la Salud (OMS) propone abordarlas desde el enfoque de los determinantes de la salud (DS), es decir, factores sociales, territoriales y ambientales. Este estudio analiza el comportamiento espacial de la demencia en Aragón (España) utilizando datos diferenciados por sexo e indicadores de DS (sociodemografía, desarrollo territorial y comorbilidades). Se aplicaron análisis de componentes principales (ACP) y regresiones ponderadas geográficamente (GWR) para reducir la dimensionalidad y explorar la variabilidad espacial en la relación entre variables. Los resultados muestran una mayor prevalencia en zonas rurales con elevada proporción de personas mayores, bajo nivel educativo, viudez y alta incidencia de hipertensión y diabetes. Sin embargo, la influencia de los DS varía según el territorio, lo que indica la existencia de áreas especialmente vulnerables. Comprender esta variabilidad local es clave para diseñar estrategias de prevención y gestión adaptadas a las necesidades específicas de cada región.

Palabras clave: Regresión Geográficamente Ponderada (GWR); análisis espacial; cartografía.

1 Introduction

The increase in life expectancy and the decline in fertility rates are the primary factors driving the shift in population age structure towards older age groups, as outlined in early models of the demographic transition (Kirk, 1996). This population ageing is strongly associated with the rising incidence, prevalence and mortality of non-communicable diseases (NCDs), as older adults are the most affected and are at greater risk of developing these conditions (World Health

Organization, 2023). Mental health disorders, such as depression, dementia and Alzheimer's disease, are among the leading causes of disability and dependency in older adults, placing severe and progressive limitations on autonomy in basic and instrumental daily activities (Martínez-Lage et al., 2018; Ministry of Health, 2021). These diseases are emerging as a growing pandemic, with profound implications for healthcare systems, families and societies worldwide (Grande et al., 2018). In 2019, it was estimated that 55.2 million people globally were living with dementia, with projections indicating this number could rise to approximately 78 million by 2030 and 139 million by 2050 (Roth et al., 2020; World Health Organization, 2021). In Spain, forecasts suggest that 4% of the population will be affected by dementia by 2050 — more than double the current rate. In 2018, this prevalence was estimated at 1.83% (over 850,000 individuals), with projections indicating it could reach nearly one million by 2025 and exceed 1.7 million by 2050 (EAF, 2020).

The scientific community widely recognises that the spatial behaviour of these diseases is influenced by factors associated with the circumstances in which individuals are born, grow, live, work and age —collectively known as the determinants of health (DH) (World Health Organization, 2008). Conceptual models describing these determinants, such as Dahlgren and Whitehead's rainbow model (1991), explain that social inequalities in health are the result of causal interactions among five domains: individual-level stable conditions; individual lifestyle factors; social and community networks; living and working conditions; and general socio-economic, cultural and environmental conditions. In the specific case of dementia, factors related to demographic structure, education level, social and familial support networks and the presence of other chronic conditions, such as hypertension or diabetes, are recognised in the literature as either protective or contributory to the development of the disease.

Ageing and the development of dementia are closely related processes, with advanced age being the most significant risk factor for dementia (Grande et al., 2018; Li et al., 2022). Up to 70% of individuals with dementia are over 75 years old (Vermunt et al., 2019). Furthermore, women are disproportionately affected, accounting for an estimated 65% of deaths due to Alzheimer's disease and other forms of dementia worldwide (OECD, 2021). In addition to age and gender, factors such as low educational attainment, lack of social support, and the prevalence of comorbidities like hypertension and diabetes increase the risk of dementia. A substantial body of literature supports the idea that education may help to protect against dementia by increasing what is known as cognitive reserve (Caamaño-Isorna et al., 2006; Sharp & Gatz, 2011; Tola-Arribas et al., 2013). This concept refers to the brain's ability to withstand age-related changes and pathologies associated with dementia without developing clinical symptoms or signs of illness (Fratiglioni & Wang, 2007; Meng & D'Arcy, 2012). Social environmental factors —including higher levels of social engagement, living with others, and avoiding isolation— have been identified as protective factors against the onset of dementia (Kelly et al., 2017; OMS, 2019). Studies suggest that individuals living in rural areas may be at a higher risk (Russ et al., 2012) due to isolation and limited access to healthcare services (Arsenault-Lapierre et al., 2023; Innes et al., 2011).

Chronic diseases such as Type 2 diabetes are associated with the major subtypes of dementia, particularly vascular dementia and unspecified dementia, the two types most evidently linked to vascular pathologies (Beeri & Bendlin, 2020; Thomassen et al., 2020). Hypertension is also related to cognitive impairment, dementia and Alzheimer's disease (Reig-Puig et al., 2011). Furthermore, depression is one of the primary comorbidities of neurological diseases, affecting between 30% and 50% of individuals with these conditions, with the highest percentages observed in certain types of dementia (Láinez Andrés, 2022). While some studies acknowledge the complexity of these associations, noting that they cannot be reduced to simple linear associations (Camafort & Sierra, 2016; Thomassen et al., 2020), evidence suggests that the prevention and early treatment of vascular risk factors and depression significantly mitigate the risk of dementia (Fernández-Martínez et al., 2008; Vega Alonso et al., 2016).

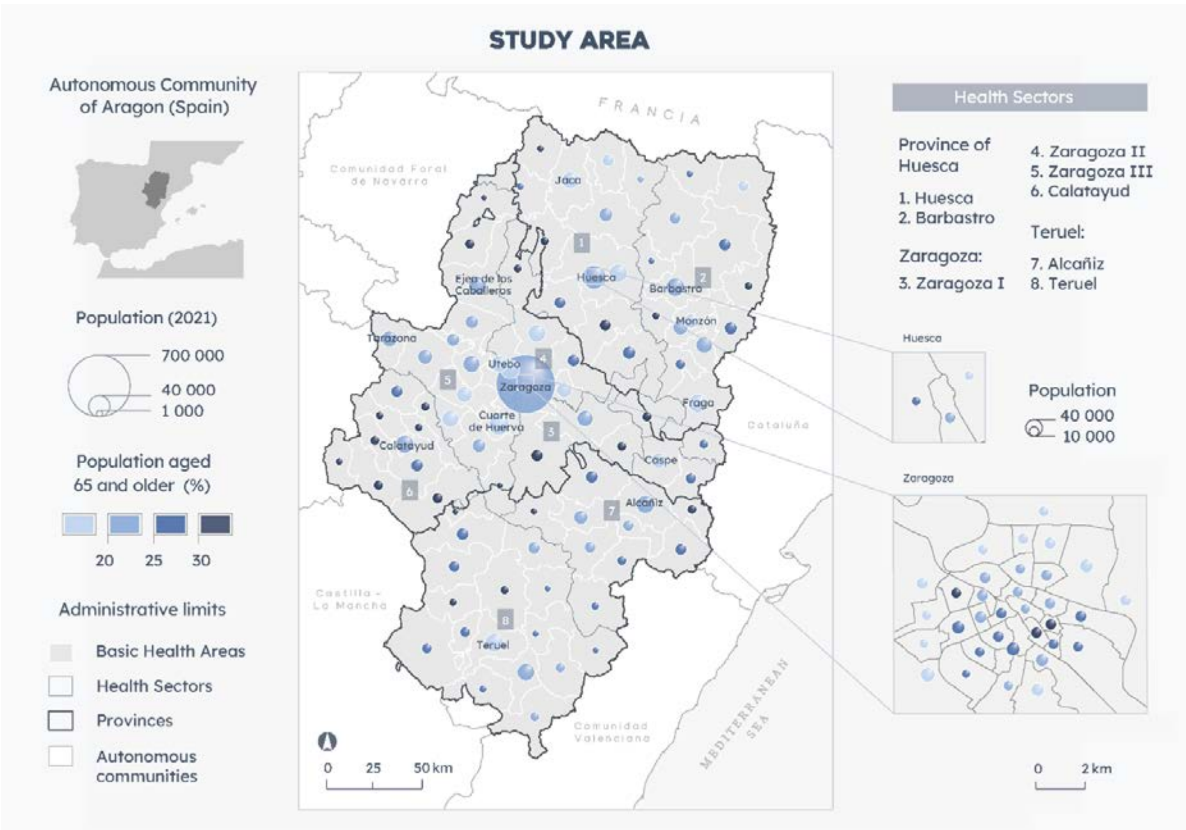
In Spain, research has documented associations between prevalence and these risk factors (Fernández Martínez et al., 2008; Soto-Gordoa et al., 2015; Tola-Arribas et al., 2013). However, studies exploring the spatial variability of these associations remain limited. Global regression models are typically employed in epidemiological studies (Bender, 2009), but they assume constant parameter estimates across locations, which neglects potential variations within the study area (Olaya, 2009). The present study is based on the premise that the spatial behaviour of DH factors may help explain the geographic variability in the prevalence of dementia. Therefore, we adopt a spatially explicit approach, using local regression models to assess the spatial variability in the statistical association between prevalence and DH indicators. These models are increasingly used in spatial epidemiology (Cromley, 2019), as they facilitate the identification of local contexts that may be particularly vulnerable and require greater attention for effective disease prevention and management.

2 Methodology

2.1 Study area

The study area is the autonomous community of Aragon (Figure 1), located in the northeastern Iberian Peninsula. Aragon spans an area of 47,719 km^2 and has a population of 1,326,315 inhabitants (2022), with a population density of 27.8 inhabitants per km^2. Administratively, the region is divided into three provinces (Huesca, Zaragoza and Teruel), 33 *comarcas* (territorial and administrative division) and 731 municipalities. Primary healthcare services in Aragon are organised into 123 Basic Health Areas (BHAs), which constitute the primary territorial units for healthcare delivery. These BHAs are further grouped into eight Health Sectors (Huesca, Barbastro, Zaragoza I, Zaragoza II, Zaragoza III, Calatayud, Teruel and Alcañiz). The boundaries of the BHAs are determined based on criteria such as population size. In urban areas like Zaragoza and Huesca, BHAs are made up of aggregated census sections, while in rural areas, they encompass entire municipalities.

Figure 1. Study area: Autonomous Community of Aragon (Spain), territorial division by Basic Health Areas (BHAs) and percentage of population aged 65 and older by BHA



Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

2.2 Study variables

The study variables are presented in Table 1. The dependent variables include dementia indicators disaggregated by sex (both sexes, men and women) across a continuous time series from 2015 to 2022. The original indicators, available at the open data portal of the Health Atlas of the Government of Aragon, represent the total diagnosed cases of dementia by BHA. These indicators were standardised by the total population of each BHA to obtain 24 prevalence rates of dementia, expressed per hundred individuals (eight rates for each category —both sexes, men and women— over the eight years of the study).

Explanatory factors (dementia risk) were also sourced from open data platforms. Territorial functionality is a normalised indicator reflecting the degree of influence a municipality exerts on the surrounding area based on a set of representative characteristics of supra-municipal functions exercised from that municipality, weighted according to their importance or scope. The Synthetic Index of Territorial Development, provided by the Government of Aragon, serves as the data source. Initially available at the municipal level, this indicator was aggregated at the BHA level by averaging the values of all municipalities within each BHA. The indicator of low educational level in persons aged 65 and older is represented by the proportion of this cohort with no education beyond primary school, expressed as a percentage of the total population aged 65 and older per BHA. Data were sourced from the 2021 Population and Housing Census (Spanish National Statistics Institute, INE). Marital status (widowhood) is another demographic indicator obtained from the 2021 Population and Housing Census. It reflects the proportion of widowed individuals aged 65 and older as a percentage of the total population in this age cohort per BHA. Hypertension and diabetes prevalence indicators were sourced from the Health Atlas of the Government of Aragon. Originally, these data represent the total diagnosed cases of hypertension and diabetes per BHA, disaggregated by sex (men and women), for each year from 2015 to 2022. Similar to the dementia indicators, these were standardised by the total population of each BHA to obtain 48 prevalence rates for hypertension and diabetes, expressed as percentages per hundred individuals (eight rates for both sexes—men and women—across the eight years of the study for each condition).

Table 1. Study variables. Dementia prevalence and risk factors

Variable	Description	Year	Source
Prevalence of dementia (both sexes, male and female)	Standardised annual prevalence rate of diagnosed dementia cases per BHA, disaggregated by sex (both sexes, male, female).	2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022	Health Atlas of Aragon (Government of Aragon)
Territorial functionality	Average value of a composite index reflecting the functional influence of municipalities within each BHA, based on supra-local service and activity characteristics.	2021	Government of Aragon
Low education level in population aged 65 and older	Percentage of the population aged 65 and older with no education beyond primary school, calculated over the total number of population aged 65 and older in each BHA.	2021	Population and Housing Census (INE)
Widowed population aged 65 and older	Percentage of widowed individuals aged 65 and older, calculated over the total population aged 65 and older in each BHA.	2021	Population and Housing Census (INE)
Prevalence of Hypertension (both sexes, male and female)	Standardised annual prevalence rate of diagnosed hypertension cases per BHA, disaggregated by sex (both sexes, male, female).	2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022	Health Atlas of Aragon (Government of Aragon)
Prevalence of diabetes (both sexes, male and female)	Standardised annual prevalence rate of diagnosed diabetes cases per BHA, disaggregated by sex (both sexes, male, female).	2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022	Health Atlas of Aragon (Government of Aragon)

Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

2.3 Methods

Although data are available for a continuous period between 2015 and 2022, the analytical design of this study is not longitudinal in the strict sense. Instead, we adopt a repeated cross-sectional spatial approach, whereby dementia prevalence and its association with health determinants are analysed separately for each year using an identical methodological framework. This strategy allows us to assess the spatial stability and persistence of patterns and relationships over time, rather than modelling individual temporal trajectories or causal trends. The temporal dimension is therefore used to evaluate the robustness of spatial associations and to identify areas where relationships between dementia prevalence and health determinants remain structurally consistent throughout the study period.

The methodological process was divided into two stages. First, we used principal component analysis (PCA), a dimensionality reduction technique that adjusts linear combinations of the original indicators to identify the dimensions that most effectively synthesise the majority of the original information. These dimensions, called principal components (PCs), capture a portion of the total variance of the original variables. The first PC captures and maximises the majority of the original variance, while the second explains the variance not accounted for by the first. This process continues until the number of components equals the number of original variables. This technique was used to reduce the dimensionality of the original DH data, preventing collinearity among explanatory factors in regression models. Collinearity can impair certain types of regression, such as ordinary least squares (OLS) and, consequently, geographically weighted regression (GWR), which was originally developed as a spatial disaggregation of OLS. Thus, by applying PCA to the selected variables, we mitigated collinearity issues among the explanatory factors in the regression models.

A total of nine PCAs were conducted. Initially, we performed six analyses to synthesise the indicators for hypertension and diabetes for the entire period (also covering both sexes, male and female). Secondly, we conducted three additional analyses to integrate the risk factors (functionality, low educational level, widowhood and the PCs of hypertension and diabetes) into a single indicator, disaggregated by sex. These indicators served as explanatory variables in the regression models. In all cases, components with eigenvalues greater than 1 were retained, as per Kaiser's criterion (Kaiser, 1960).

In the second stage, we conducted a GWR analysis to assess the spatial variability in the statistical association between prevalence of dementia and the set of DH indicators. GWR techniques enhances traditional regression models (known in this context as global regression models) by assessing local regression parameters (Fotheringham et al., 2002). GWR models operate by shifting a moving window across the study area, adjusting the regression equation for each location. Mathematically, the conventional GWR is expressed by the following equation:

$$Y_i = \sum_k \beta_k (u_i,v_i)\, x_{k.i} + e_i$$

where y_i, $x_{k,i}$ and e_i are, respectively, the dependent variable, the kth independent variable and the Gaussian error at location i; (u_i,v_i) is the x-y coordinate of the *ith* location; and β coefficients (u_i,v_i) are conditional to the location. Thus, a model is obtained for each BHA and its zone of influence, providing the local R^2, the regression coefficients, their significance and standard errors.

The weighting strategy in GWR models incorporates spatial autocorrelation principles, assigning higher weights to locations closer to the centre of the window than to those at the edges. This distance-based weighting can be classified into two types: Gaussian and biquadratic. In both cases, the weight assigned to the regression entity is 1, while the weights for surrounding entities decrease as the distance from the regression entity increases. A distinctive feature of biquadratic weighting is that, beyond a specified distance, the weights assigned to the surrounding entities approach zero. Conversely, in Gaussian weighting, all observations within the window contribute to the regression equation, though the contributions from those at the edges of the window are effectively negligible (Fotheringham et al., 2002). When determining the size of the neighbourhood region (bandwidth calibration), two strategies can be applied: (i) fixed kernel, which specifies a uniform distance threshold for each regression point, thereby considering a variable number of points in each local regression estimate (i.e., the central location plus neighbouring observations within the window); and (ii) adaptive kernel, which adjusts the bandwidth based on data density, tailoring it to a predetermined number of observations required to fit the regression. The fixed kernel strategy is generally more appropriate when observations are uniformly distributed across space, while the adaptive kernel strategy is preferable when clustered patterns are present. In this study, we compared both bandwidth selection strategies. To optimise our selection of bandwidth size, we minimised the Akaike information criterion (AIC), which was adapted for GWR by Hurvich et al. (1998). The AIC was also employed as a goodness-of-fit measure to compare the performance of local models against global models, as superior performance of the latter would support spatially dependent relationships between prevalence and risk factors. As an absolute measure of goodness of fit for the models, we used the adjusted R-squared (R^2) value.

In addition to these statistical metrics, GWR models provide other useful parameters for analysing the local behaviour of explanatory variables, such as the Student's t-test (to determine significance levels) and local R^2 value (i.e., the R^2 value of the model at the reference point and its neighbours). Having these values for each BHA enables mapping of the spatial distribution of associations through maps of local R^2, regression coefficients and their significance.

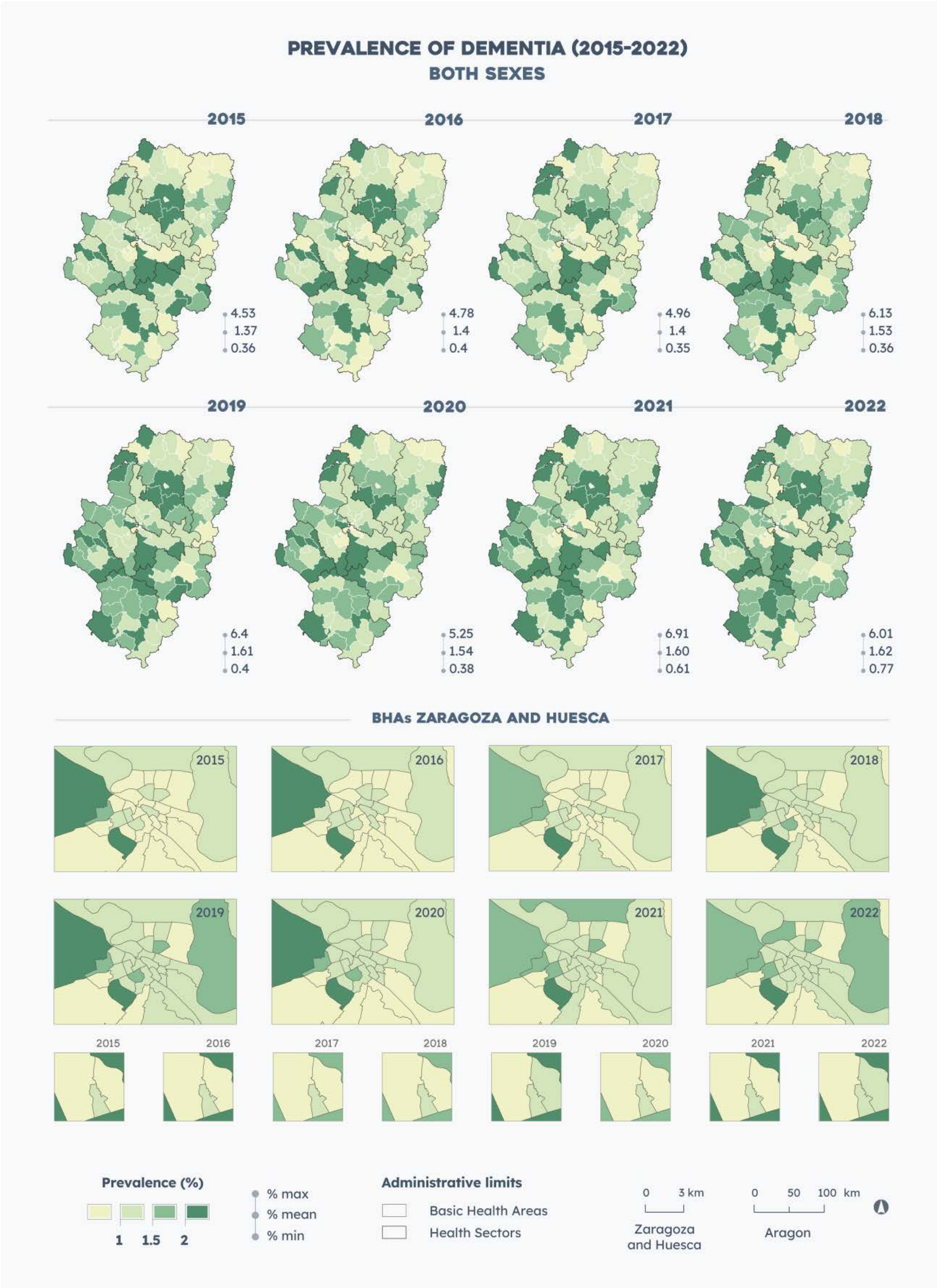
3 Results

3.1 Spatial distribution of the prevalence of dementia

Figure 2 shows the spatial distribution of the prevalence of dementia across both sexes by BHA for the study period (2015–2022). Given that the spatial behaviour for both sexes is similar, the series of maps disaggregated by sex are presented in Annexs 1 and 2. High geographic variability is observed, with notable differences between minimum and maximum values across the study area. These differences reach up to 6%, 5%, and 9.5% for both sexes, male and female, respectively. Between 2015 and 2022, the variation in prevalence remained below 0.4% in all three cases. In absolute terms, this means an increase of 4,000 diagnoses between 2015 and 2022, reaching a total of 18,059 in 2022. Notably, women account for approximately twice as many cases as men, with roughly 12,500 cases reported in 2022. The spatial distribution patterns of dementia prevalence are similar for both sexes and remain consistent throughout the study period. A distinct west-to-east gradient of decreasing prevalence is observed, with the highest rates found in the BHAs within the Huesca and Zaragoza II Health Sectors, as well as in the northern part of the Teruel Health Sector (reaching up to 6.91% for both sexes, 5.3% in males, and approximately 10% in females). These areas also exhibit the most significant increases in prevalence between 2015 and 2022. Urban BHAs display average rates below the regional average, although they still present notable internal geographic variability.

Supplementary Figure 7 shows that changes in dementia prevalence between 2015 and 2022 are predominantly positive across most BHAs, although their magnitude differs by sex. For the total population, changes range from a decrease of approximately −1.0 percentage points to an increase of 2.1, with an average increase of around 0.25. Sex-specific results reveal a more pronounced intensity of change among women: while mean changes are positive for both sexes, the maximum increase reaches nearly 4.0 percentage points in the female population, compared to just under 3.0 among men, and variability is also higher among women. In spatial terms, the largest increases tend to be observed in BHAs with higher prevalence levels and in urban BHAs, a pattern that is consistent across the total population and both sexes.

Figure 2. Spatial distribution of the prevalence of dementia in Aragon. Both sexes (2015–2022)



Source: authors' own elaboration based on data from the Health Atlas of Aragon of the Government of Aragon (2023)

3.2 PCA outputs

The results of the PCAs are presented in Table 2. The indicators for hypertension and diabetes accounted for nearly all the variance in the dataset, with percentages of around 95%. The negative values indicate a higher prevalence of hypertension and diabetes for both sexes. The risk factor indicators (Functionality, Low Education, Widowhood, Hypertension and Diabetes) were synthesised into a single indicator, labelled 'PC1 Risk factors' (referring to both sexes, male and female), used as explanatory variables in the regression models. These PCs accounted for approximately 60% of the original variance. The negative values correspond to unfavourable conditions associated with lower territorial functionality, a higher proportion of older adults with low education attainment and a greater prevalence of hypertension and diabetes.

Figure 3 presents the spatial distribution of the 'PC1 Risk factors' for both sexes, alongside the original indicators. This PC synthesises spatial patterns in the distribution of indicators. The highest values of the component are observed in BHAs where the referenced municipalities are at the top of the functional hierarchy of settlements in Aragon, such as provincial capitals, the metropolitan area of Zaragoza and the most populated BHAs. Additionally, northern BHAs, which have a lower proportion of elderly individuals who are widowed and with low educational attainment, show similar trends. A lower risk is also observed in the eastern zone, driven by lower prevalence rates of hypertension and diabetes. In contrast, the lowest values indicate situations of greater vulnerability. These are largely rural BHAs, where a high proportion of elderly individuals have low educational attainment and are widowed (surpassing 90% and 30% of the total population, respectively). These areas also exhibit higher prevalence rates of hypertension and diabetes. The values of the component for these prevalences only allow for relative comparisons. Specifically, the minimum and maximum values for hypertension range from 8% to 33.5% in men and from 6.6% to 39% in women, with an average rate for both sexes of 22.2% in 2022. The average diabetes prevalence rate for both sexes in the same year is 8.3%. When disaggregated by sex, the rates range from 2.8% to 15.5% in men and from 2% to 12.2% in women.

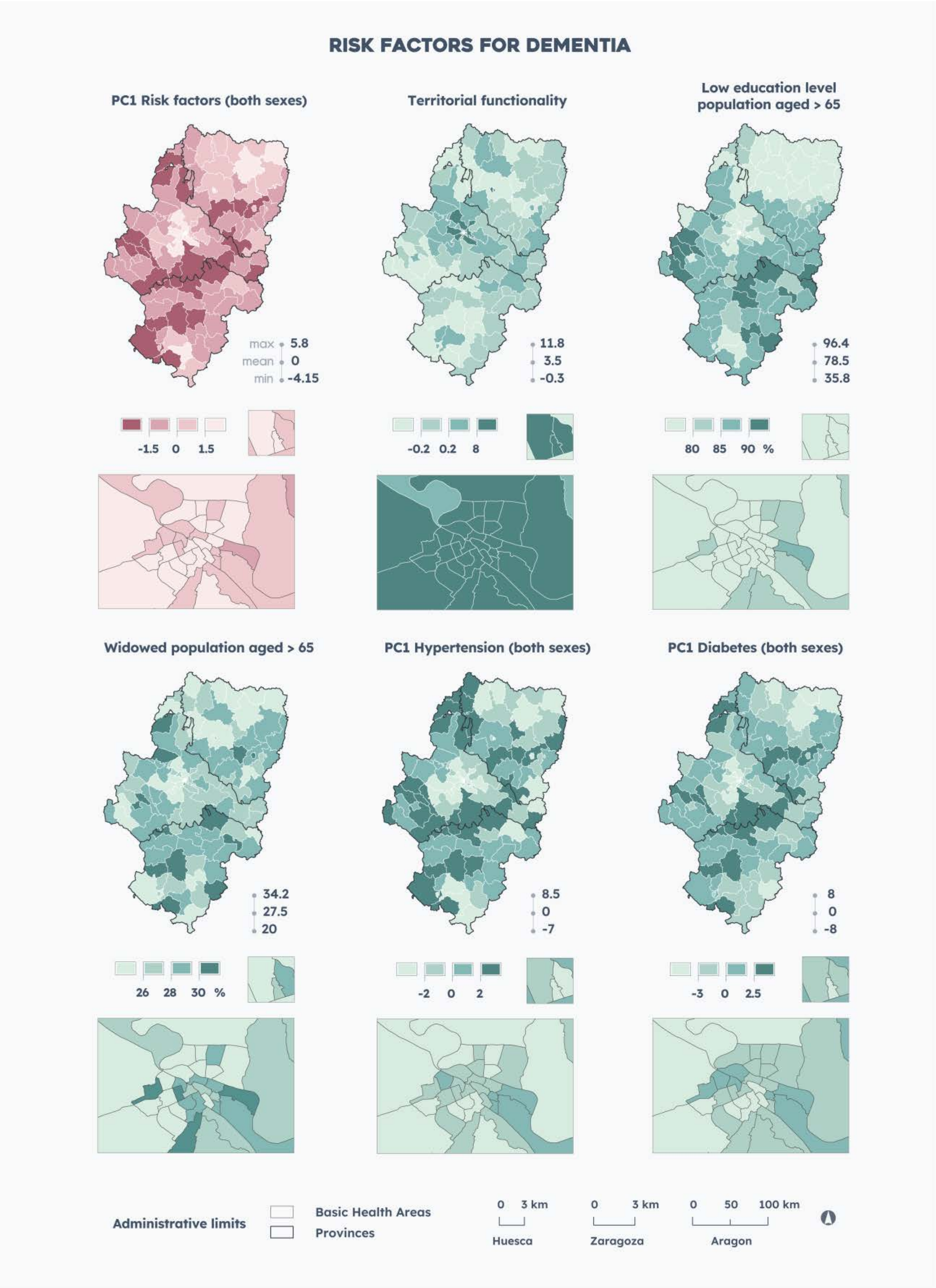
Table 2. Selected principal components (PCs): eigenvalues, variable loadings and percentage of explained variance

Selected PCs	% Variance	Variables	Eigval
PC 1 Hypertension			
Both sexes	0.937	Prevalence 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022	> 0.98
Male	0.976		> 0.98
Female	0.983		> 0.98
PC1 Diabetes			
Both sexes	0.958	Prevalence 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022	> 0.96
Male	0.958		> 0.96
Female	0.947		> 0.96
PC 1 Risk factors			
Both sexes	0.615	Territorial functionality Low education attainment Civil status: widowhood PC1 Hypertension PC1 Diabetes	0.714 -0.813 -0.581 0.862 0.883
Male	0.579	Territorial functionality Low education attainment Civil status: widowhood PC1 Hypertension PC1 Diabetes	0.724 -0.795 -0.538 0.827 0.843
Female	0.624	Territorial functionality Low education attainment Civil status: widowhood PC1 Hypertension PC1 Diabetes	0.700 -0.821 -0.621 0.875 0.897

Note: %V represents the proportion of variance captured by the PC within the block. EigVal denotes the correlation value between the original variables and the PCs.

Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

Figure 3. Spatial distribution of health determinant (DH) indicators and the principal component 'PC1 Risk Factors'



Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

3.3 Spatial variation in the association between variables

As a first step, global ordinary least squares (OLS) regression models were estimated to provide a baseline assessment of the relationship between dementia prevalence and the composite indicator of risk factors (PC1 Risk factors). OLS results revealed a negative association between dementia prevalence and the PC risk factors, suggesting higher prevalence rates in predominantly rural areas characterised by a higher proportion of elderly adults with low educational attainment, widowhood and elevated rates of hypertension and diabetes.

To account for potential spatial non-stationarity in these relationships, GWR models were subsequently estimated. These models demonstrated a better goodness of fit than OLS (Table 3). The variance explained between OLS and GWR differed by as much as 30% for both sexes, with a 40% difference in male models and up to 24% in female models (2021). Both OLS and GWR showed better results at the end of the study period (from 2018 onward), with adjusted R^2 values in GWR models greater than 0.5. In models referring to both sexes, the highest adjusted R^2 value was 0.57 in 2021, 0.64 in male models (2021) and 0.54 in female models (2019 and 2020). This improvement over time reflects greater explanatory power of the selected determinants, while reinforcing the predominance of spatial contrasts over temporal variation.

Table 3. Percentage of variance explained by regression models (OLS and GWR), by sex and year

REGRESSION RESULTS (OLS AND GWR)									
Model	Both sexes			Male			Female		
	OLS	GWR	BW	OLS	GWR	BW	OLS	GWR	BW
2015	0.32	0.43	25	0.34	0.34	152	0.29	0.45	24
2016	0.31	0.32	61	0.35	0.35	152	0.28	0.38	27
2017	0.32	0.32	81	0.32	0.32	152	0.3	0.32	62
2018	0.32	0.5	24	0.34	0.48	24	0.29	0.53	23
2019	0.3	0.5	23	0.29	0.51	21	0.29	0.54	23
2020	0.35	0.55	22	0.31	0.6	20	0.35	0.54	23
2021	0.26	0.57	21	0.23	0.64	20	0.26	0.5	23
2022	0.27	0.51	23	0.25	0.56	21	0.25	0.43	25

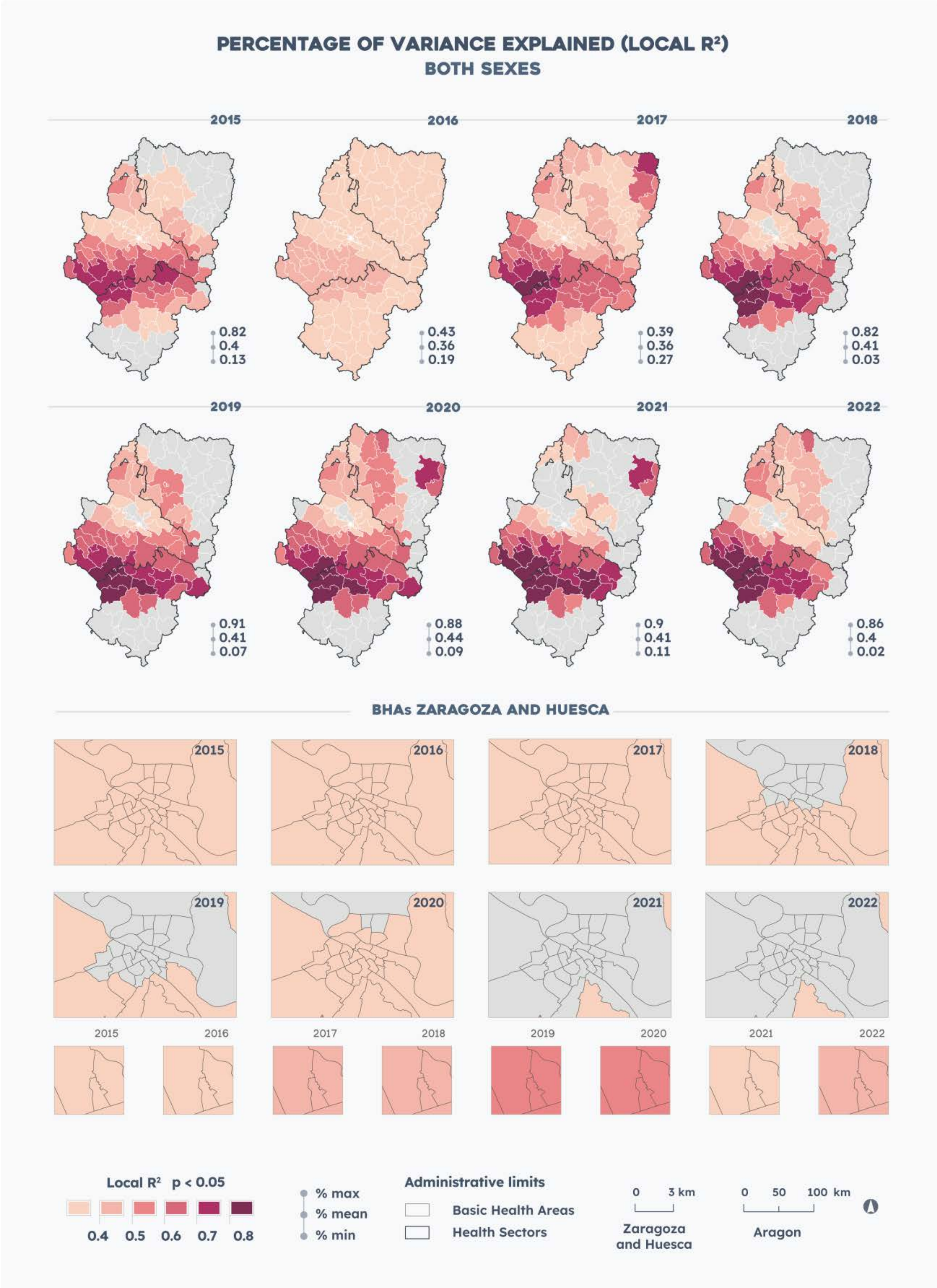
Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

Various weighting strategies and kernel types were compared, with better fits achieved using a fixed kernel and a Gaussian weighting strategy. When the bandwidth size was larger (up to 81 and 152 km in both sexes and male models, respectively), both OLS and GWR exhibited similar

R^2 values. In contrast, in nearly all other cases, the optimal bandwidth size was approximately 23 km. This indicates that neighbouring BHAs exert a stronger influence on local regression estimates, supporting the presence of spatially heterogeneous relationships across the study area.

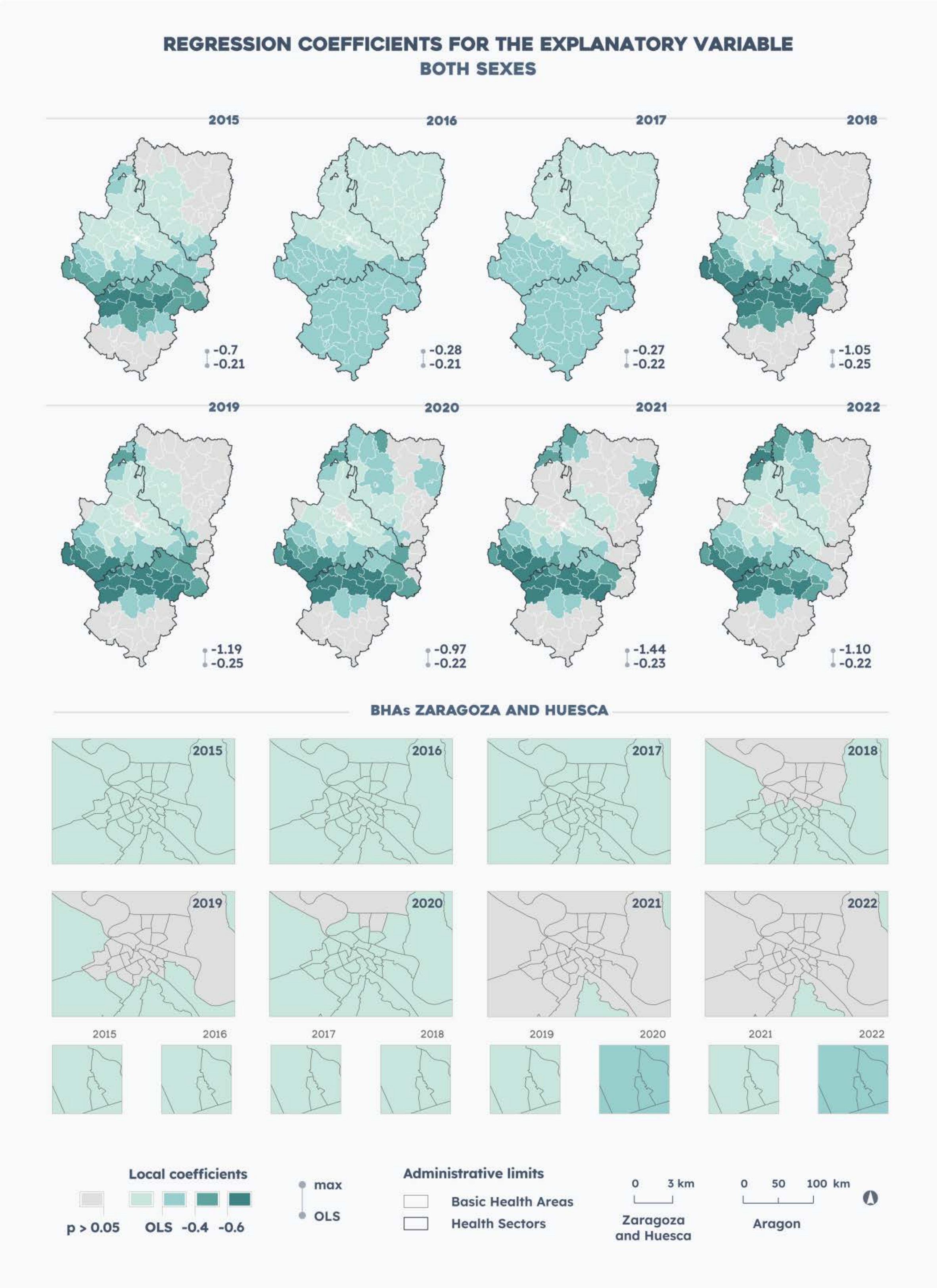
Figures 4 and 5 show the spatial disaggregation of local R^2 values and regression coefficients derived from GWR models, allowing comparison with the corresponding global OLS estimates for models referring to both sexes. The map series disaggregated by sex are presented as Annexs 3, 4, 5 and 6. In the series of coefficient maps, the first interval in the legend represents the threshold at which the estimated coefficient values differ between OLS and GWR. Beyond this interval, the estimated coefficient values exceed those of the global model. A wide range of local R^2 values is observed in the maps for both sexes, male and female, with substantial differences between BHAs. The lowest values appear in the eastern part of the region, particularly in many BHAs in Huesca and in the southern part of the province of Teruel. In these BHAs, the coefficients are either not significant or closely resemble those estimated in the OLS model. A similar pattern is observed in the urban BHAs in Zaragoza and Huesca. R^2 values gradually increase towards the northwestern part of the region (ranging between 0.4 and 0.5), covering most BHAs in the provinces of Huesca and Zaragoza. The local coefficients in these BHAs are either similar to those estimated in the OLS model or slightly higher in the BHAs in northwestern Huesca. The highest magnitudes (exceeding 0.7) are observed in the southern half of the region, where local coefficient values differ significantly from the OLS estimates. The BHAs in the Health Sector of Calatayud and those located in the northern part of the province of Teruel stand out due to the magnitude of the local R^2 and the estimated coefficients, revealing a spatial pattern that remains consistent throughout the study period, with only minor interannual variations.

Figure 4. Spatial variation in local R² values from GWR models. Both sexes (2015–2022)



Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

Figure 5. Spatial distribution of the regression coefficients for the explanatory variable. Models of both sexes (2015–2022)



Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

4 Discussion

The aim of this study was to investigate the spatial distribution of the prevalence of dementia in the autonomous community of Aragon (Spain) using an approach based on social DH. We evaluated the potential spatial variability in the statistical association between dementia prevalence and various DH to identify patterns and possible geographic disparities in these conditions. The methodological process involved several stages. First, we created databases of indicators of dementia prevalence and risk factors such as rurality, low educational attainment, marital status (widowhood) and the prevalence of hypertension and diabetes. Secondly, we applied PCA to reduce the dimensionality of the initial data and generate new context-specific indicators for Aragon. Finally, we employed GWR techniques to assess the existence of spatial variability in the associations between prevalence and risk factors. The results contribute to the existing evidence on the role of certain DH in the geographic variability in health outcomes. In the specific case of dementia in Aragon, sociodemographic factors, levels of territorial development and comorbidities commonly associated with the disease provide key insights into its spatial distribution.

The prevalence rates of dementia in Aragon exhibit remarkable geographic variability, with differences of up to 6%, 5%, and 9.5% for both sexes, male and female, respectively. Women consistently show higher prevalence rates, with crude rates indicating twice as many total cases as men. This variability has been observed in previous studies that also report greater vulnerability among women (AEF, 2020; de Pedro-Cuesta et al., 2009; Ponjoan et al., 2019). In addition, the spatial distribution of recent changes in prevalence indicates that the largest increases tend to occur in areas that already exhibit higher prevalence levels, particularly in urban BHAs, reinforcing the interpretation of persistent spatial inequalities rather than widespread temporal shifts.

Regarding risk factors, our findings reveal that prevalence rates tend to rise in predominantly rural areas characterised by a higher proportion of older adults with lower levels of educational attainment, higher rates of widowhood and increased prevalence of hypertension and diabetes. These results are consistent with previous studies highlighting the influence of social DH variables such as socioeconomic status and access to healthcare and diagnostic resources in understanding the regional differences in prevalence rates (Langa et al., 2017; Matthews et al., 2013).

Education is frequently highlighted as a protective factor against cognitive decline, due to its association with greater cognitive reserve (Caamaño-Isorna et al., 2006; Sharp & Gatz, 2011; Tola-Arribas et al., 2013; Zhang & Zheng, 2023). Prior research has also identified associations between the prevalence of dementia and experiences of loneliness, concluding that a lack of support and social isolation significantly increases the risk of cognitive decline (Kelly et al., 2017; OMS, 2019), especially in rural areas (Hackett & Steptoe, 2023). In Aragon, dementia rates are significantly higher in rural environments, where a greater proportion of elderly individuals live in single-person households (Rabanaque-Hernández, 2021). Limited access to resources exacerbates the vulnerability of older adults in rural areas (Li et al., 2022). However, rural environments can also offer protective factors against mental health disorders. These include stronger social connections and a greater sense of community, which may help mitigate some of the risks associated with isolation and limited resources (Lyons et al., 2016; Marmot, 2005). Conversely, while urban areas provide greater access to social and healthcare resources, urban living is often associated with loneliness and stress, factors linked to a higher prevalence of dementia (Cudjoe et al., 2023).

These associations may exhibit local variations within the study area. The spatial variability of both prevalence rates and social DH indicators underscores the need for spatially explicit approaches that can explore the variability in their statistical associations. The results from comparative analyses between global and local regression models (OLS and GWR) indicate that the spatial disaggregation of global models more effectively capture the combined variance of prevalence. This suggests the existence of spatially varying relationships between dementia prevalence and risk factors. In all models, we observed that smaller bandwidth sizes resulted in a better goodness of fit, thereby highlighting the local nature of the associations. The explanatory power of the 'PC1 Risk factors' exceeded 70% in certain parts of the region, particularly in the Health Sectors of Calatayud and Teruel, as well as in neighbouring BHAs in the provinces of Huesca and Zaragoza. This spatial pattern was consistent across both male and female models and remained stable throughout the study period.

Most of these BHAs are characterised by greater social vulnerability, which is associated with a higher proportion of older individuals with low educational attainment and a higher likelihood of experiencing loneliness due to widowhood. While other areas in the region share similar profiles, these BHAs report the highest prevalence rates of hypertension and diabetes. Furthermore, the geographic dispersion of municipalities within these BHAs presents further disadvantages regarding the availability and accessibility of healthcare resources. These findings highlight the advantages of employing GWR in spatial analyses, where local variations are critical to understanding underlying processes. Previous studies have stressed the importance of incorporating geographic considerations when analysing risk factors for dementia, as local conditions, healthcare access and population characteristics significantly influence regional outcomes (Bagheri et al., 2018; Lim & Park, 2022; Liu et al., 2024). Acknowledging these regional disparities is essential for designing more effective and targeted strategies to reduce dementia risk in specific populations.

Recommendations from previous studies on cognitive health and national public health strategies for dementia prevention stress the importance of standardised care pathways to ensure equitable access to diagnosis, treatment and follow-up care (Innes et al., 2011; Martínez-Lage et al., 2018). The difficulties in diagnosing conditions such as dementia and Alzheimer's disease intensified during the COVID-19 pandemic, leading to a rise in undiagnosed cases (Hoang et al., 2024). Rural areas in Aragon may have been disproportionately affected, underscoring the urgency of developing early detection initiatives. Similarly, early prevention and treatment of comorbidities associated with dementia, such as hypertension and diabetes, are crucial for reducing the risk of dementia (Fernández-Martínez et al., 2008; Vega Alonso et al., 2016). From a social and community perspective, strengthening programmes that incorporate both social and physical activities in accessible environments is vital for supporting cognitive health (Steichele et al., 2022). Moreover, increasing access to green spaces is also essential, as it promotes physical activity and social interaction, which are associated with reduced dementia risk (Jimenez et al., 2022; Mollalo et al., 2024; Yuchi et al., 2020).

The primary limitation of this study lies in its ecological design, which does not allow for definitive conclusions about causal relationships between the identified factors and the higher prevalence of dementia in specific areas. Such conclusions would subject interpretations to ecological bias, a significant limitation inherent to this type of study, which restricts its ability to firmly establish causality (Rabanaque-Hernández, 2021). Despite its limitations, the ecological approach offers valuable insights into contextual factors within specific geographic areas that influence health outcomes. This makes it particularly useful for identifying high-risk regions where prevention and disease management efforts can be more effectively targeted (Golden & Wendel, 2020; McQueen, 2013). The findings of this study have identified areas that are particularly vulnerable to dementia prevalence, indicating where such efforts should be focused.

For future lines of research, we propose a more in-depth analysis of the spatial behaviour of associations by employing alternative versions of GWR, such as the multiscale model or geographically and temporally weighted regression (GTWR) (Fotheringham et al., 2015; Wang et al., 2023). These variations provide opportunities to explore spatiotemporal variations in associations, allowing for the identification of specific spatial contexts relevant to these relationships (Oshan et al., 2019). Moreover, these techniques would be beneficial for analysing other indicators related to disease, such as incidence rates. Complementing prevalence measures with incidence indicators is crucial for gaining a deeper understanding of disease dynamics, particularly in identifying areas with higher rates of conditions such as dementia and other mental health disorders (Prina et al., 2019). Monitoring both prevalence and incidence over time can help identify trends that reflect changes in risk factors, which in turn supports the development of more comprehensive models that consider the complex interactions between social, environmental, and health factors.

5 Conclusions

This study demonstrates that the relationship between dementia prevalence and key determinants of health in Aragon (Spain) is spatially non-stationary, with marked geographic variability that cannot be adequately captured by global models, thus directly addressing the study's objective of exploring spatial heterogeneity in dementia prevalence. Higher prevalence rates are observed in predominantly rural areas, where there is a larger proportion of older adults with low educational attainment, widowhood and elevated rates of hypertension and diabetes. These patterns reflect structurally different territorial contexts in which demographic ageing, social vulnerability and the burden of chronic conditions intersect, shaping unequal spatial outcomes in dementia prevalence. In contrast, urban areas show lower overall rates of dementia compared to the regional average. However, significant internal geographic variability exists within urban environments. This finding underscores the importance of acknowledging heterogeneity in urban settings, as diverse socioeconomic and environmental factors may influence health outcomes, even within neighbouring communities. The application of GWR models reveals substantial local variation in both the strength and explanatory power of these relationships, highlighting areas where health determinants explain a much larger share of dementia prevalence than suggested by global models. These insights emphasize the need for targeted strategies in disease prevention and management. The persistence of these spatial patterns over time, despite relatively modest interannual variation, underscores the need for territorially differentiated prevention, early detection and care strategies that are sensitive to local demographic and social contexts.

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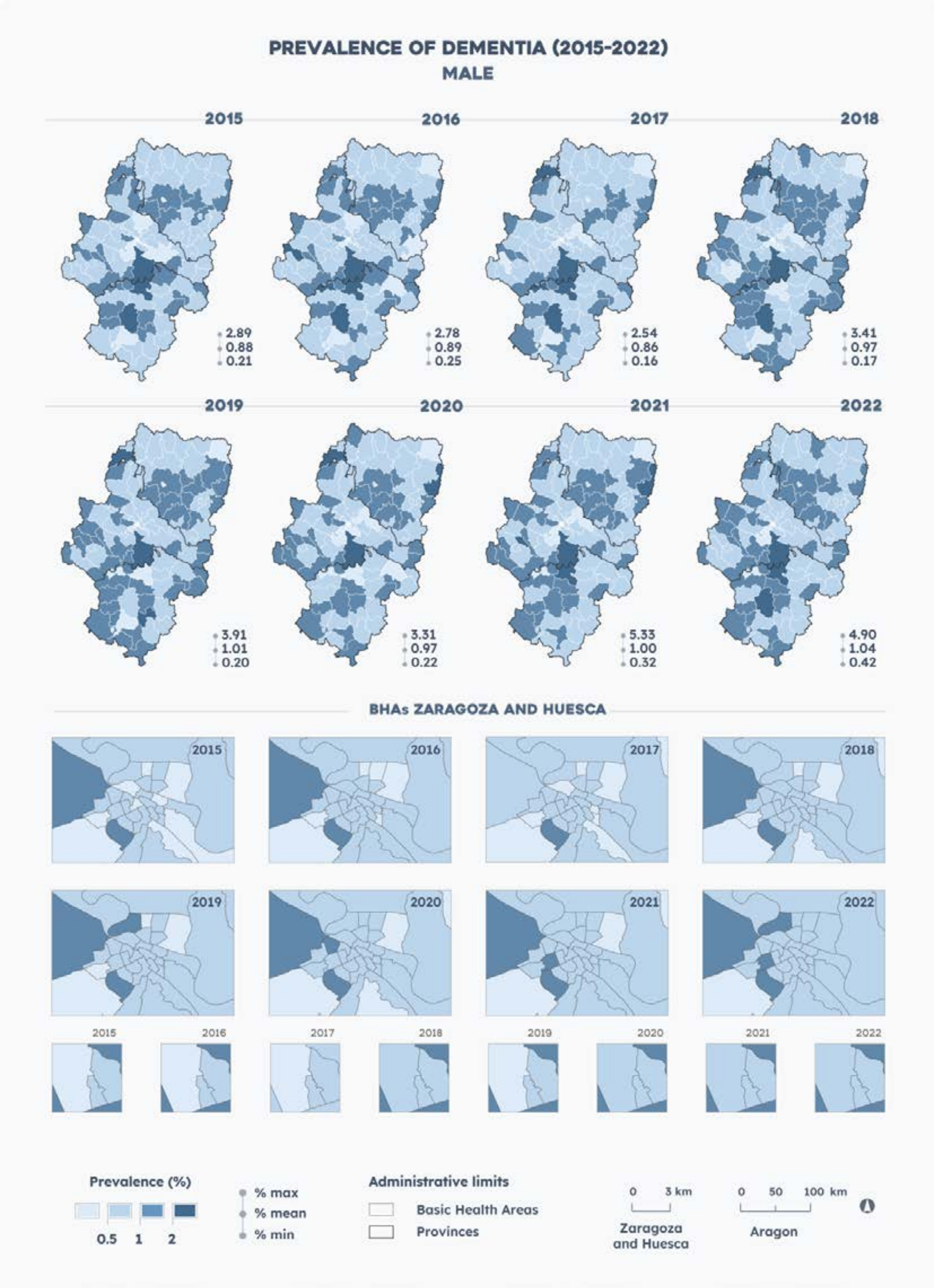
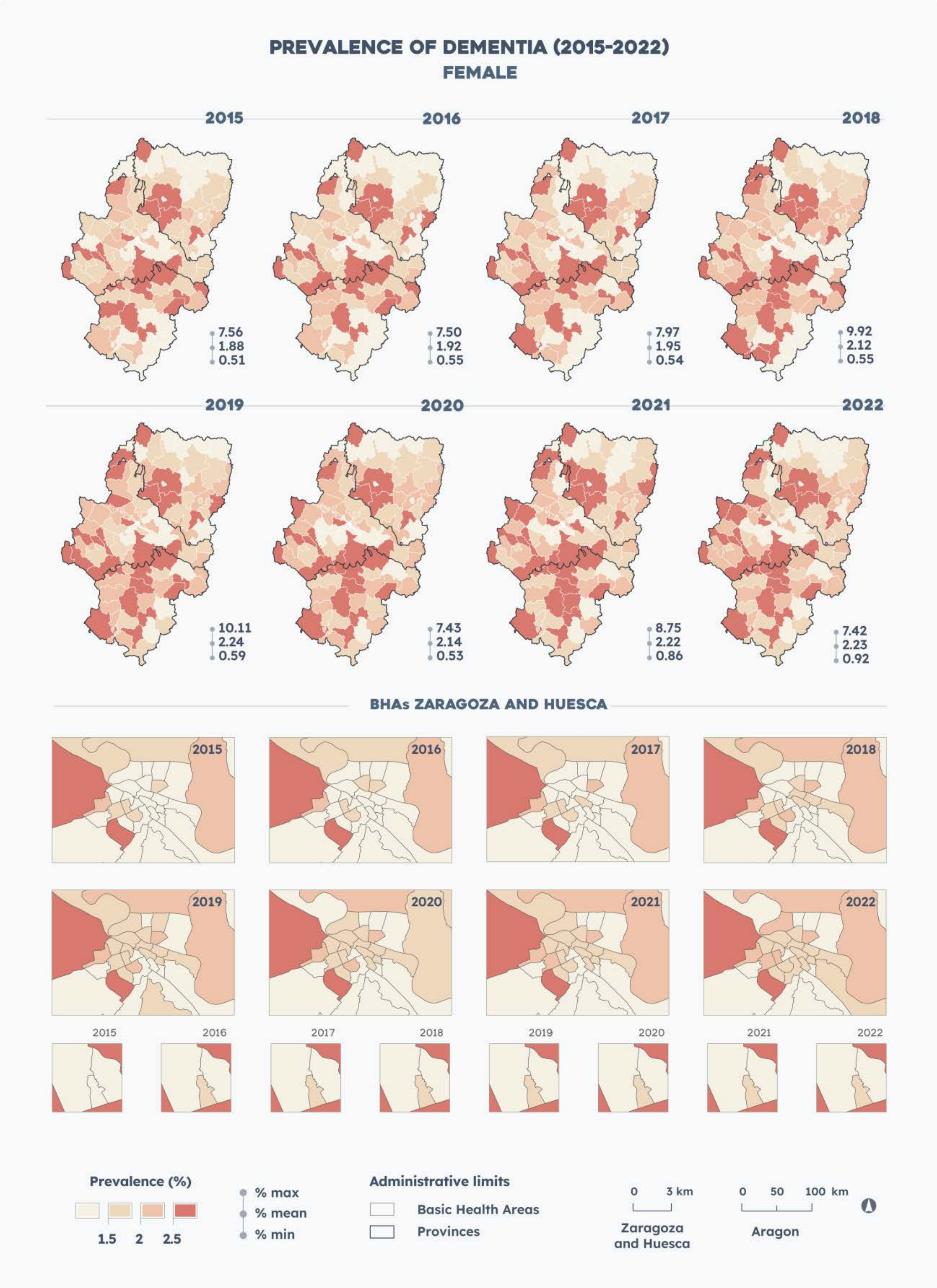
Annex I. Supplementary Figures: Spatial Distribution of Dementia and Model Outputs disaggregated by sex (2015-2022)

Supplementary Figure 1. Spatial distribution of dementia prevalence in Aragon. Male population (2015–2022)



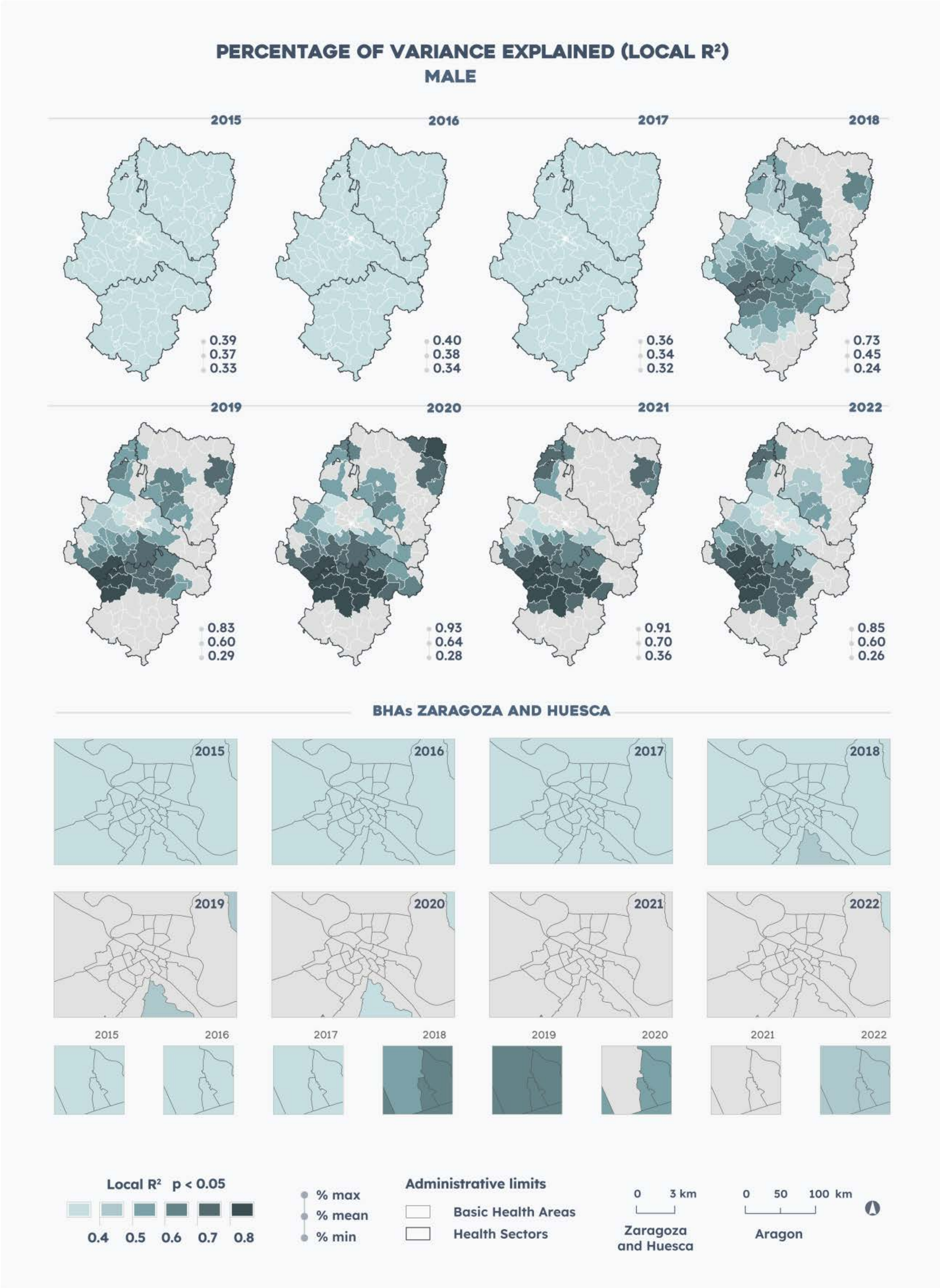
Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

Supplementary Figure 2. Spatial distribution of dementia prevalence in Aragon. Female population (2015–2022)



Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

Supplementary Figure 3. Local R^2 values from GWR models. Male population (2015–2022)

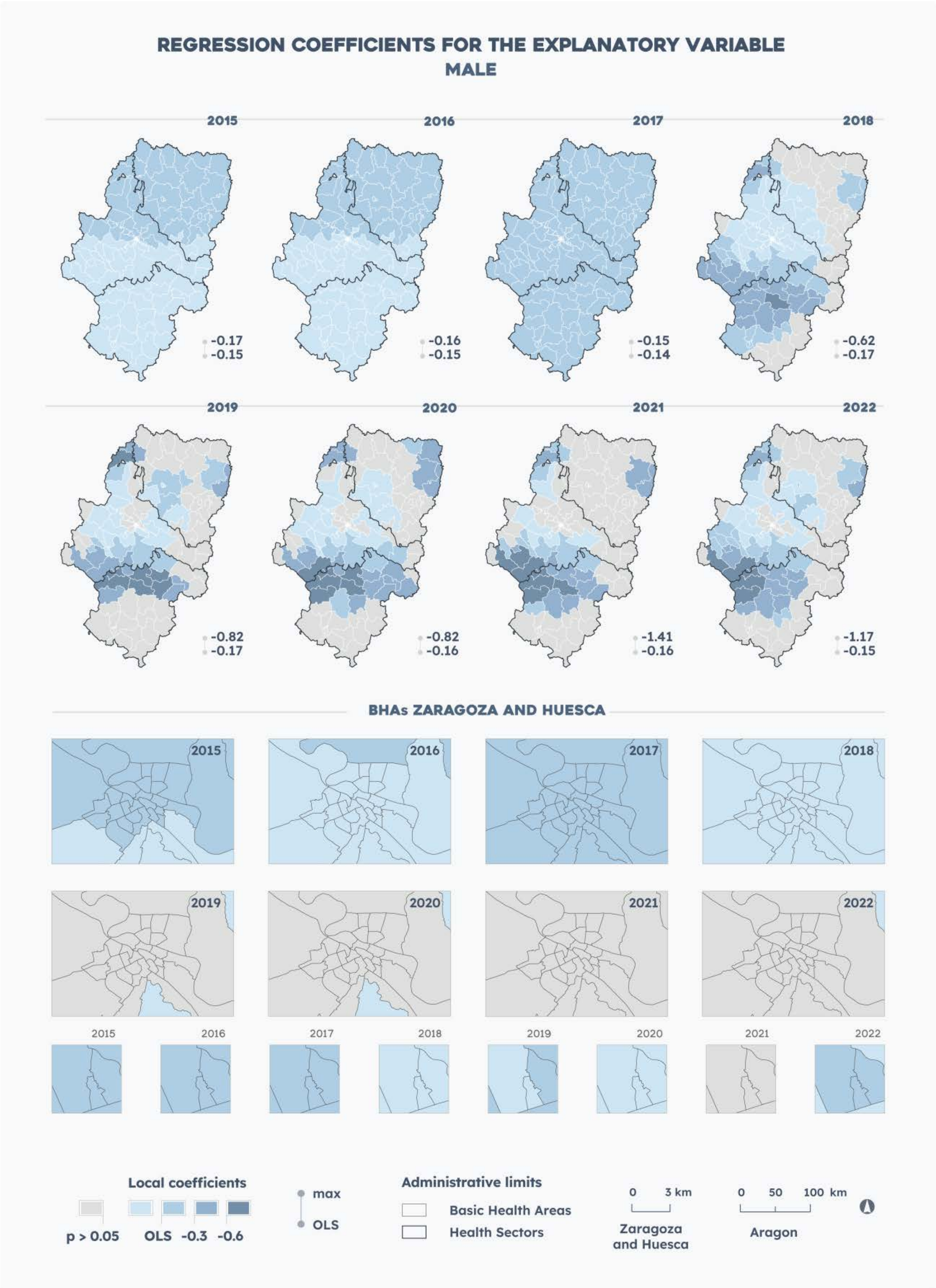


Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

Supplementary Figure 4. Local R² values from GWR models. Female population (2015–2022)

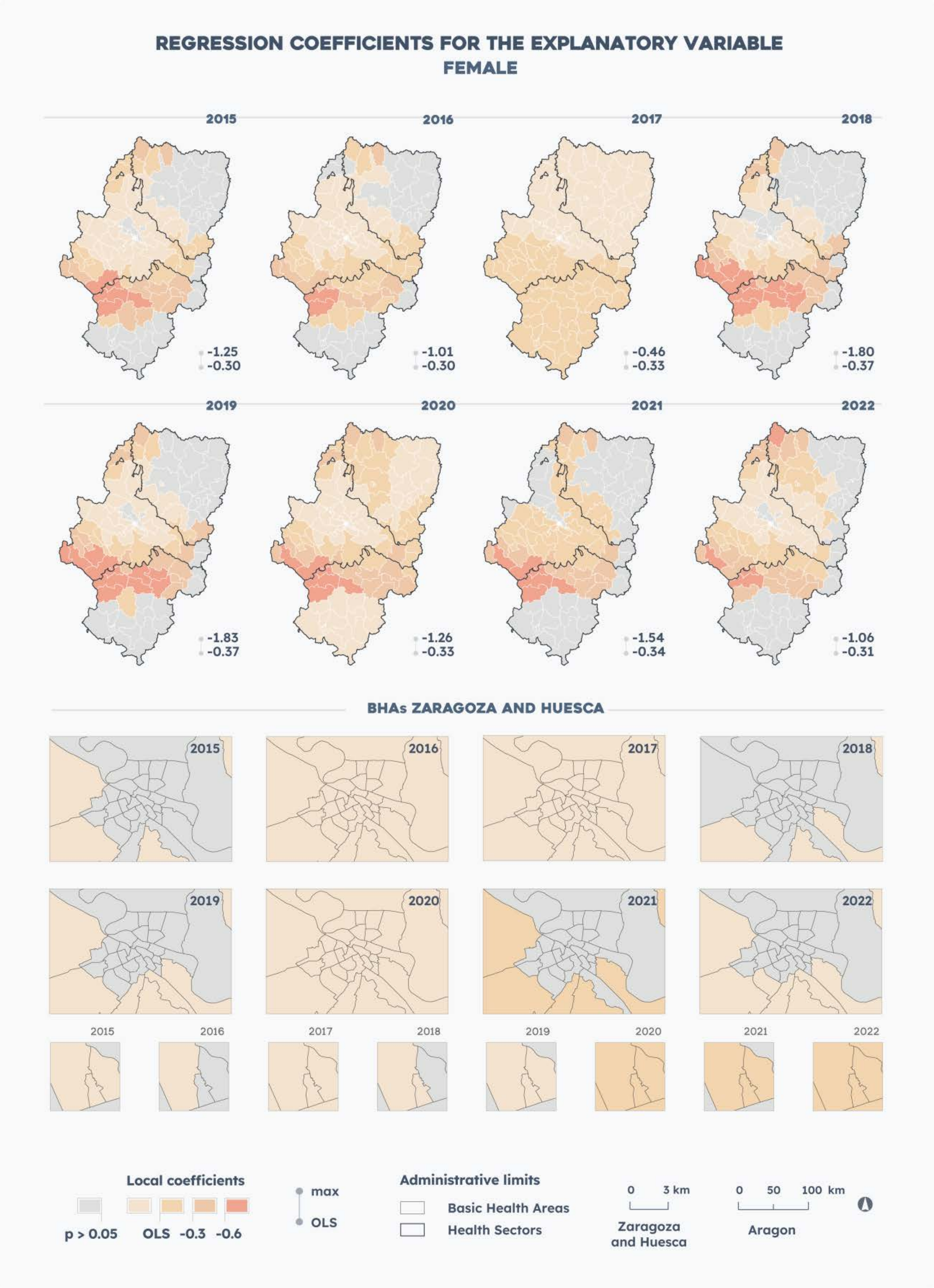
Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

Supplementary Figure 5. Local regression coefficients for the explanatory component 'PC1 Risk Factors'. Male GWR models (2015–2022)



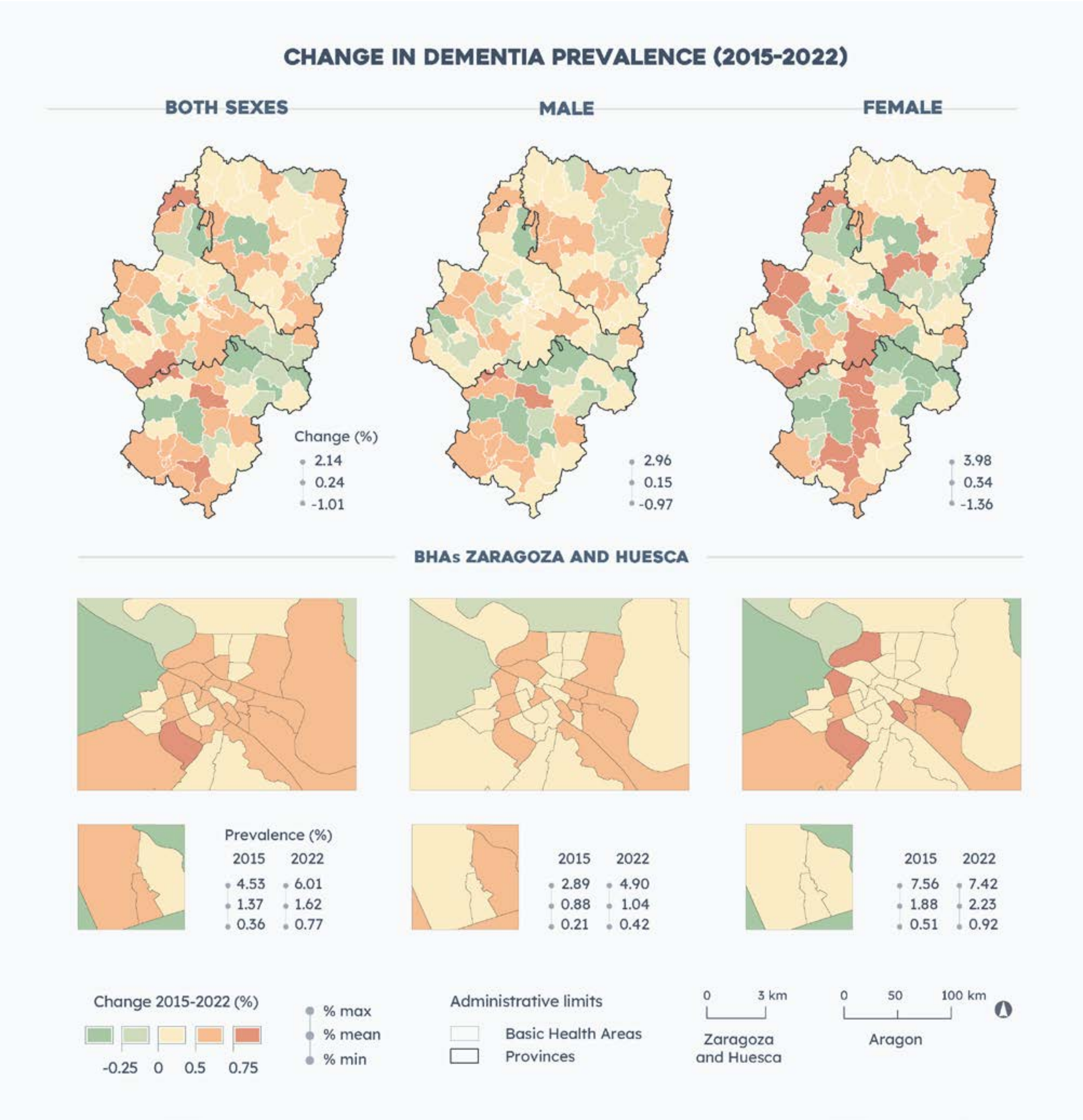
Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

Supplementary Figure 6. Local regression coefficients for the explanatory component 'PC1 Risk Factors'. Female GWR models (2015–2022)



Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)

Supplementary Figure 7. Change in dementia prevalence between 2015 and 2022. Both sexes, male and female



Source: authors' own elaboration based on data from the 2021 Population and Housing Census (INE, 2023) and the Health Atlas of Aragon of the Government of Aragon (2023)