Environmental heterogeneity in human health studies. A compositional methodology for Land Use and Land cover data

Quim Zaldo-Aubanell [a,b,*], Isabel Serra [c,d], Albert Bach [b,h], Pablo Knobel [b], Ferran Campillo i López [b,e], Jordina Belmonte [a,f], Pepus Daunis-i-Estadella [g], Roser Maneja [b,h,i]

[a] Institute of Environmental Science and Technology (ICTA), Autonomous University of Barcelona (UAB), Z building, ICTA-ICP, Carrer de les columnes, UAB Campus, 08193, Bellaterra, Barcelona, Spain

[b] Environment and Human Health Laboratory (EH² Lab), Forest Science and Technology Center of Catalonia, Ctra. de St. Llorenç de Morunys, km 2, 25280 Solsona, Spain

[c] Centre de Recerca Matemàtica, Edifici C, 08193 Bellaterra, Barcelona, Spain

[d] Barcelona Supercomputing Center, 08034 Barcelona, Spain

[e] Paediatric Environmental Health Specialty Unit, Paediatric Team of the Garrotxa Region, Olot and Garrotxa Region Hospital Foundation, Avinguda Països Catalans 86, 17800 Olot, Catalonia, Spain

[f] Department of Animal Biology, Plant Biology and Ecology, Autonomous University of Barcelona (UAB), C building, UAB Campus 08193, Bellaterra, Barcelona, Spain

[g] Department of Computer Science, Applied Mathematics and Statistics, Universitat de Girona, Carrer Universitat de Girona, 6, 17003 Girona, Spain

[h] Forest Science and Technology Center of Catalonia, Ctra. de St. Llorenç de Morunys, km 2, 25280 Solsona, Spain

[i] Geography Department, Autonomous University of Barcelona (UAB), B building, UAB Campus 08193, Bellaterra, Barcelona, Spain

HIGHLIGHTS

- Compositional methodology spotting independent effect of LULC categories
- Important effect measure modification of socioeconomic status, age group and sex
- Environmental heterogeneity as a key factor in environment-health studies
- Compositional methodology as a suitable tool assessing environmental heterogeneity

GRAPHICAL ABSTRACT
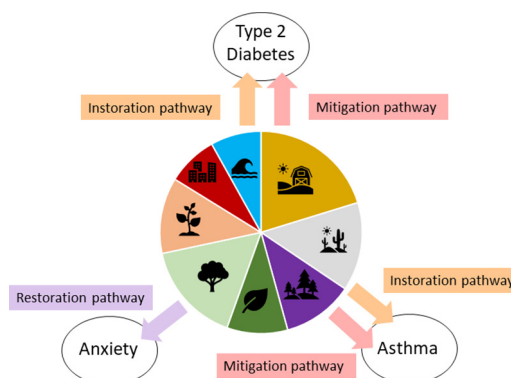
ARTICLE INFO

ABSTRACT

The use of Land use and Land cover (LULC) data is gradually becoming more widely spread in studies relating the environment to human health. However, little research has acknowledged the compositional nature of these data. The goal of the present study is to explore, for the first time, the independent effect of eight LULC categories (agricultural land, bare land, coniferous forest, broad-leaved forest, sclerophyll forest, grassland and shrubs, urban areas, and waterbodies) on three selected common health conditions: type 2 diabetes mellitus (T2DM), asthma and anxiety, using a compositional methodological approach and leveraging observational health data of Catalonia (Spain) at area level.

We fixed the risk exposure scenario using three covariates (socioeconomic status, age group, and sex). Then, we assessed the independent effect of the eight LULC categories on each health condition. Our results show that each LULC category has a distinctive effect on the three health conditions and that the three covariates clearly modify this effect.

* Corresponding author at: Environment and Human Health Laboratory (EH² Lab), Forest Science and Technology Center of Catalonia, Ctra. de St. Llorenç de Morunys, km 2, 25280 Solsona, Spain.
E-mail address: quim.zaldo@uab.cat (Q. Zaldo-Aubanell).

This compositional approach has yielded plausible results supported by the existing literature, highlighting the relevance of environmental heterogeneity in health studies. In this sense, we argue that different types of environment possess exclusive biotic and abiotic elements affecting distinctively on human health.

We believe our contribution might help researchers approach the environment in a more multidimensional manner integrating environmental heterogeneity in the analysis.

1. Introduction

In the last decades, the study of the relationship between the environment and human health has increasingly captured the scientific community's attention worldwide. As a result, growing evidence is starting to highlight the potential benefits that the environment might provide to human health (Barnes et al., 2019; Sandifer et al., 2015; Stier-Jarmer et al., 2021; Taylor and Hochuli, 2015). Until now, different metrics assessing the environment have been showcased (Bach et al., 2020); from measurements of the landscape proportion, the Normalized Difference Vegetation Index (NDVI), to the Simpson's patch diversity and percentages of tree canopy and green spaces (Cushman et al., 2008; Donovan et al., 2013; Frank et al., 2006; Hanski et al., 2012; Sarkar et al., 2013). Among these metrics, Land use and Land cover (LULC) data are gradually becoming more widely spread (Zaldo-Aubanell et al., 2021b).

LULC data is usually a low-cost and high resolution resource, which is regularly updated (Grekousis et al., 2015). Unlike other environmental data, LULC data encompasses both biophysical (e.g., temperature, humidity, biodiversity, and soil features) and socioeconomic (e.g., political, economic, and cultural) environmental information (Boada and Gomez, 2012). Moreover, LULC data is versatile and can distinguish between different types of environments, which is particularly relevant since different types of environments are suggested to have specific elements that might promote distinct benefits to human health (Astell-Burt and Feng, 2019; de Vries, 2019; Wheeler et al., 2015; White et al., 2013; Zaldo-Aubanell et al., 2021b).

Many researchers have used LULC data to describe the environment (Groenewegen et al., 2012; Maas et al., 2009a; Mitchell and Popham, 2007; van den Berg et al., 2010; Wheeler et al., 2012). However, little research has acknowledged the compositional nature of such data (Aitchison, 2009; Pearson, 1896).

The compositional nature of LULC data can be observed in the analysis of proportions of specific LULC categories composing geographical regions (Leininger et al., 2013). Each observation is a vector of proportions which has the peculiarity of being constrained, so the sum of all its parts is a constant (Aitchison and Egozcue, 2005). Thus, the vector of proportions is a D-part composition, with D components, and the "sample space" is not the real Euclidean space associated with unconstrained data (Aitchison, 2009). Therefore, D-part compositions only provide information about the relative magnitudes of the compositional components (Aitchison and Egozcue, 2005; Hron et al., 2012), and this information is completely gathered in D-1 ratios between the components.

Some researchers have avoided the singularity constraint of LULC data by classifying the percentages of LULC categories according to quantile division (Bixby et al., 2015; Lachowycz and Jones, 2014; Mitchell and Popham, 2008; Mytton et al., 2012; Wu et al., 2015). These methods represent a step forward to the proper use of LULC data. However, consideration of the compositional nature of LULC data might be a critical factor as this has been demonstrated to respect scale invariance and the relative scale issues that are completely ignored when raw data (e.g., proportions or percentages) is used (Müller et al., 2018). To our knowledge, no other study relating LULC data to human health has yet used a compositional approach for the analysis, except for one study assessing the potential contribution of LULC categories to explain the geographical distribution of both COVID-19 incidence and mortality in Catalonia (Spain) (Zaldo-Aubanell et al., 2021a).

The aim of this study is to explore, for the first time, the independent effect of eight LULC categories (agricultural areas, bare land, coniferous forest, broad-leaved forest, sclerophyll forest, grassland and shrubs, urban areas, and waterbodies) on three selected common health conditions (type 2 diabetes mellitus (T2DM), asthma and anxiety) using a compositional methodological approach. This study leverages observational health data of Catalonia (Spain) at area level (the Basic Health Areas; BHAs).

2. Materials and methods

2.1. Environmental heterogeneity: Land use and Land cover (LULC) dataset

We described the environmental heterogeneity of each Basic Health Area (BHA) according to relevant literature (Astell-Burt and Feng, 2019; Hanski et al., 2012; Wheeler et al., 2015). First, we reclassified the prior 23 LULC categories of the Land Use and Land Cover map of Catalonia (Spain) from 2012 into eight major categories: agricultural areas, bare land, coniferous forest, broad-leaved forest, sclerophyll forest, grassland and shrubs, urban areas, and water bodies (see Table S1 and Fig. S2 in Supplementary materials). Then, we calculated the vector of proportions of each reclassified LULC category for each BHA.

The 2012 Land Use and Land Cover map of Catalonia is a tool generated with automated image classification of a 30-m resolution (minimum area representing 30x30m). Images are obtained thought Landsat satellite (Landsat-5, Landsat-7, Landsat-8, and Sentinel-2) using both their sensors (Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Operational Land Imager (OLI) and Multispectral Imager (MSI)), and complementary information such as the Urbanistic Map of Catalonia and the graph of the Catalonia infrastructures network. The map also incorporates the cartographic database of forest fires from the Ministry of Agriculture, Livestock, Fisheries and Food of Catalonia, and the LIDAR database from the *Institut Cartogràfic i Geològic de Catalunya* (ICGC) (https://territori.gencat.cat/ca/01_departament/12_cartografia_i_toponimia/bases_cartografiques/medi_ambient_i_sostenibilitat/usos-del-sol/).

2.2. Health data

The prevalence rates of T2DM, asthma, and anxiety for each BHA were obtained from the Catalan Health Department and the Catalan Agency for Health Quality and Evaluation (AQuAS). The health data corresponded to 2014, they were aggregated by age group and sex, and were provided for each Basic Health Area (BHA), the fundamental territorial unit through which the Catalan Healthcare System is articulated (see Fig. S2 in Supplementary materials).

The data did not distinguish between type 1 diabetes and type 2 diabetes. However, almost 95% of all diagnosed cases of diabetes are estimated to be type 2 in adults (Centers for Disease Control and Prevention, 2011). Therefore, we assumed a well representation of individuals with T2DM in our data as previously described (Astell-Burt et al., 2014a).

2.3. Covariates

Three covariates (age group, sex, and socioeconomic status (SES)) were used for segmentation to fix the risk exposure scenario and assess the independent effect of the eight LULC categories.

We considered six age groups: paediatric (named 1 in the figures and the tables; <15 years), teenagers and young adults (2; 15–44 years), adult (3; 45–64 years), senior (4; 65–74 years), old (5; 75–84 years) and very old (6; >84 years). Besides, sex was categorised as male or female.

Furthermore, SES information was obtained using the 2015 Composed Socioeconomic Index (CSI) (Colls et al., 2020) from the Catalan Health Observatory. The CSI is a deprivation index calculated for each BHA and used in assessing resources for Primary Health. The CSI is a continuous variable (0 to 100) that includes the following information: economic income, level of education, professional occupation, life expectancy, premature death rate, and evitable hospitalizations rate (Colls et al., 2020). We used a quintile division of this index, creating five categories: very high (CSI ≤ 34.75), high (34.75 > CSI ≤ 42.60), medium (42.60 > CSI ≤ 48.99), low (48.99 > CSI ≤ 56.37) and very low SES (56.37 > CSI ≤ 100).

2.4. Data analysis

2.4.1. Compositional ilr-transformation

The use of raw compositional data to directly conduct common statistical analyses raises the problem of singularity, which was already warned as problematic over a century ago (Pearson, 1896). Instead, we propose a proper transformation of compositional data, moving the compositions isometrically from the simplex with the Aitchison geometry to the standard real space with the Euclidean geometry (Egozcue and Pawlowsky-Glahn, 2016; Hron et al., 2012). The transformation creates new coordinates in the Euclidean geometry and thus allow for popular statistical methods to be applied (Müller et al., 2018). In this case, regression modelling.

Since regression models are meaningful only when the compositional covariates are expressed on an orthonormal basis, a feasible alternative to raw data (e.g., proportions and percentages) is to use the isometric logratio (ilr) transformation (Hron et al., 2012). In particular, this could be the set of pivot logratios (PLRs), which are a succession of ilr-coordinates where the numerator in the ratio is always a single component and the denominator all those other components "to the right" in the ordered list of components (Greenacre and Grunsky, 2019).

For a better interpretation of the regression coefficients, Müller et al. (2018) suggest moving from the orthonormal to the orthogonal coordinates (see Eq. (1)). So, in a regression with non-compositional response and compositional regressors, an additive increment of one unit in the ilr-orthogonal variable ($z^{(l)*}$) is equal to a two-fold multiplicative increase in the relative dominance of the original composition variable x, if the base-2 logarithm is used (Müller et al., 2018) (see Eq. (2)). This transformation follows:

$$z_i^{(l)*} = \log_2 \frac{x_i^{(l)}}{\sqrt[D-i]{\prod_{j=i+1}^{D} x_j^{(l)}}}, i = 1, \ldots, D-1 \tag{1}$$

$$\Delta z_i^{(l)*} = \log_2 \left(2 \times \frac{x_i^{(l)}}{\sqrt[D-i]{\prod_{j=i+1}^{D} x_j^{(l)}}} \right) = \log_2(2) + \log_2 \frac{x_i^{(l)}}{\sqrt[D-i]{\prod_{j=i+1}^{D} x_j^{(l)}}} = 1 + \log_2 \frac{x_i^{(l)}}{\sqrt[D-i]{\prod_{j=i+1}^{D} x_j^{(l)}}}$$
$$i = 1, \ldots, D-1 \tag{2}$$

In our study, we used the transformation suggested by Müller et al. (2018) (Eq. (1)) to transform the vector of proportions of the eight LULC categories describing the environmental heterogeneity for each BHA.

We observed some zeroes derived from the lack of some LULC categories in specific BHAs. To simplify and given that the minimum resolution of our LULC data was 30 × 30 m, we opted for simple imputation of these zeroes. Thus, we replaced the zeroes by the minimum value of 900 m² to create a vector of positive components $w \in S^D$ that then was closured $r = C(w)$. We assumed that it was plausible to consider that each LULC category could be represented in at least one area of 30 × 30 m within each BHA. For instance, agriculture areas might take the form of urban agriculture in heavily urbanised BHA. Forested areas might also be present, shaping street trees. Even waterbodies might be represented in small pools of water.

2.4.2. Statistical analysis

Before the analyses, and to avoid potential interaction problems derived from possible associations, we used a Chi-square testing for significant differences between socioeconomic levels and the presence of LULC categories.

We fitted four different regressions to our data: Binomial, Poisson, Negative Binomial, and Beta regression. Similar results were found for all regressions, although Negative Binomial and Beta regression showed higher confidence intervals. As expected, the best-fit model according to AIC was for Negative Binomial regression. However, we noted no important differences in the estimates derived from the four regressions. Thus, we finally modelled our data using the Binomial regression with logit link, as it best represented the nature of the assessed health conditions (see Eq. (4)). Furthermore, this model was the most feasible in terms of simplicity and interpretability. The population size of each BHA was used as weights when fitting the model.

$$Y_i \sim Bernoulli(p_i) \text{ for } i = 1, \ldots, n.$$

$$Logit(\mu_i) = \log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i \times X_i^* \tag{4}$$

where Y_i was the binary (Bernoulli) response variable; p_i was the probability of successes $P(Y_i = 1)$, in this case, 1 stands for a diagnosed case; μ_i was the expected value of each Y_i which was equal to the probability of successes p_i; β_0 was the intercept, and β_i denoted the logistic regression coefficients for the design ilr-matrix X^* of covariables i.

The role of the covariates 'age group', 'sex', and 'socioeconomic status' has been extensively used to describe health status (Beyer et al., 2018; Frank et al., 2004; Mobley et al., 2006; Richardson and Mitchell, 2010; Van den Berg et al., 2016). We used these covariates for segmentation to fix the risk exposure scenario. In total, sixty segmentations were performed. Then, we assessed the independent effect of the eight ilr-transformed LULC categories on each health condition, as previously described in Müller et al. (2018).

Additionally, we also show the estimated coefficients of all explanatory variables (sex, age group, socioeconomic status, and ilr-transformed LULC categories) for each selected health condition derived from ordinary general models using non-segmented data (see Table S3 in Supplementary materials).

We conducted the statistical analyses using the R language environment for statistical computing, R version 3.6.2 (12 December 2019) (R Core Team, 2019).

3. Results

Before conducting any regression analysis, and to avoid potential interaction problems derived from possible associations, we used a Chi-square to test for significant differences between socioeconomical levels and LULC categories. The Chi-squared test showed no significant evidence to reject the hypothesis that SES was not related with LULC categories: $X^2(28, N = 369) = 28.403, p = 0.443$. Therefore, we assumed no significant relationship between socioeconomic levels of BHAs and the presence of any particular LULC category.

Hereunder, we show the independent effect of each ilr-transformed LULC category on the segmented health conditions (see Figs. 2, 3, and 4;
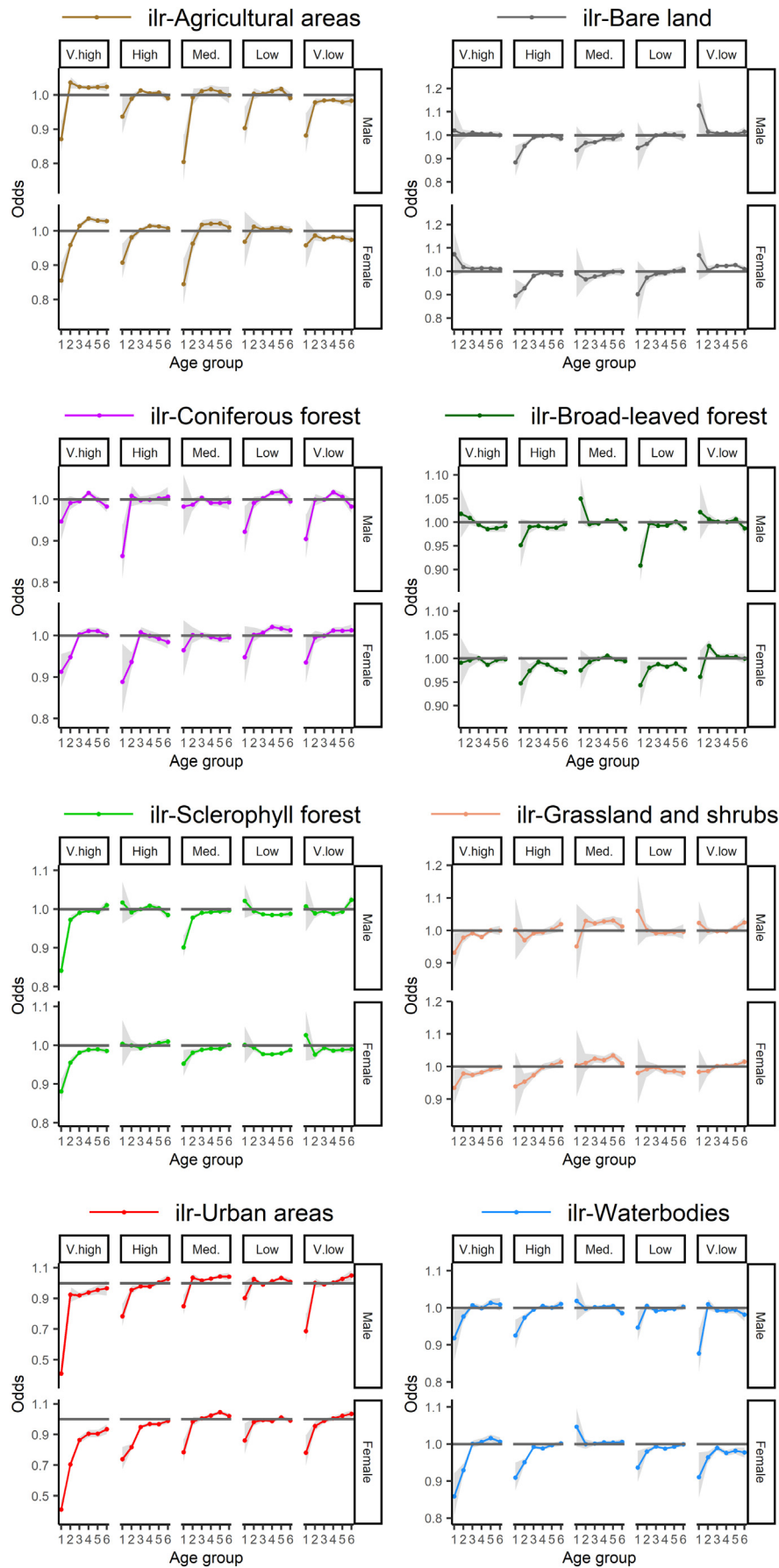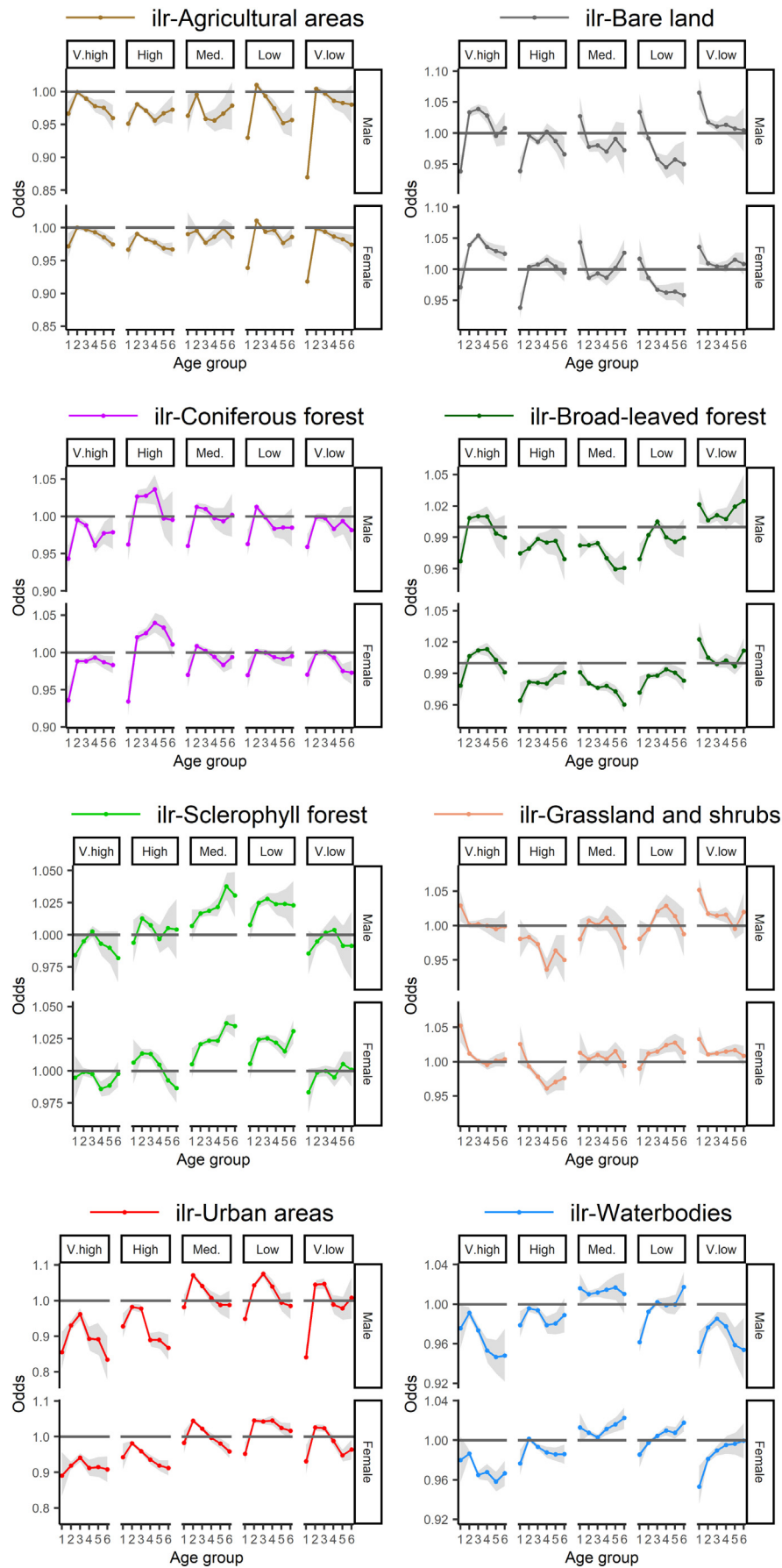
Fig. 2. Odds ratios (in colour) and 95% CI (grey bands). Associations between the prevalence of T2DM and ilr-LULC categories.
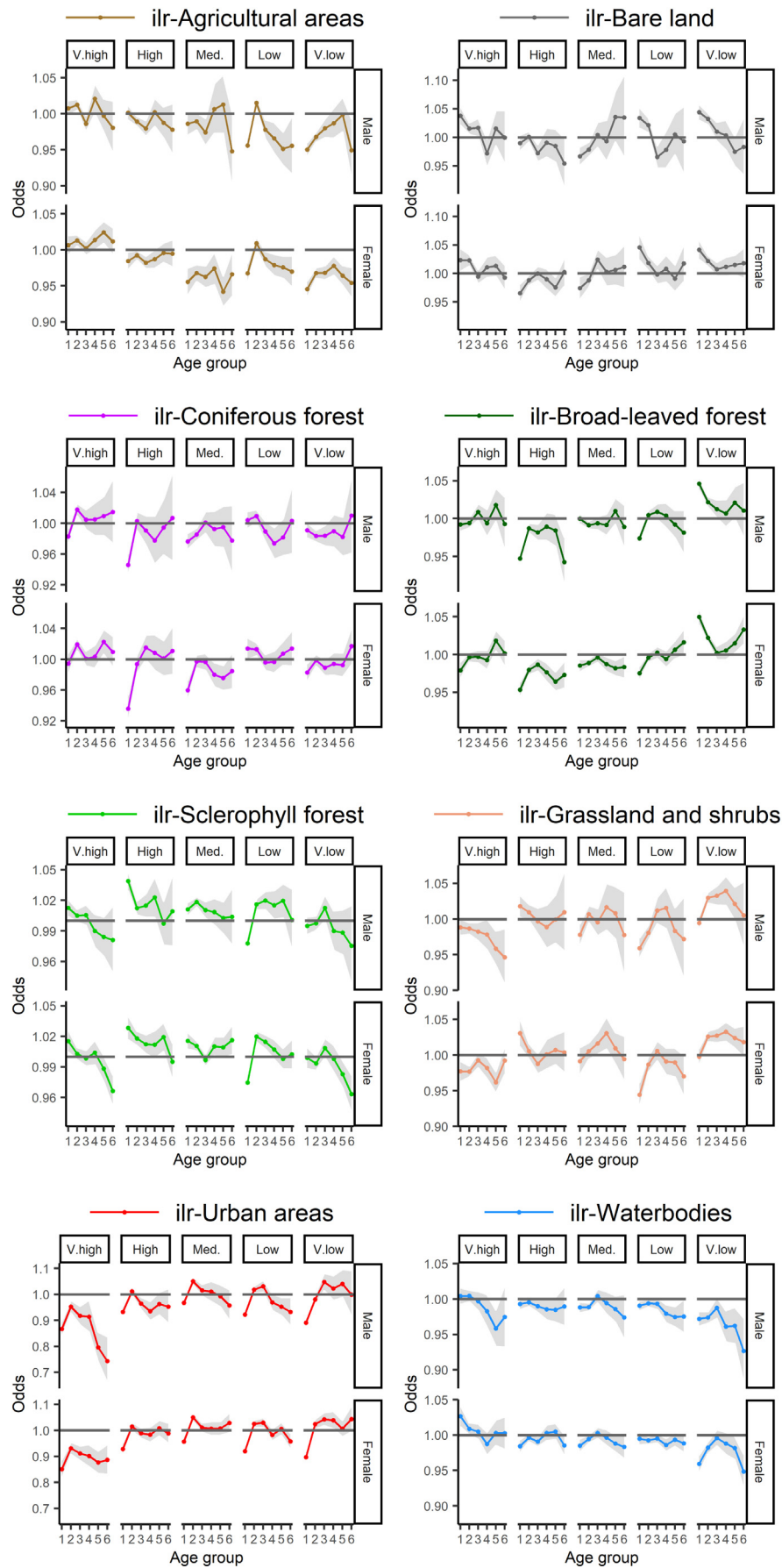
Fig. 3. Odds ratios (in colour) and 95% CI (grey bands). Associations between the prevalence of asthma and ilr-LULC categories.

Fig. 4. Odds ratios (in colour) and 95% CI (grey bands). Associations between the prevalence of anxiety and ilr-LULC categories.

coloured lines). Since we used data representing the entire population of Catalonia, inference information gathered in the *p*-values has little relevance. However, we also provide the 95% Wald confidence intervals (95% CI), reporting the precision of the estimations (Figs. 2, 3, and 4; grey bands).

3.1. T2DM

As shown in Fig. 2, most groups for ilr-agricultural areas showed an increased risk of T2DM, with some exceptions on paediatric (1), some young-adults (2), and very low SES groups.

For ilr-bare land areas, very high and very low SES groups were associated with an increased risk of T2DM, while all the rest were mainly associated with a reduced risk.

For ilr-coniferous forest, younger groups showed a reduced risk, although the majority of other groups showed an increased risk.

In the case of ilr-broad-leaved and ilr-sclerophyll forest, the majority of the estimates showed a reduced risk while some age groups, especially paediatric (1), showed the opposite effect.

As to the effect of ilr-grassland and shrubs areas, higher average risk was observed for medium SES groups, although low SES paediatric (1) male group showed the highest risk.

For ilr-urban areas, we found an increasing risk for more impoverished areas, especially for older groups.

Finally, results for ilr-waterbodies suggested a reduced risk for more impoverished areas with some exceptions in high and very high SES paediatric (1) and young adult (2) groups and low and very low SES young-adult (2) male groups.

3.2. Asthma

For ilr-agricultural areas, our results show a reduced risk for lower SES groups (see Fig. 3).

For ilr-bare land areas, most groups showed an increased risk, especially females. However, high SES groups and other age groups within each SES group showed the opposite effect.

Results for ilr-coniferous forest differed between sex groups. In general, males showed a predominant reduced risk (except for very high SES groups). On the contrary, females showed a predominant increased risk for very high, high, and low SES groups, while medium and very low groups were associated with a reduced risk.

For ilr-broad-leaved forest, results suggest an increased risk for lower SES groups. Furthermore, for ilr-sclerophyll forest, results show a predominant increased risk for all groups, except for older groups of very high and very low SES, and younger groups of low and very low SES.

Results for ilr-grassland and shrubs and ilr-urban areas suggest a progressively increased risk across SES variable.

Lastly, for ilr-waterbodies, most groups showed a predominant reduced risk of asthma, especially very low SES groups.

3.3. Anxiety

As shown in Fig. 4, we found a predominant decreased risk for most groups for ilr-agricultural areas.

For ilr-bare land, very high and very low SES groups showed a predominant increased risk of anxiety, while medium and low SES showed the opposite trend. In contrast, results for high SES groups differed between sexes. Males showed a predominant decreased risk and females showed a predominant increased risk.

As to the effect of ilr-coniferous forest, we observed a predominant reduced risk for most groups. However, some groups of high, medium and low SES showed an increased risk in both sexes. Following the same trend, we found a predominant reduced risk for ilr-broad-leaved forest except for some very high and very low SES groups.

Results for ilr-sclerophyll forest showed an increased risk for lower SES groups, although the results for very low SES groups were somewhat inconclusive. For ilr-grassland and shrubs, inconclusive results were observed for very high SES groups and an increased risk was observed for lower SES groups. Likewise, ilr-urban areas showed an increased risk for lower SES groups.

Finally, ilr-waterbodies showed a reduced risk for most of groups. However, we found some exceptions for medium SES groups and some age groups of low SES.

4. Discussion

Our study has stepped forward to detect the independent contribution of eight LULC categories to the prevalence of three assessed health conditions (T2DM, asthma and anxiety). We propose a compositional approach that shows the estimated odds ratio after segmenting the data according to the SES status, age group, and sex. Moreover, this methodology has allowed us to discuss the possible set of particular elements of each LULC category related to the studied health conditions.

4.1. Human health conditions

For this study, we used the major pathways framework suggested by Markevych et al. (2017), and hypothesised that each selected health condition was related to the environment through specific pathways.

4.1.1. Type 2 diabetes mellitus

T2DM has been associated with obesity and sedentary behaviour (low physical activity) (Colagiuri et al., 2010). Thus, the relationship between the environment and T2DM may partly occur through the instoration pathway (Markevych et al., 2017). In particular, the capacity of LULC categories to promote physical activity. In addition to this, research is also associating long-term air pollution exposure (Eze et al., 2015, 2014), as well as traffic noise (Shin et al., 2020) with increased risk of T2DM. Thus, T2DM might arguably be related to the environment through the mitigation pathway (Markevych et al., 2017).

Urban areas showed an increased risk of T2DM for medium to lower SES groups. This effect could be explained due to the fact that higher SES groups, which tend to be more physically active during leisure time (Marielle et al., 2012), are also associated with a higher presence of greenspaces in their neighbourhoods (Astell-Burt et al., 2014b). This might lead to higher levels of physical activity in higher SES groups (Frank et al., 2007; Richardson et al., 2013). Contrarily, lower SES groups, which are less able to afford gym fees (Giles-Corti and Donovan, 2002) and have little access to open public spaces (Koohsari, 2011), tend to walk in more unsupportive build environments (Adkins et al., 2017), which lack certain land-use types such as green spaces and recreation centres (Zandieh et al., 2017). These factors might arguably lead to less opportunities for physical activity in deprived neighbourhoods, increasing the risk of T2DM in lower SES groups. In fact, higher risk of T2DM and many lifestyle-related risk factors have been reported for people living in deprived neighbourhoods (Astell-Burt et al., 2014a; Feng and Astell-Burt, 2013; Williams et al., 2012). Moreover, deprived neighbourhoods are more associated with polluted areas (Bolte et al., 2010), higher perceived noise and lower perceived safety, cleanliness and aesthetic quality of their neighbourhoods (Mouratidis, 2020). In this sense, the increased risk of T2DM for poorer groups could also be explained through the mitigation pathway (Markevych et al., 2017), since both air pollution exposure and traffic noise have been related to increased risk of T2DM (Eze et al., 2015; Shin et al., 2020).

Broad-leaved forest, which generally has low undergrowth, cool temperatures, and smooth slopes, was predominantly associated with lower levels of T2DM. Likewise, sclerophyll forest, which tend to be close to urban settlements, showed a generally decreased risk of T2DM. This suggests that, despite its undergrowth densely populated

with shrubs and some lianas, people might be attracted to perform physical activity on the sclerophyll forest principal routes and paths. Regarding the coniferous forest, it might not always be accessible to people to perform physical activity (at least the high mountain forest, which is established on higher altitudes of the mountains). This might explain the predominant increased risk of T2DM observed for most groups.

Regarding waterbodies, we found a heterogeneous effect, suggesting that effect measure modification of SES and age group appeared to be especially important.

In agricultural areas, results showing increased risk of T2DM could be explained through the pesticides exposure pathway (Lee et al., 2011; Turyk et al., 2009). In a previous study, researchers found five pesticide types positively associated with incident diabetes (Starling et al., 2014). In this regard, epidemiological evidence suggests an association between exposure to organochlorine pesticides and T2DM (Evangelou et al., 2016).

4.1.2. Asthma

The relationship between the environment and asthma may occur mainly through the mitigation and instoration pathways (Markevych et al., 2017). Air quality is crucial (Toure et al., 2019), not only regarding the allergenic pollen levels that might aggravate this respiratory disease (Cariñanos and Casares-Porcel, 2011), but also concerning air pollution (Guarnieri and Balmes, 2014). In addition, other studies have explored the connection between air quality and heat events (Soneja et al., 2016) and microbial diversity (Ege et al., 2011).

A higher prevalence of asthma is directly related to the higher presence of allergenic elements in the air (D'Amato et al., 2007). We found that waterbodies show a generally reduced risk of asthma for all SES groups. This could be because waterbodies might arguably be associated with little presence of allergenic elements due to the lack of vegetation, and because the allergenic elements might be trapped in the waterbodies. In fact, Spanish researchers found that living next to the coast may protect against sensitization to pollens and *Alternaria* (Moral Gil et al., 2008).

Although a set of allergenic species might be distinguished for each LULC category, the differences across SES groups for LULC categories associated with vegetation suggest that the presence of allergenic species might not be the only relevant predictor. For broad-leaved forest and grassland and shrubs, we found a higher risk in lower SES groups. On the other hand, sclerophyll forest showed a predominant increased risk, bare land showed higher predominant risk for females, and coniferous forest showed a reduced predominant risk for males.

For urban areas, we found increased levels of asthma for lower SES groups. Some research has suggested that air polluted environments are associated with a higher prevalence of respiratory illnesses such as asthma (Annesi-Maesano et al., 2007; D'Amato et al., 2002). Furthermore, lower SES groups are known to be in worse health status and associated with more polluted areas (Bolte et al., 2010; de Vries et al., 2003; Su et al., 2011). Contrarily, the increased levels of greenspaces in richer SES neighbourhoods might lower air pollutant concentrations (Kroeger et al., 2014).

In addition, the higher risk of asthma found in lower SES urban areas would also be explained since lower SES groups have been linked with increased susceptibility to heat-associated health effects (Gronlund, 2014). In addition, extreme heat events have been linked with increasing risk of hospitalization for asthma (Soneja et al., 2016).

We found agricultural areas to be generally associated with a reduced risk of asthma for all SES groups except for very high SES groups. Some authors highlight microbial diversity and specific microbial exposure as protective factors against asthma and atopy (Bach, 2018; Jatzlauk et al., 2017). In this regard, farm environments that promote higher microbial exposure would be associated with decreased risk of asthma (Ege et al., 2011). As previously highlighted (Farfel et al., 2010; Shankardass et al., 2007), the results for very high SES groups are compatible with the so-called "hygiene hypothesis". However, other studies (Eum et al., 2019)

state that complexity in the prevalence of asthma symptoms calls for a more comprehensive framework for its understanding.

4.1.3. Anxiety

Anxiety could be mainly linked to the environment through the restoration pathway (Markevych et al., 2017). The restorative role of natural environments has been associated to the visual (Franco et al., 2017; Jacobs and Suess, 1975) and auditory stimuli (Coensel et al., 2011), to the openness of natural spaces (Han, 2007) and to species richness (Aerts et al., 2018). Many studies have highlighted the potential of the natural environment to increase feelings of restoration (White et al., 2013), and reduce stress levels (Morita et al., 2007) and heart rate (Lee et al., 2014).

Our results suggest that agricultural areas seem foster mental restoration, leading to a main decreased risk of anxiety. Agricultural areas may represent more diverse landscape configuration, such as the forest-agriculture mosaic, which can increase bird richness (Atauri and De Lucio, 2001). Concerning this, recent research has highlighted the positive association between bird diversity and people's wellbeing (Methorst et al., 2020). Moreover, the openness of agricultural scenarios might also promote restoration for individuals (Han, 2007).

Likewise, we found that environments with more waterbodies were associated with decreased anxiety levels in the majority of groups. Some authors have underscored the importance of water sounds for mental health (White et al., 2010). Others have hypothesised the independent beneficial effect on health for waterbodies (Nutsford et al., 2016), even without a full exposure but with only observation of water elements photographs (White et al., 2010).

The beneficial effect of waterbodies might also be linked to evolutionary and cultural theories such as the Biophilia effect (Browning et al., 2014), which highlights the significance of water for the biological, wellbeing and survival needs (Han, 2007; Orians and Heerwagen, 1992; Ulrich, 2016, 2014). In addition, some research points out to the role of negative ions that are present in water environments, especially by the sea (Jiang et al., 2018), in lowering depression scores (Perez et al., 2013).

Regarding forested LULC categories, only broad-leaved forests, arguably the most walkable of the forest types, showed decreased risk of anxiety for most of the SES groups. On the other hand, we found increased anxiety levels for lower SES groups in urban areas. As described above, important differences between deprived and non-deprived neighbourhoods seem to be essential elements modifying the effect of urban areas on anxiety levels. These differences include the built environment, presence of greenspaces (Astell-Burt et al., 2014b), accessibility to public open spaces (Koohsari, 2011), and other important factors mentioned above such as noise, light and air pollution. Likewise, results showing a higher risk for sclerophyll forest and grassland and shrubs might be explained by differences in quality of spaces across SES groups.

4.2. The role of covariates: SES, age group, and sex

The three covariates studied (SES, age group, and sex) have widely been described as important modifiers of nature effects (Markevych et al., 2017). Considering this, we have segmented our data accordingly. Thus, the three covariates did not play a role in the residuals of our models. Nevertheless, we can compare the effects of the covariates when comparing the estimated odds ratios across different groups (Figs. 2, 3, and 4).

We found SES to be the most important covariate as to the effect of the LULC categories on the selected health conditions. As previously reported (Knobel et al., 2021a), we found a dissimilar risk between the highest and lowest SES groups. This effect measure modification could be explained because lower SES groups might be more likely to benefit from a health promotion intervention (Bolte et al., 2010; de Vries et al., 2003; Markevych et al., 2017; Su et al., 2011), such as being exposed to particular LULC categories. Lower SES groups have been described to be less mobile (Maas et al., 2006; Schwanen et al., 2002), to have less

health status (Markevych et al., 2017), and to live in more polluted areas (Bolte et al., 2010). In this sense, lower SES groups show stronger associations with their environment (Dadvand et al., 2014; Maas et al., 2009b). On the contrary, higher SES groups might be more capable of changing the environment they live in in order to be less exposed to particular harmful conditions (Bell et al., 2010; Markevych et al., 2017). In addition, other factors such as better social environments, health care accessibility and use, residential environment preferences, and even better general behaviour and lifestyle might also be key factors linking higher SES groups with better general health (Adler and Newman, 2002).

Regarding the age group, many of the estimates showed a more intense effect on very old (6) age group than on young-adult (2), adult (3), senior (4) and old (5). Likewise, we found a recurrent intensified effect for the paediatric (1) group compared to the rest of groups. This effect was found to go either in the same direction as the rest of the age groups (e.g., prevalence of T2DM for high SES groups for ilr-broadleaved forest; Fig. 3), or in the opposite direction (e.g., prevalence of anxiety for low SES groups for ilr-bare land; Fig. 4).

On the one hand, elderly people are undoubtedly the groups with less moving capacity. This makes elders more strongly associated with their surroundings (Maas et al., 2006). On the other hand, paediatric people have unique characteristics that differ from adults (Ortega-garcía et al., 2019). Additionally, the paediatric group might be underrepresented in at least two of the health conditions considered; T2DM and anxiety. Type 1 diabetes, more associated with paediatric groups (Soltész, 2003), is an autoimmune disorder genetically mediated, while type 2 is more of a life style induced disorder (Joshi and Shrestha, 2010). Regarding anxiety, the anxiety diagnostic criteria in children might also differ from adults. Children have particular features (for instance, difficulties in communication, cognition and emotions) that create unique challenges when distinguishing between normal and pathological anxiety (Beesdo et al., 2021).

Lastly, in line with other studies (Richardson and Mitchell, 2010), we found sex to be an important variable modifying the effect of LULC categories on the three selected health conditions.

4.3. Future research

The compositional methodology used in this study has allowed us to raise many hypotheses linking LULC categories to the three assessed human health conditions. Although these hypotheses have been supported by previous studies, they should be tested further with specific study designs in future studies.

4.3.1. Complex pathways linking the environment to human health

To simplify the results interpretations, we have assumed that anxiety was related to the environment mainly through the restoration pathway. In contrast, we assumed that T2DM and asthma were related to the environment mainly through two pathways (instoration and mitigation pathways). However, it is possible that, in reality, many other pathways intertwine (Hartig et al., 2014; Markevych et al., 2017). For instance, some of the results found for T2DM needed a broad scope to be interpreted, such as the pesticide exposure for T2DM.

Moreover, differences in preferences (Han, 2007; Kiley et al., 2017; Lyons, 1983) between the different tested groups, the amount of knowledge about the environment (Aerts et al., 2018), and even the environmental quality of the LULC categories (Knobel et al., 2021b; Wheeler et al., 2015) might be important factors modifying the LULC – human health relationship. Therefore, more studies with accurate information about the variables mentioned above should be conducted to relate specific health conditions with specific LULC categories.

4.3.2. Further exploration of LULC categories

We aimed to test the independent effect of broad LULC categories on human health. However, we believe that important characteristics

might have remained unstudied in these general classifications. One example is the coniferous forest category, which gathered three forest types: low land pine tree forest, the montane pine tree forest, and high mountain forest. Each of them possessing individual and exceptional features. In this sense, we argue that using a combination of other existing datasets and GIS techniques to construct a more exhaustive classification of the different ecosystems or types of environment would result in better analyses. In the same direction, authors could make use of the present framework to conduct further research testing for differences within agricultural areas (irrigated, non-irrigated), urban (residential, sprawl, industrialized, urban greenspaces) or waterbodies (inland, marine), among other examples.

4.4. Limitations

4.4.1. Unit of analysis

We have used the Basic Health Area (BHA) as our unit of analysis to describe the living environment for individuals. However, other research encompassing LULC data and human health has used different unit of analysis, from census areas to different buffer radii (Zaldo-Aubanell et al., 2021b). In this sense, further research is needed to test our results and approach using different units of analysis.

4.4.2. Cross-sectional design

We followed a cross-sectional design. Thus, limitations derived from this methodology must be carefully considered. Although cross-sectional designs leverage population-based data and are useful to detect differences between areas, they do not allow for causal inference to be established (Wu et al., 2020).

Furthermore, we did not consider possible spatial autocorrelations derived from data. In this sense, robust spatio-temporal methodologies should be needed allowing for the establishment of causal inference.

5. Conclusions

There is a recurrent call for new methodologies that detect the independent effect of different types of environment on human health. We have proposed an innovative methodology using a compositional approach. We have defined eight types of environment using a classification of Land use and Land cover data and have tested their individual contribution on explaining three selected health conditions using observational data. In this regard, the proposed methodology has shown to be an acceptable and a feasible way to address the compositional nature of LULC data, facilitating the interpretation of the estimates through the Log2 ilr-transformation.

Our approach has led us to plausible results supported by the existing literature while has enabled us to push forward the debate on the relevance of environmental heterogeneity in health studies. We have proposed a detailed conception of the environment that goes beyond *green* and *natural*. In addition, we have discussed how different types of environment possess exclusive elements (humidity, temperature, type of flora and fauna, accessibility, walkability, openness, presence of water, sounds, air compounds and air quality, heat, and noise, light contamination, and even chemical exposure) affecting distinctively on human health. Furthermore, we have found the relationship between the environment and human health to be clearly modified by socioeconomic status, age group, and sex. Lastly, we have highlighted that other important ideas such as the preferences (or agreeableness) for specific types of the environment of certain groups and quality of the environments might be important factors and should be considered in future research.

We believe that our contribution might help researchers approach the environment in a more multidimensional scope, allowing environmental heterogeneity to be brought into the analysis.

CRediT authorship contribution statement

Quim Zaldo-Aubanell: Conceptualization, Formal analysis, Investigation, Data curation, Writing – original draft. **Isabel Serra:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Supervision. **Albert Bach:** Writing – review & editing, Visualization. **Pablo Knobel:** Writing – review & editing. **Ferran Campillo i López:** Resources, Writing – review & editing. **Jordina Belmonte:** Writing – review & editing. **Pepus Daunis-i-Estadella:** Methodology, Validation. **Roser Maneja:** Resources, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.150308.

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