Contribution of Bayesian Networks to Environmental Health Issues, Application to Etang de Berre

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Modelisation Conceptuelle des Connaissances Biomedicales

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Contribution of bayesian networks to environmental health issues, application to Etang de Berre

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Abstract

Background

The aim of this study is to examine in detail the potential links between proven pathologies in the population and the atmospheric pollution to which this population is exposed, in an industrial context (Etang de Berre) and an abundant cocktail of pollutants, in connection with the diversity of emitting sources within that space (petrochemical industry, steel industry, refining, energy production, cement works, road, sea and air transport).

Methods

A total of 178 variables of various natures (health, environmental and socio-economic) on a fine territorial scale (infra-communal) have been mobilised and simultaneously integrated within a Bayesian model based on artificial intelligence. Various unsupervised and supervised algorithms, and also sensitivity analyses provide the means to discover the links between these variables and the inhabitants' living space.

Results

By mobilising a high number of variables, broken up on a fine territorial scale, and by resorting to an appropriate tool to report on existing links between these variables, we were able to bring to the fore a number of relations between exposure and proven pathologies. For example, between cadmium and diabetes in the over 65 year-olds, or between vanadium and respiratory diseases. Threshold effects have also been revealed, notably for SO₂ which appears from a very low exposure threshold (6µg/m³), therefore far below standard, which is set at 50µg/m³. It is also the case with hydrofluoric acid (HF), the effect of which is already felt from the 0.0028 µg/m³ threshold. Also, exposure to cadmium in its particle phase, for an exposure between 0.214 and 0.250 µg/m³, disrupts insulin metabolism in the over 65. Finally, as soon as Benzo[k]fluoranthene (particle phase) exceeds the 0.672 µg/m³ threshold, it results in a higher number of hospital stays for respiratory diseases in the 15-65 age group. A vulnerability differentiated according to age groups also appeared. Comorbidities known in literature have been found (respiratory and heart diseases). Also found was the influence of socio-economy on some pathologies (single-parent families and those without qualification at 15). Finally, diffuse PCBs pollution has been observed in the study area.

Conclusion

The study has brought forward differentiated health profiles between the various IRISes¹ constituting the Pays de Martigues territory, and this should lead to the deployment of health services better suited to the needs of the population from a prevention perspective, and even to promote consultations with some specialists. For example, with a cardiologist, in those IRISes where the number of unqualified 15 year-olds is significant, since a relation has been found at that level, a relation most probably due to more difficult living and/or working conditions for these people. Likewise, prevention and social support measures should be taken to the benefit of single-parent families. At the same time, companies should go ahead with the desulfurization process of their installations, and even reduce their emissions concerning some noxious pollutants.

¹ Block groups of some 2,000 inhabitants forming the smallest statistical territorial division defined by the national institute of economic and statistical information INSEE

Trial registration Decision DE-2017-413 authorising the Métropole d’Aix Marseille Provence to carry out the processing of personal health data for a retrospective and local environmental health study titled “Air-Health study in the Pays de Martigues territory.” (Authorisation application No. 917120)

Key words petrochemical complex, etang de Berre, environmental health, Bayesian networks, artificial intelligence

Background

Open onto the Mediterranean, on the shores of the Etang de Berre, the Pays de Martigues constitutes a living area for close to 71,000 inhabitants spread over 3 communes: Martigues, Port-de-Bouc, Saint-Mitre-les-Remparts. In addition to its geography, Martigues is Europe’s leading petrochemical complex and therefore has a high concentration of polluting industries impacting the quality of air and the health of populations.

It was only from 2013 that a number of scientific studies began examining the health effects of air pollution at the Etang de Berre level. First came the REVELA study conducted by Santé Publique France between 2013 and 2016, focused on kidney and bladder cancers and acute myeloid leukaemia, that showed incidence rates for bladder cancers higher than those observed in mainland France [1]. Then, the FOS EPSEAL [2,3] study launched in 2015 and conducted in Fos-sur-Mer and Port-Saint-Louis-du-Rhône attracted considerable attention because health data were collected on a random sample of inhabitants (participatory study), [4]. Nevertheless, the study revealed that chronic diseases and acute symptoms were a health experience shared in both cities. The prevalence in adults of cumulative asthma (starting most of the time in adulthood), of cancers (notably in women) and diabetes (notably type 1 diabetes) is higher in Fos-sur-Mer and Port-Saint-Louis-du-Rhône than in France on average. Respiratory ailments (hay fever excepted) concern almost one in two adults and one in four children. The INDEX [5] study conducted in 2016 at Fos-sur-Mer by the Institut Ecocitoyen pour la Connaissance des Populations (IECP) on blood and urine samples of a selection of 138 inhabitants revealed an over-impregnation of the population exposed by inhalation with lead, with two furans characteristic of industrial emissions and with benzene, but only in the oldest people. Gardening in an exposed zone was associated with a higher impregnation with total PCBs compared to the control zone. The fact of consuming vegetables from the garden was associated with a higher impregnation with cadmium in the exposed zone, whereas the effect was protector in the contact zone (Saint-Martin de Crau). Consuming local seafood (fish, shellfish) was associated with a higher level of impregnation with PCBs, dioxins/furans, mercury and chrome. Finally, the Scenarii and POLIS [6,7] studies conducted in 2010 by AtmoSud in 66 communes around Etang de Berre and 39 substances led to calculating an excess health risk in a number of overexposed sectors.

This paper presents the results of a retrospective health geography study [8] of crossed data on pollution, impact of pollution on the environment (lichens), precariousness of residents and hospital stays by age group (i.e. 178 variables) carried out in the year 2015 in 3 communes of the Pays de Martigues, south of the Etang de Berre (Martigues, Port-de-Bouc and Saint-Mitre-les-Remparts) at the scale of the 30 Pays de Martigues IRISes, hence on a fine spatial scale.

Methods

Materials

Health data

They consist of 18 variables relating to pathologies of interest according to the 3 standard age groups (<15 years, 15-65 years, > 65 years), they relate to patients having stayed either at the Martigues Centre Hospitalier (CHM), or the Martigues Clinique privée, or in one of the 5 public hospitals² or else at the Paoli Calmettes Institute (IPC), in 2015. Therefore, these data relate to numbers of hospital stays and not to numbers of patients. It was impossible in France to obtain “patient numbers” at the time when this study was carried out. The gender, in addition to the age segmentation, could not be retained because the “age” and “gender” association is too discriminatory and could lead to a potential identification of patients.

²Hôpital de la Timone (adults and children), Hôpital de la Conception, Hôpital Nord, and the 2 South hospitals (Sainte Marguerite and Salvator)

The pathologies recognized in literature as being connected with this type of pollution [9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21] , are pathologies corresponding to the following ICD-10³ codes:

- . I00 to I199 all diseases of the circulatory system in which are found for example ischemic heart diseases, coronary diseases,
- . J00 to J199 all diseases of the respiratory system: laryngitis, pharyngitis, sinusitis, tracheitis, bronchopulmonary diseases, bronchitis, bronchiolitis, asthma, etc...
- . E10 to E14 all diabetes types (type 1 insulin-dependent and type 2 non-insulin-dependent),
- . C34 all types of bronchus and lung cancer,
- . C67 for bladder cancer,
- . C64 for kidney cancer,

The fact of dealing with a fine territorial scale imposes having enough cases per IRIS and consequently to work by batches of codes (for ex. I00 to I199) rather than by separated codes.

Air pollution data

These health variables have been related to air pollution data provided by an approved air quality monitoring association in the Sud region (AtmoSud), a partner of this study, and also date back to 2015. In recent years, AtmoSud has developed an IT tool producing mappings of the annual levels of pollutants in the ambient air [6]. Thus we had measurements concerning 44 pollutants, half in gaseous form, and the other half in particle form; their levels were estimated both on models (air emission inventories + dispersion), and on measurements (long histories or one-off campaigns carried out in recent years) (Tables No 1 & 2). We had a choice between pollution measurements at the IRIS scale or at the scale of urban areas (built-up areas to the perimeter of which a 100m buffer has been applied) (Figures No 1 & 2). We preferred the second option, which enables us to have a more accurate measurement of pollution in the population's living spaces (Map No 1), and this, all the more so since some IRISes are vast and their population sometimes gathered in a single area, as can be seen on map No 1.

³International Classification of Diseases ICD-10 organised in 21 chapters, covering the full range of morbid conditions classified by organ or functional system: http://www.departement-information-medicale.com/wp-content/uploads/2017/06/CIM10_2017_sts_20170009_0001_000.pdf

Table No 1. Gaseous pollutants provided by AtmoSud

	Pollutant	Formula	Model/measurement	Local background level ($\mu\text{g}/\text{m}^3$)
Gas	Sulphur dioxide	SO ₂	M+m*	0,6
Gas	Nitrogen dioxide	NO ₂	M+m*	8
Gas	Carbon monoxide	CO ₂	M+m	263
Gas	Hydrochloric acid	HCl	M only*	8,23E-04
Gas	Hydrofluoric acid	HF	M only*	5,29E-04
Gas	Benzene	C ₆ H ₆	M+m	0,7
Gas	Benzo[a]pyrene	BaP	M only*	2,42E-06
Gas	Polycyclic aromatic hydrocarbons	PAHs	M only*	0,0021175
Gas	Dioxins and furans	PCDD and PCDF	M only*	2,31125E-10
Gas	Mercury	Hg	M+m	0,00106 ng/m^3
Gas	Benzo[a]anthracene	BaA	M only*	3,42E-06
Gas	Benzo[b]fluoranthene	BbF	M only*	2,68E-06
Gas	Benzo[k]fluoranthene	BkF	M only*	1,88E-06
Gas	Indeno[1,2,3-c,d]pyrene	IcdP	M only*	1,52E-06
Gas	Dibenzo[a,h]anthracene	DahA	M only*	3,124E-07
Gas	Fluoranthene	Fluoran	M only*	2,24075E-05
Gas	Polychlorobiphenyls	PCB	M only*	5,663E-07
Gas	1,3-butadiene	CAH ₆	M+m	0,13
Gas	Hydrogen sulphide	H ₂ S	M only*	5,72E-06
Gas	1,2-dichloroethane	DCE	M+m*	0,03
Particle	Under 10 μm diameter particles	PM ₁₀	M+m	16
Particle	Under 2.5 μm diameter particles	PM _{2.5}	PM _{2.5} /PM ₁₀	10

Key: M: model, m: measurement, * the background is taken at the level of a point distant from any source (Etang de Rolland area). All data are expressed in $\mu\text{g}/\text{m}^3$ except for mercury (HG) expressed in ng/m^3

Table No 2. Pollutants in particle form provided by AtmoSud

Pollutant	Formula	Model/measurement	Local background level ($\mu\text{g}/\text{m}^3$)
Benzo-a-pyrene	BaP	M+m	1,63E-04
Polycyclic aromatic hydrocarbons	PAHs	M only*	1,38E-03
Dioxins and furans	PCDD and PCDF	M+m	2,16E-08
Lead	Pb	M+m	4,02E-03
Arsenic	As	M+m	3,86E-04
Cadmium	Cd	M+m	1,39E-04
Nickel	Ni	M only*	2,03E-04
Mercury	Hg	M+m	0,00E+00
Chromium	Cr	M+m	1,97E-03
Chromium VI	Cr VI	Cr VI/total Cr	1,40E-04
Copper	Cu	M+m	3,75E-03
Selenium	Se	M+m	3,65E-04
Vanadium	V	M+m	2,51E-03
Zinc	Zn	M+m	1,93E-02
Benzo[a]anthracene	BaA	M+m	1,38E-04
Benzo[b]fluoranthene	BbF	M+m	3,09E-04
Benzo[k]fluoranthene	BkF	M+m	1,36E-04
Indeno[1,2,3-c,d]pyrene	IcdP	M+m	2,32E-04
Dibenzo[a,h]anthracene	DahA	M+m	4,20E-05
Fluoranthene	Fluoran	M only*	8,28E-06
Polychlorobiphenyls	PCB	M only*	6,30E-07
Diesel particles	PM ₁₀ diesel	diesel/PM ₁₀	5,00E-01

Figure No 1. 100 m buffer applied on the perimeter of built-up areas, example with the IRIS of the Courouche plain in Martigues, Source AtmoSud

Figure No 2. Intersection of urban areas of the Courouche plain IRIS with air pollution data, Source AtmoSud

Map No 1. Urban areas in IRISes, Source AtmoSud

Lichen readings: bio-indication and bio-impregnation

Together with these 44 air pollution variables, we have 109 others corresponding to measurements carried out on lichen samples in September 2017, by the Institut EcoCitoyen pour la Connaissance des Pollutions (IECP) on specific plots (See Map No 2). These plots were selected in cooperation with the project's various stakeholders, and adapted according to the presence or absence of trees on location, where readings could effectively be carried out. In regard to the plots' spatial validity, a 500 m radius around the GPS point retained for the bio-impregnation plots can be considered. Indeed, according to a recent study carried out by the IECP [22], a variability of 35% maximum for metals, and 30% for the various congeners of PAH has been measured in a plot within a 500 m radius. The impregnation results obtained represent a 6-month integration. These measurements on living organisms such as lichens are useful to limit a confounding factor that could be linked with the residents' way of life more than with the effects of air pollution (notably addiction to smoking); incidentally, most of them are located in IRISes known for being socio-economically disadvantaged.

Map No 2. Lichen sample plots, Source IECF

Socio-economic data

Finally, we have resorted to 7 socio-economic variables, because the effects of pollution will not affect everybody in the same way. The disadvantaged might be more exposed to them, but also might have less resources to counter them (postponing medical consultations by lack of means⁴, asthma and diabetes less well controlled). These variables come from the infra-communal databases of the National Institute of statistic and economic Studies (INSEE) in 2017, they concern:

- . the number of people in 2017 in households living there for over 10 years, this variable being very useful to address the exposure of people P14_PMEN_ANEM10P
- . the number of unschooled people of 15 or over and without qualification P14_NSCOL15P_DIPL0
- . the number of people in households where the main family is a single-parent family C14_PMEN_MENFAMMONO
- . the number of people in main homes occupied by tenants P14_NPER_RP_LOC
- . the number of immigrants P14_POP_IMM⁵
- . the number of unemployed in the 15 to 64 age group P14_CHOM1564⁶

⁴ Although it is forbidden, some doctors refuse beneficiaries of the universal medical coverage, this non explicit “refusal” is expressed by excessively long delays for obtaining an appointment, which may discourage some patients who may then decide either to postpone the consultation, or not to seek care, or else to go to emergency services for quicker attention, but to the detriment of follow-up.

⁵ Variable subsequently related to the IRIS’ total population for a more meaningful %

⁶ Variable subsequently related to the IRIS’ 15 to 64 year-old working population for a more meaningful %

. median income DEC_MED14

These variables are useful to get to know the IRISes' level of precariousness or social disadvantage. We could have used a composite index, but we thought that it was important to keep these disaggregated variables, in order to see precisely on which variables differences between IRISes appear.

The whole of these variables (178) * 30 IRISes, corresponds to 5,340 cells in our database. These data are integrated within the same Bayesian model⁷, the probabilistic formalism of which is particularly suited to environmental health issues.

The Bayesian networks

Indeed, Bayesian networks allow to establish relations of dependence or independence among various variables, to analyse their interrelations, their combinations, by quantifying them using probabilities [23, 24, 25, 26, 27, 28]. The context is that of a mathematical formalism of representation of uncertain knowledge, (probabilistic) particularly well suited to health risk issues, because relations between variables in health matters are not always determinist, but rather indirect. Moreover, Bayesian networks allow at the same time to model knowledge and produce new knowledge by revealing causal relations until now hidden (causal inference), or latent variables, and this, within the framework of unsupervised analysis (causal knowledge discovery). Very often, they bring added value in terms of knowledge, and constitute an interesting tool for the quantitative modelling of complex systems in uncertain fields, whether health or others. This is the reason why they are increasingly used worldwide, in fields as diverse as industry, finance, marketing, security and many others [29].

A Bayesian network is made up of two elements: a conceptual map and a database. The conceptual map defines the network's structure, it is a tool used for knowledge organisation and representation. This map is either built from data from the database, or from expert's knowledge of the subject studied. In our case, we decided to extract knowledge included in our database⁸.

The network's structure (or conceptual map) is visually represented by directed arcs representing the whole of the causal relations linking the variables, represented by nodes.

⁷ They are discretised as soon as they are integrated into the software, so as to be compared

⁸ All processing was carried out using the specific software devoted to Bayesian networks: BayesiaLab 7.0.1

10019915ana	C6405ana	Mn	10HAP	Bpe	CB01	CB149	CB194	2,3,7,8 ToCDF	P14_CHOM194	Hg_p	BaF (2)	PM10_diesel
100199195ana	IPA	Fe	Nap	DBA	CB07	CB151	CB193	1,2,3,7,8 PnCDF	DEC_MED14	IodP_p	Butadiene	PM25
10019995ana	VOL	Co	Acy	Ipy	CB02	CB153	CB196	2,3,4,7,8 PnCDF	Aa_p	Ni_p	CO	SO2
J0019915ana	Biodiversiti	Ni	Acs	49 PCB	CB05	CB156	CB201	1,2,4,7,8 HxCDF	BaA_p	Pb_p	DahA	
J00199195ana	Abundance	Cu	Flu	PCB indicators	CB101	CB157	TEQ-2005	1,2,3,6,7,8 HxCDF	BaP_p	PCB_p	DCE	
J0019995ana	Shannon	Zn	Pha	PCB-OL	CB105	CB167	SUMDioxins + furans2,3,4,6,7,8 HxCDF	BbF_p	PCDD_PCDF_p	Fluoran		
E10E1415ana	Crustacea	Aa	Ant	CB18	CB114	CB169	SUMDioxins	1,2,3,4,6,7,8 HpCDF	BbF_p	PM10_diesel_p	HAP	
E10E14195ana	Foliacea	Mo	FIA	CB20	CB116	CB170	SUMfurans	1,2,3,4,7,8,9 HxCDF	Cd_p	Se_p	HCl	
E10E1465ana	Fruticolous	Cd	Pyr	CB28	CB123	CB174	1,2,3,7,8 PnCDD	1,2,3,4,6,7,8,9 OCDF	Cr_p	V_p	HF	
C34195ana	Al	Sn	BaA	CB31	CB126	CB177	1,2,3,4,7,8 HxCDD	P14_PMEN_ANEM10P	Cd_p	Zn_p	Hg (2)	
C3405ana	Ca	Sb	Chr	CB44	CB128	CB180	1,2,3,6,7,8 HxCDD	P14_NSCOL15P_DIPLMIN	Cu_p	BaA (2)	IodP	
CB7195ana	Ti	Hg	BbF	CB52	CB136	CB183	1,2,3,7,8 HxCDD	C14_MENFAMMONO	DahA_p	BaP (2)	NO2	
CB705ana	V	Ti	BaF	CB60	CB138	CB187	1,2,3,4,6,7,8 HpCDD	P14_MPER_IP_LOC	Fluoran_p	BbF (2)	PCB	
C64195ana	Cr	Pb	BaP	CB77	CB141	CB189	1,2,3,4,6,7,8,9 OCDD	P14_POP_IMM	HAP_p	Benz	PCDD_PCDF	

Between the nodes, causal links are drawn using an unsupervised artificial intelligence learning algorithm of the “maximum spanning tree” type, meaning that the algorithm will run until all the variables are connected with each other:

Figure No 4. The links between nodes

Thereafter, the conceptual map corresponding to our 178 variables appears in unsupervised form (A1), it represents the Bayesian network strictly speaking. (Figure No 5). In order to better distinguish the nature of the variables on the Bayesian network below, we have differentiated them by colours: orange for pathologies, green for variables resulting from lichen readings, purple for air pollutants, and blue for socio-economic variables.

Figure No 5. The conceptual map of the 178 variables, the Bayesian network

Let's consider the health variables in orange, bearing in mind that they are the very object of this study⁹ and let's see with which other variables they are connected. The first concerns the number of households living in their IRIS for over 10 years (P14_PMEN_ANEM10P) and the relative abundance of lichen species¹⁰ (this relation is 70% positive). It could be interpreted as follows: the higher the relative abundance of lichen species is the more people tend to stay where they live (amenities). There is even a negative correlation between the relative abundance of lichen species and CB194 (-0,70), however, a slight correlation (+0.6) links P14_PMEN_ANEM10P to Co (carbon monoxide), and cardiovascular diseases in the 15-65 year-old (I00I1991565ans, +0.65).

A second correlation can be observed in patients over 65 with cardiovascular (I00I19965ans) and respiratory diseases (J00I19965ans). It reveals a comorbidity which is well known by doctors [30], and already appears in younger patients

⁹ We have underlined only significant correlations (> 0.65) except for those inferring a pathology which are systematically spotted

¹⁰ The abundance relates to the sum of frequencies of each species on a plot. As the reading is done on 10 trees per plot, on all four faces of the tree and according to a 5-box observation grid, the frequency of each species on a spot is the ratio of the number of observations of the species on the plot divided by 200 (10 trees * 4 faces * 5 boxes). The abundance value is the sum of the frequencies of each species recorded on the plot

(aged between 15 and 65: I00I1991565ans and J00J1991565ans), it is explained by the chronicity of these pathologies (I00I1991565ans - I00I19965ans, +0.67), as is the case with diabetes (E10E1465ans - E10E141565ans, +0.73). We'll also note a rather strong relation (+0.78) between respiratory diseases in the over 65 and a dioxin-like PCB recognized for its toxicity: CB169¹¹ [31].

An "interesting" link is observed (+0.63) between cardiovascular diseases in the over 65 (I00I19965ans) and a socio-economic variable: no qualification P14_NSCOL15P_DIPLMIN, and also between income (DEC_MED14) and exposure to a HCl pollutant (Hydrochloric acid, negative relation of around 0.65) meaning that the more the households income increases the less they are exposed to that pollutant.

As regards bronchus and lung cancers in the over 65 (C3465ans), we observe a number of positive relations with pollutants, notably with CB187 (+0.80), TEQ-2005¹² (+0.83), 2,3,7,8 TeCDF (+0.86), 2,3,4,7,8 PeCDF (+0.84), As (+0.78) and SO₂ (+0.62). Concerning bladder cancer, relations also appear in the over 65 (C6765ans) with VDL¹³ (+0.67), CB20 (+0.64), CB114 (+0.85) and to a lesser extent CB157 (+0.52), the latter 2 PCBs (114 et 157) being also dioxin-like PCBs¹⁴.

At this stage of the analysis, it is time to examine a little closer the relations that we have found between pathologies, pollutants and socio-economy. To do so, we are going to monitor these relations in order to observe how they interact among themselves. Indeed, the contribution of the AI is not limited to establishing very easily causal inferences between all variables considered simultaneously, and representing them in a highly didactic manner in a conceptual map.

We will take the 2 strongest relations concerning pathologies and a variable of a different nature (either environmental or socio-economic). Therefore, we are going to analyse the interactions between respiratory diseases in the over 65 and CB 169, and the interactions between diabetes patients over 65 and a heavy metal in its particle phase, cadmium (Cd_p).

Interactions between variables: monitoring

Interactions between respiratory diseases in the over 65 (J00J19965ans) & CB169 (R + 0,78)

We have previously seen in analysing the relations that respiratory pathologies in the over 65 are linked with CB169 and that the relation is overall 78% positive. But what happens, more precisely, at the level of the various classes (modalities) of these 2 variables, how do these variables interact between each other? To answer this question, we are going to monitor them. The relation is first spotted in the Bayesian network (a), then we monitor the variables (b), and we see what happens at the level of some of their modalities (c). The number of modalities corresponds to the number of classes requested (K-means 5 classes).

¹¹ Toxicity factor (TEF) CB169: 0.03

¹² TEQ 2005 corresponds to the sum of PCBs and dioxins/furans expressed in toxic equivalents. The toxic equivalent of each congener is expressed by multiplying its concentration by its toxicity factor (TEF), which allows to weight the concentration of each congener by its "toxic efficiency". The TEFs used are those defined by the World Health Organisation (WHO) in 2005 (Van den Berg, 2006)

¹³ The Value of lichen diversity (standard EN 16413)

¹⁴ Toxicity factor (TEF) PCB 114 & PCB 157: 0.00003

Figure No 6. Monitoring between J00J19965ans & CB169

What is particularly interesting now is to force one of these classes, for example the modality corresponding to the highest number of stays (here: number of stays > 51.75), which then becomes green, and to observe how the associated probabilities of CB169 are then instantly updated. Thus, we can observe that if we focus on the highest numbers of stays, the values of CB169 increase, mainly for the 2 last modalities (for example evolution from 16.67 in the initial monitoring to 31.86 in d.1). Which means that when we consider the highest numbers of hospital stays recorded for respiratory pathologies in the over 65 in this territory, it is in relation with the highest values of CB169 found in the lichen readings¹⁵. The most frequent modality (44.38%) has also been forced without showing in that case notable changes in the monitoring.

Interactions between diabetes in the over 65 (E10E1465) & Cd_p R +0.52

A relation has appeared between diabetes in the over 65 and cadmium in its particle phase. Cadmium is absorbed in food (via deposits, air/soil pollution transfer) and could disturb insulin metabolism in the pancreas [32, 33]. This relation is very strong for the highest modality of diabetes patients (> 45.1 number of stays) and concerns a value of Cd_p between 0.214 and 0.250 µg/m³. For the most frequent modality, the relation already appears with the lowest values of Cd_p (38.18% under or equal to 0.181 µg/m³).

¹⁵ However, we should be careful in our interpretations, because the lichen readings are not exhaustive in the entire territory of study (for lack of time and means), nonetheless, the plots where readings were done reflect the impact of the environment in certain spots that have not been chosen at random, therefore the relations observed deserve wider investigation at a later date (more plots)

Figure No 7. Monitoring between E10E1465ans and Cd_p

. Highest E10E1465ans modality

. Most frequent E10E1465ans modality

So far the analyses were global, on the whole of IRISes in the Pays de Martigues territory. It is now time to move to a finer scale and see how these relations vary according to IRISes, and whether some are more exposed than others. This will be achieved via a new process that will produce sensitivity analyses for each of the 30 IRISes included in our area of study (the design of the study, Figure 8 below).

Figure No 8. The design of the study

Sensitivity analyses per IRIS

From now on, the IRIS variable will become the most important variable, it becomes a target variable. Below is the result of the supervised processing algorithm of the “augmented naïve” type run on the IRIS target variable, for pathologies.

Figure No 9. Supervised processing on the IRIS target variable for pathologies

Sensitivity analyses are established starting from that algorithm. The figure below represents all sensitivity analyses per pathology, it enables us to observe the heterogeneity of IRISes between each other.

Figure No 10. All sensitivity analyses per pathology for all IRISes

As an example, below is the sensitivity analysis on pathologies, carried out on IRIS 130560101 (Côte Bleue), in Martigues, which shows that respiratory diseases in the over 65 have a high probability to be found in that IRIS – approximately 50% - followed by cardiovascular diseases in the 15-65 for 35%, and so on.

Figure No 11. Sensitivity/pathologies analysis for the Côte Bleue IRIS (13560101) in Martigues

Subsequently, we have taken the probability values¹⁶ for each IRIS and solely in regard to pathologies, then these probability values have been divided by the % of individuals in each age group so as to contextualise them and eliminate possible size effects, in case the number of elderly people would be proportionally higher in one IRIS than in others. Therefore, a high value indicates a high number of stays for the pathology and the IRIS in question, and so independently from the % of elderly people in that IRIS. These values are subsequently integrated within an Ascending Hierarchical Clustering (below) so as to form groups of IRISes with a similar health profile. In total, 5 groups of IRISes can be clearly distinguished.

¹⁶ For example, concerning IRIS (130560101) on figure No 10, the probability for respiratory diseases in the over 65 is 0.5

Figure No 12: Health profiles of the 30 IRISes established via HCA

Health profiles of the IRISes

. Group No 1 includes atypical IRISes as regards their health profile; it is clearly distinguishable from the other groups, since we find here the highest rates, for all pathologies on the whole.

. The second group differs from the others by less cardiovascular, respiratory and diabetes pathologies, but a higher rate of lung cancers in the over 65 (C3465ans).

What sets group No 3 apart are the high rates of cardiovascular diseases in the under 15 and above all cardiovascular diseases in the over 65 (1,21 on average), i.e. more than in the first group (0.81). The same is true for respiratory diseases from the age of 15 with rates almost twice as high as those of group 1 (1.33 against 0.70). Diabetes in the under 15 also individualises these IRISes. Bronchus and lung cancers in the over 65, without reaching the values of the second group, are also noteworthy (0.62 on average), just like bladder cancers in the same age group, without nonetheless exceeding group 1 (0.64 on average).

. Group 4 is in a way the reverse of group 2, insofar as we can observe more cardiovascular pathologies in the over 65 (1.13 on average), respiratory pathologies in the over 65 and at the same time in the under 15, and a lower cancer rate. There is a dissociation in terms of pathologies: the fact that we observe certain pathologies doesn't mean that there will be a higher rate of cancers (notably bronchus and lung cancer). This could be linked to the different nature of pollutants which therefore do not induce the same effects.

. Finally, the last group includes IRISes with pathology rates comparatively lower than in the other groups. It will be used as control group for our second verification of the model. Indeed, we may be tempted to take a control group "out-of-area" which we estimate less exposed to pollution. Usually, a space in the "countryside" is selected. Now, the endocrine disruptors to which the population can be exposed via pesticides can induce the same pathologies (diabetes) [35, 36], which could confuse the "control cases" comparisons, since we might end up with high diabetes rates on both sides.

Looking for causal factors

Then we went in search of the causal factors of health profiles, which can be either of an environmental nature, and/or of a socio-economic nature. The combination of both can form what we call pathogenic spaces [34]. Then sensitivity analyses have been carried out on each IRIS, taking simultaneously into account all air pollutants provided by AtmoSud (44 pollutants), all 17 variables resulting from the lichen readings previously detected as playing a part on pathologies¹⁷, and the 7 socio-economic variables, i.e. a new total of 68 variables (Figure No 12). Indeed, it might be interesting to distinguish those IRISes where environmental and/or socio-economic factors have an influence.

Figure No 13. Supervised processing on the IRIS target variable for pollutants, socio-economy and lichen readings.

Then, for each sensitivity analysis, we have taken the highest probabalized variables¹⁸.

¹⁷ CB169, TEQ-2005, CB187, 2,3,4,7,8 PeCDF, As, 2,3,7,8 TeCDF, crustaceans, VDL, CB149, CB114, CB157, CB20, CB28, Co, CB194, Abundance, PCB indicators

¹⁸ Without nonetheless exceeding the threshold of a 0.20 probability, except for example when a pollutant is known for having an impact (of the PCB type or others with a value of 0.18)

We distinguished 3 main families of IRISes: IRISes where pollutants were many and formed what is commonly called a cocktail of pollutants [37, 38] which could contain either a majority of HAPs, or a majority of PCBs, or else pollutants that did belong neither to the HAP family, nor to the PCB family, and that we have therefore designated as “Others”, but of which the potential impact on health deserves our attention nonetheless.

So, in total we have 3 IRIS profiles:

Cocktail of HAP pollutants (7 IRIS)

Cocktail of PCB pollutants (8 IRIS)

Cocktail of “Others” pollutants (15 IRIS)

We saw that to the first variable that comes out corresponds a probability value spotted in the sensitivity analyses; in a way, it indicates its level of importance in the IRIS. At times, this importance has been qualified depending on the other surrounding variables. Indeed, if we take the example of the Plaine de Courouche IRIS, the first variable that comes out in the sensitivity analysis is Butadiene with 0.31, but we have preferred to retain CB20 which is just behind with 0.29, because it is a potentially more impacting PCB for health. Likewise, we have indicated when it was pertinent the socio-economic variable which came first and was integrated into the cocktail of pollutants in order to get an idea of the said context. Socio-economy, as we know, can add to the effect of pollutants and consequently have an impact but it can also in some cases offset this effect when it is favourable (better access to health care, better quality of life, better diet etc.).

HAPs group together several pollutants emitted at the same time, their number varies by a factor of two (6 to 12), with a repercussion on pathologies. The more HAPs, the more severe is the pathology. This is due to the carcinogenic nature of each of these HAPs¹⁹ (BaP, BaA, BbF, BkF, DahA, Fluoranthene, IcdP) and to their potential noxious mixing. The favourable socio-economy of the Jonquières Foulettes IRIS (130560107) seems to make up for the exposure of its residents (income above average), in the same way as for the Coudoulière IRIS (130560113), but to a lesser extent, because HAPs are less numerous in that IRIS.

Regarding the Cocktail of pollutants of the PCB type category, their health impact is essentially characterised, and even at low doses (due to their toxicity) by, for example, bladder cancers (IRIS Plan de Fossan - 130560114) in the over 65.

Finally, the last category, “Others”, refers to pollutants that cannot be classified in the previous categories. It includes “traditional” pollutants such as NO₂, or even SO₂, but also hydrofluoric acid (HF), not forgetting other potentially impacting elements such as: V_p, Hg, Zn_p, Cd_p, Cu_p and the PCDD_pPCDF.

Now let's consider the pathologies found in the IRISes and let's “correlate” them with the highest factors seen in these. The results are shown in the form of the maps below.

¹⁹ https://www.atsdr.cdc.gov/csem/polycyclic-aromatic-hydrocarbons/health_effects.html

Results

Group 1 of the HCA is exposed to particularly strong pollutants of the PCDD_PCDF type at La Lèque, CB28²⁰ at Plan Fossan, HF at PdB Centre and at St-Jean Bergerie, and to Dibenzo[a, h]anthracene (DahA_p) at Boudème. In 4 of the 6 IRISes, socio-economy (represented by white squares) combines with the pollutants and corresponds to single-parent families. In fact, it is the prevailing variable for the Rayettes IRIS (0,31).

Profile of IRISes according to the probability of the prevalence of environmental and/or socio-economic factors
Map No 3. Group 1 HCA; IRISes characterised by an increased prevalence of hospital stays for the whole of the pathologies studied

²⁰ When PCBs have been measured in lichens they are written in green, and in purple when they have been measured in the air.

As for group 2 IRISes, they are exposed to PCBs (Tassy Est **CB20**, St-Pierre & St-Julien **PCB**), to SO₂ (Tassy Ouest), and to vanadium [39, 40] in its particle phase, and at much higher levels than in other IRISes for those of Lavéra and Côte Bleue. The Jonquières Est IRIS is exposed to over 11 different HAPs, the Notre Dame Paradis IRIS to NO₂, but in the latter, like in Tassy Est, socio-economy also seems to play a pernicious part (unschooled at 15 and unemployment). The nature of pollutants (PCB, vanadium) and their multiplicity (11 different HAPs), could explain the pathologies found in the IRISes of this second HCA group.

Profile of IRISes according to the probability of the prevalence of environmental and/or socio-economic factors
Map No 4. Group 2 HCA, IRISes characterised by an increased prevalence of hospital stays related to lung cancers (>15) and bladder cancers (15-65)

Let's now have a look at the situation in group 3 IRISes. The Ferrière IRIS has a profile of the PCB type like the St-Mitre Périphérie IRIS; however, when one examines data for St-Mitre, the PCB values are not very high compared with other IRISes, but it is the first pollutant that comes out of the corresponding sensitivity analysis. In fact, this IRIS is simultaneously exposed to several pollutants (Co, Zn_p, Cr_p, Cr6_p, PCDD_PCDF, HCl, BkF_p), the value of each not being very high compared with other IRISes, except however from BkF_p which plays a part in respiratory diseases. As regards Gaps, Hg is the first pollutant that comes out, followed by Co, Cu_p and HF, whereas Croix Sainte is rather characterised by the presence of Zn_p, followed by several pollutants of the PCB type, and As. Finally, variables of a socio-economic nature seem to have a greater impact on the Colline IRIS (immigrant population, single-parent families, unemployment and unschooled 15 year-olds, the latter variable having an impact on cardiovascular diseases), and Cd_p, that disrupts insulin metabolism, is the only pollutant in this IRIS.

Profile of IRISes according to the probability of the prevalence of environmental and/or socio-economic factors
Map No 5. Group 3 HCA, IRISes characterised by an increased prevalence of hospital stays related to cardiovascular diseases (<15 and > 65) and diabetes (<15)

Starting from this 4th group, the number of stays is relatively lower; Canto Perdrix and Les Comtes Est stand out in regard to cardiovascular diseases in the over 65, with a prevalence of BkF_p for Canto Perdrix and a rather disadvantaged socio-economy and a seemingly deleterious cocktail for Les Comtes Est (DCE, V_p, Hg and HF), since the impact is also observed on respiratory diseases in the over 65.

Profile of IRISes according to the probability of the prevalence of environmental and/or socio-economic factors
Map No 6. Group 4 HCA, IRISes characterised by an increased prevalence of hospital stays related to cardiovascular diseases (> 65) and respiratory diseases (<15 and > 65)

Finally, the control group is characterised by an overall number of pathologies lower than elsewhere, and above all less dangerous pollutants and/or in lower quantity than in the IRISes of the previous groups. Moreover, socio-economy being more favourable²¹, tends to offset their effects. This is particularly true for St-Mitre Centre. Nevertheless, it is “interesting” to note that the presence of SO₂ alone has an influence on respiratory diseases in the 15-65 in the Figuerolles IRIS.

Profile of IRISes according to the probability of the prevalence of environmental and/or socio-economic factors
Map No 7. Group 5 HCA, IRISes characterised by a lower prevalence of “Control group” pathologies

²¹ Except in Comtes Ouest

The summary map below depicts HAP emissions in the north-east part of the Pays de Martigues (Jonquières, Boudème), a vanadium and SO₂ emission in Martigues' south neighbourhoods (Lavéra, Cote Bleue), and a PCB pollution over the entire territory. In the centre of the Pays de Martigues, disadvantaged socio-economy combines with the pollutants

Profile of IRISes according to the prevalence of environmental and/or socio-economic factors

Map No 8. Summary map

Discussion

Like all studies, this one has its limits which we bring to your attention. First, the health data relate to numbers of hospital stays and not numbers of patients, because when this study was conducted, we could not access patient numbers. Therefore, an overestimate of cases is possible, because some pathologies may have necessitated several hospital stays to be treated (this is particularly true concerning bladder cancers). Likewise, as we are working at a fine scale, the number of cases for some pathologies and in some IRISes can sometimes be low and induce biases. However, because Bayesian networks work, in a way, by comparing the evolution of proportion between variables, the risk of bias is minimised. The fact of having chosen annual averages for atmospheric pollutants rather than deciles tends to smooth out the effects of atmospheric pollutants. Pollutant data, like health data, are those of 2015, but we know that in the case of cancers there is a time gap that can be long between the exposure and its effect, but this seems to be less so for respiratory and cardiovascular diseases and diabetes. Finally, we only took into account residential exposure, and not professional or related to daily commuting. Finally, although the lichen plots are

scattered over the entire study territory and located according to the IRISes' socioeconomic level, had we had more of them would have enabled us to ascertain our results even better. Studies carried out on environmental health are most of the time criticised because of the difficulty to get to the root causes of pathologies. Another frequently heard argument is the multifactorial character of an individual's health. Furthermore, the design of these studies is most of the time of the ecological kind and can also lead to attribute to individuals the effect of pollutants measured in a space (ecological fallacy), but this argument is itself put into question. [42]

Nonetheless, by taking into account the highest possible number of variables in terms of pollutants and socio-economy which can potentially influence the health of residents, and doing so at a fine scale (the nearest to that of the majority of individuals living in urban areas), on the base of proven pathologies, and using an appropriate mathematical formalism, based on conditional probabilities, we can then presuppose a certain number of causal factors.

Thus, we have been able to bring forward several relations between exposure to xenobiotics and proven pathologies, sufficient enough to have required an hospital stay in 2015, and which suggest the recommendations below.

Among the relations found, efforts must focus on reducing SO₂ emissions, having observed that it has an impact from a very low threshold, far below standards. Companies must continue and ramp up the desulphurisation process of their installations, or, when possible, use a lower-sulphur fuel. However, SO₂ exposure is not only due to companies operating in the territory, the annual volume of tankers bringing their load to the Fos-sur-Mer Industrial Port zone also plays a part. There again, resorting to a lower-sulphur fuel could contribute to improving the health of residents. It appears that in this territory there is diffuse PCB pollution, linked to respiratory diseases in the over 65, which should be investigated more closely in order to take appropriate measures quickly (site remediation by phytomanagement) [43, 44].

Several thresholds have appeared, above which certain pollutants were particularly noxious, and in that sense, the Bayesian model will have contributed to revealing them, as is the case, for example, with hydrofluoric acid (HF), the effect of which already appeared at the 0.0028 µg/m³ threshold, whereas exposure to cadmium in its particle phase, for an exposure between 0.214 and 0.250 µg/m³, disrupts insulin metabolism in the over 65. Finally, as soon as benzo[k]fluoranthene (particle phase) exceeds the 0.672 µg/m³ threshold, it is reflected by a higher number of hospital stays for respiratory diseases in the 15-65.

The role of specific pollutants in the profile category such as chrome, chrome VI and vanadium in their particle phase, deserves appropriate monitoring. Therefore, emissions of these pollutants should be reduced, when it is technically and financially possible, below such thresholds (substitute products, less polluting industrial processes, more effective filters).

Conclusions

The study has revealed differentiated health profiles between the various IRISes which constitute the Pays de Martigues territory, which should lead to supplying health care that would be better suited to the needs of the population, from a prevention perspective, and even to promote consultations with certain specialists. For example, with a cardiologist, in those IRISes where the number of unqualified 15-year olds is significant, since a relation has been found at that level, a relation most probably due to more difficult living or working conditions for these people.

Likewise, prevention and social support measures should be taken to the benefit of single-parent families. As for companies in the study area, they should continue to reduce their emissions concerning the noxious pollutants found. Lastly, present-day pathologies are most of the time the result of former exposures when pollution levels were overall higher. It would be interesting to obtain older measurements concerning the incriminated pollutants and redo the calculations.

Declarations

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request, excepting the health data, because the French national commission for Informatics and Freedoms (CNIL) does not allow their sharing.

List of abbreviations

CB169: PCB 169 3,3',4,4',5,5'-Hexachlorobiphenyl

R: Correlation coefficient

BkF_p: Benzo[k]fluoranthene particle phase (a letter p after a pollutant indicates that it is this pollutant's particle phase, and not its gaseous phase)

HF: Hydrofluoric acid

Cd_p: Cadmium particle phase

HCl: Hydrochloric acid

IRIS: Block groups for Statistical Information, INSEE infra-communal breakdown

P14_PMEN_ANEM10P: number of people in households living in the IRIS in 2014 for over 10 years

P14_NSCOL15P_DIPL0: number of unschooled people aged 15 or over and without qualification

C14_PMEN_MENFAMMONO: number of people in households whose main family is a single-parent family

P14_NPER_RP_LOC: number of people in main homes occupied by tenants

P14_POP_IMM1: number of immigrants

P14_CHOM15642: number of unemployed aged 15 to 64

DEC_MED14: median income

HAP: Polycyclic aromatic Hydrocarbons

I00I9915ans: all cardiovascular diseases in the under 15

I00I991565ans: all cardiovascular diseases in the 15-65

I00I9965ans: all cardiovascular diseases in the over 65

J00J9915ans: all respiratory diseases in the under 15

J00J991565ans: all respiratory diseases in the 15-65

J00J9965ans: all respiratory diseases in the over 65

E10E1415ans: all diabetes types (I & II) in the under 15

E10E1465ans: all diabetes types (I & II) in the 15-65

E10E1465ans: all diabetes types (I & II) in the over 65

C3415ans: all types of bronchus and lung cancer in the under 15

C341565ans: all types of bronchus and lung cancer in the 15-65

C3465ans: all types of bronchus and lung cancer in the over 65

C6715ans: all types of bladder cancer in the under 15

C671565ans: all types of bladder cancer in the 15-65

C6765ans: all types of bladder cancer in the over 65

C6415ans: all types of kidney cancer in the under 15

C641565ans: all types of kidney cancer in the 15-65

C6465ans all types of kidney cancer in the over 65

PCB: Polychlorobiphenyls

PCDDF: Dioxins and Furans

Cr_p: Chromium in particle phase

Cr₆_p: Chromium VI, hexavalent Chromium

CB194: 2,2',3,3',4,4',5,5'-Octachlorobiphenyl

CO: Carbon monoxide

CB187: 2,2',3,4',5,5',6-Heptachlorobiphenyl

TEQ 2005: sum of PCBs and dioxins/furans in toxic equivalents such as defined by the WHO in 2005

2,3,7,8 TeCDF: 2,3,7,8-Tetrachlorodibenzofuran

2,3,4,7,8 PeCDF: 2,3,4,7,8-Pentachlorodibenzofuran

As: Arsenic

SO₂: Sulphur dioxide

VDL: Lichen diversity value
 CB20: 2,3,3'-Trichlorobiphenyl
 CB114: 2,3,4,4',5-Pentachlorobiphenyl
 CB157: 2,3,3',4,4',5'-Hexachlorobiphenyl
 PM10 diesel: Under 10 µm diameter particles
 PM2,5 diesel: Under 2.5 µm diameter particles
 IcdP: Indeno [1,2,3 c, d] pyrene
 BbF: Benzo[b]fluoranthene
 BaP: Benzo[a]pyrene
 BaA: Benzo[a]anthracene
 Daba: Dibenzo [a,h]anthracene
 Cu: Copper
 Benz: Benzene
 NO2: Nitrogen dioxide
 CB180: 2,2',3,4,4',5,5'-Heptachlorobiphenyl
 Ni: Nickel
 Zn: Zinc
 Se or Sn: Selenium
 Pb: Lead
 CB170: 2,2',3,3',4,4',5-Heptachlorobiphenyl
 V: Vanadium
 CB169: 3,3',4,4',5,5'-Hexachlorobiphenyl
 CB194: 2,2',3,3',4,4',5,5'-Octachlorobiphenyl
 CB187: 2,2',3,4',5,5',6-Heptachlorobiphenyl
 Bpe: Benzo(ghi)perylene
 CB195: 2,2',3,3',4,4',5,6-Octachlorobiphenyl
 CB153: 2,2',4,4',5,5'-Hexachlorobiphenyl
 1,2,3,4,6,7,8 HpCDF: 1,2,3,4,6,7,8-Heptachlorodibenzofuran
 1,2,3,4,6,7,8,9 OCDF: 1,2,3,4,6,7,8,9-Octachlorodibenzofuran
 CB149: 2,2',3,4',5',6-Hexachlorobiphenyl
 CB123: 2,3',4,4',5'-Pentachlorobiphenyl
 CB28: 2,4,4'-Tri chlorobiphenyl
 CB44: 2,2',3,5'-Tetrachlorobiphenyl
 IPA: Atmospheric Purity Index
 1,2,3,4,6,7,8,9 OCDD: 1,2,3,4,6,7,8,9-Octachlorodibenzodioxin
 CB77: 3,3',4,4'-Tetrachlorobiphenyl
 CB126: 3,3',4,4',5-Pentachlorobiphenyl
 CB153: 2,2',4,4',5,5'-Hexachlorobiphenyl
 CB138: 2,2',3,4,4',5'-Hexachlorobiphenyl
 CB128: 2,2',3,3',4,4'-Hexachlorobiphenyl
 CB101: 2,2',4,5,5'-Pentachlorobiphenyl
 DCE: Dichloroethane
 CB105: 2,3,3',4,4'-Pentachlorobiphenyl
 1,2,3,6,7,8 HeCDF: Hexachlorodibenzo-p-furan
 Fe: Iron
 CB18: 2,2',5-Trichlorobiphenyl
 CB151: 2,2',3,5,5',6-Hexachlorobiphenyl
 CB156: 2,3,3',4,4',5-Hexachlorobiphenyl
 FIA: Fluoranthene
 Ace: Acenaphthene
 Acy: Acenaphthylene
 Ant: Anthracene
 CB31: 2,4',5-Trichlorobiphenyl
 Nap: Naphthalene
 CB141: 2,2',3,4,5,5'-Hexachlorobiphenyl
 lpy: Indeno(1,2,3-cd)pyrene
 Phe: Phenanthrene

Flu: Fluorene
 CB52: 2,2',5,5'-Tetrachlorobiphenyl
 CB183: 2,2',3,4,4',5',6-Heptachlorobiphenyl
 CB196: 2,2',3,3',4,4',5,6'-Octachlorobiphényle
 CB201: 2,2',3,3',4,5',6,6'-Octachlorobiphenyl
 CB95: 2,2',3,5',6-Pentachlorobiphényle
 CB118: 2,3',4,4',5-Pentachlorobiphenyl
 CB87: 2,2',3,4,5'-Pentachlorobiphenyl
 CB92: 2,2',3,5,5'-Pentachlorobiphenyl
 Hg: Mercury
 1,2,4,7,8 HeCDF: Tetrachlorodibenzo-p-furan
 1,2,3,7,8 HeCDD: 2,3,7,8-Tetrachlorodibenzo-p-dioxin
 1,2,3,6,7,8 HeCDD: 1,2,3,6,7,8-Hexachlorodibenzo-p-dioxin
 1,2,3,4,6,7,8 HpCDD: 1,2,3,4,6,7,8-Heptachlorodibenzo-P-dioxin
 CB60: 2,3,4,4'-Tetrachlorobiphenyl
 CB151: 2,2',3,5,5',6-Hexachlorobiphenyl
 CB174: 2,2',3,3',4,5,6'-Heptachlorobiphenyl
 CB81: 3,4,4',5-Tetrachlorobiphenyl
 CB136: 2,2',3,3',6,6'-Hexachlorobiphenyl

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Ethics declarations

Consent for publication

This manuscript does not contain any individual person's data in any form.

Competing interests

The authors declare that they have no competing interests.

Figures, tables and additional files