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Research article

Crop proximity index for monitoring of peri-urban land use in agro-industrial crop regions

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ABSTRACT

The agro-industrial production of genetically modified organisms uses great amounts of pesticides, close to cities, which generates growing concern due to the numerous evidence of their negative effects on health and the environment. In a context of the lack, or inaccessibility, of official data on crop dynamics and pesticide use, environmental indicators using satellite data are needed for the proper monitoring of peri-urban areas. The objective of this research is to make a crop proximity index using satellite information to assess and monitor peri-urban agro-industrial activity. Twenty cities in Argentina and ten in the United States were selected. The CPI index is designed to evaluate a city and its peri-urban areas as a whole by taking account of the land uses and factors that can potentially influence the proximity to agro-industrial activity to the population living in those cities. Agriculture factor was weighted by proximity or remoteness using perimeter rings from the urban edge. All the necessary data for the calculation of the CPI index were obtained through the classification and processing of Sentinel 2 satellite images with software and the Google Earth Engine platform. The results show a worrying situation, 90% of cities in Argentina and 80% in the United States have a negative CPI. Most of the cities examined are extremely close to extensive areas of crops, that use a high amount of pesticides and which do not have the protection of trees or buffer zones.

1. Introduction

United States, Brazil and Argentina are the three main crop-producing countries using genetically modified organisms (GMOs) in the world, with over 139 million hectares planted annually in recent years (Slater and Holtslander, 2015). For this type of crop the ever-increasing use of the amount of pesticides generates growing concern among the population and governments in different parts of the world due to the numerous evidence of their negative effects on health (Aiassa et al., 2009; Benítez-Leite et al., 2009; Bernardi et al., 2015; Gómez-Barroso et al., 2016; Guyton et al., 2015; Loomis et al., 2015; López et al., 2012; Mendez et al., 2017; Singh et al., 2018; Swanson et al., 2014; Tsatsakis et al., 2017) and the environment (Aizen et al., 2009; Alonso et al., 2018; Guida-Johnson and Zuleta, 2013; Piquer-Rodríguez et al., 2018; Primost et al., 2017; Singh et al., 2018; Tsatsakis et al., 2017; Zaady et al., 2018).

The agro-industrial model, in many instances, takes place very close to densely populated cities, exposing the people who live in these areas to the possible pesticide contamination (Aiassa et al., 2009; Etiennot and Piazza, 2010; López et al., 2012; Primost et al., 2017; Singh et al., 2018; Soo-Jeong et al., 2011; Trajkovska et al., 2009; Vida and Moretto, 2007). This exposure occurs because there are multiple pathways of contact with pesticides or their residues: off-target spray drift, volatilization, drag by wind or rain, soil erosion, leaching, runoff and atmospheric drift (Alonso et al., 2018; Deziel Nicole et al., 2015; Garcerá et al., 2017; Mendez et al., 2017; Mugni et al., 2011; Primost et al., 2017; Singh et al., 2018; Zaady et al., 2018). In addition, there are numerous factors that should be taken into account to avoid or minimize the pesticides off-target spray drift: the droplet size, nozzle types, spray pressure, formulation adjuvants, wind direction, wind speed, air stability, relative humidity, temperature, the height of released spray relative to the target crop, volumes per area sprayed and fumigation equipment speed (Felsot et al., 2010). This complexity of factors, combined with the high frequency of spraying in large territories, makes it very difficult to monitor and control exposure to pesticides caused by this type of productive model. Another phenomenon to consider is the secondary drifts are those that can occur days, weeks or months after pesticide application, exposing the people that live

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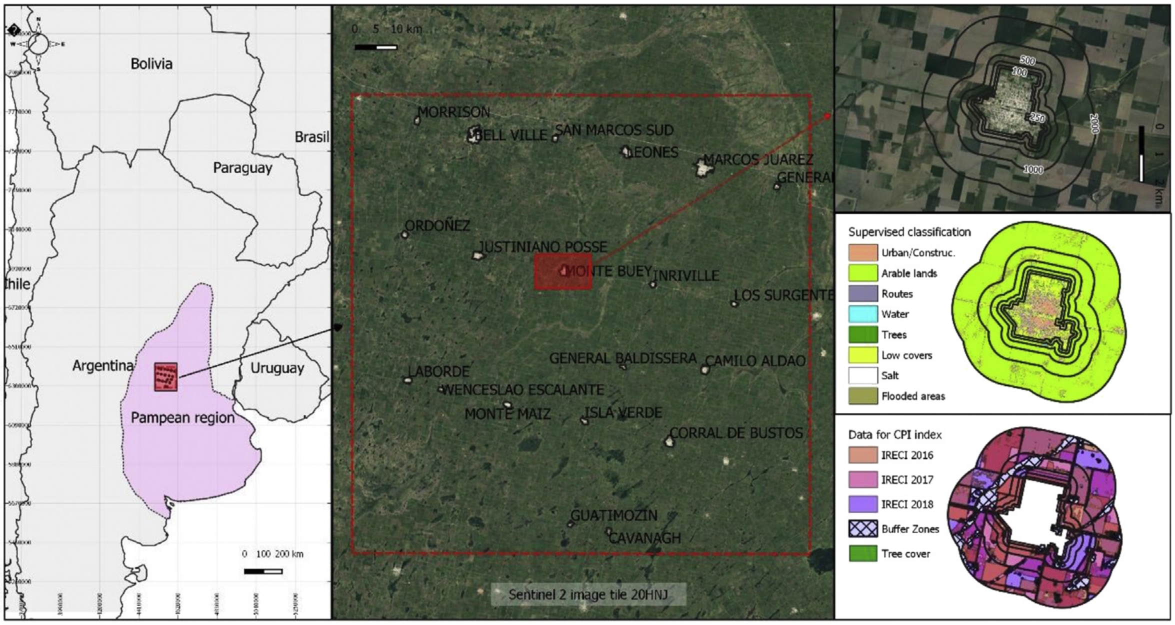

Figure 1. Argentine study area. Detail of the tile location of satellite image Sentinel 2 and an analyzed city, with their respective perimeter rings, representation of supervised classification and data for CPI index calculations. CPI = Crop proximity index; IRECI = Inverted Red-Edge Chlorophyll Index.

in cities adjacent to the crop fields in the long term (Alonso et al., 2018; Mendez et al., 2017; Soo-Jeong et al., 2011; Ward et al., 2006; Zivan et al., 2016). This kind of drift is uncontrollable since it is produced by interaction between the climatic factors and the pesticides applied (Alonso et al., 2018; Coronado et al., 2011; Epple et al., 2002; Etiennot and Piazza, 2010; Peck and Hornbuckle, 2005; Singh et al., 2018; Soo--Jeong et al., 2011; Trajkovska et al., 2009; Zivan et al., 2016).

In this context, numerous investigations in Argentina have shown that pesticides used by the agro-industrial model of GMO are transported long distances, are found in urban areas, do not degrade easily (they are pseudo-persistent), contaminate water, soil and air (Alonso et al., 2018; Aparicio et al., 2013; Bonansea et al., 2018; De Gerónimo et al., 2014; Etchegoyen et al., 2017; Hunt et al., 2017; López et al., 2012; Mendez et al., 2017; Mugni et al., 2011; Peluso et al., 2014; Primost et al., 2017; Solis et al., 2017).

In these areas of contact between human populations and agro-industrial activity, there is great social conflict. For instance, in Argentina numerous cities have established more restrictive regulations than the national or provincial jurisdictions for the use of pesticides near to urbanizations (Tittonell and Giobellina, 2018). Therefore, environmental indicators are needed for the proper assessment of the location of crops and pesticide use in order to minimize the risks of contamination from peri-urban areas (Feola et al., 2011; Reus et al., 2002; Zivan et al., 2016). Although there are numerous indicators and indices of

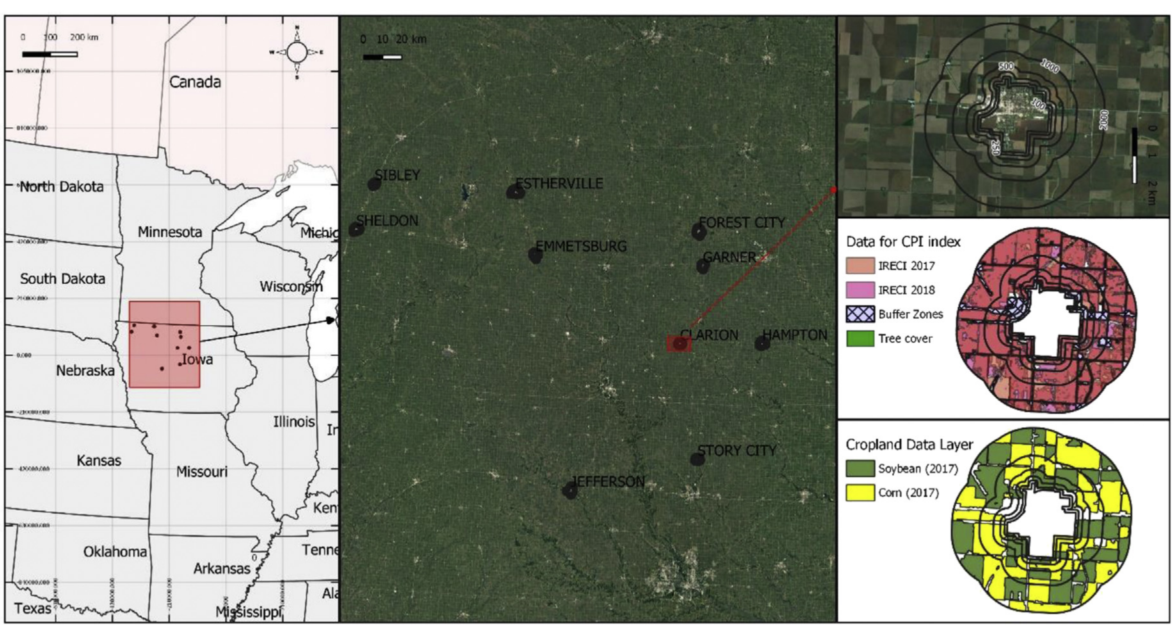

Figure 2. United States study area. Detail of location of ten cities in Iowa state and an analyzed city, with their respective perimeter rings, representation of data for CPI index calculations and Crop Data Layer soybean and corn fields for 2017. Source: Crop Data Layer, National Agricultural Statistics Service (USDA, 2019). CPI = Crop proximity index; IRECI = Inverted Red-Edge Chlorophyll Index.

contamination and exposure to pesticides (Alister and Kogan, 2006; Damalas and Eleftherohorinos, 2011; Dubny et al., 2018; Feola et al., 2011; Ferraro et al., 2003; Hunt et al., 2017; Kookana et al., 2005; Kudsk et al., 2018; Peluso et al., 2014; Reus et al., 2002; Sánchez-Bayo et al., 2002; Strassemeyer et al., 2017; Tsaboula et al., 2016; Vercruysse and Steurbaut, 2002), it is difficult to apply them in countries such as Argentina due to the lack of data on the use of pesticides required for their calculation, or due to the inaccessibility of such data. These conditions highlight the need to develop methodologies that allow the determination of primary data on the degree of proximity of crops to cities to serve as input to investigate possible cases of exposure on the populations living there. One methodological approach to solving this problem is the development of an index for assessing the proximity of agro-industrial crops to cities with satellite data. Currently, satellite data can be obtained and processed directly from the Internet on cloud platforms, such as the Google Earth Engine, that provide access to information from various sources which enables the development of environmental quality indicators without any major economic costs.

The objective of this research is to make a crop proximity index using satellite information to assess and monitor peri-urban agro-industrial activity.

2. Materials and methods

2.1. Study areas

The study area where the index was tested corresponds to the area of greatest agricultural production in Argentina, called the Pampean region (Figure 1), where almost one hundred percent of soybean and corn crops are transgenic (Trigo, 2016). Twenty cities in this region were selected for calculating the proposed index, considering population sizes greater than 1000 inhabitants (INDEC, 2010) and which are found within the limits of 100 $\times$ 100 km of the Sentinel 2 satellite images used to obtain land cover information (Figure 1).

In addition to the study area in Argentina, ten cities in one state of the United States with the greatest agro-industrial production were selected: Iowa with more than 9.3 million hectares of soybeans and corn planted in 2018 (National Agricultural Statistics Service, 2019) (Figure 2). In this country, the percentage implementation of GMO crops it is close to maximum adoption, more than 90% for both crops (Economic Research Service, 2019). This will allow us to corroborate the databases and comparative tests of the proposed index.

2.2. Peri-urban crop proximity index (CPI)

The CPI index is designed to evaluate a city and its peri-urban areas as a whole by taking account of the land uses and factors that can potentially influence the proximity to agro-industrial activity to the population living in those cities. With this objective we proposed to evaluate the proximity of peri-urban crops to cities, taking account of the factors developed in the linear equation below:

$$CPI = (Tree\ Cover\ Factor + Buffer\ Zones\ Factor + S\ Factor) - Crops\ Factor \tag{1}$$

Each factor will be developed extensively below. In general, these factors allowed us to introduce the spatial quantification occupied by agriculture, presence of tree cover and buffer zones surrounding urbanizations. The S factor provides structural variables of each urbanization: area of the city and its perimeter.

The term peri-urban in our research is defined as the interface between the land surfaces occupied by urbanizations and those used for agriculture. Specifically, we studied what happens from the edge of each city to a peripheral distance of 2000 m. We take this distance as a parameter since most of the laws regulating peri-urban spraying in Argentina have implications within the 2000 m of the periphery. Therefore, as a research objective it is interesting to study the dynamics of crops within this radius.

In order to collect information on the entire peri-urban area of each city analyzed, we proceeded to work on perimeter rings, divided into sections (like buffers). In order to carry this out, the area occupied by each urbanization was calculated using cadastral data and high-resolution satellite images. Perimeter rings were calculated from 0 to 100, 100 to 250, 250 to 500, 500 to 1000 and 1000–2000 m away from the urban edge (Figure 1), in order to be able to weight each factor by proximity or remoteness.

2.3. Tree cover, buffer zones, crops and S factor

The peri-urban surface of trees and buffer zones are considered protective factors in Eq. (1) since, together, these two classes would act as barriers to the drift of pesticides, being one of the most effective forms of mitigation according to scientific research (Brown et al., 2004; Ucar and Hall, 2001). In addition, recent research shows that tree barriers not only act to stop the primary drift of pesticides, they also prevent the spread of crop dust containing agrochemicals and other pollutants from this activity such as heavy metals (Zaady et al., 2018). Windbreaks mitigate pesticide drift by entrapment of spray droplets on the structure of the windbreak and pattern modification of the wind velocity profile as air passes over and through it (Brown et al., 2004; Wenneker and van de Zande, 2008).

In our project we define buffer zones as areas that fulfil a function of protection from agro-industrial activity, but that cannot be framed within the tree class. These buffer zones will be established from the sum of those peri-urban areas that are not occupied by tree cover or crops in the whole range of data analyzed. These zones may include areas occupied by: shrubs and pastures, bare ground and flooded areas, among others. The crop factor in the Eq. (1), quantifies the area destined for agriculture. These are summer crops in the urban periphery, corresponding to transgenic soybean and corn, in a ratio of 70–30 soybean-corn, for the study areas and temporal periods selected (Ministerio de Agroindustria, 2018).

In order to obtain all the information for each factor needed to calculate Eq. (1), two different methodologies were used. First, for the calculation on peri-urban land cover and land use data for the Argentine study area, a supervised classification of Sentinel 2 satellite image (location tile 20HNJ, February 2017) was carried out. These satellites images were corrected atmospherically and processed using SNAP 6.0.0 and QGis 2.18 software. The classification was made with the QGis SCP plugin (Congedo, 2016), in order to obtain information on the arable land surfaces, tree cover (native or exotic woody plants), constructions, water, rivers, shrubs and pastures, bare ground, roads and flooded areas. To corroborate the concordance of this classification, 400 random points were sampled (obtained by observation of high-resolution images from Google Earth), to be evaluated in a confusion matrix and to calculate the Kappa index.

Secondly, for both study areas, the Google Earth Engine platform was used to analyze and elaborate information on the peri-urban cover of active crops (crops in Eq. (1)) to a peripheral distance of 2000 m. In particular, we used the satellite classification index IRECI (Inverted Red-Edge Chlorophyll Index) to determine the active crops by the presence of chlorophyll (Frampton et al., 2013; Korhonen et al., 2017). This index shows good results in the determination of crops, as it has a strong linear relationship with the chlorophyll content of leaves, without saturation at high values (Frampton et al., 2013). A script (programming code) was developed on this platform that allows the selection of cloud-free, Sentinel 2 satellite images, making all processes and analyses in peri-urban areas defined by polygons that represent peripheral rings of 2000 m for each city. Then, this script calculated the IRECI index for the summer period (highest foliar status), from January to March in 2016, 2017 and 2018, for Argentina, and from June to August in 2017 and 2018, for the United States. The product of this analysis is a raster composite image per year. To determine the fields with agricultural activity, a mask was applied on the raster images to obtain the values that represent the highest levels of chlorophyll content in the crops. This value should be determined from field data or other reliable sources, as they vary according to the type of crop and the date of analysis. Then, the masked raster images are transformed into polygons, which allows a discrimination of the fields of more than four hectares. Polygons larger than this size were chosen to avoid counting small fields or isolated pixels, which would probably correspond to detection errors. The final result is a polygonal layer that represents the active peri-urban crops, in all the cities analyzed, for each chosen date. These data can be exported for use in geographic information system software (GIS). A validation of IRECI index data was carried out using the Argentine database, Agricultural Coverage for the period 2017–2018 (category level 2) from Spatial Data Infrastructures of Cordoba (hereafter IDECOR) (García et al., 2018) and the U.S. database, Cropland Data Layer (hereafter CDL) for 2017 and 2018, from National Agricultural Statistics Service (USDA, 2019). Using these two bases, the type, location, shape and occupied acreage of the peri-urban crops determined by the IRECI index were corroborated.

All the georeferenced datasets described so far were entered into a GIS using QGis 2.18 software to perform the calculations needed for computing Eq. (1). In order to obtain surface area data (in hectares) for each factor (tree cover, buffer zones and crops) zone statistics were carried out for all the rings surrounding each city. This information was introduced in the formula detailed below to obtain the values of Eq. (1):

$$Factor = \left(\frac{a}{Ring\ Surface} xb\right) \underset{0-100m}{Ring} + \left(\frac{a}{Ring\ Surface} xb\right) \underset{100-250m}{Ring} + \left(\frac{a}{Ring\ Surface} xb\right) \underset{250-500m}{Ring} + \left(\frac{a}{Ring\ Surface} xb\right) \underset{500-1000m}{Ring} + \left(\frac{a}{Ring\ Surface} xb\right) \underset{1000-2000m}{Ring} \tag{2}$$

where a corresponds to the area (hectares) of the specific factor in each ring, tree cover, buffer zones and crops. Where b is a constant that varies according to the factor and the ring. In the case of the crop factor in the first ring (from 0 to 100 m), b is equal to 20; in the following ring, 10; in the third, 5; the fourth, 2,5 and in the last ring 1 (exponential model). In the case of tree cover and buffer zone factors, b is equal to 1 in all the rings. This variable b allows the magnification of the factors according to the model to be tested. In our research we consider that the presence of crops close to human populations is potentially more dangerous, so the area of first rings of this factor is multiplied in a greater proportion than the surface of tree cover or buffer zones. The values used enable us to test this model, but do not represent a condition or attribute of the factors under study.

As with forest patches, cities are subject to different conditions of exposure to disturbances (of the matrix that surrounds them) according to various structural characteristics, such as shape, size, edge effect, among others (Forman and Godron, 1981). For this reason, the S factor was incorporated into the calculation of the CPI index as a variable that reflects the size of the urban area and the perimeter of each city researched (as a shape index). The size of the urban area is very important, as the smaller it is, the more likely that the total population is exposed to the proximity of crops and pesticide use. Similarly, the perimeter of urbanization can be taken as a structural variable that reflects a greater or lesser degree of contact with peri-urban agricultural activity and its possible pollutants. Cities with a long and irregular perimeter have a greater edge effect. In order to introduce this factor into the CPI calculation equation, we proceeded as follows: the area and perimeter of each city were divided by a fixed number (100 for area and 10000 for perimeter) in order to obtain a one-digit number for each variable. This was done by the differences between units and to obtain a unique value to add to Eq. (1). Then, the number corresponding to the area was subtracted from the perimeter. Thus, we obtained a single value that corresponds to the S factor in Eq. (1), and that allowed us to weight these two variables for each city.

2.4. Theoretical cities

A theoretical city was created (called theoretical city 1) in order to obtain a reference model that represented a situation of peri-urban land occupation of lesser proximity to agricultural activity. This city was created with the following characteristics: its size (1800 ha) and perimeter (30 thousand meters) corresponding to a medium to a large city, taking into account the cities of the study areas. As for peri-urban land cover, it has all the rings, from 0 to 2000 m, covered by 70% of forest (tree cover), and 30% with buffer zones. This urban and peri-urban configuration represents an extreme situation that sets a comparative parameter. With this theoretical city the highest value that the CPI index can reach will be established, and the real analyzed cities will be relativized. The final values of the CPI index will vary from 1 (the best situation) to -1 (the worst situation), or lower values, according to the land occupation model of the theoretical city.

In addition, another theoretical city was created (called theoretical city 2) that represents the worst situation, due to the size (400 ha) and perimeter (10 thousand meters) of the urbanization, corresponding to a small city, and the proximity and surfaces of peri-urban crops. The peri-urban configuration is as follows: the first ring is occupied in 60% by crops, 38% buffer zones and 2% tree cover. The second ring is 65% occupied by crops, 33% buffer zones and 2% tree cover. The third and fourth rings have 70% crop, 29% buffer zones and 1% tree cover. Finally, the fifth ring has 80% crops, 19% buffer zones and 1% tree cover. This allowed us to have a model, from which the influencing factors can be studied, and which could serve as a reference to warn about extreme situations.

2.5. United States complementary data

For determination of urban areas, we use the Census Bureau's urban-rural classification data (polygon shapefiles) (United States Census Bureau, 2010). From these urban areas the perimeter analysis rings were determined, in order to calculate the data for each factor of Eq. (1).

In contrast to the Argentine database, all data were obtained and processed using the Google Earth Engine platform. For discriminating annual crops of soybeans and corn we used the CDL database for 2017 and 2018 (USDA, 2019). This database was used for corroborating the active crops determined by the IRECI index, which has moderate resolution satellite imagery (30m resolution) and extensive agricultural ground truth. The Global Forest Change 2000–2018 database were used to determine tree and forest cover. This database results from a time-series analysis of Landsat images (30m resolution) in characterizing global forest extent and change from 2000 through 2018 (Hansen et al., 2013b). From these databases it was possible to determine all complementary data necessary for calculating the CPI index.

3. Results

3.1. Determination of land cover data

3.1.1. Argentine study area

After processing and carrying out the supervised classification of the Sentinel 2 satellite image, corresponding to the month of February of 2017, it was possible to determine the different land coverages in the five perimeter rings of the 20 cities under study. From the concordance analysis of this classification, the confusion matrix gave an overall

Table 1. Argentine study area land cover data. Urban and peri-urban data for calculation of factors for the CPI index - showing the results of zone statistics analyses and overlap percentage of precision measures for IRECI index for 2018 (0 to 2km). The data shown as Crops correspond to calculations made with the IRECI index.

City	Urban Data		Peri-urban Data											
	Urban Area (Ha)	Perimeter (m)	Ring Area 0–2km (Ha)	Tree Cover		Buffer Zones		Crops 2016		Crops 2017		Crops 2018		Overlap percentage (2018)
				Ha	%	Ha	%	Ha	%	Ha	%	Ha	%	
Bell Ville	988	27882	4239	333	7.9	3029	71.5	567	13.4	359	8.5	333	7.9	100
Camilo Aldao	371	9097	2842	42	1.5	420	14.8	1926	67.8	1931	68.0	1776	62.5	97
Cavanagh	192	6878	2473	39	1.6	474	19.2	1384	55.9	1421	57.5	1340	54.2	97
Corral De Bustos	466	11152	3072	74	2.4	849	27.6	483	15.7	1543	50.2	1360	44.3	97
General Baldissera	129	6030	2300	23	1.0	669	29.1	776	33.7	1184	51.5	746	32.4	100
General Roca	198	8261	2568	61	2.4	694	27.0	1283	50.0	1277	49.7	865	33.7	100
Guatimozín	147	6525	2338	36	1.6	562	24.0	945	40.4	1381	59.1	1385	59.2	98
Inriville	172	7302	2382	44	1.8	324	13.6	1488	62.5	1455	61.1	618	25.9	100
Isla Verde	220	8701	2647	34	1.3	503	19.0	1320	49.9	1510	57.1	1673	63.2	98
Justiniano Posse	430	11484	3156	85	2.7	647	20.5	1704	54.0	1145	36.3	1594	50.5	100
Laborde	248	9057	2576	59	2.3	610	23.7	1483	57.6	1046	40.6	769	29.9	100
Leones	498	14077	3362	68	2.0	915	27.2	1351	40.2	1415	42.1	1416	42.1	98
Los Surgentes	160	6600	2387	75	3.1	358	15.0	1610	67.4	1370	57.4	669	28.0	100
Marcos Juárez	1204	24377	4737	92	1.9	1701	35.9	1396	29.5	1767	37.3	1499	31.7	98
Monte Buey	442	12599	3255	44	1.4	594	18.3	1519	46.7	1533	47.1	1679	51.6	99
Monte Maíz	251	8519	2694	55	2.0	828	30.7	1146	42.5	987	36.6	1022	38.0	100
Morrison	218	7297	2542	104	4.1	547	21.5	1194	47.0	1041	41.0	1071	42.1	98
Ordoñez	219	6703	2458	48	2.0	931	37.9	766	31.2	789	32.1	806	32.8	100
San Marcos Sud	195	6978	2413	50	2.1	792	32.8	1311	54.3	839	34.8	576	23.9	100
Wenceslao Escalante	145	5470	2247	31	1,4	539	24,0	1249	55,6	941	41,9	995	44,3	99
Theoretical city 1	1800	30000	-	-	70,0	-	30,0	-	0,0	-	0,0	-	0,0	-
Theoretical city 2	400	10000	-	-	1,4	-	29,6	-	69,0	-	69,0	-	69,0	-

CPI = Crop proximity index; IRECI = Inverted Red-Edge Chlorophyll Index, Ha = hectares, m = meters. The percentages of areas occupied by each factor and overlap percentage of precision measures are highlighted in bold.

accuracy of 87.5%, and the Kappa index was 0.7. To determine active crops in the summers of 2016, 2017 and 2018, the IRECI index was calculated in Google Earth Engine platform for the 20 Argentine cities.

All the information obtained from the supervised classification and analyses in the Google Earth Engine platform was processed in a single database using QGIS software. Thus, polygonal data were obtained for each factor of Eq. (1), which were counted in every ring of each city, making zone statistics analyses. Table 1 shows the results of the sum of each factor, in hectares, a percentage for the total ring area (0–2000 m) of each city and the theoretical cities.

In regard to peri-urban land cover occupation, it is interesting to note that in the 20 selected cities the average area occupied by trees is 9% in the first ring (from 0 to 100 m), with a maximum of 23% and a minimum of 4%. In the following rings, the tree cover decreases, without exceeding 17% cover in any case (the average is 3%). If we analyse the areas covered by active crops (IRECI index for 2016, 2017 and 2018) occupy,

Table 2. United State study area land cover data. Urban and peri-urban data for calculation of factors for the CPI index - showing the results of zone statistics analyses and overlap percentage of precision measures for IRECI index of 2017 and 2018 years (0 to 2km). The data shown as Crops correspond to calculations made with the IRECI index. Source: Census Bureau's urban-rural classification data (United States Census Bureau, 2010) and Global Forest Change (Hansen et al., 2013b).

City	Urban Data		Peri-urban Data										
	Urban Area (Ha)	Perimeter (m)	Ring Area 0–2km (Ha)	Tree Cover		Buffer Zones		Crops 2017		Overlap percentage (2017)	Crops 2018		Overlap percentage (2018)
				Ha	%	Ha	%	Ha	%		Ha	%	
Clarion	374	10810	2979	26	0.9	444	14.9	2193	73.6	97	2123	71.3	97
Emmetsburg	486	19070	3622	216	6.0	1501	41.4	1123	31.0	96	925	25.5	94
Estherville	746	23345	4460	601	13.5	1535	34.4	2173	48.7	94	1907	42.8	91
Forest City	688	16745	3925	196	5.0	1545	39.4	2031	51.8	91	1642	41.8	92
Garner	418	11323	3193	37	1.2	499	15.6	2310	72.4	95	2399	75.1	96
Hampton	522	18796	3566	183	5.1	934	26.2	2134	59.9	95	2501	70.1	92
Jefferson	629	17475	4005	622	15.5	1118	27.9	1459	36.4	97	1836	45.9	96
Sheldon	532	15523	3551	62	1.7	965	27.2	2397	67.5	95	2035	57.3	95
Sibley	277	11048	2885	54	1.9	735	25.5	1969	68.2	97	1656	57.4	97
Story City	378	12511	3012	280	9.3	569	18.9	1887	62.6	97	1735	57.6	96
Theoretical city 1	1800	30000	-	-	70.0	-	30.0	-	0	-	-	0	-
Theoretical city 2	400	10000	-	-	1.4	-	29.6	-	69.0	-	-	69.0	-

CPI = Crop proximity index; IRECI = Inverted Red-Edge Chlorophyll Index; Ha = hectares; m = meters. The percentages of areas occupied by each factor and overlap percentage of precision measures are highlighted in bold.

Table 3. CPI data and results for the Argentine study area. The data for each factor obtained using Eq. (2), necessary for the calculation of the CPI index, are shown. The results are disaggregated by year and in a triennial average. The data shown as crops correspond to calculations made with the IRECI index.

City	Tree Cover Factor	Buffer Zones Factor	Crops Factor (IRECI)			S Factor	CPI			Average
			2016	2017	2018		2016	2017	2018	
Theoretical city 2	0.1	1.5	24.6	24.6	24.6	3.0	-1.0	-1.0	-1.0	**-1.0**
Camilo Aldao	0.2	0.8	22.0	23.3	22.9	2.8	-0.9	-1.0	-1.0	**-0.9**
Cavanagh	0.1	1.0	22.0	20.4	17.8	1.2	-1.0	-0.9	-0.8	**-0.9**
Los Surgentes	0.3	1.2	18.1	16.1	8.6	0.9	-0.8	-0.7	-0.3	**-0.6**
Monte Buey	0.1	1.0	17.2	20.1	10.5	3.2	-0.6	-0.8	-0.3	**-0.6**
Isla Verde	0.1	1.3	15.2	9.9	17.9	1.3	-0.6	-0.4	-0.8	**-0.6**
General Roca	0.2	1.1	16.3	18.3	7.0	1.2	-0.7	-0.8	-0.2	**-0.6**
Guatimozín	0.2	1.7	9.0	15.1	16.8	0.8	-0.3	-0.6	-0.7	**-0.5**
General Baldissera	0.1	1.6	12.0	15.5	11.0	0.7	-0.5	-0.7	-0.4	**-0.5**
Leones	0.1	1.7	15.1	11.5	13.2	3.6	-0.5	-0.3	-0.4	**-0.4**
Corral De Bustos	0.2	1.6	9.0	15.0	12.9	3.5	-0.2	-0.5	-0.4	**-0.3**
Morrison	0.3	1.7	13.2	6.2	9.4	1.4	-0.5	-0.1	-0.3	**-0.3**
San Marcos Sud	0.2	2.1	14.0	11.2	3.7	1.3	-0.5	-0.4	0.0	**-0.3**
Justiniano Posse	0.2	1.5	14.0	8.7	10.0	3.2	-0.5	-0.2	-0.3	**-0.3**
Inriville	0.2	1.5	9.4	14.1	2.1	1.0	-0.3	-0.6	0.0	**-0.3**
Laborde	0.3	1.8	12.8	8.6	4.4	1.6	-0.5	-0.2	0.0	**-0.2**
Wenceslao Escalante	0.2	2.2	9.2	5.3	8.7	0.9	-0.3	-0.1	-0.3	**-0.2**
Ordoñez	0.1	2.6	8.4	8.0	3.7	1.5	-0.2	-0.2	0.0	**-0.1**
Monte Maíz	0.2	2.4	7.5	6.2	5.6	1.7	-0.2	-0.1	-0.1	**-0.1**
Marcos Juárez	0.2	2.2	7.2	10.5	7.1	9.6	0.2	0.1	0.2	**0.2**
Bell Ville	0.7	3.7	1.5	0.5	0.2	7.1	0.5	0.6	0.6	**0.5**
Theoretical city 1	3.5	1.5	0.0	0.0	0.0	15.0	1.0	1.0	1.0	**1.0**

CPI = crop proximity index; IRECI = Inverted Red-Edge Chlorophyll Index. The averages of the calculated CPIs are highlighted in bold.

on average, 21% of the first ring, with a maximum of 50% and a minimum of 0%. In the following rings the average is 39%, with maximums of 80% and a minimum of 0%. As for the areas occupied by buffer zones, in the first ring, the average peri-urban land occupation is 55%, with a minimum of 32% and a maximum of 80%. In the rings that follow, from 250 to 2000 m, the average of this factor does not exceed 30% of occupation, with a minimum of 8% and a maximum of 80%.

In order to validate the data calculated using this spatial index, the polygonal layers corresponding to 2017 were compared with the Argentine database IDECOR. The method chosen was the spatial intersection of the polygons (of the complete ring, from 0 to 2000 m), between the IRECI index layer and the crops layer in the agricultural cover database. The IDECOR database used is composed of the layers of soybean, corn, wheat, peanuts and sorghum crops (overall resolution of 2.5 ha of minimum mappable unit). This gave the degree of precision for detecting summer crops, compared to the other bases, as well as the error when confused with other types of coverages. The advantage of this spatial comparison is that the degree of precision, and error, in detecting the shape and location of active crop fields is also measured. The results of these measurements are shown in Table 1, expressed in percentages of precision for detecting active crop fields in February 2018.

In general, there is a high precision in the detection of active crop fields in the peri-urban, which is reflected in the percentage of coincidence, both in form and extension. By taking account of the average of all cities, the accuracy reaches 96% coincidence, with a minimum of 93% and a maximum of 99%. Alternatively, the percentages of surfaces that are detected as active fields by means of the IRECI index that belong to other coverages, do not exceed 4% on average according to the compared database.

In addition to the overlap analyses, data from both databases were compared using simple linear regressions. The areas occupied by crops (IRECI index) in each ring for each year were compared with the areas of crops in the period 2017–2018 (IDECOR database). The results show a high correlation (statistically significant at $p < 0.0001$) between the base determined by the IRECI index (crops) and that of IDECOR. In particular, the r^2 for each year is 0.86 for 2016 (slope 1.59), 0.9 for 2017 (slope 1.64) and 0.86 for 2018 (slope 1.69).

3.1.2. United States study area

Through the processing of the proposed databases, it was possible to determine the different peri-urban land use cover of the 10 cities selected in the United States. All the data were obtained using the Google Earth Engine platform, the periods analyzed correspond to 2017 and 2018 (Table 2). To determine active crops in 2017 and 2018, the IRECI index was calculated for July and August (months in which the highest active crop coverage was detected).

In regard to peri-urban land cover occupation, the summary data shows that in the 10 selected cities the average area occupied by trees is 11% in the first ring (from 0 to 100 m), with a maximum of 25% and a minimum of 3%. In the following rings, the tree cover decreases, not exceeding 25% cover in any case (the average is 6.6%). As for the areas occupied by active crops (IRECI index for year 2017 and 2018) on average they occupy 21% of the first ring, with a maximum of 39% and a minimum of 5%. In the following rings the average is 51%, with maximums of 80% and a minimum of 12%. If we analyze the areas covered by buffer zones, in the first ring, the average peri-urban land occupation is 65%, with a minimum of 54% and a maximum of 85%. In the rings that follow, from 250 to 2000 m, the average of this factor does not exceed 32% of occupation, with a minimum of 11% and a maximum of 70%.

The polygonal information generated by the IRECI spatial index was compared with the Cropland Data Layer (CDL) for 2017 and 2018. The intersection of polygons (in the complete ring, from 0 to 2000 m) was made between the IRECI index layer and the crop layer (corn and soybean) of the CDL database. The results of these measurements are shown in Table 2, expressed in percentages of precision for detecting active crop fields in July and August 2017 and 2018. In general, there is a high precision in the detection of active crop fields in the peri-urban of 10 cities selected, this is reflected in the percentage of coincidence, both in

Table 4. CPI data and results for the United State study area. The data are shown for each factor obtained using Eq. (2), necessary for the calculation of the CPI index. The results are disaggregated by year and in a biennial average. The information and calculations carried out with two databases are shown: those of Crops, using the IRECI index, and those of CDL, using the database of Cropland Data Layer. Source: Cropland Data Layer, National Agricultural Statistics Service (USDA, 2019) and Global Forest Change (Hansen et al., 2013b).

City	Tree Cover Factor	Buffer Zones Factor	Crops Factor (IRECI)		CDL Factor		S Factor	IRECI		Average	CDL		Average
			2017	2018	2017	2018		CPI 2017	CPI 2018		CPI 2017	CPI 2018	
Theoretical city 2	0.1	1.5	24.6	24.6	24.6	24.6	3.0	-1.0	-1.0	**-1.0**	-1.0	-1.0	**-1.0**
Garner	0.1	1.4	20.4	20.3	18.6	19.6	3.0	-0.8	-0.8	**-0.8**	-0.7	-0.8	**-0.7**
Clarion	0.1	1.3	18.7	18.4	21.5	21.5	2.7	-0.7	-0.7	**-0.7**	-0.9	-0.9	**-0.9**
Hampton	0.4	1.7	13.6	16.9	15.3	15.4	3.3	-0.4	-0.6	**-0.5**	-0.5	-0.5	**-0.5**
Sheldon	0.2	2.0	15.8	14.5	15.7	16.1	3.8	-0.5	-0.4	**-0.5**	-0.5	-0.5	**-0.5**
Story City	0.5	1.5	13.8	12.4	17.1	16.4	2.5	-0.5	-0.4	**-0.4**	-0.6	-0.6	**-0.6**
Sibley	0.2	1.9	15.1	7.3	16.5	16.5	1.7	-0.6	-0.2	**-0.4**	-0.6	-0.6	**-0.6**
Forest City	0.3	2.6	11.1	7.6	10.3	10.3	5.2	-0.1	0.0	**-0.1**	-0.1	-0.1	**-0.1**
Estherville	1.0	2.0	10.9	7.4	11.2	11.2	5.1	-0.1	0.0	**-0.1**	-0.2	-0.2	**-0.2**
Jefferson	0.7	2.0	6.2	8.7	10.4	10.2	4.5	0.1	-0.1	**0.0**	-0.2	-0.1	**-0.1**
Emmetsburg	0.3	2.8	4.3	5.5	7.9	7.6	2.9	0.1	0.0	**0.1**	-0.1	-0.1	**-0.1**
Theoretical city 1	3.5	1.5	0.0	0.0	0.0	0.0	15.0	1.0	1.0	**1.0**	1.0	1.0	**1.0**

CPI = crop proximity index; IRECI = Inverted Red-Edge Chlorophyll Index; CDL = Cropland Data Layer. The averages of the calculated CPIs are highlighted in bold.

form and extension. By taking account of the average of all cities in both years, the accuracy reaches 95% coincidence, with a minimum of 91% and a maximum of 97%.

The IRECI and CDL databases were compared using simple linear regressions. The areas occupied by crops (IRECI index) in each ring for each year were compared with the areas of soybean and corn crops for 2017 and 2018 (CDL database). The results show a high correlation (statistically significant at $p < 0.0001$) between the base determined by the IRECI index (crops) and that of CDL in both years, the r^2 for 2017 is 0.98 for (slope 1.12) and for 2018 is 0.97 (slope 1,15).

3.2. CPI calculation

3.2.1. Argentine study area

After processing peri-urban land use data using Eq. (2), the values of each factor were determined. Table 3 shows this information for each city, which was needed to calculate Eq. (1). The crop data (IRECI index) are disaggregated for 2016, 2017 and 2018. In addition, this table shows the CPI indices for each year, as well as the average for these three years. The values of the CPI index are relativized with respect to the theoretical locality 1, so they vary from 1 to -1.

3.2.2. United States study area

As with the data from Argentina, after processing peri-urban land use information using Eq. (2), the values of each factor needed to calculate Eq. (1) were determined (Table 4). The crops (IRECI index) and CDL data are disaggregated for 2017 and 2018. Also, this table shows the CPI indices for each year and database, as well as the average for the two years.

4. Discussion

4.1. Land cover data

By using different tools, the land cover and use of large territorial extensions were determined with great precision in different periods of time. This made it possible to determine areas covered by peri-urban crops, forests or trees and buffer zones that otherwise could not be obtained. Platforms for the analysis of satellite information in the cloud, such as the Google Earth Engine, provide a large amount of data, with a great capacity for analysis and processing. In addition, it enables comparative work with databases from various sources, countries or regions of the world.

The calculation of active crop areas using the satellite index IRECI facilitates access to data for temporal and spatial monitoring at different scales. Although this satellite index is not widely used today because it is very new, our research showed high correlations with data from various sources. This will allow us to automate the information to obtain accessible and reliable indicators and indices for monitoring.

With respect to the differences in the total areas of active and classified layer crops between databases, in both countries, as seen in total surface counts, or by the overlap percentages or correlation measures, it is important to emphasize that the resolution, minimum mapping scale, smoothing techniques, periods of analysis, and others factors probably generate these discrepancies. In particular, the database of Argentina, IDECOR, takes account of the rainfed crops for an entire year, so it may include successive crops of soybeans or corn (commonly called second-class crops), as well as other crops such as wheat, peanuts and sorghum.

Some limitations of the IRECI index detected in our research are that when there is a high density cover of vegetation, such as forests, patches of trees or shrubs, it is difficult to discriminate effectively between fields of crops and other coverages. Although this erroneous detection is very small for our data calculated for both countries, it can be corrected by masking unwanted vegetation cover using data from sources such as the Global Forest Change or through supervised classifications such as IDECOR or CDL, or other sources or methodologies.

The land cover data estimated showed an alarming situation of agro-industrial activity in the periphery of many cities, for Argentina and United State: the areas occupied by trees are practically non-existent and agro-industrial activity with predominance of GMOs crops is extremely close to the urban edges. Thus, the ecosystem services provided by trees as a barrier to pesticide drift, direct from the fumigations or contained in the dust from the fumigated areas, are diminished, and the population is potential exposed to risks produced by agricultural activity. As Zaady et al., 2018 indicates, this ecosystem services rarely been taken into consideration by management policies of tree plantings in farmland areas.

Although the data sources are different, there is great similarity in the surfaces of the different peri-urban coverages determined in both regions of study. The average tree cover areas are smaller for the cities of Argentina. In terms of active crops (IRECI spatial index) the average percentages are very similar in both regions.

4.2. CPI assessment

The methodology and the CPI index serve as a screening tool to provide a relative assessment of proximity to peri-urban agro-industrial production. Its implementation aims to have an instrument for monitoring the location of these activities.

One of the main advantages of the CPI index is that it requires very few elements for its calculation, depending on the inputs available in the region to be investigated (e.g. land use databases). The CPI index can be calculated in any region with agro-industrial or other types of production, by using the IRECI satellite index, which showed great robustness in determining coverage of active crops.

Another advantage of the proposed methodology is the plasticity of the index, since the variables that constitute it can be modified, changed or new ones can be added. Thus, for example, toxicity calculation modules can be added to the pesticides used in each crop, measured by area or other units.

We also believe that the CPI index provides the possibility of obtaining exploratory data, necessary in the context of lack of information on the degree of exposure of urban populations to agro-industrial activity. As detailed above, there is strong evidence that inhabitants living in agro-industrial regions in Argentina would be exposed through multiple pathways to direct or indirect contact with pesticides or other agricultural chemicals (Alonso et al., 2018; Aparicio et al., 2013; Bonansea et al., 2018; De Gerónimo et al., 2014; Etchegoyen et al., 2017; Hunt et al., 2017; López et al., 2012; Mendez et al., 2017; Mugni et al., 2011; Peluso et al., 2014; Primost et al., 2017; Solis et al., 2017). In addition, the two most commonly used herbicides in this type of transgenic crops, glyphosate and 2,4-dichlorophenoxyacetic acid, were classified as "probable carcinogen" and "possibly carcinogen" in humans by the International Agency for Research on Cancer, for their genotoxic activity and oxidative stress (Guyton et al., 2015; Loomis et al., 2015). Atrazine, another of the herbicides of greater application in transgenic crops, is associated with a relatively high chronic toxicity and potential that accumulates as a recalcitrant substance in surface and groundwater, so its use is restricted in the United States and has been banned in several European Community countries (Hansen et al., 2013a).

The possibility of weighting the surfaces occupied by trees, buffer zones or crops in the different perimeter rings using the constant *b* from Eq. (2), provides the opportunity to model different study situations with the CPI index. In our research the proximity of crops to the urban edge is magnified because that way we can weight possible pesticide exposure. This is reflected in those cities where the higher percentage of crops in the first rings increase their CPI. The values used enable us to test this model, but do not represent a condition or attribution of the factors under study. This weighting constant can be modified by more complex ones that, for example, reflect the protecting function of trees as physical barriers, introduce the directionality and intensity of winds, or other variables. Concerning to the use of tree cover and buffer zones as protective factors in Eq. (1), we would like to make a few observations. The evaluation of wind breaks as barriers to pesticide drift at this scale of analysis is extremely complex. As developed in point 2.3. in the section on Materials and Methods, there is conclusive evidence that even a small barrier of trees or buffer zone can act by reducing the possible primary and secondary drift of pesticides. Therefore, in our research approach we considered these variables to evaluate their impact on the risk of exposure, without addressing the structure, composition or other characteristics. More conclusive research is needed on this topic, at scales of analysis such as those we propose, in order to determine the role of these factors in exposure to pesticide use near cities.

The use of theoretical cities is another variant that allows us to model different scenarios in order to understand the peri-urban land use factors and how the proposed index varies. In addition, it allows us to design strategies for the development of cities, since different peri-urban land use and urban growth models can be tested.

If a review of the scientific literature referring to indicators and indices of risk of contamination by pesticides is done, it will be seen that most are focused on determining contamination in diverse environmental sectors or on human health. These indicators and indices of pesticide contamination have been developed and used with the intention of reducing its use, the risks of exposure of the applicators, population and contamination of the environment (Feola et al., 2011; Labite et al., 2011; Reus et al., 2002). In Argentina, different indicators and indices of the risk of pesticide contamination have been developed and tested (Dubny et al., 2018; Ferraro et al., 2003; Hunt et al., 2017; Maiztegui, 2010; Peluso et al., 2014). These have different objectives, scales of analysis and results, however, the convergence of results is interesting, where worrying levels of contamination and exposure to pesticides stand out.

Although the use of these indicators and indices would be very useful for the cities analyzed in this research, they would be difficult to apply on a large scale due to the lack of, or inaccessibility to, the pesticide use data needed for their calculation. For this reason, we propose the CPI index as an exploratory research tool to generate information for assessment and monitoring peri-urban agro-industrial activity in numerous cities at the same time. In comparison with other indicators, the CPI index differs in that takes account of a measurement of the potential peri-urban proximity risk to agro-industrial pesticide use at the local level as a whole, by using perimeter rings, which makes it possible to evaluate the entire area surrounding a city. While most indicators are developed for the crop or farm level (Labite et al., 2011; Reus et al., 2002), the CPI index serves to monitor agro-industrial activity in large territorial extensions, allowing a first approximation to potential exposures, which saves time and money.

An important aspect of the CPI index is that it allows monthly, annual or longer time periods to be monitored, if required. Thus, patterns of spatial distribution of agro-industrial activity can be analyzed to determine the times of year of greatest exposure to pesticide application. This information can be used to perform cross analysis with environmental and epidemiological data to provide new evidence on pesticide exposure for humans and the environment.

It is also possible to evaluate the economic costs of the change in land use through the methodology that we propose or to apply a system of taxes linked to the risk of pesticide use for the fields surrounding the cities, as proposed and applied by some European countries (Kudsk et al., 2018). This could help to generate a shift from agro-industrial to agro-ecological production with less risk of contamination.

The main limitations and challenges in calculating the CPI index are described as follows. One key feature of CPI index is that is easy and quick to calculate but, this simplicity (a sought-after and recognized characteristic of good indicators) works at the expense of a more realistic representation of the agro-industrial model and the risk of exposure to the pesticide impacts. However, the main objective of this index is to generate primary information, in later instances, new variables can be added to the index to improve its representation of the phenomenon.

Another key factor, which is difficult to establish, refers to the distances to which a city model is considered without exposure to pollutants generated by agro-industrial activity. This is fundamental since the methodology that we propose bases its technique of classification of cities on the comparison with a theoretical city. In our study we based ourselves on research from Marcos Juárez, in the Argentine study area, that determined that urban populations do not suffer any evident genotoxicity only at distances greater to the range of 1500–2000 m (Bernardi et al., 2015). There are other sources of information, such as the creation of particular state regulations or judicial processes carried out by victims of pesticide fumigations (individuals or communities). These processes often resulted in restrictions on fumigation ranging from 500 m to 2000 m or more from the urban edge (Tittonell and Giobellina, 2018). At the international level, numerous studies have determined negative associations or increased health risks, on pregnant women and children that living at different distances within 2000 m from fields sprayed with pesticides: cancer (Booth et al., 2015; Gómez-Barroso et al., 2016; Malagoli et al., 2016; Rull et al., 2006, 2009), neurodevelopmental disorders (González-Alzaga et al., 2015; Gunier et al., 2017; Roberts et al., 2007; Rowe et al., 2016; Shelton Janie et al., 2014), respiratory problems

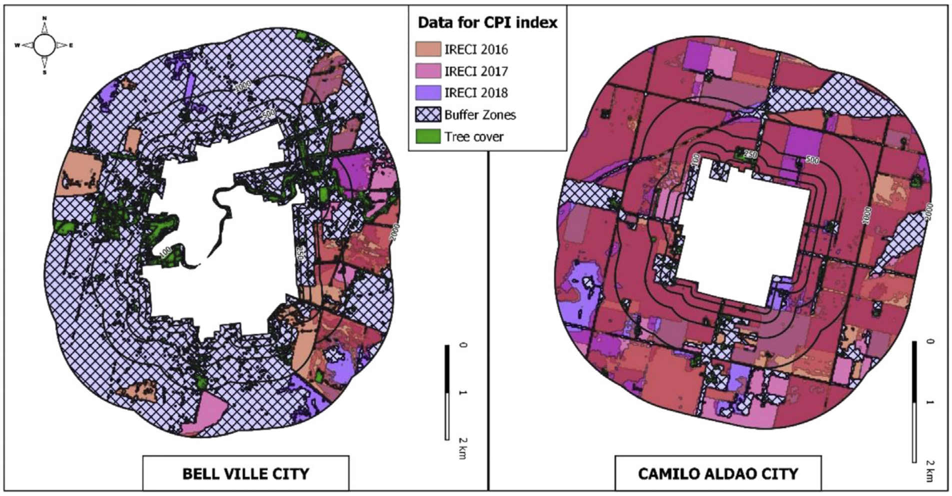

Figure 3. Argentine cities with lower and higher average CPI index (2016–2018). Coverage of active crops (IRECI index), trees and buffer zones is represented. CPI = Crop proximity index; IRECI = Inverted Red-Edge Chlorophyll Index.

(Raanan et al., 2017), malformations (Benítez-Leite et al., 2009; Rull et al., 2006) and alteration of metabolites or biological markers (Babina et al., 2012; Coronado et al., 2011; Gómez-Arroyo et al., 2013; Lu et al., 2000). These data were also taken into account when deciding the distance from the theoretical city. However, all this information is still insufficient to determine a pattern extrapolatable to all the cities and types of crops or agricultural practices of diverse countries in standardize way. For this reason, it is necessary to investigate the minimum safe distances from urban populations to this type of agricultural activities in different contexts and to establish more explicit patterns, since there is a great lack of vital information for designing public policies that safeguard collective health.

Some challenges to be overcome to achieve complete automation of this index, which will allow a better and greater use, refer to obtaining homogeneous databases of all the necessary inputs for its calculation. Although significant progress has been made in this regard, using the IRECI satellite index and databases such as Global Forest Change, there are still methodological steps to resolve the collection and processing of data that define other inputs of the CPI index. We believe that, by using the Google Earth Engine platform, new versions of the index will be advanced to minimize the amount of external information needed for its calculation.

Another factor to take into account in these results is that two to three year averages are being analyzed (depending on the country), i.e. they do not reflect additive effect of the proximity of crops in successive years. To do this, we should make a year-to-year analysis of peri-urban areas and CPI indices. Thus, we would see that the percentages of crops close to cities are high and accumulated over time. In addition, the only crops that are considered are soybeans and corn, so that exposure to pesticides may be greater with of the addition of other crops at other times of the year, such as wheat, for example.

Making a comparative analysis of the results in both regions of study, we found similar peri-urban crop proximity and land cover situations. Results in Tables 3 and 4 show that most of the CPI values are negative: 90% in the case of cities in Argentina and 80% in the case of cities in the United States. If the cities with CPIs below −0.5 are selected, 40% would be included in both study regions (8 cities for Argentina and 4 for the United States).

The following is a more detailed analysis of the results to determine which factors most influence the determination of extreme CPI indices. In the case of the Argentine city that obtained a higher CPI index (Table 3), Bell Ville (average CPI 0.5), the factors that influence these results are: large areas of buffer zones, a greater cover of trees in the 20 cities analyzed (although only 7.9% at 2000 m), few areas of cultivation and, finally, a great urban and perimeter area (Table 1). The key factors that make the CPI index higher than that of the other cities are the smaller crop areas, especially in rings close to the city, and the larger urban and the perimeter size (Figure 3). This does not mean that there is no direct contact between the fields and the urban edge, nor does it remove the chance of possible exposures to pesticide drift. This city is simply less surrounded and exposed, by proximity, to agro-industrial activity than others, within this region of study. It is important to emphasize that although Bell Ville obtains a CPI of 0.5, it is far from the ideal model, the theoretical city 1.

At the other extreme, the city with the lowest average CPI (-0.9), Camilo Aldao (Table 3), is due to large areas of crops on its periphery, close to 70% in some years (Table 1). This situation is also accompanied by the almost non-existence of tree cover and low buffer zone areas. This distribution of peri-urban coverage is represented in Figure 3, where it can be appreciated that the fields are very close to the urban border in almost the entire periphery.

For the United States study area, the city with the highest average CPI (0.1) is Emmetsburg (Table 4). Compared to other cities in the same area, this city has large buffer zones and good tree cover, although it is not the largest one (Table 2). In addition, the areas of peri-urban crops are the lowest (as a percentage of the total ring area) compared to the other cities. The opposite case, the city with the lowest average CPI index, -0.8, is Garner (Table 4). If we analyze the peri-urban coverage, we will see that the key factor to obtain this index is the large areas of crops, very close to the urban edge, and the low areas occupied by buffer zones and trees (Table 2).

5. Conclusion

The CPI index is a first methodological approach for the creation of an automated tool to monitor peri-urban agro-industrial activity in contexts of inaccessibility or lack of information.

The results, in both countries, show a worrying situation. Most of the cities examined are extremely close to extensive areas of crops, that use a large amount of pesticides, sprayed many times during the year, and that do not have any protection of trees or buffer zones.

Declarations

Author contribution statement

Lisandro Agost: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Guillermo A Velázquez: Conceived and designed the experiments; Performed the experiments; Wrote the paper.

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The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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References

Aiassa, D., Mañas, F., Bosch, B., Peralta, L., Gentile, N., Bevilacqua, S., Miralles, G., J., B.S., Gorla, N., 2009. Los plaguicidas. Su relación con la salud humana y ambiental en la provincia de Córdoba. Exp. Médica 27.
Aizen, M.A., Garibaldi, L.A., Dondo, M., 2009. Expansión de la soja y diversidad de la agricultura Argentina. Ecol. Aust. 19, 1667–1782.
Alister, C., Kogan, M., 2006. ERI: environmental risk index. A simple proposal to select agrochemicals for agricultural use. Crop Protect. 25, 202–211.
Alonso, L.L., Demetrio, P.M., Agustina Etchegoyen, M., Marino, D.J., 2018. Glyphosate and atrazine in rainfall and soils in agroproductive areas of the pampas region in Argentina. Sci. Total Environ. 645, 89–96.
Aparicio, V.C., De Gerónimo, E., Marino, D., Primost, J., Carriquiriborde, P., Costa, J.L., 2013. Environmental fate of glyphosate and aminomethylphosphonic acid in surface waters and soil of agricultural basins. Chemosphere 93, 1866–1873.
Babina, K., Dollard, M., Pilotto, L., Edwards, J.W., 2012. Environmental exposure to organophosphorus and pyrethroid pesticides in South Australian preschool children: a cross sectional study. Environ. Int. 48, 109–120.
Benítez-Leite, S., Macchi, M.L., Acosta, M., 2009. Malformaciones congénitas asociadas a agrotóxicos. Rev. Soc. Boliv. Pediatría 48, 204–217.
Bernardi, N., Gentile, N., Mañas, F., Méndez, Á., Gorla, N., Aiassa, D., 2015. Evaluación del nivel de daño en el material genético de niños de la provincia de Córdoba expuestos a plaguicidas. Arch. Argent. Pediatría 113, 126–132.
Bonansea, I.R., Filippi, I., Wunderlin, A.D., Marino, J.D., Amé, V.M., 2018. The Fate of Glyphosate and AMPA in a Freshwater Endorheic Basin: an Ecotoxicological Risk Assessment.
Booth, B.J., Ward, M.H., Turyk, M.E., Stayner, L.T., 2015. Agricultural crop density and risk of childhood cancer in the midwestern United States: an ecologic study. Environ. Health 14 (1), 82.
Brown, R.B., Carter, M.H., Stephenson, G.R., 2004. Buffer zone and windbreak effects on spray drift deposition in a simulated wetland. Pest Manag. Sci. 60, 1085–1090.
Congedo, L., 2016. Semi-Automatic Classification Plugin, 5.3.2.1. ed.
Coronado, G.D., Holte, S., Vigoren, E., Griffith, W.C., Barr, D.B., Faustman, E., Thompson, B., 2011. Organophosphate pesticide exposure and residential proximity to nearby fields: evidence for the drift pathway. J. Occup. Environ. Med. 53, 884–891.
Damalas, C.A., Eleftherohorinos, I.G., 2011. Pesticide exposure, safety issues, and risk assessment indicators. Int. J. Environ. Res. Publ. Health 8, 1402–1419.
De Gerónimo, E., Aparicio, V.C., Bárbaro, S., Portocarrero, R., Jaime, S., Costa, J.L., 2014. Presence of pesticides in surface water from four sub-basins in Argentina. Chemosphere 107, 423–431.
Deziel Nicole, C., Friesen Melissa, C., Hoppin Jane, A., Hines Cynthia, J., Kent, Thomas, Beane, Freeman Laura E., 2015. A review of nonoccupational pathways for pesticide exposure in women living in agricultural areas. Environ. Health Perspect. 123, 515–524.
Dubny, S., Peluso, F., Masson, I., Othax, N., Castelain, J.G., 2018. Application of a health risk assessment model for cattle exposed to pesticides in contaminated drinking waters: a study case from the Pampas region, Argentina. Chemosphere 196, 585–592.
Economic Research Service, 2019. Recent Trends in GE Adoption.
Epple, J., Maguhn, J., Spitzauer, P., Kettrup, A., 2002. Input of pesticides by atmospheric deposition. Geoderma 105, 327–349.
Etchegoyen, M., Ronco, A., Almada, P., Abelando, M., Marino, D., 2017. Occurrence and fate of pesticides in the Argentine stretch of the Paraguay-Paraná basin. Environ. Monit. Assess. 189, 63.
Etiennot, A., Piazza, A., 2010. Buenas prácticas de aplicación en cultivos planos extensivos: Distancias a zonas urbanas. Criterios y soluciones. Acta Toxicológica Argent. 18, 40–53.
Felsot, A.S., Unsworth, J.B., Linders, J.B.H.J., Roberts, G., Rautman, D., Harris, C., Carazo, E., 2010. Agrochemical spray drift; assessment and mitigation—a review. J. Environ. Sci. Health Part B 46, 1–23.
Feola, G., Rahn, E., Binder, C.R., 2011. Suitability of pesticide risk indicators for Less Developed Countries: a comparison. Agric. Ecosyst. Environ. 142, 238–245.
Ferraro, D.O., Ghersa, C.M., Sznaider, G.A., 2003. Evaluation of environmental impact indicators using fuzzy logic to assess the mixed cropping systems of the Inland Pampa, Argentina. Agric. Ecosyst. Environ. 96, 1–18.
Forman, R.T.T., Godron, M., 1981. Patches and structural components for A landscape ecology. Bioscience 31, 733–740.
Frampton, W.J., Dash, J., Watmough, G., Milton, E.J., 2013. Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation. ISPRS J. Photogramm. Remote Sens. 82, 83–92.
Garcerá, C., Moltó, E., Chueca, P., 2017. Spray pesticide applications in Mediterranean citrus orchards: canopy deposition and off-target losses. Sci. Total Environ. 599–600, 1344–1362.
García, C., Piumetto, M., Teich, I., Morales, H., Kindgard, A., Fuentes, M., Bosio, M., Ravelo, A., 2018. Coberturas Agrícolas 2017/2018.
González-Alzaga, B., Hernández, A.F., Rodríguez-Barranco, M., Gómez, I., Aguilar-Garduño, C., López-Flores, I., Parrón, T., Lacasaña, M., 2015. Pre- and postnatal exposures to pesticides and neurodevelopmental effects in children living in agricultural communities from South-Eastern Spain. Environ. Int. 85, 229–237.
Gómez-Arroyo, S., Martínez-Valenzuela, C., Calvo-González, S., Villalobos-Pietrini, R., Waliszewski, S.M., Calderón-Segura, M.E., Martínez-Arroyo, A., Félix-Gastélum, R., Lagarda-Escarrega, A., 2013. Assessing the genotoxic risk for mexican children who are in residential proximity to agricultural areas with intense aerial pesticide applications. Revista Internacional de Contaminación Ambiental 29 (3), 217–225.
Gómez-Barroso, D., García-Pérez, J., López-Abente, G., Tamayo-Uria, I., Morales-Piga, A., E., P.R., Ramis, R., 2016. Agricultural crop exposure and risk of childhood cancer: new findings from a case-control study in Spain. Int. J. Health Geogr. 15, 1–11.
Guida-Johnson, B., Zuleta, G.A., 2013. Land-use land-cover change and ecosystem loss in the Espinal ecoregion, Argentina. Agric. Ecosyst. Environ. 181, 31–40.
Gunier, R.B., Bradman, A., Harley, K.G., Eskenazi, B., 2017. Will buffer zones around schools in agricultural areas be adequate to protect children from the potential adverse effects of pesticide exposure? PLoS Biol. 15 (12).
Guyton, K.Z., Loomis, D., Grosse, Y., El Ghissassi, F., Benbrahim-Tallaa, L., Guha, N., Scoccianti, C., Mattock, H., Straif, K., 2015. Carcinogenicity of tetrachlorvinphos, parathion, malathion, diazinon, and glyphosate. Lancet Oncol. 16, 490–491.
Hansen, A.M., Treviño-Quintanilla, L.G., Márquez-Pacheco, H., Villada-Canela, M., González-Márquez, L.C., Guillén-Garcés, R.A., Hernández-Antonio, A., 2013a. Atrazina: un herbicida polémico. Rev. Int. Contam. Ambient.
Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chin, L., IJustice, C.O., Townshend, J.R.G., 2013b. High-resolution global maps of st-century forest cover change. Science 21, 850–853.
Hunt, L., Bonetto, C., Marrochi, N., Scalise, A., Fanelli, S., Liess, M., Lydy, M.J., Chiu, M.-C., Resh, V.H., 2017. Species at Risk (SPEAR) index indicates effects of insecticides on stream invertebrate communities in soy production regions of the Argentine Pampas. Sci. Total Environ. 580, 699–709.
INDEC, 2010. Censo Nacional de Población 2010 - Datos Definitivos. Instituto Nacional de Estadística y Censo.
Kookana, R.S., Correll, R.L., Miller, R.B., 2005. Pesticide impact rating index – a pesticide risk indicator for water quality. Water Air Soil Pollut. Focus 5, 45–65.
Korhonen, L., Hadi, D.S., Packalen, P., Rautiainen, M., 2017. Comparison of Sentinel-2 and Landsat 8 in the estimation of boreal forest canopy cover and leaf area index. Remote Sens. Environ. 195, 259–274.
Kudsk, P., Jørgensen, L.N., Ørum, J.E., 2018. Pesticide Load—a new Danish pesticide risk indicator with multiple applications. Land Use Pol. 70, 384–393.
Labite, H., Butler, F., Cummins, E., 2011. A review and evaluation of plant protection product ranking tools used in agriculture. Hum. Ecol. Risk Assess. Int. J. 17, 300–327.
Loomis, D., Guyton, K., Grosse, Y., El Ghissani, F., Bouvard, V., Benbrahim-Tallaa, L., Guha, N., Mattock, H., Straif, K., 2015. Carcinogenicity of lindane, DDT, and 2,4-dichlorophenoxyacetic acid. Lancet Oncol. 16, 891–892.
López, S.L., Aiassa, D., Benítez-Leite, S., Lajmanovich, R., Mañas, F., Poletta, G., Sánchez, N., Simoniello, M.F., Carrasco, A.E., Lopez, S.L., Aiassa, D., Benítez-Leite, S., Lajmanovich, R., Mañas, F., Poletta, G., Sánchez, N., Simoniello, M.F., Carrasco, A.E., 2012. Pesticides used in south American GMO-based agriculture: a review of their effects on humans and animal models. In: Advances in Molecular Toxicology. Advances in Molecular Toxicology. Elsevier, pp. 41–75.
Lu, C., Fenske, R.A., Simcox, N.J., Kalman, D., 2000. Pesticide exposure of children in an agricultural community: evidence of household proximity to farmland and take home exposure pathways. Environ. Res. 84 (3), 290–302.
Maiztegui, C., 2010. Niñez y Riesgo Ambiental en Argentina, 1ra ed. Programa Naciones Unidas para el Desarrollo -Defensor del Pueblo de la Nación, Unicef Argentina; Organización Panamericana de la Salud - OPS: Oficina Internacional del Trabajo. Buenos Aires.
Malagoli, C., Costanzini, S., Heck, J.E., Malavolti, M., De Girolamo, G., Oleari, P., Palazzi, G., Teggi, S., Vinceti, M., 2016. Passive exposure to agricultural pesticides and risk of childhood leukemia in an Italian community. Int. J. Hyg Environ. Health 219 (8), 742–748.
Mendez, M.J., Aimar, S.B., Aparicio, V.C., Ramirez Haberkon, N.B., Buschiazzo, D.E., De Gerónimo, E., Costa, J.L., 2017. Glyphosate and Aminomethylphosphonic acid

(AMPA) contents in the respirable dust emitted by an agricultural soil of the central semiarid region of Argentina. Aeolian Res 29, 23–29.
Ministerio de Agroindustria, 2018. Estimaciones agrícolas [WWW Document]. https://www.agroindustria.gob.ar/datosagroindustriales/ (accessed 15 April 2018).a.2017.09.004.
Mugni, H., Ronco, A., Bonetto, C., 2011. Insecticide toxicity to Hyalella curvispina in runoff and stream water within a soybean farm (Buenos Aires, Argentina). Ecotoxicol. Environ. Saf. 74, 350–354.
National Agricultural Statistics Service, 2019. Statistics by State.
Peck, A.M., Hornbuckle, K.C., 2005. Gas-phase concentrations of current-use pesticides in Iowa. Environ. Sci. Technol. 39, 2952–2959.
Peluso, F., Dubny, S., Othax, N., Castelain, J.G., 2014. Environmental risk of pesticides: applying the DelAzulPestRisk model to freshwaters of an agricultural area of Argentina. Hum. Ecol. Risk Assess. Int. J. 20, 1177–1199.
Piquer-Rodríguez, M., Butsic, V., Gärtner, P., Macchi, L., Baumann, M., Pizarro, G.G., Volante, J.N., Gasparri, I.N., Kuemmerle, T., 2018. Drivers of agricultural land-use change in the Argentine Pampas and Chaco regions. Appl. Geogr. 91, 111–122.
Primost, J.E., Marino, D.J.G., Aparicio, V.C., Costa, J.L., Carriquiriborde, P., 2017. Glyphosate and AMPA, "pseudo-persistent" pollutants under real-world agricultural management practices in the Mesopotamic Pampas agroecosystem, Argentina. Environ. Pollut. 229, 771–779.
Raanan, Rachel, Gunier Robert, B., Balmes John, R., Beltran Alyssa, J., Harley Kim, G., Asa, Bradman, Brenda, Eskenazi, 2017. Elemental sulfur use and associations with pediatric lung function and respiratory symptoms in an agricultural community (California, USA). Environ. Health Perspect. 125 (8), 087007.
Reus, J., Leendertse, P., Bockstaller, C., Fomsgaard, I., Gutsche, V., Lewis, K., Nilsson, C., Pussemier, L., Trevisan, M., van der Werf, H., Alfarroba, F., Blümel, S., Isart, J., McGrath, D., Seppälä, T., 2002. Comparison and evaluation of eight pesticide environmental risk indicators developed in Europe and recommendations for future use. Agric. Ecosyst. Environ. 90, 177–187.
Roberts, E.M., English, P.B., Grether, J.K., Windham, G.C., Somberg, L., Wolff, C., 2007. Maternal residence near agricultural pesticide applications and autism spectrum disorders among children in the California Central Valley. Environ. Health Perspect. 115 (10), 1482–1489.
Rowe, C., Gunier, R., Bradman, A., Harley, K.G., Kogut, K., Parra, K., Eskenazi, B., 2016. Residential proximity to organophosphate and carbamate pesticide use during pregnancy, poverty during childhood, and cognitive functioning in 10-year-old children. Environ. Res. 150, 128–137.
Rull, Rudolph P., Gunier, R., Von Behren, J., Hertz, A., Crouse, V., Buffler, P.A., Reynolds, P., 2009. Residential proximity to agricultural pesticide applications and childhood acute lymphoblastic leukemia. Environ. Res. 109 (7), 891–899.
Rull, Rudolph P., Ritz, B., Shaw, G.M., 2006. Neural tube defects and maternal residential proximity to agricultural pesticide applications. Am. J. Epidemiol. 163 (8), 743–753.
Sánchez-Bayo, F., Baskaran, S., Kennedy, I.R., 2002. Ecological relative risk (EcoRR): another approach for risk assessment of pesticides in agriculture. Agric. Ecosyst. Environ. 91, 37–57.
Shelton Janie, F., Geraghty Estella, M., Tancredi Daniel, J., Delwiche Lora, D., Schmidt Rebecca, J., Ritz, Beate, Hansen Robin, L., Hertz-Picciotto, Irva, 2014. Neurodevelopmental disorders and prenatal residential proximity to agricultural pesticides: the CHARGE study. Environ. Health Perspect. 122 (10), 1103–1109.
Singh, N.S., Sharma, R., Parween, T., Patanjali, P.K., 2018. Pesticide contamination and human health risk factor. In: Oves, M., Zain Khan, M., Ismail, M.I. (Eds.), Modern Age Environmental Problems and Their Remediation. Springer International Publishing, Cham, pp. 49–68.
Slater, A., Holtslander, C., 2015. Where in the World Are GM Crops and Foods? Network. Canadian Biotechnology Action.
Solis, M., Mugni, H., Fanelli, S., Bonetto, C., 2017. Effect of agrochemicals on macroinvertebrate assemblages in Pampasic streams, Buenos Aires, Argentina. Environ. Earth Sci. 76, 180.
Soo-Jeong, L., Louise, M., John, B., Brienne, D.-B., Joanne, P., Michelle, L., Justin, W., Prakash, M., Abby, S., Yvette, M., Stephanie, M.-M., Rita, G., M., C.G., 2011. Acute pesticide illnesses associated with off-target pesticide drift from agricultural applications: 11 states, 1998–2006. Environ. Health Perspect. 119, 1162–1169.
Strassemeyer, J., Daehmlow, D., Dominic, A.R., Lorenz, S., Golla, B., 2017. SYNOPS-WEB, an online tool for environmental risk assessment to evaluate pesticide strategies on field level. Crop Protect. 97, 28–44.
Swanson, N.L., Leu, A., Abrahamson, J., Wallet, B., 2014. Genetically engineered crops, glyphosate and the deterioration of health in the United States of America. J. Org. Syst. 9.
Tittonell, P., Giobellina, B., 2018. PERIURBANO hacia el consenso: ciudad, ambiente y producción de alimentos: propuestas para ordenar el territorio: resúmenes ampliados: libro 1, 1ra ed. INTA, Ciudad Autónoma de Buenos Aires.
Trajkovska, S., Mbaye, M., Gaye Seye, M.D., Aaron, J.J., Chevreuil, M., Blanchoud, H., 2009. Toxicological study of pesticides in air and precipitations of Paris by means of a bioluminescence method. Anal. Bioanal. Chem. 394, 1099–1106.
Trigo, E.J., 2016. Veinte Años de Cultivos Genéticamente Modificados en la Agricultura Argentina. ArgenBio.
Tsaboula, A., Papadakis, E.-N., Vryzas, Z., Kotopoulou, A., Kintzikoglou, K., Papadopoulou-Mourkidou, E., 2016. Environmental and human risk hierarchy of pesticides: a prioritization method, based on monitoring, hazard assessment and environmental fate. Environ. Int. 91, 78–93.
Tsatsakis, A.M., Nawaz, M.A., Tutelyan, V.A., Golokhvast, K.S., Kalantzi, O.-I., Chung, D.H., Kang, S.J., Coleman, M.D., Tyshko, N., Yang, S.H., Chung, G., 2017. Impact on environment, ecosystem, diversity and health from culturing and using GMOs as feed and food. Food Chem. Toxicol. 107, 108–121.
Ucar, T., Hall, F.R., 2001. Windbreaks as a pesticide drift mitigation strategy: a review. Pest Manag. Sci. 57, 663–675.
United States Census Bureau, 2010. 2010 Census Urban and Rural Classfication and Urban Area Criteria.
USDA, 2019. National Agricultural Statistics Service Cropland Data Layer.
Vercruysse, F., Steurbaut, W., 2002. POCER, the pesticide occupational and environmental risk indicator. Crop Protect. 21, 307–315.
Vida, P., Moretto, A., 2007. Pesticide exposure pathways among children of agricultural workers. J. Public Health 15, 289–299.
Ward, M.H., Lubin, J., Giglierano, J., Colt, J.S., Wolter, C., Bekiroglu, N., Camann, D., Hartge, P., Nuckols, J.R., 2006. Proximity to crops and residential exposure to agricultural herbicides in Iowa. Environ. Health Perspect. 114, 893–897.
Wenneker, M., van de Zande, J., 2008. Spray Drift Reducing Effects of Natural Windbreaks in Orchard Spraying.
Zaady, E., Katra, I., Shuker, S., Knoll, Y., Shlomo, S., 2018. Tree belts for decreasing aeolian dust-carried pesticides from cultivated areas. Geosciences 8, 286.
Zivan, O., Segal-Rosenheimer, M., Dubowski, Y., 2016. Airborne organophosphate pesticides drift in Mediterranean climate: the importance of secondary drift. Atmos. Environ. 127, 155–162.