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Peri-urban pesticide contamination risk index

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ABSTRACT

The massive use of pesticides in the production of food and raw materials generates growing world concern due to the numerous evidences of their negative effects on health and the environment. In countries where detailed information of agricultural pesticide use near to urban areas is not available, it is necessary have a simple methodology that does not require data that are difficult to obtain in order to create an ecological indicator of the risk of pesticide contamination at the peri-urban level. The objective of this research is to generate a peri-urban pesticide contamination risk index using satellite information and accessible scientific pesticide data. The Peri-urban Pesticide Contamination Risk Index (PUPCRI) is composed of an indicator of the toxicity of the set of pesticides used in each crop, and two factors that quantify the surface occupied by agricultural activity and the tree surface in the urban periphery. The Environmental Risk Index has been used to calculate the toxicity of herbicides, insecticides and fungicides used in soybean, corn and wheat crops. Through the classification of Sentinel 2 satellite images, data was obtained of arable land, soybean, corn and wheat crops, and tree cover, in different peri-urban rings, with a maximum distance of two kilometers from the urban edge. The PUPCRI index was tested in 20 cities pertaining to the region with the highest agricultural productivity in Argentina. The results show that most of the cities have high to very high indices of exposure to pesticides, mainly due to the proximity of agricultural activity to the urban edge and the lack of tree cover. The PUPCRI index allows a quick and simple analysis of the potential risk of exposure to the use of crop pesticides in the urban periphery.

1. Introduction

The massive use of pesticides for the production of food and raw materials, especially in crops of genetically modified organisms (GMOs), generates growing concern among the population and governments in different parts of the world due to the numerous evidences of their negative effects on health (Aiassa et al., 2009; Benítez-Leite et al., 2009; Bernardi et al., 2015; Gómez-Barroso et al., 2016; Maroni et al., 2000; López et al., 2012; Richard et al., 2005; Swanson et al., 2014) and the environment (Aizen et al., 2009; Guida-Johnson and Zuleta, 2013; Pengue, 2005; Piquer-Rodríguez et al., 2018; Rodríguez Gómez and Rodríguez Paipilla, 2015; Viglizzo et al., 2002). America is the continent with the largest production of GMO crops in the world (90%), more than 163 million hectares, mostly soybeans and corn (ISAAA, 2016; Slater and Holtslander, 2015), which means that it is one of the regions with the highest use of pesticides in the world. Within this global scheme, Argentina is the third largest producer of GMOs, with more than 24 million hectares sown in 2015–2016 (ISAAA, 2016; Slater and Holtslander, 2015).

Pesticide use laws and regulations in each country are subject to different jurisdictional levels with diverse restriction, according to their policies on health care, environment protection, agricultural practices, citizen participation, among other factors. In Argentina, numerous municipalities (minor state jurisdiction) established more restrictive regulations than national or provincial jurisdictions partly due to the active participation of the population who cares about for the use of pesticides on a massive scale for GMO crops near to urbanizations (Lerussi et al., 2018). Therefore, it is necessary have indicators and indices to manage the use of pesticides within municipal administrations and their peri-urban areas, with the object of reducing their impact on the environment and health (Feola et al., 2011; Reus et al., 2002).

In recent decades, different pesticide contamination risk indices have been developed that attempt to address possible human exposure or environmental pollution pathways (Alister and Kogan, 2006; Damalas and Eleftherohorinos, 2011; Feola et al., 2011; Ferraro et al., 2003; Kookana et al., 2005; Kudsk et al., 2018; Maroni et al., 2000; Reus and Leendertse, 2000; Sánchez-Bayo et al., 2002; Strassemeyer et al., 2017; Tsaboula et al., 2016; Vercruysse and Steurbaut, 2002). These use different approaches of greater or lesser complexity, since

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they can take into account the chemical, physical, biological, topographical, eco-toxicological parameters, methods of pesticide application or human exposure. However, the effectiveness of these indices depends on the amount of information available for their creation and the ability to be interpreted once created, due to the complexity of the risks of exposure in the environment (Feola et al., 2011; Reus et al., 2002). Analyzing another aspect, few indices evaluate or take account of the effectiveness of actions that mitigate pesticide drift. Wind breakers, such as plant barriers, are usually used for this purpose, however, there is enormous complexity in determining how and how much acts to reduce the drift. Ucar and Hall (2001) carried out an extensive review on this subject they indicated that even a small barrier of trees can reduce the possible drift of pesticides considerably. In this sense, it would be desirable to analyze this variable in an index since it would allow the evaluation of local actions that might reduce the possible exposure to pesticides.

Pesticide contamination risk indices can be grouped in two ways (Reus et al., 2002): those that, through a simple summation, are based on the properties of the pesticide and the application rate or dose, generate a risk classification by score. The other group uses indicators that represent the relationship between exposure (usually the concentration in a given environmental compartment) and toxicity to relevant organisms. The first grouping allows for the calculation of indices in the absence of data, monitoring and research on pesticide use. The second grouping generates more complex indices that require detailed data and computational analysis capacity (Feola et al., 2011; Labite et al., 2011).

Argentina, as well as other countries with a large production of GMOs, is characterized by serious negative externalities related to the use of pesticides and a general lack of government resources, i.e. data and expertise dedicated to the protection of the environment and health, and the promotion of sustainable agricultural production (Feola et al., 2011). Moreover, agricultural activities, which use a large quantity of pesticides, are located within a short distance of cities, exposing large numbers of people in the country. In this sense, state regulations are inefficient since they allow the application of pesticides, such as glyphosate, classified by the International Agency for Research on Cancer (IARC) as "probably carcinogenic to humans" (Guyton et al., 2015), zero meters from city boundaries. In this context, having a simple methodology to create an ecological indicator of the risk of pesticide contamination at the peri-urban scale, would allow the visualization, management and efficient control of application of pesticides close to populations.

The objective of this research is to generate a peri-urban pesticide contamination risk index using satellite information and accessible scientific pesticide data.

2. Materials and methods

2.1. Peri-urban pesticide contamination risk index (PUPCRI)

The PUPCRI index has three components: the first refers to the toxicity of the set of pesticides used in the crops in the study area (CT); the second is a factor that quantifies the area destined for agriculture (arable land or active crops) in the urban periphery (CF); and the third quantifies the area of trees that can act as a mitigating barrier to agricultural activity in the urban periphery (TF). Below is a simple linear equation to describe the proposed index:

$$PUPCRI = (CT \times CF) - TF \quad (1)$$

In order to better understand and use the equation mentioned above, the result will be classified at four levels or intervals of theoretical exposure that allow its interpretation: low, moderate, high, very high exposure. Like other indices, this one is relative as it assesses the risk of contamination by pesticides in the peri-urban zone. Therefore, in absolute values, the estimator means nothing, its significance lies in its comparative strength to identify municipalities or cities with different exposure potentials (Viglizzo et al., 2003).

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 will study what happens from the edge where each city ends to a peripheral distance of 2000 m.

2.2. Crops toxicity (CT)

In order to quantify the toxicity of the different pesticides used in the crops of the region under study, the methodology proposed by Alister and Kogan (2006), called Environmental Risk Index (ERI), was used. This index makes it possible to determine the environmental risk of pesticide use quickly and with easily accessible information. The ERI formula is detailed below:

$$ERI = (P + L + V + TP)D \quad (2)$$

where P is soil persistence, L the leaching, V the volatility, TP the toxicological profile and D the dose of pesticide.

To calculate the toxicological profile the authors use the following formula:

$$TP = K_{OW} + Rfd + LD_{50} + AT \quad (3)$$

where K_{OW} is the partition coefficient (octanol–water), Rfd the reference dose, LD_{50} the acute dermal lethal dose and AT the animal toxicology (measured in mallard duck, rainbow trout and honey bee).

The values in Eq. (2) are weighted in different degrees of severity taking into account the intervals defined by the ERI authors. For more details on each of the variables in the ERI calculation the original publication can be consulted (Alister and Kogan, 2006).

For our research we modified one variable of the ERI index, the acute dermal lethal dose (LD_{50}) of the toxicological profile (TP) by the acute lethal concentration by inhalation (LC_{50}). This modification allows us to determine respiratory exposure, the most likely for populations surrounded by crops. In all cases, the acute lethal concentration (LC_{50}) refers to tests on rats exposed to pesticide inhalation, mg l^{-1} units for four hours.

In order to weight the LC_{50} toxicity of the pesticides, data from Globally Harmonized System for the Classification and Labelling of Chemicals (GHS) published by the International Labour Organization, were used (International Labour Organization, 2001).

The values used for the calculation of the ERI of each pesticide come from the following open-access databases: Pesticide Properties DataBase (PPDB, 2018), PubChem (Kim et al., 2016), The EXtensionTOXicologyNETwork (EXTOXNET, 2018) and CASAFE phytosanitary products guide 2017–2019 (CASAFE, 2017).

The ERI index were calculated for each individual pesticide, and then the results were added according to the set of pesticides used in the study region for soybeans, corn (summer crops) and wheat (winter crops). To determine which pesticides and their doses were used, professionals, reports from state entities and scientific publications were consulted.

2.3. Crop factor (CF) and tree factor (TF)

These factors used in Eq. (1) allow us to introduce the spatial quantification occupied by agriculture and the presence of tree cover surrounding urbanizations. In order to be able to weight these factors by proximity or remoteness, we proceeded to work on perimeter rings, divided into sections (like buffers). To carry this out, the area occupied by each urbanization in the study area was calculated, using cadastral data from the government of the province of Córdoba (GeoPortal, 2017) and high-resolution satellite images. Perimeter rings were calculated from 0 to 100, 100 to 250, 250 to 500, 500 to 1000 and 1000 to 2000 m away (Fig. 1). Data on each factor was obtained through classification of Sentinel 2 satellite images (location tile 20HNJ), corresponding to

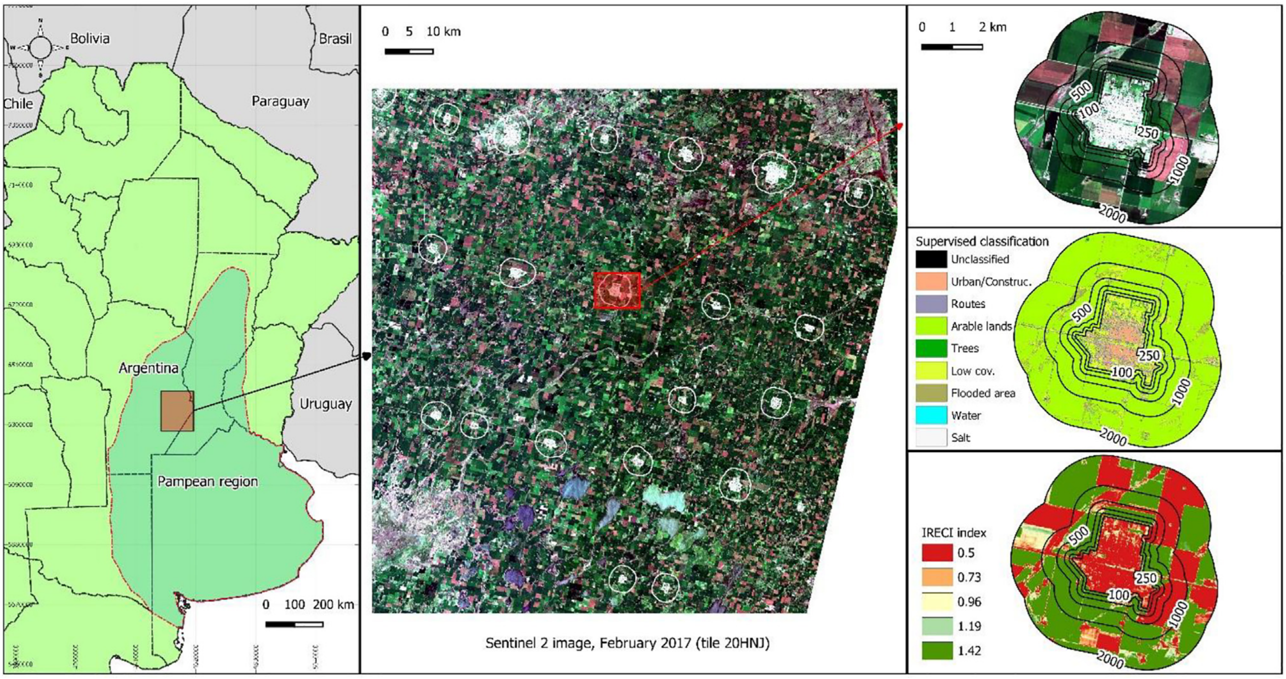

Fig. 1. Study area. Detail of the satellite image Sentinel 2 and an analysed city, with their respective perimeter rings, supervised classification and calculation of the IRECI index.

two time periods when these crops present their highest state of foliar growth (February and September 2017). These satellite images were corrected atmospherically and processed using SNAP 6.0.0 and QGis 2.18 software. A supervised classification was carried out with the QGis SCP plugin (Congedo, 2016), in order to obtain information on the arable land surfaces (fields with sowing potential), and tree cover (surfaces occupied by native or exotic woody plants). 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 matrix of confusion and to calculate the Kappa index. In addition, 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). Being able to discriminate between arable land and active crops allowed us to estimate the total area that could generate a risk of exposure, beyond the particular crops analysed on the selected dates. All georeferenced data sets was created and analysed in a geographic information system (GIS) using QGis 2.18 software.

In order to obtain surface area data (in hectares) for each factor, zone statistics were carried out for all rings surrounding each city, for the two study periods (February and September 2017). This information was introduced in the formula detailed below:

$$F = \left(\frac{a}{RingSurface}xb\right)_{\substack{Ring\\0-100m}} + \left(\frac{a}{RingSurface}xb\right)_{\substack{Ring\\100-250m}} + \left(\frac{a}{RingSurface}xb\right)_{\substack{Ring\\250-500m}} + \left(\frac{a}{RingSurface}\right)_{\substack{Ring\\500-1000m}} + \left(\frac{a}{RingSurface}\right)_{\substack{Ring\\1000-2000m}} \quad (4)$$

where a corresponds to the area (hectares) of the specific factor in each ring, arable land, crops or tree cover. Where b *is* a constant that varies according to the factor and the ring. In the case of the crops factor (CF) in the first ring (from 0 to 100 m), b is equal to 30; in the following ring, 10; and in the third, 5. In the case of tree factor (TF), in the first ring b is equal to 20; in the second, 10; and in the third, 5. This variable b allows the magnification of the surface 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 first ring of this factor is multiplied in greater proportion than the surface of trees.

2.4. Study area

The study area where the PUPCRI was tested corresponds to the area of highest agricultural production in Argentina, called the Pampean region (Fig. 1), where almost one hundred percent of soybean and corn crops are transgenic (Trigo, 2016). In ascending order of sowing, harvesting and production in tons, soybean is the first crop in this region, followed by corn and then wheat (Ministerio de Agroindustria, 2018).

Twenty cities occurring in this region were selected for calculating the proposed index, considering population sizes greater than 1000 inhabitants (INDEC, 2010) and that are found within the limits of 100 × 100 km of the Sentinel 2 satellite images used to obtain land cover information (Fig. 1). In order to obtain a reference model, a theoretical city was created, of average size with respect to the others, with the following characteristics: it has the rings from 0 to 500 m covered entirely by forest (tree cover), and the subsequent rings, from 500 to 1000 and from 1000 to 2000 m, with a 25% of surface covered with trees and 50% covered with crops (soybean and corn or wheat).

3. Results

3.1. Determination of crop toxicity

For this purpose, the set of basic pesticides used for the three crops analysed at different cultivation stages was established, during sowing and at all stages of growth until harvest. The list of possible pesticides applied to these crops is wide and varies according to the adversities, particular conditions of each crop, growth, harvest, presence of pests, crop rotation practices and the type of preparation of the field to be cultivated. Experts from the region under study were consulted to determine which pesticides are most frequently used, determining the

Table 1
Input values for ERI calculation, raw and weighted (in bold) in different degrees of severity, considering the parameters of Alister and Kogan (2006). Source: Pesticide Properties DataBase (PPDB, 2018), PubChem (Kim et al., 2016), The EXtensionTOXicologyNETwork (EXTOXNET, 2018) and CASAFE phytosanitary products guide 2017–2019 (CASAFE, 2017).

Pesticide	Persistence (days)	*P*	Leaching (LIX Index)	*L*	Volatility (mm Hg)	*V*	Toxicological Profile	*TP*	Dose (kg o l × ha)	*D*	ERI
2,4-D	10	**1**	6,25E−02	**2**	1,40E−07	**1**	19	**3**	0,5	**1**	**7**
Atrazine	55	**2**	2,84E−01	**3**	2,89E−07	**1**	14	**2**	1,5	**2**	**16**
Cypermethrin	22	**1**	0,00E + 00	**1**	4,50E−08	**1**	19	**3**	0,05	**1**	**6**
Chlorpyrifos	30	**1**	5,40E−56	**1**	1,88E−05	**3**	22	**4**	0,4	**1**	**9**
Dicamba	4	**1**	9,81E−02	**2**	1,25E−05	**2**	10	**2**	0,1	**1**	**7**
Glyphosate soybean	20	**1**	3,73E−22	**1**	3,00E−07	**1**	10	**2**	7,5	**4**	**20**
Glyphosate corn									5	**4**	**20**
Glyphosate wheat									2	**2**	**10**
Metsulfuron	20	**1**	2,33E−01	**3**	5,97E−13	**1**	15	**3**	0,005	**1**	**8**
Tebuconazole	63	**3**	1,30E−05	**1**	9,75E−09	**1**	16	**3**	0,5	**1**	**8**

ERI = Environmental Risk Index.

minimum and maximum doses per hectare. The most frequent pesticides used for the soybean crop are: glyphosate, 2,4-D (herbicides), cypermethrin and chlorpyrifos (insecticides). For the corn crop: glyphosate, atrazine (herbicides) cypermethrin and chlorpyrifos (insecticide). Finally, for the wheat crop: glyphosate, 2,4-D, metsulfuron, dicamba (herbicides) and tebuconazole (fungicide).

All the necessary information for the calculation of the ERI index of equations (2) and (3) was obtained from the proposed pesticide databases. Table 1 shows the values of equation (2), raw and weighted (in bold type) in different degrees of severity, taking into account the defined parameters of the authors of the ERI index (Alister and Kogan, 2006). The value TC, used in equation (1), results from the sum of ERI index for each pesticide used for soybean, corn or wheat crop. The values of equation (3) are summarized in Table 2.

Based on the data shown in Table 1, the toxicity of each crop (TC) is: 42 for soybean, 51 for corn and 40 for wheat.

3.2. Arable land, crops and tree cover

After processing and carrying out the supervised classification of the Sentinel 2 satellital images, corresponding to the months of February and September 2017, the surfaces occupied by arable land and trees were obtained in the five perimeter rings of the 20 cities under study. From the concordance analysis of this classification, the confusion matrix gave an overall accuracy of 87.5%, and the Kappa index was 0.7. To determine active crops in February and September 2017, the IRECI index was calculated. With this information the calculation of the CF and TF was made, using Eq. (4) (Tables 3 and 4 show the results of the sum of each factor).

With regard to the surfaces occupied by crops and trees, it is interesting to note that in the 20 selected cities the average area occupied by trees is 3.8% in the first ring (from 0 to 100 m), with a maximum of 11% and a minimum of 1.2%. In the following rings, the tree cover decreases, without exceeding 9% cover in any case. By contrast, active summer and winter crops (IRECI index) occupy, on average, 40% of the first ring, with a maximum of 78% and a minimum of 1.9%. In the following rings the average is 55%, with maximums of 80% and a minimum of 2.4%.

3.3. PUPCRI calculation

Finally, the PUPCRI was calculated using Eq. (1). In the case of summer crops (soybean and corn), the percentages of the areas occupied by these crops were extrapolated with information of departmental level (higher territorial division) since no field information was available to identify them. This gives a ratio of 70–30 soybean-corn for the year 2017 (Ministerio de Agroindustria, 2018).

The PUPCRI results for each city are shown in two tables. Table 3 corresponds to the calculation of this index considering the area of arable land, data extracted from the supervised classification of the Sentinel 2 satellital images. Table 4 shows the calculation of PUPCRI from the active crop areas, data obtained from the IRECI index. Both tables show the values of the factors of equation (1), the percentage occupied by arable land or crops in the first ring (from 0 to 100 m), the PUPCRI data of each crop (summer and winter) and the accumulated PUPCRI. The latter was calculated on the basis of the CF of both crops, summer and winter, multiplied by their respective CT, minus the TF of each city. In addition, the accumulated PUPCRI was classified into four levels of low (1), moderate (2), high (3) and very high (4) exposure by Jenk's natural breaks classification.

4. Discussion

4.1. Crop toxicity calculation

The choice of the ERI allowed us to make a simple and quick calculation of the CT, using numerous variables that attempt to represent the physical–chemical complexity and environmental and human

Table 2
Eco-toxicological values for the calculation of the Toxicological Profile (TP), raw and weighted (in bold) in different degrees of severity, considering the parameters of Alister and Kogan (2006). Source: Pesticide Properties DataBase (PPDB, 2018), PubChem (Kim et al., 2016), The EXtensionTOXicologyNETwork (EXTOXNET, 2018) and CASAFE phytosanitary products guide 2017–2019 (CASAFE, 2017).

Pesticide	log K_OW	Rfd mg kg^{-1} day^{-1}	LC_{50} mg l^{-1}	AT Mallard Duck mg kg^{-1}	AT Rainbow trout mg l^{-1}	AT Honey bee mg kg^{-1}	TP
2,4-D	2,81 **(3)**	0,01 **(2)**	1,79 **(4)**	1000 **(2)**	2 **(4)**	25 **(4)**	**19**
Atrazine	2,34 **(3)**	0,035 **(2)**	5,2 **(3)**	10,000 **(1)**	9,9 **(4)**	100 **(1)**	**14**
Cypermethrin	6,6 **(4)**	0,01 **(2)**	3,56 **(3)**	4640 **(2)**	0,0082 **(4)**	0,023 **(4)**	**19**
Chlorpyrifos	4,7 **(4)**	0,003 **(3)**	0,2 **(4)**	180 **(3)**	0,009 **(4)**	0,114 **(4)**	**22**
Dicamba	−1,88 **(1)**	0,03 **(2)**	4,46 **(3)**	2009 **(2)**	135 **(1)**	100 **(1)**	**10**
Glyphosate	−1,6 **(1)**	0,1 **(1)**	5 **(3)**	4600 **(2)**	86 **(2)**	100 **(2)**	**10**
Metsulfuron	1,8 **(2)**	0,25 **(1)**	5 **(3)**	2500 **(2)**	150 **(3)**	25 **(4)**	**15**
Tebuconazole	3,7 **(4)**	0,03 **(2)**	5,09 **(3)**	1988 **(2)**	4,4 **(4)**	200 **(1)**	**16**

log K_OW = partition coefficient (octanol–water); Rfd = Reference dose; LC50 = Acute lethal concentration; AT = Animal toxicology; TP = Toxicological profile.

Table 3
PUPCRI index of selected cities considering arable land surfaces. Input values of Eq. (1), percentage occupied by arable lands in the first ring (0–100 m), PUPCRI index of each crop (summer and winter) and the accumulated PUPCRI raw and classified at four levels of low (1), moderate (2), high (3) and very high (4) exposure (Jenk natural breaks classification) are shown.

City	% Arable lands (first ring)	CF Arable lands	CT × CF Soybean-corn[a]	CT × CF Wheat	TF	PUPCRI Soybean-corn	PUPCRI Wheat	PUPCRI Accumulated	PUPCRI Ranking
Theoretical city	0	1,0	44,7	40,0	35,5	9	5	49	1
Bell Ville	19	10,4	463,6	414,8	3,5	460	411	875	2
Ordoñez	38	20,3	909,0	813,4	0,7	908	813	1722	3
Wenceslao Escalante	32	20,4	912,4	816,4	0,8	912	816	1728	3
Laborde	33	20,6	921,2	824,4	1,7	920	823	1744	3
Monte Maíz	40	21,7	970,7	868,7	1,0	970	868	1838	3
Morrison	34	22,4	1001,9	896,5	1,5	1000	895	1897	3
Inriville	35	22,8	1021,3	913,9	0,9	1020	913	1934	3
Los Surgentes	44	25,6	1146,4	1025,8	1,5	1145	1024	2171	4
Isla Verde	49	26,0	1162,7	1040,5	0,7	1162	1040	2202	4
Corral De Bustos	47	26,3	1173,9	1050,5	0,8	1173	1050	2224	4
Marcos Juárez	46	26,4	1179,7	1055,7	0,7	1179	1055	2235	4
San Marcos Sud	51	27,3	1220,0	1091,7	0,8	1219	1091	2311	4
Guatimozin	53	27,6	1233,8	1104,1	0,9	1233	1103	2337	4
Leones	53	29,2	1305,3	1168,1	0,4	1305	1168	2473	4
Justiniano Posse	58	30,8	1377,7	1232,8	1,1	1377	1232	2609	4
General Baldissera	60	31,0	1385,1	1239,5	0,6	1385	1239	2624	4
General Roca	57	31,4	1402,6	1255,1	1,5	1401	1254	2656	4
Camilo Aldao	64	33,3	1489,0	1332,4	0,7	1488	1332	2821	4
Monte Buey	65	34,4	1535,8	1374,3	0,6	1535	1374	2909	4
Cavanagh	67	34,4	1538,8	1377,0	0,6	1538	1376	2915	4

CF = Crop factor; CT = Crop toxicity; TF = Tree factor; PUPCRI = Peri-urban Pesticide Contamination Risk Index.
[a] Calculated with an extrapolation 70–30, soybean-corn, on the basis of information obtained of departmental area occupied by each crop.

exposure, by the use of pesticides in crops and their possible risks of contamination. Furthermore, it provides a simple equation for comparing different pesticide compounds. This index is also characterized by its flexibility and its usability at different spatial scales. Modifications can be made, such as changing dermal exposure by inhalation route, allowing different risk models to be tested. This characterizes the ability of the ERI index to be used in countries, such as Argentina, where the main route of exposure to peri-urban pesticide use may be through the respiratory tract on contact with particulate matter of the soil or contaminated air. In this situation, the toxicity index should be flexible so that the user can incorporate a new component or remove it (Labite et al., 2011). The main issue with this methodology is that the breakdown between scores was not described and there is no clear transparency in the severity class definition, and that in practice it is not a widely used index despite it getting a good score in a review of Plant Protection Product Ranking Tools Used in Agriculture made by Labite et al. (2011).

In turn, this index makes it possible to highlight those pesticides that, although they have low or moderate toxicity parameters, have a high ERI due to the dose in which it is applied. This is the case of

Table 4
PUPCRI index of selected cities considering active crop surfaces (soybean-corn and wheat). Input values of Eq. (1), percentage occupied by crops in the first ring (0–100 m), PUPCRI index of each crop (summer and winter) and the accumulated PUPCRI raw and classified in four levels of low (1), moderate (2), high (3) and very high (4) exposure (Jenk natural breaks classification) are shown.

City	% Active crops (first ring)	CF Soybean-corn	CT × CF Soybean-corn[a]	CF Wheat	CT × CF Wheat	TF	PUPCRI Soybean-corn	PUPCRI Wheat	PUPCRI Accumulated	PUPCRI Ranking
Theoretical city	0	1,0	44,7	1,0	40,0	35,5	9	5	49	1
Bell Ville	2	1,4	61,9	0,2	8,6	3,5	58	5	67	1
Wenceslao Escalante	22	10,7	479,3	3,5	139,4	0,8	479	139	618	2
Morrison	22	13,4	598,7	1,3	50,5	1,5	597	49	648	2
Isla Verde	28	14,7	658,4	1,5	58,7	0,7	658	58	716	2
Laborde	24	14,7	658,4	1,9	74,5	1,7	657	73	731	2
Ordoñez	38	13,7	610,2	6,1	245,4	0,7	609	245	855	3
Monte Maíz	37	16,9	757,6	2,8	113,6	1,0	757	113	870	3
San Marcos Sud	33	18,8	838,3	1,2	46,6	0,8	837	46	884	3
Inriville	25	17,3	771,3	4,0	160,8	0,9	770	160	931	3
Leones	35	17,2	766,6	4,5	179,8	0,4	766	179	946	3
Marcos Juárez	37	16,5	737,4	6,7	266,5	0,7	737	266	1003	4
Justiniano Posse	45	13,4	597,3	10,5	421,1	1,1	596	420	1017	4
Guatimozin	46	23,7	1057,7	1,4	54,6	0,9	1057	54	1111	4
Corral De Bustos	44	20,4	909,8	5,2	206,8	0,8	909	206	1116	4
Los Surgentes	41	21,3	950,8	5,3	210,2	1,5	949	209	1159	4
General Baldissera	56	20,8	932,0	7,8	312,2	0,6	931	312	1244	4
Monte Buey	62	27,7	1238,0	4,1	162,2	0,6	1237	162	1400	4
General Roca	62	23,3	1039,9	10,3	410,6	1,5	1038	409	1449	4
Camilo Aldao	70	30,7	1371,5	5,9	235,6	0,7	1371	235	1606	4
Cavanagh	78	29,2	1305,8	11,4	455,6	0,6	1305	455	1761	4

CF = Crop factor; CT = Crop toxicity; TF = Tree factor; PUPCRI = Peri-urban Pesticide Contamination Risk Index.
[a] Calculated with an extrapolation 70–30, soybean-corn, on the basis of information obtained of departmental area occupied by each crop.

glyphosate, which has the highest ERI in our study due to the large doses in which it is applied in soybean and corn crops. This data is not minor considering that it is the most widely used herbicide in the world and that it was recently classified by the International Agency for Research on Cancer (IARC) as "probably carcinogenic to humans" due to its genotoxic activity and oxidative stress (Guyton et al., 2015). Another important fact that arises from the ERI calculation is the case of atrazine. This herbicide has a medium toxicological profile, but with a higher persistence and leachate parameters than other herbicides, which gives it a high index (16). This plaguicide has a medium application rate for the region under study, according to data obtained from experts and reports, but it must be supervised with care since it is used in large quantities being, along with glyphosate and 2,4-D, one of the herbicides of greater worldwide application (Alister and Kogan, 2006). In addition, it is associated with a relatively high chronic toxicity and potential to accumulate as a recalcitrant substance in surface and groundwater, so its use is restricted in the United States of America and has been banned in several European Community countries (Hansen et al., 2013).

The group of pesticides applied to each crop varies according to numerous factors, those that were selected in our research are those of standard use, that are always applied, but which represent a minor fraction of what is finally used in each crop. In addition, in the preparation of the fields prior to each sowing, large quantities of pesticides are also applied. Therefore, the calculation made for each CT is conservative in relation to what happens in reality. Another factor that is not taken into account is the use of mixtures with other agrochemicals to improve the effectiveness of those evaluated in our research, generally referred to as adjuvants. For example, in the application of glyphosate different adjuvants are used, such as ethoxylated adjuvants, the toxicity of which was determined as ten thousand times greater than the active principle of the herbicide alone (Mesnage et al., 2013). Therefore, the toxicity studies of pesticides should be carried out on the mixtures, i.e. the most common form of commercialization of these products (called formulations), since they are much more toxic than their active principles alone (Larramendy et al., 2010; Mesnage et al., 2014).

4.2. Crop and tree cover comparison

The land cover data estimated showed an alarming situation of agro-industrial activity in this region of Argentina and particularly in the periphery of many cities: the areas occupied by forests 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 forests are diminished and the population is exposed to risks produced by industrial agricultural activity.

The calculation of crop areas using satellite images facilitates access to data that cannot be obtained due to non-existence or inaccessibility. In addition, temporal and spatial monitoring at different scales is possible. The coverage data used for the PUPCRI can come from other sources or from other satellite indices, such as NDVI or MSAVI.

The possibility of weighting the surfaces occupied by trees or crops in the different perimeter rings using the constant b from Eq. (4), provides the opportunity to model different study situations with the PUPCRI. The values used enable us to test this model, but do not represent a condition or attribute of the factors under study. In our research the proximity of crops to the urban edge is magnified to a greater degree than tree cover because we consider the exposure to pesticide use to be more dangerous. This is reflected in those cities where the higher percentage of arable lands or crops in the first rings increase their PUPCRI (Tables 3 and 4). 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. Gauss diffusion models, already calculated in other studies, can also be used to determine areas affected by downwind drift during the application of different types of pesticide formulations (Sánchez-Bayo et al., 2002).

The evaluation of wind breakers as barriers to agrochemical drift at this scale of analysis is extremely complex. Ucar and Hall (2001), carried out an extensive review on this subject and concluded that there is enormous complexity in determining how and how much a plant barrier acts to reduce drift. However, they indicate that even a small barrier of trees can act by considerably reducing the possible drift of agrochemicals. Therefore, from our research approach we consider this variable to evaluate its impact on the risk of exposure, without addressing its structure, composition or other characteristics. In future investigations it will be possible to evaluate its effectiveness, having already discriminated the degrees of exposure per locality by means of the PUPCRI index.

4.3. PUPCRI assessment

The PUPCRI allows a quick and easy way to calculate and assess the risk of exposure to pesticides in the peri-urban area. All the necessary data for its calculation can be obtained from official sources on the Internet, which gives it versatility, reliability and repeatability. It is a theoretical index due to the origin of the data, but it allows exploratory analyses to be carried out in the event of the lack of, or inaccessibility, of field data. This index can be applied in many countries that produce GMOs on a large scale to assess the degree of peri-urban exposure to pesticides.

The PUPCRI provides a methodology for the spatial assessment of the risk of peri-urban pesticide use, facilitating the identification of factors that increase exposure to agro-industrial activities. It was developed as a screening tool to provide a relative assessment of pesticide use, which makes it a strategic instrument for controlling the location of these activities in order to preserve the health and environment of the people who live in agricultural regions.

Table 5 shows a comparison of the PUPCRI index with different pesticide ranking techniques based on key indicator characteristics, data requirements and evaluation criteria. Based on this comparison, we can say that it is the first index that takes account of a measurement of peri-urban pesticide contamination risk as a whole at the local level, by using perimeter rings, which makes it possible to evaluate areas adjacent to the cities, quantifying and evaluating how exposed the people are in those areas. This information can have a direct influence on the decisions of local governments, the actions of non-governmental organizations and the empowerment of society. While most indicators are developed for the crop or farm level (Labite et al., 2011; Reus et al., 2002), the PUPCRI index serves to control and monitor agro-industrial activity in large territorial extensions, allowing a first approximation to the possible risks for health and the environment. This makes it possible to identify problem areas and to better target policy instruments.

Continuing with the comparison with other indices, the PUPCRI index has the capacity to represent numerous environmental compartments and an assessment of the impacts on biota and human health, equal to or greater than that of other indices, but with lower data requirements (Table 5). In addition, it has a simple calculation algorithm and could be modified if necessary according to the criteria set by the user. This means that this index can be modified in the future, for example, by changing the way of calculating the toxicity of crops, when there are more precise measurements of the pesticides applied, their toxicity and the risks of contamination for humans and the environment.

In other countries, indices and indicators of pesticide contamination have been developed and used for several decades with the intention of reducing their use, the risks of exposure of the applicators, population and contamination of the environment (Alister and Kogan, 2006; Damalas and Eleftherohorinos, 2011; Feola et al., 2011; Kookana et al., 2005; Kudsk et al., 2018; Reus et al., 2002; Sánchez-Bayo et al., 2002; Strassemeyer et al., 2017; Tsaboula et al., 2016; Vercruysse and

Table 5
Comparison of PUPCRI index with different pesticides ranking techniques based on key indicator characteristics, data requirements and evaluation criteria. Source: Feola et al., 2011; Labite et al., 2011; Reus et al., 2002.

Index	Ranking approaches	Ability to represent the system under study								Impact assessment						User Friendliness		
		Site specific data	Scale of interventions			Environmental Compartments												
			Crop or Farm	Periurban	National	Air	Soil	Surface water	Groundwater	Human health	Aquatic organisms	Soil organisms	Bees	Birds	Bioaccumulation	Data requirements (number of indicators)	Easy to use	Flexibility
EcoRR	Risk ratio – Scoring Technique	Yes	×			×	×	×	×	×	×	×			×	15	Difficult	Medium
Ipest	Fuzzy system	Yes	×			×		×	×	×	×					8	Easy	High
PestScreen	Scoring Technique	No	×		×	×	×	×	×	×	×	×			×	11	Easy	Medium
POCER	Risk ratio - Scoring Technique	Yes	×			×	×	×	×	×	×	×			×	13	Easy	High
PUPCRI	Scoring Technique	Yes	×	×		×	×		×	×	×		×	×	×	10	Very easy	High
RICH	Decision Tree	Yes	×		×			×			×				×	6	Easy	Medium
SYNOPS	Risk ratio	Yes	×		×	×	×	×			×	×				11	Easy	Low

EcoRR = Ecological Relative Risk; POCER = Pesticide Occupational and Environmental Risk Indicator; PUPCRI = Peri-urban Pesticide Contamination Risk Index; SYNOPS = Synoptic Evaluation Model for Plant Protection Agents; RICH = Ranking and Identification of Chemical Hazards.

Steurbaut, 2002; Verro et al., 2009). The results of the use of these indices have led to new regulations and restrictions on pesticide use (Kudsk et al., 2018; Reus et al., 2002). Some, such as SYNOPS (Gutsche and Rossberg, 1997), Environmental Yardstick for Pesticides (Reus and Leendertse, 2000), or Pesticide Load (Kudsk et al., 2018), are interesting tools to determine the risk of exposure to pesticides. However, in our region they would be difficult to apply on a large scale due to the lack or impossibility of access to the pesticide use data needed for their calculation. In addition, it is necessary to create indices that take the regional variables and dynamics into account since they differ greatly from the types of crops and agricultural practices of the countries where these indicators were developed (Feola et al., 2011). For this reason, we propose the PUPCRI as an exploratory research tool to generate information on exposure risk, designed for assessment and monitoring agro-industrial activity in large regions of Latin America. In Argentina, different indicators and risk indices of pesticide contamination have been developed and tested (Dubny et al., 2018; Ferraro, 2005; Hunt et al., 2017; Maiztegui, 2010; Peluso et al., 2014). These have different objectives, scales of analysis and results from the index that we propose. However, the convergence of results is interesting, where worrying levels of contamination and exposure to pesticides stand out.

A highlight of the PUPCRI is that it makes it possible to identify the factor that most influences the risk of exposure, for example, the toxicity of pesticides or the proximity of fields to the city or the lack of forest cover or interactions between them. This offers the possibility of visualizing, managing and controlling the space surrounding a city, so that productive activity development is safe without compromising the health of populations and the environment. In this sense, the PUPCRI index aims to generate information for contextualizing pesticide risk use at the peri-urban scale, e.g. to understand the determinants of exposure more than to quantify levels of risk. In fact, as suggested by some authors, it might be less important to accurately quantify the exposure of people to pesticides than to understand the determinants of exposure, both in terms of risk factors and of determinants of risky behaviour (Feola et al., 2011).

Table 6 shows the disaggregated data for each ring analysed of the areas occupied by soybean-corn and tree cover. The four cities selected correspond to the highest value within each category in Jenk natural breaks classification (Table 4). This makes it possible to analyse the impact of the variation in the total areas occupied and their proximity or distance from the cities, on the PUPCRI index. It should be considered that variations between factors are dependent on the risk model chosen, with different weights for each factor and peripheral ring, and that it is a theoretical model that needs corroboration in future research.

The main limitations in the creation, calculation and application of the PUPCRI index are described as follows. One of the first observations we must make is that this index can be calculated in a simple way at the expense of a more realistic representation of pesticide impacts. Simplicity is a generally acknowledged feature of indicators. This often makes them acceptable, quick to calculate and easy to communicate (Feola et al., 2011). As described above, in conditions of inaccessibility and scarcity of data, this index can be calculated as an exploratory tool for preliminary research. In later instances, variables can be added to the index to improve its representation of the phenomenon. From the results obtained, we believe that even with the lack of information, important spatial patterns of risk are evident. Similarly, in terms of access to detailed information, other limitations refer to the assumption of a homogeneous use of pesticides throughout the growing season, not taking account of the application methodologies (aerial or terrestrial fumigation, nozzle tips, etc.) and that climatic variables are not used either. Again, although these data would greatly improve the representation of risk, we do not believe that it disables the results obtained and discussed in this article. Another limitation refers to the impossibility of directly comparing our results with those of other researches that apply risk indexes, since pesticides, applied doses, and

Table 6
Surface areas of soybean-corn crops and tree cover (hectares and percentages) in each peri-urban ring. The four selected cities correspond to the highest value within each category from Jenk natural breaks classification (Table 4). Input values of Eq. (1) (CF and TF) and soybean-corn PUPCRI index (summer crops) are shown.

City	Soybean-Corn crop cover by ring (hectares and percentage)					CF	Tree cover by ring (hectares and percentage)					TF	PUPCRI Soybean-Corn[a]
	0–100 m	100–250 m	250–500 m	500–1000 m	1000–2000 m		0–100 m	100–250 m	250–500 m	500–1000 m	1000–2000 m		
Theoretical city	0 (0%)	0 (0%)	0 (0%)	310 (50%)	847 (50%)	1	100 (100%)	147 (100%)	259 (100%)	155 (25%)	424 (25%)	36	9
Bell Ville	4 (2%)	7 (2%)	25 (6%)	146 (16%)	402 (17%)	1	26 (11%)	28 (9%)	27 (6%)	39 (4%)	44 (2%)	4	58
Laborde	18 (21%)	51 (42%)	136 (61%)	315 (57%)	1040 (66%)	15	6 (3%)	3(1%)	1 (1%)	4 (1%)	11 (0%)	2	657
Leones	39 (28%)	103 (51%)	176 (52%)	334 (45%)	996 (52%)	17	2 (1%)	2 (1%)	3 (1%)	10 (1%)	10 (1%)	0	766
Cavanagh	40 (56%)	84 (74%)	153 (72%)	376 (71%)	932 (61%)	29	2 (2%)	1 (1%)	1 (1%)	5 (1%)	8 (1%)	1	1305

CF = Crop factor; TF = Tree factor; PUPCRI = Peri-urban Pesticide Contamination Risk Index.
[a] Calculated with an extrapolation 70–30, soybean-corn, on the basis of information obtained of departmental area occupied by each crop.

other parameters are specific to the region under study. In this sense, there is a need to evaluate the methodology we propose in countries that produce GMOs on an agro-industrial scale similar to Argentina. Depending on the extent that this methodology is applied in other regions, it will be possible to corroborate the concordance of results.

Some particular challenges found during the calculation or analysis of PUPCRI, for instance the lack of marked extremes in our database, most of the selected cities have similar patterns, with very little tree cover. This deficiency could be solved thanks to the theoretical city, but in the future the geographical study area could be expanded to include cities with other patterns. Another difficulty was the impossibility of discriminating, in summer crops, between areas planted with soybeans and corn, which has impacts on the PUPCRI calculations since the CT of these crops are different. For methodological testing purposes, the data calculated for these two crops by extrapolation served to test the index. Finally, although all the data to calculate this index could be obtained from various official sources, we had limitations in determining the total number of agrochemicals applied per crop, their doses, and the method, time and location of application, among other factors that would provide greater precision and risk assessment. These limitations may vary between regions and countries, depending on how many data are available. In our case, we believe that part of the results of our research tend to underestimate the exposure to agrochemicals since the total used was not evaluated, nor the frequency of its application. This is very worrying since the results show a high risk of exposure in almost all the cities analyzed, despite this lack of data. The theoretical city created is not only intended to be taken as a point of comparison with other cities, it also allowed us to test an urban planning model with different peri-urban land uses. This is interesting because not only was the risk of contamination evaluated, but also how the change in the tree and crop cover would impact the decrease or increase of the PUPCRI. Thus, for example, for the theoretical city, a tree cover of 100% of the first three rings, and 25% in the two subsequent rings (38% summing all rings), generates an almost total decrease in the PUPCRI, summer and winter crops, and half in the accumulated PUPCRI.

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.

Also, it was possible to determine an accumulated PUPCRI, that allows the degree of exposure in an annual crop cycle to be estimated, by using the data from the three main crops and the number of hectares sown in the area under study. Thus, a time series of exposure risk can be assessed for studying different cities and regions with historical or recent agricultural activity.

The PUPCRI calculations for arable land (Table 3) provide an estimate of the potential contamination of agricultural activity in the urban periphery. Therefore, it allows us to determine the maximum level of risk since all this area is potentially cultivable with GMOs or traditional crops. In some cities there is little difference between the percentage of arable land and that used in 2017 (determined by the IRECI index: active fields). This is the case of the city Camilo Aldao, where the percentage of arable land detected in two peripheral kilometres was 84%, and, in the summer crops of 2017 it reached 74% of the occupied surface.

Continuing with the analysis of the results for arable land, the exposure to pesticide situation of the 20 cities is worrying as only one has a moderate accumulated PUPCRI, six have a high accumulated PUPCRI and 13 have a very high accumulated PUPCRI (Table 3).

By performing PUPCRI calculations using the IRECI satellite index, we were able to discriminate the presence of peripheral crops on the dates analysed and determine the level of risk of contamination for the populations. PUPCRI values, per crop and accumulated, are lower than those of arable land. However, five cities have a high accumulated

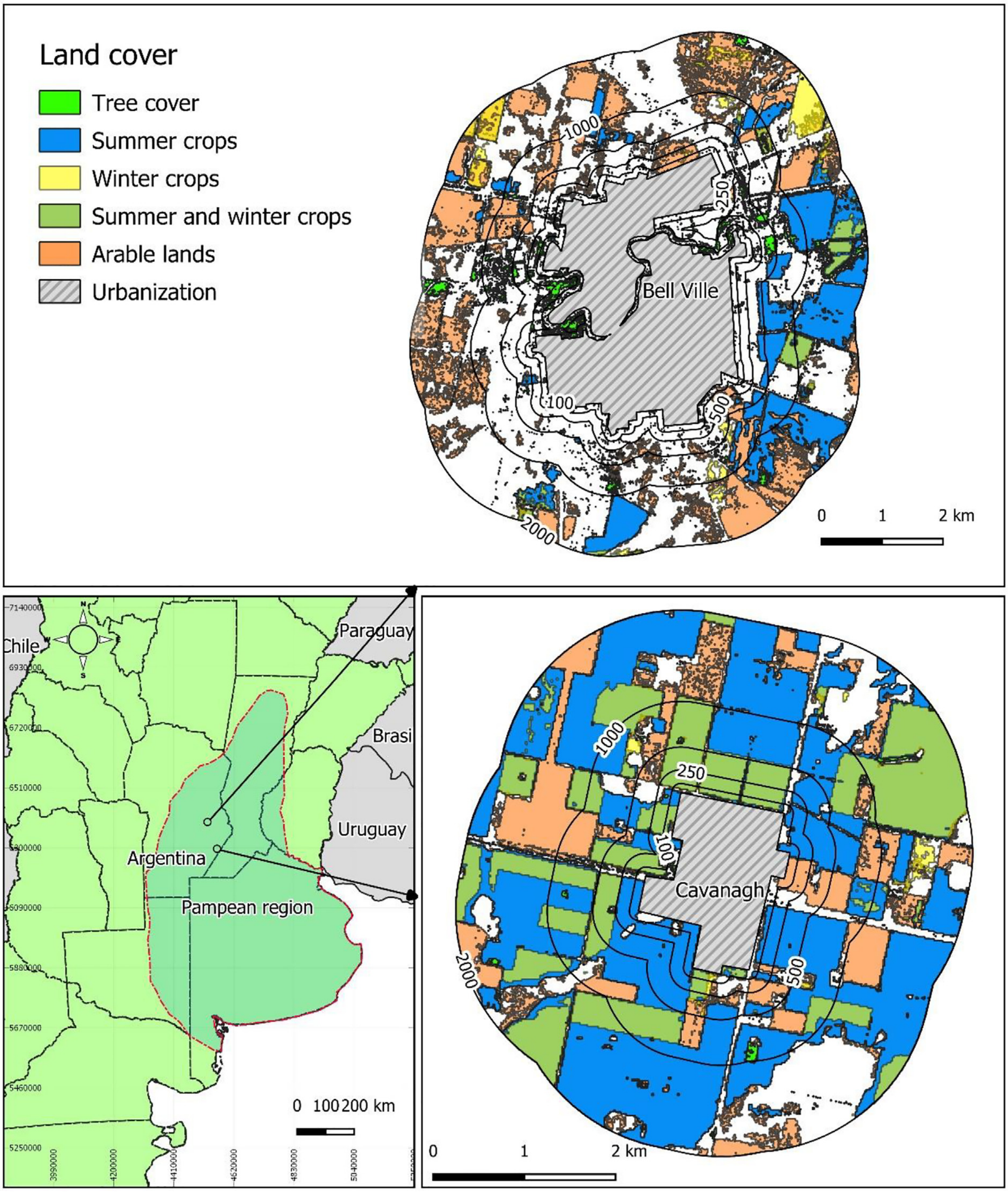

Fig. 2. Cities with lower and higher PUPCRI (accumulated). Coverage of arable lands, active crops and trees is represented.

PUPCRI and 10 very high (Table 4) which shows that agricultural activity, mostly with GMOs crops, is in direct contact with the populations that live on the periphery of many cities.

Comparing the data of both tables, it can be observed that the same ranking pattern is not followed according to the accumulated PUPCRI. The extremes are maintained: Bell Ville with the lowest index and Cavanagh with the highest (Tables 3 and 4). The one with the lowest PUPCRI is at the lower end because it only has few areas of arable land in the first three rings (25% of the total surface) or active crops (3.8%), and the largest area of peripheral trees of the 20 cities analysed (8.4% in the first three rings). Although the data from this city are the best in relation to the others, it is far from resembling the theoretical city proposed as a model. The city with the highest PUPCRI has the largest presence of arable land and active summer and winter crops of the 20 cities analysed. In addition, it records very low tree cover, which does not exceed 1% in any of the peripheral rings analysed (Table 6). Fig. 2 compares these two cities, discriminating the cover of arable land, cultivated fields and trees.

For future research, work is being done on an automated model on the Google Earth Engine platform. This will allow the proposed methodology to be applied in other regions, analyze longer time periods and make the methodology available for testing and improvement. Another line of work that is being developed is the implementation of theoretical models of land use for assessing the impacts on the risk of exposure to pesticides by changing the agro-industrial model for agro-ecological production.

4.4. Complementary context data

Finally, it is important to mention that where high PUPCRI indices were determined in our study region, several researchers have provided health and environmental indicators, some directly or indirectly related to agricultural activities. Among them we highlight studies that determined a higher incidence and mortality of specific groups of cancer (Agost, 2016; Agost et al., 2015; Díaz et al., 2007; Pou et al., 2014), genetic damage to children and adults (Bernardi et al., 2015; López et al., 2012; Peralta et al., 2011), respiratory diseases (Lerda et al., 2001), indicators of social vulnerability and health risk (Maiztegui, 2010) and indicators of environmental quality (Velázquez et al., 2010). From this group of studies, it is interesting to look at the conclusions of Bernardi et al. (2015), who studied the level of damage in the genetic material of children in Marcos Juárez, a city that has a very high accumulated PUPCRI in our study (Tables 3 and 4). In this study, significant results were obtained among children exposed at less than 500 m with respect to a group of children not exposed to pesticide application and they conclude: "Together, the frequency of micronuclei found in the city of Marcos Juárez (group 1), related to the distance from housing to pulverized areas (less than 500 m and between 500 m and 1500 m), does not show significant differences between the two. Being a relatively small city, this result shows that spraying could reach (by air) the entire city and that the vulnerable population of children is subjected to extremely high and continuous exposure, as they live surrounded by crops" (Bernardi et al., 2015).

5. Conclusions

The PUPCRI makes it possible to carry out a quick and simple analysis of the potential risk of exposure to the use of pesticides in traditional and GMO crops in the urban periphery. In addition, it is a tool for managing the geographical space, as it shows how the proximity of surfaces destined for crops or with tree cover, act as factors that increase or decrease the risk of exposure to pesticides. At the same time, different models tending to reduce the risk of exposure can be tested, and estimates of protection surfaces, costs due to changes in land use, location and type of crops, among other factors, can be made. We believe that the calculated data show a worrying situation of exposure risk, even with the little information available on the dynamics of crops and the use of pesticides, which should continue to be studied.

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CRediT authorship contribution statement

Lisandro Agost: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. **Guillermo Angel Velázquez:** Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing, Supervision.

Declaration of Competing Interest

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

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