Computer Vision as an Interface Between Geographical Information Systems and Remote Sensing : First Results of a Case Study on Urban Quality of Life and *Ambrosia artemisiifolia* (common ragweed) cartography

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Abstract

The aim of this paper is to present the preliminary results obtained through a composite system using computer vision as an interface between a Geographical Information System (GIS) and remote sensing data. The system is made of three main components : (1) A knowledge base incorporating the typical information found in an urban GIS, data from a population census and remote sensing images, (2) a feature extraction device mainly producing multivalued classifications and masks from change detection operations and (3) an inference engine using multiple correspondence analysis in order to deduce rules of spatial organisation. After having described a case study on the cartography of *Ambrosia artemisiifolia* (common ragweed), currently investigated on the Urban Community of Montreal (Canada) territory, the authors will present an overview of the methods implemented and discuss on methodological problems raised in the course of the study. Finally, avenues for future research concludes this paper.

1 Introduction

In social geography, two approaches among others allow to take up the problematic of green spaces in an urban context. The first sends back to accessibility and social equity questions such as « does the geographic distribution of green spaces allows fair access for all population groups in a given city? » (see [19] for the cities of Pueblo and Macon in the USA). The second considers green spaces as an indicator for the measurement of intra-urban quality of life. The latest is the path the authors of the present paper have decided to follow [6].

Defining the concept of intra-urban quality of life is very difficult since many interpretations are given by authors and research areas such as environmental psychology, social psychology, health sciences, sociology, anthropology and social geography. For example, one can define quality of life as the joy or satisfaction that life and environment give to a person. The characterization of the environment holds a primordial place in the evaluation of quality of life and correspond to four distinct dimensions: (1) the quality of the physical environment (land-use, vegetation, atmospheric, olfactive and noise pollution), (2) the quality of housing and habitat (habitat types, urban density, size, comfort and standing of housing), (3) the quality and access to collective equipment (recreation equipment, public transportation, neighborhood stores) and (4) the quality of the social environment (criminality and security, revenues, level of education) [2] [5] [12] [13].

Two types of indicators, often complementary, can be used in order to measure the intra-urban quality of life. On the one hand, *objective* indicators usually derived from the national census and less often from land-use maps or remote sensing images. On the other hand, *subjective* indicators obtained through surveys or interviews intending to translate the impressions of the population about its immediate environment [7] [16].

Table 1 gives an overview of the different approaches followed for data exploitation and exploration in an *objective* research context. Census data are extensively used in order to describe the social environment (demographic, socio-economic and education variables), the habitat and the level of equipment are studied at different geographical scales going from the urban block to the census district or the historical quarter. Conversely, other sources such as land-use maps, remotely sensed images are relatively less exploited even though they can be used to measure the quality of the physical environment [10] [22]. Considering the important number of variables to take into account, it is not surprising to learn that most authors encourage the use of multivariate statistical methods such as factorial and typological analysis.

The aim of this paper is to present the preliminary results obtained through a composite system using computer vision as an interface between a Geographical Information System (GIS) and remote sensing data, a very heterogeneous data set as a matter of fact. The system is made of three main components : (1) a knowledge base incorporating the typical information found in an urban GIS, data from a population census and remote sensing images, (2) a feature extraction device mainly producing multivalued classifications and masks from change detection operations and (3) an inference engine using multiple correspondence analysis (MFA) in order to deduce rules of spatial organization. After having described a case study on the cartography of *Ambrosia artemisiifolia* populations in the next section, we will present an overview of the implemented methods and discuss on the methodological problems raised in the curse of the study. Finally, avenues for future research will conclude this paper.

Table 1. Indicators and measures of the urban quality of life : synthesis of literature

Author(s)	Census data					Other sources of data			Data processing						Study area
	Demographic	Socio-economic	Housing - habitat	Education	Equipment	Land-use Maps	Surveys	Remote Sensing Images	Indices	Factorial Analysis	Typology – classification	Spatial Autocorrelation	Correlation	Aggregation	
Aureli E. et al.	✓	✓	✓							✓	✓				Roma (Italy)
Baldazzi B. et al.	✓	✓	✓	✓						✓	✓				Milan, Genoa, Palermo (Italy)
Buckley P.H.	✓	✓	✓	✓	✓					✓	✓	✓			Bellingham (Washington)
Kuz T..J.		✓	✓	✓	✓		✓			✓			✓		Manitoba urban centres (Canada)
Lo C.P.	✓	✓						✓	✓	✓	✓				Athens-Clarke County (Georgia, USA)
Pacione M.	✓	✓	✓		✓					✓					Glasgow (Scotland)
Pandey et al.	✓	✓							✓						Canadian metropolitan areas
Weber C. et al.	✓	✓	✓					✓	✓				✓	✓	Strasbourg (France)
Findlay A. et al.	✓	✓	✓	✓	✓						✓			✓	British cities
Talen E.		✓	✓			✓			✓			✓			Pueblo (Colorado, USA), Macon (Georgia, USA)

2 Background

Ambrosia artemisiifolia (common ragweed) is a very common and abundant annual plant in open spaces of north-eastern America. The pollen emitted by this plant is the principal cause of hay fever in Eastern Canada. *Ambrosia artemisiifolia* is also causing, as a bad plant, decreasing yields in many agricultural industries through the invasion of prairies and cultivated land. It is most useful to study the evolution of *Ambrosia artemisiifolia* populations under the urban dynamics angle since these populations are almost always linked to changes in vegetal covers and land use caused by human activities [1] [11].

It is believed that the *Ambrosia artemisiifolia* polulations cartography can be used as a marker of green spaces quality. Since this vascular plant is responsible for most of hay fever symptoms its presence will certainly affect one's perception of a neighborhood, which is a *subjective* indicator of quality of life. Furthermore, since the plant is always associated with low or very low quality green spaces (salt or nitrate polluted soils, disturbed or heavily compacted soils) it can be used to monitor physical quality of life, thus an *objective* indicator.

The direct remote sensing of *Ambrosia artemisiifolia* is very difficult even when using hyperspectral data. In a previous study [1] using an experimental agricultural prairie covering 7 hectares located in the suburb of Montreal (Canada), evenly spaced stations were surveyed. For each station covering 1.5 m^2 a photograph and a measure of reflectance between 400 and 1100 nanometers were taken. A reading of present species was collected and in laboratory, slides were showed to three experts for definitive identification of species and estimation of relative presence on each station. Three contingency tables were then structured in order to cross each station and the proportion of each species recorded, the proportion of *Ambrosia artemisiifolia* for each species recorded, the proportion of *Ambrosia artemisiifolia* for each station and the relative reflectance between 400 and 1100 nanometers. Finally, we compared stations completely covered by *Ambrosia artemisiifolia* or plants known to be difficult to distinguish from *Ambrosia artemisiifolia* and with their relative reflectance for selected intervals. Our data analysis results showed that it is very difficult to separate the reflectance spectra of *Ambrosia artemisiifolia* from companion plants like *Artemisia* and *Asclepias*. Furthermore, the situation is worse for mixed covers that are common in open spaces.

The conclusion of this previous study was that indirect remote sensing of *Ambrosia artemisiifolia* populations through regular means of caption could be attempted at a coarser scale and using knowledge on the ecology of the plant and thus requiring extensive use of ancillary data.

3 Methods and Preliminary Results

A case study on a portion of the territory of the Montreal Urban Community (see fig. 1) enables the use of an extensive set of variables and indicators and more important facilitates the verifications of intermediate results since this study area is situated in the close neighborhood of research centers the authors are affiliated to. Our knowledge base (tab. 2) on the area is divided in two main parts: (1) a set of physical descriptors composed of relative reflectance values given by remote sensing images (a Landsat TM image composed of three spectral bands going from the red to the medium infrared taken in august 1995 and a 1: 40 000 aerial photograph taken in panchromatic mode in the spring of 1996), data on housing and habitat from the Canadian national census together with a land-use map (fig. 2) describing the territory in 19 land-use classes for 1996 and (2) a set of social descriptors composed of variables picked for their significance in the Canadian national survey of 1996.

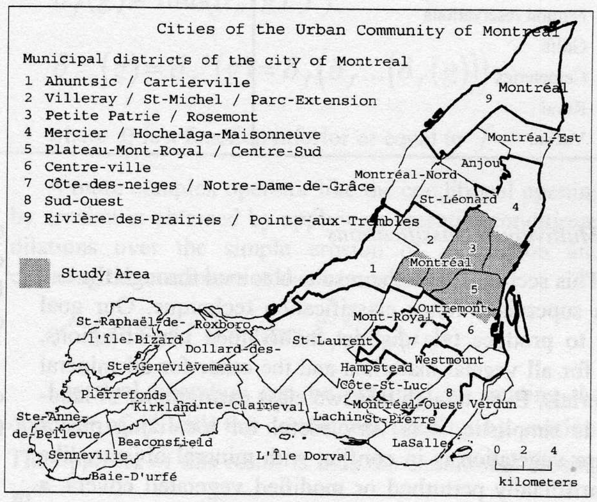

Figure 1. Territory of the Montreal Urban Community and study area

As stated in the introduction the system is divided in three main parts : the knowledge base which has just been described, the feature extraction device and the inference engine. The feature extraction device is producing multivalued classifications and masks from change detection operations and the inference engine is using multiple correspondence analysis in order to deduce rules of spatial organization. These three last operations are described below.

Table 2. Content of the knowledge base in its initial state.

PHYSICAL ENVIRONMENT		SOCIAL ENVIRONMENT
1: 40000 Aerial photographs (1996)	**Census blocks (1996) : Housing**	**Census blocks (1996)**
Landsat TM Image Bands 3 to 5 (1995)	*Housing type*	Population
Reflectance from 0.63 to 0.69 µm	Individual house (in %)	Density (inhabitants by km^2)
Reflectance from 0.76 to 0.90 µm	Semi-detached house (in %)	Area (km^2)
Reflectance from 1.55 to 1.75 µm	Line housing (in %)	*Type of household (100%)*
Land-use map (1996)	Apartment, duplex (in %)	% Married couples
Low density housing	Apartment, less than 5 stories (in %)	% Free union couples
Medium density housing	Apartment, 5 stories or more (in %)	% single-parent families
High density housing	Other individual house (in %)	*Employment and revenue*
Retail stores	Mobile home (in %)	Activity rate
Shopping malls	*Construction period of housing*	Unemployment rate
Office buildings	Construction before 1946 (in %)	Average employment revenue
Light industry	Construction between 1946 and 1960 (in %)	Average family revenues
Heavy industry	Construction between 1961 and 1970 (in %)	Average family revenues spouses
Burial sites	Construction between 1971 and 1980 (in %)	Average single-parent family revenues
Quarries	Construction between 1981 and 1990 (in %)	*Education (100%)*
Collective equipment	Construction between 1991 and 1996 (in %)	% Schooling inferior to 9 years
Public utility services	*Value of housing*	% Schooling between 9 and 13 years
Urban parks	Average rent (Can $)	% Diploma from a professional school
Regional parks	Average value of the accommodation (Can $)	% Other studies (non- university)
Natural reservations		% University studies without diploma
Golfs		% Bachelor or higher diploma
Cemeteries		
Rural		
Vacant		

Multivalued classifications

This section shows the results obtained through the use of a supervised fuzzy classification technique. Our goal was to produce two distinct multivalued classifications, one for all vegetal materials and the other for all mineral materials. Even though this two class cartography of land-use is simplistic, it is very useful for localizing places where vegetation is in conflict with mineral objects, like on artificially perturbed or modified vegetated covers, a situation that is believed to give indications of the presence of *Ambrosia artemisiifolia*. This phenomenon of conflictual identification is translated via non zero degrees of membership for both classes in a given location.

The method used for the classification is fairly simple and relies on the construction of membership functions modeled upon samples of pixels known to be pure representatives of the vegetal and mineral classes. For bands TM3, TM4 and TM5 of the Landsat image the intervals in grey levels for the maximum of the *vegetation* membership function are respectively (20, 35), (106, 140) and (75, 130). For the same spectral bands the bounds in grey levels for the maximum of the *mineral* membership function are respectively (32, 87), (38, 85) and (47, 162) and it can be seen that some conflicts of membership occur on TM5 and to a lesser degree on TM3. A sigmoid function is used as a basis for the mappings. A more complete description of the method can be found in [11].

Figure 2 shows the results of the classification for the entire territory of the Montreal Urban Community (approx. 500 km^2).

Change detection operations

A new change detection method is currently under investigation in order to produce good masks of change detection. These masks are very useful to evaluate the type of changes that occur in the urban fabric [18] [21], as measured by sequential acquisition of remote sensing images. Queries on all layers of information can be made with the masks in order to qualify the changes together with geometrical measures made on the mask themselves. Aside from the update of the knowledge base, change detection is helpful in the cartography of *Ambrosia artemisiifolia* populations in the sense that the plant is closely related to perturbations and modifications of the urban land-use such a construction works, heavy machinery displacements on vegetated areas or lawn mowing on vast surfaces.

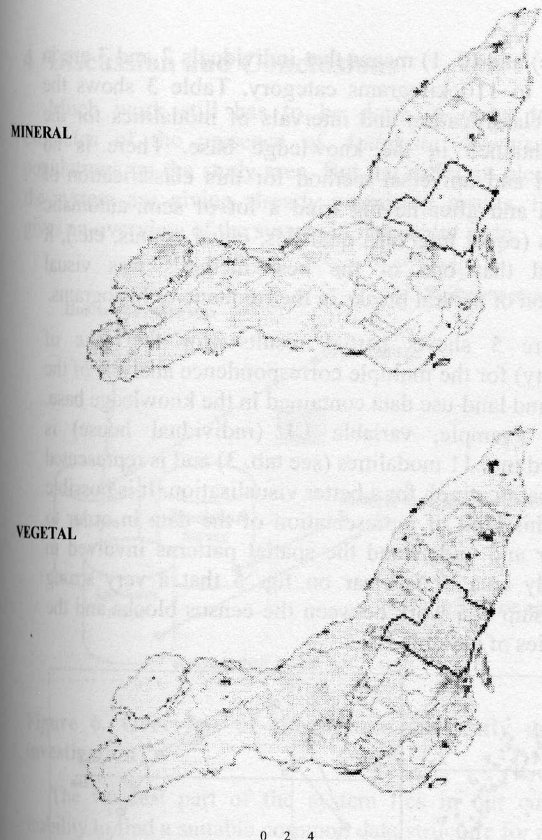

Figure 2. Multivalued classifications for the vegetation and mineral classes

The basic morphological operators used to perform the change detection on the difference images are the dilation $\delta_B(f)$ and the erosion $\varepsilon_B(f)$, using structuring element B [20].

Erosion and dilation are dual operations in which minimal or maximal values of the original image intersecting with each translation of the structuring element are affected to the central pixel of the region covered by this structuring element. The composition of an erosion and a dilation results in an opening, the dual of which being a closing. The composition of a closing and an opening (in either order) gives an alternated filter. In order to clean the difference images from the noise inherent from unfit superposition of the images taken at the different instants, it is possible to implement an alternated sequential filter, that is an alternated filter using structuring elements of growing sizes. But as shown in fig. 3 this approach corrupts the shape of the remaining objets in an unacceptable way.

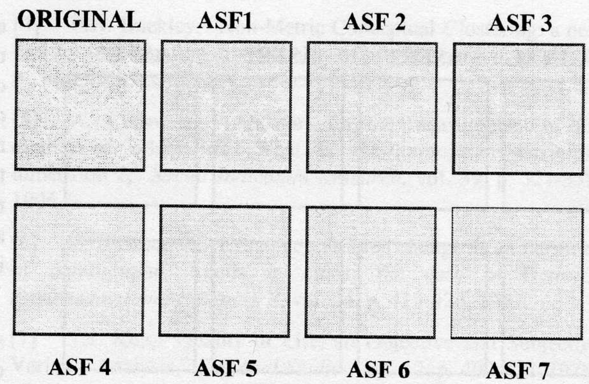

Figure 3. Intermediate results of an alternated sequential filter (ASF) of size 7.

In a previous paper [11] we proposed a method for change detection that retained the idea of using alternated sequential filters but in the reconstruction formalism of mathematical morphology as described in [20]. This framework is based on conditional operations between the processed image and its original version.

The conditional analogues of the dilation are noted :

$$\delta_f(g) = \min(\delta_B(g), f)$$

$$\delta_{f,n}(g) = \delta_f^{\,n}(g) = \delta_f\left(\delta_f \ldots \left(\delta_f(g)\right)\right)$$

where g is a function inferior or equal to f.

A more complex operator like the conditional opening by erosion is obtained by applying sequential conditional dilations over the simple erosion of a function and choosing the maximum of these transformations :

$$\gamma^{rec}\left(f, \varepsilon_B(f)\right) = \max \delta_f^{\,n}\left(\varepsilon_B(f)\right)$$

The dual operation can be obtained by treating the opposite of f with the conditional opening by erosion. The opposite of this result is thus the conditional closing φ^{rec}

The filter implemented in order to sort the changes found in the difference image is the following alternating sequential filter :

$$M_n = \left\{\gamma_i^{rec} \varphi_i^{rec}, 1 \le i \le n\right\}$$

where n is the maximal size of the alternated openings and closings.

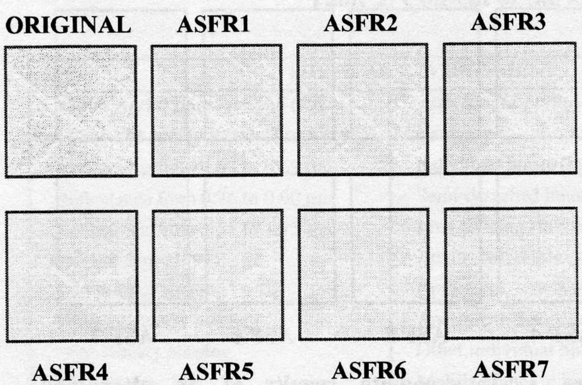

Figure 4. Intermediate results of an alternated sequential filter by reconstruction (ASFR) of size 7.

It is clear after having compared fig. 3 and fig. 4 that the reconstruction approach gives better geometrical results. Together with comparison noise suppression, this morphological technique gives the advantage of unsupervised methods in the sense that the operator only specify a geographical scale of interest corresponding to a structuring element size in order to produce the change masks. An other very interesting use of this morphological method that is currently under investigation is getting "crisper" representations of the results of the multivalued classifications. As seen in fig. 4 it is possible to move from the pixel level of representation to the object level by using morphological filtering for the homogenisation of the image data.

Multiple correspondence analysis

Multiple correspondence analysis [8] is principally used for the analysis of questionnaires and surveys. It holds much similarities with correspondence analysis (a cousin method to principal components analysis) as they are both based on singular value decomposition. Multiple correspondence analysis is based on the analysis of completely disjunctive matrices whereas correspondence analysis is based on contingency tables. Due to space limitations this method will not be described any longer. The reader is invited to consult [8] for further mathematical explanations.

Completely disjunctive matrices are transpositions of contingency tables (as used in correspondence analysis) or quantitative measure tables (as used in principal components analysis) into binary table. For example imagine a contingency table having 34, 108 and 107 kilograms for the variable *weight* for three individuals. Then it is possible, without almost no information loss, to recode the variable *weight* into the two modalities weight_1 and weight_2 and use a binary code to describe the situation of the three individuals. (1, 0) means that individual 1 is in the category 30 to 40 kilograms (for example) and (0, 1) means that individuals 2 and 3 are in the 100 to 110 kilograms category. Table 3 shows the ordinal classification and intervals of modalities for the data contained in the knowledge base. There is no accepted and universal method for this classification of the data and after having tried a lot of semi-automatic methods (equal intervals, quartiles, equal counts, etc.), it appeared that one of the best methods was visual inspection of natural breaks in the frequencies histograms.

Figure 5 shows partial results (for the sake of simplicity) for the multiple correspondence analysis of the census and land-use data contained in the knowledge base. In this example, variable L1 (individual house) is classified into 11 modalities (see tab. 3) and is represented on a separate graph for a better visualisation. It is possible to use this kind of representation of the data in order to discover and understand the spatial patterns involved in the study area. It is clear on fig. 5 that a very strong relationship is a work between the census blocks and the modalities of variable L1.

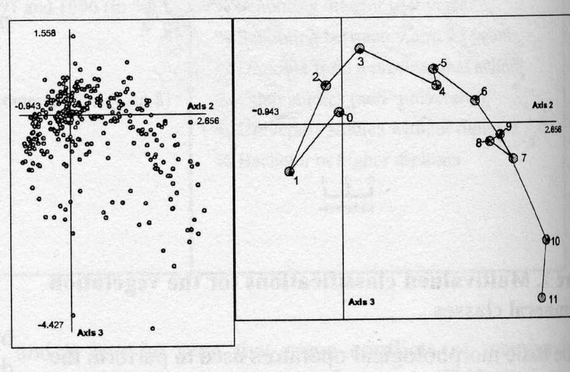

Figure 5. Partial results (axis 2 and 3) of the multiple correspondance analysis on the census blocks of the area under study. For a better visualisation, the factorial positions of the census blocks, on the left side and the variable L1 (Individual house) on the right side have been separated on two distinct graphs. For variable L1, the numbers ranging from 0 to 11 show the factorial coordinates of the 12 modalities this variable was cut into (see table 2).

The binary coding of the data seems very interesting in the prospect of spatial inference and has shown to lead to much richer interpretations compared to correspondence analysis made on a contingency table. Furthermore, it appears of great interest to use this kind of data coding as a common data structure for the entire system since it is possible, to a certain extent, to code the results of the image processing in a binary fashion. In fact [17] proposed binary partition trees that are well suited for this task, and currently under investigation by the authors.

4 Discussion and Conclusions

Much work still has to be done in order to get estimates of the presence of *Ambrosia artemissifolia* populations on the study area. But the different pieces of the system are giving already promising results. Fig. 6 gives an overview of the system in its current state.

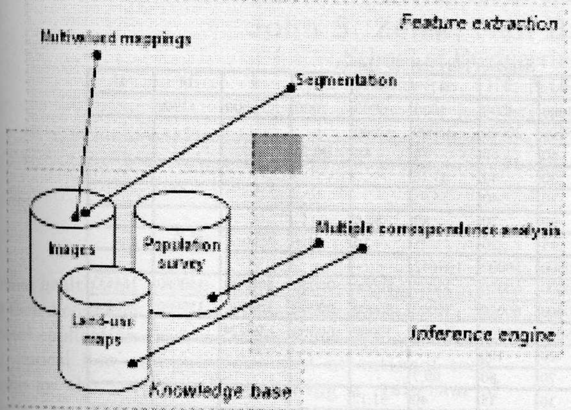

Figure 6. Overview of the system currently under investigation

The weakest part of the system lies in our current inability to find a suitable common data structure for all of the knowledge base, a structure that could greatly improve the quality of inference and data fusion. But as stated in the previous section, a current experiment using binary trees [17] could lead to interesting results.

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Table 3. Ordinal classification of the data contained in the knowledge base. This data preparation is needed for multiple correspondance analysis

				Superior intervals for classes									
	Variable / class	**0***	**1****	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
S1	Population	nd	0	1000	2000	3000	4000	5000	6000	7000	8000	12990	-
S2	Density (inhabitants by km²)	nd	0	5000	10000	15000	20000	25000	42846	-	-	-	-
S3	% Married couples	nd	0	30	40	50	60	70	80	90.55	-	-	-
S4	% Free union couples	nd	0	10	20	30	40	63.16	-	-	-	-	-
S5	% single-parent families	nd	0	10	20	30	40	55.95	-	-	-	-	-
S6	Activity rate	nd	0	40	50	60	70	80	83.6	-	-	-	-
S7	Unemployment rate	nd	0	5	10	15	20	25	30	51.1	-	-	-
S8	Average employment revenue	nd	0	20000	30000	40000	50000	103642	-	-	-	-	-
S9	Average family revenues	nd	0	30000	40000	50000	60000	70000	80000	90000	100000	150000	154633
S10	Average family revenues spouses	nd	0	30000	40000	50000	60000	70000	80000	90000	100000	150000	306116
S11	Average single-parent family revenues	nd	0	15000	20000	25000	30000	40000	50000	60000	96424	-	-
S12	% Schooling inferior to 13 years	nd	0	5	10	20	100	-	-	-	-	-	-
S13	% University studies without diploma	nd	0	50	60	70	80	99.7	-	-	-	-	-
S14	% Bachelor or higher diploma	nd	0	24.8	25	30	35	40	51.12	-	-	-	-
L1	Individual house (in %)	nd	0	10	20	30	40	50	60	70	80	90	100
L2	Semi-detached house (in %)	nd	0	10	20	30	62	-	-	-	-	-	-
L3	Line housing (in %)	nd	0	10	20	30	58.23	-	-	-	-	-	-
L4	Apartment, duplex (in %)	nd	0	10	20	33.09	-	-	-	-	-	-	-
L5	Apartment, less than 5 stories (in %)	nd	0	10	20	30	40	50	60	70	80	100	-
L6	Apartment, 5 stories or more (in %)	nd	0	10	20	30	40	50	60	70	80	90	100
L7	Other individual house (in %)	nd	0	12.03	-	-	-	-	-	-	-	-	-
L8	Mobile home (in %)	nd	0	10	12.09	-	-	-	-	-	-	-	-
L9	Construction before 1946 (in %)	nd	0	10	20	30	40	50	60	70	78.98	-	-
L10	Construction between 1946 and 1960 (in %)	nd	0	10	20	30	40	50	60	70	88.89	-	-
L11	Construction between 1961 and 1970 (in %)	nd		10	20	30	40	50	60	84.05	-	-	-
L12	Construction between 1971 and 1980 (in %)	nd	0	10	20	30	40	50	68.79	-	-	-	-
L13	Construction between 1981 and 1990 (in %)	nd	0	10	20	30	40	50	60	70	84.40	-	-
L14	Construction between 1991 and 1996 (in %)	nd	0	10	20	30	84.44	-	-	-	-	-	-
L15	Average rent (Can $)	nd	0	400	500	600	700	800	900	1000	1844	-	-
L16	Average value of the habitation (Can $)	nd	0	10000	20000	30000	40000	745948	-	-	-	-	-
L17	Average of rooms per accommodation	nd	0	4	5	6	7	8	9.4	-	-	-	-
L18	Percentage of tenants	nd	0	10	20	30	40	50	60	70	80	90	100
O1	Low density housing	nd	0	10	20	30	40	50	60	70	80	100	-
O2	Medium density housing	nd	0	10	20	30	40	50	60	70	80	97.15	-
O3	High density housing	nd	0	10	20	30	40	82.88	-	-	-	-	-
O4	Retail stores	nd	0	10	20	30	46.63	-	-	-	-	-	-
O5	Shopping malls	nd	0	8.98	23.64	-	-	-	-	-	-	-	-
O6	Office buildings	nd	0	8.43	30.08	-	-	-	-	-	-	-	-
O7	Light industry	nd	0	10	20	30	40	50	75.65	-	-	-	-
O8	Heavy industry	nd	0	10	20	51.77	-	-	-	-	-	-	-
O9	Burial sites	nd	0	8.26	-	-	-	-	-	-	-	-	-
O10	Quarries	nd	0	46.86	-	-	-	-	-	-	-	-	-
O11	Collective equipment	nd	0	10	20	30	40	50	80	-	-	-	-
O12	Public utility services	nd	0	10	20	30	40	50	61.80	-	-	-	-
O13	Urban parks	nd	0	10	20	30	60	100	-	-	-	-	-
O14	Regional parks	nd	0	10	20	26.39	65.36	-	-	-	-	-	-
O15	Natural reservations	nd	0	10	14	42.72	-	-	-	-	-	-	-
O16	Golfs	nd	0	10	31.05	-	-	-	-	-	-	-	-
O17	Cemeteries	nd	0	10	50	95.02	-	-	-	-	-	-	-
O18	Rural	nd	0	15	21.87	-	-	-	-	-	-	-	-
O19	Vacant	nd	0	10	20	30	40	55.43	-	-	-	-	-

* Data not available ** Value of 0