Development of a Remote Sensing-Based Method to Map Likelihood of Common Ragweed (*Ambrosia artemisiifolia*) Presence in Urban Areas

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***Abstract*—Common Ragweed (*Ambrosia artemisiifolia*) is a plant that constitutes an important and growing public health concern worldwide as it is probably expanding with climate change, which brings forward the need for improved mapping tools. Our final purpose is to operationalize the use of optical remote sensing for the automated mapping and surveillance of *Ambrosia artemisiifolia*. Analyses considering the probable spectral instability originating from the variability of the urban landscape and from that of sensors characteristics were developed. Worldview 2, Rapid Eye and SPOT 4 HRVIR sensors were used together with geolocalized surveys of Common Ragweed in Montréal and Valleyfield (Quebec, Canada). Images were standardized and various derivatives variables such as multiple vegetation indexes were created. Spectral confusion, statistical analyses, object-oriented technology and Fuzzy-logic functions were used to develop predictive risks maps of Common Ragweed potential presence. The results showed that the green bands (510–590 nm) of higher spatial resolutions sensors had a higher potential to cope with spectral confusions and changing landscape characteristics and to predict the likelihood of *Ambrosia artemisiifolia* presence with a recurrent stability. The good agreement between observed and predicted ragweed revealed an important potential for the operationalization of this method.**

***Index Terms*—Common Ragweed, confusion, fuzzy-logic, habitat, object oriented, operationalization, radiometric spectrum, rapid eye, risk maps, SPOT 4, vegetation, WorldView 2.**

I. Introduction

COMMON Ragweed (*Ambrosia artemisiifolia*) is a native North American species, widely spread in eastern Canada including Quebec [1]. This invasive plant is expanding worldwide; it seems to be abundant between 40 and 50 degrees of north latitude, particularly in Central and Western Europe, China, Japan and Australia [2], [3]. In Quebec, *Ambrosia artemisiifolia* is present from May to September. Its seeding stem and seed leaves are green and are often splotched with purple. Its seed leaves are about 6 mm long, spoon-shaped or nearly round, somewhat thickened. Short whitish hairs cover the leaves and stem (Fig. 1(a)). Its height varies from a habitat to another and from a phenological step to another; it can reach 2 m in some cultivated fields like soy and maize [1]. This plant is characterized by a large ecological amplitude and is highly present in urban and peri-urban areas of Quebec where it usually shares its habitat with other invasive plants [4]. It can be found as urban colonies in non-built areas (Fig. 1(b)), near roads pavements (Fig. 1(c)) and in most open fields like sport fields (Fig. 1(d)). Its development is influenced by a photoperiod and light radiations adapted to a large amplitude of temperatures [5]. Common Ragweed positively responds to the increase of atmospheric CO2 concentrations, and could therefore be favored within a context of climate change [6], with dramatic public health consequences. It has been estimated in 2005 that the pollen of this plant is involved in about 75% of rhinitis cases in Québec, with about \$155 million (CAD) in yearly health costs. Common Ragweed therefore constitutes an important public health concern in Quebec and elsewhere [3], [7]–[9].

Fig. 1. *Ambrosia artemisiifolia* illustration in Montreal. (a) Physical appearance of ragweed's leaves. (b) A colony of Common Ragweed in an non-built field. (c) Common Ragweed on roadsides. (d) Common Ragweed in a sport field. (Source: Direction de la Santé Publique Montréal).

Existing predictive methods of Common Ragweed are mainly based on pollen distribution; they are limited by a number of shortcomings with the most important one being that they do not inform on the location of the pollen as pollen can be transported up to 64 kilometers from its source [10]. Preventing Common

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Ragweed's effects on human health implies developing spatial surveillance and control strategies that could more efficiently help in the reduction of *Ambrosia artemisiifolia* presence and probable spatial extension. Because of its fast and area-wide assessment possibilities remote sensing can be presented as an ideal candidate for this task. An optimized perspective would be to develop remote sensing-based semi-automatic or automatic predictive models.

Since Common Ragweed is native to North America many biological-oriented and ecological-oriented studies have been dedicated to this plant in this geographical area. To date we are not aware of any study that used a variety of multispectral products having different spatial and spectral resolutions and at the same time dedicated to the isolation of the radiometric spectrum of Common Ragweed in North America. Neither are we aware of any project aimed at implementing automatic detection methods of ragweed in North America, based on remote sensing techniques. However, a few studies of the remote sensing of Common Ragweed in urban milieus in general can be found. In Quebec one such study is that of Maupin and Apparicio [11]. Using Landsat data they mixed landscape variables and NDVI together with census data to map potential ragweed presence in Montreal. Maupin and Boivin [12] advocated using hyper spectral sensors in the wavelength between 750 and 875 nm to detect ragweed in Montreal. Other studies dedicated to the remote sensing of Common Ragweed outside Quebec were mostly conducted in rural areas to identify *A. artemisiifolia* among cultivated fields in France [13], [14] and Hungary [15]. Another study using canopy imaging spectrometer techniques to analyze the controlling effect of *Ophraella Communa* on Common Ragweed was realized recently in China [16].

In this study, an assessment of the possibilities of retrieving robust spectral information was conducted as the first step for an improved mapping of the likelihood of Common Ragweed presence in urbanized Quebec. It was based on the analysis of optical multispectral data having various spatial resolutions, as well as presenting important geographical differences in terms of phenological steps and habitats of *Ambrosia artemisiifolia*. The next section presents the data that were used and the methodology that was developed. The methods are sequentially divided into four main parts: images standardization and predictive candidate variables definition and selection, statistical analyses, Object-Based Image Analysis (OBIA) and spectral confusion analysis, and finally Fuzzy logic prediction and mapping. The results section presents the discriminatory power of selected variables, revealing the spectral, spatial and statistical differences as well as likelihoods arising from the three sensors. The last section evaluates and discusses the results in regards with their robustness and use for operationalization.

II. Materials and Methods

A. Three Sensors and Two Study Sites With Georeferenced Surveys of *Ambrosia artemisiifolia*

Samples representing Common Ragweed presence were collected in the Isle of Montreal (898 inhabitants per square kilometer [17]) and Salaberry-de-Valleyfield (397 inhabitants per square kilometer [17]. It should be noted that data were exclusively collected in urban zones and for different purposes. Thus they were not standardized between Montreal and Valleyfield and were showing differences in terms of the techniques and material used as well as information extracted. For example Differential Global Positioning System DGPS (Mobile Mapper CE, Magellan) were used for the campaign in Valleyfield; while a simple metric accuracy GPS was used in Montreal (commercial name not provided). In Montreal the field campaign was conducted from the end of the summer to the beginning of autumn between September 14 and October 15, 2010. Data in Montreal consisted of 292 measured non-differential Global Positioning System (GPS) points relating the in situ presence of ragweed. Additional polygons representing cadastral zones where Common Ragweed was collected and where it was not collected were also available (Fig. 2). For cadastral parcels a level of infestation was measured. An infestation equal to 0 corresponded to the absence of ragweed (Fig. 2(a)). In Montreal 36.5% of the data were collected in non-built grounds, 25.5% in residential zones, 11.8% in Parks, 4.4% in industrial zones, 4.3% in railways right of way. We estimated that 17.5% of the Montreal sample was situated at less than 10 meters from an asphalted road. Additional phytosocial elements were measured: surface area of Common Ragweed colonies, height and sociability.

In Salaberry-de-Valleyfield, a city situated 10 km south of Montreal (and separated from it by the St. Lawrence River), 311 GPS points were measured. They were representing presence (64%) or absence (36%) of ragweed, and were collected in summer between June 23 and July 28, 2009 (Fig. 2(b)). 55% of the points were located in residential zones, 23% in built grounds, 16% in perturbed zones, and 6% in industrial zones. We calculated that 5% of the survey was situated at less than 10 m of a railway line, while 19% of the points were situated at less than 10 m of an asphalted road. The survey of Valleyfield was less informative on phytosocial characteristics of Common Ragweed as it only included the number of Common Ragweed plants in 0.5×0.5 m quadrates.

We used three different optical sensors having various spatial and spectral resolutions. They corresponded to images archives having the closest dates to those of the Common Ragweed field survey collection. For Montreal, a Worldview 2 (WV2) (Fig. 2(a)) and a SPOT 4 High Resolution Visible and Infrared (HRVIR) images were used, respectively of 1.8 m and 20 m spatial resolution [18], [19]. Montreal images were both taken on September 1, 2010. This period corresponds to the maturity stage of *Ambrosia artemisiifolia*. For Valleyfield, a Rapid Eye image taken on June 24, 2009 (Fig. 3) was used, with a spatial resolution of 5 m [20]. This corresponded to a summer period with probably dryer conditions than that when the images on Montreal were taken. At this earlier period, *Ambrosia artemisiifolia* is still growing.

The consideration of various types of sensors with differences in their spectral and spatial characteristics was motivated by two important fundamental aspects: firstly, a perspective consisting on the integration of relatively new optical wave lengths in urban vegetation analysis as characterized by the Red edge (705–745 nm) and the Near Infrared 2 (860–1040 nm) bands of

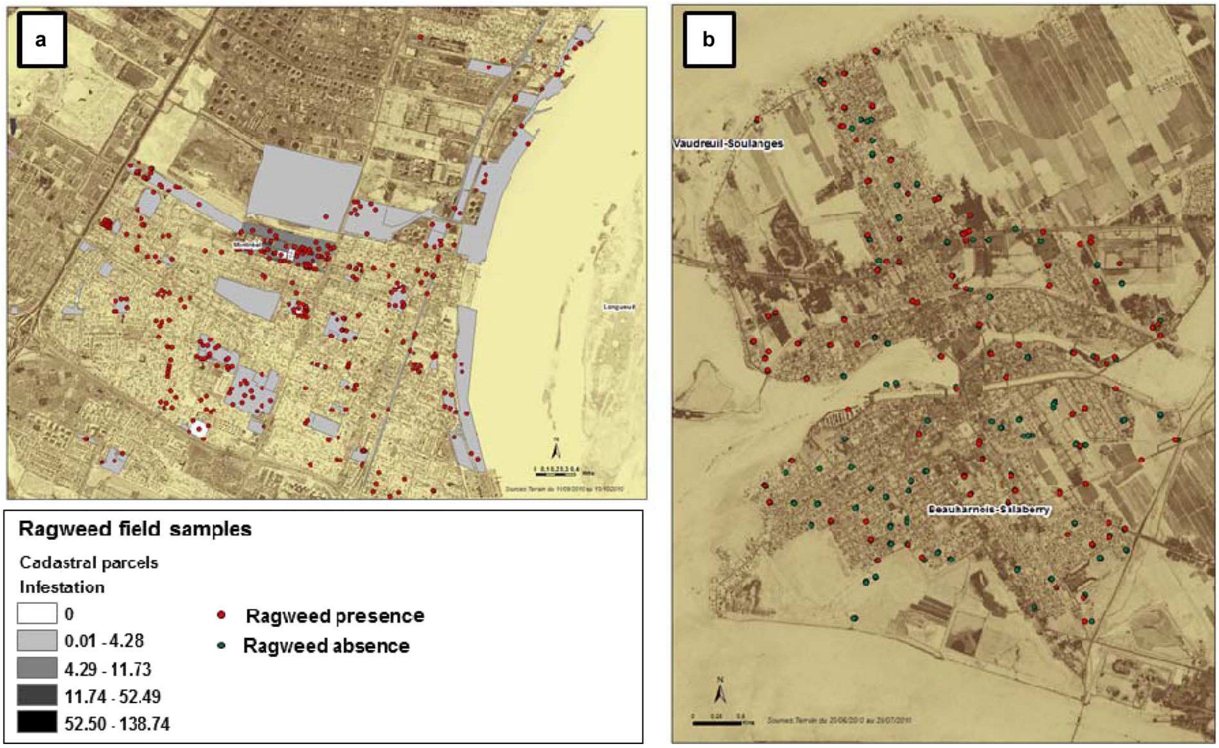

Fig. 2. (a) Common Ragweed field data sample of Montreal layered on a Worldview 2 image. (b) Field data sample of Valleyfield layered on a Rapid Eye image.

Fig. 3. Segmentation and classification of Worldview 2 images of Montréal.

WV2 and, secondly, the impact of spatial resolutions on the accuracy of the predictive maps. Those two aspects are transversal with the ultimate objective being the identification of the most robust Common Ragweed spectral conditions for operationalization purposes. The perspective of an operationalization of the predictive method required consideration of resources optimization, hence the need to consider various types and costs of optical remote sensing products.

In order to reduce GPS measurements errors all the GPS points in the surveys (not only Common Ragweed) not visually (zooming process on maps) corresponding to vegetation in the multilayers maps (Figs. 2 and 3) were deleted before further analyses. It implied that plants or plants colonies for which the surface was lower than the spatial resolution of the imagery were excluded. It was not possible to consider individual isolated ragweed plants, for instance.

B. Radiometric Standardization of the Images and Creation of New Variables

One of the main challenges of this study was to obtain robust stable and reproducible information which can be extrapolated. An important step was to render data from various sensors comparable by applying a radiometric standardization. Images were orthocorrected prior to any further exploitation. The image-based COST method of Chavez [21] was used for the radiometric atmospheric corrections. Uncertainties arising from the atmospheric transformation process were assessed through the correlation values between original images DN values and their transformed reflectance values.

Vegetation indexes (VIs) combine bands that are classically dedicated to the study of vegetation in new variables that could better express the greenness/wetness of the studied area. VIs effectively express a variation in the photosynthetic activity of plants. Therefore, they were considered as derivative variables that could help better describe the photosynthetic activity of ragweed as well as discriminate between Common Ragweed and other plants. Red and Near-IR bands are traditionally used as key bands in the calculation of VIs. The availability of Red edge bands in WV2 and Rapid Eye and that of Near-IR 2 band in WV2 allowed the calculation of additional VIs using those new bands. Some of the VIs are better adapted to urban areas [22]. In effect, in highly urbanized areas such as Montreal and Valleyfield, the probability of spectral confusion is high. In order to consider this probability of spectral confusion, a set of VIs integrating soil adjustments factors [23] as a key variable were calculated together with classical VIs (Table I). Soil profiles were calculated by integrating the intercept and the slope of the background soil line obtained by performing a simple linear regres-

TABLE I
LIST OF CALCULATED VEGETATION INDEXES

Vegetation index	Definition	Independent variable in the soil profile calculation	Applied to
NDVI	Normalized Difference Vegetation Index		WV2, Rapid Eye, SPOT 4
TVI	Transformed vegetation Index		WV2, Rapid Eye, SPOT 4
TTVI	Thiam's Transformed Vegetation Index		WV2, Rapid Eye, SPOT 4
Ratio	Ratio		WV2, Rapid Eye
MSAVI1	Modified Soil-Adjusted vegetation Index 1		WV2, Rapid Eye
MSAVI 2	Modified Soil-Adjusted vegetation Index 2		WV2, Rapid Eye
TSAVI1	Transformed soil Adjusted vegetation Index 1	Red, Red edge	WV2, Rapid Eye
TSAVI2	Transformed soil Adjusted vegetation Index 2	Red, Red edge	WV2, Rapid Eye
RVI	Ratio Vegetation Index		WV2, Rapid Eye, SPOT 4
NRVI	Normalized Ratio Vegetation Index		WV2, Rapid Eye, SPOT 4
PVI	Perpendicular Vegetation Index	NEAR-IR 1 et 2	WV2, Rapid Eye
PVI1	Perpendicular Vegetation Index1	NEAR-IR 1 et 2	WV2, Rapid Eye
PVI2	Perpendicular Vegetation Index2	Red, Red edge	WV2, Rapid Eye
PVI3	Perpendicular Vegetation Index3	Red, Red edge	WV2, Rapid Eye
DVI	Difference Vegetation Index		WV2, Rapid Eye
WDVI	Weighed Difference Vegetation Index	NEAR-IR 1 et 2	WV2, Rapid Eye
CTVI	Corrected Transformed Vegetation Index		WV2, Rapid Eye, SPOT 4
AVI	Ashburn Vegetation Index		WV2, Rapid Eye
SAVI	Soil Adjusted vegetation Index		WV2, Rapid Eye

sion on bare soil pixels in the red and infrared bands. This regression was run on a sample set of bare soil pixels. Formulas and more details on the calculation of each VI are provided in Appendix A.

Additional variables were created by applying standardized and non-standardized Principal Component Analysis (PCA) to each of the products (WV2, Rapid Eye and SPOT 4). From original bands, PCA produces new images that are decorrelated between them. The first three images components generally express 95% to 99% of the variance of original bands. They can help to distinguish between very dry, very humid and relatively humid objects. PCA analyses have been shown to have special application in environmental monitoring [24], [25]. In doing PCA analysis of the images, the objective was to use decorrelated images as basis for the discrimination of *A. artemisiifolia*.

C. Discrimination and Prediction of Common Ragweed

1) Object Oriented Classification of Vegetation: In discriminating between Common Ragweed and other plants, a fundamental step was to discriminate between vegetation and other landscapes. This was done by running classifications. For WV2 and Rapid Eye data an object oriented segmentation [26] integrating the original bands as input was run under eCognition Developers (Trimble). A shape factor of 0.4 and a compactness of 0.9 gave satisfactory results for both WV2 and Rapid Eye, but their scale parameters were respectively of 10 and 30. A sampling process identifying impervious surfaces, water bodies, dense and less dense vegetation cover was made, followed by a Nearest Neighbour supervised classification. Because of the higher spatial resolution of SPOT 4 data, pixel based classifications were better adapted. Maximum likelihood methods were used to classify the SPOT 4 imagery. OBIA allows a higher extraction capacity of real world objects with a higher accuracy, in both their shape and semantic representation [26] (Fig. 3). It implied that segmented and classified objects representing vegetation could be advantageously used to sample Common Ragweed presence.

2) Ragweed Sampling and Spectral Confusion Analyses: Ragweed GPS sample points were transformed into buffers of 30 meters and integrated within eCognition Developers in order to obtain new samples of Common Ragweed presence according to the segmented and classified images of WV2 and Rapid Eye. Buffers were only used for visualization purposes (to better visualize the location of Common Ragweed surveys). The centers of the buffers representing geolocalized Common Ragweed (on the field) were used to identify classified vegetation objects, potentially considered as being ragweed. Thus an object was definitively sampled as ragweed if it was previously classified as vegetation. In addition, it was visually possible to validate the class attribution of sampled objects (Fig. 4).

At the end of the sampling process in eCognition (Trimble), it was possible to have visual and quantitative elements describing the level of overlap between sampled Common Ragweed and the other vegetation samples according to the various input variables, including original bands, vegetation indexes and derivatives from PCA analysis. Additionally, endmember and separability analyses using divergence and transformed divergence [27] of the created samples were run in order to evaluate the

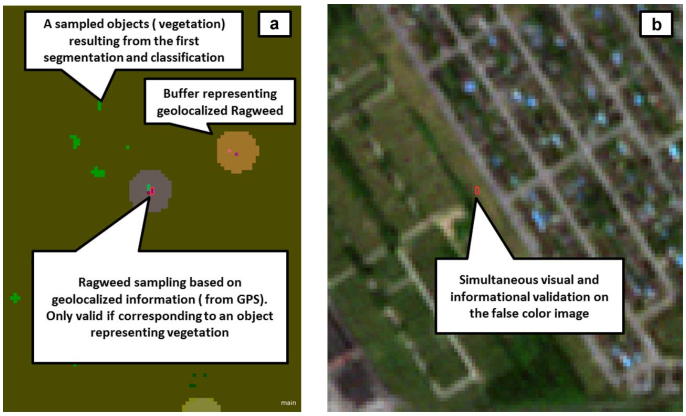

Fig. 4. Visual-based sampling process of Common Ragweed using an object-oriented classification. (a) Ragweed's GPS samples transformed into radial buffers and layered on an object-based classified image. (b) Simultaneous visual control of samples on a false color and segmented images.

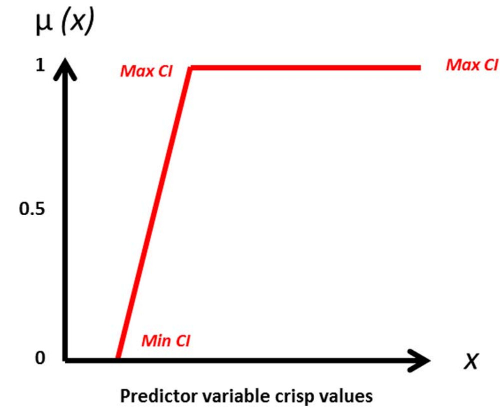

Fig. 5. Monotonically increasing linear membership function.

degree of confusion between Common Ragweed and the other types of objects (vegetation, nude soil, impervious and water) on one side, and also to obtain elements that could indicate ecological differences between Montreal and Valleyfield. It was assumed that those ecological differences could impact on the stability of the final radiometric spectrum of ragweed.

3) Statistical Analysis of the Spectral Stability of Predictors: GPS points were used to extract the values of previously created variables (Corrected bands, VIs and PCA), using ArcGIS 10 (ESRI). The resulting tables were then introduced within Stata (Stata Corp.) in order to run simple Spearman rank correlation analyses at 95% of confidence intervals. This process allowed identifying and selecting the predictors that were significantly associated with the presence of ragweed.

A statistical assessment of the capacity of selected predictors (from the sampling process in eCognition Developer and from Spearman correlations) to predict Common Ragweed presence with a higher stability (i.e., in various geographical conditions and for various types of remote sensing images characteristics) was made through analysis of variances and means. Variance and mean values of selected predictors when Common Ragweed is present (in the GPS samples) were calculated for the various habitats described in Section II.D.1. Median values for obtained variances were then calculated for each of the selected predictor. Student tests were run to assess statistical differences of the means of selected variables between Montreal and Valleyfield on one side, and between the various ecological habitats on the other side. Additional Spearman correlations were conducted with the objective to characterize the statistical relationships between collected phytosocial information and variables created from remote sensing products (bands, VIs). The objective was to analyze the spectral variations of Common Ragweed in various habitats and phenological steps, in regards with variables such as ragweed density, height and sociability.

This step was central in the sense that it helped providing some answers to important hypothesis on the spectral characteristics of ragweed, their stability and the possibilities to use them for operationalization. The first hypothesis was related with the necessity to consider the geographical variation of the studied sites, the second one was related with the possibility for one or several of the predictors to be used as potential and unique key element (to simplify the system) in the perspective of automating the predictive method.

4) Fuzzy Logic Prediction of Ragweed: The fuzzy logic theory deals with the concepts of uncertainty. One of the challenging difficulties in predicting the presence of ragweed is to decrypt, with an acceptable precision, the ecological conditions favouring its presence among other plants. The fact that Common Ragweed probably shares those conditions with other invasive plants [4] renders this process somewhat uncertain. The strength of fuzzy logic is precisely found in the measurement of uncertainty related with the identification of Common Ragweed [28], [29]. A fundamental element in designing fuzzy sets is Fuzzy membership. In eCognition, fuzzy membership functions automatically designed from the samples are available but there also exist possibilities to design an original membership function that better expresses the logic of the variables to be fuzzified and defuzzified. Sampling *A. artemisiifolia* in eCognition allowed running automatic classifications using those samples (see Section II.D.2). However, those automatic functions still produced a very high level of overlap with vegetation samples. In order to improve the accuracy of the separation between Common Ragweed and vegetation various memberships and fuzzy rules designs were tested and evaluated including Gaussian and Sigmoidal membership's functions. Finally, and because they were producing the most satisfactory results, a monotonically linear increasing membership function was selected and used to predict ragweed's presence for the selected variables (i.e. same function for all the variables). Crisps measurements (input values) of the functions were provided by the calculation of confidence intervals of predictive variables from Common Ragweed presences in GPS surveys (95%). Explicitly, the tables obtained from the spatial extractions process (predictors to GPS points) described in Section II.D.3 were used to calculate confidence intervals values for all the selected predictors, when Common Ragweed was described as being present. A monotonically increasing fuzzy logic function was precisely adapted to the positive correlation of Common Ragweed with input variables. It simply implied that the higher the crisp value indicating Common Ragweed presence was, the higher was the output value (between 0, and 1) (Fig. 5).

TABLE II
CORRELATIONS OF COMMON RAGWEED NDVI VALUES AND PHYTOSOCIAL VARIABLES

Variables	Coefficient of correlation	P value
Surface area of Common Ragweed colonies*	-0.18	0.01
Height	-0.10	0.16
Sociability*	-0.17	0.01
Number of Common Ragweed plants (for Valleyfield)	-0.01	0.90

*Significant at 95% confidence intervals.

The mathematical formulation of this function was designed as follows:

$$\mu(x) = \begin{cases} 0 \text{ if } x < \mathrm{minCI} \\ \text{otherwise } (x - \mathrm{minCI})/(\mathrm{maxCI} - \mathrm{minCI}) \end{cases} \quad (1)$$

where μ is the fuzzy possibility value for crisp measurement x of a given grid cell of a particular predictive variable, maxCI represents the maximum value (of the confidence intervals/control points) when Common Ragweed is present, minCI represents the minimum value (of the confidence intervals/control points) when Common Ragweed is present.

5) Models Validation: A proportion of 20% of the Common Ragweed GPS samples was reserved for the performance tests of predictions (tests data). Sensitivity and specificity analysis were conducted. Sensitivity measures the proportion of true positives which are correctly identified. Specificity measures the proportion of true negatives which are correctly identified.

Additional Kappa Index of Agreement (KIA) and expected agreement between the observed and predicted presence of Common Ragweed were calculated for selected predictors and various types of habitats. Predictive values were obtained by making spatial extractions on fuzzy maps, using ArcGIS 10 (ESRI). For polygon data type representing cadastral zones where Common Ragweed was surveyed in Montreal predicted fuzzy maps were used to calculate a mean value of infestation proportional to the surfaces of the polygons. Observed and predicted polygons infestations were then used to calculate sensitivity and specificity.

III. RESULTS

A. Conditions of a Stressed Plant With Spectral Confusion

The manual sampling of Common Ragweed reflectance trough object oriented segmentation and nearest neighbour classification resulted in a higher degree of confusion between Common Ragweed samples and less dense vegetation cover samples. The lowest degree of overlap (0.12) was revealed by the red band of Rapid Eye (630–685 nm) followed by the Near-IR band 1 of WV2 (770–895 nm) (0.15). The Near-IR band of Rapid Eye (760–860 nm), the Red edge band of WV2 (705–745 nm) and the Weighed Difference Vegetation Index from WV2 showed an equal capacity of discrimination between Common Ragweed and less dense vegetation covers (0.17).

Student tests showed a statistically significant (at 95% of confidence intervals) difference between the mean NDVI value of Common Ragweed survey in Valleyfield (0.39) and that in Montreal (0.46) (with unilateral $= 0$, bilateral $= 0.0001$, $\mathrm{t} = -4.11$ degrees of freedom $= 79$). Despite this difference, Common Ragweed NDVI values equally draw negative correlations with phytosocial variables (Table II). In effect, a classical vegetation index such as NDVI systematically showed a negative relationship with the presence of Common Ragweed for all the sensors as indicated by statistical correlations analysis (Table III). However the correlation of ragweed presence (surface area) and sociability index was positive and significant ($\mathrm{r} = 0.7$ and P value $= 0$).

Ragweed's NDVI mean value of residential areas in the survey of Valleyfield (0.42) was statistically significantly equal to that of Montreal (0.43) (with $\mathrm{t} = -0.9595$. $\Pr(|\mathrm{T}| > |\mathrm{t}|) = 0.3395$ and degrees of freedom $= 107$). In Montreal the highest ragweed's NDVI mean values were found in parks (0.49) and near railroads (0.48). The lowest values were found in industrial (0.42) and residential areas (Fig. 6(a)). In Valleyfield the highest ragweed's NDVI mean values were found in residential areas (0.42) and built grounds (0.40). The lowest values were found in perturbed (0.34) and industrial areas (0.34) (Fig. 6(b)). This variability of the NDVI values was symmetric to that of the NIR in Montreal (Fig. 7). In Valleyfield NDVI and NIR mean values are only symmetric in residential and built grounds (Fig. 6(b)).

Endmember and separability analyses revealed a very low divergence between Common Ragweed and vegetation samples and between Common Ragweed and impervious samples in Valleyfield (Fig. 8(a)). In Montreal the divergence was low between Common Ragweed and vegetation samples, and between Common Ragweed and nude soil samples (Fig. 8(b)). The separability indices of common ragweed were overall lower in Montreal than in Valleyfield (Fig. 7).

B. A Higher Discrimination Potential for the Green Band

Among predictors' candidates the green bands (500–590 nm) showed an important potential to predict Common Ragweed with highest confidence. This was based on the results of the analysis of variances and on the resulting agreement between observed and predicted ragweed for all sensors. Analysis of variances showed a higher stability of the green band when considering various types of habitats (Fig. 8). However, the overall mean reflectance value of Common Ragweed survey sample in the green band of WV2 (0.06) was significantly inferior to that of rapid Eye (0.03) at 95% of Confidence intervals (with $\mathrm{t} = -22.2$; $\Pr(\mathrm{T} < \mathrm{t}) = 0.00$; degrees of freedom $= 185$).

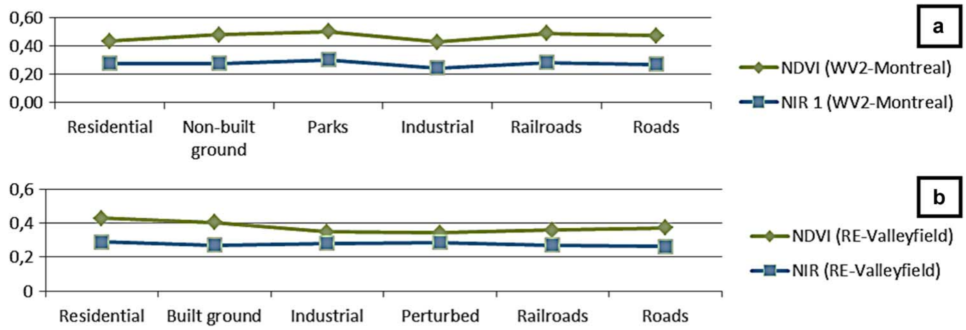

Fig. 6. Mean NDVI and spectral values of Common Ragweed in Near infrared Channels (760–895 nm) for various habitats; (a) in Montreal; (b) in Valleyfield.

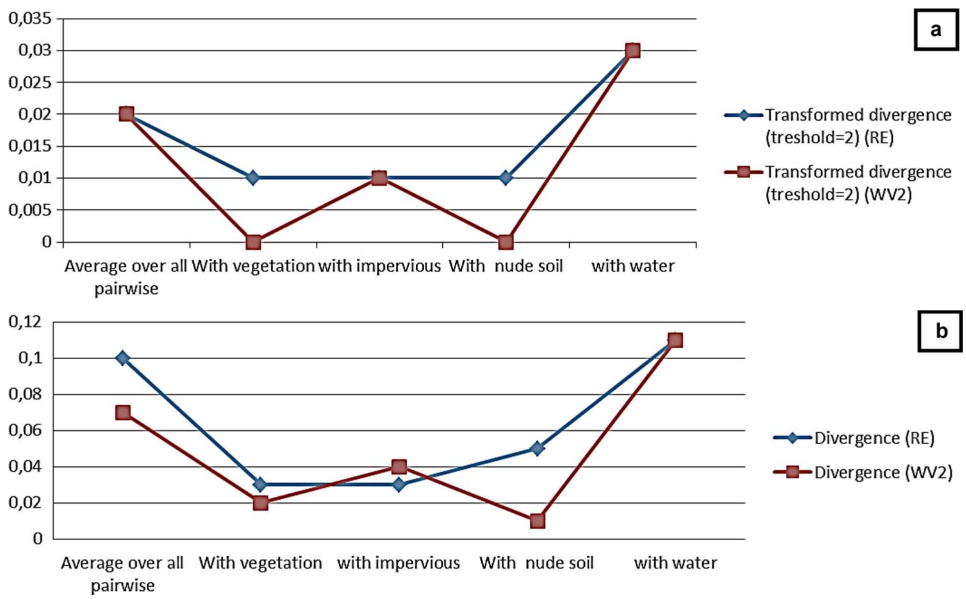

Fig. 7. Transformed divergence (a) and divergence (a), (b) for spectral samples from Rapid Eye and Worldview 2.

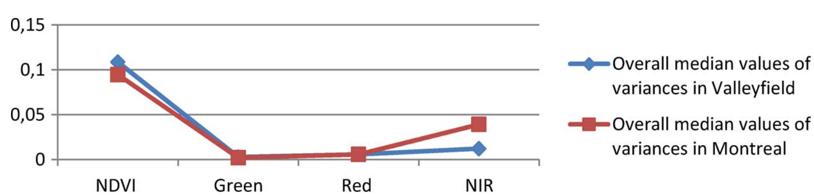

Fig. 8. Overall median variances values of common ragweed through various habitats for selected predictive variables for Worldview 2 in Montreal and rapid eye in Valleyfield.

Results from statistical and Fuzzy-logic analysis showed a consistent potential of the green bands to discriminate between Common Ragweed and other features. In effect, regardless of the sensor type the green bands consistently showed correctly predicted values superior to 50% (Table IV). Another variable that showed an interesting potential to discriminate between Common Ragweed and other features is the component 3 of WV2 with up to 70% of sensitivity and 96% of specificity (Table IV).

Results of student's tests comparing the overall mean value of Common Ragweed in the green band of WV2 with each of the value of various habitats revealed significant equalities at 95% of confidence intervals. The same analysis made with the green band of Rapid Eye showed that the overall mean value (0.06) of Common Ragweed in the green band was significantly superior (at 95% of confidence intervals) to those in built areas ($\mathrm{t} = -2.08$; $\Pr(\mathrm{T} < \mathrm{t}) = 0.02$; degrees of freedom $= 43$) and significantly inferior to those in perturbed areas ($\mathrm{t} = 3.79$; $\Pr(\mathrm{T} > \mathrm{t}) = 0.00$; degrees of freedom $= 29$). It was significantly equal to those of industrial, railroads and roads areas.

At the opposite of the green bands there was a higher proximity for the spectral values of Common Ragweed between Wv2 and Rapid Eye in the infrared channels (Fig. 9). But those channels revealed a higher instability than the green bands when statistically comparing Common Ragweed spectral values of various habitats (Fig. 8). The infrared bands also

TABLE III
STATISTICALLY SIGNIFICANT CORRELATIONS OF COMMON RAGWEED WITH VARIABLES FROM THE THREE SENSORS (WORLDVIEW 2, RAPID EYE, SPOT 4 HRVI)

Variables	Description	Coefficient of correlation	P value
Band 1(WV2)		0.3	0.00
Band 2(WV2)		0.34	0.00
Band 3(WV2)		0.3	0.00
Band 4(WV2)		0.33	0.00
Band 5(WV2)		0.32	0.00
NDVI (WV2)	Red & NIR 1	-0.18	0.009
NDVI (WV2)	Red & NIR 2	-0.29	0.00
NDVI (WV2)	Red edge et NIR 2	-0.17	0.01
CTVI (WV2)	Red & NIR 1	-0.18	0.09
CTVI (WV2)	Red edge & PIR 1	-0.33	0.00
DVI (WV2)	Red & NIR 2	-0.22	0.00
DVI (WV2)	Red edge & NIR 2	-0.22	0.00
MSAVI 2 (WV2)	Red & NIR 1	-0.14	0.04
MSAVI 2 (WV2)	Red edge & NIR 2	-0.17	0.01
NRVI (WV2)	Red & NIR 1	0.18	0.00
NRVI (WV2)	Red edge & NIR 2	0.17	0.01
PVI (WV2)	Red & NIR 1	-0.22	0.00
PVI (WV2)	Red edge & NIR 2	-0.27	0.00
PVI1 (WV2)	Red edge & NIR 1	-0.22	0.00
PVI1 (WV2)	Red edge & NIR 1	-0.22	0.00
Ratio (WV2)	Red & NIR 1	-0.18	0.00
RVI (WV2)	Red & NIR 1	0.18	0.00
RVI (WV2)	Red edge & NIR 2	0.17	0.01
TSAVI 2 (WV2)	Red edge & NIR 1	-0.17	0.01
TTVI (WV2)	Red & NIR 1	-0.18	0.00
TTVI (WV2)	Red edge & NIR 2	-0.17	0.01
TVI (WV2)	Red & NIR 1	-0.18	0.09
TVI (WV2)	Red edge & NIR 2	-0.17	0.01
WDVI (WV2)	Red edge & NIR 1	-0.19	0.00
WDVI (WV2)	Red edge & NIR 2	-0.15	0.02
PCA 3 (WV2)	Principal Component Analysis	0.37	0
STD PCA 1 (WV2)	Standardized Principal Component Analysis	0.21	0.00
Std PCA 3 (WV2)	Standardized Principal Component Analysis	0.34	0
Band 2(RE)		0.17	0.01
PCA 1 (RE)	Principal Component Analysis	0.15	0.03
Band 1 (SPOT 4)		0.24	0
Band 2(SPOT 4)		0.24	0
NDVI (SPOT 4)	Normalized Difference Vegetation Index	-0.11	0.04
NRVI (SPOT 4)	Normalized Ratio Vegetation Index	0.11	0.04
CTVI (SPOT 4)	Corrected Transformed Vegetation Index	-0.11	0.04
RVI (SPOT 4)	Ratio Vegetation Index	0.11	0.04
TTVI (SPOT 4)	Thiam's Transformed. Vegetation Index	-0.11	0.04
PCA 1 (SPOT 4)	Principal Component Analysis	0.32	0.00

showed a poorer and less consistent statistical association with ragweed reflectance values.

When visually analyzing the resulting predictive maps of Common Ragweed potential presence in Montréal (Fig. 10(a)), one can note that the risk is less present in residential areas than in the other areas. This is confirmed by the KIA analysis of the prediction per habitat (Fig. 11(a)). The risk is also remarkably well predicted near railroads as testified by the higher agreement index (87.5%) (Fig. 11(a)). The same index revealed a low agreement of Common Ragweed presence near roads in Montreal which is not the case for Valleyfield (Fig. 11(a) and 11(b)). In Valleyfield, predicted Common Ragweed presence risk is also remarkably high by paved roads shoulders and in the borders of plots within agricultural fields. In effect, the predicted presence risk is not systematic within agricultural fields; the infestation is visually more present in residential zones than in agricultural fields (Fig. 10(b)). This visual analysis is in line with the results obtained from the

TABLE IV
CORRECT PREDICTIONS OF VARIABLES STATISTICALLY SIGNIFICANTLY CORRELATED WITH THE PRESENCE OF COMMON RAGWEED. LEGEND: * FOR ABSENCE AND PRESENCE OBSERVATIONS ONLY VARIABLES THAT SHOWED A SENSITIVITY AND SPECIFICITY HIGHER THAN OR EQUAL TO 50% ARE REPRESENTED; KAPPA INDEX OF AGREEMENT WAS CALCULATED ONLY FOR VARIABLES THAT SHOWED RECURRENT SENSITIVITY AND SPECIFICITY VALUES HIGHER THAN 50% FOR AT LEAST TWO OF THE THREE SENSORS (WORLDVIEW2. RAPID EYE AND SPOT4); ** FROM FUZZY-LOGIC ANALYSIS OUTCOME THRESHOLD OUTCOME VARY FROM 0 TO 1

Geographic objects for analysis	Polygons (infested and non-infested cadastral surveys)				Points (ragweed presence only)		Points (ragweed presence and absence)				
Measures of agreement*	Sensitivity		Specificity		Presence correctly predicted	KIA	Sensitivity		Specificity		KIA
Positive outcome threshold**	0.1	0.5	0.1	0.5			0.1	0.5	0.1	0.5	
Variables											
PCA 3 (WV2 Montréal)		70%		96%	67%						
PCA 1 (RE-Valleyfield)							58%	54%	68%	82%	54%
Standardized PCA 1 (WV2 Montréal)					60%						
band 3 (green) (WV2 Montréal)		61%		52%	57%	57%					
band 2 (green) (RE-Valleyfield)							61%	56%	70%	95%	55%
Band 1 (green) (SPOT 4-Montreal)	59%	69%	58%	86%	50%	57%					
TSAVI 1 (WV2 Montréal)					88%						
Band 4 (Yellow) (WV2 Montréal)					51%						
NRVI (SPOT 4-Montreal)					58%						

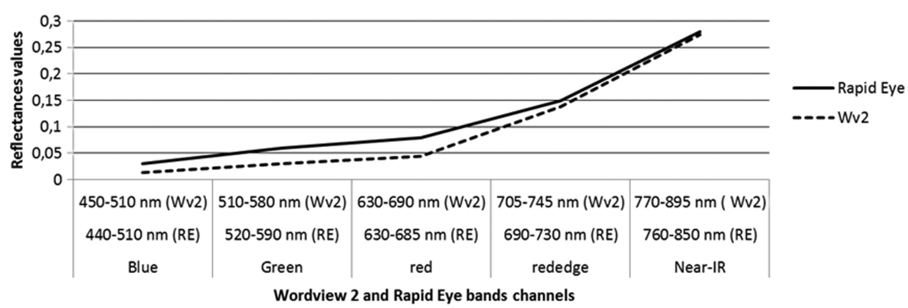

Fig. 9. Mean reflectance values of *A. artemisiifolia* from Worldview 2 imagery of Montreal and from rapid eye imagery of Valleyfield.

KIA (Fig. 11(b)). The predictive Common Ragweed presence risk map from SPOT 4 imagery of Montréal did not allow identification of Common Ragweed by roads shoulders. This map also showed a lower outcome level of potential presence than those obtained from WV2 and Rapid Eye (Fig. 10(c)).

IV. DISCUSSION

A. High Spectral Confusion in Varying Geographic Conditions

This study revealed the difficulty to isolate and standardize a radiometric spectrum for ragweed particularly in urban settings. Whatever the difference in spatial resolution between WV2 and Rapid Eye, the spectral confusion remains high between Common Ragweed and surrounding objects as testified by the endmember and separability analyses. This confusion will vary from a habitat to another and from a season to another. The higher overall NDVI values in Montreal suggest the influence of moisturized conditions of the nude soil. The lowest NDVI values in Valleyfield suggest the influence of the season (June) that favors less moisturized conditions, but also that of the Common Ragweed survey in which the residential habitat was represented in majority (55%). This probably explains the higher spectral confusion with impervious surfaces.

Despite the varying conditions of NDVI in habitats and seasons. Common Ragweed was overall characterized by its proximity with variables describing stressed conditions and this could be partly due to the spectral confusion favored by the less dense cover status of Common Ragweed. This

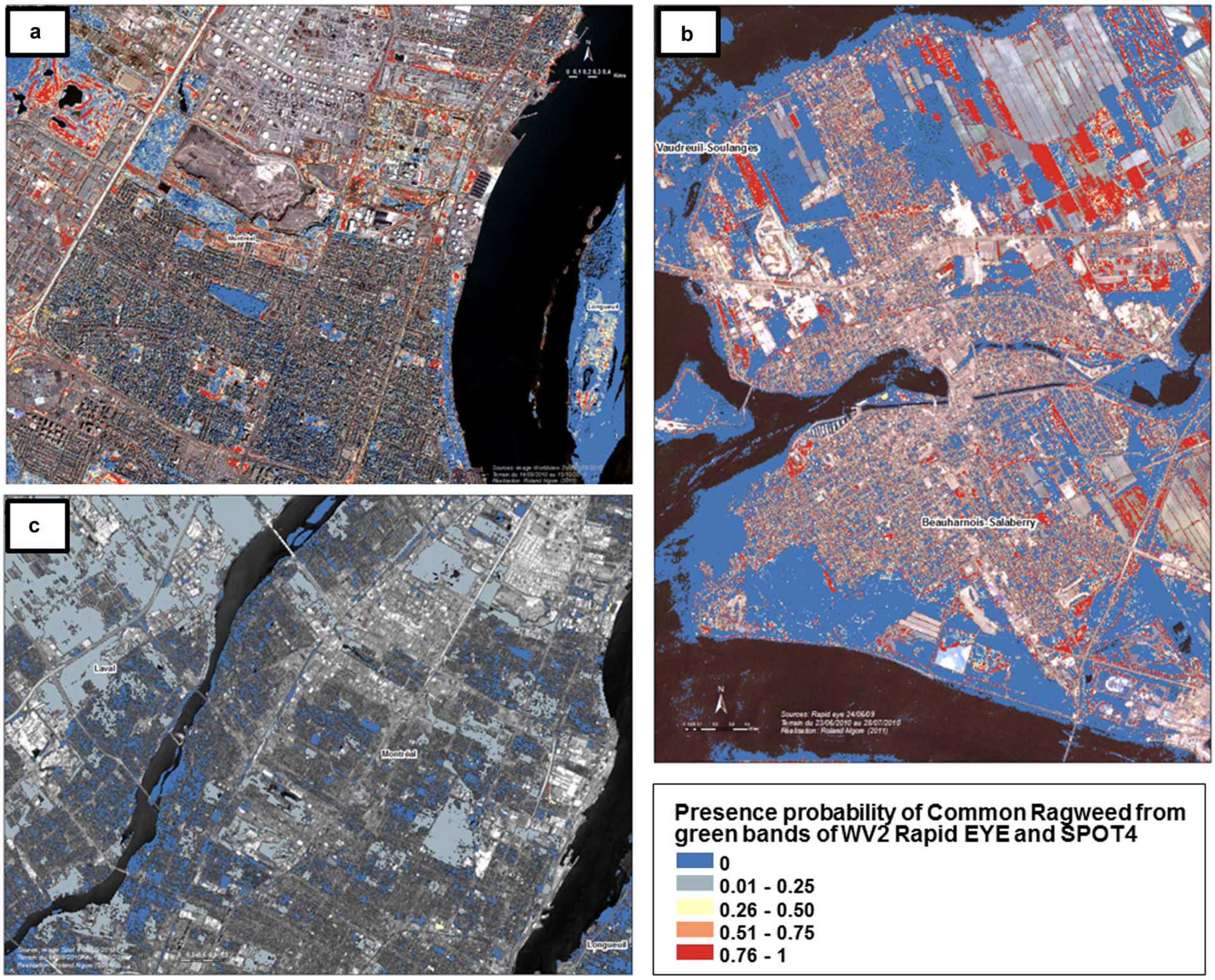

Fig. 10. Predictive maps of *A. artemisiifolia*: (a) from the green band of Worldview 2 imagery of Montréal; (b) from the green band of Rapid Eye imagery of Salaberry-de-Valleyfield; (c) From the green band of SPOT 4 imagery of Montreal.

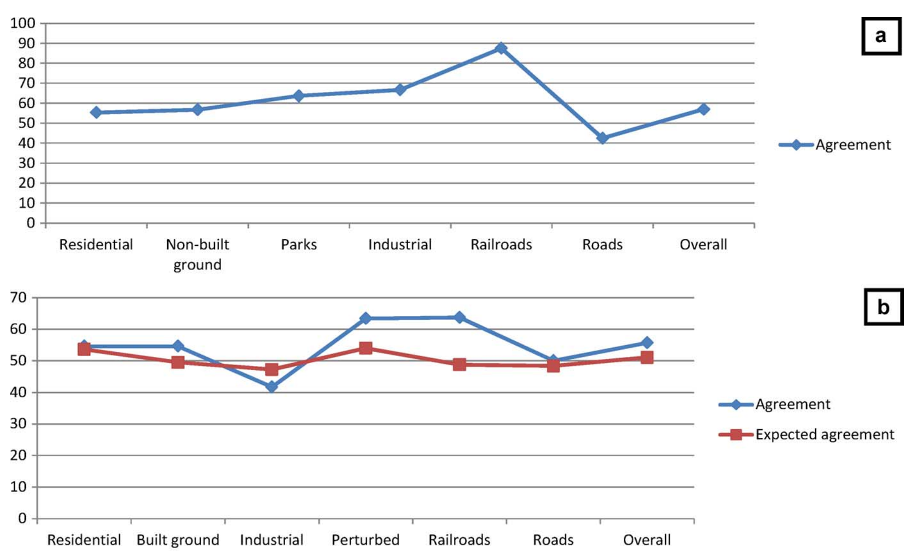

Fig. 11. Kappa index of agreement between observed and predicted common ragweed for various habitat: (a) in Montreal; (b) in Valleyfield.

conclusion is in line with that of Maupin and Apparicio [11]. In studying the correlations between Common Ragweed and multiples variables in Montréal, those authors concluded that the correlation between Common Ragweed and NDVI was not important. This implies that in using optical remote sensing for Common Ragweed detection one must accommodate with the high probability of spectral confusion. It also implies that the spectral channels that are generally sensitive to the presence of vegetation such as the NIR (760–860 nm) are somewhat disqualified as ideal candidates for a robust prediction of Common Ragweed likelihood trough optical remote sensing. This last statement is at least sustained by the statistical instability that characterized the analysis of relationships between Common Ragweed presence and NIR channels in this study notably the degree of variability of Common Ragweed spectral values in various habitats. It also does not agree with the conclusions of Maupin and Boivin [12]. After studying Common Ragweed radiometric characteristics in Montréal, those authors recommended using wavelengths between 750 and 875 nm to identify ragweed. Moreover, these statistical results are not in line with the conclusions of Hongmu and his colleagues. In studying the effect of *O. Communa* on the control of *Ambrosia artemisiifolia* in agricultural fields with multispectral radiometer, they concluded that the canopy reflectance of Common Ragweed decreased with the increasing damage level of *O. Communa* at 710 to 810 nm within the NIR light region [16].

The importance of the green bands in statistical analysis and its higher stability in predicting the likelihood presence of Common Ragweed can be associated with the landscape complexity of the studied areas and the resulting spectral confusion. The importance of the association between the green band and Common Ragweed was also revealed by the study of Hongmu and his colleagues [16]. They concluded that the canopy reflectance of Common Ragweed decreased with the increasing damage level of *O. Communa* at 560 nm within the green light region. The canopy spectrum reflectance at the green light region of 560 nm was significantly negatively correlated with the damage level of *O. Communa* [16]. This conclusion validates the hypothesis that a spectral proximity between Common Ragweed in urban settings and Common Ragweed in agricultural settings exists within the green band (500–590 nm). This conclusion is sustained by the results of Nádor *et al.* [14] and Simard and Benoit [7] in rural settings. The response curve of Common Ragweed in Montreal (WV2) is very similar to that of the study conducted by Nádor *et al.* [15] in rural cultivated fields in Hungary and also using WV2 imagery. Their response curve also showed pikes in infrared channels. However, at the opposite of the present study their inquiries revealed the importance of the Yellow band (585–625 nm). Simard and Benoit [7] studied the distribution of Common Ragweed in the rural areas of Valleyfield; they concluded that the density of Common Ragweed was higher by paved roads than by cultivated fields and inside the fields themselves. Their study was conducted at the same period of the present one (summer 2009).

Compared to a variable such as PCA which also showed an interesting ability to predict Common Ragweed presence, the green band offers a higher stability. In fact, if it is assumed that geographical conditions impact on the stability of the radiometric spectrum of ragweed, it can be hypothesized that varying geographical conditions such as moisture will affect the values and stability of PCA variables. However, this hypothesis should be tested in further analyses including varying geographical conditions for the same study site.

B. *Implications for Operationalization*

Despite the fact that there exist dozens of invasive plants that could share the same ecological conditions as *A. artemisiifolia* [4] this study is an important step towards the utilization of optical multispectral remote sensing as a planning tool that could help in reducing the resources and time allocated by the municipalities for the identification and destruction of ragweed. This confidence is sustained by the results of Vincent and Bergeron [4] who studied the distribution of Common Ragweed and other invasive plants in Montréal. They concluded that Common Ragweed was present in each transect they made with a minimum proportion of 70%. This conclusion is also supported by the positive and significant correlation of Common Ragweed presence with their sociability index in the present study. This actually indicates a high presence of Common Ragweed among invasive plants.

The low ability of SPOT 4 data to detect colonies of less dense vegetation covers and per deduction Common Ragweed likelihood presence as well as core areas of potential ragweed presence revealed the importance of considering high spatial resolution sensors for the prediction of the potential presence of Common Ragweed particularly for urban areas. Even for agricultural fields a coarser spatial resolution could be a limiting factor depending on the types of culture and the fact that chemicals or other treatments against weeds were applied. The conclusions of Simard and Benoit [7] suggest that a better detection of Common Ragweed presence likelihood is possible with the use of sensors having high spatial resolutions, since Common Ragweed was confined to rural roadsides and fields borders. Thus and at the opposite of the conclusion of Burai [29], using low spatial resolution images such as MODIS could be of a negligible interest for the surveillance of Common Ragweed spatial extension within agricultural fields.

In the perspective of the operationalization of the present results this study helped in identifying additional key elements. The combination of OBIA techniques with statistical analysis and Fuzzy-logic functions effectively helped in reducing the level of confusion between Common Ragweed and other features including invasive plants. It also helped in defining the importance of the green band (500–590 nm) in the process of isolation of an ideal radiometric spectrum that could help in predicting *Ambrosia artemisiifolia* with a higher stability particularly in urban settings. However, in the perspective of an automated prediction system of Common Ragweed presence likelihood through optical remote sensing, one should consider geographic variations of the study sites in terms of seasonal and landscape variability. Even if the utilization of confidence intervals applied on reflectance values helps in discriminating ragweed with a higher confidence than simply using the entire green channels. The values of those confidence intervals seem to be highly dependent on landscape, season and characteristics of sensors.

Although the robustness of green band has been demonstrated, in the perspective to achieve and optimize present results, confidence intervals values of ragweed cannot automatically be extrapolated from one site to another. In such, it could be useful to consider a functional ecological segregation of the

TABLE V
CALCULATED VEGETATION INDEXES AND THEIR FORMULAE

Vegetation index	Definition	Formulae	authors
NDVI	Normalized Difference Vegetation Index	$\frac{NIR-RED}{NIR+RED}$	*Tucker. 1979*
TVI	Transformed vegetation Index	$(NDVI+0.5)^{0.5}$	*Tucker. 1979*
TTVI	Thiam's Transformed Vegetation Index	$\sqrt{abs\left\{\frac{NIR-RED}{NIR+RED}\right\}+0.5}$	Thiam. 1997
Ratio	Band ratio	$\frac{NIR}{RED}$	*Tucker. 1979*
MSAVI1	Modified Soil-Adjusted vegetation Index 1	$\frac{NIR-RED}{NIR+RED+L}*(1+L)$	Qi et al.. 1994
MSAVI 2	Modified Soil-Adjusted vegetation Index 2	$\frac{2NIR+1-\sqrt{(2NIR+1)^2-8(NIR-RED)}}{2}$	Qi et al.. 1994
TSAVI1	Transformed soil Adjusted vegetation Index 1	$\frac{a_1(NIR-a_1(RED)-a_0)}{RED+a_1(NIR)-a_1.a_0+X(1+a^2)}$	Barel et al.. 1989
TSAVI2	Transformed soil Adjusted vegetation Index 2	$\frac{a_1(NIR-a_1(RED)-a_0)}{RED+a_1(NIR)-a_1.a_0+0.08(1+a^2)}$	Barel et al.. 1989
RVI	Ratio Vegetation Index	$\frac{RED}{NIR}$	Richerdson and Wiegand. 1977
NRVI	Normalized Ratio Vegetation Index	$\frac{RVI-1}{RVI+1}$	Baret and Guyot. 1991
PVI	Perpendicular Vegetation Index	$\frac{[NIR-a_1(RED)-a_0]}{(1+(-a_1)^2)^{0.5}}$	Wiegand et al.. 1991
PVI1	Perpendicular Vegetation Index1	$\frac{bNIR-RED+a}{\sqrt{b^2+1}}$	Perry and Lautenschlager. 1984
PVI2	Perpendicular Vegetation Index2	$\sqrt{\frac{NIR-a*RED+b}{\sqrt{a^2+1}}}$	Perry and Lautenschlager. 1984
PVI3	Perpendicular Vegetation Index3	$apNIR-bpRE$	Qi et al.. 1994
DVI	Difference Vegetation Index	$gNIR-RED$	Richerdson and Wiegand. 1977
WDVI	Weighted Difference Vegetation Index	$NIR-a_1*RED$	Qi et al.. 1994
CTVI	Corrected Transformed Vegetation Index	$\frac{NDVI+0.5}{abs(NDVI+0.5)*\sqrt{Abs(NDVI+0.5)}}$	Perry and Lautenschlager. 1984
AVI	Ashburn Vegetation Index	$sNIR-RED$	Richerdson and Wiegand. 1977
SAVI	Soil Adjusted vegetation Index	$\frac{(NIR-RED)}{(NIR+RED+L)}*(1+L)$	*Huete. 1988*

study site as well as the probable variation induced by multi temporal data prior to any prediction. A further development of this study could therefore consists of using only one sensor for optimizing *Ambrosia artemisiifolia* spectral values according to the ecological specificities of functional parts of the study site and to compare the variability of those spectral values from one site to another and one season to another. Choosing a unique sensor is not only associated with the impact of varying characteristics of sensors but also with the costs of an automated system. This element is of very practical importance for potential end users. This study demonstrated that for such a system it is possible to use sensors in the range of visible with an interesting agreement between the spatial resolution, the width, the revisit frequency and the price of the product. Sensors such as Rapid Eye offer a good alternative to higher spatial and spectral resolution sensors such as WV2 at a much lower price. A standardization of GPS surveys of *Ambrosia artemisiifolia* could also help to improve the statistical outputs since the values of the confidence intervals are highly dependent of that of the means.

V. Conclusion

With the ultimate purpose to operationalize the use of optical remote sensing for the surveillance and mapping of the likelihood of *A. Artemissifolia presence*, the images of two urban settings presenting geographical variations were obtained from three optical sensors having different spectral and spatial resolutions. The study used images standardization techniques together with statistical analyses, OBIA and confidence intervals values to optimize the radiometric spectrum for Common Ragweed and predict its potential presence using fuzzy logic techniques. Results showed a high spectral confusion of *A. artemisiifolia* with less dense vegetation cover as attested by the low separability with nude soils and impervious surfaces and by the negative statistical correlations of *A. artemisiifolia* surveys with all the variables describing a denser or healthier condition of the vegetation. The study also revealed that landscape and seasonal variations will impact on the robustness of that radiometric spectrum. When considering those characteristics only the green band (500–590 nm) showed a high capacity to predict the potential presence of Common Ragweed with a recurrent and higher stability. Results also showed the importance of using sensors having very high spatial resolutions since a medium resolution sensor such as SPOT 4 HRVI showed a poor capacity to predict Common Ragweed in urban settings. Because Common Ragweed develops on roadsides and field shoulders rather than in agricultural field themselves (related to heavy herbicide usage for cultivation in North America), present results also suggest that using green bands of sensors having a very high spatial resolution could better detect Common Ragweed in surrounding agricultural fields, depending on the types of cultures and the usage or not of herbicides. If the calculation of confidence intervals within the green bands helped in the optimization of the radiometric spectrum of ragweed, variations of those conditions from a habitat to another suggest that a better prediction performance could be achieved through a functional ecological segmentation of the study site prior to any fuzzy calculation and mapping of ragweed. Given the documented high presence of Common Ragweed in urban areas as compared to other invasive plants it can be concluded that the present results are a decisive step towards the effective operationalization of optical remote sensing tools in Common Ragweed control campaigns aimed at reducing human exposure to its potent aeroallergens. Channels in the visible could be advantageously used to optimize the cost of a remote sensing-based Common Ragweed potential presence surveillance system.

Appendix A

The calculated vegetation indexes and their formulae are shown in Table V.

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