

# Spatial and Spectral features for Horticulture mapping

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## Abstract

Remote sensing data allows the continuous mapping of horticultural crops in periurban areas. These are very important for their functions in the provision of local food and for other ecosystem services they provide.

This work presents a methodological development and the results of a hierarchical classification of the horticultural periurban area of Córdoba city, based on the spectral and spatial properties of satellite imagery. The methodology present is automatable, making it suitable for continuous monitoring. The classification obtained with the RF algorithm yields a global kappa of 0.77 and in particular for the horticultural class a precision of 0.82. With a hierarchical classification only of the horticultural area result in an amount of 1860 ha.

With spectral information taken in radiometer fields campaigns evaluated by spectral angle mapper, we can observe as using Sentinel 2 spectra and parrot camera produce better separability of horticultural crops that the hyperspectral one.

## 1 Introduction

The peri-urban food regions (FR) are an urban planning tool that contributes to local food security, protects ecological integrity, conserves biodiversity, cares for local water quantity and quality, and provides recreation and buffer zones for urban expansion [1, 2]. The destiny of areas for vegetable cultivation decreases drastically [3, 5, 6, 9], due to an extra-limited advance of the urban frontier, which grows on natural and agricultural systems strategic for the sustainability of cities.[9]. In Córdoba the history of remote identification of multi-species horticulture, in urban-rural interface zone, show results that differ between 3167 ha for 2014 [3], and 1780 ha for 2015 [9].

In this context the objective of the present work was to explore hyperspectral data of horticultural crops and develop a pixel-based classification, rooted in spectral and textural information, for the identification and quantification of horticultural production area in the urban-rural interface that surrounds Córdoba city.

## 2 Exploiting Spatial Characteristics

### 2.1 Materials and Methods

**Study Area** The study area it around 180,000 ha, which includes part of the metropolitan region of Córdoba and focuses on understanding the historical irrigation area, and horticultural use, surrounding the city of Córdoba. The peri-urban food regions (FR) is the territory with family and commercial orchards that surround the cities, and where vegetables are produced to supply the urban population [5, 6].

**Satellite Imagery** The study area was represented by a mosaic of two Sentinel 2A (ESA) images (JML and JLL) from 19/02/2019 preprocessed to surface reflectance. Bands 2, 3, 4, 8 with 10m spatial resolution and bands 5, 6, 7, 8a, 11 and 12 resampled by georeferencing at a pixel of 10 m were used.

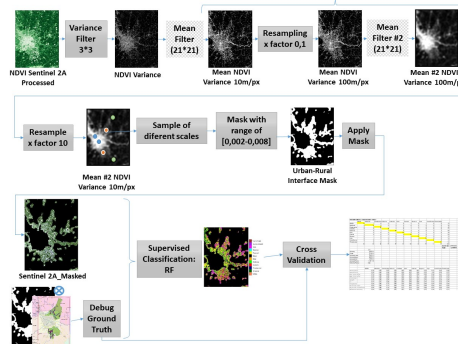


Figure 1: Work flow diagram for Urban-Rural Interface Scale Mask and Supervised Classification RF

Five features were added to the 10 spectral bands of Sentinel 2. These are based on the *NDVI variance filter*. The variance calculated with a  $3 \times 3$  kernel was binarized to detect the presence or absence of *boundaries*. Mean filters were processed on the binary classification, in order to describe the boundaries proportion in contexts of 0.25 ha; 0.81 ha; 2.25 ha; 4.41 ha and 9.5 ha.

**Classification Algorithm** Random Forest (RF) implemented in *R* [7] that with the classic Breiman algorithm [4] is used. For its optimization parameters the *caret* package (abbreviation of Classification And REgression Training) was used.

**Ground Truth (GT) and Land Cover Class Definition** The area of study was visited on February 15 and 16 of the current year, georeferencing land cover and uses, with a GPS.

Registered GT were grouped into land cover classes, by analyzing spectral and textural separability. The proposed classes are 10: water, alfalfa, trees groves, construction, under cover crops, horticulture, corn, soybean, ploughed soil, mix-use land.

#### Urban-Rural Interface Scale Mask

It is proposed to address the different types of management or use areas by analyzing the NDVI (Normalized Difference Vegetation Index). The horticulture fields presents a *pattern* of high spacial variance in the NDVI, but inferior to the urban area. In order to define *regions*, a linear mean filter was applied to the image variance filter of the NDVI, which assigns to each pixel the value of variance in a neighborhood.

This processing allowed defining ranges or thresholds of variance values of the NDVI, that discriminate between scales: urban zones, urban-rural interface, and extensive agricultural. A mask was constructed for all those pixels outside the range of values that identify *urban-rural interface scale*. With the 70% of GT, RF classifier was executed. Cross validation was performed with the rest (30% of GT), and a confusion matrix was constructed. Overall Accuracy (OA) and kappa coefficient ( $k$ ) were calculated, also other precision metrics by class, see figure 1.

## 2.2 Results and Discussions

**Classification Accuracy Assessment** Interpretation of the kappa coefficient shows that the result of the classification is *very good*.

The RF rating on the urban-rural interface area are a OA of 74% and a kappa of 0.73. In addition to those, other precision metrics by class were evaluated. *Precision*, low values indicate a large number of false positives, the *Recall* is a measure of the integrity of a classifier, and low values indicate many false negatives, then the *F1 score* express the balance between precision and recall. The results for Horticultural class indicates a very good metrics, with a precision of 0.82, a recall of 0.72 and a F1 score of 0.77, as it presented in Table 1.

**Horticultural Area Results - Hierarchical Classification** The interest class, was overestimated with an area of 7,604 ha. However, there was a categorical improvement in the approximation to the amount of this class, with respect to the total image classified analysis. This affirms the hypothesis that

Table 1: Precision by classes of RF Urban-Rural Interface.

	Water	Alfalfa	Plough	Tree Grove	Construction	Cover	Horticultural	Corn	Mixed-use	Soy
Sensitivity	1.00	0.85	0.81	0.69	0.91	0.72	0.72	0.72	0.69	0.91
Specificity	0.99	0.98	0.97	0.98	0.98	0.99	0.95	0.97	0.94	1.00
Pos Pred Value	0.84	0.58	0.70	0.80	0.84	0.78	0.82	0.62	0.71	0.95
Neg Pred Value	1.00	0.99	0.98	0.97	0.99	0.98	0.91	0.98	0.93	0.99
<b>Precision</b>	0.84	0.58	0.70	0.80	0.84	0.78	0.82	0.62	0.71	0.95
<b>Recall</b>	1.00	0.85	0.81	0.69	0.91	0.72	0.72	0.72	0.69	0.91
<b>F1 Score</b>	0.91	0.69	0.75	0.74	0.87	0.75	<b>0.77</b>	0.67	0.70	0.93
Prevalence	0.04	0.04	0.07	0.08	0.09	0.07	0.25	0.07	0.18	0.06
Detection Rate	0.04	0.03	0.06	0.06	0.09	0.05	0.18	0.05	0.13	0.06
Detection Prevalence	0.05	0.05	0.08	0.07	0.10	0.06	0.22	0.08	0.18	0.06
Balanced Accuracy	1.00	0.91	0.89	0.84	0.95	0.85	0.84	0.84	0.82	0.95

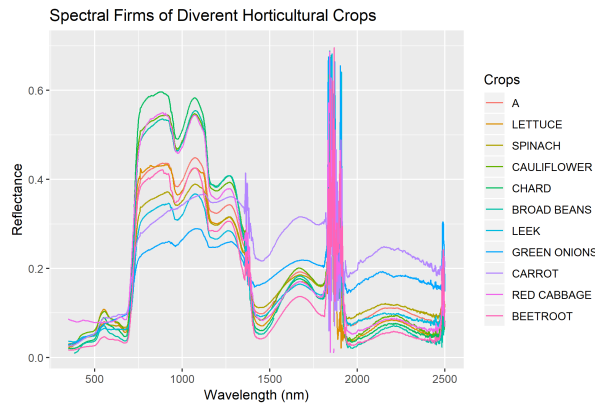


Figure 2: Spectral signatures of horticultural winter crops

urban and suburban built-up areas negatively affect the horticultural class identification.

By means of exhaustive observation of the areas allocated to horticultural class, errors of assignment of “Borders” (limit of agricultural lots and grove of streets) are found. This confusion, has its causes in the non-existence of that class previously in the model and that the 5 additional characteristics of the model, singularize the horticultural areas by the presence of continuous “jumps” or “borders” in the variance of NDVI.

On the classified image 760 points were selected, 380 of them are *Well Classified Horticultural* and the remaining 380 points designated as *Badly Classified Horticultural*, selecting those surrounding extensive agricultural lots and avenue edges.

The Horticultural class was extracted and sub-classified (with an RF model) in the two mentioned classes. For sub-classification, OA precision measurements of 84% and a Kappa coefficient of 0.68 were obtained. Above this sub classification, a constructed urban mask was applied. This mask is an average threshold of R G B bands, with a mean filter. In this final distribution of classes, the **Horticulture area reaches 1,860 ha**, characterized by the production of multi-species of vegetables in the urban-rural interface.

### 3 Exploiting Spectral Characteristics

#### Spectral Signatures of Horticultural Winter Crops

The hyperspectral data, in a field campaign, using a radiometer belonging to CONAE, in august 2018. With the collected data, 10 spectral signatures of horticultural winter crops were generated. Figure 2, shows the results by crop, with a radiometric resolution of one *nm*.

#### Spectral Angle Mapper (SAM)

The spectral similarity can be obtained by considering each spectrum as a vector in *n*-dimensional space, where *n* is each *nm* measurement. The SAM determines the spectral similarity by calculating the angle between two spectra, treating them as vectors in a space with dimensionality equal to the number of *nm* measurement [8].

The spectral angle is calculated between a reference vector built with the average of all the collected data for each *nm* and the test vector built for each reference crop (spectral signature of each horticultural

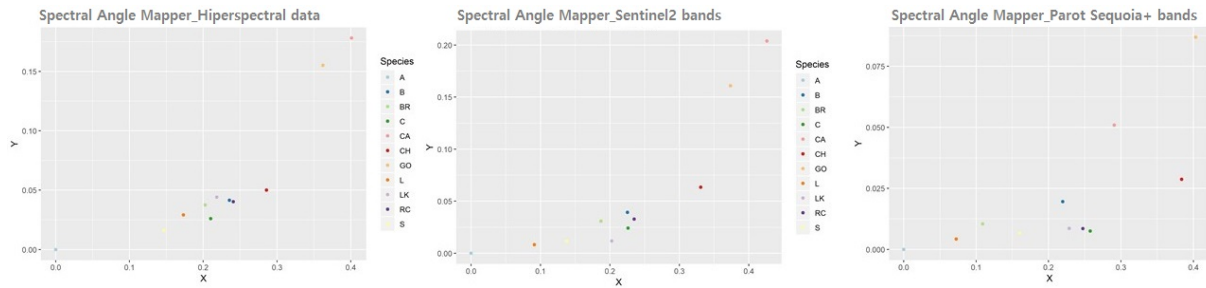


Figure 3: Spectral Angle Mapper, hyperspectral Information i) from 350 to 2500 nm, ii) by Sentinel 2 bands ranges iii) by Parot-sequoia+ bands ranges

crop). The SAM algorithm generalizes this geometric interpretation to n-dimensional space. In this work we examined the spectrum with different ranges i) from 350 nm to 2500 nm, ii) with the Sentinel 2 bands range<sup>1</sup> and iii) with Parot-sequoia+ bands range<sup>2</sup>.

SAM determines the similarity plotting the hyperspectral data in a polar graph by applying the following equation:

$$\theta = \arccos\left(\frac{a_i \times l_i}{|a| \times |l|}\right), R = \frac{|a_i - l_i|}{|a|} \quad (1)$$

Where,  $a$ : average spectral vector,  $l$ : crop spectral vector (spectral signature). Also a measure of the distance between the curves of each crop spectra and the build reference  $A$  was considered.

Surprisingly we can observe that using Sentinel 2 and parrot camera spectra produced better separability than the hyperspectral one.

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<sup>1</sup><https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-2/instrument-payload/resolution-and-swath>

<sup>2</sup><https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-2/instrument-payload/resolution-and-swath>