FIRST LARGE EXTENT AND HIGH RESOLUTION CROPLAND AND CROP TYPE MAP OF ARGENTINA

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ABSTRACT:

The availability of spatially explicit information about agricultural crops for large regions in Argentina is scarce. In particular, due to temporal dynamics of agricultural production (i.e. changes in planted crops from year to year) and spectral similarities among herbaceous crops it is difficult to generate crop type maps from remote sensing. Large regions with marked climatic variations, like the main agricultural areas of Argentina, represent an additional challenge. Here we generated a map based on supervised classifications using field samples along 14 agricultural zones. Best classification accuracies were obtained by combining seasonal indices (year, summer and winter), with indices that describe the temporal dynamics of vegetation. Accuracy was increased at regions with high and balanced number of samples and with longer growing seasons. The map allows to identify areas with clusters of one, two or three crops and to characterize areas with different spatial distribution between cropland and no cropland areas.

1. INTRODUCTION

Satellite images and processing capability available nowadays allows the generation of high resolution maps over large regions. Identification of crop types from satellite images is still a challenge since it is necessary to separate covers with high similarities: i.e. herbaceous vegetation in homogeneous stands growing over similar environmental conditions. Available methods vary from empirical decision trees to automatic supervised classification methods. Difficulties depend on the number and similarities/dissimilarities among crop types (planting dates, reflectance properties, etc.), that can be relevant when analysing large areas.
Previous works in Argentina were oriented to map specific crops (soybean (Song et al., 2017); Sugar cane (Benedetti, 2018)), small regions (Badwart et al., 1987; Pressuti et al., 2001; Zelaya et al., 2016), or to describe crop types only over cropland areas (Volante et al., 2006). The generation of crop type maps at national level require the simultaneous acquisition of ground truth information (for training or validation) covering the range of cropping systems along the country, as well as the acquisition and processing of high temporal and spatial resolution satellite images that covers the study region.

2. MATERIALS AND METHODS

Supervised classifications (i.e. the utilization of samples for training and validation of classification algorithms) were performed using satellite images to generate crop type maps for the growing season 2018/2019.

2.1 Study area

The mapped area covers the main agricultural areas of Argentina (Figure 1). The region was divided in 14 zones, following Buenos Aires Grain Exchange (2019) zonation, which is based on crop production statistics at county level. Original areas were modified intersecting an agroecological zonation (Burkart, 1989) to avoid the inclusion of arid regions in the Western zones. High variability in crop production systems exists along a high temperature and precipitation gradient, with changes in crop species presence and diversity, cropping intensity and planting and harvesting dates. Southern areas have a dominance of winter crops (wheat and barley); In the Center is located the main agricultural area with prevalence of soybean, maize and double crops; in the Northern areas specific crops appears like common bean, cotton, and sugarcane. There are also changes in the proportion of cropland and other land uses, with higher proportion of rangelands in the South, South West and Center West (Entre Ríos province); in the Chaco region there persists natural forest covers and its conversions to pastures.

2.2 Field sampling

On road surveys following the JECAM (2018) protocol were performed over all the regions to get information for training and validation of classification algorithms (Figure 1). Surveys were performed twice a year: 1) from October to November to cover winter crops and summer crops fallows; 2) from March to April to cover summer crops and winter crops fallows. Georeferenced points were registered over fields and patches along the roads. Fourteen classes were defined in order to characterize the crop (or crops) that occurred along the growing season (Table 1). For each zone, main crops that represent

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together up to 90 % of cropland area, based on county level statistics (MINAGRO, 2019), were considered. Number of samples obtained for each class and zone is described in Table 2. From GPS point samples, polygons of 100 m radius were generated semi-automatically and assigned to fields or homogeneous patches based on visual interpretation of boundaries using HR images from Google Earth.

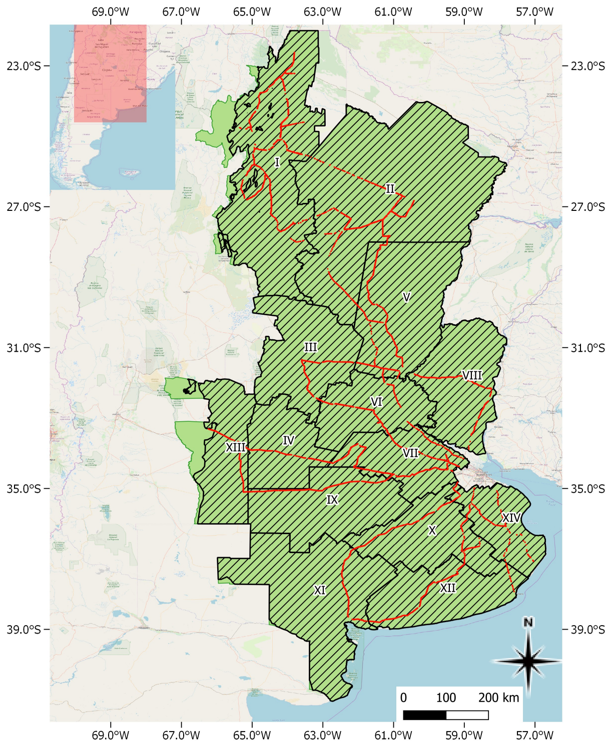

Figure 1. Study region covering Pampa and Chaco, the main agricultural areas of Argentina. Green: Buenos Aires Grain Exchange zonation; Shaded: Modified zonation; red lines: on road surveys.

Class ID	Description
Maize	Single Crop
Soybean	Single Crop
WC- Soybean	Winter Crop followed by Soybean
WC- Maize	Winter Crop followed by Soybean
Peanut	Single Crop
Winter Crop	Single Crop
Cotton	Single Crop
Sunflower	Single Crop
Common Bean	Single Crop
Sugar Cane	Single Crop
Sunflower-SC	Sunflower followed by Summer crop
Planted Woody	Planted forests and woody Fruitcrops
Rangelands	Land for cattle grazing
Natural Woody	Natural woody vegetation

Table 1. Classes defined for mapping

Zone	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV
Maize	103	39	75	29	13	98	138	47	20	12	14	32	41	10
Soybean	160	35	65	26	27	103	105	70	28	3	14	36	35	
WC- Soybean	31	10	59	20	30	83	111	68	27	2	14	21		
WC- Maize	53	9	16	5	6	16	8	5	18					
Peanut				9									8	
Sunflower		9			1					9	11	14		
Winter Crop											30	91		
Rangelands	192	196	30	54	357	41	244	254	50	195	176	118	35	135
Natural Woody	178	95	5	1	67	3	1	50			4		22	
Planted Woody	82							13				6		
Cotton		18												
Common Bean	92													
Sugar Cane	90													
Sunflower-SC		29												
Total	981	393	250	144	501	344	607	507	143	221	263	318	141	145

Table 2. Number of samples generated for each class and zone surveyed during winter and summer season.

2.3 Satellite images and derived indices

Landsat 8 image Collections for the study area from June 1st, 2018 to May 30th, 2019 were considered as input data. We tested 3 feature spaces composed of different type of indices: 1) statistical description indices for fixed periods (SDI); 2) single descriptors of vegetation temporal dynamics (VTD); and 3) parameters of sinusoidal functions (SF). In the first case, 3 fixed periods were considered: annual, winter (from August 1st to November 30th) and summer (from January 1st to March 30th) composites. Statistical metrics included: percentiles 5, 25, 50, 75 and 95, and standard deviation. Indices included NDVI, SAVI, SWVI, and spectral unmixing derived indices (Souza and Barreto, 2000). VTD summarized the dynamics of NDVI along the growing season with the following parameters: number of peaks, peak value, peak time, amplitude and growing season duration. Third approach (SF) consisted in the modelling the NDVI temporal dynamics by means of 2nd order harmonic regressions. . Thus input data for the RF classifier consisted on the 5 parameters derived from the harmonic regression fitted at each pixel. Image processing was performed using Google Earth Engine and its catalogue.

2.4 Classification

Classification was performed using the Random Forest methodology considering 70 trees. Independent classifications were performed for each of the 14 zones. Samples were split for training (60 %) and validation (40 %). In cases were the number of samples of a class identified as relevant in a zone was low, samples of this class were joined with ones from boundary zones from a same latitude gradient. Accuracy for each zone and class was determined, together with the estimation of Kappa index. A spatial filter (Souza and Azevedo, 2017) was applied to avoid the presence of isolated pixels inside a field or patch. Water and water bodies, urban related areas, and wetlands were masked using information from Pekel et al., (2016), IGN (2019) and Volante et al., (2010) respectively.

3. RESULTS AND DISCUSSION

3.1 Feature space evaluation

Comparing each feature space separately, VTD showed higher accuracy and Kappa coefficient. Nevertheless, the highest accuracies were obtained combing together SDI and VTD or with the combination of all bands. This result highlights the importance of including temporal description indices to discriminate crops when using satellite images. Following results are based on classifications using the SDV+VTD combination of bands.

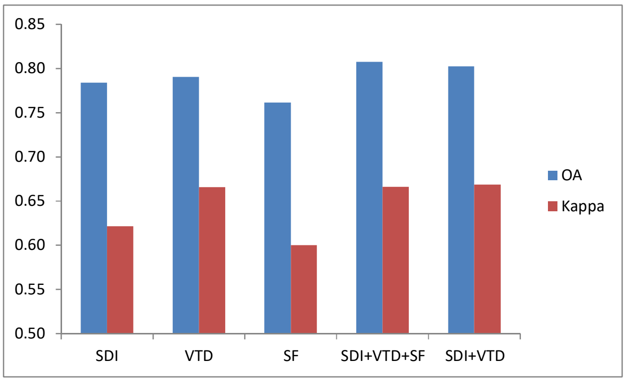

Figure 2. Overall Accuracies (OA) and Kappa coefficient for different feature spaces or combination of them: statistical description indices for fixed periods (SDI); single descriptors of vegetation temporal dynamics (VTD); and parameters of sinusoidal functions (SF).

3.2 Accuracy of final map

Overall accuracy and Kappa showed variable results among the different zones (Table 3). Accuracy values ranged from 0.63 in zone I to 0.91 in zone XIV, while Kappa ranged from 0.52 in zone V to 0.85 in zone VII. In general zones with high accuracy (i.e zones VI and VII) showed a high and balanced number of samples among different classes (Tables 2 and 3).

Zone	OA	Kappa	N classes
I	0.67	0.61	9
II	0.77	0.69	9
III	0.86	0.83	6
IV	0.75	0.69	7
V	0.80	0.52	7
VI	0.83	0.77	6
VII	0.90	0.85	6
VIII	0.84	0.80	7
IX	0.71	0.59	6
X	0.90	0.83	5
XI	0.82	0.60	7
XII	0.85	0.78	7
XIII	0.73	0.65	5
XIV	0.91	0.75	4

Table 3. Overall accuracies (OA), Kappa coefficient and number of classes (N classes) obtained for each zone.

User and producer accuracies were high in zones III, VI, VII and VIII for the classes Soybean, Maize, WC- Soybean and Rangelands (Tables 4 and 5). On the other hand, zones I, II and V showed low user and producer accuracies in several classes, reflecting higher confusion among classes. Several high accuracy zones represents areas located in the Center of the study area with a longer growing season than the rest in relation to better water conditions and moderate temperatures, generating a higher range of variation in planting dates. On the contrary, low accuracy zones located in the North have shorter growing season limited by water in winter and lower differences in planting dates among crops. This variability or homogeneity of growing periods for different crops can explain the observed variability in confusion of classes.

Zone	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV
Maize	0.6	0.8	0.8	0.9	0.9	0.9	0.9	0.8	0.5	0.9	-	-	0.8	-
Soybean	0.6	0.8	0.9	0.8	0.6	0.9	0.9	0.9	0.7	0.8	-	-	0.6	-
WC- Soybean	0.7	-	0.8	0.7	0.5	0.7	0.9	0.7	0.6	0.9	-	-	-	-
WC- Maize	0.8	-	0.9	-	-	0.9	-	-	-					
Peanut				-									-	
Sunflower		-			-					-	-	-		
Winter Crop											1	0.9		
Rangelands	0.5	0.7	0.9	0.7	0.8	0.7	0.9	0.8	0.8	0.9	0.8	0.8	0.8	0.9
Natural Woody	0.8	0.9	-	-	1	-	-	1	1		-		1	
Planted Woody	1							-				-		
Cotton		-												
Common Bean	0.7													
Sugar Cane	0.9													
Sunflower-SC		0.9												

Table 4. User accuracies for each zone and class. Only values from classes with more than 20 samples are shown.

Zone	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV
Maize	0.4	0.5	0.9	0.9	0.1	0.9	0.9	0.9	0.8	0.2	-	-	0.7	-
Soybean	0.8	0.5	0.8	0.9	0.5	0.8	0.9	0.8	0.5	1	-	-	0.9	-
WC- Soybean	0.2	-	0.8	0.9	0.4	1	0.9	0.9	0.7	0.9	-	-		-
WC- Maize	0.5	-	0.4	-	-	0.2	-	-	-					
Peanut				-									-	
Sunflower		-			-					-	-	-		
Winter Crop											0.3	0.9		
Rangelands	0.8	1	0.7	0.9	1	0.7	0.9	1	0.8	1	1	1	0.8	1
Natural Woody	0.8	0.8	-	-	0.5	-	-	0.8	0.7		0.6		0.8	
Planted Woody	0.6							0.8				0.2		
Cotton		-												
Common Bean	0.3													
Sugar Cane	0.8													
Sunflower-SC		0.7												

Table 5. Producer accuracies for each zone and class. Only values from classes with more than 20 samples are shown.

3.3 Map Description

Figure 3 shows the spatial distribution of crops as well as rangelands and woody vegetation. The map show areas with dominance of one crop, like Maize in zones III and XII, Winter Crops in zone XII, as well as mixed patterns of two crops (Maize and Soybean in South West of zone III and North West of zone IV), or three crops patterns (Soybean, Maize and WC-Soybean in Zones VII and VII).

The map also shows differences in spatial distribution of cropland in relation to no cropland classes. Areas mainly dominated by croplands are observed in South West of zone III, and Center of zone VI. Cropland areas fragmented with low proportion of rangelands are observed in several regions: West of zone III, zone IV, North of zone VI and zone VII. Zone VIII show a pattern with no dominance of cropland or no cropland classes with mixed patches of natural woody vegetation. Also it is possible to identify large rangeland dominated areas with a clear limit with cropland dominated areas (Zones X, XI and XII). Northern regions show high proportion of natural woody

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vegetation, surrounded by small (zone I) or large (zone II) cropland or mixed cropland-rangeland areas.

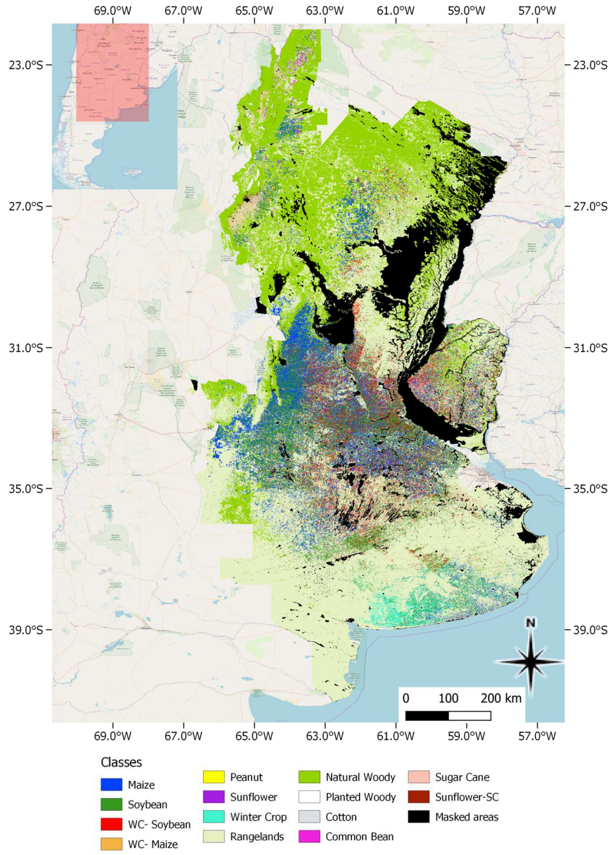

Figure 3. Cropland and crop type map of main agricultural areas of Argentina for the 2018/2019 growing season. Classes are described in Table 2.

4. CONCLUSSIONS

We generated a high resolution extensive cropland and crop type map covering main agricultural areas of Argentina for the growing season 2018/2019 based on field observations. The information provided by this crop type map complements and adds to the county level data, currently considered to describe agricultural related aspects in Argentina. Quantitative information derived from this map is not only suitable for estimation of cropland area, as it can be used to optimize the distribution of transport infrastructure like roads, railways and harbours for specific crops. Spatial distribution analysis can be used to characterize agricultural systems along the country, or to analyse the presence of animals related to described land covers patterns (biodiversity analysis, plague incidence, etc.). Repetition in time of these maps will allow the characterization of agricultural expansion, changes in agricultural systems, and spatial distribution of crop sequences (i.e crop rotation and monoculture). The map is available at GEOINTA platform (http://geointa.inta.gob.ar).

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