Remote Sensing and Machine Learning Modeling to Support the Identification of Sugarcane Crops

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ABSTRACT One of the main concerns of agricultural financing institutions is to make sure the loans they grant are used for the stated objective when the loan was requested. Specifically, when Banco Agrario de Colombia grants loans for crop farmers, it schedules verification visits to the cultivation sites to check if the crop stipulated in the loan agreement exists and assess its health. These visits are challenging to make due to the number of visits over vast areas that they need to schedule, lack of trained personnel, and difficulty of access. This article proposes a software tool, based on a machine learning model for processing free satellite imagery, to support the bank’s identification of non-compliant crops with the investment plan before making field visits, minimizing the loss of investment by focusing on those areas to prioritize the visits. Sugarcane along the department of Boyacá, Colombia was chosen as the case of study. Free access satellite imagery through the Colombian Data Cube (CDCol) was used and machine learning models were applied on them to classify the land and predict the presence of the crop, a Random Forest model achieved an overall F1-score of 91% using Landsat-8 imagery and a K-nearest Neighbors model achieved an overall F1-score of 98% using Sentinel-2 imagery.

INDEX TERMS Investment Monitoring, Landsat-8, Machine Learning, Remote Sensing, Sentinel-2, Sugarcane Crops

I. INTRODUCTION

Banco Agrario de Colombia (BAC) is the Colombian government entity in charge of implementing financial support initiatives for the country’s farmers. One of BAC’s main objectives is to support Colombian farmers through loans that allow them to grow and harvest agricultural products.

Agricultural and rural credits are regulated by Colombian state legislation and, therefore, their “processing and granting must comply with the provisions contained in Colombian Laws 16 of 1990 and 1731 of 2014, as well as the other regulations that add or modify them. They must also comply with the Resolutions issued by the National Agricultural Credit Commission, the Circulars of the Financial Superintendency of Colombia, Superfinanciera, or the Superintendency of the Sector of Cooperatives, Supersolidaria. In addition, the agricultural sector development financing agency, Finagro, has a Service Manual that states: “The credits are granted by financial intermediaries, entities that have a direct relationship with the beneficiary, which must monitor the correct use of monetary resources, and certify to Finagro compliance with the regulations that govern them” [1].

In January 2018, Finagro modified the Title Five of its Service Manual, adjusting its "Commitments, monitoring, control and verification procedure" of those operations registered with Finagro, "which directly affects the verification process of the investment controls and the commitments that the beneficiaries of the credits with re-discount resources and those who receive subsidies from the National Government must assume" [2]. The new modification established that “the
client must make the expenses and investments contemplated in the financed project within the foreseen time and report any changes, such as: financed item, investment impact, either due to climatic or phytosanitary problems, among others, that may partially or totally affect the investments, in order for the BAC to evaluate the viability of authorizing the proposed modification and present it again to Finagro” [1].

Currently, BAC carries out the process called Controls of Agricultural Investment just after the end of the credit-granting process. The aim of this process is the follow-up and control of the investments made by the bank’s customers in order to detect, in time, any inconvenience in the productive development of the investments, for timely decision making.

The monitoring process involves the following activities: (1) Generating the list of visits according to the coverage area established by the bank, (2) visits assignment to the staff of the bank according to the capacity and coverage established for each of them, (3) the assignments are checked to ensure that they correspond to the coverage area, and the feasibility of the visit, (4) contact the clients in order to verify the status of the investments and scheduling the follow-up visit, (5) carrying out the visits that involve staff travel to planned sites, (6) collecting information about the status of the crop, georeference points of the farm where the crop is located, and photographic evidence of the vegetative state of the premises; and, after the visit, (7) validating the investment status and (8) making decisions about the investment progress [3].

The great demand for productive agricultural projects financed by the bank represents a major problem that currently makes it impossible to effectively monitor projects advancements which financing comes from the BAC. Currently, the BAC has one hundred and one (101) specialized advisers in charge of monitoring around 880,000 productive projects approved per year. They barely manage to cover 36,000 visits, which falls short of the visits required by law - a minimum sample of 10% of the approved projects - that must be reported to Finagro.

This imbalance makes it difficult to cover 100% of the investment monitoring. According to projections made by the Investment Controls and Appraisals Office of BAC, the mentioned imbalance could be corrected increasing the human resource capacity; this hiring would have represented an annual payroll expense for the BAC of more than $1M USD [1].

Concerning the visits, into a report provided by the Agricultural Technical Monitoring Sub-management, the five (5) main causes of non-compliance were: (1) The farmer did not carry out the investment, (2) client not found, (3) diversion of resources, (4) public order, and (5) climatic factors.

Another issue in the Colombian countryside is the poor condition of the tertiary road network, which connects municipal capitals and small towns or towns with each other; this network represents 69% of the national road network. This problem, joined with the public order situation in Colombia, hinders the work of the Bank’s commercial advisers in placing loans on site and in monitoring the agricultural investment requested by control entities for agricultural loans, which operate under Finagro conditions.

Last but not least, according to the National Agricultural Census conducted in 2014 [4], 70% of the food produced in the country comes from small producers who carry out agricultural production work on their farms, most of which are less than 5 hectares in size. Therefore, the crops areas are not extensive.

To deal with these issues, an application to support the agricultural investment control process is suggested. Specifically, we propose the use of free satellite (Landsat-8 and Sentinel-2) images through the Open Data Cube (ODC) infrastructure, to handle the images storage and processing, and, based on this, develop a Machine Learning model to predict the presence of specific crops in areas of interest of the bank.

In consequence, a tool is provided to determine whether loans given to farmers to plant a specific crop are actually being used to fulfill the loan’s purpose, by verifying the geospatial location of the property and identifying the crop. The aim is to support the identification process of crops with non-compliance in the investment plan, validate areas with fraud problems before making field visits, minimizing the loss of investment by focusing on the areas to be visited, and prioritizing those visits that must be reported to Finagro.

Taking into account the diversity of crops financed by the bank and Colombia’s territorial extension, the focus of this case study is the identification of sugarcane crops in the Department of Boyacá (around 23,000 km²).

According to reports presented by Agronet, sugarcane is one of the crops with the greatest economic and social importance for Colombia, due to the high number of people who work in the sugarcane life cycle and its high per capita consumption. In the same way, in a report on sectoral indicators for the period between 2008 and 2013, published by the Ministry of Agriculture and Rural Development in 2013, the sugarcane cultivation is the second in the country in generation of direct and indirect jobs, after coffee, with a contribution of 11.5% [5].

Likewise, 2018’s report from the Ministry of agriculture [6] remarks the importance of sugarcane to the country’s economy; furthermore, it showed that more than 350,000 families develop this crop. Also, it generates about 287,000 direct jobs, equivalent to 45 million wages per year and employs 12% of the economically active rural population. The departments with the greatest productive influence in this subsector are: Boyacá, Cundinamarca, Cauca, Antioquia, Santander, Nariño, Valle del Cauca, Tolima, Caldas, Norte de Santander, Risaralda and Huila, where 83% of the cultivated area is concentrated.

Figures provided by Fedepanela - Fondo de Fomento, for the year 2017 the country reached a total of 228,976 hectares planted, a harvested area of 205,156 hectares, an average yield of 5.66 tons of panela (which is one of the final products made from the sugarcane juice that, by successive boiling, loses moisture and solidifies into blocks) per hectare and
a total production of 1,284,141 tons of panela, in 29 out of
32 departments of the country covering 564 municipalities.
The planted areas were centered in the departments of Cundinamarca, Antioquia, Santander, Boyacá, Cauca, Nar-
iño, Tolima, which represent 77.35% of the total sugarcane
production; it should be noted that only 4 departments, Cun-
dinamarca, Antioquia, Santander and Boyacá have 53.37% of
the area planted nationwide [5]. Likewise, in [7], it was
evidenced that in terms of figures related to production, the
Department of Boyacá occupied the third place out of 29 in
the country’s total production with 13.7%.

This representative place is still kept within BAC because
taking into account that data provided by the Investment Controls and
Appraisals department of BAC, 21% out of the 1,217 moni-
toring and control visits to the investment in 2019 were car-
ried out in the Department of Boyacá (251 visits). Similarly,
BAC reports that, for sugarcane, 24,282 credits were granted
through Finagro between 2018 and 2019, for a value of
286,130 million COP and of this figure, 22,189 credits were
rediscounted, for a value of 101,920 million COP; which
confirms its importance. Furthermore, sugarcane is the fourth
(4th) agricultural activity with the highest number of credits
approved by the bank after coffee, fruit trees and plantain.

This paper is organized as follows: section II describes
the state of the art in crop monitoring. In section III, we
explain the methodology used for the development of the
identification models of sugarcane in the Department of Boy-
acá, emphasizing the use of data cubes for the construction
of training data and highlighting the fact that, although the
information sources are different (Landsat-8 and Sentinel-2),
the methodology for developing the models is the same. The
general discussion and insights of the process are presented in
section IV and, finally, section V presents the conclusions
and future work.

II. LITERATURE REVIEW

Studied on crop classification date back to 1987, when
Landsat Multispectral Scanner System (MSS) and Thematic
Mapper (TM) images were used to apply maximum like-
lihood (probabilistic) algorithms, visual interpretation, un-
supervised classification, and threshold-based segmentation.
Results from studies made between 1987 and 1997 achieved
precision values between 70% and 93%, where the best
precision was achieved using the active satellite ERS-1
with the maximum likelihood algorithm for rice grading [8].
Regarding the use of multispectral imaging, in 2015,
a Chilean research group analyzed the use of Landsat-8
images for the phenological classification of fruit tree crops
[9]. In this study, they compared the performance of three
classifiers applied to the images (linear discriminant analysis
(LDA), Random forests (RF), and Support Vectorial Machine
(SVM)) using different operations on images such as NDVI,
normalized difference water index (NDWI), and time series
using all image bands. As a result, they found that using
time series with all image bands provides a more accurate
classification than using NDVI and NDWI, specifically ap-
plying LDA and time series over reflections in each band. The
same year, Kharat and Musande used the k-means algorithm
to map cotton crops using Landsat-8 images achieving an
accuracy of 98.01% for a k-value (number of groups in the
algorithm) of 10 [10].

Concerning delimiting sugarcane crops, Wang et.al (2020)
proposes the joint use of optical multispectral images,
obtained by Landsat-8 and Sentinel-2 satellites, and SAR
images, obtained by the Sentinel-1 satellites, to generate
annual maps of sugarcane at the field scale over large regions.
Through the use of geo-referenced polygons, the authors
obtain the base pixels to calculate spectral indices (NDVI,
EV1, LSWI, and mNDWI); subsequently, they proposed the
use of a pixel-phenological algorithm, supported by time
series and classification trees, to determine the presence of
sugarcane in a given region. After performing the system test,
they obtained an overall identification accuracy of 96%. The
main challenges reported in the study were: (i) the small size
of sugarcane crops in this province (< 1 ha); (ii) the presence
of other surrounding crops, such as rice or corn; (iii) the
topography of the region; and (iv) the frequent cloud cover.

Shendryk, Davy & Thorburn (2020) conducted a study to
predict field-level sugarcane yield in the northeast Queens-
land region of Australia. In this study, they used Sentinel-1
and Sentinel-2 satellite imagery in combination with climate,
soil and elevation data. Authors implemented four different
types of predictive machine learning models (Random Forest,
Gradient Boosting, Extreme Trees and Extreme Gradient
Boosting) in order to forecast the cane yield (t/ha), commercial
cane sugar (CCS, %), sugar yield (t/ha), crop varieties
and ratoon numbers. The model with the best performance
was Gradient Boosting, using this model they found that sug-
arcane varieties could be mapped with an accuracy of up to
73.4%, while the differentiation of planted and ratoon crops
exhibited the lowest accuracy of 45.4%. The main challenges
reported in the study were: (i) the climate variability in the
region; (ii) soil types; and (iii) harvesting processes in the
area.

Concerning the delimitation of the sugarcane crops in
Colombia, the Cane Research Institute, Cenicaña, published
in 2009 "Principles and Applications of Remote Sensing in
Sugarcane Crops in Colombia” [12]. This book constitutes
a guide for sugarcane remote sensing using different statisti-
cal methods. First, it discusses the importance of spectral
vegetation indices as it generates an efficient estimation of
soil vegetation cover. In second place, statistical methods are
proposed aiming to detect sugarcane. These methods are:
Principal components analysis, linear analysis of spectral
mixtures, Tasseled cap transformation (index), and texture
treatment in the image. Physical methods, genetic algorithms,
and hybrid methods are also mentioned (hybrid methods
include decision trees, support vector machines, and neural
networks). The research that led to the publication of the
mentioned book referred to studies that used Moderate Res-
olution Imaging Spectroradiometer (MODIS), Landsat-5/7,
National Oceanic and Atmospheric Administration (NOAA)
There are cross-cutting challenges; the following should be considered: (1) Varieties. However, with the review carried out of the most relevant studies in Colombia around satellite remote sensing, there are cross-cutting challenges; the following should be highlighted:

1) Variable reflectivity due to factors such as moisture, leaf pigments, physiological status, and morphological characteristics of the species.

2) Changes in soil reflectance; this can occur due to tides (in coastal areas), rain, and, in general, water on the leaves, which produces a fall in the reflectance of the red band and near infrared compared to dry soils.

3) Lack of standardization [WG] that can lead to duplication of efforts and increased expenditure of resources.

### III. SOLUTION PROPOSAL

From the detailed analysis of the sugarcane cultivation and a deep understanding of its climatic, morphological and contextual factors, the methodology that allows us to obtain sugarcane crop identification models using both Landsat-8 and Sentinel-2. This methodology is based on the Machine Learning life cycle that includes 4 main stages which are implemented as follows: (1) Data acquisition, (2) Data preparation, (3) Model training, and (4) Model evaluation.

### A. DATA ACQUISITION

The activities developed in the data acquisition process include the field visits programmed by BAC to the sugarcane crops. In these activities, the crops delimitations were geo-referenced which were then turned into polygons expressed in Keyhole Markup Language (KML). Context information about those polygons, including age of the crop, variety, density, and whether this was the only plant contained in the polygon (mixing different crops is a common practice among some farmers) was also requested.

Using the geolocated polygons, Landsat-8 and Sentinel-2 images covering the study area were collected. It is important to note that having the goal of training a multi-class classification algorithm, BAC provided not only sugarcane polygons but also maize, forest, yucca and other coverage. The gathered satellite imagery dates ranged from the day the visit was made back to the month the crop was first planted; this was done in order to increase the sample size and to make sure we included all phenological stages of the crop. All these images were stored in the data cube and studied to understand their characteristics.

Specifically, the bank supplied 40 polygons delimiting the areas of sugarcane crops to be analyzed. However, after the validation process, only 28 polygons were further studied. 12 polygons were discarded since they contained multiple crops (e.g., sugarcane and maize). Figure [1] depicts the variety types of sugarcane represented in the set of polygons. The variety RD7511 is the most represented one with 16 polygons of the total set. There are also 12 polygons of other varieties, these varieties are palmireña, common, and ZC.

The age of the polygons integrated in the set are mostly represented between four and seven months with a total of 14 polygons in this range, as shown in Figure [2].

As we mentioned before, the 28 polygons collected on land were exported to KML files; every file was associated with its corresponding metadata located in a csv file. The files describe crop’s age, variety type, KML file location in the file system, and KML creation date, where the KML creation date tells us the date on which the crop’s age in months was registered.
B. DATA PREPARATION

In this phase the data sets needed to build the classification models were generated from the spectral bands and the ground truth data was used to label the pixels. Then, exploratory analysis techniques (statistical measurements like mean, median, standard deviation, outliers and data distributions) were used to know the characteristics of these data sets and to verify their quality. Based on this knowledge, we resampled unrepresented classes, eliminated outliers and standardized the values to improve data representation for learning algorithms.

1) Spectral Information Extraction Algorithm

The 28 KML files along with a csv file containing the metadata of each KML were fed into the spectral information gathering algorithm, with the aim to create the Sentinel-2 and Landsat-8 training data sets. The algorithm carried out the following steps: (1) read a KML file and the metadata associated with it (2) extract the KML file coordinates and KML creation date (3) generate a bounding box of the KML polygon based on its coordinates, (4) query the ODC for an image matching the bounding box and KML creation date, (5) extract spectral information of every point within the polygon boundaries as a vector of features, (6) add the metadata of the polygon to the vector of features, and (7) place the vector data of every collected point in a row of a csv file.

In addition to the training data sets, the algorithm also provides images serving validation purposes. These images depict which points were collected on every satellite image so that we can validate the correctness of the spectral information gathering algorithm and the data sets generated. When images were validated, we noted that low confidence cloud points covering sugarcane polygons were part of the collected Landsat-8 and Sentinel-2 data sets.

2) Clouds Removal Strategy

Both satellite sensors, Sentinel-2 and Landsat-8, contain quality bands that are useful to determine, in general terms, the type of coverage that the image has at the pixel level.

Accordingly, pixels are classified by these quality bands into several categories including cloud, vegetation, water, among others in Sentinel-2 but only clear, clouds, water, snow and terrain occlusion pixels in Landsat-8. Dense clouds are correctly classified by these quality bands so, using the cloud mask provided by the quality band, these pixels were removed from the data sets. However, with this approximation we still found low confidence clouds or cirrus pixels in the training data sets that were not detected as such by the quality bands.

In Sentinel-2, sparse clouds or cirrus were being classified as non-vegetated ground as shown in Figure 3. This observation was used to extract a second version of the Sentinel-2 data set, filtering out pixels that were classified as non-vegetation. This was supported by the fact that the sugarcane crop is classified as vegetation from the second month. With this process, only vegetated pixels within polygons labeled as sugarcane were taken as part of the training data set which yielded to the best results.

Landsat-8 images, unlike Sentinel-2 ones, do not provide pixel quality band classes such as vegetated and non-vegetated ground, that enable cirrus clouds discrimination.

Here, a heuristic was formulated to automate the identification of cirrus and programmatically remove those images of the set to be considered in the spectral information gathering procedure. The blue band provides a leeway in identifying thin clouds. This approach consists in the calculation of the mean for the blue band values of pixels in an image, then replicate this calculation in the image time series and identify particularly bright timesteps. Figure 4 presents a time series analysis for one of the images considered in the spectral information gathering procedure. We noted that values for the blue mean reflectance higher than 500 reflectance units (ru) represented images with cirrus or low confidence clouds. This approach is applied after pixels classified as clouds by the quality bands are excluded from the data to remove any remaining timesteps that are particularly bright. Finally, images exhibiting a discontinuous behaviour in time were removed. Removing thin clouds also yielded better results for the Landsat-8 data set.
3) Description of the generated Data Sets

The resulting data sets contained 35686 training examples (pixels of satellite images that represented sugarcane crops) in the case of Sentinel-2 imagery, and 1169 pixels in the case of Landsat-8. These resulting numbers correspond to 22.6% and 32% respectively of the initial total number of pixels. This was due to clouds and defective pixels.

Other coverage such as urban zone, water, forest, bare soil, sand, rocks, yucca and maize were also identified and processed, for Sentinel-2 and Landsat-8 images, with the spectral information gathering algorithm, the resulting data sets comprise the coverage shown in Table 1. Furthermore, Table 2 presents the bands and vegetation indices considered for each data set. Since the vegetation indices are calculations over the bands, we decided to add them to the data set as new types of bands in order to have more information, increasing the size of the training data provided to the algorithms.

Figures 5 and 6 describe the Landsat-8 and Sentinel-2

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**TABLE 1:** Classes considered in Sentinel-2 and Landsat-8 data sets and number of samples per class

| Coverage          | Sentinel-2 | Landsat-8 |
|-------------------|------------|-----------|
| sugarcane         | 35686      | 1169      |
| urban zone        | 188298     | 4450      |
| water             | 545018     | 95301     |
| forest            | 204299     | 44547     |
| bare soil         | 19750      | 8561      |
| sand              | 1976       | 0         |
| rocks             | 7952       | 494       |
| yucca             | 903        | 0         |
| maize             | 1149       | 0         |
| cloud             | 0          | 3000      |
| high confidence cloud | 0          | 3000      |
| low confidence cloud | 0         | 3000      |
| medium confidence cloud | 0       | 3000      |
| cloud shadow      | 0          | 3000      |

**TABLE 2:** Features for the training samples in Sentinel-2 and Landsat-8 data sets

| Feature       | Sentinel-2 | Landsat-8 |
|---------------|------------|-----------|
| red           | x          | x         |
| green         | x          | x         |
| blue          | x          | x         |
| nir           | x          | x         |
| swir1         | x          | x         |
| swir2         | x          | x         |
| pixel_qa      | x          |           |
| scl           | x          |           |
| narrow_nir    | x          |           |
| water_vapor   | x          |           |
| veg5          | x          |           |
| veg6          | x          |           |
| veg7          | x          |           |
| ndvi          | x          | x         |
| evi           | x          | x         |
| evi2          | x          | x         |
| rvi           | x          | x         |
| savi          | x          |           |
sugarcane final data sets by age respectively. From these figures we can see that crops between one and two months of age are best represented in the Landsat-8 data set and crops between one and six months are best represented in the Sentinel-2 data set.

FIGURE 5: Sugarcane Landsat-8 data set crop’s age count

FIGURE 6: Sugarcane Sentinel-2 data set crop’s age count

C. MODEL TRAINING

In this process, multiple classification algorithms such as Random Forests, K-Nearest-Neighbors, Support vector Machine (SVM), Neural Networks and Gradient Boosting were applied. Before applying data pre-processing techniques, data sets were divided into training set and test set (80 % for training and 20 % for testing). The pre-processing included balancing the unrepresented classes using resampling. The resampling rate was obtained by applying cross validation; however, experiments were also conducted with imbalanced data to determine their effect on the performance of the algorithm. In addition, to determine how vegetation indexes influenced the model’s ability to identify sugarcane we also used data sets without that excluding such indexes.

As we mentioned before, five learning algorithms were used for the construction of the classification models. To calibrate these algorithms a search for the best values of hyperparameters was made; for this purpose, k-fold cross validation technique was applied to training set using k = 10.

Once the hyperparameter values were obtained, a model was built based on them and applied to the test set to determine its generalization performance on new data. The mentioned hyperparameters include for Landsat-8 and Sentinel-2 models are detailed in Table 3.

TABLE 3: hyperparameter configuration of the models.

|                | Landsat-8                        | Sentinel-2                     |
|----------------|----------------------------------|--------------------------------|
| Random Forest  | Criterion: Entropy               | Class weight: Balanced         |
|                | Max Depth: 50                    | Criterion: Entropy             |
|                | Number of Estimators: 100        | Max Depth: 25                  |
|                |                                  | Min Samples in Leaves: 5       |
|                |                                  | Number of Estimators: 120      |
| SVM            | C: 100                           | C: 100                         |
|                | Gamma: scale                     | Gamma: scale                   |
|                | Decision function shape: one     | Decision function shape: one   |
|                | versus one                       | versus rest                    |
| KNN            | Number of Neighbours: 7          | Number of Neighbours: 1        |
|                | p: 1                             | p: 1                           |
|                | Weights: Distance                | Weights: Uniform               |
| Gradient       | Learning Rate: 0.05              | Learning Rate: 0.1             |
| Boosting       | Max Depth: 5                     | Max Depth: 5                   |
|                | Max Features: Auto               | Max Features: Auto             |
|                | Number of estimators: 120        | Number of estimators: 120      |

D. MODEL EVALUATION

The models were evaluated on the test set using standard classifier metrics. Based on this analysis, the best model was selected and tested on new polygons provided later by BAC.

1) Performance Metrics

Performance of the classifiers obtained was measured using the well-known recall, precision and F1-score metrics; Recall measures positive accuracy, indicating how many examples of this class are correctly classified (is also known as the True Positive rate or Sensitivity); Precision measures how many examples qualified as positive actually belong to this class; and F1-score provides the geometric mean of these two measurements.

\[
\text{Recall} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}}
\]
\[
\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False positive}}
\]
\[
F1 = \frac{(2 * \text{recall} * \text{precision})}{\text{recall} + \text{precision}}
\]

2) Evaluation of Classification Performance

In this section, we present the results obtained for the classifiers (Random Forests, SVM, Nearest Neighbors, and Gradient Boosting) generated from the Landsat-8 and Sentinel-2 training data sets along their variations; unbalanced without vegetation indices, and balanced with vegetation indices. The classification performance is evaluated on the corresponding test data sets. The average values for recall, precision, and F1-score are shown for different validations of the classifiers.
on the test sets.

About Landsat-8 classifiers
Recall, precision and F1-score metrics for the Landsat-8 classifiers are depicted in Tables 4 and 5. The first table describes the performance of the classifiers that were generated from the unbalanced data set; the second describes the performance of the classifiers generated from the balanced counterpart of the data set.

TABLE 4: Results from Landsat-8 models, Unbalanced data set

| Model | With vegetation indexes | Without vegetation indexes |
|-------|-------------------------|---------------------------|
|       | Recall | Precision | F1-score | Recall | Precision | F1-score |
| KNN   | 0.83   | 0.84      | 0.83     | 0.84   | 0.82      | 0.83     |
| RandomForest | 0.90  | 0.91      | 0.90     | 0.90   | 0.92      | 0.91     |
| SVM   | 0.69   | 0.75      | 0.71     | 0.70   | 0.76      | 0.71     |
| GradientBoosting | 0.91  | 0.91      | 0.90     | 0.90   | 0.90      | 0.90     |

As shown in Table 4 Random Forest algorithm achieved the best overall F1-score classification performance, 91% trained with and without vegetation indexes. However, the one classifier generated with the imbalanced-without-indices data set was the best sugarcane classifier, since it delivered 72% F1-score for sugarcane classification against 70%. In terms of individual classes, 9 out of 11 classes achieved a F1-score higher than 84% in both classifiers. The confusion matrix of the best sugarcane classifier is shown in Table 6.

To conclude, we found that the use of vegetation indices such as; NDVI, EVI, EVI2 and RVI did not improve the sugarcane classification accuracy. Although it was expected that the use of the NDVI would improve the classification accuracy as reported on related reports [21], the combination of this index with others caused a negative incidence in the classification. As a result of this observation, the use and evaluation of alternative combination of vegetation indices is proposed as future work. At the same time, considering the amount of sugarcane data that we managed to obtain from Landsat-8, 1416 samples, and the sensor resolution per pixel 30 m², data about 4,248 ha was collected which is short in comparison with the sentinel-2 data set and other Landsat-8 sensor related reports [21]. The low representation of the sugarcane class may cause the model to have reduced capacity to generalize to new data, since the spectral variability in the cane found in crops is large and this variability could not be sufficiently represented in the data set.

Despite these limitations, we consider that the resulting classifier proof a significant performance in cane classification. This model can be improved as more data for sugarcane and other coverage surrounding the crop is available. Also, the use of other vegetation indices and combination of them should be considered for the improvement.

About Sentinel-2 classifiers
As with the Landsat-8 classifiers, recall, precision and F1-score metrics generated for the Sentinel-2 classifiers, for both the unbalanced and balanced data sets were analyzed and are presented in Tables 7 and 8.

TABLE 7: Results from Sentinel-2 models, Unbalanced data set

| Model | With vegetation indexes | Without vegetation indexes |
|-------|-------------------------|---------------------------|
|       | Recall | Precision | F1-score | Recall | Precision | F1-score |
| KNN   | 0.80   | 0.83      | 0.81     | 0.96   | 0.96      | 0.96     |
| RandomForest | 0.92  | 0.73      | 0.83     | 0.92   | 0.98      | 0.94     |
| SVM   | 0.79   | 0.89      | 0.88     | 0.92   | 0.71      | 0.75     |
| GradientBoosting | 0.70  | 0.79      | 0.73     | 0.87   | 0.89      | 0.87     |

The model that achieved the best overall F1-score is the KNN algorithm as shown in table 7. In terms of individual classes, this model achieved over 84% for every class and 7 out of 9 classes achieved an F1-score of 94% or more. Specifically, the F1-score of this model over sugar cane is 98%, the classes that achieved the lowest F1-score were Maize and Yucca with 88% and 85% respectively. However, it is worth noting that these were the least represented classes in the training data set, as shown in Table 1.

A result of classification over a Yucca crop is shown in Figure 2. On the other hand, there were classes that achieved a 100% F1-score on the test data set, these were urban zone, water, forests and bare soil.

As it was the case with the Landsat-8 classifiers, the best Sentinel-2 classifier was trained without the vegetation indexes; Including the vegetation indexes in the training data set not only did not improve the performance of the model, but it negatively impacted its accuracy. Performance of models trained with and without vegetation indexes can be contrasted in tables 7 and 8.
Also, as we can see in tables 7 and 8, for KNN and Random forests algorithms an unbalanced data set enhances their performance and, in contrast, SVM and gradient boosting algorithms achieve better results when trained with balanced data sets.

Results of classification over other images are shown in Figure 8 and Figure 9. The first figure shows a classification over a sugar cane crop area, and the second figure shows the classification over a cloudy area that contains a maize crop.

It is important to note that the clouds and cloud shadows classified in the second figure are classes that, as mentioned in section III-B2, are contained in the sentinel scene classification band. Table 9 shows the confusion matrix of the types of cover the algorithm was trained for.

### IV. DISCUSSION

#### A. CONCERNING THE USE OF REMOTE SENSING DATA

Intrinsic features in remote sensing such as temporal, spatial, spectral, and radiometric resolution introduce several challenges when considering land cover detection and classification tasks, in particular, crop detection. It is important to note that these tasks strongly depend on the quantity and quality of the information obtained from the scenes of the different remote sensors.

Regarding temporal resolution, Landsat-8 sensor offers up to 2 scenes per month, while Sentinel 2A and 2B sensors provide 6 scenes per month. By increasing the temporal resolution, the number of scenes per month may require more storage capacity. For Sentinel the required capacity is around 6GB (1GB per scene); therefore, obtaining the information of a specific scene from Sentinel-2 for a whole year represents to the users a 72GB storage requirement.

Specifically, for the department of Boyacá, approximately 90% of the territory can be covered using 6 scenes from Sentinel-2, which corresponds to 432GB of storage per year. The above panorama proposes challenges related to the storage and processing for this increasing data volume.

Concerning radiometric resolution, slight changes on the crop are difficult to perceive by a sensor.

The atmosphere is composed of gases that cause distortion of the image by the interaction of light with the gases (diffraction). This challenge can be divided into two: the first, related to the distortion of the images due to the gases that make up the atmosphere, even though they allow light to pass through; and the second, related to the appearance of clouds that block the passage of light towards the earth’s surface.

To face the first challenge, we developed an algorithms to calculate the impact of this layer of gases, to correct distortions on the satellite image that these gases produce. These algorithms are usually based on the use of a dark surface to determine how an area should look without the atmospheric effects; taking this type of surfaces as a base, the algorithm can predict and counteract the effect of gases on the image.

#### TABLE 6: Confusion matrix for Random Forest On Landsat-8

| Classified as | Urban Zone | Water | Sugarcane | Bare Soil | Rocks | Forest | cloud | Shadow | low_conf_cl | high_conf_cl | med_conf_cl |  |
|---------------|------------|-------|-----------|-----------|-------|--------|-------|--------|-------------|--------------|-------------|---|
| Urban Zone    | 2437       | 0     | 18        | 4         | 33    | 12     | 21    | 1      | 0           | 1            | 142         |  |
| Water         | 0          | 1804  | 3         | 0         | 0     | 0      | 0     | 0      | 0           | 0            | 0           |  |
| Sugarcane     | 8          | 4     | 1713      | 0         | 0     | 0      | 0     | 27     | 0           | 0            | 17          |  |
| Bare Soil     | 1          | 0     | 0         | 57075     | 1     | 4      | 6     | 12     | 0           | 0            | 0           | 1 |
| Rocks         | 9          | 0     | 2         | 0         | 500   | 10     | 0     | 54     | 6           | 5            | 100         |  |
| Forest        | 2          | 0     | 5         | 4         | 3175  | 1      | 0     | 49     | 124         | 124          | 1122        |  |
| cloud         | 37         | 0     | 28        | 13        | 13    | 207    | 0     | 0      | 0           | 0            | 6           |  |
| Shadow        | 1          | 0     | 0         | 36        | 0     | 0      | 267   | 3      | 0           | 0            | 17          |  |
| low_conf_cl   | 0          | 2     | 4         | 0         | 0     | 0      | 0     | 0      | 0           | 0            | 0           |  |
| high_conf_cl  | 1          | 4     | 12        | 0         | 0     | 0      | 0     | 0      | 20          | 1749         | 4           |  |
| med_conf_cl   | 296        | 1     | 2         | 49        | 124   | 137    | 8     | 73     | 4           | 4            | 1122        |  |

FIGURE 7: Scene classification over yucca polygon in Sentinel-2
Secondly, the appearance of clouds in images avoids the correct detection of the ground. To mitigate this inconvenience, algorithms are used to detect their presence and, in this way, only those pixels that have a low probability of clouds are used. Also, radar images like Sentinel-1, provided by active sensors, help to avoid this kind of problems.

**TABLE 9: Confusion matrix for Nearest Neighbors on Sentinel-2**

| Classified as | Urban Zone | Water | Forests | Rocks | Sugarcane | Maize | Yucca | Sand | Bare Soil |
|---------------|------------|-------|---------|-------|-----------|-------|-------|------|-----------|
| Urban Zone    | 37946      | 0     | 0       | 23    | 0         | 0     | 0     | 0    | 3811      |
| Water         | 0          | 108848| 0       | 0     | 0         | 0     | 0     | 0    | 0         |
| Forests       | 0          | 40832 | 0       | 34    | 0         | 0     | 0     | 0    | 0         |
| Rocks         | 0          | 0     | 0       | 1529  | 0         | 0     | 0     | 0    | 0         |
| Sugarcane     | 0          | 92    | 0       | 6924  | 17        | 190   | 0     | 0    | 0         |
| Maize         | 0          | 0     | 0       | 20    | 166       | 0     | 0     | 0    | 0         |
| Yucca         | 0          | 0     | 0       | 0     | 0         | 0     | 0     | 0    | 0         |
| Sand          | 3          | 0     | 0       | 0     | 0         | 0     | 0     | 0    | 3811      |
| Bare Soil     | 0          | 0     | 0       | 0     | 0         | 0     | 0     | 0    | 3811      |

B. CONCERNING THE USE OF MACHINE LEARNING ALGORITHMS

The comparative analysis carried out with four learning algorithms and different data sets revealed that the best algorithms were Random Forest and KNN. From these results we can conclude that it is possible to use machine learning techniques to build models that allow the identification of sugarcane crops in the Boyacá region, using data from free access satellite images (Landsat-8 and Sentinel-2).

However, in order to build the labeled data sets needed to apply the modeling techniques, BAC had to reprocess information the had already gathered and include new steps in their visits that were new to their staff. It is important then to establish mechanisms that facilitate the generation of data sets from the moment a loan is granted.
C. CONCERNING THE USE OF THE OPEN DATA CUBE

The use of the python-based API ODC allowed a fast analysis of the remote sensing information. Using this API enabled users to request the pixels that were interesting for analysis directly, instead of manually individual satellite files. Before using the ODC, merging different bands for spectral analysis required a manual resampling method due to the different resolutions of bands coming from different remote sensing sensors. In contrast, requesting information of different bands with the ODC automatically resamples the bands into a desired resolution and returns them into a single variable ready for analysis.

A process was created in Jupyter notebooks for analysing areas of interest which had multiple options for requesting the information to the ODC. One of the most used ones was requesting pixels by polygon, which returned a square surrounding the desired polygon. This is a highly replicable process, and analysts can change the desired polygons, dates and bands by only specifying them in a set of variables, new analysts can change the variable values to classify a new area.

D. CONCERNING THE FUTURE USE OF GENERATED MODELS FOR CROP MONITORING

Although to the problems identified, satellite images constitute a valuable source of information on land surface data. For instance, they would allow with great agility and precision, the geospatial location of the properties presented as a guarantee of credits, as well as the identification of the crop developed in the mentioned property. In this way, this solution facilitates to the area of Control and Appraisals of BAC, directly responsible for the monitoring and control process, the verification of effective compliance with the conditions agreed in the loan origination stage. Such verification would allow to identify deviations from the investment plan established for the crop, making a filter to identify crops with non-compliance in the investment plan, validating areas with fraud problems, before making a field visit, thus minimizing the loss of the investment by focusing on the areas to visit, prioritizing field visits to those that will be reported to Finagro.

Additionally, it allows the monitoring of crops of products sown with resources disbursed by the Bank in a specific area, by recognizing the area and identifying anomalies in the crops that are the object of investment. This can be done at a property level but also at a regional and even national levels, optimizing the use of resources and the establishment of informed policies within the Bank.

V. CONCLUSIONS AND FUTURE WORK

This paper presents the development of a software tool, based on a machine learning model for processing free satellite imagery, with the aim to support the BAC in the Controls of Agricultural Investment process in order to identify crops with non-compliance in the investment plan before making field visits and thus prioritize those visits. As a case study, we selected the identification of “panela” sugar cane crops since it is one of the most important economic and social crops for Colombia.

Based on the results obtained of this work, we found that it is possible to generate reliable models that identify “panela” sugarcane crops in the Boyacá region from free access satellite images. These results reinforce the aim of the BAC to continue the exploration of remote sensing imagery in order to identify the characteristics of production projects supporting the investing control process. However, the generated models are susceptible to many improvements. Some of them are:

- To improve the acquisition of field information, through the capture of crop lots from origination and a protocol more focused on getting useful information for training the Machine Learning models.
- To improve the schedule of visits, in order to get better-balanced information collected training the model. This includes the age of the crops, the variety of cane grown, and whether there are combinations of crops, among others.
- Generate more information on other elements on land that are not cane, as they help the model distinguish between cane and other land covers. This exercise included some cassava and maize, correctly identified by the model, but with more examples, we will obtain better results. Specifically, we propose the inclusion of grasslands into the training data set. This is based on the fact that grass is from the same family as sugar cane, "Poaceae", and the high probability of presence of grass areas in the region of study.
- Include among the model variables the altitude of the lot being cultivated, which determines its development.

More strategically, other useful actions for BAC can be:

- Apply this methodology to productive systems with similar phenologies and homologous growth habits (rice, cut pastures, maize, among others).
- Generate models for other productive systems. The data used in this project for maize and cassava is a good start.
- Retrain the model periodically, every six months, for example, since in any case, the visits are still carried out and information is collected in each of them.

Finally, since cloud cover is one of the constant problems in the use of optical images, it is possible to consider the use of active sensor images, in particular Sentinel 1, which, being based on radar signals, do not present disadvantages with cloud coverage.

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