Classification Analysis of NDVI Time Series in Metric Spaces for Sugarcane Identification

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Abstract: In Brazil, agribusiness is an important task for the economy, since it provides a substantial part of the country's Gross Domestic Product. Besides that, interest in biofuels has grown, considering they make viable the use of renewable energy. Brazil is the world's largest producer of sugarcane, which enables a large ethanol production. Thus, to monitor agricultural areas is important to support decision making. However, the amount of generated and stored data about these areas has been increasing in such a way that far exceeds the human capacity to manually analyze and extract information from it. That is why automatic and scalable data mining approaches are necessary. This work focuses on the sugarcane classification task, taking as input NDVI time series extracted from remote sensing images. Existing related works propose to analyze non-metric features spaces using the DTW distance function as a basis. Here we demonstrate that analyzing the multidimensional space with Minkowski distance provides better results, considering a variety of classifiers. *k*NN using L_2 distance performed similarly or better than using DTW. We also demonstrate a data configuration with geolocation for training XGBoost, with results better than state-of-the-art.

1 INTRODUCTION

In recent years, the impacts caused by global warming and climate changes have been highlighted. In this sense, interest in biofuels has grown since they are crucial to reduce greenhouse gases emissions by the reason they make viable the use of renewable energy instead of fossil fuels.

Brazil has some peculiarities (*i.e.* favorable climate, soil, water abundance, relief and luminosity) that contribute to the development of agribusiness. In 2016, the sector accounted for 23% of the country's Gross Domestic Product (GDP), which is equivalent to USD 413.8 billion (Brasil, 2016; Bank, 2017). Brasil is the world's leading producer of sugarcane (Service, 2017), which propitiates ethanol production. In this way, considering the large Brazilian territorial extension, it is relevant for the local government and companies related to agriculture to monitor those areas over the years, as to perform studies such as production estimation, expansion identification, as well as providing relevant information to support decision making for agricultural producers and/or funding agencies.

However, the volume of data that is currently extracted from these areas, like satellite images, easily reaches the hundreds of megabytes for storage and millions of instances to process, which exceeds the human capacity of manually analyze and extract significant information from them. That is why leveraging data mining methods, such as clustering (Kyrgyzov et al., 2007) and classification (Julea et al., 2011) is almost mandatory in this setting.

Considering the temporal information within those data and applying data mining methods, sugarcane areas are commonly identified and monitored. Usually it is used satellite images to monitor these crops. This analysis aims to consider, for each subarea of the region of interest, corresponding to one pixel of a satellite image, a series of values that indicate the vegetation behavior of that subarea in a certain period of time. Information about vegetation is usually obtained from the Normalized Difference Vegetation Index (NDVI) (Price, 1993). NDVI is related to the amount and concentration of vegetation biomass and it is widely used in agricultural researches

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(da Silva et al., 2011; Scrivani et al., 2017; João et al., 2018). In this sense, it is possible to differentiate sugarcane areas from native forests, since they have distinct behaviors.

There are many researches that use NDVI as a measure to classify or cluster crops (Romani et al., 2011; da Silva et al., 2011; Amaral et al., 2014), and most of them employ non-metric space analysis and normally obtain their best results by using the Dynamic Time Warping (DTW) to measure the distance between two time series. Sugarcane classification methods that employ distances such as DTW have some drawbacks, since its time complexity is quadratic. Another reason is that DTW is not performed on a metric space and, thus, cannot benefit from improvements in speed on the same scale that other methods performed on a metric space do. By its definition, the metric space is a set with a metric distance that respects the following characteristics: non-negativity, symmetry, triangular inequality and identity. Using these properties, pruning methods can be applied (Mao et al., 2016).

These constraints make the investigation of viable alternatives to DTW-based methods for sugarcane classification in time series a task to be seriously considered. The same can be said for the choice of distance functions to be used by the classifier, considering the general speed advantages of metric spaces, such as fast indexing of data and efficient pruning.

In this work, we perform the aforementioned investigation and aim to clarify those assumptions. Are DTW-based methods, which take advantage of temporal relations, unmatched in terms of accuracy, precision and recall or, if otherwise, what other methods have comparable results? We begin from the hypothesis that the DTW, considering the main features that are desirable for a classifier, is not a prime choice for sugarcane time series classification and that L_p distances, when combined with adequate classifiers, are viable options for this classification task.

This paper is organized as follows. Section 2 presents the Related Works and Section 3 describes Background concepts that allows a better understanding about the approach. Section 4 details how the investigation was conducted, including the dataset analysis, followed by Section 5 which explain the experiments and results. After all, the Conclusions are presented in Section 6.

2 RELATED WORK

Satellites are important for agribusiness, since they allow the remote sensing of regions (Romani et al., 2011; da Silva et al., 2011; Amaral et al., 2014; Scrivani et al., 2017; do Valle Gonçalves et al., 2017). Additionally, they make feasible free access to data. In this way, agricultural producers can monitor their crops, identify anomalies and take corrective actions throughout the harvest, obtaining better productivity results (Amaral et al., 2014).

Many researches in the literature idealize the creation of computational tools to semi-automatically identify and monitor agricultural cultures, such as sugarcane. The main difficulty of this task lies in the small amount of labeled data compared to the total amount of data (Amaral et al., 2014). An author (Amaral et al., 2014) introduced a new framework to classify sugarcane crops. In (da Silva et al., 2011), it is proposed a supervised approach based on features extraction to the coefficients obtained by time series in Fourier decomposition.

In (Scrivani et al., 2017), the authors employ time series for generating mathematical models that estimate sugarcane production using linear regression with the following variables: NDVI / MODIS, Water Requirement Satisfaction Index (WRSI), planted area and sugarcane production. Their paper evidenced that NDVI and WRSI are representative variables for analyzing sugarcane regions with one-year period time series.

The work of (do Valle Gonçalves et al., 2017) describes a methodology that comprises two main processes. The first one is the satellite images preprocessing, where images are converted into SITS. The second process employs clustering method on NDVI time series, following the principle that time series are grouped by their similarity. NDVI series are clustered by the k-means algorithm under the DTW distance function. The purpose is to analyze NDVI time series of one or more sugarcane crop seasons.

Another approach for classifying NDVI time series uses association rules (João et al., 2018). The researchers (João et al., 2018) analyzed their method's accuracy results using some traditional approaches, such as Naive Bayes (NB), Random Forest (RF) and Support Vector Machine (SVM). They demonstrated that these traditional approaches do not attain an accuracy average higher than 55%.

3 BACKGROUND

3.1 Temporal Data

Temporal data are frequent in a variety of fields, such as economics (*e.g.* number of sales, price of products), medicine (*e.g.* disease detection, patient progress evaluation) and agrometeorology (*e.g.* evolution of a given crop) (Maimon and Rokach, 2005; Mitsa, 2010).

According to (Mitsa, 2010; Esling and Agon, 2012), time series is the most common type of temporal data and they represent ordered real-valued measurements at regular or irregular temporal intervals. A time series can be univariate or multivariate. If only one variable is used to construct time series, it is called univariate, otherwise, we have a multivariate time series.

A univariate time series Ts is defined as $Ts = [(t_1, v_1), (t_2, v_2), ..., (t_n, v_n)]$ and, for each time t_i, where i assumes a value in the range $1 \leq i \leq n$, there is a value v_i associated.

3.2 Classification

Classification consists in the task of assigning a new sample to a set of previously known classes (Mitsa, 2010). Because of the supervised nature of this task, additional knowledge about the problem must be taken into account. This knowledge can be obtained by domain experts or by a sample of labeled data, which is commonly referred as the training dataset.

The classification algorithms used in this work are: k-Nearest Neighbors (kNN) (Cover and Hart, 1967), Naive Bayes (NB) (Larsen, 2005), Decision Trees (DT) (Tanha et al., 2017), Multilayer Perceptron (MLP) (Boughrara et al., 2017) and Extreme Gradient Boosting (XGBoost) (Chen and He, 2015).

The kNN technique consists in an algorithm that makes predictions based on the instances stored in the dataset. The NB classifier consists in a statistical approach (Larsen, 2005). Decision Trees is an approach that aims to divide a complex decision into a set of simpler decisions (Tanha et al., 2017; Mitsa, 2010). MLP consists in a neural network which are suited to solve problems that are not linearly separable (Boughrara et al., 2017). XGBoost, a scalable and portable approach based on Gradient Boosting, consists in an ensemble of other prediction models (*e.g.* CART Trees) (Chen and He, 2015).

3.3 Distance Functions

Distance functions measure how much the objects are distant. In classification task, they are useful to check how distant (or dissimilar) two objects are, and choosing the correct function is essential to obtain high-quality results. Advantages and limitations of each function should be considered, as well as the nature of the data to be analyzed.

There is a wide variety of distance functions, for example the Minkowski distance (L_p) that is a metric in a normed vector space. Given two vectors of real numbers $A = \{a_1, a_2, \ldots, a_n\}$ and $B = \{b_1, b_2, \ldots, b_n\}$, the Minkowski distance is formalized by:

$$L_p = \left(\sum_{i=1}^{n} |a_i - b_i|^p \right)^{1/p} \quad (1)$$

However, the Minkowski distances concentrate at calculating the direct distance between two vector points, wherein the vectors must have the same baseline, scale and length (Mitsa, 2010). An alternative is Dynamic Time Warping (DTW), which consists in a non-linear distance function that uses dynamic programming to find the best alignment between time series, not necessarily with the same length each other. Given two time series $X = \{x_1, x_2, \ldots, x_r\}$ and $Y = \{y_1, y_2, \ldots, y_s\}$, the $DTW(X,Y)$ cost of a warping path P between X and Y is defined by:

$$DTW(X,Y) = \min \sum_{p=1}^{P} \gamma(x_{i_p}, y_{j_p}) \quad (2)$$

This warping path aims to evaluate the recurrence, using dynamic programming (Ratanamahatana and Keogh, 2004). Where $\gamma(x_i, y_j)$ is the cumulative distance of $d(x_i, y_j)$ and the minimum cumulative distances from up to three forwardly adjacent cells (Kim et al., 2001).

3.4 Satellite Image Time Series

This work used satellites with low spatial resolution and high temporal resolution images, namely the Advanced Very High Resolution Radiometer (AVHRR) sensor, aboard the National Oceanic and Atmospheric Administration (NOAA) satellite.

A common approach in satellite image analysis consists in classifying each pixel or a subset of pixels from an image using data mining techniques (Romani et al., 2011; da Silva et al., 2011; Scrivani et al., 2017; do Valle Gonçalves et al., 2017; João et al., 2018). In the context of this work, we used a method oriented to Satellite Image Time Series (SITS), where time series are generated by one-year period, corresponding to a twelve monthly satellite images from April to March of 2004/2005.

For these images, each pixel represents a region of approximately 1km x 1km and has a NDVI value associated with its respective real coordinate. In this way, each pixel is represented by a time series $Ts = [(t_1, v_1), (t_2, v_2), \ldots, (t_{12}, v_{12})]$. We conduct this work with the same dataset used in (Amaral et al., 2014) which contains images and geographical informations about Sao Paulo/Brazil provided by Embrapa[1].

4 PROPOSED INVESTIGATION

4.1 Dataset Analysis

This analysis aims to examine the classes in dataset. Table 1 shows the classes distribution, and it is notable that the quantity of non-sugarcane instances is greater than that of sugarcane instances. As such, we observe the correlation between the sugarcane and non-sugarcane classes. The instances used in this correlation analysis were chosen manually by domain experts and it propitiates the creation of an ideal configuration for applying the classification approach, considering the fact that the most representative instances were selected. Figure 1.1 represents sugarcane time series and Figure 1.2 corresponds to non-sugarcane time series. Additionally, the NDVI average is indicated by the highlighted line.

Table 1: Dataset: class proportion distribution.

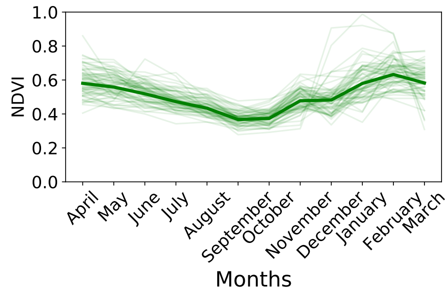
Class	Amount	Proportion
Sugarcane	26.964	13.58%
Non-sugarcane	171.534	86.42%
Total	198.498	100.00%

Analyzing the graphs of Figure 1, it is possible to infer that the NDVI average for the time series are approximately the same. To notice that, we calculated the Pearson correlation between both classes. After calculating the correlation between sugarcane instances, a bi-dimensional matrix was generated and the average value from the lower triangle was extracted, disregarding the main diagonal. The same process is accomplished both for non-sugarcane instances and sugarcane against non-sugarcane instances. The results are showed in Table 2 and they demonstrate that elements in non-sugarcane class have lower correlation values than non-sugarcane class if compared with non-sugarcane/sugarcane.

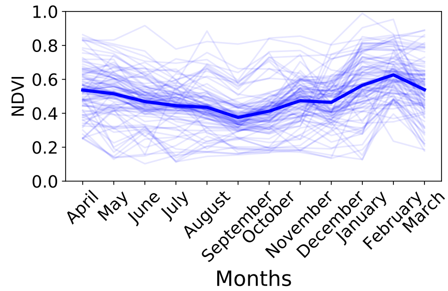
Table 2: Pearson correlation between sugarcane and non-sugarcane instances.

Class	Sugarcane	Non-sugarcane
Sugarcane	0.7399	**0.6120**
Non-sugarcane	0.6120	0.5312

[1]Brazilian Agricultural Research Corporation. https://www.embrapa.br/



(a) Sugarcane



(b) Non-sugarcane

Figure 1: Sugarcane Times Series x Non-Sugarcane Time Series.

4.2 Geographical Coordinates

Assuming that sugarcane is grown throughout vast and nearby areas, latitude and longitude of instances were added to the features vector in order to improve the information gain. When DTW is computed, its distance is incremented with L_2 calculations using lat and lon values of the instance in question, where $[lat_x, lon_x]$ augments X and $[lat_y, lon_y]$ augments Y. $DTW_{locality}$ distance is defined by Equation 3:

$$DTW_{locality}(X,Y) = DTW(X,Y) + L_2([lat_x, lon_x], [lat_y, lon_y]) \quad (3)$$

$L_{p-locality}$ is an improvement by the actual lat and lon values for each instance, such that it results in the vectors $X_{locality} = [v_{x1}, v_{x2}, \ldots, v_{x12}, lat_x, lon_x]$ and $Y_{locality} = [v_{y1}, v_{y2}, \ldots, v_{y12}, lat_y, lon_y]$. At last, the vectors with (lat and lon) augmentation are used in $L_p(X_{locality}, Y_{locality})$ distance function.

4.3 Evaluation Metrics

In order to evaluate the classification performance, we calculated the Matthews Correlation Coefficient (MCC) coefficient (Matthews, 1975), accuracy, recall and precision (Maimon and Rokach, 2005).

Table 3: Experiment 1: Accuracy.

Distance	1NN	3NN	5NN	7NN	9NN	11NN
DTW 1	0.761	0.821	0.844	0.857	**0.859**	**0.856**
DTW 2	0.805	0.843	0.846	0.863	0.858	0.853
DTW Inf	0.805	0.843	0.847	0.863	0.858	0.853
L_1	0.805	0.843	0.847	0.863	0.858	0.853
L_2	0.805	0.843	**0.847**	**0.863**	0.858	0.853
L_3	**0.807**	**0.844**	0.847	0.856	0.856	0.853

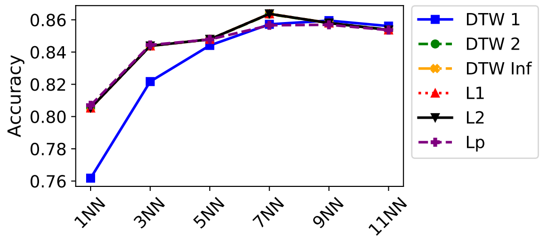


Figure 2: Experiment 1: Accuracy.

Table 4: Experiment 1: Precision.

Distance	1NN	3NN	5NN	7NN	9NN	11NN
DTW 1	0.045	0.034	0.025	0.026	0.019	0.019
DTW 2	0.030	0.014	0.006	0.005	0.001	0.001
DTW Inf	0.045	0.034	0.025	0.026	0.019	0.019
L_1	0.045	0.034	0.025	0.026	0.019	0.019
L_2	**0.045**	0.034	**0.025**	**0.026**	**0.019**	**0.019**
L_3	0.043	**0.036**	0.022	0.023	0.017	0.019

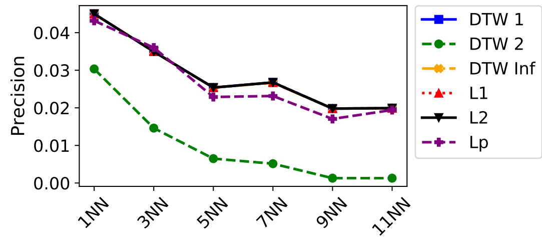


Figure 3: Experiment 1: Precision.

5 EXPERIMENTS AND RESULTS

We have conducted a set of experiments in order to answer some questions about classification task in NDVI time series for sugarcane identification. Those experiments are described as follows:

- Experiment 1 was performed to evaluate the efficiency of metric space distance functions, testing variations of L_p family and the DTW distance.
- Experiment 2 attempts to analyze if geographical location information can improve the performance of the classification task.
- Experiment 3 aims to identify a good configuration for the classifier training, considering sugarcane and non-sugarcane instances. Besides that, it investigates the efficiency of some classification algorithms and the impact that geographical location information has on these classifiers. Also, maximizing the MCC value by using predefined parameters found in previous experiments. The results of experiment are compared with state-of-the-art.

In the experiments, the settings adopted by Multilayer Perceptron algorithm assumed one hidden layer with 100 neurons, learning rate of 0.001 per iteration and 100,000 as the max number of iterations. In case of XGBoost, the used parameters are: 3 as max depth, 200 as estimator number and learning rate of 0,015. kNN under some variations of k. Decision Tree uses entropy. Finally, Naive Bayes' standard configuration doesn't need parameters.

5.1 Experiment 1

In the first experiment, we evaluate some variations of P to DTW and some variations of p to L_p distances. The propose of this experiments are the compute efficiency of DTW and L_p. The tests were conducted under DTW distance, which is traditionally used to compare time series. The objective is to evaluate its performance compared with the distance algorithms for multidimensional spaces (*i.e.* Minkowski family distances). To perform this experiment, we used 200 random instances for training and 10,000 random instances for testing. This procedure was performed 10 times and the final results are the average of the iteration results. The $k\text{NN} = \{1,3,5,7,9,11\}$ was performed under the DTW and L_p distances, where DTW used the following configurations: $P = 1$ (DTW 1), $P = 2$ (DTW 2) and $P = \infty$ (DTW Inf), while the L_p was performed with $p = 1$ (Manhattan distance / L_1), $p = 2$ (Euclidean distance / L_2) and $p = 3$ (L_3).

Table 5: Experiment 1: Recall.

Distance	1NN	3NN	5NN	7NN	9NN	11NN
DTW 1	0.270	0.217	0.161	0.176	0.126	0.122
DTW 2	0.170	0.086	0.041	0.033	0.008	0.007
DTW Inf	0.270	0.217	0.161	0.175	0.126	0.122
L_1	0.270	0.217	0.161	0.176	0.126	0.122
L_2	**0.270**	0.217	**0.161**	**0.176**	**0.126**	**0.122**
L_3	0.260	**0.223**	0.146	0.150	0.108	0.118

Table 3 and Figure 2 describe the general accuracy of each algorithm using the aforementioned definitions. The first relevant observation is that DTW 2 and DTW Inf presented high accuracy compared with the DTW 1. In addition, it is visible that the algorithms using L_p distances in the multidimensional space presented similar accuracy matching the DTW approaches in all cases. In this way, we conclude that DTW 2 is sufficient for this context and L_p distances have results similar to those obtained using the DTW.

Table 4 and Figure 3 indicate the precision of the evaluated algorithms. Relating Figure 3 to Figure 2, it is possible to note that as the general accuracy increases, precision decreases and recall increases (Table 5). This condition directly affects the accuracy, since the number of non-sugarcane instances is greater than the number of sugarcane instances, as showed in the Table 1.

In addition, observing the precision (Table 4) and recall (Table 5), we noticed that the distances that presented the highest precision were the ones of the Minkowski family, standing out the L_2 distance that in almost all the kNN tests, presented the highest accuracy. Therefore, DTW does not present gain in this application, since the multidimensional space distances presented better results without using the temporal information itself.

5.2 Experiment 2

Another observation from Experiment 1 (Section 5.1), $k\text{NN} = 7$ presented better results in terms of accuracy, precision and recall. Therefore, the other experiments adopted this configuration for kNN algorithm.

In Experiment 2 we will test the inclusion of locality in distance algorithms, as reported in Section 4.2. Appending the real geographical coordinate (*i.e.* latitude and longitude) of the instances, a better instances classification is expected, since sugarcane is grown throughout nearby areas.

Analogously to the previous experiment, we tested DTW 1, DTW 2, DTW Inf, L_1, L_2 and L_3 distance functions. It also followed the setup of 200 random instances for training and 10,000 random instances for testing.

Table 6 presents the results obtained in this experiment. Observing the accuracy in Table 6 and Table 3, we notice that in some algorithms there was an increase in their accuracy. In addition, it is noted that the precision and recall of the experiments with locality (Table 6) increased compared to the precision (Table 4) of the experiments without locality. In this way, the distance functions presented a better performance with the addition of the locality, representing an information gain.

Again, we can see that the distance L_2 stood out in relation to the other distances, while the other ones presented similar results. Thus, besides the fact that distances of the multidimensional space have a lower computational cost than DTW, they also presented superior results, demonstrating that for the problem in question there was no advantage in using temporal information of the time series.

Table 6: Experiment 2: 7NN with distance using locality, evaluating accuracy (Acc), precision, recall and MCC.

Distance	Acc	Precision	Recall	MCC
DTW 1	0.856	0.0344	0.2134	0.2449
DTW 2	0.860	0.0375	**0.2457**	0.2559
DTW Inf	0.862	0.0362	0.2333	0.2635
L_1	0.862	0.0359	0.2314	0.2636
L_2	**0.864**	**0.0375**	0.2426	**0.2750**
L_3	0.862	0.0366	0.2360	0.2635

5.3 Experiment 3

In the previous experiment we concluded that use of geographic coordinates gives better results. In the current experiment, the objective is find the best ratio for training between both classes, testing in some classifiers (*i.e.* kNN, MLP, XGBoost, DT and NB). To perform this experiment, we used 700 elements to training, the ratio between positive and negative $r = \{0.3, 0.4, 0.5, 0.6, 0.7\}$, and if the test data without geographic information (Table 7 and Figure 4) and with location (Table 8 and Figure 5). For this experiment we used 1,000 elements for testing, and we run all algorithms 10 times, and the average is extracted.

As verified in Experiment 2 (Section 5.2), using location information is better than to do not use, and the current experiment confirms that fact, since all algorithms performed better with geographic information, except MLP. Checking the average of higher MCC values, it is possible to conclude that the best positive ratio lies somewhere between 0.4 and 0.5. Considering the two classifiers that obtained higher MCC value (XGBoost and kNN L_2), the best configuration, using simple vote, has ratio 0.4. The current experiment found the best distribution between classes, that is 40% of training set composed by class sugarcane and 60% of class non-sugarcane and the Experiment 4 assumes that ratio for the next tests.

After finding the best ratio value between both classes, we want to know the effects of varying training dataset sizes by several experiments analyzing the performance of MCC. Observing Figure 6 it is visible that as bigger the training dataset gets, better the performance. However it is stabilized about sizes 1,000 to 3,000. It is interesting to observe that with 700 elements for training is possible to beat traditional algorithms that use non-metric distances which $\text{MCC} = 0.343$ (Amaral et al., 2014). The kNN L_2 and XGBoost beat with 0.363 and 0.360 respectively, and other algorithms show good results but do not have beat the state-of-the-art. Also, MLP lost in all cases.

Table 7: Experiment 3: Evaluating MCC. Normal NDVI time series.

Classifier	0.3	0.4	0.5	0.6	0.7
*k*NN L_2	0.257	**0.292**	0.252	0.25	0.228
MLP	0.143	0.252	**0.253**	0.204	0.118
XGBoost	0.295	**0.335**	0.275	0.251	0.236
DT	0.17	**0.212**	0.187	0.186	0.175
NB	**0.211**	0.202	0.196	0.173	0.184

Table 8: Experiment 3: Evaluating MCC. NDVI time series with locality.

Classifier	0.3	0.4	0.5	0.6	0.7
*k*NN L_2	0.353	0.359	**0.360**	0.329	0.303
MLP	-0.008	0.035	0.072	**0.080**	0.007
XGBoost	0.357	**0.387**	0.351	0.331	0.279
DT	0.247	0.251	0.234	**0.262**	0.240
NB	**0.260**	0.234	0.220	0.220	0.221

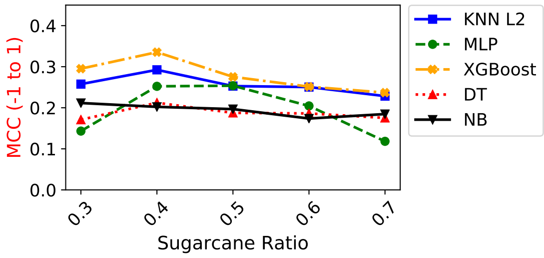


Figure 4: Experiment 3: Evaluating MCC. Normal NDVI time series.

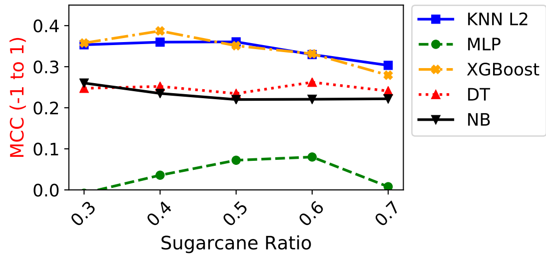


Figure 5: Experiment 3: Evaluating MCC. NDVI time series with locality.

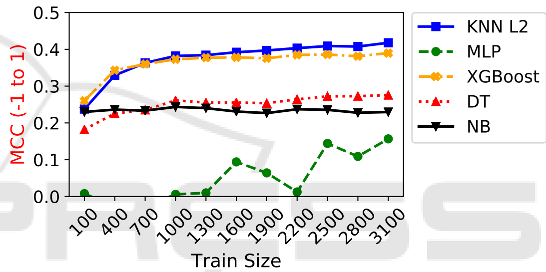


Figure 6: Experiment 3: Evaluating MCC. NDVI time series with locality, variating in training dataset size.

6 CONCLUSIONS

Sugarcane classification is a very time-consuming process when done manually. Thus, it is important to develop scalable and efficient methods to accomplish this work. As the need for knowledge in agribusiness grows, crop classification remains an important tool for the experts, since it allows the monitoring of a culture that has high relevance in the economy of Brazil.

We performed a series of experiments with several combinations of classifiers (i.e. Naive Bayes, Decision Tree, Multilayer Perceptron, XGBoost an *k*NN) and distance functions (i.e. L_1, L_2, L_p and DTW), and also the addition or not of geographic coordinates into the input data that is sent to the classifier. We have concluded that the use of geographic information may help the sugarcane classification task and, in fact, it did exactly that for the highest performing classifiers in our experiments, namely XGBoost and *k*NN using L_2 distance. The experimental results showed *k*NN using L_2 distance obtaining similar accuracy than *k*NN using DTW. *k*NN using DTW did not outperform XGBoost or *k*NN L_2 in terms of accuracy, precision, recall and MCC. Taking into account the higher computational cost of DTW distance, we also conclude that XGBoost and *k*NN using L_2 are better choices than *k*NN using DTW. Also, XGBoost have accuracy higher than state-of-the-art (Amaral et al., 2014), for the task of sugarcane classification.

Since L_2 distance calculations are performed on a metric space, they can benefit from the triangle inequality property of metric spaces which allows pruning of instances, thus speeding up the computations. This is especially important for processing large data volumes. This feature could be further explored by a future work. We aim to apply indexing methods in order to reduce the computational cost during classification. Even at the point up to where we reached with our experiments, the improvements in computational cost for simply using a L_p distance instead of DTW are significant.

Table 9: Experiment 3: Evaluating MCC. NDVI time series with locality, variating in training dataset size.

Classifier	100	400	700	1000	1300	1600	1900	2200	2500	2800	3100
*k*NN L_2	0.237	0.329	**0.363**	0.382	0.384	0.392	0.396	0.403	0.408	0.407	0.417
MLP	0.007	-0.028	-0.026	0.005	0.009	0.094	0.064	0.012	0.144	0.108	0.156
XGBoost	0.260	0.342	**0.360**	0.372	0.377	0.378	0.375	0.384	0.385	0.381	0.389
DT	0.182	0.225	0.235	0.261	0.255	0.255	0.253	0.264	0.272	0.272	0.275
NB	0.229	0.236	0.233	0.243	0.240	0.23	0.226	0.237	0.235	0.227	0.229

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