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Time-series classification of Sentinel-1 agricultural data over North Dakota

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ABSTRACT

Accurate measurements of agricultural land cover are important for monitoring global food security, economic stability, and environmental conditions. Since significant portions of global agricultural land are frequently cloud covered, synthetic aperture radar (SAR) has been shown to be a reliable form of gathering crop measurements, even in regions where acquiring clear optical imagery is challenging. In this work, repeat coverage from the C-band Sentinel-1 satellite over a portion of North Dakota is used to classify individual agricultural land-cover types. In this approach the times series forms the basis of a classification algorithm, where individual pixels are compared against a model of average crop backscatter response and classified as the crop with the least difference from the model. Multiple variations on the analysis are run to test the influence of polarization, iterations in model building, number of training fields, and validation input on the classification accuracy. It is shown that both VV and VH polarizations individually and combined are routinely able to produce overall accuracies above 90% when using multiple iterations in model building. These results show the potential for SAR-based agricultural land cover classifications built from comprehensive time series data.

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1. Introduction

With a growing population increasingly threatened by climate change, regular monitoring of global agricultural production is a vital part of ensuring food security. Local land management decisions, meteorological conditions, and the results of unforeseen disasters make agricultural forecasting in need of on-going and frequent updates. The sheer size of the task in terms of spatial and temporal coverage makes monitoring via only ground-based surveys impractical, with remote sensing being the most practical option (Justice and Becker-Reshef 2007). Current global scale operational monitoring is mostly limited to coarser-resolution (250 m+) optical sensors (i.e., Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Very High Resolution Radiometer (AVHRR)). The coarse spatial resolution of these sensors makes them less suitable for field-based production monitoring, despite the daily coverage (Becker-Reshef et al. 2010). Sensors with better spatial resolution in return have less frequent coverage, which combined with the diversity of climactic conditions around the world means that

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despite the vast amounts of optical data available in near real time, there are still challenges to getting cloud-free images at the desired spatial and temporal resolution of all the necessary regions of the globe (Whitcraft et al. 2015).

As a form of active remote sensing that is mostly independent of atmospheric conditions and with resolution high enough for field-based monitoring, synthetic aperture radar (SAR) could help mitigate some of these issues, allowing for reliable data collection in areas of frequent cloud cover. In addition, radar data provides information about the stem and leaf structure of vegetation, as well as about soil roughness and moisture content, independently making SAR of key interest for agricultural applications (Ulaby, Moore, and Fung 1986). SAR data is different from and complementary to optical data, which in some cases makes it superior for crop differentiation (McNairn et al. 2009b). While not yet widely used for operational crop monitoring, plenty of research has been done studying the usefulness of SAR for agricultural land cover classification, both as a standalone data source and in combination with optical data (Blaes, Vanhalle, and Defourny 2005; McNairn et al. 2009a; Stankiewicz 2006). The radar response to vegetation structure is dependent on both the frequency and signal polarization, with these factors determining the contribution of the various vegetative components and underlying soil. Past work has found C- and L-band to be the most effective wavelengths for capturing these details over a wide range of crops (Hoekman and Vissers 2003; McNairn et al. 2009b; McNairn and Shang 2016), and have found cross-polarized data to be particularly sensitive to crop structure due to its ability to capture vegetative volume scattering (Ferrazzoli et al. 1997; Satalino et al. 2014; Skriver et al. 2011). Multi-temporal data sets have been found to be more effective than single images in classifying agricultural land cover due to their ability to capture multiple stages of crop growth and varying types of crop structure, allowing for better differentiation between individual crops (Deschamps et al. 2012; McNairn et al. 2009a). Such multi-temporal data sets have also been used to model crop phenology (Satalino et al. 2014; Whelen and Siqueira 2017). Furthermore, it has been shown that more comprehensive temporal coverage is particularly important in regions with a diverse range of crops that do not all share the same season and growth rate, or when working between years with varying meteorological conditions (Satalino et al. 2014; Skriver et al. 2011; Stankiewicz 2006).

As a continuation to the studies described above, this letter demonstrates the use of frequent temporal coverage by Sentinel-1 C-band data of an agricultural region in North Dakota to perform a radar-only land cover classification. In this work, a full-season time series forms the basis of the classification algorithm, differentiating between individual crops based on their varying backscatter responses over time. This builds on previous work done with airborne L-band data (Whelen and Siqueira 2017), testing how well the algorithm works with C-band satellite data in a better time series, and over different crops.

2. Data

This study used dual-polarized (VV/VH) C-band imagery from the European Space Agency's (ESA) Sentinel-1A and 1B satellites, which provide repeat coverage approximately every 12 days. Sixteen images from April through November 2016 were used in the analysis after first being preprocessed in Sentinel's Application Platform (SNAP). All images were captured in Sentinel-1's Wide Swath Mode with an ascending orbit, and were downloaded from ESA in Level 1 GRD format, which provides backscatter normalized with respect to area. SNAP was used to apply Sentinel-1 orbit corrections, multilook the images to 100 m pixels, and apply terrain correction. The fields are so large in this region that higher resolution imagery than 100 m would have made the data sets significantly larger without a major benefit in field identification. No additional speckle filters were used because the images had already been multilooked, and the time series analysis of images consists of the statistical behaviour of thousands of pixels, making the effect of speckle negligible. Because Sentinel-1 data are not fully polarimetric, polarimetric decomposition methods were not available to be included in the analysis. Both polarizations were examined separately as well as in combination.

Imagery was captured over a portion central North Dakota, which is a part of the United States' Midwestern breadbasket. A wide variety of staple crops are grown across the state, including corn, soybeans, winter and spring wheat, oilseeds, sugar beets, and pulses. The specific region used in analysis was chosen for the large number of fields per crop and minimal non-crop area. The main agricultural land-cover types in this region were corn, soybeans, spring wheat, and grass/pasture. Fields ranged in size from only two or three hectares to as large as two hundred forty hectares.

Ground truth information for training and validation came from the Cropland Data Layer (CDL), an agricultural land cover classification product which is released annually by the United States Department of Agriculture (USDA) National Agricultural Statistics Service (Boryan et al. 2011). Production of the CDL combines optical data with high quality ground truth data as input for sophisticated decision-tree classification software, with the 2016 North Dakota CDL using imagery from the Deimos-1, Landsat 8, and UK-DMC-2 satellites, and producing a classification with 30 m pixels (USDA 2017). Nationwide, the CDL has an overall accuracy of around 80% for all agricultural land-cover types, with major crops such as corn, soybeans, wheat, cotton, and rice frequently having accuracies over 90% (Boryan et al. 2011). Because North Dakota is a major agricultural state with many major crops, its 2016 overall accuracy was 87%, with the major crops in this study classified to around 95% accuracy (USDA 2017). While not entirely accurate, the CDL, as one of the best national-level agricultural classifications, provides data for far more fields than could be reasonably covered by site visits, with an updated classification provided every year. The combination of high accuracy, relatively high resolution, and annual updating means that the CDL can be used as a reasonable large coverage source of training data for other remote sensing applications (Matton et al. 2015; Pittman et al. 2010; Waldner et al. 2015).

3. Methods

A two part analysis was used in this study, first creating a model of the average backscatter response per crop over time, and then second, using an error metric derived from this model to create a crop classification layer (Figure 1). This type of classification, separating one crop from another, can be viewed as the final step of a classification such as those used in the production of the CDL or Agriculture and Agri-Food Canada's Annual Crop Inventory, that first classify crops from non-crops, and then differentiate between individual crops (Boryan et al. 2011; Fisette et al. 2013). Multiple variations on the analysis were run to test the influence of polarization, iterations in model building, number of training fields, and validation input. After initial image preprocessing within SNAP (see Data section), in-house scripts were built using python and ArcGIS for the rest of the processing and classification.

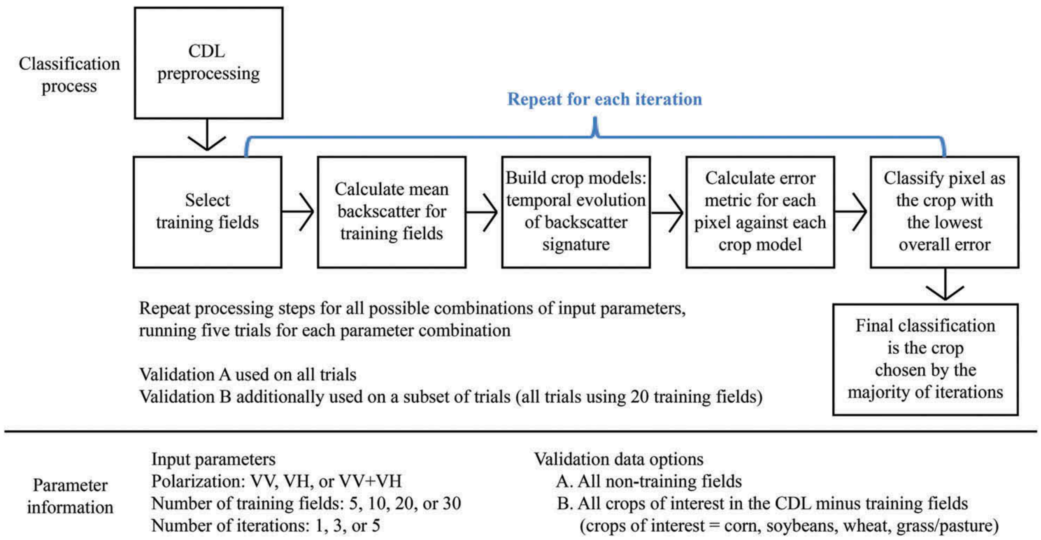

Figure 1. Flowchart of classification processing steps. All processing steps are shown in order, along with a list of the input parameters.

Since reference data collected on site were not available in this region, the CDL was first preprocessed to divide it into training and validation fields that approximated regions for which crop type could be collected on site. To mitigate error in the CDL found at the boundaries between individual land-cover types, all pixels not surrounded by their same type of land cover were masked out (i.e., not used in the evaluation). The remaining pixels were polygonized, and non-crop land-cover types and polygons smaller than two hectares were deleted. These smallest polygons were removed as another way to ignore regions where the CDL had difficulty in classification. For this project, grass/pasture was included as an agricultural land cover and hence included as part of the classification. The remaining fields formed the set of possible training and validation regions. Training fields were randomly selected in the script based on user-defined constraints related to the size and number of fields per crop. Depending on the trial, either five, ten, twenty, or thirty fields between five and sixty hectares were used from each land cover for training. All other fields were used for validation. While the crop models were based on fields of data, the following classification and validation steps were done on a per pixel basis.

The first step in classification was modelling the temporal evolution of the backscatter signature for each crop, creating temporal profiles like those developed in Matton et al. (2015). The crop backscatter model was built by taking the mean backscatter response for each training field for each image, averaging the responses within each crop per image, and then sequentially plotting the average crop response against the image date. The model was not based on any predetermined function. This model was then used with an error metric to form a supervised classification.

A modified version of the error metric developed in previous work was used to determine the most likely crop type on a pixel by pixel basis (Whelen and Siqueira 2017). For each image over time, every pixel was compared individually to each crop model by calculating the difference between the observed backscatter and the model. The total error over time was then summed for each crop model, with the classified crop type determined by the lowest total error over the entire timespan. In the case of the dual-polarization classification, the polarizations were treated separately through error creation, and then the classification was based on the total summed error. The error metric value, err_{class}, is the error observed assuming that a particular pixel belongs to a given crop class. To improve the statistical characterization of the algorithm, the algorithm described in Whelen and Siqueira (2017) was changed from using an absolute value of the differences to using the Root Mean Squared Error (RMSE) distance instead. That is, for each crop type, this metric was determined by

$$err_{\text{class}} = \left(\sum_{N} \frac{\left(\sigma^{\circ}_{\text{obs}}(n) - \sigma^{\circ}_{\text{class}}(n)\right)^2}{\text{var}\left(\sigma^{\circ}_{class}(n)\right)} \right)^{1/2} \tag{1}$$

where $\sigma^{\circ}_{\text{obs}}(n)$ and $\sigma^{\circ}_{\text{class}}(n)$ are the observed (per-pixel) and class-related mean backscatter as a function of the observation number, n (equivalently an observation date), and var($\sigma^{\circ}_{\text{class}}(n)$) is the variance of the field mean backscatter values for each crop class-date combination. N is the total number of time series observations. The minor modification from absolute value to RMSE had the effect of improving the classification accuracy by a few percentage points for all crops analysed in this work. It is also equivalent to the well-known statistical measure of the Mahalanobis distance when the covariance matrix is diagonal (Dougherty 2013).

The advantage of normalizing the error metric in this way is that it creates a unitless, probability-based measure of the error, as well as taking into account the variations that occur at specific times of the year. For instance, during the planting and harvesting seasons, where field-to-field variations are expected to dominate the overall error, normalization by the variance reduces the effect of these variations on the overall error metric given in Equation (1). A land cover with a wider range of potential field behaviour might have a larger difference between the observed backscatter and the crop class model, but it would also be expected to have a larger variance, thus mitigating the effect of the increased field variation.

In order to mitigate the potential effects of abnormal or CDL-misclassified fields being included in the training sample, the user can run the model multiple times, each time using a new training sample drawn from all possible training fields, and then making a final classification of the pixels based on the most common classification from each run of the model. This is a variation on ensemble classifiers, where different independent classifiers are combined in order to increase accuracy (Waske and Braun 2009). In this analysis, the aforementioned training field parameters were all tested with one, three, and five iterations of model creation, given that finding the most common classification requires an odd number of iterations. With three polarization combinations (VV, VH, VV+VH), four different numbers of training fields, and three possible numbers of iterations there were a total of thirty-six sets of parameters. To test the consistency of the results, each variation of parameters was tested five separate times, for a total of one hundred eighty trials. Overfitting of the model in this study area is unlikely, since based on the above input parameters and total fields in the region, any single trial would use at most a third of all fields.

All trials were validated on a per pixel basis using the selected validation fields. When using multiple iterations, the validation data included only those fields that had not been used in any training set. In order to compare the validation accuracy between this subset of the CDL and the original non-subsetted CDL, a second accuracy test was done on a portion of the classifications. This second accuracy test was done using all of the pixels in the CDL classified as the four main crops of interest minus the training field pixels. All other land cover classes were masked out. For purposes of discussion, these two potential validation layers are referred to in the text as 1.) the selected validation fields and 2.) the full CDL minus training pixels. The difference between the two validation sets is that the full CDL minus training pixels includes the field edge pixels and smallest fields.

4. Results and discussion

The method of classification presented in this work shows promising results when compared with the selected validation fields, especially when using multiple iterations of classification and at least twenty training fields. Trials using five or ten training fields had noticeably lower accuracy than those using twenty or thirty. The decrease in accuracy was more pronounced with five fields than with ten, and additionally there was less consistency between trials of the same parameters. This was particularly true for single iteration trials when using fewer training fields. There were no discernible differences between using twenty or thirty fields.

For the twenty and thirty training field trials, overall accuracies (OA) based on selected validation fields were all over 85%, with most over 90%. All of the trials that used multiple iterations had above 90% OA. In contrast, when using five or ten training fields the multiple iteration trials all had at least 80% OA, with just over half above 90%, but almost a third of the single iteration trials were below 80%. The five and ten training field trials were also more likely to have at least one user or producer accuracy value blow 60%.

For each set of five trials done using identical parameters, the twenty or thirty training field multiple iteration tests had OA within 2–4% of each other, whereas the OA for the single iteration tests varied 3–7% between trials with the same parameters. When using five or ten training fields these numbers increased respectively to 5–9% and 7–14%, showing that there is greater variation in results between trials when using this few of training fields. These ranges do not include the worst classification of all trials, and the only one with an OA under 75%, which was a VH single iteration trial with five training fields that had 46% OA. Overall these results suggest that multiple iterations, in lessening the effects of extremely good or bad classifications, provide greater consistency between trials. This consistency would be a benefit when comparing classifications made in multiple years of the same area because there would be a reduced chance of any single year being much more or less accurate as compared to the other years. There was not a discernible difference between three and five iterations for any number of training fields which suggests that while multiple iterations are useful in lessening the effect of randomly selecting a poor training sample, extra iterations beyond the minimum of three do not provide additional improvement.

Past work has repeatedly found cross-polarized data (VH or HV) to be the best single polarization for agricultural land cover classification (McNairn and Shang 2016), including in use with a similar algorithm where VH and VV showed similar crop behaviour patterns, but with greater separability between crops when using VH (Whelen and Siqueira 2017). Classifications based on multiple polarizations have been found to be more accurate than using only a single polarization due to their ability to capture more types of scattering (McNairn and Shang 2016). Hence, it was anticipated that the VH-polarized imagery would provide superior classifications to the VV-polarized imagery, but that the VV+VH classification would be better than either single polarization. This work had mixed results, with neither single polarization clearly triumphing over the other. In the twenty and thirty training field trials VH classifications were slightly superior to VV classifications in the single iteration trials, with no apparent difference between the two polarizations when using three or five iterations. In contrast when using only five or ten training fields the VV classifications did the same or slightly better than the VH classifications for all numbers of iterations. All of the differences between single polarizations were slight enough to be the result of other factors than polarization. The combination of both polarizations proved only slightly better than either single polarization. Per set of parameters the VV+VH combination tended to have 2–3% OA than either of the single polarizations, however for any individual trial within each set there was usually at least one VV or VH trial that was higher than the lowest VV+VH trial.

Two types of validation were used side by side on the classifications based on the twenty training field trials as a way to compare the CDL as is, versus the using only selected fields. Twenty training fields were chosen as the best compromise between fewest fields with high accuracy. The use of selected field regions for validation, as opposed to the full CDL minus training pixels had a drastic improvement on the accuracy of the classifications in this analysis (Figure 2 and Table 1). All twenty training field trials, no matter the polarization or number of iterations, produced classifications that with selected validation fields had 85–96% OA, whereas with the full CDL layer (minus training pixels) had only 65–74% OA. This shows that the selected validation fields better match the crop models developed from the training data. It also shows that these crop models had difficulty in similar areas to where the CDL struggles, especially edge areas between different land-cover types, as the full CDL minus training pixels validation data is potentially a much noisier data set. The two versions of validation data show the importance of accurate validation data, as well as how this can be derived from a larger data set like the CDL. Given that the CDL and its Canadian counterpart have an operational target accuracy of at least 85% (Boryan et al. 2011; Fisette et al. 2013) the results from selected validation fields appear promising. Comparing confusion matrices shows that the individual user's and producer's accuracies that were lowest in the original selected fields' validation also tended to be the least accurate in the full CDL validation.

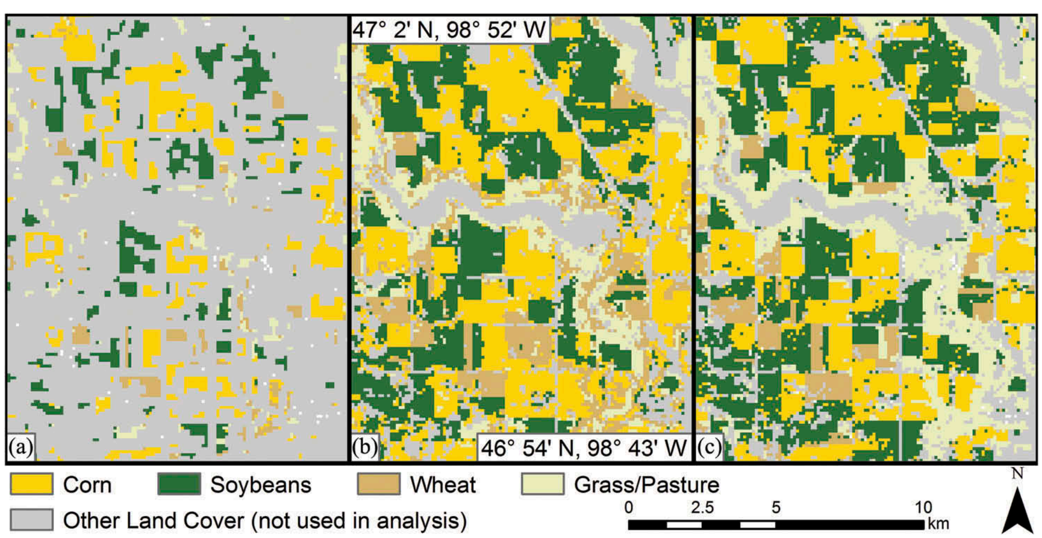

Figure 2. Comparison between classification validations and CDL. This figure shows a VH three iteration 20 training field classification masked using the selected validation fields (a), the same classification masked using the full CDL minus training pixels (b), and the CDL (c). In order to be able to differentiate individual fields this figure shows only a subset of the entire testing region.

Table 1. Confusion matrices for the classification shown in Figure 2.

	Corn	Soybeans	Wheat	Grass/Pasture	Total	Producer's Accuracy
Table 1A						
Corn	7854	261	134	377	8626	0.911
Soybeans	349	19,663	82	654	20,748	0.948
Wheat	61	72	2319	198	2650	0.875
Grass/Pasture	142	101	895	5993	7131	0.840
Total	8406	20,097	3430	7222	39,155	
User's Accuracy	0.934	0.978	0.676	0.830		0.915
Table 1B						
Corn	22,325	4642	1915	2586	31,468	0.709
Soybeans	7144	46,923	3056	5908	63,031	0.744
Wheat	1454	1442	9339	1955	14,190	0.658
Grass/Pasture	3462	4313	7378	17,826	32,979	0.541
Total	34,385	57,320	21,688	28,275	141,668	
User's Accuracy	0.649	0.819	0.431	0.630		0.681

These accuracy values are for the full study area for the VH three iteration 20 training field classification used in Figure 2, with only validation pixels used in the calculations. Categories on the left side of the table are the CDL ground truth, and along the top are the classification land-cover types. Table 1A (top) shows the accuracy values for validation using selected fields, and Table 1B (bottom) shows the accuracy values for validation using the full CDL minus training pixels. The table values for each category show the number of pixels and hectares, as each pixel is one hectare. The category with the most frequent confusion across all tests was grass/pasture being mistaken for wheat. This makes sense as wheat and grasses share a more similar structure with each other than with corn or soybeans.

To compare the algorithm described above against other more common classification algorithms, we tried classifying the full time-series of VH-polarized images using a random forest (RF) classifier, specifically the Random Trees tool built into ArcGIS Desktop 10.5. This tool is a version of Breiman's (2001) Random Forests algorithm, which is an ensemble classifier based on decision trees, known for its robustness and accuracy. Various implementations of RF have been used successfully for SAR-based agricultural land cover classification in works such as Deschamps et al. (2012), Torbick et al. (2017), and Waske and Braun (2009). Only VH-polarized data was used, as the improvement between VV+VH and VH was deemed too small to be worth doubling the size of the dataset used with RF.

Under a wide range of input parameters related to the RF structure (number and depth of decision trees, etc.) and using the selected validation fields described above it was found that RF had slightly better results for a single year, consistently classifying to an overall accuracy of 95–96%. The advantage of the method presented here over RF would be for repeated years of classification over the same crops, where the algorithm is capable of building crop models using training data from a single year, and then interpolating these models to fit subsequent sets of image dates. Any major phenological differences between years, such as a significantly early/late planting or harvest would need to be accounted for when interpolating the model, for example by shifting the start date of the crop model. In contrast, RF would either require a new set of training data every year, or would require all of the images to be interpolated to match the dates of the original time series, thus incurring significant logistical and/or computational costs.

5. Conclusion

This letter presents a full season time series as the basis for a SAR-only agricultural land cover classification, and tests it using C-band data from Sentinel-1 collected throughout the entire 2016 growing season. The best classification for least amount of processing appears to be using VV or VH data with twenty training fields, and three iterations of training. If only a single iteration is used then VH data is preferable. More than twenty fields and more than three training iterations proved to be unnecessary extra processing. Similarly, while the VV+VH results provided slightly higher accuracy when considering all the trials, the increase was small enough to question whether it is worth doubling the amount of data being processed. The results show that this method can produce classifications above the 85% accuracy threshold needed for operational agricultural land cover products when validated with accurate ground truth. This builds the basis for further work testing the strength of this algorithm on areas with a wider variety of crops, fine-tuning crop model interpolation between years, and using L-band data as other frequent repeat satellites are launched in the next few years. Improved methods of SAR-based land cover classification will help improve agricultural monitoring in regions with frequent cloud cover, where optical methods currently prove inadequate.

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