CROP CLASSIFICATION USING REDUCED-DIMENSIONALITY NDVI TIME SERIES

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Remote sensing, crop classification, time series, NDVI, time series fitting, feature extraction, dimensionality reduction, UMAP

ABSTRACT

The paper considers the problem of classification of agricultural crops. As is known, to solve this problem, it is much more efficient to use not instantaneous remote sensing data or calculated vegetation indices, but their historical series. Time series formed by index values for a fixed spatial point at different dates are characterized by a high level of missing values, caused primarily by cloudiness on some dates. A study of known methods of time series approximation has been carried out. The question of whether reducing the dimensionality of the approximated time series can improve the quality of crops classification is also investigated. In the experimental part of the work, NDVI time series calculated from the Sentinel-2 multispectral satellite data were used. The classification of corn, sunflower, wheat and soybeans was studied. The paper shows that UMAP usage for dimensionality reduction leads to 1.5 times increase of classification quality in terms of average the F1-measure compared to using the original dimension data. A new crop classification method based on cubic spline approximation of NDVI time series, extraction of features of low dimension by the UMAP algorithm and their classification by the k nearest neighbors method is proposed.

INTRODUCTION

In recent years, the utilization of satellite remote sensing (SRS) data in monitoring land has increased due to the advancement of big data analytics in agriculture (Yakushev et al. 2019). Contemporary satellite sensing programs and especially shooting from an unmanned aerial vehicle (UAV) offer frequent and high-resolution information about the Earth's surface, complementing the data obtained through surface-level monitoring. Remote sensing data are actively used in the framework of precision or digital farming (Blohina 2018; Bakhtadze et al. 2020) – the concept of effective management of agricultural production using modern information technologies.

At present, there is a growing effort to develop methods that utilize satellite data for creating and updating agricultural boundary maps (Pavlova et al. 2023), as well as for estimating and predicting crop yields and mapping terrains (Sishodia et al. 2020). The development of automated methods for crop type identification is of particular importance since this information is crucial for effective agricultural management (Orynbaikyzy et al. 2019). In addition, automatic classification of crops can contribute to the improvement of methods for equalizing survey conditions based on the use of special image zones for which a priori assumptions about the spectral functions of surface reflection are known (Pavlova et al. 2022).

It is well known that vegetation reflectance significantly varies across different wavelengths of the incident radiation spectrum (Cherepanov and Druzhinina 2009). Spectral indices of the Earth's surface can be derived from sets of different channels of multispectral satellite images. Indices that are employed to analyze the vegetation are commonly referred to as vegetation indices.

The growth peculiarities of different plant species affect the dynamics of their spectral indices.

Several studies (Bartalev et al. 2006; Pugacheva and Shevyrnogov 2008; Sun et al. 2019; Plotnikov et al. 2011) have demonstrated that crops can be differentiated based on their spectral time profiles even during the early stages of vegetation. Crops with similar spectral characteristics at a certain time interval may exhibit significant spectral differences at another time interval (Murmu and Biswas 2015). Therefore, classifying crops based on time series or values series is more effective than using instantaneous values (Pavlova et al. 2023). Several studies (Sun et al. 2019; Plotnikov et al. 2011) showed that increasing the number of observations during the active vegetation period can improve the quality of classification. However, the amount of available data is often limited due to cloud cover. If the data that fell into the cloud shadow region can be restored with some accuracy (Bocharov et al. 2022), the data at the points of dense cloud regions cannot be used. To address this issue, various studies (Zhang et al. 2011; Rußwurm and Körner 2020; Vorobyeva and Chernov 2017; Hird and McDermid 2009) have proposed approximating time series values. Vorobyova and Chernov (Vorobyeva and Chernov 2017) found that a spline model provided the best quality among a number of alternative models. In this paper, we compare the performance of the spline model with that

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of a Gaussian process regression, since the latter was not considered by Vorobyova and Chernov. The gaussian process regression was previously shown to be a promising method for handling gaps in data by Belda et al (Belda et al. 2020). In order to compare different approximation models we adopted several quality criteria. Unlike the other works for all using criteria we simulated missing values caused by cloud cover by randomly removing a certain fraction from the time series.

It is well established that extraction of the most informative features from input data can significantly improve the quality of classification compared to using the raw input data (Velliangiri et al. 2019). The former approach can mitigate the risk of overfitting and reduce the computational cost of the classifier. Nonetheless, identifying the optimal features for training the classifier remains challenging. In a recent study by Yang et al. (Yang et al. 2020), the authors proposed constructing the feature space using various spectral and textural characteristics computed at three specific dates selected by experts and then searching for the most useful features with one of the suggested algorithms. Another approach proposed by Pugacheva and Shevyrnogov (Pugacheva and Shevyrnogov 2008) involves different expert-selected features: the slope angles of normalized difference vegetation index (NDVI) curve during the growth and ripening stages, as well as the maximum index value throughout the entire vegetation season. This method reduces the NDVI time series to only three values.

In this study, we also employ feature extraction for classification. We use the time series NDVI as the initial feature space as in (Pugacheva and Shevyrnogov 2008). Unlike the studies that utilized expert-selected features mentioned in the previous paragraph, we do not want to rely on any expert-selected features. Instead, we propose to use the UMAP algorithm (McInnes et al. 2018) for the dimensionality reduction of the time series data. While UMAP has been previously applied to crop classification in (Rußwurm and Körner 2020), it was only used for exploratory data analysis and clustering, i.e. to establish the classification possibility. Dimensionality reduction has been suggested previously (Gilbertson and Van Niekerk 2017), it was applied to spatial and spectral feature space and not the time series.

The classification of crops based on remote sensing is performed using various models. Chakhar et al. (Chakhar et al. 2021) investigated classification methods that combine radar data from Sentinel-1 and vegetation indices derived from Sentinel-2 optical data. The authors obtained the best results using support vector machines (cubic SVM). Li et al. (Li et al. 2020) proposed a novel generative neural network model to classify crops into three categories (soybean, corn, and others) using multi-temporal satellite data of three dates. Reedha et al. (Reedha et al. 2022) introduced a classification neural network model based on a visual transformer. SVM and random forest (RF) methods were used for crop classification in (Sun et al. 2019). The authors in (Firsov et al. 2021) proposed a spectral-spatial convolutional neural network for the classification of hyperspectral data. Gilbertson and Van Niekerk (Gilbertson and Van Niekerk 2017) investigated SVM, decision trees (DT), k-nearest neighbors (k-NN), as well as RF for classification. The latter three methods showed improvement in quality when a preliminary feature extraction step was introduced. In our work, the k-NN algorithm is used as a classifier, which outperformed the SVM and DT algorithms in another problem of classifying remote sensing images, according to the results of (Bouteldja and Kourgli 2020).

Let us summarize the contribution of this work is as follows:

- We conducted comprehensive time series approximation model comparison, including two of the most successful models to date (spline model and gaussian process regression), which have not been compared before.
- We propose to use dimensionality reduction as automatic feature extraction for time series classification. It is shown that this modification is useful. PCA and UMAP algorithms are investigated.

STUDY AREAS AND DATA

The time series of the vegetation index NDVI, consisting of 40 multiple observations, was studied. Each observation is a pair of an index image of 5730x5730 pixels with a spatial resolution of 10 m, calculated from the data of Sentinel-2 satellite multispectral images, and a cloud map used to eliminate areas of data uncertainty. The number of time series corresponds to the number of pixels in one image. The classifier was trained and the quality of the algorithm was assessed on the basis of land use data in the Krasnodar region of the Russian Federation, presented as coordinates of the boundaries of the land plot and the corresponding crop class label. A total of 390415 pixels were marked up. The data contains the following class labels: “Corn” (48029 time series), “Sunflower” (43678 time series), “Wheat” (119811 time series), “Soybean” (27663 time series), “Other” (151234 time series). The “Other” class on the selected images includes uncultivated fields, forest and park areas, road sections and urban areas. The test sample included one field of each class, the remaining fields were used for training.

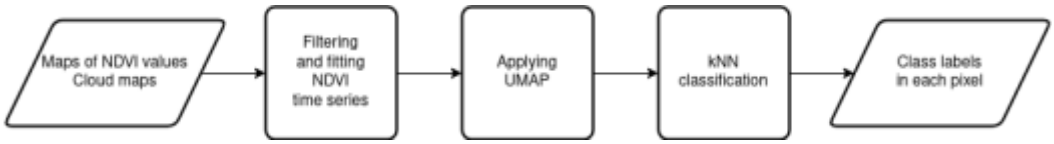

Figure 1:Flowchart diagram of the proposed classification method

PROPOSED METHOD

The proposed crop classification method involves three main steps (Fig. 1): (1) approximation of the vegetation index time series, (2) dimensionality reduction of input data, and (3) classification using k-NN.

In the first step, the missing data caused by cloud cover should be compensated, noise should be removed, and a uniform grid of values should be obtained. To accomplish this, the NDVI time series is approximated with a cubic spline, which provides both accuracy and efficiency, making it suitable for processing large datasets. A comparison of different functions is demonstrated in the "Vegetation index time series approximation" subsection of the "Experiments" section. From these uniform time series, the features are extracted via the UMAP algorithm resulting in a feature space with the dimension of two. Finally, the extracted features are classified using the k-NN method.

EXPERIMENTS

This section provides the techniques of two experiments. The first experiment aims to compare different models for approximating the vegetation index time series. The second experiment evaluates the impact of dimensionality reduction as a preliminary stage in classifying the NDVI time series.

Simulation based time series approximation quality assessment

The objective of this experiment is to identify the optimal mathematical model which could represent the vegetation index tendencies throughout the data gaps. We considered the following models: second and third degree polynomials (Groten 1993; Vorobyeva and Chernov 2017), a cubic spline model (Vorobyeva and Chernov 2017) and gaussian process regression (Belda et al. 2020).

The experiment involved analyzing a dataset of NDVI represented by a two-dimensional matrix, where each row corresponds to the NDVI measurements performed throughout the calendar year of 2018.

To simulate the data gaps due to the cloud cover, a certain fraction of data points was randomly removed from the time series. The behavior of the approximating functions was analyzed for simulated data with missing points fractions of 0.2, 0.33, and 0.5. The corresponding fraction of points was selected randomly and uniformly from the data range. The index values were then approximated using the models in question, and the performance in terms of the selected metrics is compared throughout the models. Finally, based on the approximation accuracy as well as runtime performance, the optimal model is selected.

The method of least squares was employed for the optimization of models. All metrics were compared for each missing data fraction. To evaluate the mean-square reproducibility error, each simulated time series was generated 10 times based on a random set of points from the original time series based on the considered missing data fraction.

For considered approximation models we evaluated three quality measures as well as average execution time (experiments were performed on Intel(R) Core(TM) i5-4690K CPU @ 3.50GHz, Python3 implementation). The following quality measures were utilized to compare the considered models:

1. **Mean squared error**

The mean squared error (MSE) indicates the average quality of the approximation. It is calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2,$$

where y_i, $\hat{y}_i$ – is the ground truth and approximation of the NDVI at i-th point, n – is the number of points.

2. **Maximum error**

The maximum error gives an idea of the maximum deviations of the NDVI values from the approximating function, which makes it possible to assess the applicability of this function to the subject area under consideration. In this paper, the value of the maximum error was estimated as the 99th percentile of all deviations of the NDVI time series estimates from their true values.

3. **Mean-square reproducibility error**

We introduce the mean-square reproducibility error to evaluate the robustness of the approximating function to data gaps caused by cloud cover and corresponding shadows. To implement this measure, we simulated data with different random sets of missing points, and such simulated time series were approximated. At each point of the original time series, we calculated the differences between the resulting approximations. Therefore, we can establish if the choice of missing data points impacts the approximation based on the functions in question. Mean-square reproducibility error is calculated as follows:

$$MSE_{reprod.} = \frac{1}{n(m-1)} \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=i+1}^{m} (\hat{y}_{i,j} - \hat{y}_{i,k})^2,$$

where m – is the number of approximations performed for each point, n – is the number of considered points, $(\hat{y}_{i,j} - \hat{y}_{i,k})$ – the difference between the results of j-th and k-th approximation at point i.

Comparison of classification with different dimensionality reduction methods

The objective of this experiment is to select a dimensionality reduction algorithm for the extraction of features that improve the classification accuracy compared to the raw data classification. As an implementation of the UMAP algorithm, the umap-learn library in Python3 was used with the following parameters: *n_neighbors* = 200, *min_dist* = 0.1, *n_components* = 2, *metric* = 'euclidean'.
The classification itself was performed by the k-NN algorithm (k = 5). The input data are the approximated vegetation index time series. The test set consisted of a single land plot from each class, while the remaining land plots were utilized for training the classifier. Based on these experiments, the confusion matrices and classification reports were generated to assess the performance of the classifier for each class and the overall weighted average. The following metrics were used:

1. *precision* represents the fraction of objects identified as positives by the classifier and which are indeed positives according to the ground truth among all positives identified by the classifier. It is calculated for each class using the following formula:

$$precision = \frac{TP}{TP+FP},$$

where *TP* – true positive classifier answers number, *FP* – false positive classifier answers number.

2. *recall* indicates the fraction of objects identified as positives by the classifier and which are indeed positives according to the ground truth among all ground truth positives. This metric is calculated as follows:

$$recall = \frac{TP}{TP+FN},$$

where *FN* – false negative classifier answers number.

3. *F1-score* – is the harmonic mean of precision and recall, and it is calculated using the following formula:

$$F1 = 2\frac{precision * recall}{precision + recall}.$$

RESULTS

This section provides the results of two experiments. First for the approximation models, second for the classification methods, both with including the best approximation model taken from the first experiment results.

Comparison of approximation functions

Time series approximation experiments (see the results in Fig. 2) indicate that the cubic spline allows for the lowest mean squared error and maximum error while requiring minimal approximation execution time (0.01 ms in average versus 0.4, 0.6, 238.5 ms in average for quadratic polynomial, cubic polynomial and GPR respectively). However, its performance in terms of the mean-square reproducibility error is medium. Consequently, among all the functions proposed and tested for approximating the vegetation index time series, the cubic spline can be deemed the optimal function based on the combination of the considered criteria.

Comparison of dimensionality reduction methods

The results of classification based on raw data, PCA-preprocessed data, and UMAP-preprocessed data are presented in Tables 1-3. These tables report the metrics used in the experiment for each class. Also there are weighted average rows that correspond to the results of each class weighted by its relative volume, i.e. the number of time series of a class divided by the total number of time series.
Tables 1 and 2 demonstrate that employment of PCA for feature extraction step results in an enhanced f1 score for only two classes ("Wheat", "Soybean") when compared to the classification using raw data, while in terms of the weighted average, the classification based on the PCA features is inferior across all metrics. On the contrary, when utilizing UMAP for dimensionality reduction of the input data, a significant improvement in classification quality is observed, with the weighted average of the f1 metric increasing from 0.66 to 0.94, representing a 1.5-fold improvement.

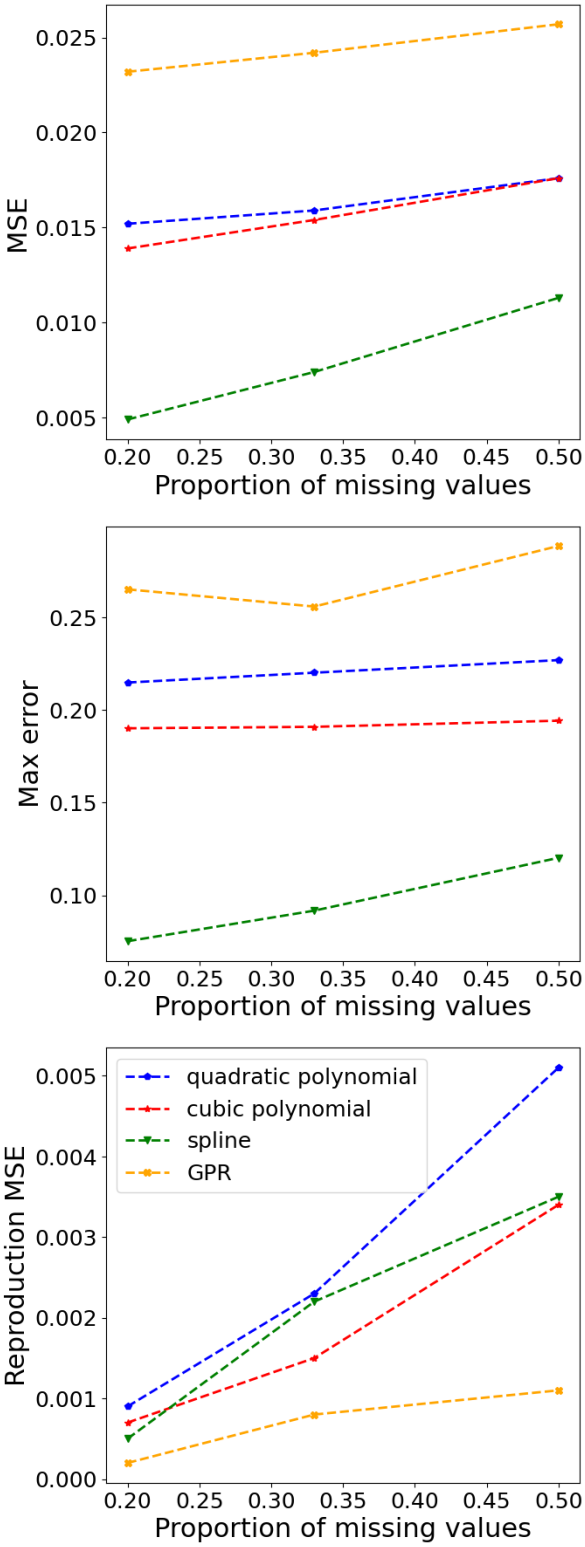

Figure 2: Dependences of quality measures on the proportion of missing values

Table 1: Classification quality using data of original dimensionality

Class	Precision	Recall	F1
Corn	0.51	0.34	0.41
Sunflower	0.77	0.99	0.87
Wheat	0.99	0.97	0.98
Soybean	0.03	0.05	0.04
Other	0.98	0.89	0.94
Weighted average	0.66	0.65	0.66

Table 2: Classification quality using PCA-preprocessed data

Class	Precision	Recall	F1
Corn	0.37	0.39	0.38
Sunflower	0.52	0.58	0.55
Wheat	0.99	0.99	0.99
Soybean	0.27	0.22	0.24
Other	0.98	0.89	0.93
Weighted average	0.65	0.64	0.64

Table 3: Classification quality using UMAP-preprocessed data

Class	Precision	Recall	F1
Corn	0.96	0.99	0.98
Sunflower	0.92	0.99	0.96
Wheat	0.99	0.99	0.99
Soybean	0.98	0.98	0.98
Other	0.99	0.90	0.94
Weighted average	0.97	0.96	0.96

Figures 3 and 4 illustrate the result of the entire fragment classification. In each image, the color of pixels represents the assigned class label superposed against the captured area. Corresponding land plots based on the ground truth data were marked with color contour. Most pixels in an image are of reddish-brown hue since the classifier assigned them to the “Other” class. The images demonstrate that the colors of pixels within the outlined contours are more uniform and more often correspond to the ground truth (see corn and sunflower classes) if prior to the classification the input data were processed with UMAP rather than PCA.

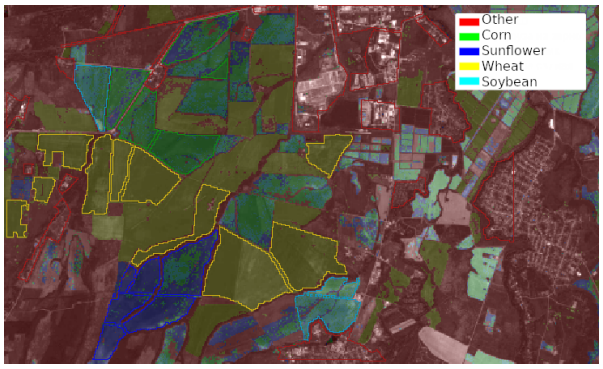

Figure 3: Classification results with preliminary dimensionality reduction by the PCA algorithm

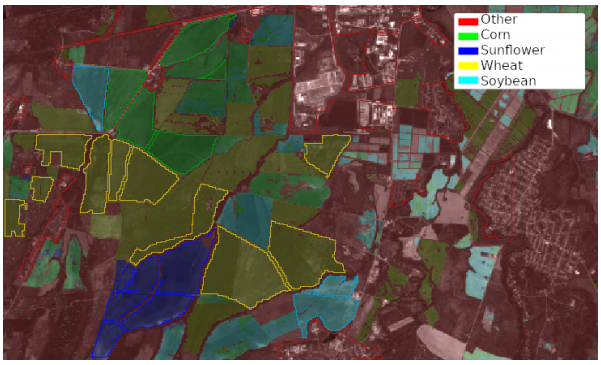

Figure 4: Classification results with preliminary dimensionality reduction by the UMAP algorithm

CONCLUSION

This paper investigates the classification of crops based on NDVI dynamics. Our study concentrates on two auxiliary subtasks: approximating missing data caused by cloud cover, and feature extraction. Since we are not concerned with the classification algorithm itself, a relevant k-nearest neighbors algorithm was employed. A study of NDVI time series approximation models was conducted, comparing a cubic spline model to the promising Gaussian process regression. The spline model proved to be superior to polynomial models and the Gaussian process regression model. We proposed the crop classification algorithm that utilizes spline approximation of time series followed by UMAP algorithm for dimensionality reduction and k-NN for classification. Our results demonstrate that applying UMAP for the dimensionality reduction task improves classification quality by 1.5 times on average in comparison to classification based on raw input data or data preliminarily reduced with PCA.

Possible direction of the further research includes investigation of the proposed approach in relation to UAV survey data. This type of survey can be done much more frequently than satellite surveys. This leads to an increase in the total volume of data, which in turn increases the relevance of using dimensionality reduction methods.

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