Classification of crop types with satellite imagery

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Remote Sensing and Image Processing - Final Project

***Abstract*—This report aims at identifying the best data sources for classifying crop types in the Marchfeld region, Lower Austria. Thereby, we are examining the feasibility of using Sentinel-2, Sentinel-1 and the leaf area index as well as a combination of those, as data sources for crop type classification. The results show that a fusion of all data sources, as well as a higher number of training samples, have a positive impact on the performance of the classifier.**

I. INTRODUCTION

This report describes the crop type classification in the Marchfeld region of Lower Austria (Lat. 48.20 °N, Long. 16.72 °E, Fig. 1) for the season 2018.

Crop type classification using multi-temporal Sentinel-2 (S2) imagery was already performed with great success by [1]. However, also other earth observation (EO) data can be used to successfully classify crop types [2]. One remote sensing data source that is not affected by cloud coverage is Synthetic Aperture Radar (SAR) imagery. [3] showed the feasibility of using SAR to classify crop types, whereby the fusion of both data sources, SAR data from Sentinel-1 (S1) and multispectral data from S2, showed the best classification results. Furthermore, biophysical variables, such as the leaf area index (LAI) calculated from remote sensing images with the S2 Toolbox is another data source that can help to classify crops [4].

In this report, we investigate firstly the performance increase of adding S1 high-resolution SAR and LAI as data sources in addition to S2 multi-spectral imagery and secondly the performance impact of combining two data sources to increase the number of training samples.

TABLE I
CROP TYPE CLASSES AND NUMBER OF REFERENCE PIXELS OF THE ORIGINAL TRAIN SET, THE EXTENDED TRAIN SET AND THE TEST SET.

Crop type	Train original	Train extended	Test
Maize	100	2000	400
Sugar beet	100	1999	400
Winter cereal	100	1998	400
Vegetables	100	1998	400
Potatoes	100	2000	400
Soybean	100	1999	400
Pumpkin	100	1995	400
Sunflower	100	1999	400
Rapeseed	100	1998	400
Alfalfa	100	1993	400
Pea	100	1997	380
Wine grape	100	1954	204
Total	1200	23930	4584

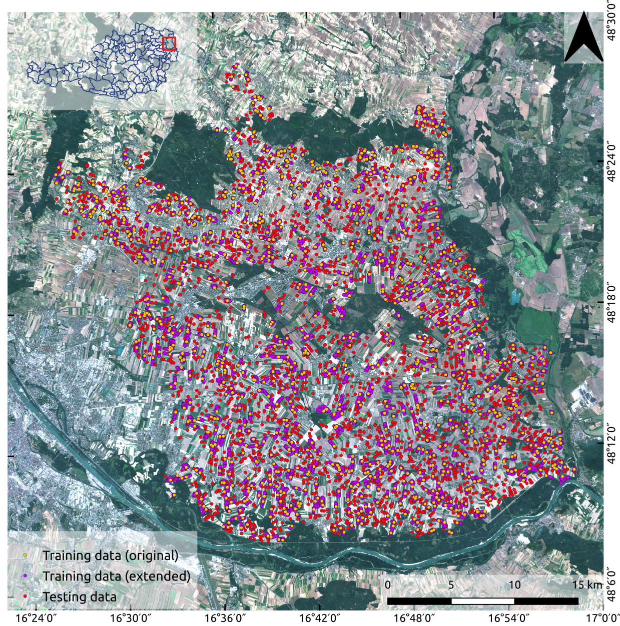

Fig. 1. Reference points in the Study area of Marchfeld, Austria. Original train set (yellow), extended train set (violet) and test set (red) are illustrated on top of a S2 true color image.

II. MATERIALS AND METHODS

A. Refernce Data and preprocessing

The reference data consist of 5784 point recordings of crop types collected during the season of 2018. As the data was provided by the Geomatics institute of the BOKU, they were already split into training (Train original) and testing data (Test) (TABLE I). We created a second training set (Train extended) by using the field boundaries from [5] to extend the provided data. In particular, we intersected the provided point recordings with the polygons from AMA and received only polygons that had at least one training point inside. Afterwards, a buffer area of 10 m was subtracted from the borders of these polygons to avoid obtaining mixed pixels. Furthermore, an 10 m circular area around all test points was generated and subsequently subtracted from the previously intersected polygons. Within these processed polygons we created 19 randomly sampled points that had a minimum distance of 10 m to each other. If a polygon was too small to accommodate all the 19 points we created, we created the maximum number of points given the constraints. Finally, we added the newly created random points with the

TABLE II

S1 AND S2 ACQUISITION DATES FOR CROP TYPE CLASSIFICATION. S1 DATA AS GRD PRODUCT, INSTRUMENT MODE IW, POLARIZATION VV AND VH. S2 DATA AS 2A PRODUCT, BANDS 2, 3, 4, 5, 6, 7, 8, 8A, 11, 12.

Satellite	March	April	Mai	June	July	August	September
S1A	03 11 15 23 27	04 08 16 20 28	02 10 22 26	03 07 15 19 27	01 09 13 21 25	02 06 14 18 26 30	07 11 19 23
S1B	05 09 17 21 29	02 10 14 22 26	04 08 16 20 28	01 09 13 21 25	03 07 15 19 27 31	08 12 20 24	01 05 13 17 25 29
S2	22	21	13	17	02 20	09 21	20

corresponding crop type class to the originally provided training data, thus enlarging the training data from the initial 1200 points to 23930 points (TABLE I).

B. Satellite Image Data and prepossessing

For this project, multi-temporal images from both S1 and S2 data were used since crop classification with multi-temporal data improved results over single acquisitions [1]. First, S2 cloud-free images with the right time intervals were identified for the growing season 2018 (TABLE II). Using the S2 value adder tool [6] all S2 and LAI images were downloaded, S2 imagery as Level 2A products, hence radiometrically, geometrically and atmospherically corrected using the sen2cor version 2.9 algorithm and LAI imagery computed with the ESA S2 Toolbox [7]. In contrast, the S1 Ground Range Detected (GRD) product was acquired through Google Earth Engine (GEE), that underwent thermal noise removal, radiometric calibration, terrain correction using SRTM 30 and value conversion into decibels via log scaling (10*log10(x)) using the S1 Toolbox. Given that SAR can penetrate clouds and is not dependent on cloud-free acquisitions, all acquisitions that covered the whole study area during the period between 01.03.2018 and 30.09.2018 table (TABLE II) were utilised in this project.

C. Classification and evaluation

For the classification the following 3 machine learning algorithms were used, Naive Bayes (NB), Random forest (RF) and Support vector machines (SVM). Hyperparameter-tuning was done via a grid search on the original train set with 10-fold cross-validation. The optimal hyperparameters were then additionally applied on the extended train set to avoid the computationally expensive task of performing a grid search on such a big data set. All classifiers are implemented in the Sklearn package and all code was written in Python and can be found on Github [8]. Except for filtering and mapping the S1 image values on the reference points, which was done using GEE, all data prepossessing and training was done on a PC with an AMD Ryzen 3700X and 16 GB RAM. The performance was evaluated using the overall accuracy.

III. RESULTS AND CONCLUSIONS

A. Satellite Data Sources

First, we can observe from TABLE III that for the original train set as well as for the extended train set, the classifiers RF and SVM are superior to NB. Moreover, the SVM achieves slightly better results compared to the

TABLE III

OVERALL ACCURACY (OA) OF THE BEST MODELS BY CLASSIFIER ON THE ORIGINAL TRAIN SET AND EXTENDED TRAIN SET. COMPUTED WITH 10-FOLD CROSS VALIDATION. CLF = CLASSIFIER.

				Train - Original			
Clf	LAI	S1	S2	LAI+S1	LAI+S2	S1+S2	All
NB	0.574	0.774	0.763	0.810	0.757	0.835	0.832
RF	0.705	0.790	0.885	0.857	0.888	0.910	0.908
SVM	0.688	0.855	0.886	0.881	0.889	0.914	**0.917**
				Train - Extended			
Clf	LAI	S1	S2	LAI+S1	LAI+S2	S1+S2	All
NB	0.566	0.775	0.760	0.808	0.755	0.842	0.840
RF	0.910	0.878	0.980	0.936	0.981	0.979	0.980
SVM	0.766	0.968	0.993	0.981	0.993	**0.996**	**0.996**

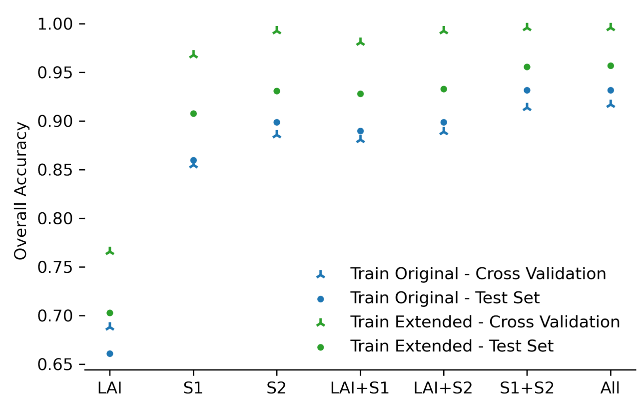

Fig. 2. Overall accuracy (OA) of the best SVM models for crop type classification by data sources. DS = data source for training, Org = trained on original train set, Ext = trained on extended train set. The model used: classifier=SVM, kernel=RBF, cost=10, gamma=0.001.

TABLE IV

OVERALL ACCURACY (OA) OF THE BEST SVM MODELS FOR CROP TYPE CLASSIFICATION BY DATA SOURCES. DS = DATA SOURCE FOR TRAINING, ORG = TRAINED ON ORIGINAL TRAIN SET, EXT = TRAINED ON EXTENDED TRAIN SET. THE MODEL USED: CLASSIFIER=SVM, KERNEL=RBF, COST=10, GAMMA=0.001.

DS	LAI	S1	S2	LAI+S1	LAI+S2	S1+S2	All
Org	0.661	0.860	0.899	0.890	0.899	0.932	0.932
Ext	0.703	0.908	0.931	0.928	0.933	0.956	**0.957**

TABLE V

Confusion matrix of the test data, upper confusion matrix created by a model trained on the original training data, bottom confusion matrix created by the model trained on the extended training data, UA user accuracy, PA producer accuracy, classifier SVM with c=5, kernel=rtf, gamma=0.1. MZ = Maize, SB = Sugar beet, WC = Winter cereal, VG = Vegetables, PO = Potatoes, SY = Soybean, PK = Pumpkin, SF = Sunflower, RS = Rapeseed, AL = Alfalfa, PE = Pea, WG = Wine grape, PA = Producer accuracy, UA = User accuracy.

	MZ	SB	WC	VG	PO	SY	PK	SF	RS	AL	PE	WG	UA
Original													
MZ	369	1	1	18	2	1	4	1	0	1	1	1	0.922
SB	2	381	0	15	2	0	0	0	0	0	0	0	0.952
WC	0	0	391	6	0	0	0	0	0	0	2	1	0.978
VG	5	6	6	336	9	0	2	0	2	8	20	6	0.840
PO	2	14	0	8	335	3	7	16	0	0	15	0	0.838
SY	2	7	0	18	3	364	2	2	0	0	0	2	0.910
PK	0	0	0	6	3	3	382	4	0	0	0	2	0.955
SF	1	1	0	4	14	3	8	367	0	0	2	0	0.918
RS	0	0	0	2	0	0	0	0	388	0	10	0	0.970
AL	0	0	1	4	0	0	0	3	0	387	3	2	0.968
PE	3	0	0	1	3	0	0	0	0	3	370	0	0.974
WG	0	0	0	0	0	0	0	0	0	0	0	204	1.000
PA	0.961	0.929	0.98	0.804	0.903	0.973	0.943	0.934	0.995	0.97	0.875	0.936	0.931
Extended													
MZ	376	0	2	10	1	6	2	2	0	0	0	1	0.940
SB	4	389	0	5	2	0	0	0	0	0	0	0	0.972
WC	0	0	396	2	0	0	0	0	0	1	1	0	0.990
VG	6	7	6	345	7	0	1	1	2	6	16	3	0.862
PO	0	11	0	5	355	1	9	5	0	0	14	0	0.888
SY	5	2	0	9	2	381	0	0	0	0	0	1	0.952
PK	1	0	0	2	1	4	392	0	0	0	0	0	0.980
SF	1	0	0	1	7	0	1	389	0	0	1	0	0.972
RS	0	0	0	0	0	0	0	0	396	0	4	0	0.990
AL	0	0	0	0	0	0	0	2	0	394	3	1	0.985
PE	3	0	0	1	4	0	0	0	0	0	372	0	0.979
WG	0	0	0	0	0	0	0	0	0	0	0	204	1.000
PA	0.949	0.951	0.98	0.908	0.937	0.972	0.968	0.975	0.995	0.983	0.905	0.971	0.957

RF classifier, except for the case where LAI is the training source. When comparing the models trained on different original train sets sources and evaluated on the test set (TABLE IV), we can see the preeminence of the S1 (best OA: 0.860) and the S2 (best OA: 0.899) imagery over LAI (OA: 0.661) imagery as sole data input. That makes sense since LAI is a compressed derivative from the S2 bands 3-8A, 11 and 12. Further, we can deduct that even with its 70 observation dates, S1 data (OA: 0.860) cannot achieve the OA of S2 multi-spectral data (OA: 0.899) captured on 9 observation dates. However, feeding the SVM classifier with a combination of data sources results in better-performing models. The OA of the best model 0.932 evaluated on the test set was achieved by using a merger of all data sources (All) and applying SVM with a cost of 5, an RBF kernel and gamma set to 0.001.

B. Data Extension

When extending the training data from 1200 to 23930 data points we can improve the OA in all cases when using the classifier SVM Fig. 2. When comparing the SVM model trained on the original train set with all input sources with the SVM model trained on the extended train set with all input sources, we can examine an increase of 7.9% from an OA of 0.917 to an OA of 0.996. Nonetheless, this OA was computed using 10 fold cross-validation and might suffer from overfitting. To get a better estimate of the model quality we have to examine the performance on the test data in TABLE IV. There we can see that although the extended training set does not reach the OA of the cross-validated train set of 0.996 it achieves an accuracy of 0.957 which is still 2.5% higher compared to the OA of 0.932 when the model was trained on the original train set. Hence, increasing the training data points helps to improve model accuracy as can be seen in TABLE V. The best model was used to compute the crop type classification map (Fig. 3).

C. Conclusion

The results of the project confirm the initial assumption stating that combining S1 and S2 data can improve the classification accuracy of the model [2]. Furthermore, we showed that an increase in training data by fusing several data can improve results considerably. Further research can address the problem of applying this model to images acquired in the following year since the cloud-free acquisition dates change yearly and so does the phonology.

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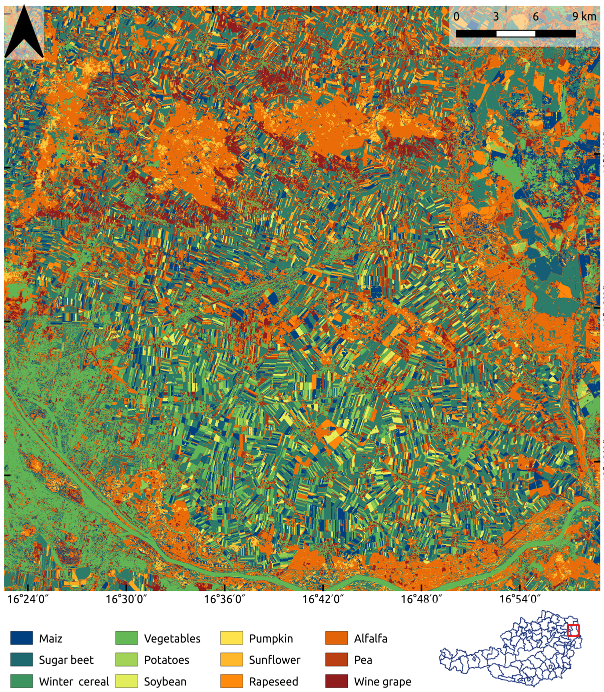

Fig. 3. Crop type classification map classified with the best model.

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