IECAG 2021

The 1st International Electronic Conference on Agronomy

03–17 MAY 2021 | ONLINE

Cropland mapping using Earth Observation derived phenological metrics

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Background

The information provided by increasing availability of Earth Observation (EO) data makes satellite images of paramount importance for identify, characterize and map crop typologies in both space and time dimensions

Multitemporal satellite images have proven to be successfully used to estimate vegetation biophysical parameters and identify phenological patterns

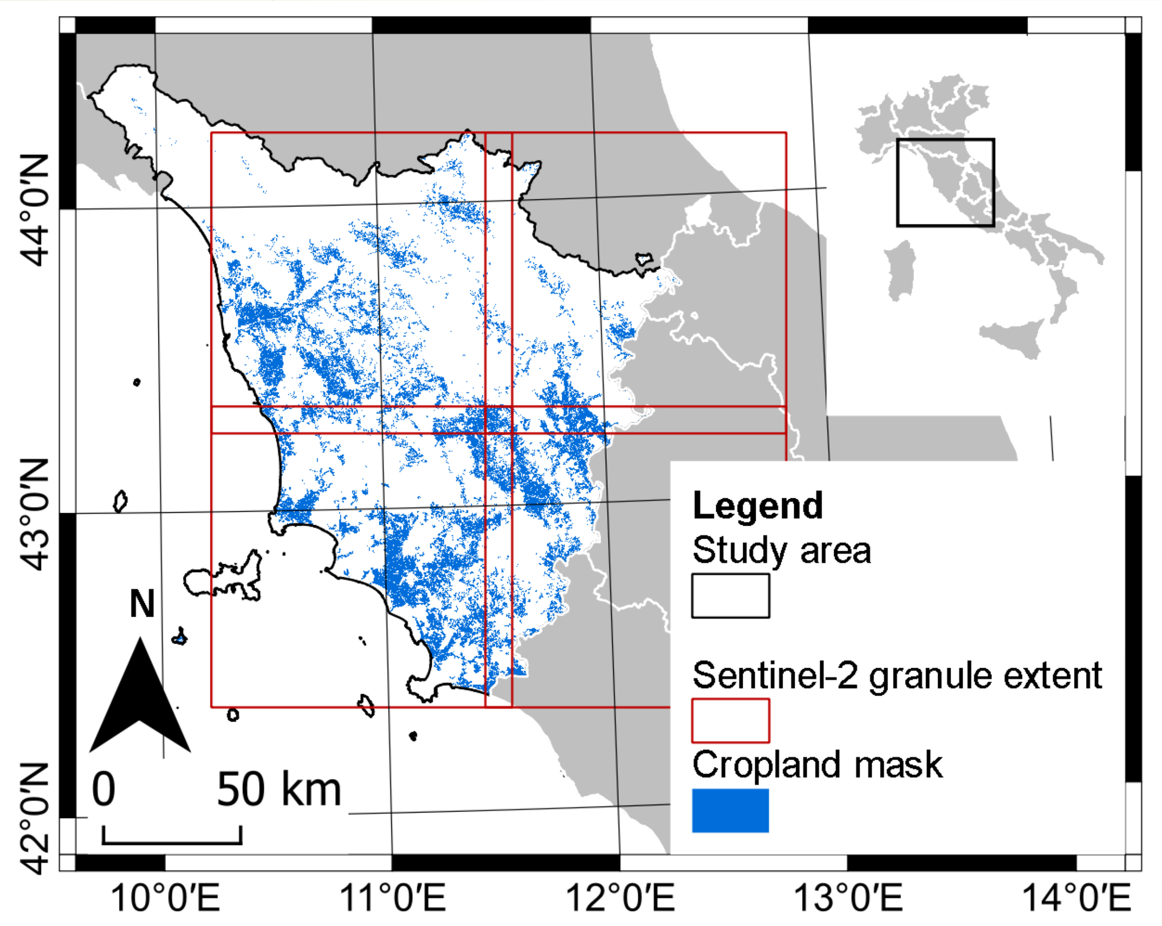
Advances in analytical techniques, such as the machine learning algorithms, enable dealing with fast and robust analysis applied to Big Data

Digital agriculture approach that integrates EO big data analytics, based on supervised machine learning model using temporal statistics and phenological metrics estimated from satellite time series, to identify and map the main crops types is presented

Objectives

- Integrate EO big data analytics to identify and map the main crops types
- Calibrate supervised machine learning models from phenological metrics predictors, using Random Forests algorithm, to produce crop types classified maps
- Compare classification performances of two supervised machine learning models, calibrated for a study area in central Italy using phenological metrics estimated from NDVI and LAI time series

Study area



Tuscany region is located in central Italy and covers about 23,000 km^2.

The cultivated areas represent about 39% of the region mainly characterized by arable land, vineyards and olive groves.

Data processing

- Sentinel-2 MSI atmospheric correction with MACCS-ATCOR Joint Algorithm (MAJA)
- Spatial resampling at 10 m
- Invalid pixel masking (e.g. cloud, topographic_shadow, snow)
- Calculation of Normalized Difference Vegetation Index (NDVI)

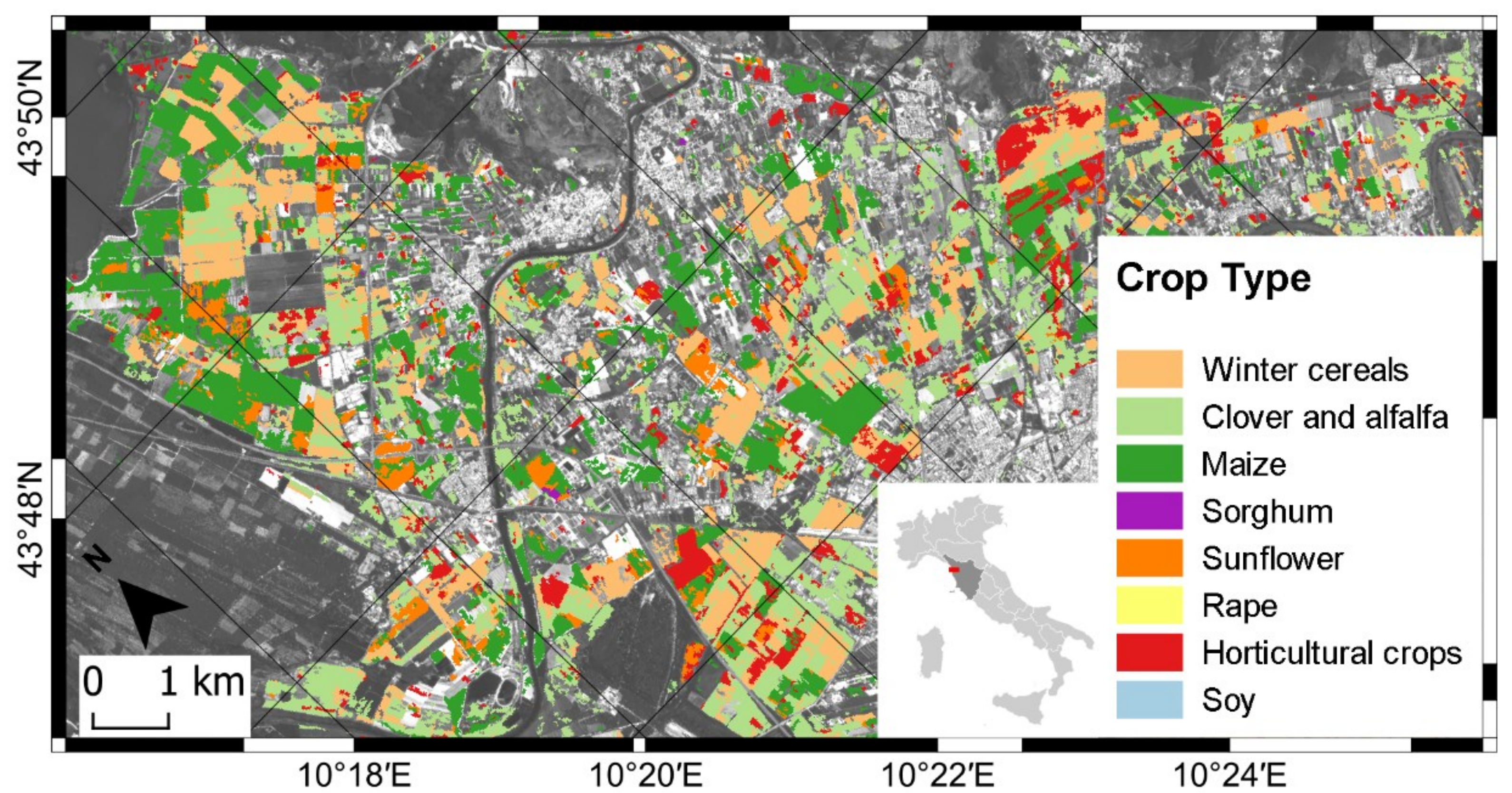
$$NDVI = \frac{NIR - RED}{NIR + RED}$$

- Estimation of Leaf Area Index (LAI) using SNAP biophysical processor
- Time series stacking and gap-filling
- Daily interpolation and temporally smoothin
- Calculation of temporal statistics
- Phenological metrics estimation

Classification

- Reference thematic crop maps collection
- Crop typologies selection and merging
- Polygons centroid extraction
- Spatial query on temporal statistics and phenological metrics
- Stratified sampling of model response variable
- Model predictors selection based on variable importance
- Random Forests hyperparameters tuning
- Random Forests model calibration
- Crop types classification using calibrated model
- Confusion matrix
- Accuracy metrics calculation
- Picking variable importance from calibrated model

Results



Crop types map of year 2019 for the area of Pisa (Italy)

Results

	Classification									
Reference map	**Winter cereals**	**Clover and Alfalfa**	**Maize**	**Sorghum**	**Sunflower**	**Rape**	**Horticultural crops**	**Soy**	**Total**	**PA %**
Winter cereals	**3804**	1609	4	2	8	24	44	0	5495	69,2
Clover and Alfalfa	2974	**17084**	53	45	36	29	410	0	20631	82,8
Maize	2	21	**528**	62	215	0	71	11	910	58,0
Sorghum	1	1	8	**11**	11	0	9	0	41	26,8
Sunflower	6	20	139	34	**230**	0	62	3	494	46,6
Rape	7	1	0	0	0	**11**	0	0	19	57,9
Horticultural crops	10	16	28	29	54	0	**540**	0	677	79,8
Soy	0	0	0	0	0	0	0	**3**	3	100
Total	6804	18752	760	183	554	64	1136	17	**28270**	**OA %**
UA %	**55,9**	**91,1**	**69,5**	**6,0**	**41,5**	**17,2**	**47,5**	**17,6**	**OA %**	**78,6**

K = 0.54

Confusion matrix of RF result from the NDVI time series analysis

Results

Reference map	Classification									
	Winter cereals	Clover and Alfalfa	Maize	Sorghum	Sunflower	Rape	Horticultural crops	Soy	Total	PA %
Winter cereals	**9759**	2510	0	0	0	62	40	0	12371	**78,9**
Clover and Alfalfa	2170	**7743**	0	0	0	13	146	0	10072	**76,9**
Maize	0	0	**19**	5	4	0	2	1	31	**61,3**
Sorghum	0	0	4	**20**	1	0	2	0	27	**74,1**
Sunflower	0	0	3	0	**12**	0	0	2	17	**70,6**
Rape	13	0	0	0	0	**9**	0	0	22	**40,9**
Horticultural crops	5	2	0	5	0	0	**428**	1	441	**97,1**
Soy	0	0	0	1	1	0	0	**3**	5	**60,0**
Total	11947	10255	26	31	18	84	618	7	**22986**	**OA %**
UA %	**81,7**	**75,5**	**73,1**	**64,5**	**66,7**	**10,7**	**69,3**	**42,9**	OA %	78,3

K = 0.59

Confusion matrix of RF result from the LAI time series analysis

Results

Selected variables importance
NDVI calibrated model

Name	Description	Unit	Importance
avg	Annual average value	dl	25089.92
jja_avg	Summer (June, July, August) average value	dl	26029.03
jja_max	Summer (June, July, August) maximum value	dl	24610.40
SGS_value	Start of Growing Season value	dl	23572.20
EoS_value	End of Season value	dl	22521.31
amplitude	Amplitude value	dl	27390.47
greenup_doy	Greenup DoY	DoY	47205.49
greenup_rate	Greenup rate	dl	24246.63
senescence_doy	Senescence DoY	DoY	57316.61
senescence_rate	Senescence rate	dl	20347.07
plateau_slope	Rate of change during the maturity plateau	dl	23675.63
DoS	Duration of season	Days	23237.03
STI	Seasonal time integrated value	dl	22737.46

Selected variables importance
LAI calibrated model

Name	Description	Unit	Importance
avg	Annual average value	m^2/m^2	1910.118
std	Standard deviation value	m^2/m^2	4332.682
min	Annual minimun value	m^2/m^2	3486.984
jja_avg	Summer (June, July, August) average value	m^2/m^2	2817.965
SoS_doy	Start of Season DoY	DoY	1890.944
SoS_value	Start of Season value	m^2/m^2	-
SGS_doy	Start of Growing Season DoY	DoY	2243.904
PoS_doy	Peak of Season DoY	DoY	2611.057
EGS_doy	End of Growing Season DoY	DoY	2653.588
amplitude	Amplitude value	m^2/m^2	2052.926
DoS	Duration of season	Days	1627.551
LMP	Length of Maturity Plateau	Days	1450.587

Results

- Overall accuracies and Cohen's kappa coefficient are similar for both the NDVI (OA=78.6 ; k=0.54) and the LAI (OA=78.3 ; k=0.59) model, comparing the results for individual classes, the latter showed slightly higher performances
- High misclassifications of horticultural crops may be related to different seeding time of the horticultural species, that could increase the variability in terms of predictors values range
- Small number of reference crops used for model calibration and validation of soy and rape crop types could be the reason for such a low classes accuracy

Conclusions

Earth Observation high-resolution imagery sensed by Sentinel-2 satellites constellation, combined with training dataset, and the use of advanced computational analytic techniques (RF algorithm), allowed to crop type classification in heterogeneous, small, and fragmented agricultural systems.

The supervised machine learning model, applied to a wider spatial extent, could contribute to support the sustainability measurement and assessment foreseen by the European Green Deal strategy, in terms of sustainable agricultural practices and environmental monitoring, climate change mitigation and adaptation in accordance with the stakeholder requirements.