Parcel Based Analysis

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Abstract

The objective of this study is to use time-series of Sentinel-1 Interferometric coherence per field to determine crop types. Cloud cover severely hampers the ability of optical imagery to provide invaluable information about crop growth and development. The goal is to prove that InSAR is sensitive to the temporal evolution of crops and has potential for crop classification. A one-year time-series of Sentinel-1 images acquired over an agricultural area in the city of Hanford, King's County, California dominated by agricultural farmlands (among others: corn, wheat, alfalfa, cotton, pistachios, almonds) and pasture for cattle and goats is used for this study. Results shows that interferometric coherence coefficient provide notable classification accuracy between 70-80% and use of all available intensity images perform best, hence, taking advantage of the six day revisit time-period provided by sentinel-1 for crop monitoring. Based on this study, Sentinel-1 data can be used to monitor crop growth and development. Also, Sentinel-1 imagery is guaranteed to be available in cloudy conditions which ensures food producers, farmers, and regulatory bodies will be able to monitor their crops with confidence.

Introduction

A valuable product of satellite remote sensing is the concept of thematic maps of agricultural crops. The maps in this category provide accurate and dependable information to governments, whether they are local or national. With today's abundance of high-resolution optical data, agricultural applications are opened up to unprecedented possibilities. Due to their well-known sensitivity to crop biophysical properties, most crop classification approaches use optical or multispectral data as input features. However, Optical sensors are unable to look through clouds, resulting in cloud-induced gaps in observations, hence making it impossible to retrieve the complete time series of a vegetation index. To provide useful information on crop status, it's important to monitor on a regular basis, certainly during times when conditions on the field change drastically. These limitations can be overcome by the use of SAR data which is independent of weather conditions and sun illumination as it produces its own light and can collect day/night data. SAR is very sensitive to small changes in elevation on earth's surface, it provides frequent and regular imaging and different polarizations are sensitive to different target properties. These properties along with free availability of sentinel-1 images provides key motivation to exploit this information for crop classification.

The Sentinel-1 mission comprises two identical satellites, each carrying an advanced radar instrument to provide a day-and-night, all-weather supply of images of Earth's surface ((SINCOHMAP), 2019)[i]. The SAR data consists of two components Amplitude and Phase, amplitude is the signal that returns to the sensor (backscatter coefficient) and it is sensitive to the physical and dielectric properties of the target. High dielectric properties objects have high signal return, VV polarization is sensitive to surface roughness and VH polarization is sensitive to volume scattering such as vegetation canopy. Phase is the location of the signal along its wave cycle when it returns to the sensor. In this study our focus is on the use of phase as it forms the basis of SAR interferometry.

Interferometric coherence is measured by calculating the phase difference between two (or more) SAR images with different orbits and/or times. Phase difference between two images of same area at different times is called the repeat pass interferometry. This same technique is used in this study. Repeat-pass SAR interferometry (InSAR) is useful to detect changes in the scene between the two acquisitions since they cause a decrease in interferometric coherence. This loss of coherence is usually denoted as temporal decorrelation. For the specific application of crop-type mapping, temporal decorrelation is present in areas with vegetation due to wind (and other weather events) and also due to changes in the scene induced by the vegetation itself (Mestre-Quereda et al., 2020)[ii].

In this study we will be exploiting Sentinel-1 interferometric coherence coefficient in dual polarizations (VV & VH) for crop type classification.

Literature Review

Globally, the majority of countries and regions are increasingly using satellites to monitor their land cover. Wardlow et al. (2007)[iii], for example, used dense time series of 250 m Moderate Resolution Imaging Spectrometer (MODIS) data to classify major crop types in the US Central Great Plains, where fields were ~32.4 ha or larger. Satellite-based methods for mapping and monitoring crops need to be Satellite-based methods for mapping and monitoring crops need to be (a) consistent, (b) flexible, and (c) geographically portable over large areas, where timely information might not be easy to obtain[iv]. Consistency and portability have proven to be problems with methods based on combined SAR-optical datasets. Davidson et al. (2017)[v] pointed out that cloud cover often varies considerably by region, which results in differences in accuracy between regions. Several studies conclude that crop types can be distinguished using Sentinel-1 SAR alone following the launch of the instrument in 2014, with many concluding that it provides new opportunities for mapping crops[vi]. A study by Veloso et al.[vii]compared Sentinel-1 data to measures of normalized difference vegetation index (NDVI) based on optical data and ground measurement measurements of precipitation, temperature, green area index, and fresh biomass. In their study, they demonstrated that Sentinel-1 data, particularly the ratio of VH to VV, is useful for crop development. Particular attention was given to the possibility of detecting crops by analyzing backscatter over time. More recently, Vreugdenhil et al.[viii] studied Sentinel-1 backscatter data and polarization ratio (VH/VV) to examine how they relate to vegetation water content (VWC), height, biomass, and leaf area index (LAI). Based on Sentinel-1 imagery, Random Forest modeling was shown to be suitable for estimating VWC.

Datasets and Methods

Reference Data

The a priori knowledge of your data is necessary for a supervised classification. As a consequence, we must be aware of what types of crops grow on each site. For this purpose California National Resources Agency's Statewide Crop Mapping[ix] is used. The area of interest lies is the city of Hanford, and its surrounding landscapes in King's County, California which are dominated by agricultural farmlands (among others: corn, wheat, alfalfa, cotton, pistachios, almonds) and pasture for cattle and goats. Symb_class attribute used for Main Season (summer) crops will be taken as class label. Class codes are:

- G - Grain and hay crops (' G'),
- R - Rice (' R'),
- F - Field crops (' F'),
- P - Pasture (' P'),
- T - Truck, nursery, and berry crops (' T'),
- D - Deciduous fruits and nuts (' D'),
- C - Citrus and subtropical (' C'),
- V - Vineyards (' V'),
- I - Idle (' I'),
- S - Semi-agricultural and incidental to agriculture ('S '),
- U - Urban - residential, commercial, and industrial, unsegregated ('U ')

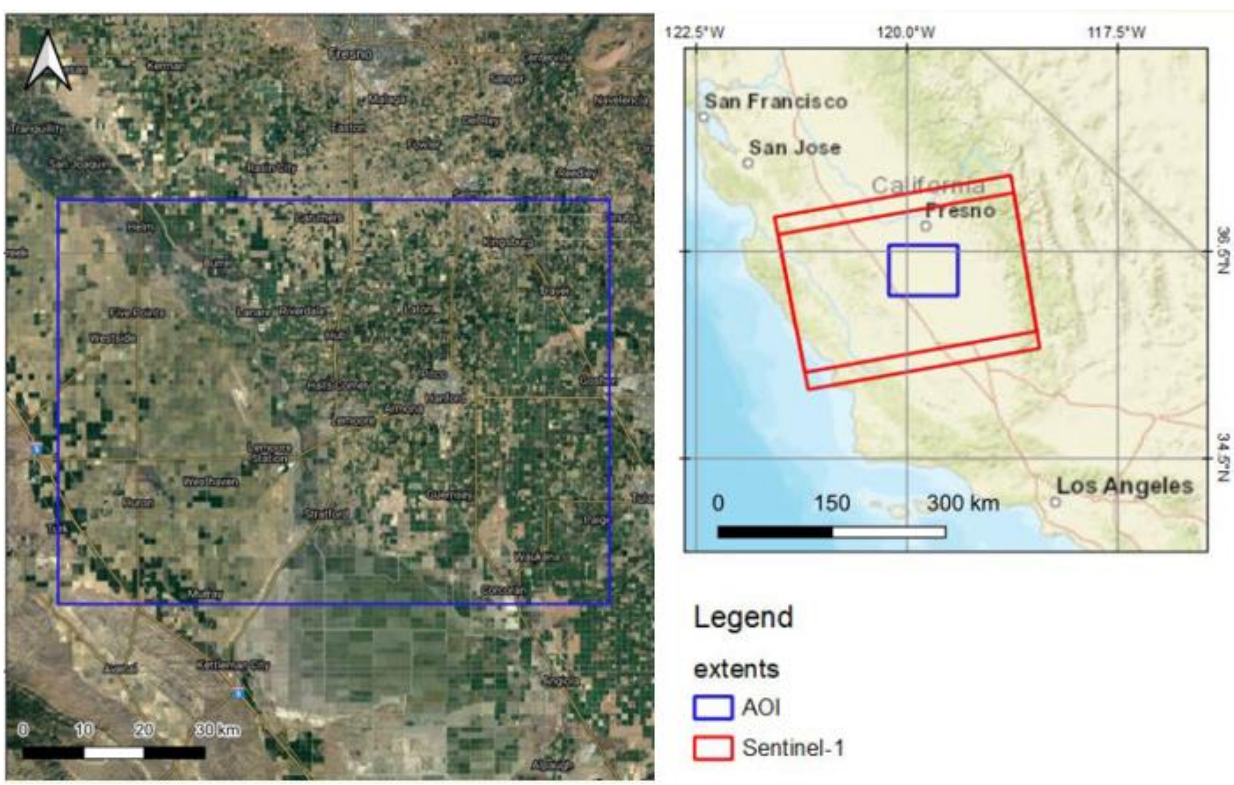

Figure 1 Study Area

Sentinel-1 Data

For using interferometric coherence single look complex (SLC) images of the study area in interferometric swath mode are required because they contain phase information.

Pre-processing of Sentinel-1 Data

Sentinel-1 data cannot be used in raw form and it requires a lot of pre-processing steps for calculating interferometric coherence among images, these pre-processing steps are:

1. Coregistration of all SLC images to a common master
2. Radiometric calibration to σ0
3. Interferometric stack generation
4. Speckle filtering and coherence estimation.
5. Geocoding: all coherence and calibrated intensity data

Analysis Ready Data

Analysis Ready Data are time-series stacks of overhead imagery that are prepared for a user to analyze without having to pre-process the imagery themselves (Holmes, 2018)[x]. The ability to perform large-scale time-series analysis of SAR highly depends upon the geometrically and radiometrically consistent imagery. Pre-processing of SAR takes is time-taking apart from actual analysis, to reduce the burden the available InSAR ARD data was used in this study. Alaska search facility (ASF) is supported by NASA for providing on demand ARD products of sentinel-1 and other sensors. The dataset is free and open source and it was utilized for this study.

Classification Method

The classification was carried out with Random forest classifier using the object-based image classification methodology in eCognition. Sample-based statistics approach was followed in this process. Vector based segmentation was performed. The training and validation samples were selected randomly from the reference dataset with 60% and 40% respectively. Sample statistics were calculated for samples and were used as an input to random forest classifier.

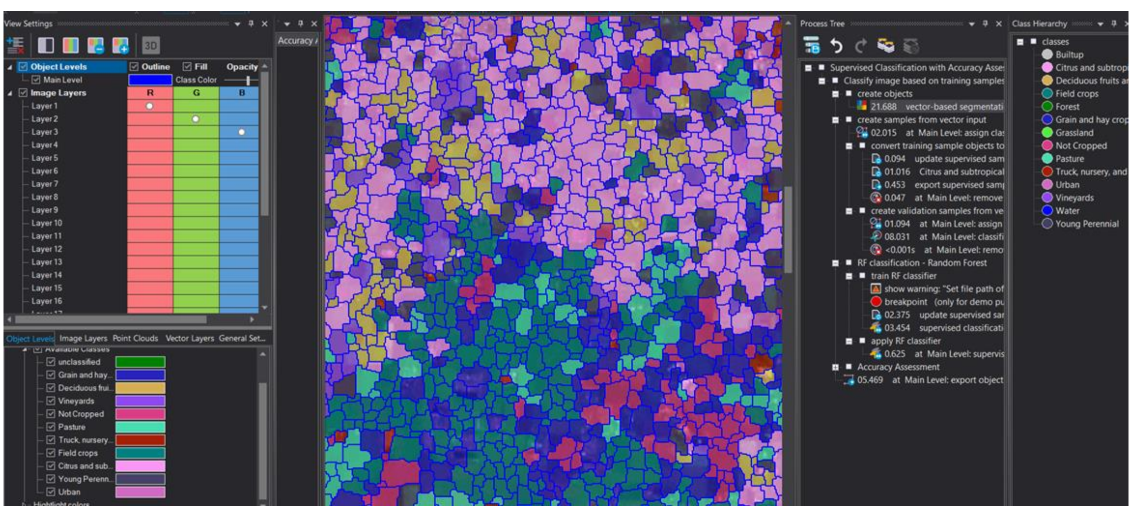

Figure 2 Ruleset for Random forest classification

Results

Inspection of Input InSAR coherence features

As a first step before performing any classification testing, it is worthwhile to observe the evolution of all the observables that will be used as input features, as these will give us insight into their temporal dynamics. Figure 3 shows RGB composites for different periods: 3 months 9 months and 11 months.

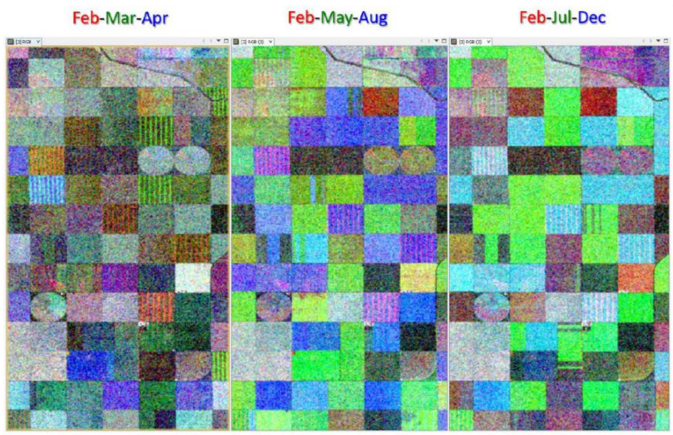

Figure 3 Multi-temporal image composites

The above image shows how the spatial signature of crop fields changes over time, owing to a change in backscatter intensity caused by the growth of the stems, leaves, and grains of the crops. Because each crop type progresses differently, this temporal signature is a crucial indicator for crop classification. Figure 4 shows HSV composite of the temporal image stack where hue is determined by the average, a saturation by the maximum, and a value (brightness) by the standard deviation. Although difficult to interpret, it shows additional similarities, differences, and patterns among the various crop areas.

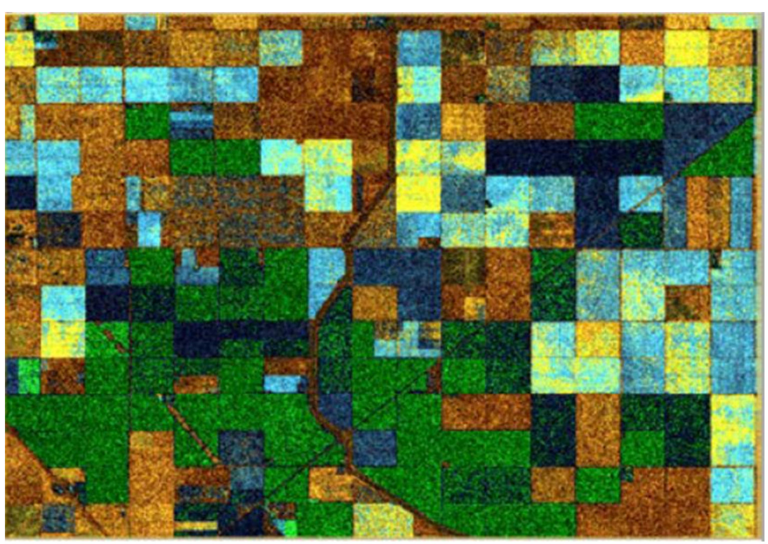

Figure 4 HSV composite of temporal average, maximum and standard deviation

Chronologies of each crop type follow its growing cycle. Thus, each crop type has a specific crop cycle, including sowing, growing, and harvesting. Through the evolution of coherence, we are able to identify these intervals. Because parcels are barefields (i.e. have not yet been planted or harvested), there is less time decorrelation, thus there is a higher coherence value. Alternatively, as the crop grows, the coherence is expected to weaken because the plants in the field are dynamically changing from one observation to the next, in addition to weather changes that affect the vegetation. This growing period of the crops can be observed in the graphs shown in Figure 5. In the case of most crops, the interval with minimum coherence is different than the remainder, which is a good indicator for classification. For example, From January through September, alfalfa displays a long growing season, resulting in a low coherence, whereas maize has a very short growing cycle that is concentrated in summer.

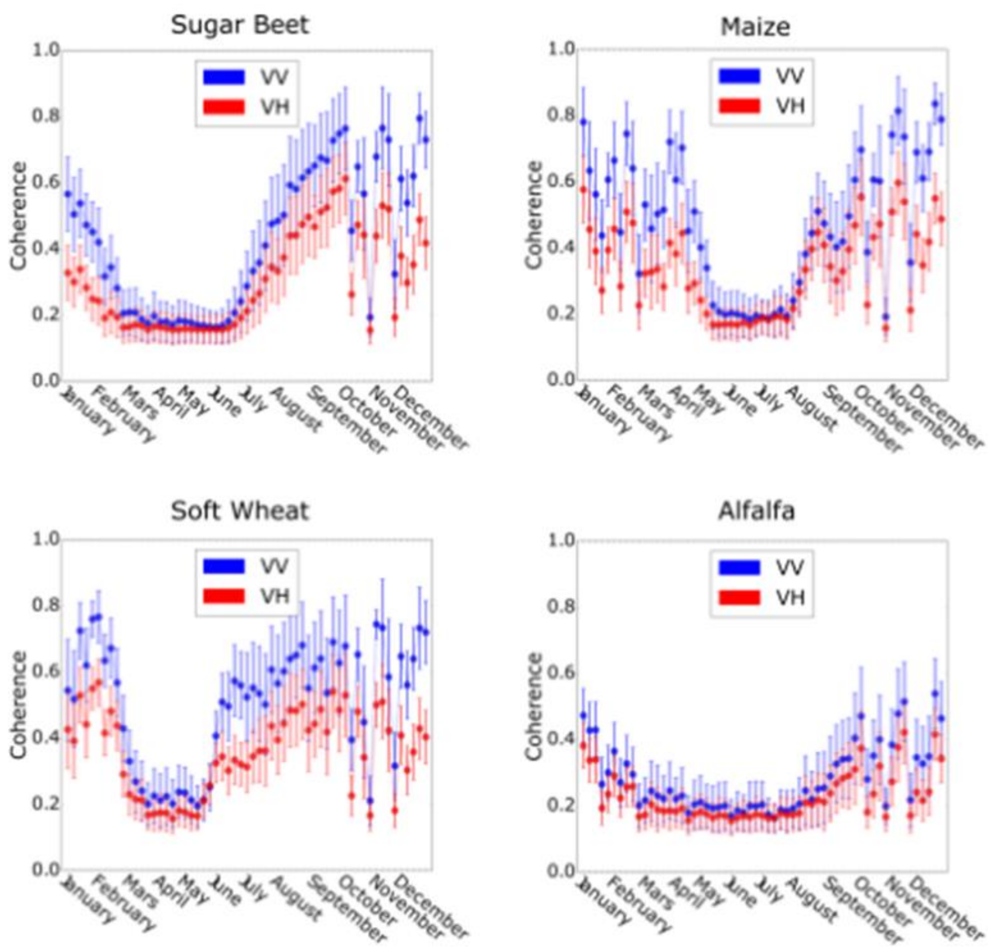

Figure 5 Temporal evolution of the interferometric coherence at VV and VH channels, Image Source ((Mestre-Quereda et al., 2020b)[xi]

From the above figure it can be observed that the coherence of channel VV is always higher than that of channel VH even though both exhibit a very similar evolution. The reason for this is twofold. Firstly, in the cross-polar channel at C-band, the response from vegetation is expected to be more sensitive to the vegetation layer rather than the ground. That is why VH polarization is influenced more by temporal decorrelation than VV polarization. Furthermore, the VV channel shows a higher backscattering level, which leads to a higher signal-to-noise ratio (SNR) and less decorrelation[xii].

Classification Evaluation

For this classification, Random Forest classifier was trained based on coherence statistics for all training sites. Once the model is trained and applied to the whole study area, evaluation is performed on the set of validation samples (40% of the total fields). The figures below shows the comparison between ground truth reference map and classification.

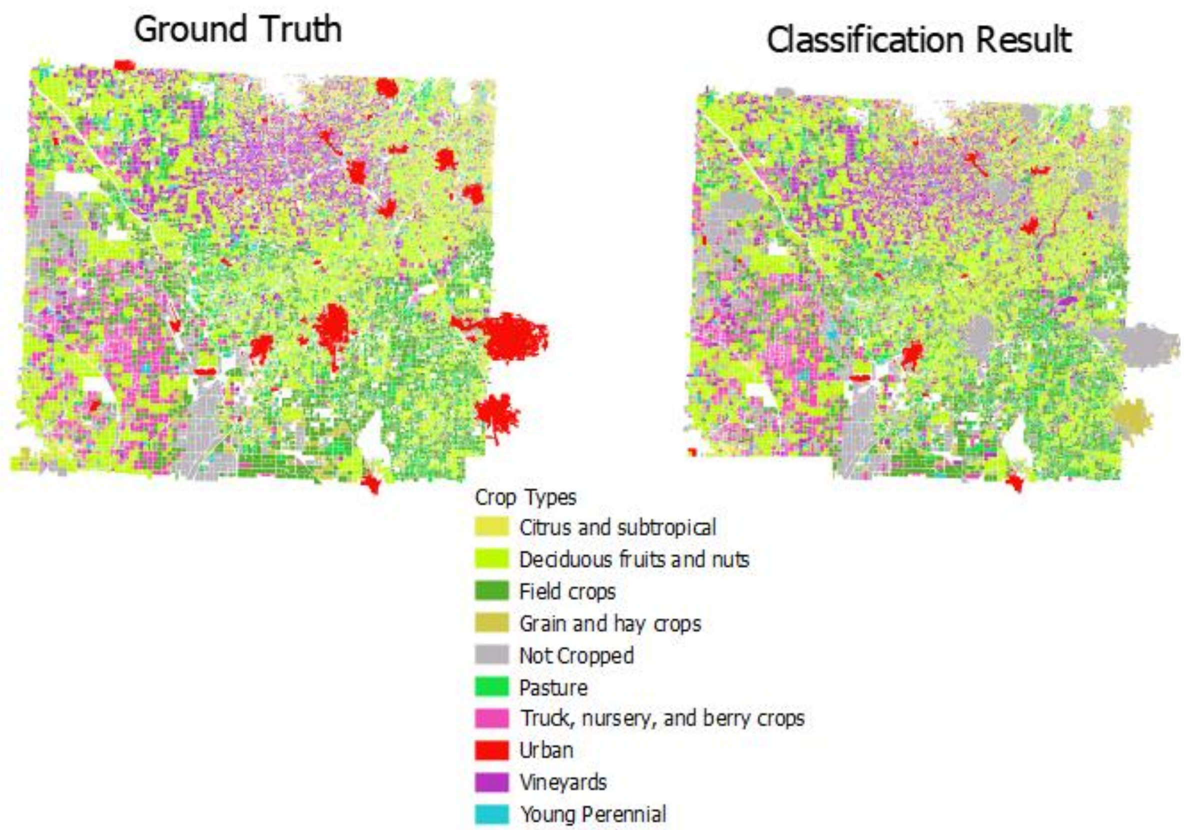

Figure 6 Classification Result

From the results obtained, confusion matrix is computed and some metrics are derived: overall accuracy, Kappa coefficient, producer’s accuracy and user’s accuracy. The resulting confusion matrix and assessment metrics are shown in figure 7.

Error Matrix based on Samples

User Class \ Sam...	Grain and hay cro...	Deciduous fruits a...	Vineyards	Not Cropped	Pasture	Truck, nursery, an...	Field crops	Citrus and subtro...	Young Perennial	Urban
Confusion Matrix										
Grain and hay crops	91	11	2	18	9	6	22	1	2	0
Deciduous fruits an...	8	2780	181	127	38	24	44	32	66	0
Vineyards	4	105	982	53	17	16	19	15	14	1
Not Cropped	24	96	43	625	34	56	57	15	14	3
Pasture	21	25	9	22	258	6	46	3	3	1
Truck, nursery, an...	3	29	13	30	4	454	29	5	3	1
Field crops	20	18	8	27	56	30	636	0	2	0
Citrus and subtropi...	3	53	20	49	12	13	4	366	26	0
Young Perennial	2	67	27	29	4	8	4	16	148	1
Urban	0	5	1	4	3	2	0	2	0	7
unclassified	0	0	0	0	0	0	0	0	0	0
Sum	176	3189	1286	984	435	615	861	455	278	14
Accuracy										
Producer	0.517	0.8717466	0.7636081	0.6351626	0.5931034	0.7382114	0.7386760	0.8043956	0.5323741	0.5
User	0.5617284	0.8424242	0.801	0.6463289	0.6548223	0.795	0.798	0.6703297	0.4836601	0.2916667
Hellden	0.5384615	0.8568346	0.7818471	0.6406971	0.6224367	0.7655987	0.7671894	0.7312687	0.5068493	0.3684211
Short	0.3684211	0.7495282	0.6418301	0.4713424	0.4518389	0.6202186	0.6223092	0.5763780	0.3394495	0.2258065
KIA Per Class	0.5074232	0.787	0.7225983	0.587	0.5728076	0.7188535	0.7108911	0.7906096	0.5144583	0.4985488
Totals										
Overall Accuracy	0.7653443									
KIA	0.702									

Figure 7 Accuracy Assessment

It is observed that overall accuracy is moderately high (76.5%). Crop groups with best classification results are deciduous fruits, citrus and subtropical, field crops, vineyards, trucks, nursery and berry crops with values of PA and UA ranging from 87% to 73%. Classes with worst accuracy are urban, young perennial, grain and hay crops their PA and UA values range from 48% to 56%. From the observation of the error matrix and time series of coherence it can be said that their temporal signatures are very similar and hence classifier wasn't able to distinguish between them. These results prove that interferometric coherence coefficient is undoubtedly complimentary to crop type classification. Even the least producer's accuracy for poorly classified classes is above 50% and this result can may be improved with post-processing of classification results.

Conclusion

In this study, we evaluate the potential for generating thematic maps of crop types based on Sentinel-1 interferometric data. We conclude from the time-series of interferometric coherence measured for all crop types at this site that the growing season of most species corresponds with a period of very low coherence. Crop calendar is well identified by the coherence magnitude. An important aspect that was observed is that polarization plays an important role in the idea that the behavior of both channels compliments one another, since it improves the accuracy of classification by simultaneously making use of the data of both polarizations. A temporal coherence profile can be used to determine how crops are developing phonologically. As heads emerge, the coherence level decreases, and it is sensitive to the moisture level of the grain, so it can help farmers determine optimal fertilizing and harvesting times. Finally for future research, to further confirm the results obtained in this study, more tests can be performed over a wider range of geographical areas and/or where different types of crops are present.

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