Crop Classification Using Multiconfiguration C-Band SAR Data

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***Abstract*—This paper reports on an investigation aimed at evaluating the performance of a neural-network based crop classification technique, which makes use of backscattering coefficients measured in different C-band synthetic aperture radar (SAR) configurations (multipolarization/multitemporal). To this end, C-band AirSAR and European Remote Sensing Satellite (ERS) data collected on the Flevoland site, extracted from the European RAdar-Optical Research Assemblage (ERA-ORA) library, have been used. The results obtained in classifying seven types of crops are discussed on the basis of the computed confusion matrices. The effect of increasing the number of polarizations and/or measurements dates are discussed and a scheme of interyear dynamic classification of five crop types is considered.**

***Index Terms*—Crop classification, neural networks, synthetic aperture radar (SAR).**

I. Introduction

THE POTENTIAL of synthetic aperture radar (SAR) in discriminating among different agricultural crop species has been demonstrated in several studies [1]–[3]. The accuracy of classification depends on the sensitivity of the used backscattering coefficients to the differences of the biomorphological structures of the plants, hence to the different interaction behavior between the electromagnetic wave and the structure of the canopy [4].

It has been experienced that measurements taken by a SAR system in a single configuration, that is one image at given frequency, polarization and incidence angle, are often inadequate to attain the required accuracy of classification. Given the dependence of the scattering mechanisms in vegetation canopies on frequency, polarization and incidence angle, improvements are expected by multifrequency and/or multipolarization and/or multiangle measurements [5]–[8]. Alternatively, multitemporal single-frequency, single-polarization data collected by repeated overpasses can improve the accuracy, since they are affected by the peculiar variations induced in backscattering by the growth cycle of a given plant [9]–[11].

To be successful, suitable classification algorithms should be used, which are capable of exploiting the information embedded in multipolarization and multitemporal SAR measurements. A variety of classification schemes have been proposed and used, some recent examples of which can be found in [12]–[14].

Due to several interesting and peculiar features, neural network algorithms (NNAs) have also been considered for classification purposes [15]–[17]. With respect to statistical methods, neural networks use an essentially different approach, so that they do not rely on probabilistic assumptions neither need particular requirements about normality in datasets.

This paper reports on an investigation aimed at a systematic evaluation of the information content, hence of the classification potential, of different consistent sets of C-band backscattering coefficients of agricultural fields. Multipolarization data consist of the set of measurements collected over Flevoland, The Netherlands, by the National Aeronautics and Space Administration Jet Propulsion Laboratory (NASA/JPL) AirSAR system during the 1991 MAC-Europe campaign, while multitemporal data over the same site were acquired by the European Remote Sensing Satellite 1 (ERS-1) SAR in the years 1993, 1994, and 1995. The data used in this study have been extracted from the European Radar-Optical Research Assemblage (ERA-ORA) Library, assembled through a concerted action funded by the European Commission within the Research and Technology Development Programme on Environment and Climate (Fourth Framework Programme) in the field of space techniques applied to environmental monitoring and research [18]. The classification algorithm, consisting of a multilayer neural network with feedforward configuration, has been fed by sets of data of varying completeness. The corresponding variation of classification accuracies of selected crop species, as expressed by the confusion matrices, is discussed and related to the type of input measurements. The results obtained by the neural net are compared with those of a maximum likelihood algorithm [8]. A dynamic classification scheme, aimed at discriminating the crops during their development phase is also presented and examined.

Our classification exercise makes use of data taken at high incidence angles. This choice reduces the possibly detrimental effects of the underlying soil, but, from a practical point of view, it would limit to the far range the portion of an airborne SAR image over which classification is expected to be performed effectively. Extending the area requires the adoption of suitable

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methods to cope with the dependence of the crop backscattering coefficients on the incidence angle. A viable consistent approach could be based on a neural net trained with multiangle measurements. In principle, the learning process and the nonlinear inputs combination taking place in the net is expected to be equivalent to alternative methods like the application of compensation functions or the use of ratios between backscattering coefficients.

The classification is carried out on a *per-field* basis, rather than at the pixel level. Although the method we describe can be also used on pixels and segments, both the variability of the scattering patterns associated with a given type of vegetation or with local soil conditions and the influence of the speckle, which depends on the number of independent looks and is very small for entire fields, possibly limits the generality of the results. However, some major civilian applications of remote sensing in several European Countries, can count on the *a priori* knowledge of the position and delineation of cultivated parcels to be classified. This is the case, for instance, for the control of area-based agricultural subsidies, for which the field boundaries are provided by the farmers [19].

II. Datasets

The data collected by the AirSAR are at three frequencies, P- (0.45 GHz), L- (1.3 GHz), and C- (5.3 GHz) band and fully polarimetric. They are also partially multitemporal, since in 1991 the Flevoland site was overflown four times in summer time, i.e., on June 15 and on July 3, 12, and 28. In the following, only C-band measurements are considered, in view of a more direct comparison with the multitemporal ERS data. The C-band intensity measurements, extracted from the ERA-ORA ensemble of data, have been rearranged in subsets of varying complexity, starting from the single configuration system, i.e., vv polarization one date, and subsequently adding further polarizations and number of overpasses, up to the complex which includes co- (hh, vv) and cross- (hv) polarizations for all four overpasses. The subsets of data containing both vv and hh polarizations have been subsequently augmented by the inclusion of the corresponding relative phase to appreciate the contribution of this kind of information to the classification.

ERS data are single frequency and single polarization, but they cover the whole year with the 35-day repeat cycle of the satellite, hence including the observation of both the early stage and the senescence of the various crops. The ERA-ORA database makes available three years of measurements (1993 to 1995) for both ascending and descending orbits.

Numerous crops were present on the Flevoland site in the mentioned years, including maize, sugarbeet, potato, oil-seed rape, barley, wheat, lucerne, onions, peas, flax, beans, carrots, grass, and bush. Out of them, we generally selected the crops with the higher number of fields to increase the statistical significance of the results. The number of fields for each crop and set of radar data are detailed in Table I.

The state of the soils was generally moist during the first 3 weeks and dry in the second three weeks. On its turn, the state of representative crops from mid-June to July evolved as follows:

TABLE I
Dataset Characteristics

	AirSAR 1991		ERS ('95 vs. '95)		ERS ('93 + '94 vs. '95)	
crop	training	test	training	test	training	test
barley	10	4	5	3	18	8
maize	2	2	8	4	0	0
grass	11	8	21	9	68	30
potato	28	25	15	15	109	30
rape	4	3	1	1	0	0
s.beet	23	19	18	12	95	30
wheat	33	18	19	11	123	30
total	111	79	87	55	413	128

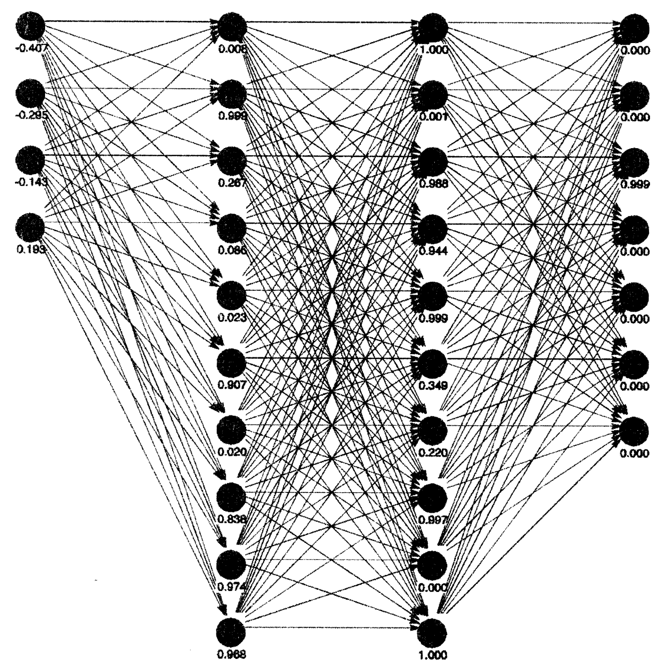

Fig. 1. Neural network feedforward topology.

- *maize:* crop cover develops from 5% to 90%, height from 10–160 cm;
- *potato:* crop cover develops from 50% to 90%, height from 30–55 cm;
- *sugar beet:* crop cover develops from 20% to 90%, height from 15–45 cm;
- *wheat:* crop cover was stable at 90%, height from 80–95 cm.

III. Neural Network Classification Algorithm

The classification algorithm makes use of an artificial neural network [20] with feedforward configuration. The neural network simulator (SNNS) developed at the University of Stuttgart, Germany [21], has provided the basic software for implementing the algorithm. The net consists of a multilayer perceptron with two hidden layers, as shown in Fig. 1.

A possible network overdimensioning and consequent loss of generalization properties can be curbed by the pruning procedure. Our classification exercise has first been carried out

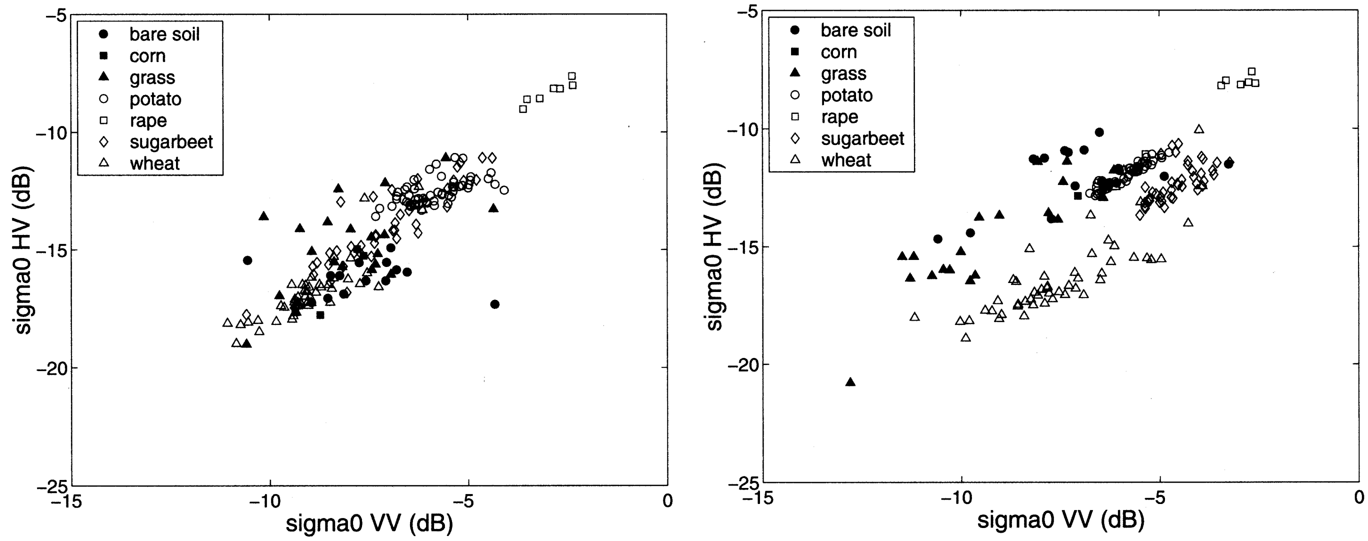

Fig. 2. Scatter plots $\sigma^0_{\rm hv}$ versus $\sigma^0_{\rm vv}$ of seven crop types on the Flevoland MAC-Europe test site; measurements refer to incidence angles $45° \le \theta \le 62°$; acquisition dates are June 15, 1991 (left) and July 12, 1991 (right).

through the network in its full configuration, subsequently by using a pruned topology.

Training has been pursued by a scaled conjugate gradient (SCG) algorithm. This is a member of the class of conjugate gradient methods, general-purpose second-order techniques that help minimizing goal functions of several variables. Second order indicates that such methods use the second derivatives of the error function, while a first-order technique, like standard backpropagation, only uses the first derivatives. By using the SCG method, the nets have generally been trained after a few hundreds of epochs, i.e., the training phase was very short-time consuming. Here, for the purpose of classification, in the training phase the component of the output vector corresponding to the true class has been set to one while the others to zero. In the test phase, a winner-and-take approach has been considered.

A direct comparison against the results yielded by a different classification technique using some of the 1991 Flevoland AirSAR dataset has been carried out. This technique follows a maximum likelihood (ML) approach using a joint Gaussian distribution (on the decibel values) [8]. Indeed, by application of the K-S test, a Gaussian distribution for intensity values expressed in decibels has been found to be appropriate. Details on the method, as well as on the distributions of phase difference and coherence magnitude and on the influence of the speckle on the distributions, are reported in the cited paper. Note that the extension to multitemporal data is straightforward.

IV. Impact of Data Features on Classification

A main purpose of this investigation is assessing the benefit that a per-field neural-network classification algorithm derives from the availability of SAR measurements at more than one polarization, with and without phase information, and/or at more than one date. For a consistent analysis of the results, all measurements are at C band, taken by the AirSAR in the multipolarization and limited multitemporality case, and by the ERS SAR in the full multitemporal exercise and the dynamic classification scheme.

A. Multipolarization in Classification

Discriminating among crops requires a suitable sensitivity of the radar to the biophysical peculiarities of the plant types. A comprehensive survey of the radar response of several common crops is given by Ferrazzoli [4]. His review also contains considerations and suggestions on the choice of SAR parameters for effective monitoring of cultivated surfaces and, in particular, stresses the importance of cross-polarization. Fig. 2 reports two examples of scatter plots $\sigma^0_{\rm hv}$ versus $\sigma^0_{\rm vv}$ relative to the first (June 15) and third (July 12) 1991 AirSAR data acquisition over Flevoland. The diagrams show that the signatures of the crops are only partially separable at a relatively early stage, whereas, in this plane, discrimination becomes generally apparent as the plants grow up. Clustering of rape plants, sugar beet, and wheat is particularly manifest. Given these features, the ENVISAT Advanced SAR (ASAR), which has cross-polarization capability, is expected to yield some significant progress in crop monitoring: in particular, the combined use of the partial polarimetric modes in the frame of a multitemporal approach is expected to improve the amount of information.

For our analysis on the effect of multipolarization, we selected the measurements collected on the third date, when the signatures of the well developed plants appear to be well separated (Fig. 2). The data refer to the higher angles of incidence, i.e., from about 45° to 62°, since the number of fields imaged in this range was relatively large. We add that the intensity of backscattering at high incidence angles is essentially sensitive to the vegetation canopy, given the low contribution from the underlying soil, whose state is less influential. The data were subdivided into independent training and test sets for the number of fields detailed in columns 2 and 3 of Table I, respectively. For a given date of overflight, the number of linear polarizations in both sets was increased from the single vv to three, vv, hh, and hv. The neural network algorithm was trained by each training

TABLE II
CONFUSION MATRIX DESCRIBING NNA CROP CLASSIFICATION PERFORMANCE. ALGORITHM INPUT: ONE POLARIZATION ($\sigma^0_{\rm vv}$), ONE DATE (JULY 12, 1991), AIRSAR, FLEVOLAND. TOTAL NUMBER OF SAMPLES: 79. CORRECTLY CLASSIFIED: 44. OVERALL ACCURACY: 55.7%

classified	true class						
as	barley	maize	grass	potato	rape	s.beet	wheat
barley	2	1	3	0	0	1	8
maize	0	1	0	5	0	0	0
grass	0	0	3	0	0	0	3
potato	1	0	1	14	0	0	2
rape	0	0	0	0	2	0	0
s.beet	0	0	0	5	1	18	1
wheat	1	0	1	1	0	0	4

TABLE III
CONFUSION MATRIX DESCRIBING NNA CROP CLASSIFICATION PERFORMANCE. ALGORITHM INPUT: THREE POLARIZATIONS ($\sigma^0_{\rm hh}$, $\sigma^0_{\rm vv}$, $\sigma^0_{\rm hv}$), ONE DATE (JULY 12, 1991), AIRSAR, FLEVOLAND. TOTAL NUMBER OF SAMPLES: 79. CORRECTLY CLASSIFIED: 72. OVERALL ACCURACY: 91.1%

classified	true class						
as	barley	maize	grass	potato	rape	s.beet	wheat
barley	3	0	3	0	0	0	0
maize	0	2	0	0	1	0	0
grass	1	0	5	0	0	0	0
potato	0	0	0	25	0	0	2
rape	0	0	0	0	2	0	0
s.beet	0	0	0	0	0	19	0
wheat	0	0	0	0	0	0	16

subset and used to classify the test fields by each subset of test data relative to the same number of polarizations. This procedure was carried out both for a single overpass and using the ensemble of data collected by all four overpasses.

As expected, the classification performance improves with adding more polarizations. In case measurements are relative to a single date, the overall accuracy (OA) increases from $OA = 55.7\%$ when only $\sigma^0_{\rm vv}$ polarization is used (Table II), to $OA = 91.1\%$ when exploiting $\sigma^0_{\rm vv}$, $\sigma^0_{\rm hh}$, and $\sigma^0_{\rm hv}$ data (Table III). The results in Table II suggest that the single vv polarization is moderately able to discriminate among classes of canopies with essentially dissimilar geometries, as the ramified potato, the wide-leaf sugar beet, the small-stem rape seed plants [3]. Barley and wheat, characterized by a similar vertical cylindrical structure, tend to be confused. Analogous results are obtained by the ML-based method. The accuracy of this latter, $OA = 46.8\%$ for single polarization and 88.6% for three polarizations, is moderately lower than that of the neural net.

At present, no satellite provides σ^0 measurements at three polarizations; hence, it can be interesting to consider the classification capability of an algorithm using σ^0's at two pairs of polarizations, as ENVISAT is making available. The performance of the two-pol algorithm can be appreciated from the confusion matrix in Table IV. A comparison of Table IV with Tables II and III points out the high discriminating potential of cross-polarization, particularly sensitive to the random orientation of the canopy scattering elements, and the moderate improvement brought into by the addition of $\sigma^0_{\rm hh}$. Again, the accuracy of the ML technique is lower ($OA = 72\%$ against 86.1%).

TABLE IV
CONFUSION MATRIX DESCRIBING NNA CROP CLASSIFICATION PERFORMANCE. ALGORITHM INPUT: TWO POLARIZATIONS ($\sigma^0_{\rm vv}$, $\sigma^0_{\rm hv}$), ONE DATE (JULY 12, 1991), AIRSAR, FLEVOLAND. TOTAL NUMBER OF SAMPLES: 79. CORRECTLY CLASSIFIED: 68. OVERALL ACCURACY: 86.1%

classified	true class						
as	barley	maize	grass	potato	rape	s.beet	wheat
barley	3	1	4	0	0	0	0
maize	0	0	0	0	0	0	0
grass	0	0	3	0	0	0	0
potato	1	1	1	25	1	0	2
rape	0	0	0	0	2	0	0
s.beet	0	0	0	0	0	19	0
wheat	0	0	0	0	0	0	16

TABLE V
CONFUSION MATRIX DESCRIBING NNA CROP CLASSIFICATION PERFORMANCE. ALGORITHM INPUT: TWO POLARIZATIONS ($\sigma^0_{\rm hh}$, $\sigma^0_{\rm vv}$) PLUS hh − vv PHASE DIFFERENCE, ONE DATE (JULY 12, 1991), AIRSAR, FLEVOLAND. TOTAL NUMBER OF SAMPLES: 79. CORRECTLY CLASSIFIED: 67. OVERALL ACCURACY: 84.8%

classified	true class						
as	barley	corn	grass	potato	rape	s.beet	wheat
barley	3	0	2	0	0	0	1
corn	1	2	0	0	0	0	0
grass	0	0	4	0	0	0	2
potato	0	0	0	25	0	1	1
rape	0	0	0	0	1	0	0
s.beet	0	0	0	0	2	18	0
wheat	0	0	2	0	0	0	14

A C-band polarimetric spaceborne system is expected to operate in the near future, hence it is also interesting to analyze the performance of the classification algorithm exploiting the hh − vv relative phase. By comparing the confusion matrices of Tables V and III, we notice a moderate decrease of accuracy when using the phase information in place of the cross-polar backscattering. Indeed, this latter is mainly affected by the orientation and by the spatial distribution of the elements in the plant canopy, whereas the relative phase depends in a compounded and possibly elusive fashion on a number of crop features and on the soil reflection.

B. Multitemporality in Classification

1) Multipolarization AirSAR Data: Like using multiple polarizations, a corresponding increase of accuracy is expected when the input to the classification algorithm consists of measurements taken on more than one date, since σ^0 is affected by the variation of scattering induced by the temporal evolution of both canopy structure and water content. Since in the course of the 1991 MAC-Europe experiment the AirSAR overflew the Flevoland site on four different days, in principle the data are multitemporal. However, the duration of the campaign, limited to one and a half month in the summer, was too short to produce a really multitemporal dataset. A favorable circumstance was that the dates of the overflights fell within the period of full development of the crops, so that, in spite of the short time

TABLE VI
CONFUSION MATRIX DESCRIBING NNA CROP CLASSIFICATION PERFORMANCE. ALGORITHM INPUT: ONE POLARIZATION (σ^0_{vv}), FOUR DATES (JUNE 15, JULY 3, 12, 28, 1991), AIRSAR, FLEVOLAND. TOTAL NUMBER OF SAMPLES: 79. CORRECTLY CLASSIFIED: 67. OVERALL ACCURACY: 84.8%

classified	true class						
as	barley	corn	grass	potato	rape	s.beet	wheat
barley	3	1	0	0	0	0	0
corn	0	0	1	0	0	0	0
grass	0	0	6	0	0	0	2
potato	0	0	1	23	0	1	0
rape	0	0	0	0	3	0	0
s.beet	0	0	0	2	0	18	2
wheat	1	1	0	0	0	0	14

TABLE VII
CONFUSION MATRIX DESCRIBING NNA CROP CLASSIFICATION PERFORMANCE. ALGORITHM INPUT: THREE POLARIZATIONS (σ^0_{hh}, σ^0_{vv}, σ^0_{hv}), FOUR DATES (JUNE 15, JULY 3, 12, 28, 1991), AIRSAR, FLEVOLAND. TOTAL NUMBER OF SAMPLES: 79. CORRECTLY CLASSIFIED: 76. OVERALL ACCURACY: 96.2%

classified	true class						
as	barley	maize	grass	potato	rape	s.beet	wheat
barley	4	0	0	0	0	0	0
maize	0	2	0	0	0	0	0
grass	0	0	7	0	0	0	0
potato	0	0	1	25	0	0	1
rape	0	0	0	0	3	0	0
s.beet	0	0	0	0	0	19	1
wheat	0	0	0	0	0	0	16

interval, the information content of the data is considerable. Indeed, when using σ^0_{vv} measured on all four overflight dates, we obtain an overall classification accuracy $OA = 84.8\%$ (81% with ML), with the confusion matrix shown in Table VI. This result suggests that the imprinting by the 43-day evolution of the plants on the single vv polarization is sufficient to raise the discrimination capability up to values close to that of joined co- and cross-polarizations.

As expected, the use of all polarizations further increases the accuracy (Table VII) up to the quite high value $OA = 96.2\%$ (91.1% for the ML algorithm). It is worth pointing out that such a high accuracy is achieved by using only C-band and linear polarization data. Adding the hh − vv phase information produces a slight improvement, bringing the accuracy to approach 97.5%. However, if σ^0_{hv} is replaced by the the hh − vv phase, the accuracy slightly decreases (Table VIII).

Again, it is interesting to limit the multidate algorithm inputs to pairs of σ^0_{vv} and σ^0_{hv}, like the data from ENVISAT. In this case, the accuracy increases from about 86% for one date to about 91% for two dates, up to 94% when the measurements acquired on the four dates are used.

The above classification results have been obtained by using the neural network in its full configuration (Fig. 1), i.e., with a number of connections comparable to the number of data. Given the independency of the training and test sets, the classification performance is not expected to be biased by an overfitting effect, but the topology of the net may not be optimal. Hence we carried out a pruning procedure by cutting off the connection with the minimum weight (in magnitude) and retraining the new

TABLE VIII
CONFUSION MATRIX DESCRIBING NNA CROP CLASSIFICATION PERFORMANCE. ALGORITHM INPUT: TWO POLARIZATIONS (σ^0_{hh}, σ^0_{vv}) PLUS hh − vv PHASE DIFFERENCE, FOUR DATES (JUNE 15, JULY 3, 12, 28, 1991), AIRSAR, FLEVOLAND. TOTAL NUMBER OF SAMPLES: 79. CORRECTLY CLASSIFIED: 75. OVERALL ACCURACY: 94.9%

classified	true class						
as	barley	corn	grass	potato	rape	s.beet	wheat
barley	4	0	1	0	0	0	1
corn	0	2	0	0	0	0	0
grass	0	0	6	0	0	0	0
potato	0	0	1	25	0	0	0
rape	0	0	0	0	3	0	0
s.beet	0	0	0	0	0	19	1
wheat	0	0	0	0	0	0	16

TABLE IX
SUMMARY OF PERFORMANCE OF THE NNA CROP CLASSIFICATION ALGORITHM USING VARIOUS POLARIZATIONS AND DATES, JUNE AND JULY 1991, AIRSAR, FLEVOLAND; $\phi_{\mathrm{hh\,vv}}$ DENOTES hh − vv RELATIVE PHASE; % CONNECTIONS IS THE PERCENTAGE OF THE INITIAL NUMBER OF CONNECTIONS LEFT AFTER PRUNING

Combination	# Errors	Error %	% connections
1vv	35	44.3	15
1vv, 1hv	11	13.9	20
1hh, 1hv	9	11.4	18
1vv, 1hh	13	16.5	39
1vv, 1hh, 1hv	7	8.9	23
1vv, 1hh, 1$\phi_{hh\,vv}$	12	15.2	31
1vv, 1hh, 1hv, 1$\phi_{hh\,vv}$	6	7.6	33
2hh, 2hv	7	8.9	23
2vv, 2hv	7	8.9	24
3hh, 3hv	5	6.3	22
3vv, 3hv	5	6.3	26
4vv	12	15.2	26
4vv, 4hv	5	6.3	32
4hh, 4hv	4	5.1	31
4vv, 4hh	6	7.6	40
4vv, 4hh, 4hv	3	3.8	23
4vv, 4hh, 4$\phi_{hh\,vv}$	4	5.1	28
4vv, 4hh, 4hv, 4$\phi_{hh\,vv}$	2	2.5	28

network for as many epochs as required by the early stopping procedure [20]. The same procedure has then been applied to the new configuration, repeating the sequential pruning and training for several cycles, until further removal of connections resulted in an increase of the classification error with respect to that of the full net. The outcome of pruning has been a considerable reduction (by at least 60%) of the number of connections, hence of the computational effort, for a given accuracy.

Table IX provides a synthetic overview of the performance of the NNA when several combinations of multipolarization and multidate measurements are employed in the classification exercise. The single-date measurements are those of July 12, when the crop separability appears the highest, at least in the $\sigma^0_{\mathrm{hv}} - \sigma^0_{\mathrm{vv}}$ plane.

The two dates are June 15 and July 28, i.e., with the largest time span available, while the measurements taken on July 3 are

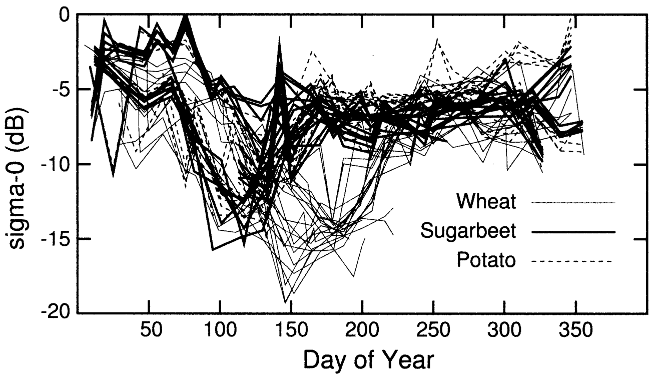

Fig. 3. Trend of σ^0_{vv} measured by ERS SAR for three kinds of crop in the Flevoland site in the years 1993 to 1996.

TABLE X
CONFUSION MATRIX DESCRIBING THE NEURAL ALGORITHM CROP CLASSIFICATION PERFORMANCE. ALGORITHM INPUT CHARACTERISTICS: ONE POLARIZATION (vv), 27 DATES, ERS MEASUREMENTS, FLEVOLAND, 1995. TOTAL NUMBER OF SAMPLES: 55. CORRECTLY CLASSIFIED: 54. OVERALL ACCURACY: 98.2%

classified	true class						
as	barley	maize	grass	potato	rape	s.beet	wheat
barley	3	0	0	0	0	0	0
maize	0	3	0	0	0	0	0
grass	0	0	9	0	0	0	0
potato	0	0	0	15	0	0	0
rape	0	0	0	0	1	0	0
s.beet	0	1	0	0	0	12	0
wheat	0	0	0	0	0	0	11

skipped in the three-date case. Both the substantial improvement of accuracy brought in by the addition of the cross-polarization data in the single-date case and its further improvement when more than one date is considered, are apparent.

Table IX also reports the final number of connections of the neural net, in percentage of the initial one, still yielding the same classification accuracy. The reduction in the network complexity, hence in the computation time, is considerable in all cases.

2) Single-Polarization ERS Data: The polarimetric data collected by the AirSAR cover only a limited period of summertime, hence are expected to introduce a bias into the above classification results. On their side, the single-polarization measurements by ERS, acquired at 23° incidence angle, extend over the whole year, so that the classification process can benefit from the full temporal evolution of σ^0_{vv}, which follows sprouting, growth and possible decay or harvest of the vegetation canopy, as sketched in Fig. 3 for three kinds of crops.

Inspection of the backscattering data suggests that, when at the beginning of the year the agricultural crops are absent, surface scattering dominates and the observed variations of σ^0 are mainly related to soil conditions (moisture effects, essentially). As a consequence, small and irregular differences are observed among samples belonging to the same site and year, while site-to-site or year-to-year variations may be larger, given the possible climatic differences. Once the vegetation develops on cultivated fields, typically after Day of Year $\mathrm{DoY} \simeq 75$, σ^0 undergoes large and consistent changes, which generally depend on the type of crop, as displayed in Fig. 3. After harvest, say after $\mathrm{DoY} \simeq 240$, surface scattering again prevails and σ^0 resumes its random fluctuations. As already observed for the AirSAR partially multitemporal case, time series of backscattering data including the vegetation cycle contains the imprinting of the kind of crop being observed and is suitable for classification.

To gain quantitative information on the potential of single-polarization radar measurements covering the whole lifetime of the vegetation in discriminating crops, a classification exercise has been performed, using the ERS data collected in 1995 over the Flevoland test site. The available data include acquisitions on 27 dates from DoY 10 to DoY 355. A training set of backscattering coefficients has been generated, with data relative to a number of fields including the same crops considered in Section IV-B.1. Then, the trained neural network has been used to classify the remaining fields, which formed the independent test set, as indicated in columns 4 and 5 of Table I, respectively. The resulting confusion matrix is reported in Table X, which shows a good classification performance, with only one field misclassified $(OA = 98.2\%)$. Note that if the available *a priori* information, such as the sowing and harvesting dates in a given year, hints that on the earlier and later dates the crops are possibly absent, the corresponding measurements can be skipped.

The ML approach yields similar results, the percentage of success being about 95% (four fields misclassified).

C. Interyear Dynamic Classification

The above exercise refers to an *a posteriori* classification procedure. For other purposes, a real-time classification could be desirable to provide an inventory of the crop fields as soon as discrimination becomes feasible. This is the case, for instance, of the operational control of subsidized agricultural surfaces, for which the time constraint is severe, since the results of the classification based on remote sensing data should possibly trigger timely in situ inspections of the fields [19].

We adopted the following scheme of interyear dynamic classification. The neural network algorithm has been initially trained by the first σ^0 measurement taken by ERS on Flevoland in 1993 and applied to classify the surface by using the first measurement acquired in 1995. The number of training measurements has been progressively increased by adding the subsequent 1993 measurements and augmented by including the 1994 data at the closest available dates. The algorithm, trained by the augmenting set of data, has been used to classify the 1995 fields from the 1995 measurements at the corresponding dates. This procedure simulates a continuous update of classification following the availability of each new satellite measurement. The number of fields of each crop used for training (with 1993 and 1994 data) and for testing the algorithm (with 1995 data) are reported in columns 6 and 7

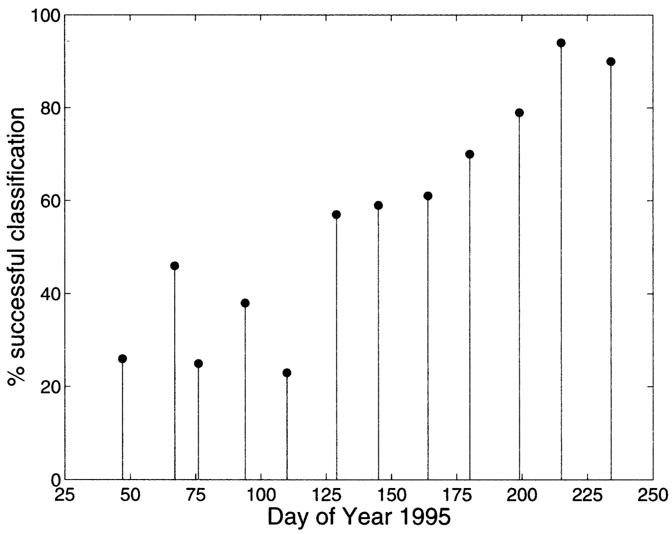

Fig. 4. Percentage of successfully classified fields versus measurement number.

of Table I, respectively. In this exercise, we did not consider maize and rape fields, since their number was not sufficient to be statistically significant.

The obtained results, altogether shown in Fig. 4, are summarized as follows. The overall accuracy in classifying all fields being imaged in 1995 remains below 50% up to DoY 110. Starting from the 57% of global accuracy attained on DoY 129 (six measurements), the fraction of correctly classified fields rises steadily to the maximum value $OA = 94\%$ reached on DoY 215 (11 measurements), then starts decreasing with the senescence or the harvest of the crops, which makes further classification meaningless. The variation with time of the fraction of fields of individual crops successfully classified appears to depend on the type of vegetation. Wheat fields, with the relatively early development of their canopy, are already discriminated with an accuracy of 90% on DoY 94 (four measurements), followed by potato fields, classified with an accuracy above 80% starting from DoY 129. More than 80% of barley fields are detected from DoY 164, while accuracy in discriminating sugarbeet remains below 60% up to DoY 215. Spontaneous grass parcels exhibits a peculiar behavior, since more than 70% of fields are detected in the first two images. Indeed, the spontaneuos vegetation present on uncultivated fields yields values of σ^0 consistently lower than those of the other types of rough surfaces, which initially are mainly bare and moist. In the subsequent measurements, the backscattering from grass merges into that of the other sprouting crops, and only after DoY 199 the uncultivated parcels are again discriminated with high accuracy (80% to 100%).

The analysis of the time series indicates that both the average and the standard deviation of σ^0 change from 1993 to 1995. However, the observed dispersion is not wide enough to confound the patterns bearing the imprint of the growth cycle of each type of crop. This observation is supported by an analysis based on the interclass separability [11] (results not reported here). Although the generally well established cultivation practices are expected to produce relatively stable results, the particular climatic conditions of a year, if considerably different from the usual, can delay the fields identification.

V. Conclusion

The results reported in this paper allow some insight into the crop classification potential of multitemporal and multipolarization radar measurements at C band. Our analysis has been carried out both by using only intensity measurements, i.e., without phase information, consistently with the specifications of present satellite instruments, and by including the hh $-$ vv relative phase. Two sets of data taken over agricultural parcels of Flevoland have been considered: a multipolarization set, acquired by the AirSAR and a multitemporal one, obtained from ERS. The AirSAR data refer to high angles of incidence, at which backscattering is contributed essentially by vegetation, while the ERS SAR measurements are at about 23°, hence are affected by the underlying soil too. The classification was based on a neural network algorithm, trained by subsets of data and tested on the remaining ones. Suitable comparison with a technique based on the maximum likelihood approach has also been conducted. The neural networks have been systematically pruned to control the memorization effect. The outcome of pruning has been a general considerable reduction, by at least 60%, of the number of connections, hence of the computational effort, albeit attaing the same accuracy. For the same inputs, the maximum-likelihood approach yields a lower classification accuracy.

As far as the benefits offered by multipolarization are concerned, the results point out that joining cross-polar backscattering measurements to the single copolar set raises the classification accuracy from about 55% to above 85%. Joining the phase information to the copolar measurements also improves the classification results, but to a lesser extent.

The sensitivity of multitemporal data to the development cycle peculiar to each type of vegetation, results in enhancing the accuracy of classification using measurements at a single copolarization. Accuracy approaches 85% when only a portion of the development cycle is observed, but reaches 98% when all year is covered (at the 35-day repeat cycle of ERS). A similar accuracy is attained by the ML approach.

Finally, the performance of an interyear dynamic classification scheme has been assessed, by training the algorithm with an increasing sequence of measurements taken in the two preceding years and testing it on a correspondingly increasing sequence of measurements in the subsequent year. The results indicate that, at least for Flevoland and for the considered years (1993–1995), wheat fields are successfully classified first, followed by potato and barley. This exercise simulates a procedure intended for near real-time classification of developing crops from satellite radar data.

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REFERENCES

[1] F. T. Ulaby, R. K. Moore, and A. K. Fung, *Microwave Remote Sensing: Active and Passive*. Norwood, MA: Artech House, 1986, vol. III.

[2] B. A. M. Bouman and D. H. Hoekman, "Multi-temporal multi-frequency radar measurements of agricultural crops during the Agriscatt-88 campaign in The Netherlands," *Int. J. Remote Sens.*, vol. 14, pp. 1595–1614, 1993.

[3] P. Ferrazzoli, L. Guerriero, and G. Schiavon, "Experimental and model investigation on radar classification capability," *IEEE Trans. Geosci. Remote Sensing*, vol. 37, pp. 960–968, 1999.

[4] P. Ferrazzoli, "SAR for agriculture: Advances, problems and prospects," in *Proc. 3rd Int. Symp. Retrieval Bio-Geophysical Parameters From SAR Data for Land Applications*, Sheffield, U.K., 2002, ESA SP-475, pp. 47–56.

[5] A. Freeman, J. Villasenor, J. D. Klein, P. Hoogeboom, and J. Groot, "On the use of multi-frequency and polarimetric radar backscatter features for classification of agricultural crops," *Int. J. Remote Sens.*, vol. 15, pp. 1799–1812, 1994.

[6] P. Ferrazzoli, S. Paloscia, P. Pampaloni, G. Schiavon, S. Sigismondi, and D. Solimini, "The potential of multi-frequency polarimetric SAR in assessing agricultural and arboreous biomass," *IEEE Trans. Geosci. Remote Sensing*, vol. 35, pp. 5–17, Jan. 1997.

[7] M. S. Moran, A. Vidal, D. Troufleau, Y. Inoue, and T. A. Mitchell, "Ku- and C-band SAR for discriminating agricultural crop and soil conditions," *IEEE Trans. Geosci. Remote Sensing*, vol. 36, pp. 265–272, Jan. 1998.

[8] D. H. Hoekman and M. J. Quiñones, "Land cover type and biomass classification using AirSAR data for evaluation of monitoring scenarios in the Colombian Amazon," *IEEE Trans. Geosci. Remote Sensing*, vol. 38, pp. 685–696, Mar. 2000.

[9] T. Le Toan, F. Ribbes, L.-F. Wang, N. Floury, K.-H. Ding, J. A. Kong, M. Fujita, and T. Kurosu, "Rice crop mapping and monitoring using ERS-1 data based on experiment and modeling results," *IEEE Trans. Geosci. Remote Sensing*, vol. 35, pp. 41–56, Jan. 1997.

[10] H. Skriver, M. T. Svendsen, and A. G. Thomsen, "Multitemporal C- and L-band polarimetric signatures of crops," *IEEE Trans. Geosci. Remote Sensing*, vol. 37, pp. 2413–2429, Sept. 1999.

[11] P. Saich and M. Borgeaud, "Interpreting ERS SAR signatures of agricultural crops in Flevoland, 1993–1996," *IEEE Trans. Geosci. Remote Sensing*, vol. 38, pp. 651–657, Mar. 2000.

[12] Y. Wong and E. C. Posner, "A new clustering algorithm applicable to multispectral polarimetric SAR images," *IEEE Trans. Geosci. Remote Sensing*, vol. 31, pp. 634–644, May 1993.

[13] A. H. S. Solberg, T. Taxt, and A. K. Jain, "A Markov random field model for classification of multitemporal satellite imagery," *IEEE Trans. Geosci. Remote Sensing*, vol. 34, pp. 100–113, Jan. 1996.

[14] J. S. Lee, M. R. Grunes, and E. Pottier, "Quantitative comparison of classification capability: fully polarimetric versus dual and single-polarization SAR," *IEEE Trans. Geosci. Remote Sensing*, vol. 39, pp. 2343–2351, Nov. 2001.

[15] J. A. Benediktsson, P. H. Swain, and O. K. Ersoy, "Neural network approaches versus statistical methods in classification of multisource remote sensing data," *IEEE Trans. Geosci. Remote Sensing*, vol. 28, pp. 540–552, July 1990.

[16] Y. C. Tzeng, K. S. Chen, W. L. Kao, and A. K. Fung, "A dynamic learning neural network for remote sensing applications," *IEEE Trans. Geosci. Remote Sensing*, vol. 32, pp. 1096–1102, Sept. 1994.

[17] K. S. Chen, W. P. Huang, and F. Amar, "Classification of multifrequency polarimetric SAR imagery using a dynamic learning neural network," *IEEE Trans. Geosci. Remote Sensing*, vol. 34, pp. 814–820, May 1996.

[18] *http://eraora.disp.uniroma2.it/* [Online]

[19] X. Blaes, L. Vanhalle, G. Dautrebande, and P. Defourny, "Operational control with remote sensing of area-based subsidies in the framework of the common agricultural policy: What role for the SAR sensors?," in *Proc. Third Int. Symp. Retrieval Bio-Geophysical Parameters From SAR Data for Land Applications*, Sheffield, U.K., 2002, ESA SP-475, pp. 87–92.

[20] C. M. Bishop, *Neural Networks for Pattern Recognition*. Oxford, U.K.: Oxford Univ. Press, 1995.

[21] A. Zell, G. Mamier, M. Vogt, N. Mache, R. Hübner, S. Döring, K. U. Herrmann, T. Soyez, M. Schmalzl, T. Sommer, A. Hatzigeorgiou, D. Posselt, T. Schreiner, B. Kett, G. Clemente, J. Wieland, M. Reczko, M. Riedmiller, M. Seemann, M. Ritt, J. DeCoster, J. Biedermann, J. Danz, C. Wehrfritz, R. Werner, M. Berthold, and B. Orsier, "SNNS Stuttgart Neural Network Simulator, user manual, version 4.1," Univ. Stuttgart, Inst. Parallel and Distributed High Performance Systems, Stuttgart, Germany, Rep. 6/95, 1995.

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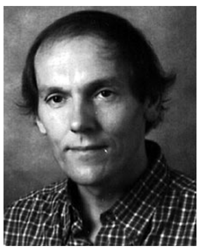

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