Use of Neural Networks for Automatic Classification of SAR imagery

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Goals and Objectives

The global view of urban areas makes satellite missions a valid instrument for updating urban maps and carrying out the analysis of settlement dynamics.

Remote sensing in the optical band is a well established tool for producing maps of urban land cover and monitoring changes, but it can suffer from atmospheric limitations.

The management of emergencies over LARGE AREAS relies on near-real time information, irrespective of the time of day and of the cloud cover: to this purpose the availability of SAR acquisitions is essential.

Goals and Objectives

The new generation satellite missions, such as the Canadian Radarsat 2, the German TerraSAR-X and the Italian COSMO-SkyMed will make available LARGE ARCHIVES of images.

In the following, we discuss the identification and use of single-polarization SAR image features for land cover applications.

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Simulation of emergency acquisitions in a minimal configuration/processing.

Three configurations are considered:

- *short-term* classification scheme intended for providing information in near-real time
- *long-term* scheme aimed at observing the urban changes at year time scales
- *fully automatic* classification scheme

Data Set

Site Information		Images Information			
Location	Dimension (km^2)	Acquisition Date	Satellite	B_p (m)	Dimension (pixels)
Rome, Italy	836	January 25, 1994	ERS 1	89	1245 x 1300
		January 31, 1994	ERS 1		
		March 26, 1994	ERS 1	157	
		March 29, 1994	ERS 1		
		July 13, 1994	ERS 1	-	
		February 13, 1999	ERS 1	211	
		February 14, 1999	ERS 2		
		March 20, 1999	ERS 1	65	
		March 21, 1999	ERS 2		
		July 4, 1999	ERS 2	-	

Input Features

Careful selection and suitable processing are required to exploit the various pieces of information embedded in the amplitude, its time-space behavior and phase of the radar return:

backscattering → mean intensity / intensity st. deviation

interferometric coherence → late winter / early summer coherence

textural features → Gray-Level Co-occurence Matrix (GLCM)

↓

Contrast – Energy (literature review)

↓

Window size : 7x7, 11x11 and 15x15

Input Features

For *long-term* monitoring, the time-average amplitude of the backscattering coefficient, the degree of interferometric coherence corresponding to the late winter and early summer, and the seasonal variations are exploited together with two textural (*Contrast* and *Energy*) parameters of the radar amplitude image.

↓

6 inputs

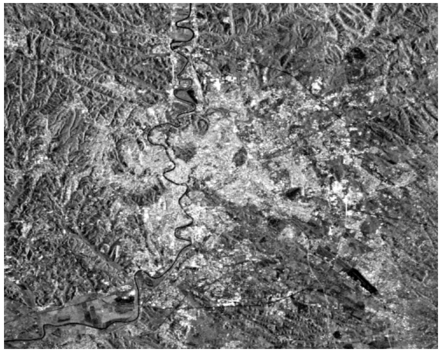
Short-term monitoring is based on the same data set, abridged by excluding the seasonal variations of the backscattering and one of the coherence values.

↓

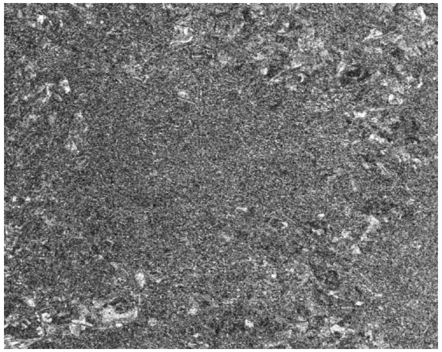
4 inputs

Input Features

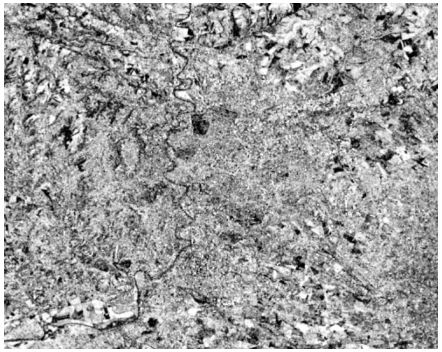
Mean Int.



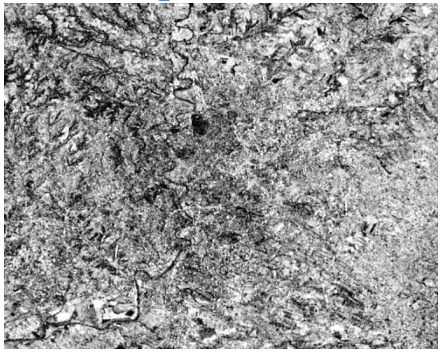
Int. St. Dev.



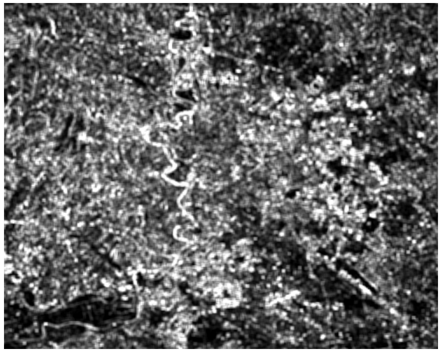
Wint. Coh.



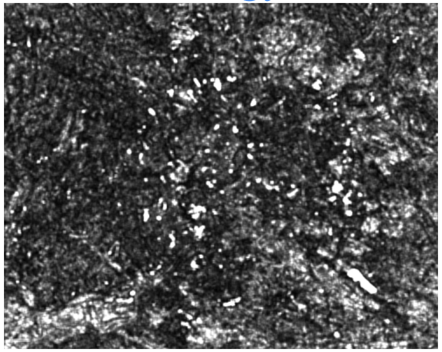
Spr. Coh.



Contrast



Energy



Long-term	
1	Mean Int.
2	Int. St. Dev.
3	Wint. Coh.
4	Spr. Coh.
5	Contrast
6	Energy

5 images

Short-term	
1	Mean Int.
2	Spr. Coh.
3	Contrast
4	Energy

2 images

Class Definition

These sets of 6 and 4 parameters respectively are exploited to discriminate among seven urban/sub-urban classes, including water surfaces (WS), vegetation (VE), forest (FO), asphalted surfaces (AS), isolated large buildings (IB) and continuous high/low density residential areas (HD/LD).

Classes	TR	VS
Asphalt (AS)	511	219
Forest (FO)	2592	1326
High Density (HD)	648	278
Isolated Buildings (IB)	122	433
Low Density (LD)	4900	6130
Vegetation (VE)	3535	6008
Water (WS)	892	382
Total	13200	14776

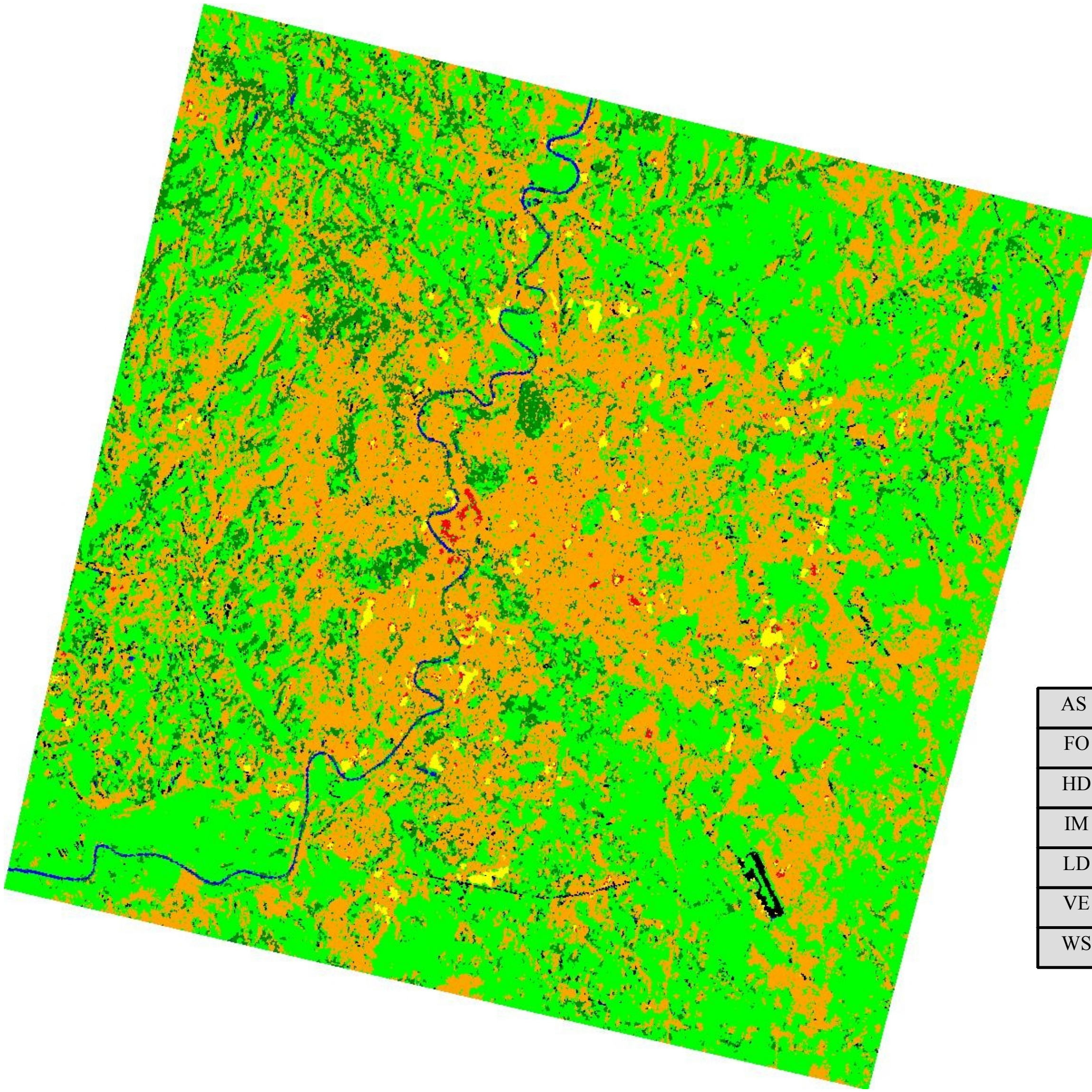
Neural Network Approach

The pieces of information extracted from the SAR images are fused and processed by a supervised Multi-Layer Perceptron (MLP) neural network which is known to show a considerable ease in using multi-domain data sources.

We recorded the classification accuracies yielded by a varying number of hidden neurons, starting from a small topology (6-12-12-7) to end with a large one (6-100-100-7). The variance of the accuracy for different initializations of the weights was computed to monitor the stability of the algorithm.

The Magnitude Based Pruning procedure has then been applied to thin the net.

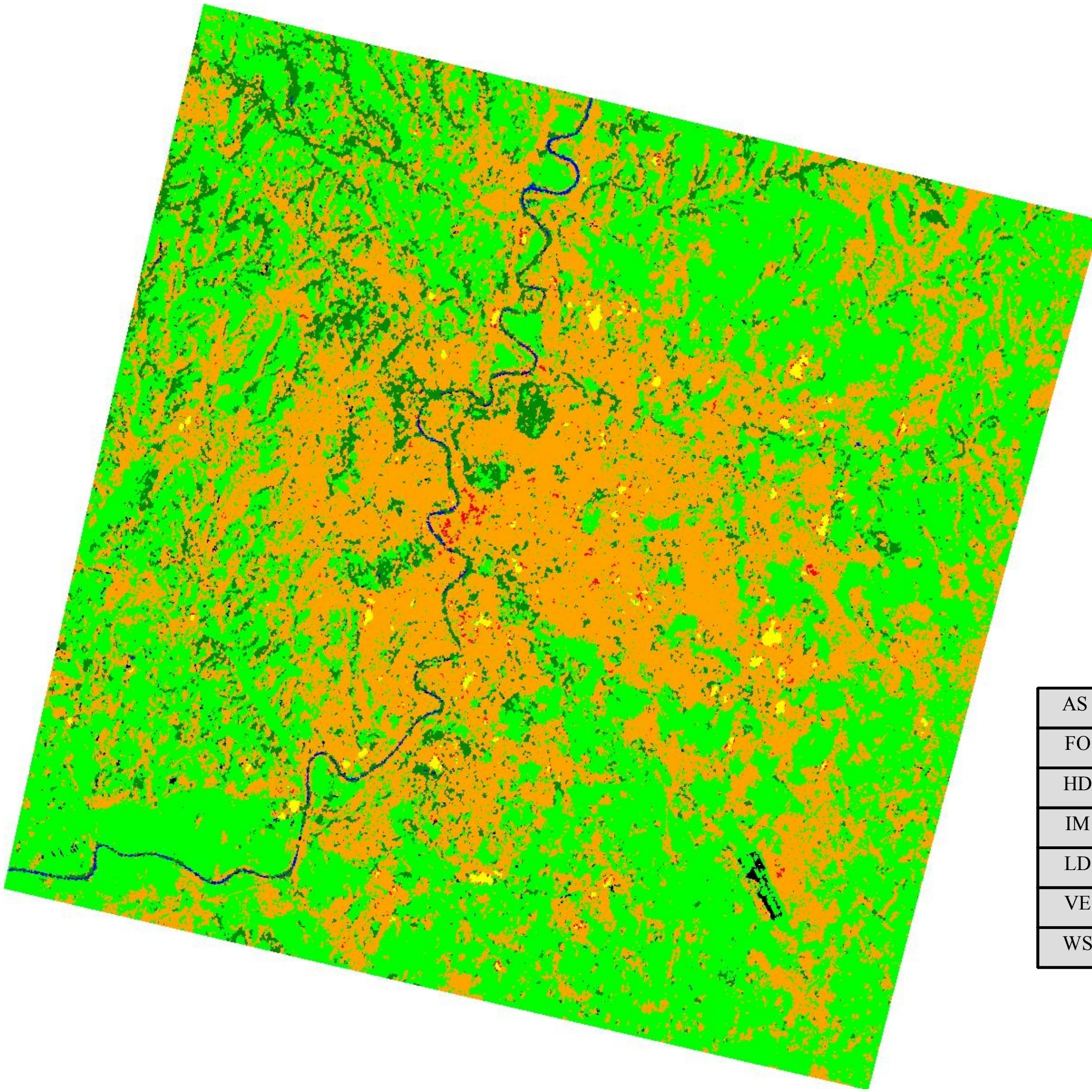
Short-term classification - 4 inputs 1994



Classes
Asphalt (AS)
Forest (FO)
High Density (HD)
Isolated Buildings (IB)
Low Density (LD)
Vegetation (VE)

	AS	FO	HD	IM	LD	VE	WS
AS	74.18	2.75	0.00	0.00	0.00	19.23	3.85
FO	0.00	81.39	0.00	0.00	16.71	10.05	1.49
HD	0.00	0.00	36.32	1.42	61.32	0.94	0.00
IM	0.00	0.00	1.12	96.21	2.68	0.00	0.00
LD	0.07	0.95	0.23	0.11	96.99	1.65	0.00
VE	0.39	1.08	0.00	0.00	7.66	93.50	0.01
WS	1.22	1.52	0.00	0.00	0.30	0.30	93.92
	Overall Er. (%)		8.12		k-Coefficient		0.863

Short-term classification - 4 inputs 1999



Classes
Asphalt (AS)
Forest (FO)
High Density (HD)
Isolated Buildings (IB)
Low Density (LD)
Vegetation (VE)

	AS	FO	HD	IM	LD	VE	WS
AS	52.97	1.83	0.00	0.00	1.37	42.01	1.83
FO	0.15	79.34	0.00	0.00	9.05	8.82	2.64
HD	0.00	0.00	23.02	1.80	73.74	1.44	0.00
IM	0.00	0.00	0.23	94.00	5.54	0.23	0.00
LD	0.03	0.78	0.52	0.10	96.15	2.40	0.02
VE	0.80	2.18	0.08	0.02	7.86	88.96	0.10
WS	4.71	9.69	0.00	0.00	1.05	1.31	83.25
	Overall Er. (%)		10.69		k-Coefficient		0.834

Short-term classification

The classification accuracy is slightly less than 0.84.

OSS: due to the decametric size of the resolution cells at ground, mixed pixels are likely to occur, especially in a sub-urban landscape, where heterogeneous land covers coexist within short distances.

As expected from physical considerations, the classification errors mainly consist in misclassification between:

- high- and low-density residential areas
- asphalt and low vegetation
- low vegetation and low-density residential areas

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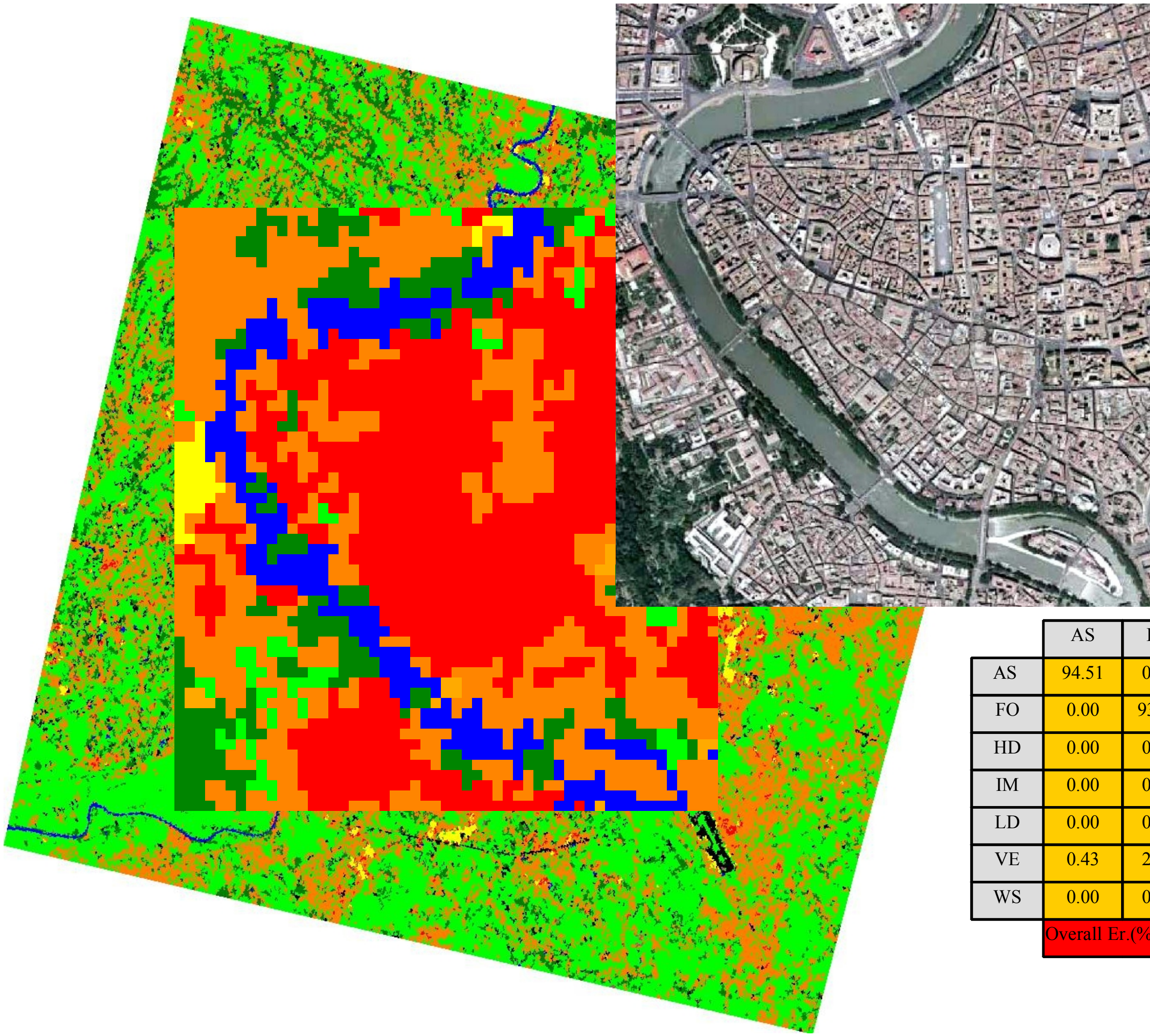
Adding the seasonal information is expected to improve the results.

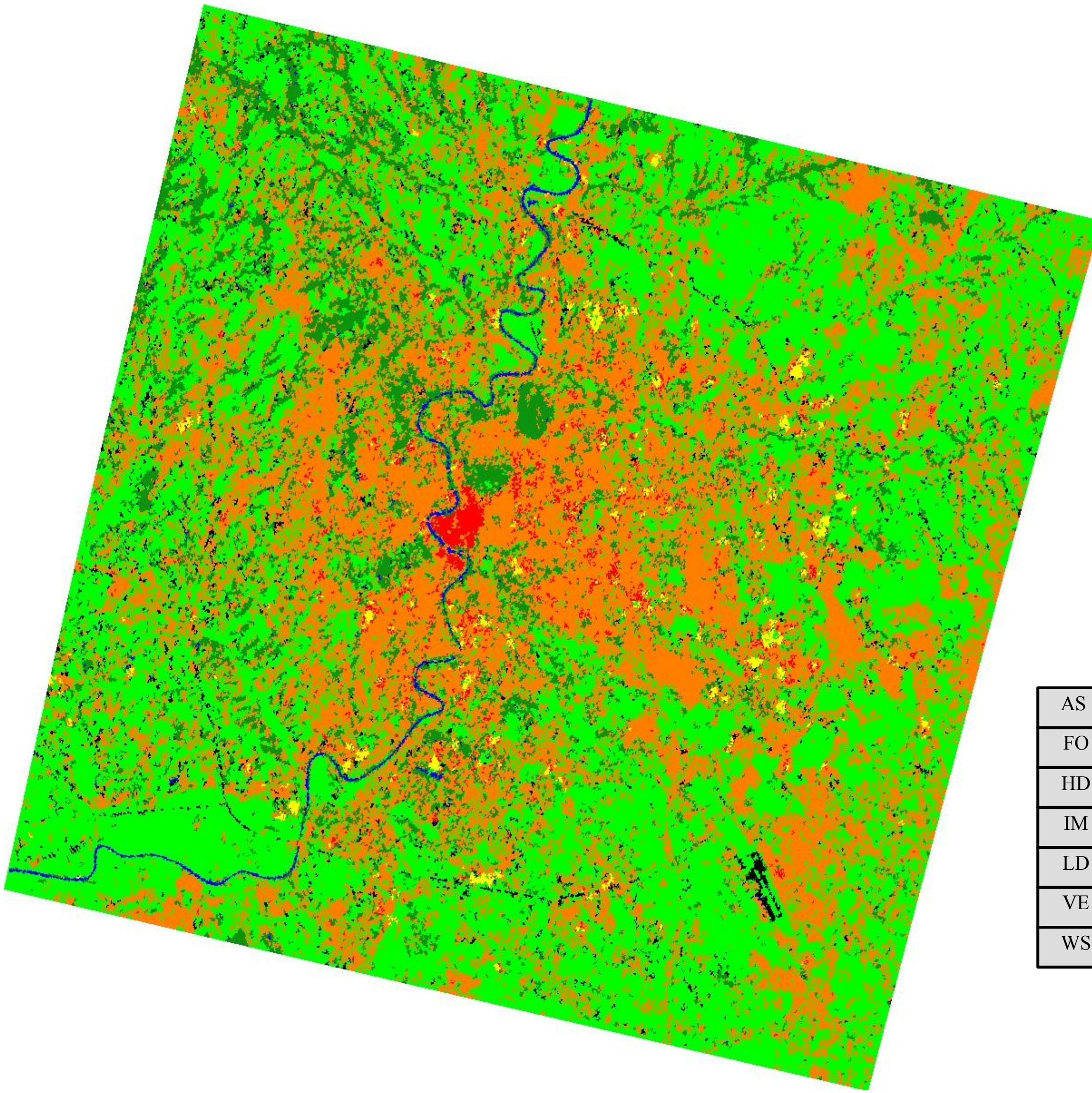
Long-term classification - 6 inputs 1994



Classes
Asphalt (AS)
Forest (FO)
High Density (HD)
Isolated Buildings (IB)
Low Density (LD)
Vegetation (VE)

	AS	FO	HD	IM	LD	VE	WS
AS	94.51	0.00	0.00	0.55	0.55	4.40	0.00
FO	0.00	93.07	0.00	0.00	2.85	3.80	0.27
HD	0.00	0.00	87.74	0.00	11.32	0.94	0.00
IM	0.00	0.00	3.35	93.75	2.68	0.22	0.00
LD	0.00	0.34	1.67	0.08	95.39	2.52	0.00
VE	0.43	2.47	0.00	0.15	1.80	95.16	0.00
WS	0.00	0.30	0.00	0.00	0.00	0.00	96.96
	Overall Er.(%)		4.91		k-Coefficient		0.923

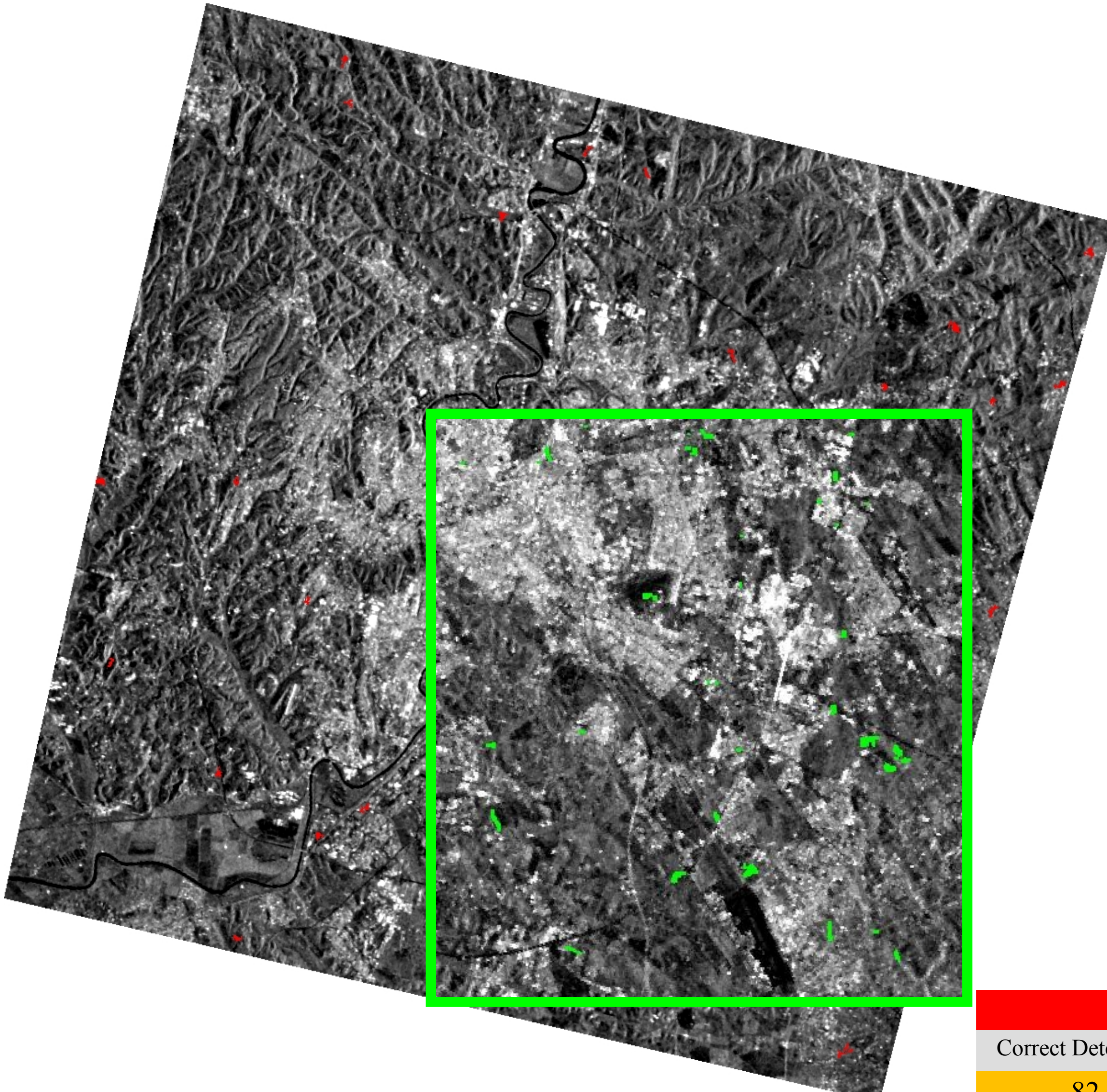
Long-term classification - 6 inputs 1999

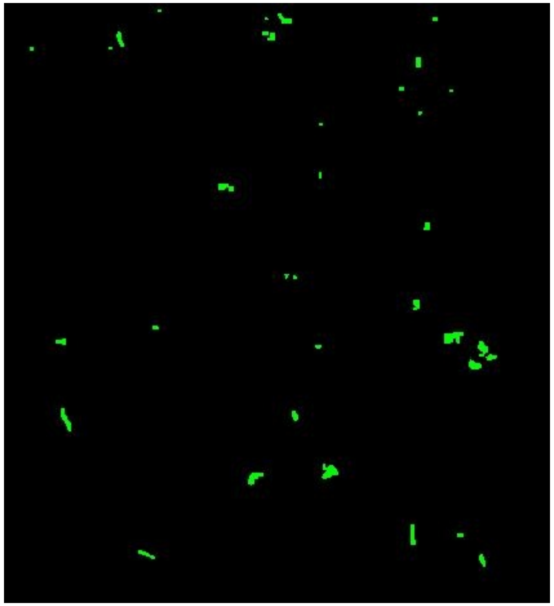


Classes
Asphalt (AS)
Forest (FO)
High Density (HD)
Isolated Buildings (IB)
Low Density (LD)
Vegetation (VE)

	AS	FO	HD	IM	LD	VE	WS
AS	87.21	0.91	0.00	0.00	1.37	10.05	0.46
FO	0.60	93.21	0.00	0.00	3.17	2.71	0.30
HD	0.00	0.72	90.29	0.00	8.99	0.00	0.00
IM	0.00	0.00	1.85	85.68	3.46	9.01	0.00
LD	0.03	0.57	2.07	0.03	95.73	1.52	0.05
VE	0.15	3.01	0.02	0.08	3.30	93.43	0.02
WS	0.79	3.66	0.00	0.00	0.26	1.05	94.24
	Overall Er.(%)		6.00		k-Coefficient		0.909

Change Detection 1994-1999





Rome SE: 160km² - 423x465pixels		
Correct Detection (%)	False Alarms (%)	Missed Alarms (%)
82.17	17.83	0.26

The fully automatic mode

The results reported in previous sections have shown how SAR imagery and neural networks may be effective in producing classification and change detection maps.

However each image is processed by its own network (trained off-line) which takes into account different conditions (e.g. baseline, soil moisture, …).

This might not meet the need of a fully automatic scheme for a fast processing chain.

GOAL: design a neural network capable of classifying images whose pixels have not considered at all during the training phase.

The fully automatic mode

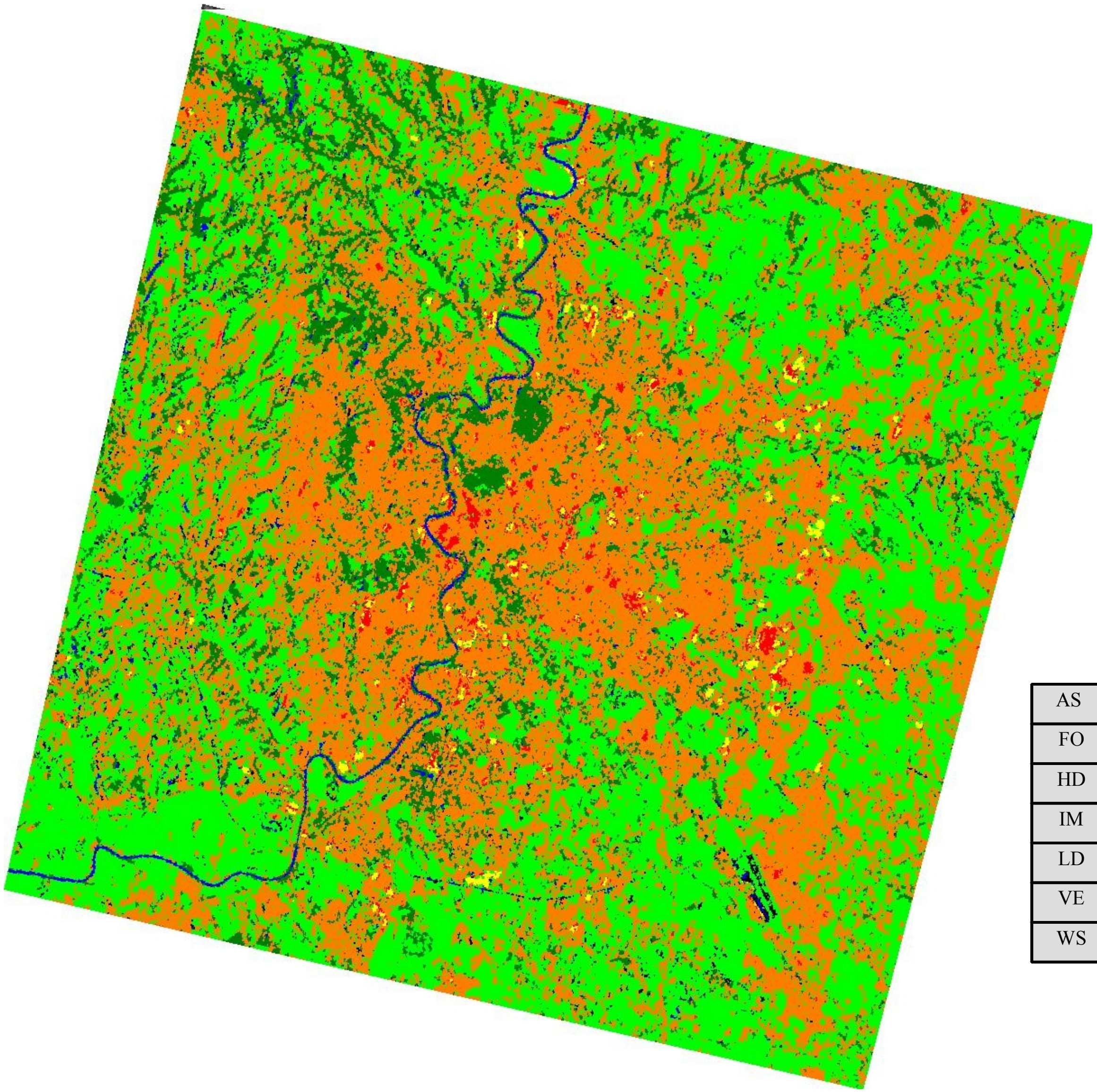
For this purpose we used another set of images over the same test site, but corresponding to another year.

Site Information		Images Information			
Location	Dimension (km^2)	Acquisition Date	Satellite	B_p (m)	Dimension (pixels)
Rome, Italy	836	February 24, 1996	ERS 1	12	1245 x 1300
		February 25, 1996	ERS 2		
		March 30, 1996	ERS 1	106	
		March 31, 1996	ERS 2		
		July 14, 1996	ERS 2	-	

The classification procedure follows the same scheme illustrated before in terms of the physical quantities to be considered as input and classes to be discriminated.

A set consisting of 26,400 pixels has been created stemming ONLY from 1994 and 1999 images.

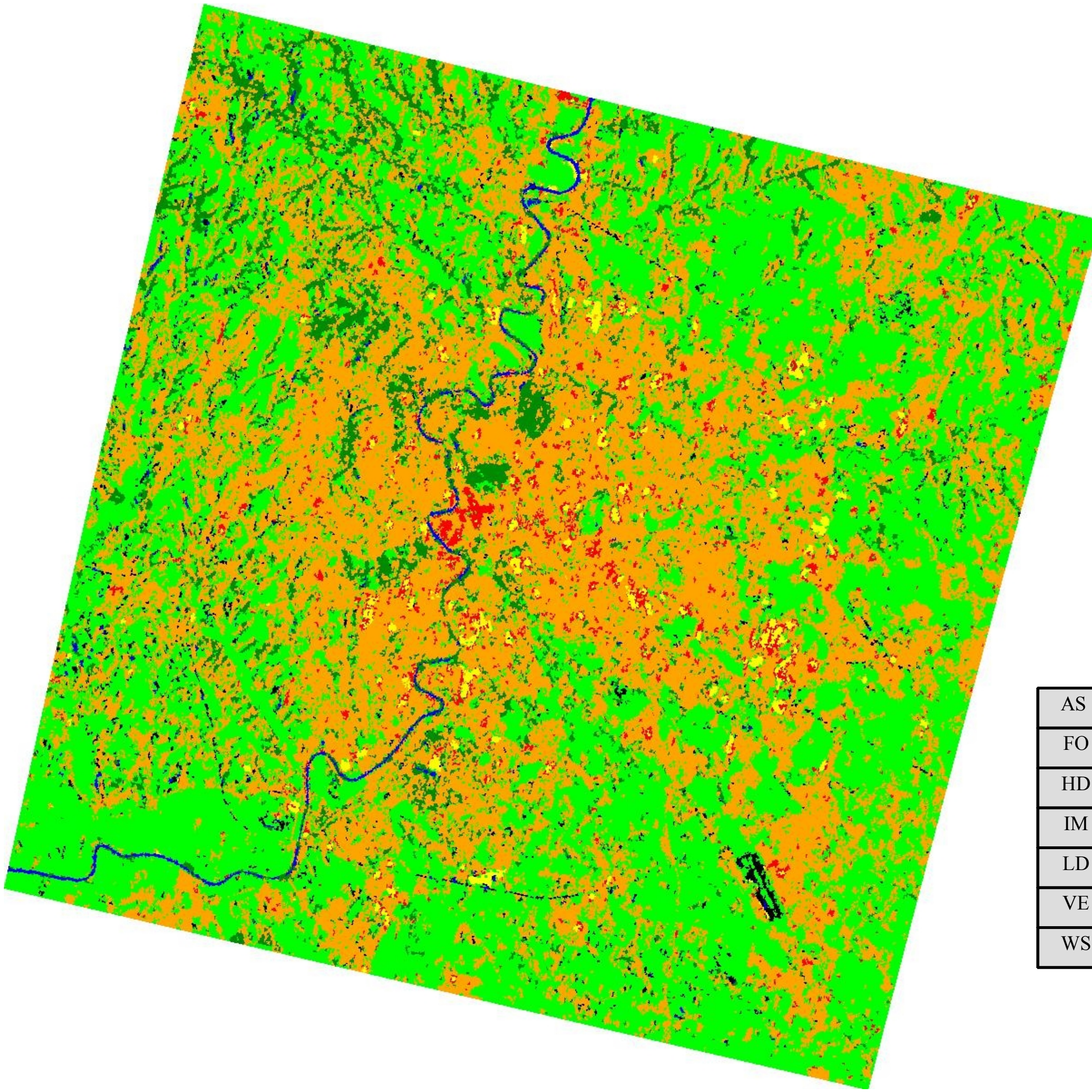
Short-term automatic mode - 4 inputs 1996



Classes	
Asphalt (AS)	
Forest (FO)	
High Density (HD)	
Isolated Buildings (IB)	
Low Density (LD)	
Vegetation (VE)	

	AS	FO	HD	IM	LD	VE	WS
AS	46.15	1.65	0.00	0.00	1.10	43.41	7.69
FO	1.90	69.16	0.00	0.00	15.22	10.60	3.13
HD	0.00	0.47	26.42	0.00	72.64	0.47	0.00
IM	0.00	0.00	4.91	78.13	13.84	3.13	0.00
LD	0.05	2.79	0.39	0.00	91.34	5.39	0.03
VE	1.29	2.55	0.00	0.00	8.08	87.94	0.13
WS	1.22	3.95	0.00	0.00	0.00	3.95	88.15
	Overall Er.(%)		13.52		k-Coefficient		0.780

Long-term automatic mode - 6 inputs 1996



Classes
Asphalt (AS)
Forest (FO)
High Density (HD)
Isolated Buildings (IB)
Low Density (LD)
Vegetation (VE)

	AS	FO	HD	IM	LD	VE	WS
AS	47.80	0.55	0.00	0.55	5.49	42.86	2.75
FO	0.41	71.74	0.00	0.00	15.22	11.14	1.49
HD	0.00	0.00	43.40	0.00	56.13	0.47	0.00
IM	0.00	0.00	16.52	79.46	3.13	0.89	0.00
LD	0.02	0.64	5.92	0.67	89.28	3.48	0.00
VE	1.35	1.44	0.21	0.01	4.71	92.23	0.04
WS	0.91	6.69	0.00	0.00	0.91	2.43	86.32
	Overall Er.(%)		11.73		k-Coefficient		0.811

Long-term automatic mode - 6 inputs 1996

The origin of most of the errors relies in the misclassification of HD as LW, which, given the contiguity of the two classes, can be recognized as a minor drawback.

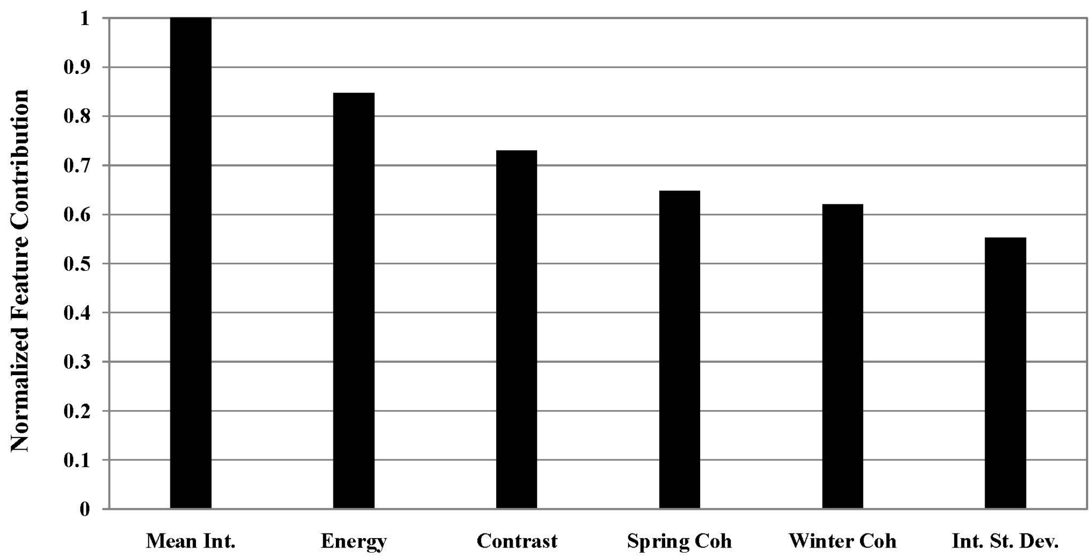
If we merge these two classes, the overall accuracy reaches 91.5% (K-Coeff.=0.860) which can represent a satisfactory target for this type of application.

Classes
Asphalt (AS)
Forest (FO)
High Density (HD)
Isolated Buildings (IB)
Low Density (LD)
Vegetation (VE)

	AS	FO	HD	IM	LD	VE	WS
AS	47.80	0.55	0.00	0.55	5.49	42.86	2.75
FO	0.41	71.74	0.00	0.00	15.22	11.14	1.49
HD	0.00	0.00	43.40	0.00	56.13	0.47	0.00
IM	0.00	0.00	16.52	79.46	3.13	0.89	0.00
LD	0.02	0.64	5.92	0.67	89.28	3.48	0.00
VE	1.35	1.44	0.21	0.01	4.71	92.23	0.04
WS	0.91	6.69	0.00	0.00	0.91	2.43	86.32
	Overall Er.(%)		11.73		k-Coefficient		0.811

Feature Contribution

The relative information content of the six input quantities has been evaluated by computing the contribution of each input.



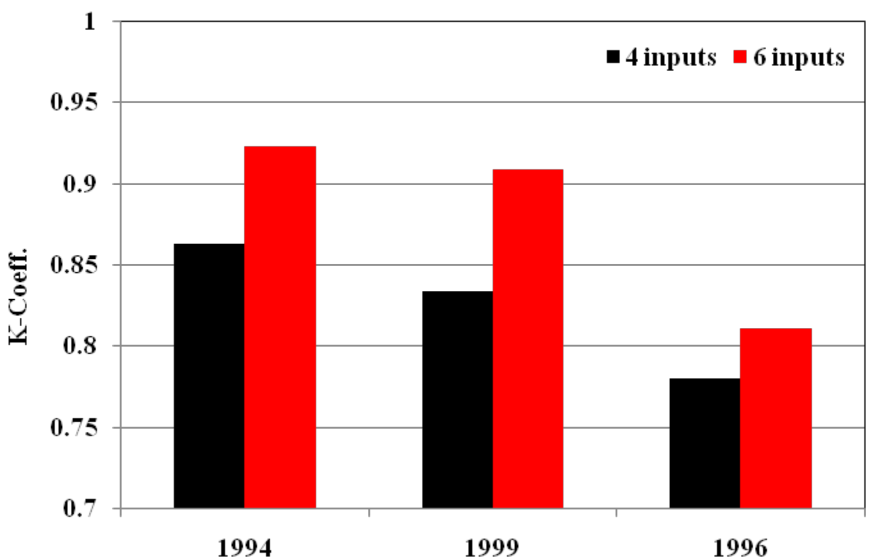
The backscattering intensity carries the maximum information, followed by energy, contrast and spring coherence, while the standard deviation of intensity contributes the least.

Conclusions

We explored the potential of single-polarization decametric SAR data by discussing the extraction of suitable features and by using them in producing land cover maps through a Neural Network algorithm.

Backscattering intensity, GLCM energy and contrast turned out to be the most effective parameters in classifying the landscape.

The accuracy in classify AUTOMATICALLY 7 types of surface from a single interferometric acquisition exceeded 86%, with a k-Coeff. larger than 0.78.



Thank you for your attention!

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