Self-organizing neural networks for unsupervised classification of complex landscapes by polarimetric SAR data

Fabio Del Frate, Marco Del Greco, Giovanni Schiavon, Domenico Solimini
Earth Observation Laboratory, DISP, Tor Vegata University, Rome, Italy

Cosimo Putignano
GEO-K, Roma, Italy

Tor Vergata University, DISP, Via del Politecnico 1, 00133 Rome, Italy
delfrate@disp.uniroma2.it

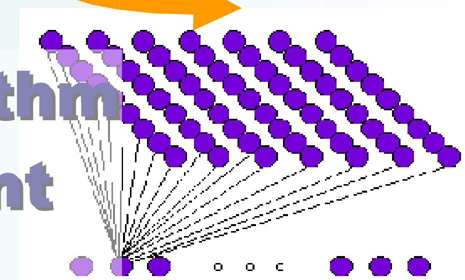
GEO - K

Aim

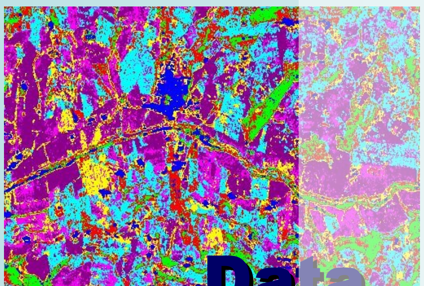
- To assess discrimination capability of self-organizing Neural Networks fed by polarimetric L-band data acquired on a complex landscape

Planning

SAR data analysis

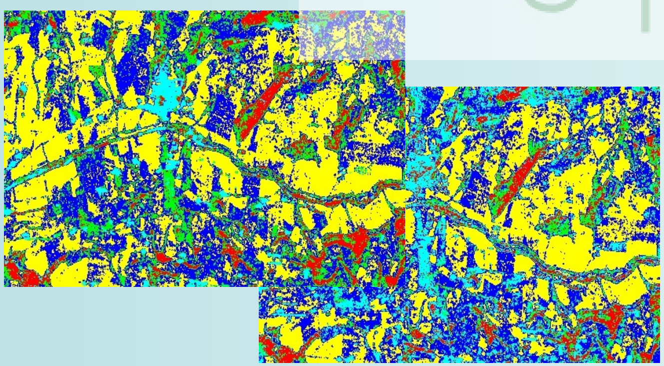


SOM algorithm development



Data classification

Ground-truth comparison

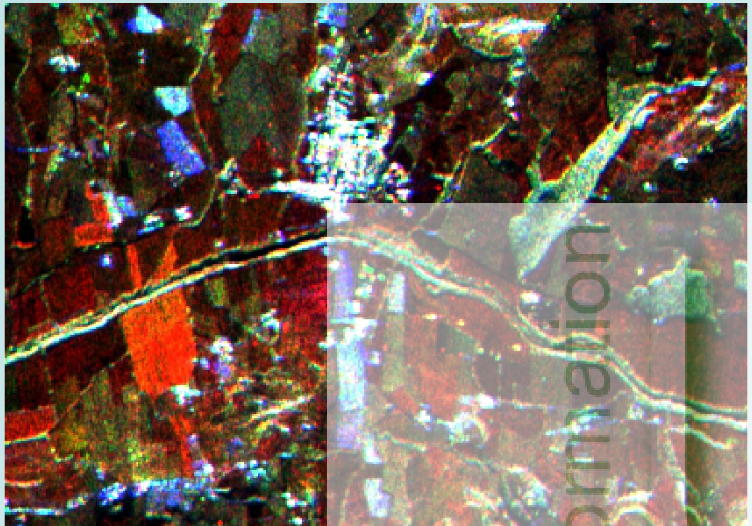


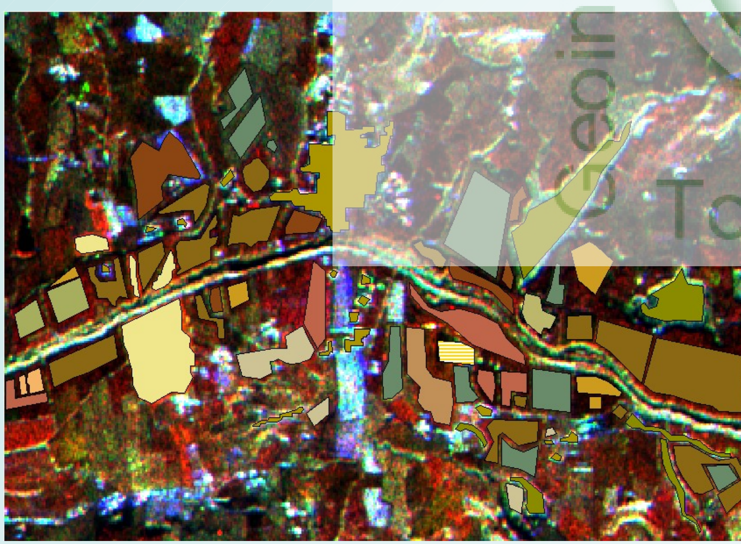
CPW comparison

Data set

- collected in summer 1991 by JPL/NASA AirSAR on Montespertoli, a rural area SW of Florence, Italian test site of MAC-Europe campaign
- complex hilly landscape (woodlands, agricultural, urban)
- L-band, polarimetric, θ = 50°, 16 looks, 12m x 6.6m drawn from ERA-ORA European project database (http://eraora.disp.uniroma2.it/)

Ground-truth





A: alfalfa
B: bare soil
C: mine
M: corn
OL: olivegrove
P: pasture
R: rape
S: sorghum
SF: sunflowers
U: untilled
UR: manufacts and urban
V: vineyard
W: wheat
Y: arboreus and forest

CPW classification

Cloude and Pottier, “An Entropy-based classification scheme for land applications of polarimetric SAR”, IEEE TGARS,1997

Polarimetric data

↓

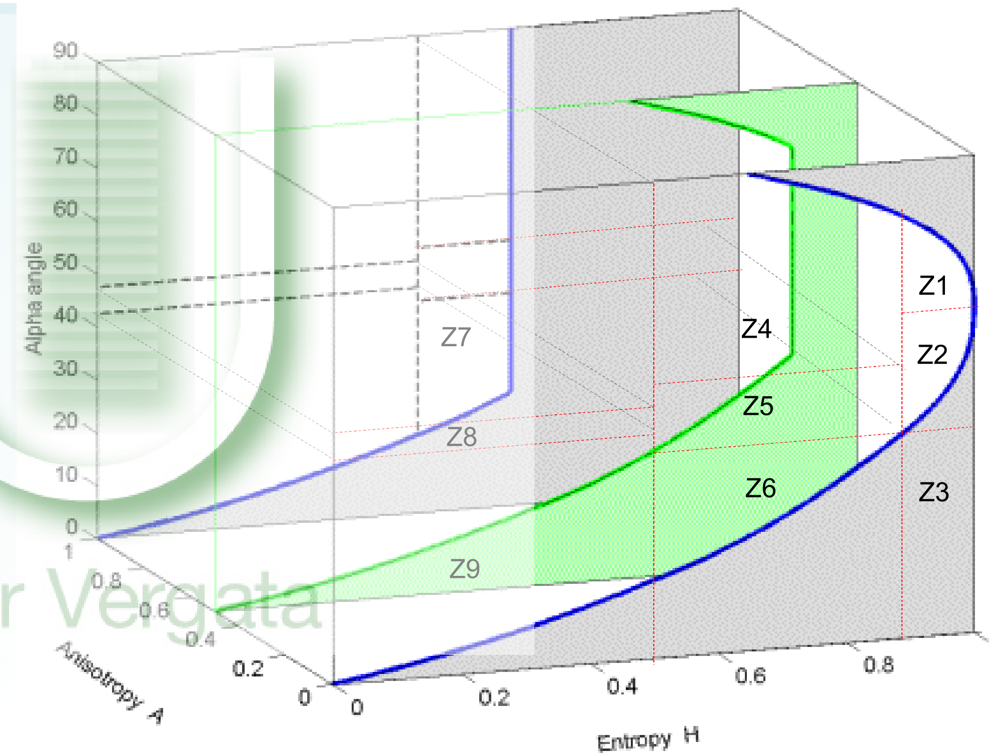
H, A, α parameters synthesis

↓

Points location in the 3D space (H, A, α)

↓

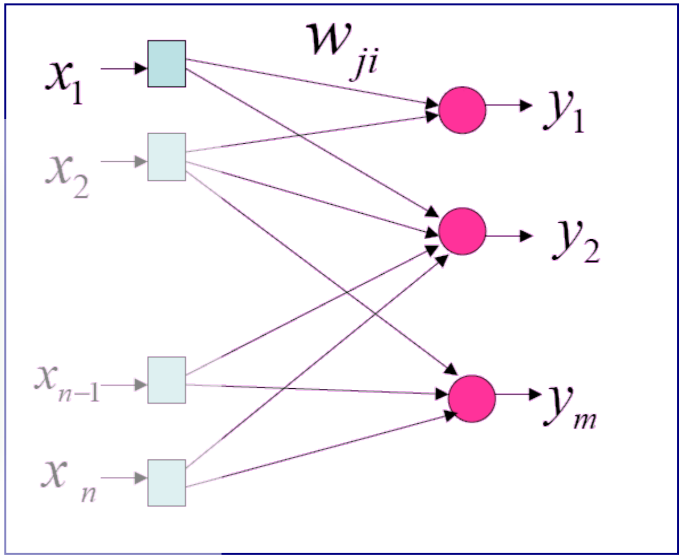
Classify according to the position in the (H, A, α) space



Disadvantage:
Fixed number of subspaces

Unsupervised Neural Networks

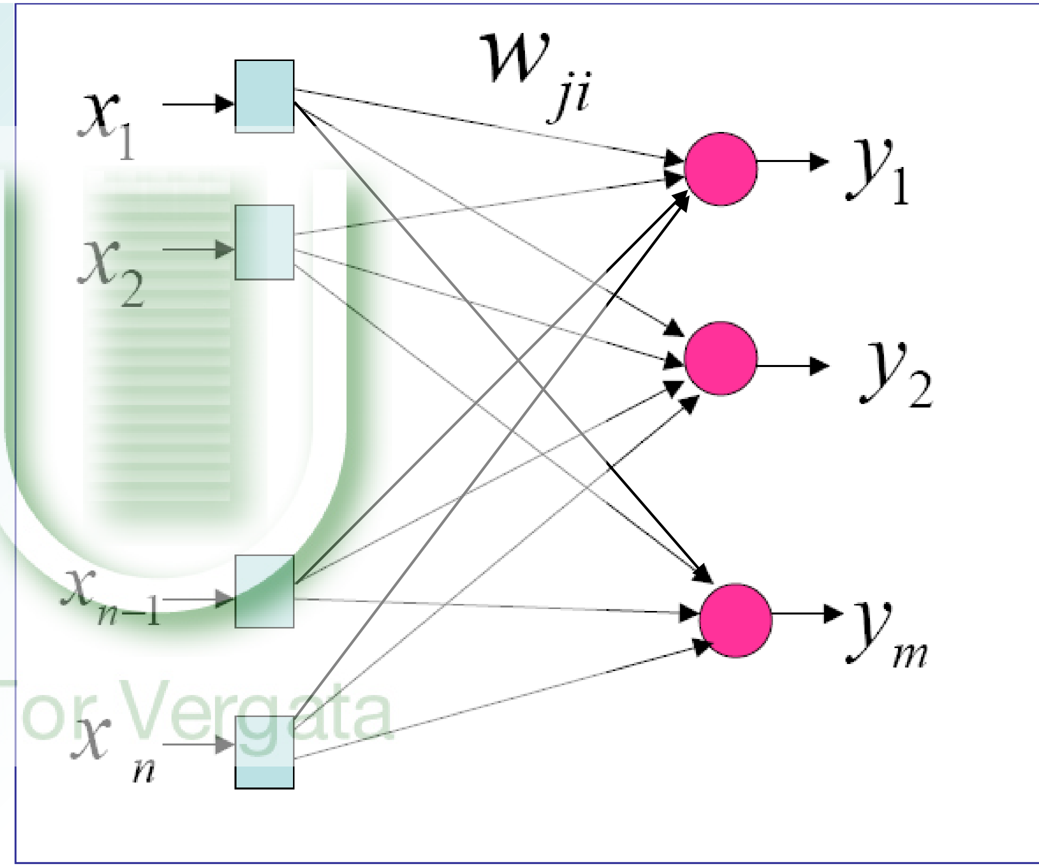
A **neural network** model typically consists of **computational elements** or **nodes** linked through weights which adapt iteratively to attain an optimal performance for the classification case. The nets used as classifiers are **Self-Organizing Maps** (Kohonen)



The **principal goal** of the self-organizing map is to transform non linear statistical relationships among high-dimentional data into simple geometric relationships usually represented by regular two dimensional grid of nodes.

SOM model

$$y_j = \sum_{i=1}^{n} w_{ji} x_i$$



$\mathbf{x} = [x_1, x_2, \ldots, x_n]^T$

$\mathbf{w}_j = [w_{j1}, w_{j2}, \ldots, w_{jn}]^T$

$\mathbf{y} = [y_1, y_2, \ldots, y_m]^T$

where $j = 1,2,\ldots, m$
(m: total number of neurons)

Each output neuron is fully linked with the input vector

Learning algorithm

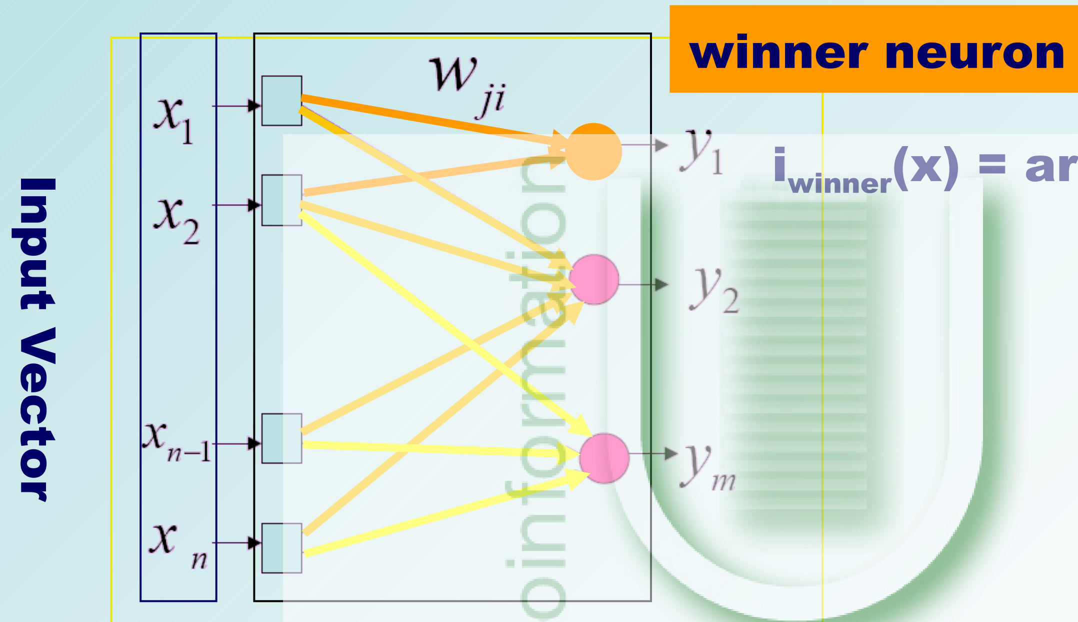
- **Competition**: a continuous input space of activation patterns is mapped onto a discrete output space of neurons by a process of competition among the neurons in the network. The neuron with weight vector **W** nearest to the input vector **X** is declared "winner".

$$i_{winner}(x) = \arg\min_j \|\mathbf{x} - \mathbf{w}_j\|$$

- **Cooperation**: the winner neuron is linked to its neighbourhood and in this area the synaptic weight will be updated.

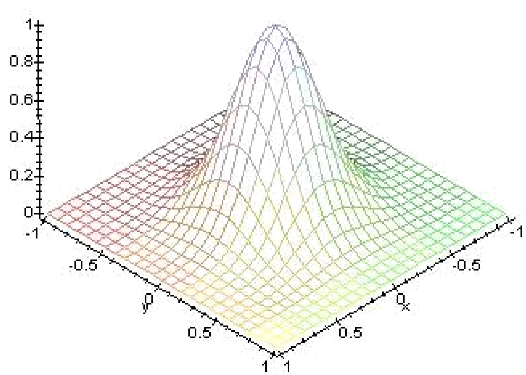
- **Synaptic Adaptation**: the synaptic weight vector w_j of winning neuron is moved toward the input vector x. Upon repeated presentations of the training data, the synaptic weight vector tend to follow the distribution of the input vectors due to the neighborhood updating → topological ordering

SOM model



$i_{winner}(\mathbf{x}) = \mathrm{argmin}_j \|\mathbf{x} - \mathbf{w}_j\|$

$$\mathbf{w}_k(t+1) = \mathbf{w}_k(t) + \eta \cdot \lambda_i \left(\mathbf{x}(t) - \mathbf{w}_k(t) \right)$$



η **learning rate**

λ_i **neighborhood function**

How SOM works

Input x

Polarimetric data

Trained SOM

Winner neuron

Winner neuron location in the map

Winner neuron synaptic weight vector

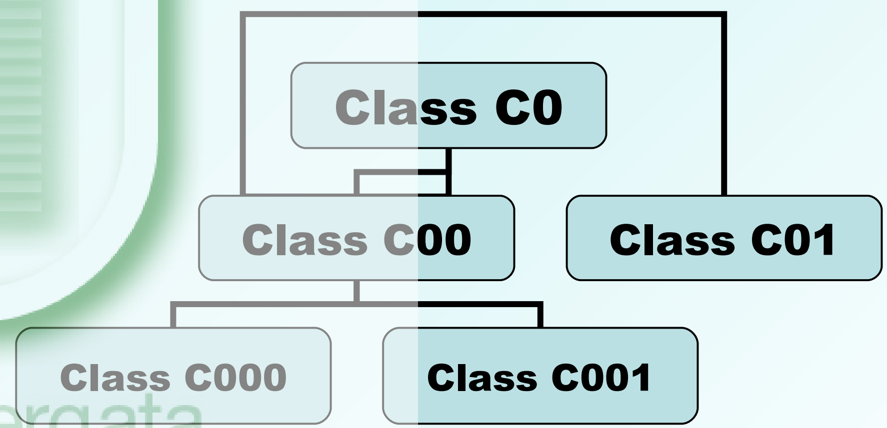
classifier

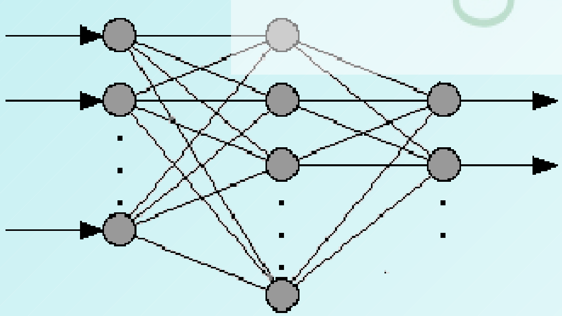
codifier

Classification algorithm

Features:

- Codify & classify
  SOM 4x4 → 2x1
- Dichotomous
- Iterative





Designing the Algorithm

HH HV

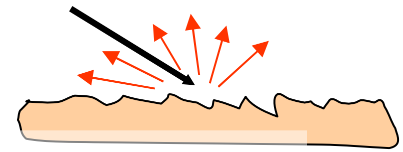
Buildings, Forest

soil, crops, olivegrove, vineyard

Buildings and Forest feature:

High HV values

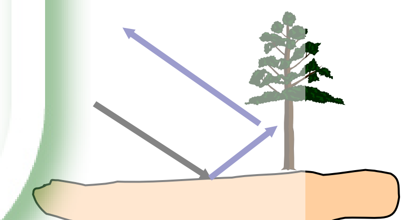
Surface scattering



HH < VV

$\varphi_{HH}-\varphi_{VV} \approx 0°$

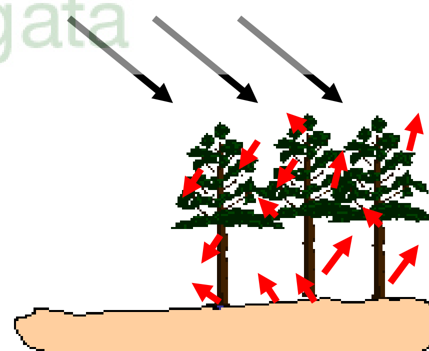
Double bounce scattering



HH > VV

$\varphi_{HH}-\varphi_{VV} \approx \pm\pi$

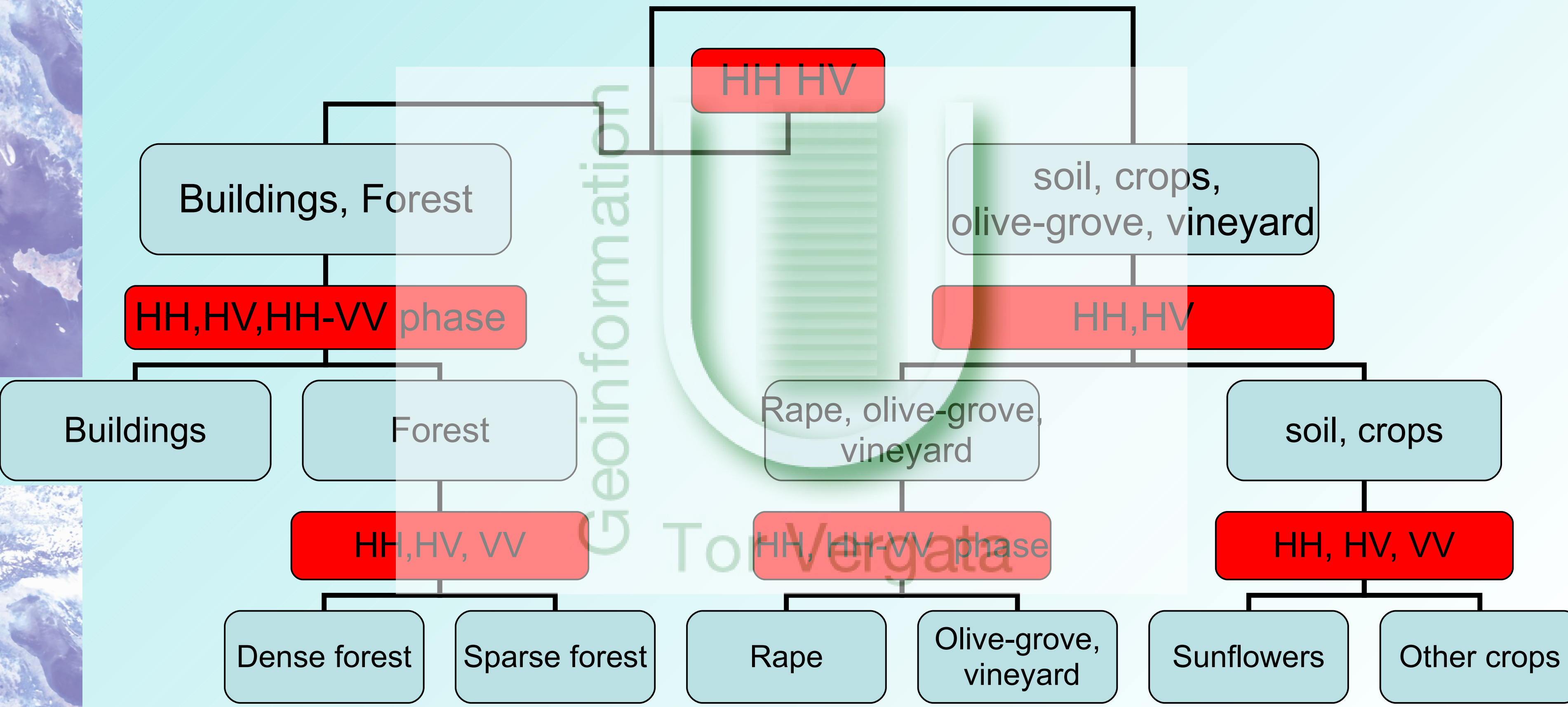
Volumetric scattering



HV high

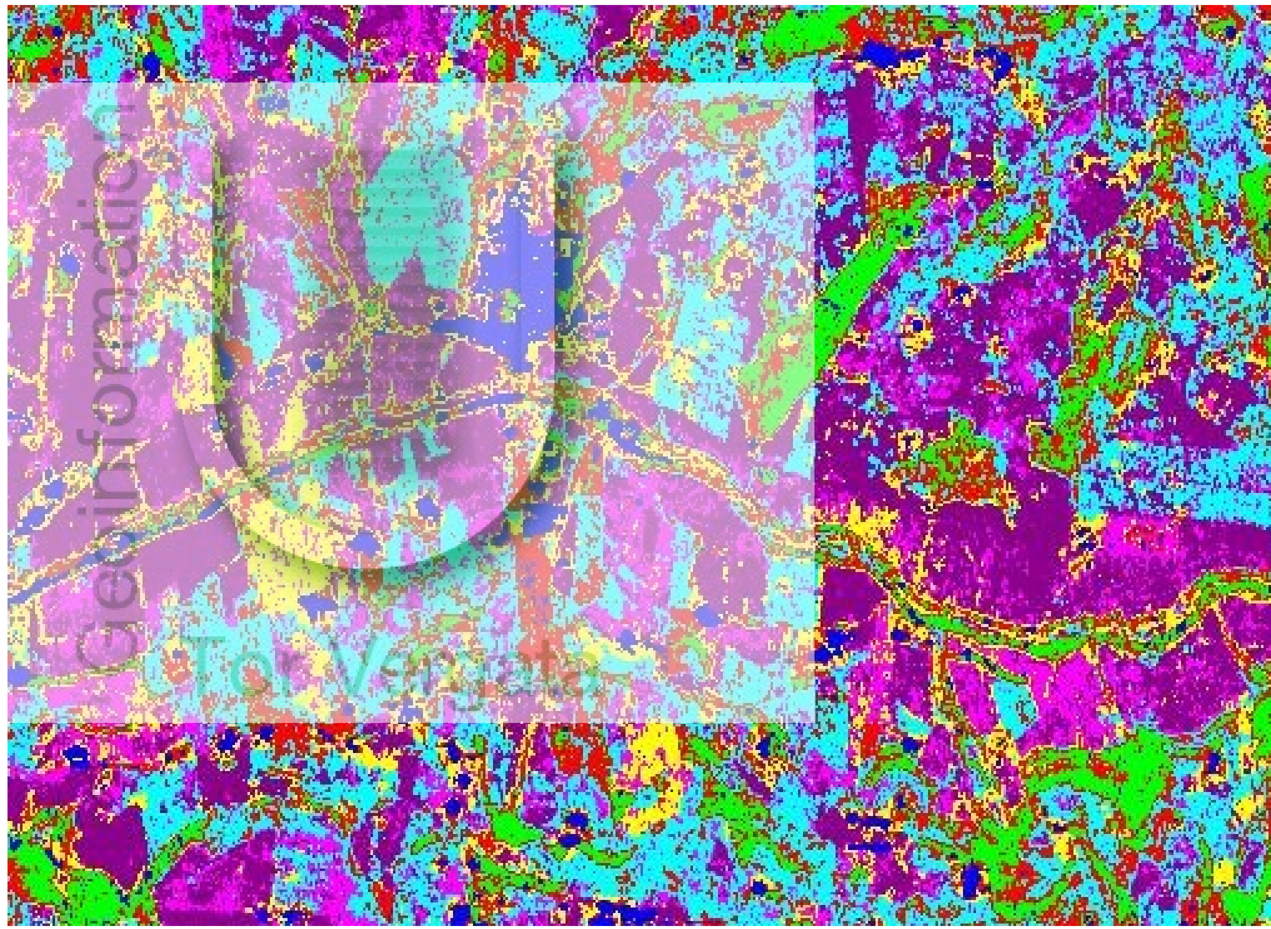
$\varphi_{HH}-\varphi_{VV} \approx 0°$

Designing the Algorithm



NN classification

- LD forest
- HD forest
- Urban
- Olive-grove, Vineyard
- Sunflower
- Colza
- Other crops



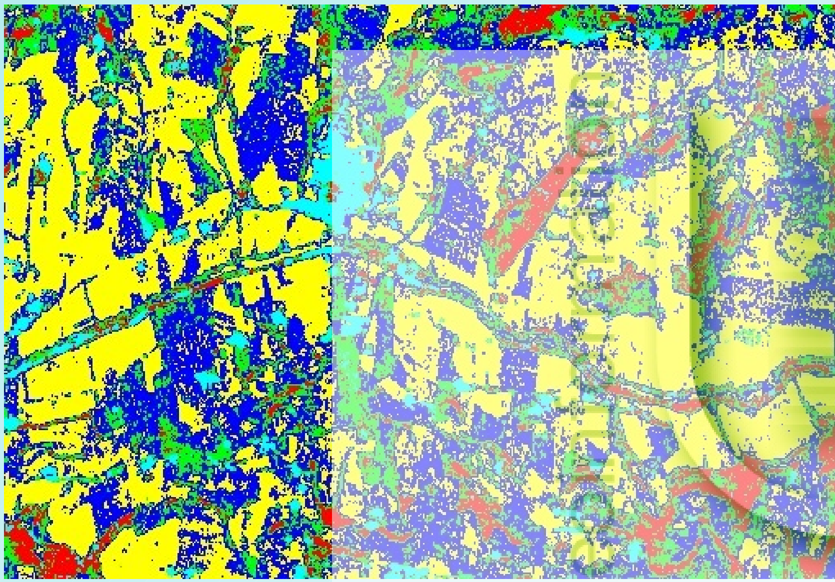
Confusion matrix

Overall Accuracy = (11977/16566) 72% Kappa Coefficient = 0.64

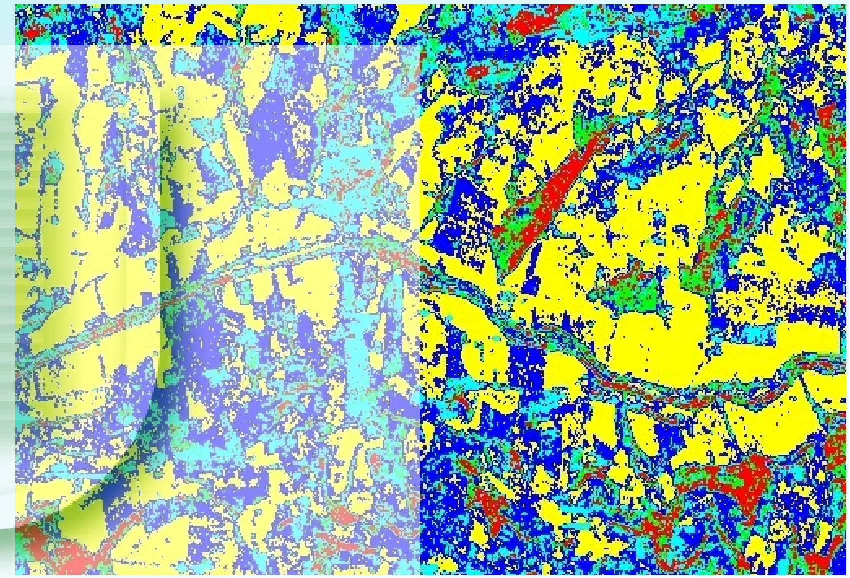
	(Ground truth Percent)						
Class	LD forest	HD forest	Urban	Rape	V&OL	Sunflowers	Surface Scattering
LD forest	54,5	21,1	3,5	11,0	7,2	0	2,2
HD forest	32,1	76,2	7,9	0,4	0,1	0	0,3
Urban	0	2,3	86,9	0,2	0	0	0,1
Colza	3,6	0,1	1,3	70,6	7,5	4,8	3,7
V&OL	9,8	0,3	0	8,2	74,9	10,9	5,7
Sunflowers	0	0	0,4	9,3	6,1	59,8	18,5
Surface Scattering	0	0	0	0,5	4,3	24,5	69,5

Comparison

NN



CPW



- Low Density Forest
- High Density Forest
- Urban
- Surface Scattering
- Rape, vineyard, olive-grove

CPW

Overall Accuracy = (13438/16566) 81% Kappa Coefficient = 0.71

Class	Ground Truth (Percent)				
	HD forest	LD forest	R&V&OL	Surface scattering	Urban
HD forest	62,8	17,6	0	0,1	21,1
LD forest	28,5	57,0	4,1	0,4	2,7
R&V&OL	1,4	12,3	78,2	8,4	0,7
Surface Scattering	0	0	11,3	88,4	0
Urban	7,3	13,1	5,9	2,7	75,5

NN

Overall Accuracy = (13887/16566) 84%   Kappa Coefficient = 0.76

	Ground Truth (Percent)				
Class	LD forest	HD forest	Urban	R&V&OL	Surface Scattering
LD forest	54,5	21,1	3,6	8,4	2,1
HD forest	32,1	76,2	7,9	0,1	0,3
Urban	0	2,3	86,9	0,1	0,1
R&V&OL	13,4	0,4	1,3	81,2	9,8
Surface scattering	0	0	0,3	10,2	87,7

Conclusions

- The designed algorithm has allowed to assess the potentiality of SOM neural networks to classify polarimetric SAR data.

- The obtained overall accuracy is equal to 72% for seven classes and equal to 84% for five classes.

- The overall accuracy of NNs is 3% greater then CPW method.

- More flexibility for the number of the output classes