Project team

- Consiglio Nazionale delle Ricerche, Istituto di Studi sui Sistemi Intelligenti per l'Automazione (CNR-ISSIA), Bari (F. Mattia, G. Satalino, A. Balenzano)

- Consiglio per la Ricerca e Sperimentazione in Agricoltura, Unità di Ricerca sui Sistemi Colturali per gli Ambienti caldo-aridi (CRA-UR-SCA), Bari (M. Rinaldi, S. Ruggieri)

- Università degli Studi “Federico II” di Napoli (UNI-NA), Dipartimento di Ingegneria Agraria ed Agronomia del Territorio, Napoli (G. D’Urso, F. Capodici)

- Politecnico di Bari (POLI-BA), Dipartimento di Ingegneria delle Acque e di Chimica, Bari (V. Iacobellis, P. Milella, A. Gioia)
Background

- Land process models (i.e. hydrologic & crop growth models), which simulate energy and mass exchanges between the soil, vegetation, and atmosphere, are crucial to improve land and water resources management at regional & global scale, e.g.
  - crop irrigation scheduling & early forecast of yield production & monitor/mitigate flood and drought impact etc.

- However, a limitation of these models is the need for numerous input parameters concerning the soil & crop characteristics, i.e. landcover, soil water content, crop development and management, etc., which are seldom available at the appropriate spatial and temporal scales. This lack of information often leads to erroneous model predictions.

- An integrative use of remote sensing and land process models is needed to overcome these limitations.
  - SAR data hold a great potential for the monitoring of crop and soil parameters at the high spatial (and temporal) resolution.
Objectives of the project

- improve, assess and tailor existing methods and algorithms for landcover classification and surface parameter retrieval to CSK SAR data;

- integrate the output of these algorithms into existing hydrological/crop growth models to improve, for instance, yield forecast and water management over selected agricultural sites in Southern Italy

Outline

- Selection of:
  - land process models & surface parameters
  - classification & retrieval algorithms

- Experimental data:
  - Ground & CSK data

- Results:
  - classification and retrieval algorithms
  - Integrative use of CSK data & land-process models

- Recommendations for future work
Land process models & Surface parameters

Three main application fields that can benefit from an integrative use of SAR data have been selected:

- Early forecast of yield production (AQUATER DSS model, CRA)
- Identification and monitoring of water stress indices over agricultural areas (SWAP model, UNI-Na)
- Flood and drought monitoring (DREAM model, POLI-Ba)

Spatial scale: watershed (10-100km); resolution: 50-500m
Temporal scale: few months (i.e. growing season); resolution: 1 week

A sensitivity analysis of selected models to surface parameters indicated that the most critical surface information, retrievable from SAR, are:

- land use maps, i.e. crop maps
- leaf area index (LAI), related to fresh biomass
- soil moisture content ($m_v$)

The selected algorithms exploit dense time series of dual polarization CSK data
Classification & Retrieval algorithms

- Crop Classification algorithm applied to time series of SAR data
  - (Supervised) Classification algorithm: Multi-dimensional Maximum Likelihood (ML) for multivariate Gaussian distributed data

- LAI and fresh biomass retrieval
  - empirical and/or semi-empirical approaches

wheat (small stems): radar response dominated by soil attenuated mechanisms

Sugar beet (broad leaves or branching structure): radar response dominated by volume scattering
Soil moisture content ($m_v$) retrieval

SMOSAR algorithm using backscatter temporal change

- The SMOSAR retrieval algorithm requires dense (revisiting time 6-12 days) temporal series of SAR data.

- Under the hypothesis that the time series of N SAR images is dense the backscatter change between two subsequent acquisitions is mainly related to the temporal change of soil moisture content, which is characterized by a temporal scale of few days, and poorly related to the temporal changes of vegetation biomass or crop canopy or surface roughness, which are usually characterized by a temporal scale of few weeks.


SMOSAR has been tailored to X band data (SMOSAR-X) and L-band data (SMOSAR-L)
The experimental activities & CSK data
- Sites & in situ measurements
Experimental sites and activities

- **Foggia site** (Candelaro basin)
- **Salerno site** (Sele basin)
- **Matera site** (Bradano basin)
- **Yanko site** (Australia)
- **Castelvetrano site**
- **Mazara site**

- **2011 and 2010 COSMOLAND campaigns in Italy**: ground data were collected over the Italian sites. Matera site was excluded, as no CSK images were received.
- **CNR-ISSIA** took part in the **SMAPEX campaigns over Yanco (Australia)** in the framework of NASA SMAP mission in July and December 2010 and September 2011.
- **CSK data were acquired** over the experimental sites in 2010 and 2011.
COSMOLAND in situ measurements 1/

Monitored crops over Foggia (CRA-SCA): durum wheat, sugar beet and tomatoes.
Period: March/April – August/September
Ground measurements (every one/two weeks):
- Phenological phase
- Fraction cover
- Leaf Area Index
- fresh and dry biomass
- Plant height
- Soil moisture with gravimetric method (0-5 cm, 0-20 cm and 21-40cm)
- Soil moisture with Thetraprobe instrument (0-5 cm)
- Commercial yield at harvest

2011 - Sugar Beet - Forte Farm
Leaf Area Index (m² m⁻²)

2011 - Tomato - Carafa Farm
Leaf Area Index (m² m⁻²)
COSMOLAND in situ measurements 2/

Monitored crops over Salerno (UniNa): corn and alfalfa.
Period: June – September
Weekly ground measurements:
• Leaf Area Index

Monitored crops over Sicilian sites (UniNa): vineyard and olive trees.
Period: May or July
Ground measurements:
• Leaf Area Index

Monitored area: Yanco, Australia
Continuous soil moisture measurements
Hourly measurements:
• Soil moisture content

Temporal behaviour of the soil moisture values at 0-5cm (red line) and 0-30cm (blue line) depth and the daily precipitation in spring (September – November) 2010 measured by Y9 station.
### CSK data gathered in the project

**Data set of 2010-2011 CSK images**

<table>
<thead>
<tr>
<th></th>
<th>Foggia</th>
<th>Matera</th>
<th>Salerno</th>
<th>Yanco</th>
<th>Sicilian sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>April</td>
<td>May</td>
<td>November</td>
<td>May</td>
<td></td>
</tr>
<tr>
<td>HH/HV Stripmap at low inc.</td>
<td>8</td>
<td>0</td>
<td>2</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>HH/HV Stripmap at high inc.</td>
<td>5</td>
<td>0</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH or VV Spotlight</td>
<td>5</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2011</td>
<td>April-July</td>
<td>August</td>
<td>January-October</td>
<td>June-August</td>
<td></td>
</tr>
<tr>
<td>HH/HV Stripmap at low inc.</td>
<td>9</td>
<td>0</td>
<td>5</td>
<td>24</td>
<td>0</td>
</tr>
<tr>
<td>HH/HV Stripmap at high inc.</td>
<td>1</td>
<td>0</td>
<td>5</td>
<td>39</td>
<td>14</td>
</tr>
<tr>
<td>HH or VV Spotlight</td>
<td>2</td>
<td>0</td>
<td>7</td>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>TOT</td>
<td>25</td>
<td>0</td>
<td>19</td>
<td>91</td>
<td>32</td>
</tr>
</tbody>
</table>

Stripmap requested every 8-16 days, but received with **temporal gaps**

CSK data have calibrated, co-registered, temporally and spatially filtered.

---

Examples of results concerning:

- the agricultural crop classification based on CSK time series & maximum likelihood method

- the LAI retrieval based on CSK data & semi-empirical approaches

- the soil moisture retrieval based on SMOSAR-X software
Crop classification from multi-temporal CSK data: Foggia case study (5 classes)

Crop classification using 4 HH & HV CSK images acquired on 14/04/11, 08/05/11, 01/06/11, 11/07/11

Overall classification accuracy of multi-temporal, single/multi-polarization CSK images, acquired in 2011, vs the number of images (test results)

- The best overall accuracy test OA ~ 85% by using 9 HH+HV images (similar OA accuracies are obtained by selecting 4 HH & HV images acquired in critical phenological stages)
Crop classification from multi-temporal CSK data: Yanco case study (12 classes)

Overall classification accuracy of multi-temporal, single/multi-polarization CSK images, acquired from Nov. 2010 to January 2011, vs the number of images (test results)

- multi-temporal StripMap PingPong CSK data are well-suited for the agricultural crop classification, in particular the HV channel is crucial for improving the classification accuracy.

Crop classification using 8 HH+HV CSK images
Example of LAI retrieval over Foggia site

- CSK data can be used for the LAI retrieval, and, in particular, the HV (or VH) polarization holds the highest potential for such an application.

UNINA LAI retrieval algorithm

- LAI retrieval algorithm is based on a regression analysis ($r^2 \approx 0.8$) between changes of optical (e.g. DEIMOS) and CSK observations:

$$V_{t2} = V_{t1,\text{optical}} + \Delta V_{\text{CSK}} = V_{t1,\text{optical}} + (\alpha \cdot \Delta \text{CSK}_{t2-t1} + \beta)$$

**LAI$_{\text{CSK}}$ vs LAI$_{\text{DEIMOS}}$ over the whole Sele plain**

Avg. st. error $\sim 0.34$ (m² m⁻²)

- LAI maps derived from CSK data have been used as input to the SWAP agro-hydrological model, which predicts the presence of crop water stress.

Deimos CIR image of the Improsta farm, corn (white bounded) and alfalfa (green bounded) fields used for validating $V_{\text{CSK}}$. 

Examples of soil moisture maps of bare fields over Yanco site using 4 HH CSK imgs & SMOSAR-X code

- Dense time-series of CSK data at HH polarization have shown a good potential (rmse ≈6%) for the soil moisture retrieval of bare or sparsely vegetated fields.

Rain event on 05/02/2011
Examples of integrative use of CSK-derived parameters and land process models for:

- crop yield forecast (AQUATER DSS)
- crop water stress monitoring (SWAP)
- flood/drought monitoring (DREAM)
AQUATER DSS model – CRA-SCA

- AQUATER DSS simulates the crop growth & forecast yield production

- Critical parameters: either input or easy to assimilate
  - Land use maps & Leaf area index (at medium/high temporal resolution, e.g. 7-14 days)

- Additional input
  - Plant emergence (related to sowing date) & Soil moisture content at start of simulation & Crop management & Soil texture & Meteo data

- Output: crop yield

**Input:** territorial units obtained from crop classification

**LAI assimilation through forcing**

Comparison between curves LAI tomatoes, with and without LAI data forcing
Assessment of the improvement of yield forecast

- Assimilation of COSMO-SkyMed-derived LAI maps (covering the three main crops present in Capitanata plain, namely wheat, sugar beet and tomato), through LAI forcing technique, into the AQUATER DSS.

Results indicate a significant improvement in terms of yield forecast, especially when the COSMO-SkyMed derived LAI maps covered the most critical crop growth periods.

Improvements of yield forecast with LAI forcing with respect to no forcing

<table>
<thead>
<tr>
<th>Crop</th>
<th>Best date (21 May, 27 April, 9 August)</th>
<th>All dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat</td>
<td>Grain yield</td>
<td>No significant improvements because of the good performances of DSS AQUATER in wheat simulations</td>
</tr>
<tr>
<td></td>
<td>Total dry matter</td>
<td>+12%</td>
</tr>
<tr>
<td>Sugar beet</td>
<td>Root yield</td>
<td>+10%</td>
</tr>
<tr>
<td></td>
<td>Total dry matter</td>
<td>+12%</td>
</tr>
<tr>
<td>Tomato</td>
<td>Fruit yield</td>
<td>+1%</td>
</tr>
<tr>
<td></td>
<td>Total dry matter</td>
<td>+1%</td>
</tr>
</tbody>
</table>
Assessment of the improvement of vegetation water stress SWAP model – UniNa

SWAP agro-hydrological model predicts the presence of crop water stress.

- Critical input parameter:
  - Leaf area index (at medium/high temporal resolution, e.g. 7-14 days)
  - Output: daily values of actual transpiration \( T \) and soil evaporation \( E_s \) (needed to evaluate the presence of water stress in the crop)

- LAI maps derived from CSK data provided as input to the SWAP agro-hydrological model. Assessment of the SWAP performances as a function of the number of LAI maps provided in input.

- Results indicate that the larger the number of LAI maps provided the better are the SWAP performances, the observed accuracy improvements are better for corn than for alfalfa crops.
Improvement of the DREAM hydrological model performances using EO data - PoliBa

- DREAM model uses the soil water content as a state variable and provide maps of runoff source areas as well as maps of soil water content and of saturated areas suitable for comparison with soil moisture SAR measurements.
  - Integration of the Richard equation in the DREAM model to simulate soil moisture content in the top soil layer.
  - Application of the DREAM model to Celone basin.
  - Comparison between model results and observations by satellite data in terms of soil moisture.

- Model results and SAR-derived soil moisture values are in fairly good agreement (rmse 4%-6%). Such a kind of results can be very useful for improving the calibration/validation of hydrologic models by means of EO-derived data.

DREAM Soil moisture map on 01/06/2011

Celone basin

CSK vs DREAM

Recommendations for future works

- The most advanced application that can be recommended for a pilot project is the assimilation of CSK derived maps of agricultural land crops and correspondent LAI values into crop growth models, such as the AQUATER DSS, in order to improve the yield forecast and the management of irrigation water resources. Such a pre-operational service would require the acquisition of 4-6 CSK StripMap PingPong products at low incidence angles and HH and HV polarization during the critical periods of the agriculture growing season (e.g. 3-4 months).

- A second interesting application is the integration of SAR-derived soil moisture maps into hydrologic models in order to improve the hydrological real time forecasting, which is a pre-requisite for the prediction and/or mitigation of flood disasters.