Assimilation of COSMO-SkyMed-derived LAI maps into the AQUATER crop growth simulation model. Capitanata (Southern Italy) case study

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Abstract
AQUATER is a Decision Support System (DSS) developed to drive crop management decisions at district level in a Mediterranean area; it integrates information from soil and climatic databases with a crop growth simulation model and provides estimates of crop yield at regional scale. AQUATER can assimilate LAI maps derived from Earth observation data in order to mitigate the risk of erroneous model predictions over large areas. In this study, time-series of LAI maps derived from COSMO-SkyMed SAR images, acquired over the Capitanata plain (Puglia region) in 2010 and 2011, have been assimilated by a forcing procedure in AQUATER and the improvements of its predictions have been assessed. Results indicate that the LAI assimilation leads to significant improvements in the yield forecast of sugar beet and tomato crops, whereas in the case of wheat the improvements are marginal.

Keywords: Leaf area index, decision support system, crop yield, COSMO-SkyMed.

Introduction
Crop production management and its interaction with the environment require the use of crop growth models that simulate the physical processes occurring at soil, plant and atmosphere levels, under different environmental and management conditions, including limiting and forcing factors related to parameters such as soil, weather, water, nitrogen. In this regard, these models are valuable tools for assessing optimal crop growing conditions and have the potential of supporting management decisions over large areas.

As an example, the AQUATER software is a prototype of a Decision Support System (DSS),
developed during a national research project that integrates soil and climatic data with a crop growth simulation model [Acutis et al., 2010]. In particular, AQUATER simulates the most representative field crops in Southern Italy, i.e. wheat, sugar beet and tomato and, for instance, can forecast crop yields at district scale.

However, a limitation of such models is the need for numerous input parameters concerning the soil characteristics, the landcover, the crop management, etc., which are seldom available at the appropriate spatial and temporal scales. This lack of information often leads to erroneous model predictions. In this regard, Earth observation (EO) can supply spatial and temporal distributed information on vegetation cover, crop type as well as on state variables of the models, such as canopy biomass and Leaf Area Index (LAI), which can be assimilated into the crop growth models with a significant improvement in their predictions [Bach et al., 2003; Launay and Guerif, 2005; Dorigo et al., 2007; Pauwels et al., 2007]. EO LAI has usually been derived from optical data, which are however prone to the cloudiness condition. A complementary source of EO LAI lies in the Synthetic Aperture Radar (SAR) systems that are insensitive to cloud cover and therefore can acquire time-series of images during all the critical plant phenological periods. On the other hand, the drawback of SAR data is that they are significantly influenced also by the soil moisture and roughness conditions particularly during the first plant phenological stages and, in addition, their sensitivity to LAI is indirect through the vegetation water content. Therefore, the LAI retrieval from SAR data is limited to those phenological stages that show a strong correlation between vegetation water content and LAI [Mattia et al., 2003]. Nevertheless, the availability of new SAR missions with advanced observational capabilities, such as the TerraSAR-X [Werninghaus et al., 2010] and COSMO-SkyMed (CSK) [Covello, 2009] satellites or the forthcoming European C-band Sentinel-1 constellation [Torres et al., 2012], encourages the investigation of SAR data for agricultural applications and LAI monitoring [Baghdadi et al., 2008; Baghdadi et al., 2009; Paris Anguela et al., 2010; Bach et al., 2012; Fieuzal et al., 2012; Capodici et al., 2013].

The objective of this study is to investigate the extension to which the assimilation of LAI maps into the AQUATER model improves the yield forecast of the main crops of a semi-arid agricultural area located in the Capitanata plain in Southern Italy. LAI maps have been derived from time-series of X-band SAR data acquired by the CSK system in Spring-Summer 2010 and 2011. The retrieved CSK LAI maps have been validated against LAI maps derived from SPOT images.

In the next section, the ground, CSK SAR and optical data analysed in the study are described. Then, the LAI retrieval algorithm is presented and the adopted DSS is illustrated. Finally, the effects of the integration of CSK LAI into the DSS are discussed and summarized.

**Ground, SAR and optical data sets**

*Study area and ground measurements*

The experimental site is an agricultural area of approximately 150 km² located in the Capitanata plain (Foggia district in Puglia region, Southern Italy). The study area, shown in Figure 1, has a flat topography and is mainly devoted to wheat cultivation. According to the local crop management scheduling, durum wheat is usually sown between November and the end of December and harvested at mid-June. Other annual main crops of the region are sugar beet (sown in autumn and harvested in June-July) and tomato (sown in April and
Several private farms were monitored in 2010 and 2011 campaigns. In particular, LAI measurements were gathered approximately every 2 weeks, in the periods March-May for durum wheat, March-July for sugar beet and June-August for tomatoes. Only the measurements close to CSK overpassing have been considered. Crop management, crop yield measurements and phenology information were also collected. The wheat fields were not irrigated, while sugar beet fields were irrigated by supplemental sprinkler irrigation (2-3 supplies, 100-150mm per season) and tomato fields were fully irrigated by drip method (20-25 supplies, 350-400mm per season) and transplanted at 3 plants m\(^{-2}\) density in twin rows (1.80m apart). The three crops are characterized by different vegetation distribution: for wheat, high plant density (approximately 210 plants per m\(^2\), on
average), long and narrow leaves and vertical distribution (about 0.8m height), with a LAI ranging from approximately 2.0 m$^2$ m$^{-2}$ in March to 6.5 m$^2$ m$^{-2}$ during heading at the end of April; for sugar beet, 10 plants per m$^2$, well-spaced, large leaves and short plants (0.3-0.5 m height), with a LAI from 1.0 to 6.0 m$^2$ m$^{-2}$ in the measurement period; for tomato, the soil was not completely covered by vegetation due to the large space between the rows (about 1.8 m) up to July, while LAI values ranged from 0.5 to 5.0 m$^2$ m$^{-2}$ and plant height was about 0.7 m.

The wheat LAI measurements were performed using LiCOR LAI2000 area meter, which measures the blue light (320-490nm) in 5 concentric cones (with 148° field of view) averaging 6 measurements at random georeferenced locations within each field.

At harvest of each crop, samples of 1 square meter of plants were collected at three georeferenced locations for each field to measure commercial yield (grain for wheat, root for sugar beet and fruit for tomato). Total plant dry biomass (TDM) was measured by drying the plant samples in oven at 72°C until constant weight.

Finally, it is worth noting that the ground measurements were planned in coincidence with the CSK acquisitions. However, due to some temporal shifts of the satellite passages, some mismatches occurred.

**COSMO-SkyMed and SPOT data**

CSK images at HH and HV polarization and at 26° mean incidence angle were acquired over the Foggia site from April to August in 2010 and from April to July in 2011 (Tab. 1). The data set consists of 8 StripMap Ping-Pong level 1C-Geocoded Ellipsoid Corrected (GEC) products in 2010 and 9 StripMap Ping-Pong level 1C-Geocoded Terrain Corrected (GTC) products in 2011. It is worth noting that there are no CSK acquisitions in June 2010 and only one in May 2011, which is an important period of the growing season. Figure 1 shows, as an example, the HH StripMap Ping Pong acquired on 3rd April 2010. The CSK images have been calibrated, coregistered and temporally [Quegan and Yu, 2001] and spatially filtered with a boxcar window of 5x5 pixels.

| Polarization | Date       | ∆t  | Date       | ∆t  |
|--------------|------------|-----|------------|-----|
| HH+HV        | 03/04/2010 |     | 06/04/2011 |     |
| HH+HV        | 27/04/2010 | 24  | 14/04/2011 | 8   |
| HH+HV        | 21/05/2010 | 24  | 22/04/2011 | 8   |
| HH+HV        | 29/05/2010 | 8   | 08/05/2011 | 16  |
| HH+HV        | 08/07/2010 | 40  | 01/06/2011 | 24  |
| HH+HV        | 24/07/2010 | 16  | 17/06/2011 | 16  |
| HH+HV        | 01/08/2010 | 8   | 25/06/2011 | 8   |
| HH+HV        | 09/08/2010 | 8   | 03/07/2011 | 8   |
| HH+HV        |           |     | 11/07/2011 | 8   |
SPOT images were acquired over the study area on 4th and 22nd July 2010 and on 19th April, 24th June and 6th August 2011. The optical data are all SPOT 5 images except the one on 4th July, 2010, which is SPOT 4. SPOT bands have been normalised converting the Digital Number (DN) into the Top Of Atmosphere (TOA) reflectance. Since the experimental area is fairly flat, the effects of the local topography have been disregarded. Moreover, since SPOT data were acquired in clear sky conditions and precise atmospheric profiles were not available over the study area, no atmospheric correction was applied. The impact on LAI error at local scale is expected marginal as the assessment study has shown.

**LAI retrieval from COSMO-SkyMed data**

Many theoretical and experimental studies have demonstrated the sensitivity of the SAR backscattering coefficient to vegetation (e.g. biomass and LAI) and soil (e.g. soil roughness and moisture) parameters [e.g. Wigneron et al., 1999; Macelloni et al., 2001; McNairn and Brisco, 2004; Paloscia et al., 2012; Gao et al., 2013]. More specifically, the LAI retrieval from SAR data has been discussed in [Guissard et al., 2005; Manninen et al., 2005; Dente et al., 2008; Chen et al., 2009; Jiao et al., 2010]. These studies show results obtained by means of empirical models derived from a regression analysis between the backscattering coefficient and observed LAI. In this regard, the developed expressions cannot be generalized to other sites; however, those studies demonstrate the possibility of adopting similar simplified and robust approaches as a viable procedure for studies at regional scale. Indeed, this is the approach adopted to retrieve LAI from CSK images acquired over the Foggia site during the 2010 and 2011 growing seasons. The regression analysis has been carried out per crop, to take into account the different scattering mechanism of each crop under investigation, and per polarization, considering the availability of the HH and HV polarizations. The evaluation metric consists of the root mean squared error (rmse) and the correlation coefficient (R).

**CSK LAI**

In the first instance, the calibration data set for estimating the fit parameters has been organized as follows. LAI observations have been averaged per field and organized per crop (i.e. wheat, sugar beet and tomato), for a total of 27 fields and 242 measurements (first row of Tab. 2). Then, LAI values have been interpolated by using a polynomial function of third degree in order to obtain observations coincident with the CSK acquisitions. As an example, Figure 2 shows the temporal behaviour of LAI observed over a field of wheat, sugar beet and tomato in 2010. The error bars represent the standard deviation of the in situ measurements, and the continuous lines are the interpolating curves. It is worth noting that there is an overlap between the growth curves of the three crops. LAI values on the Day of the Year (DoY) of CSK acquisitions have been extracted from the interpolated curves, thus obtaining a total of 121 interpolated LAI observations accounting for the 3 crops in 2 years (see the second row of Tab. 2). These LAI values have been finally matched with the corresponding CSK backscatter, which have been extracted from the images at HH and HV polarizations and averaged per field. To increase the statistics of data related to wheat fields, 9 LAI measurements and the correspondent backscatter values acquired at X-band and only at HH polarization by the E-SAR system during the AGRISAR’06 campaign [Hajnsek et al., 2007] have been added. It is worth noting that the calibration data set accounts for one
inter-season crop variability, and this is an important feature to increase the robustness of the regression analysis.

![Figure 2 - LAI temporal behaviours observed over one field of wheat, sugar beet and tomato in 2010. Vertical bars represent standard deviations of the in situ measurements. The continuous lines are the interpolating curves.](image)

**Table 2 - Number of fields, LAI observations, and interpolated LAI observation per crop for the 2010-2011 growing seasons.**

| Observations                      | Wheat | Sugar beet | Tomato |
|-----------------------------------|-------|------------|--------|
|                                   | 2010  | 2011       | 2010  | 2011   | 2010 | 2011 |
| Nr of fields/LAI observations     | 4/42  | 5/18       | 4/50  | 3/23   | 7/82 | 4/27 |
| Nr of interpolated LAI observations | 16    | 16         | 28    | 16     | 31   | 14   |

Table 3 shows the rmse and R between the measured LAI and the CSK-derived LAI values found by exploiting the linear regression expressions derived from the calibration data set. The best X-band polarizations for LAI retrieval, i.e. those with the lowest rmse and the highest R values, are HH for wheat and HV for sugar beet and tomato. The rmse are 1.13 m$^2$ m$^{-2}$, 1.06 m$^2$ m$^{-2}$ and 0.87 m$^2$ m$^{-2}$, respectively, with an average of approximately 1.0 m$^2$ m$^{-2}$. This result indicates that HV backscatter over broad leaf or/and ramified crops, e.g. sugar beet and tomato, is highly sensitive to the canopy biomass and then to LAI, whereas over wheat fields the most indicate radar feature for LAI retrieval is HH. The best linear relationships are:

1. LAI = -0.74 -0.34HH (HH in dB & wheat);
2. LAI = 0.97+75.8 HV (HV linear & sugar beet);
3. LAI = 0.54+143.4 HV (HV linear & tomato).
Table 3 - Rms errors and R correlation coefficients between observed and CSK-derived LAI values.

|          | Wheat |         | Sugar beet |         | Tomato |         |
|----------|-------|---------|------------|---------|--------|---------|
|          | rmse  | R       | rmse       | R       | rmse   | R       |
| HH       | 1.13  | 0.58    | 1.09       | 0.68    | 0.89   | 0.66    |
| HV       | 1.37  | 0.46    | 1.06       | 0.69    | 0.87   | 0.67    |
| HV/HH    | 1.53  | 0.14    | 1.32       | 0.42    | 1.06   | 0.44    |

As a result, Figure 3 illustrates the scatter plot of LAI measured versus LAI retrieved from CSK data for the three crops. The LAI retrieved, which ranges approximately from 1.0 m$^2$ m$^{-2}$ to 6.0 m$^2$ m$^{-2}$, is not biased and its slope is close to 1.

As a further step, the above linear relationships have been applied to the SAR images to retrieve the LAI maps. This task has been performed at field scale with the support of a seasonal land use map of the area, which has been derived from the multi-temporal 2010 and 2011 SPOT data following the methodology described in [Satalino et al., 2009]. As an example, Figure 4 shows LAI maps derived from CSK acquired on 14$^{th}$ April and 11$^{th}$ July, 2011. On the first date, the most developed crops were wheat and sugar beet, whereas, on the second date, tomato was the most present. An independent validation of these maps has been carried out by using LAI estimates derived from the SPOT images acquired in 2010 and 2011.

Figure 3 - Scatter plot of LAI observed versus LAI retrieved from CSK data. The linear fit line is superimposed to the 1:1 line.
The LAI SPOT maps have been obtained by exploiting the empirical relationships between the Normalized Difference Vegetation Index (NDVI) and LAI developed in a previous study, which encompassed a large data set acquired on the same study area in 2006-2008 and led to a rmse for wheat, sugar beet and tomato of 0.76 m$^2$m$^{-2}$, 0.90 m$^2$m$^{-2}$ and 0.79 m$^2$m$^{-2}$, respectively, with an average of approximately 0.81 m$^2$m$^{-2}$ [Satalino et al., 2010].

The LAI maps derived from the SPOT images acquired in 2010 and 2011 have been used as benchmark for the LAI CSK maps. However, in order to firstly characterise their accuracy, they have been tested against the LAI observations collected in 2010 and 2011 and appropriately interpolated. The rmse between the LAI SPOT and LAI observed in 2010 and 2011 is approximately 1.3 m$^2$m$^{-2}$ for the three crops.

### CSK LAI validation

LAI maps derived from SPOT and CSK data acquired on as close as possible dates (i.e. 4$^{th}$ and 8$^{th}$ July 2010; 22$^{nd}$ and 24$^{th}$ July 2010; 19$^{th}$ and 22$^{nd}$ April 2011; 24$^{th}$ and 25$^{th}$ June 2011, respectively) have been compared in order to assess the quality of CSK LAI maps. Figure 5 shows the scatterplot between the SPOT and CSK-derived LAI values estimated at a pixel size of 90m over wheat, sugar beet and tomato fields. The LAI range for wheat and sugar beet is limited due to the short period of the available couples of SAR and optical acquisitions, whereas it is significantly larger for tomato. The overall rmse and correlation are 0.84 m$^2$m$^{-2}$ and 0.82, respectively, with a bias of 1.1 and a slope of 0.7. The rmse evaluated per crop is 0.77 m$^2$m$^{-2}$, 0.77 m$^2$m$^{-2}$, and 0.98 m$^2$m$^{-2}$, for wheat, sugar beet and
tomato, respectively. As a result it is possible to infer that the LAI maps retrieved from CSK data have an accuracy comparable to that of the LAI maps retrieved from SPOT data, i.e. rmse approximately 1.3 m²/m². However, it is worth emphasising that Figure 5 indicates a systematic overestimation of CSK-derived LAI for low LAI values (i.e. lower than 2.5), which mainly refers to tomato crops and it is likely due to a significant soil contribution to the backscatter, as at early phenological stages tomato plants partially cover the soil surface [Prevot et al., 1993; Satalino et al., 2012]. In particular, the variability of soil moisture content of tomato and sugar beet fields, due to an inhomogeneous scheduling of irrigation in the area, largely contributes to the LAI scatter observed in Figure 5. Conversely, at high LAI values a certain underestimation is observed over wheat fields.

Decision Support Systems and LAI assimilation
The DSS AQUATER has been conceived integrating a crop model with a GIS software [Acutis et al., 2009]. A number of software tools have been added in order to link the simulation model to the GIS software, to map the input and output data and to read the database (soil climate, crop and management). The model can read the data stored in shape files and update all the different variables. In addition, in the DSS software a tool for the map representation has been included and recently improved. The crop model has been developed based on the Unified Modelling Language (UML) using, when possible, existing free modules and components. The software has been
developed for “COM” environment using VB6 language and is in development its porting in “Net” environment using VBNet and C# programming languages.

The correct description of the different HRUs (Hydrologic Response Units), characterized by specific soil, crop types and weather data, is the first requirement for a territorial scale software analysis. HRUs, even not geographically contiguous, can be characterized by the same data set. Table 4 shows a set of software requirements, divided in functional categories.

The crop growth model is based on gross assimilation of CO$_2$ and on maintenance and growth respiration to get the final net carbon assimilation. The model simulates the root water uptake allowing the compensation of the different water availability at different soil depths. Moreover it is characterized by three options to simulate water redistribution into the soil; default option is the finite difference solution of the Richards’ equation [van Dam and Feddes, 2000].

| Table 4 - General overview of AQUATER Decision Support System. |
|---------------------------------------------------------------|
| **Data access** | **Modelling** | **Output report** | **“What-if” analysis** |
| Specific soil parameters and meteorological data have to be provided to each HRU (Hydrological Response Unit) | Crop water requirement using FAO56 methodology or direct estimation of crop resistance | Water requirement and water supplied at territorial scale | Evaluation of crop and water management based on historical data |
| Real time updating of meteorological data main water and crop variables | Soil water dynamics using: cascading; ISBA; Richards’ equation | Production of shape files for the main water and crop variables | — |
| Real time access to remote information for LAI forcing | Development and growth of main Mediterranean field crops | Real time HRU specific alerts of water stress condition | — |

Earth observation data can be used in the simulation analysis. When land cover data, LAI and crop sowing dates are available as maps, remote sensing information can be used in assimilation by means of a forcing procedure, based on LAI retrieved values. Then AQUATER model updates the value of leaves weight, as a function of the Specific Leaf Area (m$^2$ g$^{-1}$, SLA) simulated values; from leaf weight the biomass of the different organs of the plant is also computed through partition coefficients of dry matter among the different plant organs, computed at each phenological development stage, and, consequently, the total plant biomass is simulated.

**Assessment of LAI assimilation improvements**

The assessment of the improvements due to the LAI assimilation into the crop growth model implemented in the DSS AQUATER has been carried out by means of a spatial simulation over an area of approximately 130 km$^2$ in the district of Capitanata plain, using daily meteorological and soil data as previously described.

Different runs of the model, without and with assimilation of CSK-derived LAI maps on single available dates and with all the available dates, have been assessed in order to obtain a final yield simulation closer to the measured values.

The assessment of the improvement has been evaluated comparing averages, standard deviations and absolute values of percentage differences of simulated versus measured values ($\Delta$% Sim. vs Meas.).
Results for 2010
The simulation for durum wheat of 2010 results in very good agreement with measurements even without LAI assimilation. This is due to the large calibration/validation activities carried out in Italy and in other European countries over the past years [Garofalo et al., 2009; Ventrella et al., 2011]. The total aboveground dry matter yield is particularly well simulated by the DSS AQUATER (less than 4% of underestimation) (Tab. 5).

Table 5 - Commercial yield and total plant dry matter (TDM) in 2010 campaign for the three crops and for the different AQUATURE DSS simulation options. * Δ % indicates the means of absolute values of percentage difference of each field (\(((\text{Sim. } - \text{Meas.})/\text{Means.})\times 100\)).

| Crop       | N. of fields | Measured | Simulated without assimilation | Simulated with COSMO-SkyMed LAI assimilation – the best date | Simulated with COSMO-SkyMed LAI assimilation – all the dates |
|------------|--------------|----------|-------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|
|            |              | avg and std (kg ha\(^{-1}\)) | avg and std (kg ha\(^{-1}\)) | Δ % Sim. vs Meas. \(\ast\) | avg and std (kg ha\(^{-1}\)) | Δ % Sim. vs Meas. \(\ast\) | avg and std (kg ha\(^{-1}\)) | Δ % Sim. vs Meas. \(\ast\) |
| Durum wheat| 4            | 4909 ± 418 | 4653 ± 342 | [10.68] | 4658 ± 425 (21 May) | [9.84] | 4515 ± 298 (3 dates) | [11.45] |
|            | TDM          | 12438 ± 704 | 12003 ± 424 | [3.39] | 12000 ± 389 (21 May) | [3.38] | 11328 ± 458 (3 dates) | [5.25] |
| Sugar beet | 4            | 18829 ± 3004 | 15568 ± 495 | [15.05] | 17198 ± 1657 (27 April) | [5.57] | 13338 ± 589 (7 dates) | [21.54] |
|            | TDM          | 23858 ± 2856 | 19370 ± 587 | [17.51] | 21618 ± 2541 (27 April) | [7.35] | 18778 ± 1240 (7 dates) | [20.36] |
| Tomato     | 7            | 4719 ± 1543 | 4920 ± 33 | [31.94] | 4927 ± 65 (9 August) | [30.24] | 4844 ± 121 (6 dates) | [3.57] |
|            | TDM          | 8435 ± 2253 | 7750 ± 138 | [17.19] | 7758 ± 112 (9 August) | [15.81] | 8273 ± 189 (6 dates) | [5.21] |

However, the other two crops, autumnal sugar beet and spring tomato, are not simulated accurately; in particular, the DSS underestimates the sugar beet root yield and total dry matter (TDM) yield, with large differences among the four fields. On the contrary, tomato is overestimated by the DSS, more in the case of the dry fruit yield than the aboveground dry matter, with large differences among the seven fields. The absolute differences reported in Table 5, shows the highest values for tomato fruit yield (about 32%). Consequently, for these two irrigated crops it is evident the need of improving the simulation, through the assimilation of EO LAI.
The evaluation of the LAI assimilation into the DSS AQUATER has been carried out for the three crops and the different fields, by using the LAI maps derived from the CSK images acquired in 2010 (i.e. 3 LAI maps for durum wheat, 7 for autumnal sugar beet, and 6 for tomato). The durum wheat response to the assimilation of LAI shows a very limited improvement, more
effective in the late growth cycle period (May, during wheat heading) (Tab. 5).
For the other two crops, the LAI assimilation leads to an improvement of the simulation with
the following specific differences. For sugar beet, the improvement is found only when the LAI
assimilation occurs during the spring season (April). Conversely, it results not effective in all
the other available dates (Tab. 5). In particular, the assimilation during April (03/04 or 27/04), at
the beginning of the vegetative active growth with a LAI of about 2.5-3.5 m² m⁻², shows a very
significant improvement of simulation. This can be quantified in approximately 6% of absolute
difference between simulated and measured values for the root yield vs. 15% without forcing
and can be considered a very good result from an agronomic point of view, to forecast the sugar
beet yield more accurately.
For tomato, on the contrary, using all the available dates of LAI, the simulation of fruit yield and
the total dry matter is very close to the measured ones (4% and 5%, respectively). The different
canopy evolution between the two crops (larger uncovered soil during most part of the cycle and
a better irrigation water supply in tomato than in sugar beet) explains these different results.

**Results for 2011**
The simulation of DSS AQUATER without LAI assimilation follows and confirms, in
general, the results obtained in 2010 (Tab. 6).

| Crop          | N. of fields | Measured avg and std (kg ha⁻¹) | Simulated without assimilation avg and std (kg ha⁻¹) | Δ % Sim. vs Meas. | Simulated with COSMO-SkyMed LAI assimilation – the best date avg and std (kg ha⁻¹) | Δ % Sim. vs Meas. | Simulated with COSMO-SkyMed LAI assimilation – all the dates avg and std (kg ha⁻¹) | Δ % Sim. vs Meas. |
|---------------|--------------|--------------------------------|-----------------------------------------------------|------------------|---------------------------------------------------------------------------------|------------------|--------------------------------------------------------------------------------|------------------|
| Durum wheat   | 5            | Grain yield 5369 ± 858          | 4835 ± 36                                           | 13.98            | 4793 ± 22 (8 May)                                                              | 13.98            | 4818 ± 30 (3 dates)                                                            | 13.47            |
|               |              | TDM 15249 ± 1177               | 12525 ± 45                                          | 17.36            | 12383 ± 13 (8 May)                                                            | 18.29            | 12560 ± 175 (3 dates)                                                           | 17.03            |
| Sugar beet    | 3            | Root yield 20952 ± 4679         | 14640 ± 62                                          | 26.35            | 16620 ± 4181 (22 April)                                                        | 20.85            | 16450 ± 4883 (3 dates)                                                          | 20.97            |
|               |              | TDM 28356 ± 4965               | 18177 ± 136                                         | 33.71            | 21493 ± 5087 (22 April)                                                        | 19.62            | 22823 ± 7071 (3 dates)                                                          | 19.22            |
| Tomato        | 4            | Fruit yield 6440 ± 2279         | 5020 ± 52                                           | 31.11            | 5120 ± 121 (17 June)                                                           | 30.76            | 4905 ± 29 (3 dates)                                                             | 21.85            |
|               |              | TDM 10766 ± 3185               | 8407 ± 117                                          | 25.59            | 9378 ± 419 (17 June)                                                           | 25.03            | 8850 ± 282 (3 dates)                                                            | 18.67            |
In general, the simulation accuracy is a little bit lower than the previous year results, with absolute differences of 14% and 17% for grain yield and TDM of wheat, 26% and 34% for root yield and TDM of sugar beet and 31% and 26% for fruit yield and TDM of tomato. However, the simulation activity has in general confirmed the positive effect of LAI assimilation in improving crop simulation models forecast.

As in 2010, the advantage of assimilation of LAI values in DSS AQUATER performance is minimum for durum wheat. For sugar beet, the improvement is satisfying: from 26% without assimilation to 21% with assimilation for root yield, and from 34 to 19% for the TDM, without difference if one or all the three dates are used. For tomato, the accuracy of simulation increases thanks to LAI assimilation of the three dates, especially for the TDM (from 26 to 19%).

Discussion and conclusions
For durum wheat the benefit of LAI assimilation, in terms of yield forecast, is marginal (if any), essentially because the DSS performed extremely well even without any additional LAI information. This is likely due to the fact that the authors have accumulated an outstanding experience in modelling and simulating the growth and development of cereal crops characteristic of the Capitanata plain. However, different results may be obtained over areas not yet deeply investigated (e.g. North Africa, Ukraine). The obtained results confirm the previous findings about the possibility to assimilate LAI data derived from EO and the small improvement for durum wheat yield simulation [Dente et al., 2006, 2008].

For sugar beet and tomato, the assimilation of CSK-derived LAI maps indicates a significant improvement in terms of yield forecast, especially when the LAI maps covered the most critical growth periods. In particular, for autumnal sugar beet the best period of assimilation is at the beginning of spring growth (April), when the LAI is about 2.5-3.5 m² m⁻², and the optimal number of assimilation dates is one or two. Conversely, for tomato, due to its very short growing period (i.e. 3 months), the assimilation of all the available dates (6, in the 2010 and 3 in 2011) is more effective than a single one in the improvement of simulation. Furthermore, the CSK-derived LAI assimilation during April-May can further improve the simulation estimating, on a large scale, the actual transplanting dates.

A global evaluation of the forcing procedure of LAI values in the growth model is reported in Figure 6, which shows an increase of R² between simulated and measured yield values. As a consequence, the availability of frequent EO-derived LAI maps, such as in the case of using CSK images, is surely a key point for improving the crop model predictions.

Finally, the DSS has recently been updated by implementing the AQUATER Visualizer tool, which allows to visualize the results of “what-if” investigations and to compare the effects of techniques to control soil moisture deficit and optimize water use in a GIS-style interface. All the DSS output can be elaborated by default or customized queries calculating and visualizing a large number of indicators (about 40) which concern crop related variables, e.g. LAI and yield, the water amount consumption, the soil moisture deficit and water content.

An example of the capability of the DSS at district scale is shown in Figure 7. Commercial yield of durum wheat is mapped with and without LAI assimilation. In this way, it is possible to highlight when the assimilation is more effective on the simulated yield results, to carry out multiple runs and to show the cumulate irrigation requirements at district level.
Figure 6 - Comparison among simulated and measured data of commercial yield (upper) and total plant dry matter (TDM) yield (lower) for wheat, sugar beet and tomato (in blue, green and red, respectively): without LAI values forcing (left side) and with LAI forcing using one LAI map derived from CSK (right side).

Figure 7 - Spatial simulation of yield of durum wheat in 2011 by AQUATER crop growth model: no forcing (left side) vs forcing of LAI values derived from CSK (right side).
By an adequate assimilation of LAI values derived by EO data, the DSS can be run at district levels with a good accuracy in simulating several crops in hundreds of fields, obtaining yield and water indicators useful for yield forecasting and a better distribution of irrigation water.

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