Potentiality of optical and radar satellite data at high spatio-temporal resolutions for the monitoring of irrigated wheat crops in Morocco

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Abstract

The potential of FORMOSAT-2 and ENVISAT/ASAR for the monitoring of irrigated wheat crops over the Tensift/Marrakech semi-arid plain in Morocco is investigated. The green leaf area index (GLAI) was obtained from time series of vegetation index acquired by the FORMOSAT-2 instrument with a 25% accuracy. This information was then incorporated into a canopy functioning model to provide spatial estimates of GLAI, aerial biomass and top-soil moisture. These outputs were evaluated by comparing them to ground data collected on eight wheat fields monitored during the 2005–2006 agricultural season. The model accurately simulates the time courses of GLAI and aerial biomass during the vegetative phase. Finally, we analysed the spatio-temporal variations of ASAR backscattering co-polarization ratio ($\sigma_{HH}/\sigma_{VV}$) as a function of biomass water content on the basis of simulations performed over 69 other wheat fields. The purpose of such analysis is to retrieve this last biophysical variable from ASAR images. The sensitivity of ASAR data to vegetation appears to be deteriorated by the sensitivity of $\sigma_{HH}/\sigma_{VV}$ to the variability of soil conditions encountered in the study area (roughness and moisture).

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1. Introduction

Half of the world food production originates from irrigated and drained soils on about 20% of cultivated lands (e.g. Bastiaanssen et al., 2007). Effective management and monitoring of environmental resources require integrating hydro-ecologic parameters in biophysical modelling. However, although models performances have continuously been improved over the past years, regional applications for the monitoring of water and vegetation are limited (Boote et al., 1996; Moulin et al., 1998). The main reason lies in the shortage of input modelling data over large areas. As a substitute, the scientific community has investigated remotely sensed data to provide spatial estimates of crop yield (Guérit and Duke, 2000; Lobell et al., 2003; Olioso et al., 2005).

Optical data have been used in the context of crop monitoring and management (e.g. Scotford and Miller, 2005), and it appears that simplified model based on vegetation indices can be used to retrieve the plant biophysical variables in an operational way. In contrast, there is still a poor understanding of the radar response of annual crops (Moran et al., 2002). For wheat canopies, the sensitivity of the radar backscattering co-polarization ratio is caused by the differential attenuation of horizontally and vertically polarized electromagnetic waves that propagate through a medium with vertical structure (Bracaglia et al., 1995; Picard et al., 2003). Some attempts at using simplified relationships between ASAR backscattering coefficient and wheat canopy characteristics have been performed (Mattia et al., 2003; Dente et al., 2008). However, a few issues are still to be addressed before the use of radar data in an operational inversion scheme.

The objective of this study is to evaluate the potentialities of optical and radar data for the retrieval of the vegetation characteristics using simple semi-empirical relationships. We performed a comparative analysis using time series of both FORMOSAT-2 and ASAR images for the monitoring of irrigated wheat crops in the semi-arid Tensift/Marrakech area. We first used FORMOSAT-2 images to characterise the spatio-temporal variations of green leaf area index using a vegetation index. In a second step, this information is incorporated into a simple canopy functioning model to provide spatial estimates of aerial biomass and top-soil moisture. These outputs are evaluated by using ground data collected on eight wheat fields. Finally, we capitalize on the knowledge of soil–plant conditions in order to analyze the spatio-temporal variations of ASAR backscattering co-polarization ratio.
2. Materials and methods

2.1. Experimental data set

The experiment was set up during the 2005–2006 agricultural season on an irrigated area located at 40 km East of Marrakech in Morocco (Fig. 1). This area was intensively monitored between 2003 and 2006 to understand the processes that affect the water and energy balances of semi-arid areas at the basin scale (see for example, Duchemin et al., 2006; Hadria et al., 2006, 2007; Chehbouni et al., 2008). It covers about 2800 ha and is almost flat, with deep (~1 m) and rather homogeneous soil with fine texture. Climate is basically of semi-arid type with an annual average rainfall of about 250 mm, whereas the evaporative demand is around 1500 mm per year. The dominant crop is wheat.

The experimental data set includes information on irrigation practices on 69 wheat fields of variables size (from 2 to 6 ha). Amongst them, eight test fields (delineated in red in Fig. 1b and c) were monitored to measure green leaf area index (GLAI) and aerial biomass following the protocols described in Hadria et al. (2006) and Duchemin et al. (2006). The total area of green leaves per area of soil was estimated from allometric and phenological observations (size and number of leaves per stem and plant density) over 3 plots of 1 m × 1 m in each field. Biomass refers to the aerial weight of the plants per square meter. It was measured by destructive measurements on the same plots. The plant water content was derived by comparing fresh and oven-dry biomass. All these measurements were collected at the middle of the agricultural season (from March 20 to March 24, 2006). GLAI ranges from 1.2 to 6.2 m²/m² and dry aerial biomass from 200 to 750 g/m². Soil moisture profiles were measured to 1 m depth on 4 of the 8 fields, using a gravimetric method and 3 or 4 plots per field. Topsoil humidity varied over a wide range between 0.06 and 0.32 m³/m³ since the measurements were performed during an irrigation period. In contrast, wheat plant humidity was found rather stable, varying between 79% and 90% over the 8 test fields, with an average value of 85%.

Standard meteorological data were measured by a standard station located at the centre of the study area (31°86’80”, 7°83’80W) apart from rainfall that was computed from the average of five rain gauges located in the vicinity (less than 10 km). The beginning of the 2005–2006 season was very dry until December 2005 and exceptionally wet in January and February (accumulated rainfall about 160 mm). In addition, daily reference evapotranspiration (ET₀) was calculated according to the FAO-Penman–Monteith equation (Allen, 2000).

2.2. FORMOSAT-2 and ENVISAT ASAR images

The Remote Sensing Instrument (RSI) has been launched on-board FORMOSAT-2 by the National Space Organization of Taiwan (NSPO, http://www.nspo.org.tw/) on May 2004. RSI provides 8-m resolution images in 4 spectral bands (blue: 0.45–0.52 μm, green: 0.52–0.60 μm, red: 0.63–0.69 μm, near-infrared: 0.76–0.90 μm.). The FORMOSAT-2 images used in this study have been acquired during the 2005–2006 season with a nominal time step of 4 days (Duchemin et al., 2008a). Fifty images were acquired from the sowing (November 2005) to the harvesting (June 2006) period, with a constant viewing angle of 18°. The cloud-free images were (1) selected by visual examination; (2) co-registered using a cross-correlation algorithm; (3) geolocated using ground control points (about half pixel accuracy); (4) corrected from atmospheric perturbations (see Hagolle et al., 2008 for details). This processing provided us with 19 images of surface reflectances, from which theRatio Vegetation Index, RVI, were calculated (Jordan, 1969).
The high spatial resolution of FORMOSAT-2 images allowed to determine easily field borders as shown in Fig. 1b.

The Advanced Synthetic Aperture Radar (ASAR), onboard the ENVISAT mission (http://envisat.esa.int/) launched in March 2002, operates at C-band, with 7 different beam modes that feature incidence angles ranging between 15° and 45° at a spatial resolution of about 30 m in the Alternating Polarisation mode (12.5 m pixel size).

The standard beam modes are called IS1, IS2, . . . , IS7. The revisit time for a given configuration is 35 days, but the combination of different incidences allows increasing the repetitivity of observations. Between December 2005 and May 2006, 15 ASAR images were acquired, all in ascending pass. The images were acquired in dual polarisations (VV and HH) at high incidence angles (IS5–IS7, 35.8–45.2° incidence angle), for which the sensitivity to vegetation is known to be maximal since direct return from the canopy exceeds soil return (Brown et al., 2003; Mattia et al., 2003). Radiometric calibration was performed following the procedure specified in Rosich and Meadows (2004) and a spatio-temporal filter was applied to reduce speckle effects (Lopes et al., 1993). Finally, the images were co-registered on FORMOSAT-2 data (about 1 pixel accuracy). Fig. 1c shows an example of ASAR image zoomed on the study area.

2.3. Soil/plant modelling

The simple algorithm for yield estimates (SAFY) (Duchemin et al., 2008b) is a daily time step vegetation model. It simulates the time courses of green leaf area index (GLAI) and the dry aboveground biomass (DAM). Simulations start at an emergence day (D0). Daily DAM production depends on the photosynthetically active portion of solar radiation absorbed by plants as described by the Monteith theory using effective light-use efficiency (ELUE). During the growing period, a fraction of the daily DAM production is dedicated to the daily leaf production following the partition-to-leaf function developed by Maas (1993). Leaf mass is converted to leaf area with the specific leaf area measured at field. Leaf senescence occurs at a prescribed rate when the air temperature accumulated from emergence reaches the senescence temperature threshold (STT). GLAI is updated from the balance of leaf production and senescence. The model only requires climatic forcing variables (daily incoming global radiation and daily average air temperature) and the knowledge of the above cited key parameters (D0, ELUE and STT). These parameters were calibrated by minimizing the difference between simulated GLAI and that derived from FORMOSAT-2 RVI. After this calibration, the SAFY model provided with estimates of GLAI and DAM at a daily time step. The fresh above ground biomass was obtained by multiplying DAM by the average value of plant water content observed at field.

The outputs of SAFY model were used to control the evapotranspiration component of a soil–water balance. The model calculates soil evaporation and plant transpiration using a dual-crop coefficient approach adapted from FAO-56 (Allen, 2000).

Three layers are implemented to describe soil–water transfers: (1) a 5-cm depth top layer; (2) a root zone; (3) a deeper layer, down to 1 m. The soil layers were characterised by their water capacity, which were derived from the difference between humidity at wilting point ($\theta_{wp}$) and at field capacity ($\theta_{fc}$). From field measurements, they were considered constant at an average value of 0.19 m$^3$/m$^3$ ($\theta_{wp}$) and of 0.34 m$^3$/m$^3$ ($\theta_{fc}$).

3. Results and discussion

3.1. Green leaf area index from optical data

A high correlation ($R^2 = 0.77$) was observed between RVI vegetation index and GLAI measured in field at the plot scale (Fig. 2). The relationship between these two indices appears linear. The root mean square error (RMSE) between the GLAI measured at field and that derived from RVI is 0.78 m$^2$/m$^2$ (23% in relative). The scatter in Fig. 2 may be due to: (1) differences in spatial resolution between plot measurements (1 m$^2$) and satellite estimates (footprint of 64 m$^2$); (2) errors in both field measurements and analytical modelling; (3) the sensitivity of reflectances to others variables than GLAI such as the soil characteristics, the stem density or the leaf angle distribution. Nevertheless, the resulting error appears of the same order than that reported in review articles (e.g. Weiss et al., 2004).

3.2. Simulations of soil–plant biophysical variables

The SAFY model is calibrated with time series of field-averaged GLAI values derived from FORMOSAT-2 images (see Sections 2.3 and 3.1). The simulations were performed on the 69 fields where irrigation data are available and evaluated on the 8 test fields where soil–plant variables were measured at ground (Fig. 3 and Table 1). Their analysis showed that:

Table 1

<table>
<thead>
<tr>
<th>Field</th>
<th>Biomass water content (mg/m$^2$)</th>
<th>Topsoil moisture (m$^3$/m$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Observation</td>
<td>Observation</td>
</tr>
<tr>
<td></td>
<td>Model</td>
<td>Min</td>
</tr>
<tr>
<td>1</td>
<td>2.9</td>
<td>2.3</td>
</tr>
<tr>
<td>2</td>
<td>1.2</td>
<td>0.8</td>
</tr>
<tr>
<td>3</td>
<td>2.6</td>
<td>2.1</td>
</tr>
<tr>
<td>4</td>
<td>2.1</td>
<td>2.1</td>
</tr>
<tr>
<td>5</td>
<td>1.6</td>
<td>1.2</td>
</tr>
<tr>
<td>6</td>
<td>1.5</td>
<td>0.9</td>
</tr>
<tr>
<td>7</td>
<td>4.1</td>
<td>4.1</td>
</tr>
<tr>
<td>8</td>
<td>4.7</td>
<td>4.6</td>
</tr>
</tbody>
</table>

Mean    | 2.6   | 1.9 | 2.30 | 2.8 | 17.4 |

Error$^a$ = 100 x (simulation – observation)/observationmean.
(1) The model is an acute interpolator of GLAI, both in time and space. Time series of GLAI estimates are captured by the model with a tight correlation ($R^2 = 0.98$) and low errors (RMSE $< 0.2$ m$^2$/m$^2$). This shows the efficiency of the calibration procedure through variables agronomic conditions (maximum GLAI ranging from 2.8 to 5.8 m$^2$/m$^2$). GLAI simulations are also in a better agreement with field measurements than that resulting from the inversion procedure ($R^2 = 0.86$; RMSE $< 0.25$ m$^2$/m$^2$).

(2) The accuracy of water biomass content simulations appears also good, except for two fields where an important over-estimation (more than 50%) is recorded. On the remaining fields, the error is less than 26%, despite no specific calibration was performed for this variable. The model appears able to track the high spatial variability of wheat water content ($R^2 = 0.81$, for measured values ranging from 1200 to 4800 g/m$^2$).

(3) In contrast, the simulation of topsoil moisture appears less accurate, with error ranging from −43% to 35%. This is not surprising given the various causes of simulation errors (lack of account of soil heterogeneity and inaccuracy on water irrigation date and amount). The distribution of topsoil humidity over the 69 fields of study is used to analyse $\sigma_{HH,VV}^0$ variations as a rough indicator of the moisture spatial heterogeneity.

3.3. Potential of ASAR data for estimating wheat biomass water content

The radar backscattering co-polarization ratio is analyzed as a function of wheat water content and topsoil moisture. We focus on beam mode IS6 but similar conclusions can be drawn from IS5 and IS7. We mixed the data of three images acquired during wheat growing period when green foliage is dominant. The results of this comparison are presented in **Fig. 4.** Topsoil moisture of the 69 studied fields looks rather homogenous for all acquisition dates except for the last one where simulated topsoil moisture varied from 0.07 to 0.34. In such conditions, the variation of radar backscattering co-polarization ratio could be affected principally by vegetation water content and soil roughness.

At the beginning of the agricultural season, the radar backscattering co-polarization ratio ($\sigma_{HH,VV}^0$) varies rapidly from −2 to 2 db. The range of variation is large even when biomass water content is low (<1000 g/m$^2$) and when the top-soil moisture is rather homogeneous. The explanation could be related to surface roughness. Indeed, there are three categories of surface states at this period of year, depending on agricultural practices (Hadria et al., 2009): fields may be ploughed in depth, harrowed (prepared to be sown), or smooth (not ploughed neither harrowed). These conditions result in large variation of surface roughness, with root mean square error of surface height profiles from 0.5 to 6 cm according to the classification of Davidson et al. (2000). For the last acquisition date, we observe a notable stability of backscattering co-polarization ratio even if biomass water content varies largely from 1000 to 6000 g/m$^2$. At this date, the topsoil roughness is low and homogeneous for all fields because of irrigation and rainfall, but there is no clear relationship between $\sigma_{HH,VV}^0$ and biomass water content. As such, the relation between the backscattering co-polarization ratio and biomass water content could be represented by a polynomial function of degree 2 (for IS6: $Y = -1E - 07 \times X^2 + 0.001 \times X - 1.08$; $R^2 = 0.63$). These results contrast with those of Mattia et al. (2003) who find a linear correlation between $\sigma_{HH,VV}^0$ and biomass water content. Nevertheless, their range of biomass values did not exceed 2500 g/m$^2$.

Finally, we attempted at quantifying accuracy the retrieval of wheat aerial biomass water content (BWC) from ASAR images (co-polarization ratio $\sigma_{HH,VV}^0$) using an empirical model. The model, of exponential type $BWC = A \times \exp(B \times \sigma_{HH,VV}^0)$, was chosen after analysing the shape of BWC versus $\sigma_{HH,VV}^0$ scatterplots for the nine images acquired during the growing season from mid-January to mid-April. A and B parameters were calibrated on the data acquired with the same incidence angle (either IS5 or IS6 or IS7, three images each time) using BWC simulated by the SAFY model.

**Fig. 3.** Green leaf area index (GLAI) simulated by the SAFY model (lines), estimated from RVI (stars) and measured at field (vertical bars, which represents the minimal and maximal value over the three 1 m$^2$ plots). The date is given in number of days after November 25. The bottom-right figure shows the scatterplot between model simulations and estimates from RVI.
over the 69 studied fields. The performance of the inversion procedure was quantified by computing the correlation coefficient ($R^2$), the root mean square error (RMSE) and the relative root mean square error (RRMSE) between BWC simulated by the SAFY model and BWC inverted based on the exponential model with co-polarization ratio $\sigma_{\text{HH/VV}}^0$ as an input.

Table 2 summarizes the values of the model parameters ($A$, $B$) and the statistics resulting from the inversion ($R^2$, RMSE, RRMSE) together with extreme and average values of the biomass water content and the topsoil moisture simulated by SAFY model over the 69 studied fields. The large variations of $A$ and $B$ parameters between the difference incidence angles show how the exponential relationship is unstable. The performance of inversion procedure was evaluated either by incidence angle (three images) or by date (one image). In the first case, the relations between BWC and $\sigma_{\text{HH/VV}}^0$ appear significant ($R^2$ from 0.37 to 0.49), but errors in inversion are in the same order of the mean BWC value (RRMSE around 90%). The performance of the inversion procedure appears also generally unsatisfactory when looking at a particular date. The correlation coefficients are null at the beginning of the growing season, though the topsoil moisture appears very homogeneous (see the cases of 14/1/06 and 16/1/06 in Table 2). As discussed before, the high scatter is likely due to differences in soil surface roughness at the beginning of the agricultural season. The saturation of $\sigma_{\text{HH/VV}}^0$ to BWC also limits the accuracy of the inversion after the middle of the growing season (see the cases of 25/3/06, 28/3/06 and 13/4/06 in Table 2). The most significant relations between BWC and $\sigma_{\text{HH/VV}}^0$ appear for intermediate values of BWC and rather wet soils, but errors in inversion are still very large (see the cases of 2/2/06, 18/2/06, 21/2/06 in Table 2, with $R^2$ between 0.48 and 0.72 and RRMSE from 80% to 130%).

4. Conclusions

We used FORMOSAT-2 and ENVISAT/ASAR images to monitor irrigated wheat crop in the Tensift/Marrakech plain in Morocco. The remote sensing data were acquired during the wheat growing season from November 2005 to June 2006. Optical data were first
used to derive GLAI of wheat and to parameterize a simple crop functioning model. The latter simulates aerial biomass and its water content that were then analysed as a function of radar backscattering co-polarization ratio derived from ASAR data.

Optical data allows retrieval of the green leaf area index for wheat at 25% accuracy. The accuracy of the simple functioning model simulations are also comparable to that obtained in many other studies by using more complex models. The empirical analysis of exponential relationships between radar backscattering co-polarization ratio and biomass water content of wheat shows the complexity of the radar response when surface roughness and topsoil moisture is highly variable. In addition, the signal seems to reach a saturation level from intermediate values of biomass water content (about 2000 g/m²). In the best case when topsoil humidity is high and homogeneous after rainy days, the accuracy of the inversion of biomass water content was found around 80% in relative value.

The future works will consist in a modelling study for a more in-depth analysis of the radar response mechanisms and the synergistic use of the radar and optical data in the model through a data assimilation method. The retrieved vegetation characteristics from FORMOSAT-2 will be used as a priori information for the radar model. As such, the radar data would be dedicated to the retrieval of the soil moisture and roughness.

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