

Combined use of optical and radar satellite data for the detection of tillage and irrigation operations: Case study in Central Morocco

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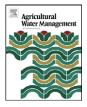
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Combined use of optical and radar satellite data for the detection of tillage and irrigation operations: Case study in Central Morocco

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ABSTRACT

The objective of this study is to present a new application of optical and radar remote sensing with high spatial (\sim 10 m) and temporal (a few days) resolutions for the detection of tillage and irrigation operations. The analysis was performed for irrigated wheat crops in the semi-arid Tensift/Marrakech plain (Central Morocco) using three FORMOSAT-2 images and two ASAR images acquired within one week at the beginning of the 2005/2006 agricultural season.

The approach we developed uses simple mapping algorithms (band thresholding and decision tree) for the characterisation of soil surface states. The first images acquired by FORMOSAT and ASAR were processed to classify fields into three main categories: ploughed (in depth), prepared to be sown (harrowed), and not ploughed-not harrowed. This information was combined with a change detection analysis based on multitemporal images to identify harrowing and irrigation operations which occurred between two satellite observations.

The performance of the algorithm was evaluated using data related to land use and agricultural practices collected on 124 fields. The analysis shows that drastic changes of surface states caused by ploughing or irrigation are detected without ambiguity (consistency index of 96%). This study provided evidence that optical and radar data contain complementary information for the detection of agricultural operations at the beginning of agricultural season. This information could be useful in regional decision support systems to refine crop calendars and to improve prediction of crop water needs over large areas. © 2009 Published by Elsevier B.V.

1. Introduction

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9 Half of the world food production originates from irrigated and 10 drained soils (Bastiaanssen et al., 2007), and the monitoring of soil 11 management practices is of prime importance in agri-environ-12 mental sciences. Tillage operations affect many biophysical 13 processes such as soil erosion, leaching, run-off and infiltration, 14 nutrient uptake, or carbon sequestration, as well as water and CO₂ 15 exchanges (Guérif et al., 2001; Conant et al., in press; Lobb et al., 16 2007). On short- and mid-term concerns, mechanized soil 17 preparation influences the fragmentation and location of crop Q1 residues (Guerif et al. 2001) as well as the soil infiltration capacity 18 19 and thermo-hydric properties (Xu and Mermoud, 2003; Chahinian 20 et al., 2006). As a result, tillage has many roles in soil water balance 21 and crop production (Ogban and Babalola, 2002; Aboudrare et al., 22 2006; Jin et al., 2007). This is particularly true in semi-arid regions 23 as tillage operations affect soil evaporation and water use

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efficiency (Mrabet, 2000; Aboudrare et al., 2006; Casa and Lo 24 Cascio, 2008). 25

26 Sustainable management of agricultural and water resources requires to perform accurate simulations with crop-water balance 27 coupled models at a regional scale. However, shortage of 28 29 geolocated data on agricultural practices limits the operational use of crop models over large areas (Boote et al., 1996; Moulin 30 et al., 1998; Faivre et al., 2004; Bastiaanssen et al., 2007). An 31 alternative approach may consist in using remote sensing data to 32 detect changes in soil surface states and relate them to agricultural 33 operations. 34

In the optical domain, it is known from the early seventies that 35 top-soil water causes a general decrease of surface reflectance 36 (Skidmore et al., 1975; Muller and Décamps, 2000; Lobell and 37 Asner, 2002). As well, the increase of surface roughness causes 38 shadowing and a subsequent reduction of reflectances depending 39 on illumination and viewing measurement conditions (Cier-40 niewski, 1989; Jacquemoud et al., 1992). In addition, many 41 properties affect soil spectra, e.g. mineral composition, amount 42 of organic matter, particle size distribution, presence of crusts 43 (Jacquemoud et al., 1992; Mathieu et al., 1998; Nagler et al., 2000; 44

Chappell et al., 2006). However, these last properties experience a
much lower spatio-temporal variability than surface roughness
and topsoil moisture.

48 Synthetic Aperture Radar (SAR) imagery is known to be 49 governed by two key parameters: surface roughness and soil 50 dielectric constant, the latter being linked to soil moisture (e.g. 51 Ulaby et al., 1986; Beaudoin et al., 1990; Fung et al., 1992; 52 Benallegue et al., 1995; Davidson et al., 2000; Zribi et al., 2005). The 53 general trends of the radar response as a function of both these 54 surface parameters and the sensor characteristics (frequency, 55 incidence, polarisation) are well captured by backscatter models, 56 but the operational applicability of inversion schemes is still challenging. The explanation is twofold: (1) land surfaces are 57 58 complex and it is difficult to estimate appropriate roughness 59 parameters (Davidson et al., 2000), (2) the relative impact of 60 surface roughness, top-soil moisture and vegetation canopies is 61 hard to decouple (Wagner et al., 1999; Satalino et al., 2003).

62 Given the sensitivity of optical and radar data to surface 63 roughness and topsoil moisture, the recent design of satellite 64 sensors providing both high spatial resolution (~10 m) and 65 frequent revisit time (a few days) may offer interesting perspec-66 tives. This is the case of: (1) the FORMOSAT-2 satellite (http:// 67 www.nspo.org.tw), launched in May 2004, which can observe a particular area every day at 8 m spatial resolution in the 68 69 multispectral mode; (2) the Advanced Synthetic Aperture Radar 70 (ASAR) onboard the ENVISAT mission (http://envisat.esa.int/), 71 which provide images at a spatial resolution of about 30 m in the 72 Alternating Polarisation mode. The orbital cycle of ENVISAT/ASAR 73 is 35 days, but the revisit time is a few days when acquisitions with 74 different sun-target-sensor geometry are combined.

75 In Duchemin et al. (2008a), we have illustrated how some 76 agricultural operations (disking, harrowing, irrigation) cause 77 rapid changes in surface reflectances derived from time series of 78 FORMOSAT images. In this study, the objective is to apply 79 mapping algorithms on both FORMOSAT and ENVISAT/ASAR data 80 for the detection of these agricultural operations over a short 81 period of time. The analysis was performed for an irrigated area 82 located in the semi-arid Tensift/Marrakech plain - Central 83 Morocco – where wheat crops are dominant. We used three 84 FORMOSAT images and two ASAR images acquired within one 85 week at the beginning of the 2005-2006 wheat cropping season. 86 After the presentation of this material (Section 2), we successively 87 discussed (Sections 3-5) the methods and results in relation to 88 three questions: (1) How to identify tillage practices using the 89 first satellite observations? (2) How to monitor harrowing and 90 irrigation operations between two successive observations ? and 91 (3) How to map soil management practices by combining the 92 previous results? Conclusions and perspectives were then drawn in Section 6. 93

94 2. Material

95 2.1. Remote sensing data and processing

96 The FORMOSAT-2 Taiwanese satellite was launched in May 97 2004. The Remote Sensing Instrument (RSI) onboard FORMOSAT-2 98 provides high spatial resolution images (8 m in the multispectral 99 mode at nadir viewing) in four narrow spectral bands ranging from 100 $0.45 \,\mu\text{m}$ to $0.90 \,\mu\text{m}$ (blue, green, red and near-infrared). Unlike 101 other systems operating at high spatial resolution, FORMOSAT-2 may observe a particular area every day with the same viewing 102 103 angle. However, only a part - about the half - of the Earth may be 104 observed. More details about the specific orbital cycle and other 105 characteristics of the FORMOSAT-2 mission could be found in 106 Chern et al. (2006, 2008) as well as on internet (http:// 107 www.nspo.org.tw, http://www.spot-image.com).

We used three FORMOSAT images as part of a time series 108 collected in the semi-arid Tensift/Marrakech plain in Morocco 109 (Duchemin et al., 2008a). They were acquired at the beginning of 110 the wheat cropping season $\overline{1}$ December 8, 12 and 16, 2005, 111 around 10:30 GMT _ with a nearly constant sun-target-sensor 112 configuration (viewing angle of 18.5°, solar elevation of about 113 35°). The images were georeferenced using an autocorrelation 114 algorithm and a set of ground control points collected with GPS. 115 Accuracy in geolocalisation was estimated to about half-pixel 116 (4 m). The atmospheric correction was performed using the 117 SMAC code (Rahman and Dedieu, 1994) with atmospheric water 118 vapour content and aerosol optical depth collected by CIMEL 119 sunphotometers installed in the vicinity of the study area. The 120 quality of atmospheric correction is discussed in Hagolle et al. 121 (2008).122

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The Advanced Synthetic Aperture Radar (ASAR), onboard the ENVISAT mission (http://envisat.esa.int/) launched in March 2002, operates at C-band (frequency 5.33 GHz, wavelength 5.6 cm) with 7 different incidence angles between 15° and 45°. The orbital cycle of ENVISAT/ASAR is 35 days, but the combination of different illumination/viewing configurations allows to increase the repetitivity of observations (e.g. 10 passes during the 35-day orbital cycle at 45° latitude). Between December 2005 and June 2006, 16 ASAR Alternating Polarisation images were collected, all in ascending pass and at high incidence angles (IS5 to IS7). The images were acquired in vertical and horizontal polarisations (VV and HH) at a spatial resolution of about 30 m. Radiometric calibration was performed following the procedure specified by the European Space Agency (Rosich and Meadows, 2004). All the images were superimposed using an automatic correlation algorithm based on contrasted objects visible in the images. After superimposition, a spatio-temporal filter was applied to reduce speckle effects. The filter is described in Lopes et al. (1993), Le Toan et al. (1997), and Quegan and Yu (2001).

After this pre-processing, we selected the two ASAR images collected at the beginning of the wheat cropping season, December 10 and 13, 2005, acquired with 35.8° and 45.2° incidence angle, respectively. These two ASAR images were coregistered on FORMOSAT data using image-to-image correction (ENVI software, ©ITT Visual Information Solutions). Accuracy in coregistration was estimated to about 1 pixel (12.5 m).

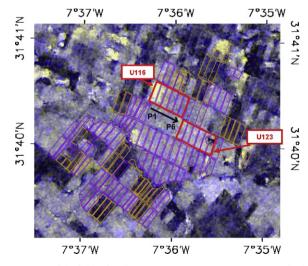


Fig. 1. Location of the fields of study on an ASAR composite image (image of 13/12 in Q5 red and green, image of 10/12 in blue). Wheat and non-cultivated fields are delineated by magenta and orange lines, respectively. Magenta lines show two particular irrigation units, with the field numbering direction indicated by the arrow. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

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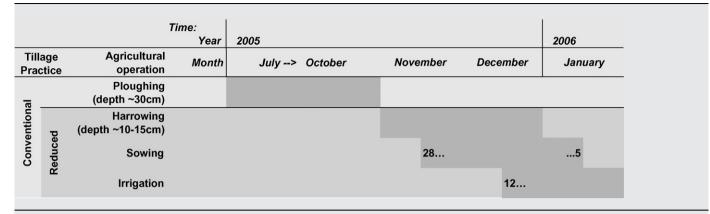
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Table 1

Timing of successive agricultural operations for wheat fields under conventional and reduced tillage. Starting and/or ending day is indicated when known.



149 2.2. Experimental set up

The experiment was set up during the 2005–2006 wheat agricultural season on an irrigated area located at 40 km East of Marrakech. This area was intensively monitored as part of the SUDMED program (Chehbouni et al., in press; Duchemin et al., 2006, 2008a,b; Hadria et al., 2006, 2007; Er-Raki et al., 2007). It covers about 2800 ha and is almost flat (slope less than 1%), with deep soil of xerosol type and a fine, clay to loamy, texture.

157 Land-use information and soil management practices were 158 collected on 124 fields within the study area. The fields were 159 delineated by digitizing the FORMOSAT images, and, after the 160 filtering procedure, they can be easily identified on ASAR images 161 (Fig. 1). Amongst these fields, about the quarter (35) was not 162 cultivated. The remaining fields were cultivated with wheat under 163 conventional or reduced tillage practices on 64 and 25 fields, 164 respectively.

165 Table 1 presents the timing of the successive soil management 166 operations associated to conventional tillage (CT) and reduced 167 tillage (RT). In the first case, the soil is ploughed to a depth of 30-168 40 cm immediately or few weeks after harvest (July to October). In 169 both cases (CT and RT), the soil is harrowed to a depth of 10-15 cm 170 a few days or just before the sowing (November to December) in 171 order to level the surface and to prepare seedbed. In what follows 172 these two operations are referred to as ploughing and harrowing, 173 respectively. Finally, wheat seeds are placed using a conventional 174 planter with a seeding rate ranging from 100 to 150 kg/ha (Hadria 175 et al., 2007). Sowing dates ranged between November 28, 2005 and 176 January 05, 2006. The fields were not flattened with a roller after 177 sowing and there was no significant difference in soil surface states 178 between harrowed and sown fields.

179 The study area is subdivided in many irrigation units that 180 consist of an average of six fields of 4 ha (e.g. units 116 and 123 in Fig. 1). Irrigation is of flooding type, with the water provided by the 181 182 regional public agency in charge of dam water management 183 (ORMVAH). Irrigation water is supplied to the fields through an 184 aerial network of concrete channels. About 3 weeks are required to 185 irrigate the whole area. In 2005, the first irrigation round started on 186 December 12 (see Table 1).

Climate is basically of semi-arid continental type. Climatic data 187 188 were provided by a meteorological station installed at the center of 189 the study area (near irrigation unit 116, see Fig. 1), and five rain 190 gauges of the ORMVAH network located in the vicinity of the study 191 area. According to these data, the beginning of the 2005-2006 192 agricultural season was very dry. Two minor rainfall events (10-193 15 mm) occurred mid- and end-November, after which no rain was 194 recorded until December 21. As a consequence, the soil moisture 195 was low, except in case of irrigation. Soil water content was measured using a gravimetric method on eight fields (3-5 samples 196 by field) between November 26 and December 20. Soil moisture 197 ranged from 0.04 to 0.09 m^3/m^3 in the top layer (0–3 cm), and from 198 0.07 to $0.19 \text{ m}^3/\text{m}^3$ in the 3–15 cm layer. Given the clay-loamy 199 texture of soils, these values indicate very dry surfaces. Another 200 consequence of this drought is that plant emergence was delayed. 201 This year, emergence mainly occurred after the first effective 202 rainfall at the end of December (see Duchemin et al., 2008b). 203

3. Characterisation of initial soil state identification of tillage 204 practices 205

The optical and radar responses were first analysed from the 206 207 two first images, i.e. the FORMOSAT image acquired on December 8 and the ASAR image acquired on December 10, both before the first 208 irrigation round. The average values of surface reflectances (ρ) and 209 backscattering coefficient (σ^0) were computed over all the fields of 210 study. The detection of surface states was thus investigated at the 211 field scale, without accounting for the intra-field variability. We 212 restricted the analysis to the fields with a minimum size of 1.6 ha; 213 this corresponds to about 100 ASAR pixels, resulting in an accuracy 214 on σ^0 of 0.3 dB at 90% of confidence interval. 215

Fields were distinguished using four categories: (1) non-216 cultivated; (2) already¹ sown, thus harrowed; (3) not yet¹ harrowed 217 - Conventional Tillage (ploughed); (4) not yet¹ harrowed - Reduced 218 Tillage (not ploughed). The two first categories were directly 219 extracted from the field database, while we retained the fields that 220 were sown the latest (from December 27, 2005 to January 5, 2006) to 221 222 define the two last categories. These categories are associated to different surface roughness (see Davidson et al., 2000 for a statistical 223 study), and three distinctive groups of fields were discriminated in 224 order to analyse the radar and optical responses: 225 226

- 1) Group P Ploughed fields corresponding to the 3rd category.
- 2) Group H Harrowed fields corresponding to the 2nd category.
- Group NP/NH Nor Ploughed/Neither Harrowed fields which encompasses the 1st and 4th categories.

Fig. 2 shows the comparison between field-averaged reflectances23B $(\rho_{\rm NIR}, FORMOSAT$ observations) and backscattering coefficients233 $(\sigma_{\rm VV}^0, ASAR$ observations). The dynamic ranges of satellite observations were the largest for the near infrared (NIR) waveband and the238vertical (VV) polarisation, but additional plots obtained with other240FORMOSAT spectral bands and with backscattering coefficient in241horizontal polarisation look quite similar (not shown here).242

 $^{^{1}}$ The terms 'not yet' and 'already' are relative to the time of acquisition of the images.

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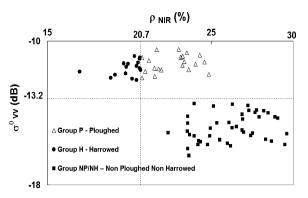


Fig. 2. Scatterplot of ASAR backscattering coefficient in VV polarisation (σ_{VV}^0 , December 10) versus FORMOSAT near infrared reflectances (ρ_{NIR} , December 8) for the three categories of surface states. The values correspond to field averages. Dotted lines indicate the cluster boundaries used to classify soil surface states.

242 In Fig. 2, it can be seen that the NIR reflectances vary from about 243 15 to 30%, with a clear differences between smooth surfaces (group 244 NP/NH, $\rho_{\text{NIR}} > 22.5\%$) and sown fields (group H, $\rho_{\text{NIR}} < 20.7\%$), 245 while intermediate values are observed for the ploughed fields 246 (group P, ρ_{NIR} between 20.8% and 25%). There is not the same 247 hierarchy between these levels of reflectances and the ranges of 248 roughness established by Davidson et al. (2000). It can be 249 understood that recently harrowed fields display more shadows 250 (sharp clods without crusts) and higher topsoil moisture than old 251 ploughed fields that were smoothed by wind erosion, crusting and drying. As a consequence, there are overlaps in the reflectances 252 253 between ploughed and non-cultivated fields.

254 In contrast, the ASAR backscattering coefficient appears very 255 sensitive to surface roughness, whatever its origin, i.e. recent 256 harrowing or older ploughing (Fig. 2). σ_{VV}^0 ranges between -16.4 dB and -13.5 dB for the group NP/NH (smooth surfaces), 257 258 whereas it is always higher than -12.2 dB for both group P and H (rough surfaces).² It can be observed that the gap in σ_{vv}^0 values 259 between the two groups is much larger than the uncertainty on σ_{VV}^0 260 (0.3 dB). However, it appears impossible to separate ploughed 261 262 fields from harrowed fields. The explanation lies in the saturation 263 of the radar response to surface roughness (see Ulaby et al., 1986; 264 Altesse et al., 1996; Zribi et al., 2005).

265 Finally, one can notice the complementarity of FORMOSAT and 266 ASAR observations: reflectances allow to clearly identify fields of 267 group H (red circles in Fig. 2), while backscattering coefficients 268 allows to separate those of group NP/NH (brown squares in Fig. 2). 269 By crossing optical and radar observations, it is thus possible to 270 discriminate the three groups (NP/NH, H and P) without ambiguity. 271 We used simple band thresholding (20.7% on $\rho_{\rm NIR}$ and -13.2 dB on 272 $\sigma_{\rm VV}^0$) as a clustering procedure to obtain the three following 273 classes:

275 (1) harrowed fields, with high backscattering coefficients and low reflectances;

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279 (2) ploughed fields, with both high reflectances and backscattering coefficients;

289 (3) not ploughed-not harrowed fields, with high reflectances and low backscattering coefficients, non-cultivated areas being included in this last category.
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This clustering was applied to obtain a complete map of initial
soil surface states over the fields of study. The fields that were not
used to analyse satellite data in Fig. 2 were all classified as

harrowed or ploughed on December 10. This appears in agreement289with their sowing dates recorded from field survey, which ranged290from December 13 to 26.291

4. Change detection—identification of ploughing and irrigation practices

Time series of field-averaged near infrared reflectances (ρ_{NIR} from FORMOSAT, December 8, 12 and 16, constant sun-targetsensor geometry) and backscattering coefficients (σ_{VV}^0 from ASAR, December 10 and 13, with two different incidence angles) were analysed on several particular fields for which the timing and the nature of agricultural operations were accurately collected. Fig. 3a–f shows three typical cases of ρ_{NIR} and σ_{VV}^0 time courses on fields where no change, harrowing or irrigation occurred.

4.1. Stable surfaces

Fig. 3a and b display four fields where no changes were observed between the first and the last satellite observations. ρ_{NIR} remains quite stable around a value that depends on the initial surface state, with a slight positive slope of about 3% in relative value (Fig. 3a). The slight increase of reflectances can be due to residual error in atmospheric correction, the small decrease of sun elevations between December 8 and 16, or a trend of the surface to become smoother (erosion) and/or dryer (last rainfall observed on November 30).

In contrast of reflectances, there is a general decrease of backscattering coefficients from December 10 to 13 (Fig. 3b),³ due to the increase of ASAR incidence angle from IS5 to IS7 configuration. The level of σ_{VV}^0 appears governed by surface roughness, though quite the same for old ploughed and recently harrowed fields. The decrease of σ_{VV}^0 with incidence angle appears similar for both smooth and rough surfaces (around -1.7 dB). This appears promising in the perspective to normalise ASAR images acquired in different geometric configurations.

4.2. Harrowing

Fig. 3c and d present five fields that were harrowed between December 8 and 16. Looking at ρ_{NIR} and σ_{VV}^0 time courses on the three adjacent fields within irrigation unit 123 (full lines in Fig. 3c and d) is very instructive. Indeed, a visual examination of the second FORMOSAT image acquired on December 12 allows to verify that the farmer was harrowing the p2 field⁴ at the exact time of the satellite overpass; more precisely, the p3 field⁴ was already totally harrowed, about two-thirds of the p2 field was harrowed, while the p1 field was not yet harrowed. This is consistent with the time courses of near infrared reflectances (Fig. 3c): ρ_{NIR} displays a continuous decrease of reflectances between December 8 and 16 on the p2 field while the decrease is more obvious and limited in time, either between December 8 and 12 (p3 field, harrowed before the second FORMOSAT overpass) or between December 12 to 16 (p1 field, harrowed after the second FORMOSAT overpass). In contrast, the temporal variation of $\sigma_{
m VV}^0$ (Fig. 3d) appears the same as those of stable areas, even for p2 field that was harrowed on December 12 between the two ASAR acquisitions. This is due to the fact that these fields were ploughed in depth before being harrowed (conventional tillage).

Looking at ρ_{NIR} and σ_{VV}^0 time courses on the two remaining fields (irrigation unit 20, dotted lines in Fig. 3c and d) confirmed that both ASAR and FORMOSAT offer the possibility to detect

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² These two ranges of backscattering coefficients clearly appear in ASAR images (compare in Fig. 1 the brightness between wheat fields and non-cultivated areas).

 $^{^{3}\,}$ This decrease also explains the general blue colour in the time composite image presented in Fig. 1.

⁴ These fields are located in Fig. 1.

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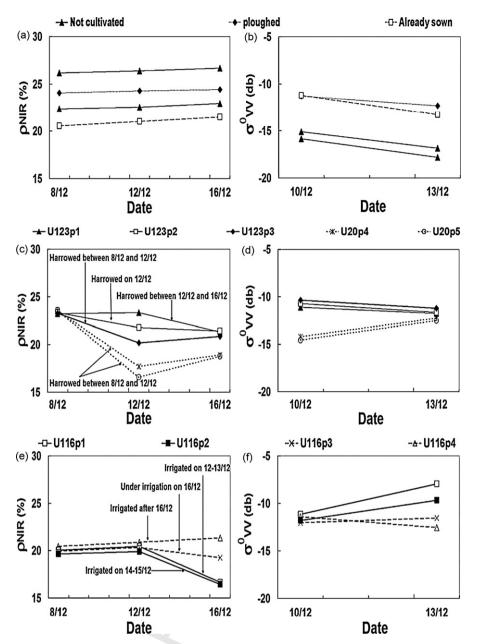


Fig. 3. Time courses of field-averaged reflectances (ρ_{NIR} , December 8–16: subparts a, c and e) and backscattering coefficients (σ_{VV}^0 , December 10–13, 2005: subparts b, d and f) over particular fields with different land use and agricultural operations. The legend indicates soil surface state (subparts a and b) and field number/irrigation unit (subparts c-f).

345 harrowing on the fields cultivated with reduced tillage practices. 346 These fields were not ploughed before being harrowed, and there is 347 a sharp increase of σ_{VV}^0 between December 10 and 13, which 348 contrasts with the general decreasing trend. This atypical 349 behaviour is caused by the increase of surface roughness after 350 harrowing. For these two fields, it is thus possible to use both radar 351 and optical images to date the harrowing between December 10 352 (ASAR first acquisition) and 12 (FORMOSAT second acquisition).

353 4.3. Irrigation

In Fig. 3e and f, the time courses of near infrared reflectances
and backscattering coefficients are plotted for four fields where
irrigation occurred before December 16. These fields, which belong
to irrigation unit 116, were all sown around December 1. The field
database also indicates that the whole irrigation of unit 116 (6
fields, see Fig. 1) was achieved in nine days, between December 12

and 20, starting by p1 field. These irrigations can be clearly 360 detected by a drop of ρ_{NIR} between December 12 and 16 and a rise 361 of σ_{VV}^0 between December 10 and 13. This is not surprising since 362 irrigation results in both an increase of topsoil moisture and a 363 decrease of surface roughness (water erosion). 364

However, the schedule deduced from the two types of images 365 appears somewhat inconsistent. Looking at FORMOSAT images and 366 $\rho_{\rm NIR}$ time courses (Fig. 3e) allowed to state that: (a) p1 and p2 fields 367 were irrigated between December 12 and 16; (b) p3 field was 368 under irrigation at the exact time of satellite overpass, on 369 December 16; (c) the p4 field was not yet irrigated on December 370 16. This is consistent with the information recorded by field 371 survey: two fields and half were irrigated in less than four days; 372 this duration is coherent with the period of nine days needed to 373 irrigate the six fields of the irrigation unit. On the other hand, σ_{VV}^0 374 increases on the p1 field, the p2 field and, though on a less extent, 375 on the p3 field (Fig. 3f). This seems to indicate that these three 376

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377 fields were irrigated before December 13, in contradiction with the 378 previous statements on irrigation duration. This anomaly is 379 the result of the filtering applied on radar data, which is based 380 on the assumption of surface stability on a spatial neighbouring (11 381 pixels, about 140 m). It appears that fields with low σ_{VV}^0 in the 382 surroundings of fields with large $\sigma_{\rm VV}^0$ appeared contaminated, and 383 their backscattering coefficients were overestimated. This con-384 tamination is noticeable around irrigation unit 116 in field p1 as 385 well as in some other parts of the study area (e.g. nearby the two 386 northern studied fields or at the eastern part of the study area, see 387 Fig. 1). In patchy agricultural landscapes, it may be more 388 appropriate to incorporate the actual delimitation of fields during 389 the processing scheme of radar data.

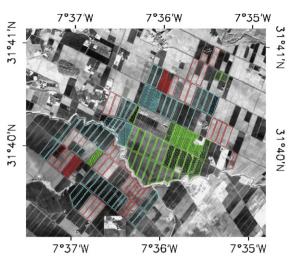
390 5. Mapping of soil management practices: algorithms and 391 results

392 The final algorithm is a decision tree that integrates the *a priori* 393 knowledge on schedules of agricultural operations (Section 2.2), 394 the map of initial soil surface states (Section 3), and two additional 395 rules derived from the change detection analysis (Section 4). These 396 rules are applied on the successive satellite observations: a 397 decrease of near infrared reflectances, by more than 1% in relative 398 value, as well as an increase of backscattering coefficients, 399 indicates either harrowing or irrigation. Initial surface states 400 provide the three main branches at the basis of the decision tree, 401 which operates as follows: 402

- 403 (1) On "not ploughed-not harrowed" fields: a change indicates that 404 harrowing occurred, and the combination of ASAR and 406 FORMOSAT images allows an optimal dating of the operation. (2) On "ploughed-not harrowed" fields: a change is also a harrow,
- 408 409 but it can only be detected on FORMOSAT images. 400
- (3) On harrowed fields, a change indicates that irrigation occurred, 409 and both ASAR and FORMOSAT can be used to detect this 410 operation, provided the pre-processing of radar data was 41452637 improved.

The decision tree was applied to time series of field-averaged $\rho_{\rm NIR}$ and $\sigma_{\rm VV}^0$ acquired between December 8 and 16. It provided a map containing the initial surface states and, if a change is 419 detected, both the type of agricultural operation and the period of 420 its occurrence (Fig. 4). This map was evaluated against the field data collected on the study area (Tables 2 and 3). This analysis confirmed the performance of the algorithm:

- 424 All the changes identified from ASAR images, between December 425 10 and 13, were also identified with FORMOSAT, either between 426 December 8 and 12 or between December 12 and 16. 427
- No change was detected on non-cultivated fields (compare red 428 empty polygons in Fig. 4 and orange polygons in Fig. 1,) 429
- There was only one field for which a harrowing is detected after 430 the sowing date declared in the database (Table 2, consistency 431 index of 97%). Amongst wheat fields included in the 'not 432 ploughed-not harrowed' category, the sowing dates of the four 433 fields where a harrowing was identified between December 10 434 and 12 (red dashed polygones in Fig. 4) ranged between 435 December 10 and 14, the – single – field where a change was 436 identified between December 13 and 16 (red dotted polygone in 437 Fig. 4) was declared sown on December 14, and no change was 438 detected on the remaining three fields that were declared sown 439 after December 16. 440
- Irrigation was detected on the 6 fields that were sown the earliest 441 (between November 28 and December 6). These 6 fields were 442 recorded as irrigated between December 12 and 16, except one 443 for which the irrigation date was December 18 in the database 444



Initial State —	Change detection		Plots	
	Period	Туре	number	Legend
Not ploughed- Not harrowed	10-12		4	
	13-16	Harrow	1	
	None		38	
Ploughed	8-12	Harrow	6	
	12-16	Hallow	9	
	None		16	
Harrowed	12-13		4	
	13-16	irrigation	2	
	None		44	

Fig. 4. Map of agricultural practices over the study area. The legend indicates the initial soil surface state (first column) as well as the period and type of agricultural operations that occurred between December 8 and 16, 2005 (second main column).

Table 2

Evaluation of harrowing detection results from field observation data. Consistency index corresponds to the number of fields for which the detection is consistent with the observation (in percentage).

Detected harrowing period	Fields	Observed	Consistency
	number	sowing period	index
Before 08/12	16	24/12-5/01	100%
08/12-12/12	6	26/12-31/12	100%
10/12-12/12	4	10/12-14/12	100%
12/12-16/12	9	13/12-31/12	100%
13/12-16/12	1	14/12	100%
After 16/12	3	14/12-27/12	66%

(Table 3, consistency index of 83%). Conversely, the fields where no irrigation was detected were all declared irrigated after December 20. These findings appear satisfactory with regard to the accuracy of the field survey.

Table 3

Evaluation of irrigation detection results from field observation data. Consistency index corresponds to the same as in Table 2.

Detected irrigation	Fields	Observed	Consistency
period	number	sowing period	index
13/12–16/12	2	4/12-6/12	100%
12/12–13/12	4	1/12-13/12	75%

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453 **6. Conclusions and perspectives**

454 In this study, we aimed at demonstrating the feasibility to 455 detect tillage and irrigation operations using optical and radar 456 satellite data with high spatial resolution (\sim 10 m) and temporal 457 repetitiveness (a few days). The demonstration was performed 458 using five images (three from FORMOSAT and two from ASAR) 459 acquired within one week at the beginning of the wheat cropping 460 season in the semi-arid Marrakech/Tensift plain. Simple mapping 461 algorithms, i.e. band thresholding and decision tree, were applied 462 on these images with two objectives: (1) classify soil surface states 463 in relation with land cover and tillage practices and (2) detect the 464 agricultural operations that occurred during the week of study.

465 FORMOSAT and ASAR images were found complementary to 466 classify soil surface states. On one hand, it was shown that recently 467 harrowed fields can be discriminated from ploughed fields on 468 FORMOSAT images. On the other hand, the high sensitivity of ASAR 469 data to surface roughness was useful to distinguish smooth surfaces (non-cultivated areas or wheat fields not prepared for sowing) from 470 471 others (ploughed or recently harrowed fields). In this experiment, 472 there was thus a noticeable complementarity of the two sensors, 473 beyond the increase of the temporal density of observations.

474 The most innovative part of this research concerns the 475 detection of the agricultural operations that occurred during one 476 week. There is a general stability of FORMOSAT successive 477 observations due to constant viewing angles. This allowed to fully 478 take advantage of the sensitivity of reflectances to soil surface 479 states. In contrast, the use of ASAR data is less trivial due to the 480 variation of the sun-target-sensor geometry from the first 481 observation to the second, the saturation of the radar response 482 to surface roughness and the high heterogeneity of the area of 483 study. Nevertheless, large spatial variations of reflectances and 484 backscattering coefficients were observed, even between fields belonging to the same category of surface roughness/soil manage-485 486 ment practices. Despite this variability, drastic changes caused by 487 ploughing or irrigation were identified without ambiguity and 488 with accuracy in their timing.

The conditions prevailing during the experiment were optimal:
no clouds, low and uniform soil moisture, and absence of
vegetation. Rain events, resulting in a uniform variation of satellite
observations (drop of reflectances and rise of backscattering
coefficients), are obviously one of the main limitation of such
change detection analysis.

495 Besides this limitation, which is not often encountered in semi-496 arid areas, one major interest of our approach is the possibility to 497 monitor agricultural operations at the beginning of the agricultural 498 season. The perspectives concern real-time updating of land use 499 maps (proportion of cultivated land, distribution of sowing dates, 500 ...). This appears promising to establish prior estimates of seasonal 501 crop water needs and to refine irrigation planning. The approach 502 could be incorporated in decision support systems in agricultural 503 Q2 water management and planning at a regional scale (see for 504 instance Leenhardt et al., 2004; Satti and Jacobs, 2004; Simon-505 neaux et al., 2007).

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