Land use and crop evapotranspiration in Tensift/Marrakech plain: inter-annual analysis based on MODIS satellite data

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Abstract

In this study, we aim at monitoring the water balance over the semi-arid plain of Tensift/Marrakech, a 2000 km² intensively cropped area in center of Morocco. This requires firstly to map the land use, secondly to monitor the vegetation dynamics, and thirdly to evaluate evapotranspiration, which is the key-variable of water balance in semi-arid plains. In this context, we investigate the potential offered by Terra-MODIS satellite, which provide a costless daily global coverage of the Earth. We use a six-year archive of 16-day composite NDVI images from 2000-2001 to 2005-2006 agricultural seasons. However, the use of medium (250 m) spatial resolution data makes difficult to directly monitor land surfaces. Indeed, each pixel (mixed pixel) generally includes different types of surface, and consequently its spectral response results from the contribution of each land classes.

In a first phase, the land use and the vegetation dynamics are retrieved using linear unmixing model applied on NDVI time series. Identification of end-members, i.e. the specific NDVI time course of individual land classes, is based on the assumption that pure pixels can be identified directly from MODIS NDVI images. The approach is set up to map the land use fractions of the three classes that are the most important for agricultural water management in the study area (non cultivated areas, orchards, annual crops).

In a second phase, the information on land use and vegetation dynamics is used to estimate evapotranspiration. The method is adapted from the FAO-56 algorithm, which computes crop water needs from a reference evapotranspiration (ETo) and cultural crops coefficients (Kc). ETo is calculated by applying spatial interpolation of the meterorological data available in the study area. The crop coefficients, which vary according to the crop type, phenological stage and soil water content, are retrieved for each land classes according to their NDVI time courses using various scenarii of irrigation. The spatio-temporal patterns of evapotranspiration maps are analysed to regional driving variables (climate and water availability).

1. Introduction

Changes in Land Use and Land Cover (LULC) is a major question in Environmental Science, related to climate change, carbon cycle and biodiversity (Aspinall and Justice 2003; Lepers *et al.* 2005). Agricultural water management is also a key issue to ensure sustainable development, especially in semi-arid regions. In southern Mediterranean countries, the quantity of irrigation water represents a large proportion of total water use, up to 90% (*FAO 2005. Irrigation in Africa in figures. AQUASTAT Survey*). These regions are characterized by a strong increasing demand in contrast of the scarcity of available water resources. There is thus a crucial need to develop tools for quantifying land use as well as agricultural and water resources at a regional scale. This is one of the primary objectives of the SudMed project (Chehbouni *et al.* 2008), which is the frame of this study. In this context, we are interested in soil-plant evapotranspiration, which is the key-variable of water balance in semi-arid plains.

Remote sensing is well-suited to achieve regional monitoring since it allows observations regularly distributed in space and time. Multi-temporal images are widely investigated for the mapping of land-use and evapotranspiration. At the present time, time series of images can be obtained at a high spatial resolution by programming a series of SPOT or FORMOSAT-2 acquisitions. These images with both high spatial resolution (~10 m) and high temporal repetitivity (a few days) offer strong opportunities to monitor the dynamics of land surfaces over small areas: 25x25 km² for FORMOSAT-2, 60x60 km² for SPOT. However, constraints related to acquisition, cost and processing often prevent the use of high spatial resolution data. Multi-temporal data acquired by low or moderate spatial resolution sensors such as SPOT-VEGETATION or TERRA-MODIS are thus preferred for regional and continental studies (e.g. Hansen *et al.* 2000, Lunetta et al. 2006, Benhadj *et al.* 2008). Indeed, they offer a costless global coverage of the Earth on a daily basis. However, the spatial resolution of large field of views sensors – from 250m for MODIS (Salomonson *et al.* 1989) to 1 km for VEGETATION (Maisongrande *et al.* 2004) – is generally much higher than the size of homogeneous areas (units) at the Earth surfaces. These sensors provide image with pixels that most of times include a mixture of different units (mixed pixel). Consequently, the use of low spatial resolution data for a directly monitoring of LULC is not straightforward. Furthermore, conventional classification approaches based on signature clustering (like maximum likelihood) are not suitable since they aim to label each pixel with one single class.

For these reasons, the linear unmixing model has been developed based on the following assumption: the signature of a mixed pixel results from a linear combination of the distinctive signatures (endmembers) that are representative of the various land surfaces included in the study area. These typical signatures must describe as well as possible a pure component having meaningful features for an observer (Strahler *et al.* 1986). Knowing these signatures is a prerequisite for applying the linear unmixing model. There is two categories of unmixing models depending on how the endmembers are estimated: (1) Supervised approaches, which use the spectral signatures of endmembers as *a priori* information, (2) Unsupervised approaches, which automate the identification of endmembers. The use of prior information may be not appropriate since differences in the acquisition conditions may occur between endmembers and the data to be unmixed (Song and Woodcock 2003). In unsupervised algorithms (see Plaza *et al.* 2004 for a review), the endmembers are directly retrieved on images, thus at the same scale and conditions than the data to be unmixed.

The temporal variability of observations is an important source of information. In particular, the time courses of vegetation indices such as the Normalized Difference Vegetation Index NDVI allow to monitor the phenology of vegetation, which can be very useful for discriminating land classes and for providing estimates of evapotranspiration (e.g. Duchemin *et al.* 1999, Er-Raki *et al.* 2007, Simonneaux *et al.* 2007)

In this context, the general objective of this research is to monitor water resources over the semi-arid plain of Tensift/Marrakech, a 3000 km² intensively cropped area in center of Morocco where shortage of irrigation water occurs. In a first phase, the land use and the vegetation dynamics are retrieved using MODIS NDVI time series. The methodology is based on a statistical iterative approach for identifying endmembers directly from multi-temporal images. It is applied on a six-year archive of MODIS NDVI data to provide estimates of the dominant land classes (orchard, non-cultivated areas and annual crop) during six successive agricultural seasons from September 2000 to August 2006. In a second phase, the information on land use and vegetation dynamics is used to estimate evapotranspiration. The method is adapted from the FAO-56 algorithm (Allen 2000), which computes crop water needs from a reference evapotranspiration (ETo) and cultural crops coefficients (Kc).

2. Study area and satellite data

The study area is the eastern part of the semi-arid Tensift plain located in center of Morocco (figure 1). It covers about 3000 km², surrounded by the 'Jbilet' hills at North and the High-Atlas mountain range at South. The climate of this region is of a semi-arid continental type, with annual rainfall ranging from 150 mm/year and 350 mm/year, while the evaporative demand is very high, around 1500mm/year (Duchemin *et al.* 2006, Chehbouni *et al.* 2008). The High-Atlas mountain range experiences much higher precipitations and provides irrigation water to the plain (Chaponniere *et al.* 2005).

According to statistical surveys conducted by the regional public agency in charge of agricultural water management (ORMVAH), there are three dominant land classes that represent more than 80% of land surfaces in the Tensift plain: (1) orchards, most of it with perennial vegetation (olive and citrus trees); (2) cereal crops, mainly wheat, to less extent barley; (3) non-cultivated areas. Additional land classes include forages (mainly alfalfa, colza and oat), vineyards, broad-leave orchards (apple, apricot and peach trees), and small vegetable crops.

There are three types of irrigation systems: the modern network connected with dams, the traditional network connected with High-Atlas wadis, and pumping stations (Duchemin *et al.* 2008). The main irrigated areas are supplied by dam water and managed by ORMVAH. They cover 1176 km², about one third of the study area, with three distinct sub-regions:

- The western NFIS sub-region (yellow lines in figure 1), is mainly cropped with orchards with fields of irregular size, very small (~ 100 m²) to rather large (~ 10 ha);
- The central Haouz sub-region (black lines in figure 1) is mostly cropped with cereals; the landscape appears rather uniform with relatively larger fields (3-4 ha);

The eastern Tessaout sub-region (cyan lines in figure 1) is very patchy with a mixture of various annual crops and orchards cultivated on very small fields (100 to 1000 m²).

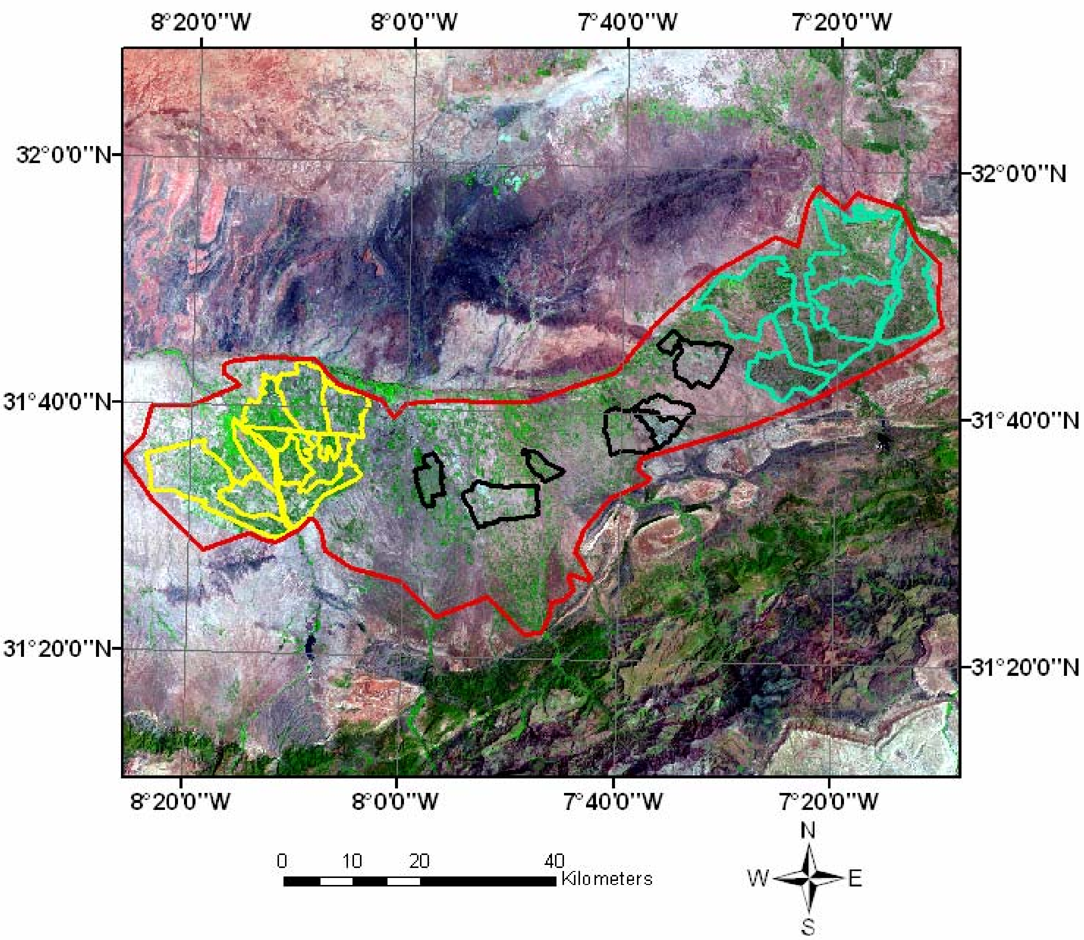

Figure 1. Delimitation of the study area (in red) and its 3 main irrigated sub-regions – NFIS (in yellow), Haouz (in black) and Tessaout (in cyan) – on a Landsat7 image.

Terra-MODIS data are freely available from the NASA website (http://delenn.gsfc.nasa.gov/). We have downloaded 16-day composite images (MOD13Q1 product) from the 2000-2001 to the 2005-2006 agricultural seasons. These images contain atmospherically corrected reflectances and NDVI at 250m spatial resolution based on the Constrained View Maximum Value Composite algorithm (Huete *et al.* 2002). They are resampled at 270m spatial resolution using the cubic convolution technique in order to be comparable with high spatial resolution data (30m) then subset to the Tensift-Marrakech plain. They are stack into 6 multi-temporal NDVI images (from September 2000 to August 2001, September 2001 to August 2002 etc). A total of 141 images are processed and visually examinated in order to detect eventual anomalies. Most of images are of good quality excepted three images (18/02/2001, 23/04/2001 and 01/01/2003) that are eliminated because they display geometric problems. All images are free of clouds. This is expected since the time step of compositing is rather long (16 days) and the cloudiness is low in the study area, ranging between 20 and 45% depending on the season (Hadria *et al.* 2006).

3. Land Use

3.1. Linear unmixing of MODIS data

To predict the land use fractions of the three dominant land classes, the linear unmixing model is applied to MODIS multi-temporal NDVI images. It assumes that the NDVI of a mixed pixel can be calculated as the sum of the NDVI values of the different land cover classes weighted by their corresponding fraction within the pixel (equation 1):

$$NDVI_i(t) = \sum_{j=1}^{3} \pi_{ij} \times NDVI_j(t) + \varepsilon_i(t) \qquad (1)$$

where $NDVI_i$ is the NDVI of MODIS mixed pixel *i* at the date *t*, π_{ij} is the fraction of class *j* in pixel *i*, $NDVI_j$ is the endmember of class *j* (*j* = 1 to 3) and ε_i is an error term of the pixel *i*.

In a first step, we try to retrieve the typical NDVI time courses (endmembers) for each class. Their identification is operated directly from MODIS multi-temporal NDVI as follows: firstly, an unsupervised classification "k-means" is applied to MODIS multi-temporal NDVI images in order to group the pixels which have similar NDVI seasonal courses. The result is N mean NDVI profiles corresponding to N groups[1]. We set N to 20, which appears as a good compromise allowing a reasonable computing time cost while keeping a sufficient level of details to describe the NDVI space-time variability within the study area. Furthermore, the grouping of pixels with the same vegetation seasonality allows the reduction of local noise due to: (1) imperfect superimposition of MODIS data before temporal compositing, (2) inaccuracy in atmospheric correction and, (3) the variation in sun-target-sensor geometry between successive acquisitions.

In a second step, an iterative test is applied for all possible triplets of endmembers (three land classes) among the series of N mean NDVI profiles. The total number of iteration nb is C_N^3. Each triplet is considered as an endmember potential candidate and the associated land use fractions are retrieved for the remaining 17 (i.e. N-3) groups by minimizing the Root Mean Square Error (RMSE, equation 2) between the NDVI profiles observed by MODIS and reconstructed from the endmembers.

$$RMSE_i = \sqrt{\frac{1}{T} \times \sum_{t=1}^{T} [\varepsilon_i(t)]^2} \qquad (2)$$

$$\text{With } \pi_{ij} \geq 0 \text{ and} \sum_{j=1}^{3} \pi_{ij} = 1$$

Where *T* represents the number of MODIS data

[1] The term 'groups' is used to refer the classes identified by the K-means method in order to avoid confusion with those derived from MODIS data after unmixing.

In a third step, we calculate an error term (M_k, equation 3), which represents the ability of the triplet number k to explain the NDVI response for the 17 groups. Finally, the triplet are sorted according to this error term: the triplet for which the error is minimal is called triplet rank 1, the following is called triplet rank 2, etc.

$$M_k = \sqrt{\frac{1}{\left[(N-3)\times T\right]} \times \sum_{i=1}^{N-3}\sum_{t=1}^{T}\left[\varepsilon_i(t)\right]^2} \qquad (3)$$

$$\text{With } k \in [1, nb] \text{ and } nb = C_N^3 = \frac{N!}{3!\times(N-3)!}$$

Once the endmembers are identified, they are assigned to the appropriate land use class and the surface covered by each class within each pixel (land use fraction) is retrieved by minimizing the RMSE (equation 2) between the NDVI profiles observed by MODIS and reconstructed from the endmembers. This process is applied pixel by pixel using land use fractions ranging from 0 to 1 and under the constraint that the sum of fractions (%orchard + %bare soil + %annual crop) is equal to 1.

3.2. NDVI time series and endmembers

The NDVI profiles of the 20 groups identified with K-means classification obtained on the 2002-2003 agricultural season are displayed in figure 2 as an example. The 20 NDVI profiles can be discriminated through the combination of NDVI seasonal amplitude and average value. It appears that the K-means method groups pixels according to the density of perennial vegetation (hierarchy of rather stable NDVI profiles with average values from 0.15 to 0.55) and according to the vegetation seasonality (contrast between high NDVI values during the agricultural season and low values in summer).

When looking at the endmembers (figure 2), it is noticeable that the algorithm tends to select the profiles that display extreme values and rejects intermediates ones. Furthermore, the endmembers appear descriptive of the three dominant classes: the first one, with maximum NDVI values below 0.2, corresponds to the bare soil class; the second one, with NDVI always high (between 0.45 and 0.65), appears representative of a dense perennial vegetation (orchard class); the third one, with a large NDVI dynamics, can be associated to the class annual crop. The latter displays minimum values in November (at the sowing period), then a rapid increase to maximum values mid-March when cereal reaches full development, and a final decrease until June after total senescence of plants. This analysis makes easy to label each endmember.

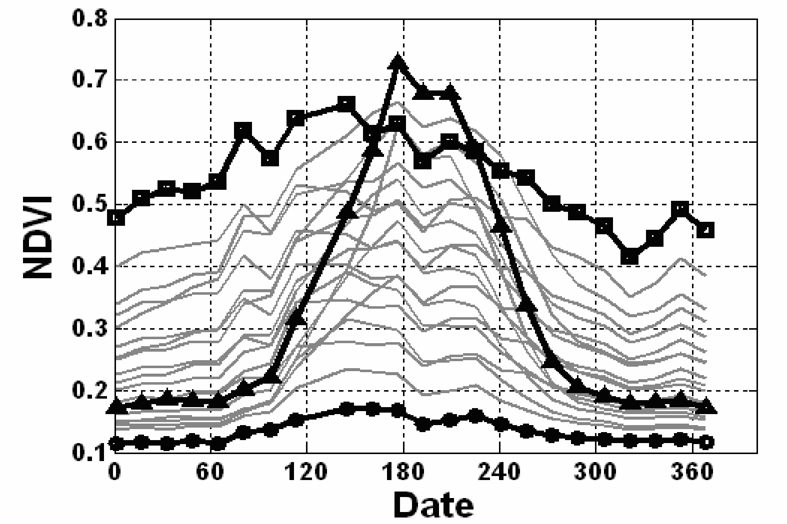

Figure 2. 2002-2003 NDVI profiles averaged over the 20 groups of pixels resulting from the k-means classification. Bold lines with symbols highlight the NDVI endmembers associated to orchard (■), bare soil (●), and annual crop (▼). The first day is September the 1st, 2002.

For the 2000-2006 period, the endmembers expected for the orchard and the bare soil classes are always selected (figure 3), the first ones with rather high NDVI values (>0.4) and low seasonal amplitudes (~0.2), the second ones with flat and very low values (six-year maximum of 0.22). There is a general stability of the endmembers from one year to the other. In contrast, the NDVI profiles with the highest amplitudes (annual crop endmembers, figure 4) display a higher variability. The pattern of NDVI profiles is generally consistent with the phenology of cereal crops (growing season from December to April, and NDVI values below 0.2 outside), but two exceptions can be noticed:

- For the 2001-2002 season, the increase of NDVI is delayed (after April) and largely reduced (peak of NDVI around 0.4). This year is characterised by a shortage of irrigation water after the severe drought that occurs during the 1999-2001 period. As a consequence, the 2001-2002 annual crop endmember appears not suitable for the retrieval of annual crop fractions. As an alternative, we replace the 2001-2002 annual crop endmember by the average NDVI profile of the endmember identified on other 'normal' years ("4-year average" in fig.3).

- The same analysis is performed for the endmembers selected for annual crop in the 2003-2004 which exhibits an early NDVI increase from 0.2 to 0.4 between November and December ("03-04 (rank 1)" in figure 4). This pattern appears coherent with rainfall data, which occurs mainly at the very beginning of the season, resulting in early sowing or growth of natural vegetation before sowing. The analysis of other NDVI profiles allows to identifying a good substitute to represent the phenology of cereal crop ("03-04 (rank 2)" in figure 4): this profile is similar to the ones observed for the 'normal' years, and have a good ability, when associated to bare soil and orchard endmembers, to explain the NDVI response of the remaining 17 groups (second rank in the minimisation process, see section §3.1).

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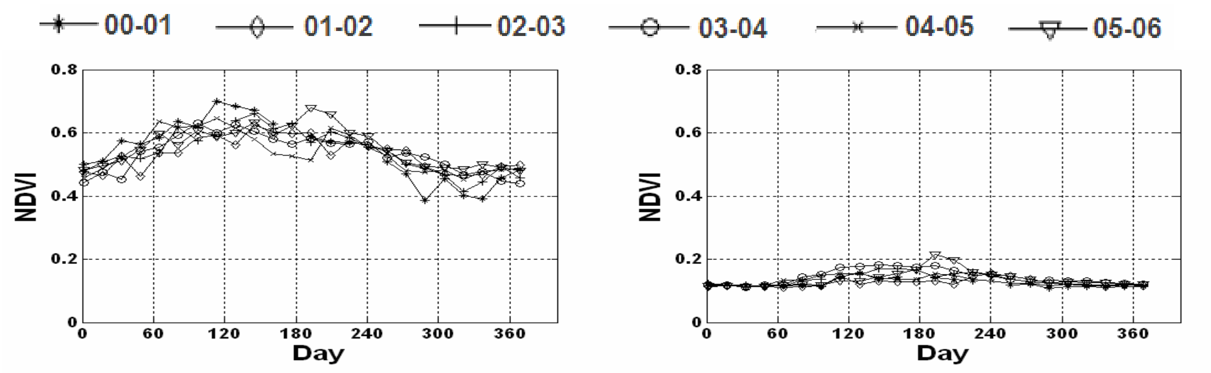

Figure 3. Estimated endmembers from 2000-2001 to 2005-2006 agricultural seasons on orchard (left) and bare soil (right) classes. On X-axis, first days are 1st September.

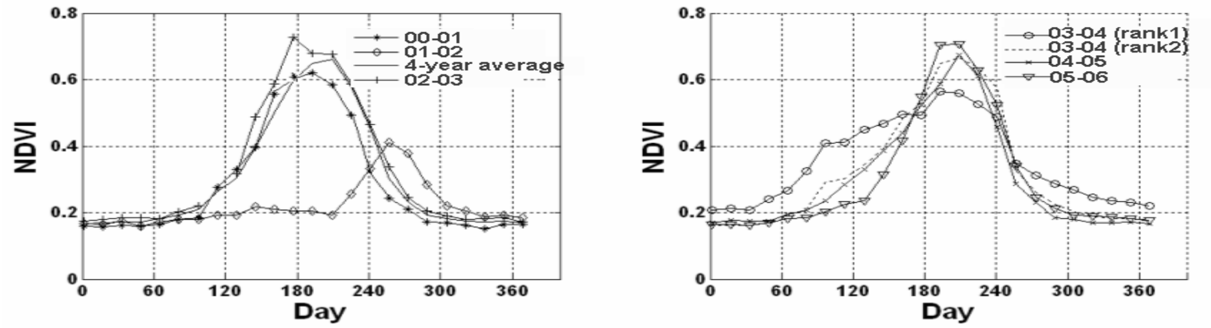

Figure 4. Same as figure 3 for annual crop endmembers through 2000-2003 (left) and 2003-2006 (right) periods.

3.3 Spatio-temporal variability of land use maps

A visual examination of land use fractions maps (figure 5) shows that the algorithm always detects the same region with low or high proportion of each class. Orchard fractions appear especially stable during the six years, in coherence with the duration of tree plantations. On the contrary, there are some compensations in the fractions of the two other classes (bare soil and annual crop). In particular, there is a high proportion of bare soil and a low proportion of annual crop for the 2001-2002 agricultural season compared to others.

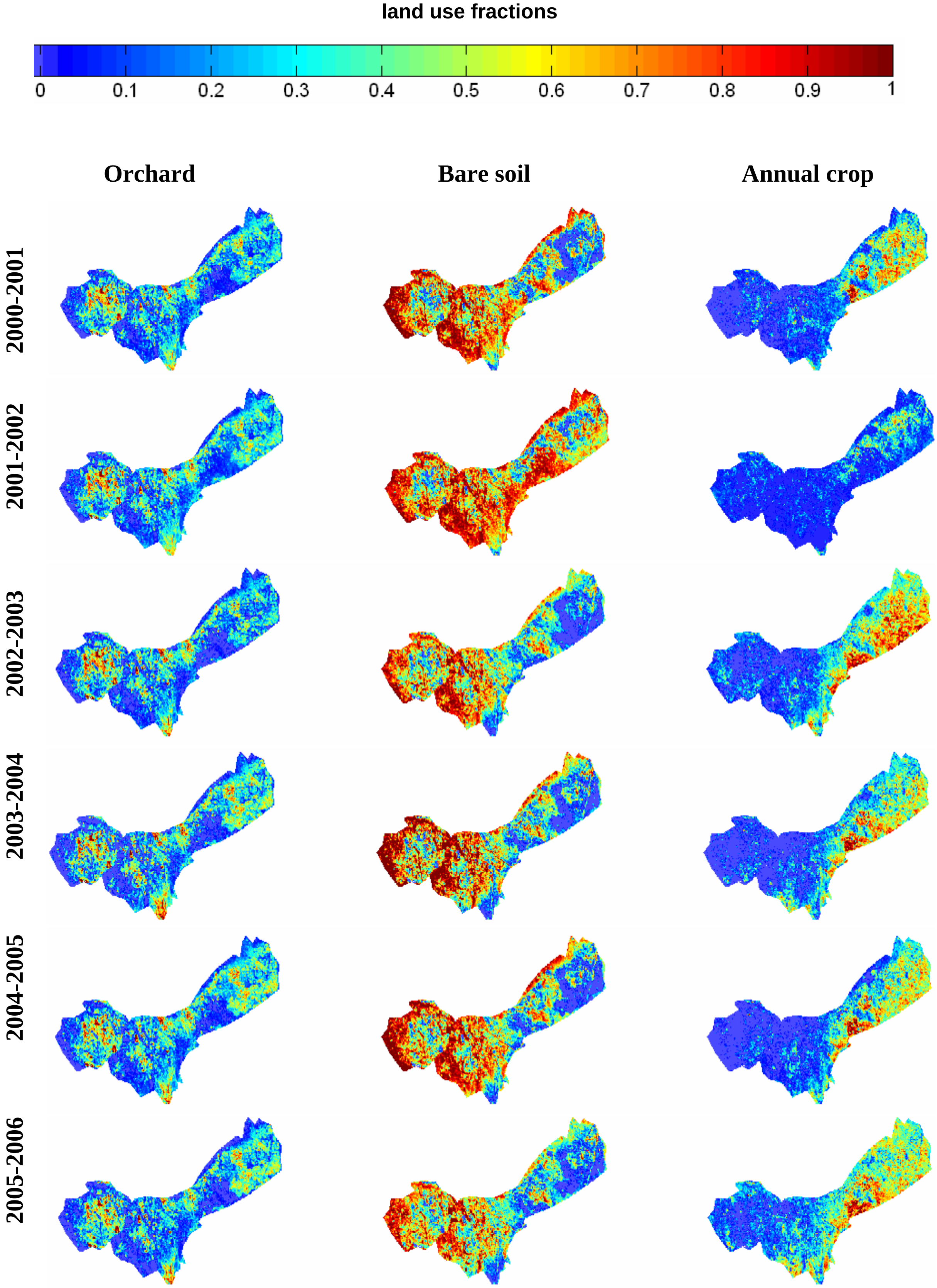

Figure 5. Maps of land use fractions derived from MODIS data from 2000-2001 (top) to 2005-2006 (bottom) agricultural seasons: orchard (left), bare soil (middle) and annual crop (right).

4. Evapotranspiration

4.1. Driving of FAO-56 method with MODIS data

The information on land cover and on the vegetation dynamics previously obtained is used to estimate evapotranspiration over the Haouz plain. The method is adapted from the FAO-56 algorithm (Allen *et al.* 2000) under the assumption that crop evapotranspiration is equal to the crop water needs. The FAO-56 algorithm computes the crop water need from the reference evapotranspiration (ETo, i.e. the evaporative demand of the atmosphere), and cultural crops coefficients (Kc) which indicates the evapotranspiration rate of well-watered plants. The method is set up using ETo calculated by spatial interpolation of the meteorological data available in the Marrakech/Al Haouz Plain.

The crop coefficients, which vary according to the crop type and phenological stage, have been retrieved for each land cover class as follows. The Kc of orchards is fixed to 0.6 according to the FAO-56 tables and local observations (Er-Raki et *al.* 2007, 2008). For annual crop, we used the dual approach which consists of splitting Kc into one coefficient for transpiration (Kcb) and one for soil evaporation (Ke). The Kcb is calculated from the NDVI time course of endmembers using the relation described in Duchemin *et al.* (2006). Ke is fixed to 0.3 and weighted by the fraction of the soil surface not covered by vegetation which is also derived from NDVI profiles. The total evapotranspiration is calculated at a daily time step as the sum of the individual evapotranspiration of each land class weighted by their proportion within each pixel of the area of interest, then seasonal ET is estimated.

4.2. Validation of ET estimates (field scale)

Figure 6 and table 1 presents the comparison between MODIS-estimated ET and those measured on the fields monitored during the SudMed program (4 wheat fields during the 2002-2003 season, and 5 tree crops from 2002 to 2006, see Chehbouni *et al.* 2008). ET was collected using three 2-meter towers equipped with sonic anemometers and fast hygrometers (see Duchemin *et al.* 2006 for wheat). At a daily time step, the largest error occurs when there is difference in phase between the NDVI annual crop end-member and the actual wheat phonological cycle (wheat W2 in fig.6). In spite of these problems, there is a good agreement of accumulated seasonal ET (12% error in relative value, table 1). The accuracy of ET estimate for tree crops (14%) is comparable to that of annual crops. These errors are of the same order than possible biases on measurement. There is an overall slight overestimation, which can be due to plant water stress (wheat W2 in fig.6) or in difference in characteristics between the hypothesis use for modelling and the actual crop status (e.g. T5 is young trees equipped with a drip system, while the Kc value we used is representative of dense canopies).

Table 1. Estimated and observed evapotranpiration (ET).

Crop	Type	Year	N	observed ET (mm)	estimated ET (mm)	Difference
W1	wheat	2002-2003	72	160,8	160,7	-0,1
W2	wheat	2002-2003	71	240,9	258,4	17,5
W3	wheat	2002-2003	55	145,3	199,9	54,6
W4	wheat	2003-2004	147	329,8	363,8	34,0
		Sesonal Error For Wheat (mm)				*27 (12%)*
T1	olive tree	2002-2003	245	654,6	762,6	108,0
T2	olive tree	2003-2004	199	620,2	622,9	2,7
T3	orange tree	2003-2004	276	573,8	630,0	56,2
T4	orange tree	2005-2006	204	579,6	687,1	107,5
T5	olive tree	2005-2006	178	492,9	573,5	80,6
		Sesonal Error For Trees (mm)				*71 (14%)*

N is the number of day for which measurements were available

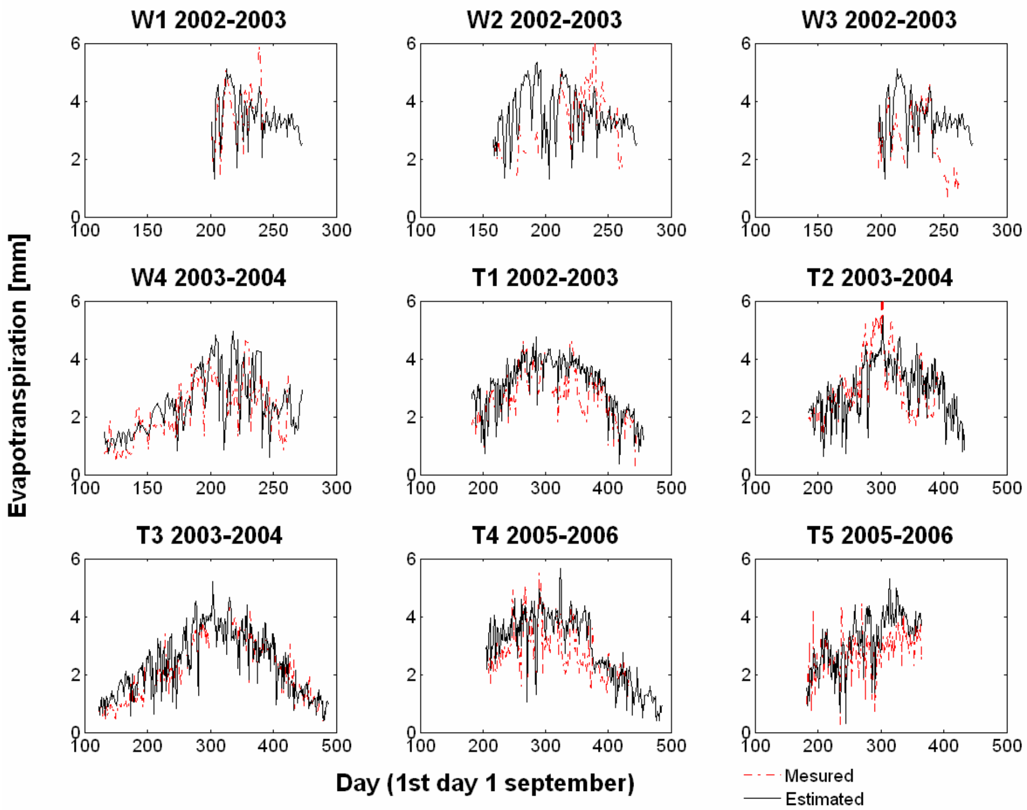

Figure 6. Time courses of estimated and observed evapotranpiration (ET) on 4 wheat fields (W1 to W4) and 5 tree crops (orange or olive trees, T1 to T5)

4.3. Evaluation of seasonal ET maps (regional scale)

Figure 7 displays the seasonal ET map over the Tensift/Marrakech plain. The value range from about 100mm to 1000mm. These extremes encompass the range of crop water needs, with minimal values observed for pixel with a majority of non-cultivated areas (100% bare soil class), and maximal values observed for pixel with a majority of tree crops (100% orchards). There is a high degree a coherence between ET (fig.7) and land use maps (fig.5).

Table 2 allows the comparison between these seasonal estimates and the main driving variables (land use, climate and water availability). There is a clear hierarchy between the 3 main irrigated areas:

- The Tessaout area, where non-cultivated lands are of few extent (20%, 2001-2002 excepted) and ETo is the largest (20mm higher than for Haouz et 100mm higher than for NFIS on an annual basis), displays the largest ET.
- Minimal values are observed on the Haouz area where tree crops fractions are the lowest and bare soil fractions are rather large (about 40%%, 2001-2002 excepted)
- Intermediate values are observed on NFIS, which display both the highest fractions of tree crops (maximal crop water needs) and of non-cultivated areas.

From table 2, it can be also seen that there is a large inter-annual variability of ET estimates, due to differences in ETo, rainfall and available irrigation water. Minimum values are observed during year 2001-2002, and corresponds to an anomaly detected in annual crop fractions (e.g. less than 10% instead of 40% the other years within the Haouz area). This anomaly seems a good indicator of the water shortage experienced this year (e.g. less than 50 mm dam irrigation water instead of 100 to 200 the other years for the Haouz area).

Finally, it can be noticed that there is no clear relationship between ET estimates and dam irrigation water, and that ET estimates is larger than the sum of dam water irrigation and rainfall. In order to understand this, we have to keep in mind that dam water is not the only source for irrigation, but also wadis from High-Atlas (traditional network) and deep water (pumping stations).

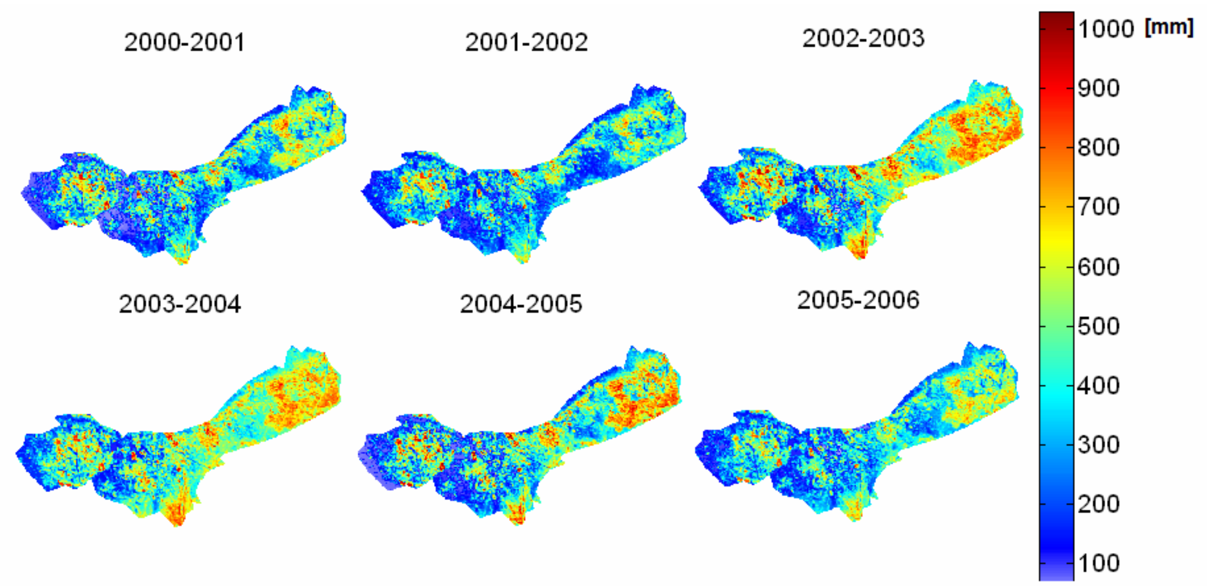

Figure 7. Maps of ET estimated with MODIS data from 2000-2001 to 2005-2006.

Table 2. Regional climatic and land use characteristics together with ET estimates over the three main irrigated sub-regions for 2000-2001 to 2005-2006 agricultural seasons

	Year	ET0 [mm/an]	P [mm/an]	ET [mm/an]	*Tree*	*Bare soil*	*Annual crop*	Irrigation (dam) [mm]
NFIS	2000-2001	1542	126	449	*39%*	*52%*	*9%*	105
	2001-2002	1446	212	436	*39%*	*55%*	*6%*	86
	2002-2003	1589	223	509	*40%*	*51%*	*9%*	142
	2003-2004	1459	210	469	*40%*	*51%*	*9%*	213
	2004-2005	1602	120	459	*40%*	*54%*	*6%*	297
	2005-2006	1405	275	475	*38%*	*50%*	*12%*	258
HAOUZ	2000-2001	1639	139	362	*17%*	*45%*	*39%*	116
	2001-2002	1543	194	288	*20%*	*72%*	*8%*	47
	2002-2003	1686	229	459	*18%*	*43%*	*39%*	124
	2003-2004	1556	286	487	*21%*	*34%*	*46%*	165
	2004-2005	1699	137	434	*20%*	*40%*	*40%*	201
	2005-2006	1502	251	424	*18%*	*36%*	*46%*	157
TESSAOUT	2000-2001	1658	147	520	*29%*	*23%*	*48%*	111
	2001-2002	1562	164	432	*31%*	*48%*	*21%*	84
	2002-2003	1705	297	656	*27%*	*17%*	*56%*	105
	2003-2004	1574	318	644	*38%*	*17%*	*45%*	198
	2004-2005	1718	148	624	*37%*	*19%*	*44%*	240
	2005-2006	1522	270	570	*35%*	*19%*	*47%*	178

5. Conclusion

The general objective of this study was to establish the water balance over the semi-arid plain of Marrakech/Tensift, a 2000 km² intensively cropped area in center of Morocco. This required firstly to map the land cover, secondly to monitor the vegetation dynamics and thirdly to set up evapotranspiration models.

We first used NDVI time series derived from a 6-year archive of MODIS data at 250m resolution (2000-2006). We applied a linear unmixing method to predict land cover fraction of the dominant land cover classes (orchard, bare soil and annual crop). The method provided annual land cover maps during the 2000-2006 period along with the vegetation dynamics (typical time courses of NDVI).

In a second step, the land use information was incorporated into the FAO-56 algorithm to estimate surface evapotranspiration, the main term of the water balance in this semi-arid, flat area. The crops coefficients (Kc) were adjusted for each land cover class, and those of annual crop were calculated as a function of NDVI. Estimates of evapotranspiration were evaluated over nine field were measurements were available, and the error of the method was found to around 13% on a annual basis. This accuracy appears very satisfactory given the simplicity of the modelling.

Finally, maps of annual evapotranspiration were analysed on the three areas where dam irrigation water are available. The spatial and temporal variations of MODIS estimates were found coherent with the main characteristics available to describe the Tensift/Marrakech plain (land use, climate and water availability). The results confirmed the potential of low spatial resolution data to manage water resources at a regional scale.

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