ABSTRACT - Various models have been derived for estimating evapotranspiration from remote sensing data. These models have usually been designed for homogeneous canopies which are considered as having homogeneous characteristics at local scale. At a larger scale, landscape heterogeneity and model non-linearity can lead to substantial errors in the estimation of evapotranspiration (Bouguerzaz, 1999). In this work, the linearity of the simplified relationship model (as proposed by Seguin and Itier, 1983) is investigated. Namely, we consider a pixel region covered with various homogeneous cover types for which the evapotranspiration can be calculated. Aggregated calculations are used to define heterogeneous pixel radiances and landscape evapotranspiration. This analysis has been applied to the Alpilles dataset which includes high resolution maps of surface temperature and spectral reflectances over a small agricultural area. The results showed that the non-linearity effect on evapotranspiration induces an error of several tenths of mm/day at a given surface temperature. This effect is mainly linked to the non-linearity of the simplified relationship toward aerodynamic roughness. The way of estimating roughness over heterogeneous pixels has also a very significant influence on the results. In a second step, in order to analyse the effect of roughness, a two-dimensional boundary layer model was used for estimating the aerodynamic roughness at the pixel scale.

1 INTRODUCTION

Daily evapotranspiration is an important factor for monitoring water requirements of crops and water consumption at a regional scale. The integrated evapotranspiration through the whole phenological cycle is also closely related to the crop final productivity. Many attempts have been made in the past for estimating evapotranspiration using remote sensing (for a review see Olioso and Jacob 2002). Semi-empirical and more deterministic approaches have been developed. Most evapotranspiration estimations from remote sensing are residual approaches based on the assessment of the energy balance. Evapotranspiration corresponds to the latent heat flux (LE), which can be calculated as the residual of the net radiation (Rn) minus the soil and sensible heat fluxes (G and H):

\[ LE = Rn - G - H \] (1)

Rn and H are calculated by a series of variables, some of which can be estimated instantaneously by remote sensing (albedo, emissivity and radiometric surface temperature). Recently, some operational applications have even been implemented (ex. EARS), although some important fundamental problems still remain to be solved. Major difficulties in obtaining more precise and more useful, distributed LE estimates are (1) the estimation of daily flux values on the basis of instantaneous measurements; (2) fulfilling the need for (distributed) micrometeorological data (like wind speed and air temperature); (3) the application of physical equations with only local validity to heterogeneous pixels, a still largely ignored problem.

This paper mainly focuses on the last mentioned problem. Since the early eighties, experimental studies use coarse spatial resolution remote sensing in order to obtain regional evapotranspiration estimates (Vidal et al., 1987; Lagouarde & Brunet, 1989). At the same time it is common knowledge that the physical equations used are only valid for homogeneous and continuous land cover types. This makes the use of coarse remote sensing data like the often used AVHRR (1 km² resolution), especially on fragmented agricultural areas, a very delicate operation. This is though not only due to the non-linearity of the physical equations, but also to the difficulty of estimating some parameter values at levels where they are no more homogeneous (like estimating the
2 METHODS

Our assessment is based on the consistent experimental data set which has been acquired during the ReSeDA program over the Alpilles test site in the South-East of France in 1997. This flat area of 5×5km² is well suited to study the scale change problem, because it’s divided into rather small fields with varying land use. Main crops are wheat and sunflower, but alfalfa, maize, vegetables and orchards are also present. The data set comprises continuous micrometeorological field measurements and optical and infrared remote sensing data, acquired throughout the cultural season at different resolutions by a series of sensors (airborne Inframetrics760 and PolDER, spaceborne SPOT, Landsat and AVHRR). These data have already been used in the past for deriving physical variables that are used in our work (ex. diurnal albedo, Jacob et al., 2002; Jacob & Olioso, 2002).

The effect of scale change is assessed by calculating the energy fluxes, first using high spatial resolution input data and a second time using a spatially degraded version of these input data. Then the resulting high resolution energy fluxes are integrated to the level of the coarse resolution energy flux estimations, allowing for comparison.

The spatially distributed input variables are provided at a 20m resolution by the airborne sensors. This means that most pixels cover surfaces that can reasonably be considered as a continuous and homogeneous cover, thereby allowing for energy flux estimations respecting the physical principles.

2.1 Estimating energy fluxes

The net radiation flux density \( R_n \), i.e. the budget governing the energy fluxes at the surface, can be computed from incident radiation, surface albedo \( (\alpha) \), emissivity \( (\varepsilon) \) and surface temperature. Incident radiation is provided by the micrometeorological ground station, \( \alpha \) is obtained from multi-directional PolDER data (Jacob et al., 2002) and \( \varepsilon \) is estimated using the PolDER nadir estimates based NDVI (Olioso, 1995b). Surface temperature is calculated following the approach of Olioso (1995a), using the Inframetrics760 (8-14 µm spectral band) brightness temperature \( (T_b) \) and \( \varepsilon \).

The instantaneous sensible heat flux \( H \) of the surface cover is defined as follows:

\[
H = \rho c_p h_a (T_s - T_a) \tag{2}
\]

where \( \rho \) and \( c_p \) are respectively the air density and specific heat at constant pressure, \( h_a \) the turbulent exchange coefficient and \( T_a \) the air temperature at a given reference height. To avoid spatial variation we used midday \( T_a \) at 25m above the ground provided by the French meteorological numerical weather prediction model Arpège.

\( h_a \) is determined by the classical equation of Brutsaert (1982) where \( h_a \) is a function of \( u_a \) at the reference height (so no spatialisation required! Provided by Arpège), the aerodynamic roughness length \( z_{0m} \) (commonly a simple fraction of crop height), the roughness length for heat transfer \( z_{0h} \), and the Monin-Obukhov length \( L \). \( z_{0h} \) is taken to be 1% of \( z_{0m} \).

A spatialised estimate of \( G \) is hard to obtain as there is no direct relation with remotely sensed radiation. Daily \( G \) is often considered to equal zero.

2.2 A residual approach for estimating daily LE

To obtain a daily evapotranspiration estimate, we are now confronted to the fundamental problem of relating instantaneous measurements to daily estimates as stated in the previous paragraph. Remote sensing typically provides only instantaneous radiation measurements. Some more or less strong hypothesis (notably a constant \( H/R_n \) ratio throughout the day and a daily \( G \) close to zero) allow to obtain a daily LE estimate for clear sky days.

The solution we adopted is based on the so-called simplified relationship: As originally observed by Jackson et al. (1977), the difference between instantaneous surface and air temperature can statistically be related to daily LE if daily \( R_n \) is known:

\[
LE_d - R_n_d = A - B(T_s - T_a) \tag{3}
\]

Seguin & Itier (1983) proposed to use this relationship to obtain regional \( LE_d \) estimates using satellite measured midday \( T_s \), with ground measured \( R_n \) and \( T_a \) being considered constant throughout the more or less homogeneous area studied. The statistically determined parameters \( A \) and \( B \) can give a good estimate for a given clear sky day and homogeneous \( R_n \) and \( T_a \) provided that the instantaneous \( H/R_n \) ratio remains constant throughout the day. For operational use, \( A \) and \( B \) are considered to be constant and characteristic of the area studied, which adds one more hypothesis: the midday ratio \( R_n/R_a \) should be constant throughout the year.

Many authors have used this relationship ever since and tried to propose a more analytical, but operational, parameterisation either by a theoretical analysis (Riou et al., 1988) or using SVAT models (Vidal et al., 1987; Lagouarde, 1991; Carlson et al., 1997).
This has resulted in several semi-deterministic models to estimate A and B. In fact, the offset A corresponds to an average daily soil heat flux $G_d$ and is therefore generally considered to equal zero. Regression slope B is often defined as a “mean exchange coefficient”. Because B is found to depend on the surface roughness $z_0$, its dependence upon land cover type is still recognized by the scientific community.

But the definition of B as a “mean exchange coefficient” contains a contradiction in terms. B indeed is related to the instantaneous sensible heat flux and can be defined as:

$$B = c \cdot \rho \cdot h_a$$  

(4)

where the average concerns the crop season average and $c$ being the constant $Rn_d/Rn_i$ ratio. But $h_a$ and so B, is determined by the highly variable $u_a$, $z_0$ and the atmospheric stratification (expressed by L). So B can vary strongly from day to day, which is why Seguin & Itier (1983) advised to sum results over two to four week periods. But still then the evolution of crop height versus a fixed B value induces an error.

On the other hand, the examination of the ReSeDA micrometeorological ground measurements database revealed that the clear sky day midday $Rn_d/Rn_i$ ratio is not constant neither, but shows a considerable evolution (figure 1). This same figure also shows that the daily soil heat flux cannot be neglected. This daily soil heat flux is variable, but a general annual tendency can be discerned.

So affecting unique A and B values to each field, generally on the basis of land cover information only (Courault et al., 1996) will not provide a precise estimation of LE.

We therefore adopted a more mechanistic way to estimate daily LE, reducing the fundamental hypotheses to the number of two:

1) the classical hypothesis stating that the instantaneous $H/Rn$ ratio remains constant throughout clear sky days;

2) the hypothesis that the value of A is not zero, but spatially constant and equal to the daily $G$ flux that can be approximated by a yearly sinusoidal evolution (figure 1):

$$G_d = 17 \sin \left( \frac{2 \pi (D + 100)}{365} \right)$$  

(5)

where $G_d$ is the daily soil heat flux (W/m²) and D the Julian day. This is a coarse approximation, but it reduces the error with respect to the zero flux hypothesis.

Instantaneous and local values of B are calculated through the distributed midday $h_a$ and $Rn_d/Rn_i$ values. The daily $Rn$, the remaining unknown, is calculated by considering diurnal values for $u_a$ as provided by Jacob & Olioso (2002) and a daily longwave upward radiation estimated by the daily integration method proposed by Lagouarde et al. (1991).

Figure 1  ReSeDA field measured energy fluxes from 7 sites pooled together. 1a (top) shows the annual evolution of the $Rn_d/Rn_i$ ratio; 1b (bottom) shows the daily integrated measured soil heat flux.

2.3 Upscaling of input variables

Let us now consider the spatially distributed variables required as input for calculating $Rn$, $H$ and LE: albedo, NDVI based emissivity, $T_s$ and crop height (linearly determining $d_0$, $z_{0m}$ and $z_{0h}$). These variables are available at a 20 m resolution, allowing for individual flux calculations for each crop and land cover type. To evaluate the effect of non linearity by calculating these fluxes on input data with heterogeneous pixels, we performed a scale change on these input variables, degrading them from 20 m down to a 1 km resolution. Corresponding to the resolution of AVHRR data, the differences found will be an indication of the error that can be committed by AVHRR based flux estimates in comparable areas.

Bouguerzaz et al. (1999) showed that albedo is almost insensitive to heterogeneity, because expressed as a quasi linear function of red and near infrared.
reflectances. The upscaled 1 km² resolution albedo could therefore be considered to correspond to the average of the 50×50 20 m resolution pixels. Upscaled emissivity is calculated using the aforementioned relation with NDVI. NDVI in turn was calculated using upscaled red and near infrared reflectances.

Things become more complicated when considering Ts. In fact temperature has to be transformed back into an energy flux; the radiation emitted by the surface. After upsampling (averaging) we retransform the result into temperature.

A final but crucial difficulty is how to determine crop height for pixels covering crops of varying height. Theoretical studies on determining effective roughness length $z_{0m}$ resulted in different models that have recently been compared by Bottema et al. (1998). They found important differences between model predictions (as did Klaassen & Claussen, 1995) and concluded that the choice of the model parameters remains a major point of concern. Having the opportunity to confront these models to real data, we tested different upsampling methods. The roughness length at 20 m resolution is a function of the crop height ($h$) and the average of the roughness length mode ($z_0$) for the time of peak values. As first approximations we used the crop weighted roughness length mode (height of the dominant crop) and the average of the logarithm as proposed by Taylor (1987):

$$z_{0m}^{eff} = e^{(0.6z_{0m})}$$  \hspace{1cm} (6)

We also estimated surface roughness, both at 20 m and 1 km resolution, from NDVI by the empirical relationship as used by evapotranspiration models such as the SEBAL model (Jacob et al., 2002):

$$z_{0m} = e^{(6.38NDVI – 6.665)}$$  \hspace{1cm} (7)

A more mechanistic method uses the logarithmic wind profile:

$$u_z(z) = \frac{\langle u \rangle}{k} \left[ \ln \left( \frac{z}{z_{0m}} \right) - \Psi_m \left( \frac{z}{L} \right) \right]$$  \hspace{1cm} (8)

where $k$ is the Von Karmann constant and $\Psi_m$ the atmospheric stability correction function for momentum. $\langle u \rangle$ is the effective friction velocity which is taken as the root mean square of the high resolution $u_*$ provided upon calculation of $h$. Resolution of the equation provides the effective roughness length.

A last and still more sophisticated method to estimate $z_{0m}^{eff}$ at the 1 km² pixel scale followed the same approach but this time based on the high resolution $u_*$ provided by a two-dimensional boundary layer model (Hasager & Jensen, 1999).

In all cases effective $z_0$ is continued to be set to 1% of effective $z_{0m}$ (§ 2.1). The last two nearly complete parameterisations of $z_{0m}$ have also been used in combination with a proper parameterisation of $z_{0h}$ through the temperature profile (similar to the wind profile used for $z_{0m}$).

3 RESULTS

3.1 Impact of non-linearity on emissivity and surface temperature

Figure 2 shows the impact of pixel heterogeneity on these variables for one specific day. Table 1 provides a summary for all data acquisition dates. For comparison with upscaled estimates, observed emissivity on homogeneous sub-elements can be integrated to the lower scale level in two ways depending on its use. This results in a directional e-emissivity and a directional r-emissivity as defined by Norman & Becker (1995). e-emissivity is to be used to calculate Ts when used to estimate the sensible heat flux and r-emissivity should be used in the longwave radiation absorption term of Rn. In both cases, comparison with the 1km² resolution NDVI based emissivity shows that the latter somewhat overestimates homogeneous pixel emissivity. The effect of the scale change of Tb is shown by comparison with the per pixel averaged Tb. Although such an averaging does not have a real physical meaning, this allows us to notice that Tb has a near linear behaviour. The combined effect of the Tb and emissivity non-linearities on Ts is assessed through the impact on the longwave upward radiation term. Comparison with the per pixel means suggests that upscaled emissivity counterbalances the slight non-linearity of Tb, resulting in a negligible non-linearity for Ts.

Table 1 shows the scale change errors for these variables remain very small. Tb estimation error increases somewhat up to 0.5K with absolute temperature rise in summer, but remains acceptable. More so since the combined effect of Tb and $\varepsilon$ on Ts results in a negligible error (less than 1W/m² for a flux of about 400 to 500W/m²).

This result is related to the characteristics of the study area. To provide a preliminary answer to the question whether our findings would have been very different on other areas, we artificially modified the high resolution input data: bare ground emissivity was lowered to 0.85, increasing the influence of NDVI, and thereby the spatial contrast, especially in the beginning of the growing season. Tb contrast was increased by applying a sigmoidal transform to the 20m resolution data.
Figure 2  Non-linearity of input parameters for March 26th 1997: NDVI based emissivity compared to ε-emissivity (upper left) and r-emissivity (upper right), Tb compared to the per km mean (and standard deviation in error bar, bottom left), εσTs\(^4\) compared to the per km mean and standard deviation.

<table>
<thead>
<tr>
<th>Acquisition date</th>
<th>Tb</th>
<th>ε (vs. r-ε)</th>
<th>ε (vs. e-ε)</th>
<th>εσTs(^4) (W/m(^2))</th>
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<tr>
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<td>0.002</td>
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Table 1  RMSE for the four scale change errors illustrated by figure 2, summarised for all data acquisition campaigns realised at 3000m flight height. The general average also includes 1500m flight height campaigns.

The resulting increased within pixel (1km resolution) variation induces larger scale change effects. As the range of emissivity values increased, the absolute error also did. Tb RMSE now varies through time from some tenths of K to over 2K and the general RMSE is 1.2K. Finally, the effect on Ts as shown by εσTs\(^4\) remains very small for the simulated extreme case: εσTs\(^4\) RMSE varies through time from 0.5 to 4.5 W/m\(^2\).

3.2 Impact of scaling on roughness and fluxes

Using these upscaled input data allowed us to run the flux estimation models on heterogeneous pixels, using the different ways for upscaling \(z_0\) as described in section 2.3.

As discussed in this same section, the only spatially distributed and non-linear variables influencing daily net radiation are Ts and ε. Comparing 1km\(^2\) means of “locally” estimated Rn\(d\) with the 1km resolution estimates in the same way as done in figure 2 showed that the slight non-linearity of these input parameters does not have a measurable impact (an average relative RMSE of 0.2%).
Sensible heat flux calculation additionally requires the roughness length $z_0$. The upscaled versions of $z_{0m}$ as obtained by equation 8 and the temperature profile based $z_{0h}$ are considered to be the true effective roughness lengths, because they are made to fit the measured heat flux. Figure 3 illustrates for one date (March 26$^{th}$) the considerable discrepancies with these “true” values as caused by the other upscale methods. The area weighted roughness mean gives a considerable overestimation, especially for $z_{0h}$. The other two illustrated methods underestimate $z_{0m}$. The NDVI based roughness only provides acceptable estimates at very low roughness values, whereas the 1% logarithmic average $z_{0m}$ (eq. 6) gives a surprisingly good fit to effective $z_{0h}$.

The impact of scale change on the heat flux estimate is illustrated by using these data (and those of figure 2) as input for calculation. In figure 4 the resulting values are compared to the 20m resolution estimates integrated to the 1km resolution level. The results clearly are strongly influenced by the roughness upsampling method used. As expected, the use of equation 8, with $u^*$ from the one or two dimensional boundary layer models, provides a near perfect fit. Dominant roughness (mode) based $H$ estimates are worst, but $H$ based on NDVI or area average roughness also shows unacceptable errors. The latter structurally gives an overestimation, whereas the former underestimates $H$. Regarding the non negligible discrepancies in figure 3 for the logarithmic average roughness estimate, the resulting low upscaled $H$ estimation error is surprising. These results appear to be representative of the results obtained on other days. On all dates, the NDVI based roughness estimate results in a considerable underestimation of $H$ (-34 W/m$^2$ on average), while the inverse is true for area weighted roughness average (+57 W/m$^2$ on average). The mode based roughness estimate gives a very variable $H$ estimation error and a structurally high RMSE (88 W/m$^2$ on average). The use of the logarithmic average roughness always gives a very slight underestimation, but this error is nearly negligible (+4.7 W/m$^2$ on average), confirming the structural character of the observations made on figure 4. The corresponding RMSE is higher than that for the estimations based on complete parameterisations of roughness, but the difference remains very small (res. 12.9 and 9.5 W/m$^2$). Best results are always provided by the 2D boundary layer based roughness estimate, but the improvement is insignificant in our case. It is important to notice here that the quality of the estimations based on complete parameterisations of roughness (e and f) appear to be strongly influenced by upsampling of $z_{0h}$: estimating $z_{0h}$ as 1% of the equation 8 based $z_{0m}$ caused a considerable bias to appear.

As the other input variables for estimating daily evapotranspiration ($\S$ 2.2) are either non spatialised (A, Ta) or demonstrate a near linear behaviour (R$\text{ni}$, R$\text{nt}$, Ts). It is therefore not surprising that the evolution of the daily evapotranspiration estimation scale change error (table 2) follows the same trend as $H$. Of course $E_{T_d}$ is overestimated where $H$ was underestimated and vice versa. Table 2 shows the magnitude of the impact of the $H$ estimation error on $E_{T_d}$: about 0.5mm or more when $H$ was based on one of the little accurate effective roughness estimations, an RMSE of only 0.1mm for logarithmic average roughness based $H$, i.e. as weak as those originating from the fully parameterised roughness based $H$ estimations.

Figure 3 Comparison between estimations of $z_{0m}$ (left) and $z_{0h}$ (right), based on the weighted average (+), on equation 6 (dots), on equation 7 (*) on one side (with $z_{0h} = 0.01z_{0m}$), and the results of the effective roughness (equations 8 for $z_{0m}$) on the other. The 1km$^2$ data of March 26$^{th}$ 1997 are used.
Figure 4  Midday heat flux estimates at 1km resolution on March 26th 1997, as obtained when based on the different roughness upscaling methods (x axis), compared 20m resolution fluxes integrated to 1km² areas (y axis, with standard deviation in error bars). H flux plotted on x axis are based on: ndvi based $z_{0m}$ (upper left, H a); the area weighted average $z_{0m}$ (H b); eq. 6 (H c); mode of $z_{0m}$ at 20m level (H d); $z_{0m}$ from eq. 8 and similarly parameterised $z_{0h}$ (H e); as H e, with $u^*$ from a 2D boundary layer model (H f).

<table>
<thead>
<tr>
<th>Day</th>
<th>ET a mean E</th>
<th>ET b mean E</th>
<th>ET c mean E</th>
<th>ET d mean E</th>
<th>ET e mean E</th>
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Table 2  1km resolution daily latent heat flux estimation errors, summarised for all data acquisition campaigns realised at 3000m flight height. The general average (bottom) also includes 1500m flight height campaigns. mean E gives the mean absolute error (mm). RMSE is also given in mm. The suffixes a to f refer to the different upscaled roughness estimation methods (Fig. 4). x: not available.
4 CONCLUSIONS

The impact of non-linearity on flux estimations was studied, using different scenarios for upscaling input parameters. In all cases this impact was measurable. Net surface radiation (Rn, Rs) was shown to have a near linear behaviour. H, and ETd on the contrary exhibit a significant non linearity, strongly depending upon the way effective surface roughness is estimated. For the fragmented, cultivated area studied, area weighted average, dominant land cover and NDVI based effective roughness estimates induce considerable instantaneous heat flux errors. The logarithmic average results in heat flux estimates of a quality nearly as high as nearly entirely mechanistic estimates.

Using a mechanistic adaptation of the simplified relationship, the impact of this non-linearity on daily evapotranspiration estimates could be quantified. Using the logarithmic average for effective surface roughness the impact of non-linearity was limited to about 0.1mm on average.

Model results appeared to be very sensitive to effective roughness length for heat transfer, z0m. Further study is required to evaluate the role of the 0.01z0m rule used to determine z0m in the good results provided by the effective z0m based on logarithmic averaging. The ratio z0m/z0h is known to differ between homogeneous and heterogeneous surfaces (Hopwood, 1995) and forcing it to remain constant maybe partially compensates the z0m estimation error when based on the logarithmic average.

5 ACKNOWLEDGEMENTS

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6 REFERENCES


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