Possibilities of deriving some useful agrometeorological parameters from the remotely sensed data-from current and new sensors-with the integration with other sources of information

Dr. Gheorghe STANCALIE

Eng. Antonio PERDIGAO

Dr. Luis PESSANHA

WG1.1.

Budapest, Hungary, 27 - 28 September 2001

TABLE OF CONTENTS

1. Introduction ***3***

2. Applied Models ***4***

2.a. Empirical approaches **4**

2.b. Physical modelling approaches **6**
2.b.1. **At the Leaf level** 7
2.b.2. **At the canopy and growing stage level** 7

2.c. Soil-Vegetation-Atmosphere Transfer (SVAT) models **8**
2.c.1. **Simple Monolayer models** 8
2.c.1.1. **ISBA** 8
2.c.1.2. **MAGRET** 9
2.c.2. **Complex multi-layer models** 9
2.c.2.1. **SiSPAT** 9
2.c.2.2. **SOIL** 10
2.c.3. **Land SAF project and SVAT models** 11
2.c.4 **Estimation of real evapotranspiration (ETR)** 11
2.c.6. **SEBAL method** 12

2.d. Soil water model (SWAP) 16
2.d. **Other Methods** 17
2.d.1. **Based on the adaptation of the Marchand model** 17
2.d.2. **Based on the energy balance of the surface** 17
2.d.3. **Estimation of AE over sparsely vegetated surfaces (arid and semi-arid)** 20
2.d.4. **Model of Chehbouni et al., 1997** 20
2.d.4.1. **Short description of the model** 20
2.d.4.1.a. **Available energy** 20
2.d.4.1.b. **Sensible and latent heat flux** 21
2.d.4.2. **Results** 22
2.d.4.3. **Conclusions** 23
2.d.5. **Model of Hurtado and Artigao, 1997** 23
2.d.5.1. **Short presentation of the method** 23
2.d.5.2. **Results** 25
2.d.6. **Model of TESSEL to be used in the Land SAF project** 25
2.d.6.1. **First version of the algorithm** 25
2.d.6.2. **Second version of the algorithm (using radiative temperature)** 27
2.d.7. **Estimation of LAI** 29
2.d.7.1. **Inverting optical reflectance to estimate LAI** 30
2.d.7.1.1. **Introduction** 30
2.d.7.1.2. **Model of Qiu et al., 1998** 30
2.d.7.1.3. **Results** 31
2.d.7.1.4. **Observations** 31
2.d.7.1.5. **Application to satellite data** 31
2.d.7.1.6. **Conclusions** 32
2.d.8. **Fraction of Photosynthetic Active Radiation absorbed (FPAR)** 32
2.d.8.1. **Processing Steps** 32
2.d.9. **Land SAF project vegetation parameters estimation** 32

COST ACTION 718
‘Meteorological Applications for Agriculture’

3-rd Management Committee and Working Groups Meeting
Budapest, Hungary, 27 - 28 September 2001

WG 1.1. REPORT on

Possibilities of deriving some useful agrometeorological parameters from the remotely sensed data (from current and new sensors) with the integration with other sources of information

1. Introduction

This report refers to the Evaluation of the use of remote sensing data to estimate some useful agrometeorological parameters from remotely sensed data (from current and new sensors) with the integrated with other related sources of information.

The study includes the inventory and analysis of the theory and general methodologies available for deriving agrometeorological parameters like real evapotranspiration (ETR), potential evapotranspiration (ETP), leaf area index (LAI), fraction of photosynthetically active radiation absorbed (FPAR), etc.

The new generation of EUMETSAT space sensor systems presents a real challenge to improve our knowledge of surface processes on a short-term basis. The SEVIRI instrument on board MSG will offer the opportunity to depict vegetation changes on a daily time scale, due to a high temporal resolution (15 minutes) associated with more appropriate spectral bands to assess vegetation status. SEVIRI will also provide data with multiple illumination angles of the surface whereas AVHRR-3 on board NOAA and future EPS/METOP will allow for sampling a view angle and provide a complete global coverage. The combination of geostationary and polar systems is therefore expected to bring new insights to our knowledge of the anisotropyc properties of the surface.

EUMETSAT have already taken initiative and had approved a Satellite Application Facility (SAF) for Land Surface Analysis (LSA-SAF) known as Land SAF.

As shown in Table 1, SEVIRI and AVHRR-3 respectively on-board MSG and NOAA/EPS present common spectral capabilities that can be used to monitor land surface properties. For instance, in the past decade, data sets from the AVHRR sensor have proven to contain suitable information to characterise land surface properties. However most traditional approaches (Govaerts, 2000) have relied on empirical or statistical exploitations of the spectral information (e.g. composite images) that may introduce biases since large fluctuations related to the surface anisotropyc properties are usually induced on time series of reflectances (Gutman, 1989, Roujean et al., 1992).

Table 1. SEVIRI/MSG and AVHRR-3/EPS spectral characteristics

SEVIRI/MSG		Remarks	AVHRR-3/EPS	
Channel	Band (μm)		Channel	Band (μm)
HRV	0.50 – 1.00	Solar		
VIS 0.6	0.56 - 0.71	Solar (RED)	1	0.58 - 0.68
VIS 0.8	0.74 - 0.88	Solar (NIR)	2	0.727 - 1.00
IR 1.6	1.50 - 1.78	Solar	3A	1.58 - 1.64
IR 3.9	3.48 - 4.36	Window	3B	3.55 - 3.93
IR 6.2	5.35 - 7.15	Water vapour		
IR 7.3	6.85 - 7.85	Water vapour		
IR 8.7	8.30 - 9.10	Window		
IR 9.7	9.38 - 9.94	Ozone		
IR 10.8	9.80 - 11.80	Window	4	10.30 - 11.30
IR 12.0	11.00 - 13.00	Window	5	11.50 - 12.50
IR 13.4	12.40 - 14.40	CO_2		

2. Applied Models

Three general classes of approaches have been applied to obtain land cover biophysical properties:

a) Empirical approaches relying basically on the correlation of surface reflectance, including vegetation indices, to the biophysical characteristic of interest;

b) Physical modelling approaches modelling the relationship between leaves, canopy, biophysical characteristics and radiation reflected and emitted.

c) Soil-Vegetation-Atmosphere Transfer (SVAT) models

2.a. **Empirical approaches**

The empirical approaches are based on "spectral vegetation indices (SVI)", various linear and non-linear combinations of spectral bands, maximising sensitivity of the index to the canopy characteristic of interest (e.g., fraction of photosynthetically active radiation absorbed Fpar) while minimising the sensitivity to the unknown and unwanted canopy characteristic (e.g., background reflectance). A popular index of this type is the Normalised Difference Vegetation Index (NDVI), which is a good example reducing the effects of canopy structural shadowing on reflectance.

The SVI have also been used to follow seasonal dynamics of vegetation, inferences can be made regarding phenology and crop growth development, from analysis of the temporal shape of the

NDVI. Parameters such as beginning of leaf growth, green peak, growing season width have been estimated on the basis of the temporal profile analysis. The seasonally integrated SVI have also been used as a measure of accumulated photosynthetically active radiation absorbed by a canopy and correlated with above-ground primary production on an annual basis.

The potential of empirical algorithms can be illustrated by the FASIR (*Sellers et al., 1994*), a global algorithm to estimate some canopy biophysical parameters. FASIR relies on composite $1°x1^{o}$ NDVI data set from the AVHRR using a stratified, map based on different NDVI-FPAR relationships.

For canopies homogeneous very closed, both empirical and ground-truth data showed that NDVI, as well as other vegetation indices are increasing functions of canopy FPAR. It is assumed that Simple Ratio (SR) is linear in FPAR and using a radiative transfer model other biophysical variables of interest, such LAI and albedo can be derived.

More approaches might be considered with data from other platform, such MODIS, MISIR from EOS AM. It must be noted that LANDSAT and SPOT could provide useful synergy with the EOS sensors.

The Bi-directional Reflectance Distribution Function is the basic quantity that geometrically characterises the reflecting properties of a surface independently of atmospheric conditions. The BRDF concentrates the information on the properties of the Scattered Radiance Field for a given scanned target. This is an intrinsic property of the land surface thematic areas, which provides a full description of the medium anisotropy for light-matter interaction. In practice, a strict definition of a measurement depends on the degree to which the direct solar irradiance strongly dominates and diffuse irradiance is negligible. Other surface parameters will also benefit from the BRDF product since it will contribute to improve their derivation. The BRDF measurements will also allow for estimates of spectral hemispherical reflectances or albedos, which control the fraction of solar energy available at the surface.

The new generation of space sensors systems such as POLDER, MODIS and MISR are able to look at a given point of the Earth's surface under various viewing angles and therefore allow characterising the BRDF. The forthcoming SEVIRI/MSG and AVHRR-3/EPS instruments will also provide an angular sampling of the BRDF thanks to data acquisition under various solar zenith angles. Therefore, those meteorological satellites will be complementary to obtain a full determination of the BRDF. According to the reciprocity principle, it is therefore expected that SEVIRI and AVHRR-3 will finally contribute to disseminate a BRDF product with a quality comparable to the one derived from multi-angular sensor systems.

MSG system will provide access to directional information on a daily composite basis, allowing a proper sampling of effects of surface anisotropy on the observed radiances. In fact, the SEVIRI instrument will provide multiple illumination angles of the surface whereas AVHRR-3 will allow multi-angular viewing of a given ground target. A better determination of anisotropic properties of the land surface is therefore to be expected thanks to the synergy between sun-synchronous and geostationary sensor systems.

Figures 1 and 2 are representing the Flow Diagram of the determination of BRDF, AL and AE inside of the Land SAF project of the EUMETSAT.

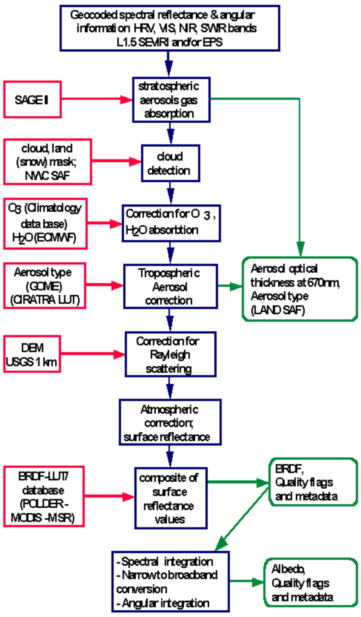

Figure 1. Flow Diagram of BRDF, AL and AE algoritmms

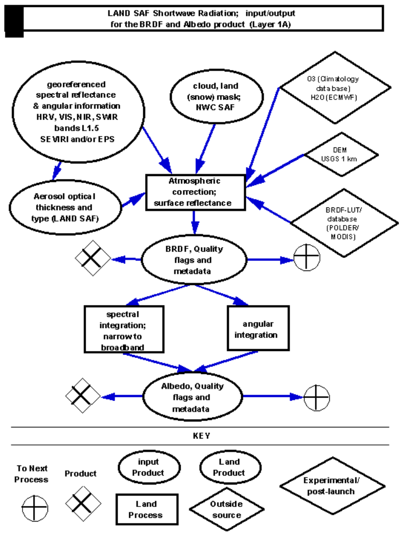

Figure 2. Flow diagram of input and output data for BRDF and AL products

2.b. **Physical modelling approaches**

Physical modelling approaches normally indicated, as canopy reflectance models. Once developed and tested, the understanding obtained from the models that can then be used to develop algorithms to relate biophysical characteristic to reflectance or the reflectance models can be used directly in the so-called inverse model, for the biophysical parameters on a basis of a reflectance input.

Spatial resolution of remotely sensed surface reflectance measurements to obtain canopy level structural and biophysical characteristics, must be as precise as possible. This means the transferring and biophysical property relationships from the leaf level, where they can be easily measured and related to leaf composition and structure, at pixel level, where leaf optics interact with canopy structure, under crop growth characteristics, view and illumination geometry to produce a complicated relationship among pixel-level reflectance, stand structural, biophysical and leaf optical properties. In general, when extrapolating leaf-level optical properties to the stand level, the physical assumptions used for horizontal layers of leaves do not hold, yielding unrealistic solutions. Modelling efforts that have addressed this problem are numerous, and can be placed into four classes of models (*Goel, 1988*):

1. turbid medium models (*Suits, 1972; Verhoef, 1984*),
2. geometric models (*Li and Strahler, 1985*),
3. hybrid combinations of (i) and (ii)
4. complex computer, simulation models, for example (*Goel, 1991*).

These models compute canopy and pixel-level reflectance in terms of not only leaf optical properties, but other biophysical parameters such as leaf area index, leaf angle distribution, dark area index, crown and shape and spacing etc. The models have been used to infer biophysical characteristic, from pixel-level measures of reflectance by numerical iteration and convergence, that is, matching reflectance values to parameter sets, a process referred to as "inversion" (*Goel, 1989*).

The intrinsic dimensionality of the remotely sensed data for a single viewing angle and date is determined by the number of physically independent (uncorrelated) wave bands, generally no more than three to four.

2.b.1. **At the Leaf level**

At the leaf level, the visible wave band reflectances have an answer similar to the physical absorption and scattering process by plant pigments, thus these reflectance are highly correlated and do not form a linearly independent set.

The near-infrared bands are generally uncorrelated with the visible wavelengths, but near-infrared reflectance is largely driven by leaf cell structure and thus different near-infrared bands correlated with each other. Exceptions are the near and middle infrared regions where protein, lignin and starch molecules absorb strongly at certain frequencies. These regions have been investigated for their ability to provide information on canopy chemical composition.

Thermal infrared bands are sensitive primarily to canopy radiative temperature and thus are independent of the visible, near and mid-infrared bands, however, their use adds additional parameters to be estimated and parameters related to turbulent heat and long-wave radiative transfer within the canopy.

Mid-infrared reflective bands, which answers to plant water content are, in live vegetation, highly correlated to plant chlorophyll.

2.b.2. **At the canopy and growing stage level**

At canopy and growing stage level, all bands are sensitive to shadowing and canopy background that can induce correlation among them providing information on canopy structural variables and morphology. Thus, at least, three to four independent bands are available to estimate the most part of the biophysical parameters integrating complex canopy reflectance models, from whom the invisible and near-infrared, seem to provide most of the information about canopy structure and leaf properties.

The problems highlighted, requires other research:

- Based on unknown parameters, estimating the data from non-remote sensing sources,
- Attempting to reduce the influence on reflectance of canopy biophysical parameters, using the vegetation indices; three frequently referenced indices are: the Normalised Difference Vegetation Index (NDVI), Simple Ratio (SR), and the Kauth-Thomas (KT) greenness index. A number of studies showed that these indices are sensitive to biomass, LAI, and FPAR (*Sellers, 1985*), but relatively insensitive to shadowing effects, and thus view and illumination angles. However, they are also sensitive to canopy structure and atmospheric absorption and scattering. Other vegetation indices have been proposed to deal with variations induced by atmospheric aerosols (*Kaufman and Tanre, 1992*) and variations in background reflectance (*Hall et al., 1990; Huete et al., 1994*).

Thus, the physically based algorithms have not been widely used to estimate biophysical parameters from satellite multispectral data. However, a number of field studies have been conducted to investigate the feasibility of inverting canopy radiative transfer models to estimate such parameters.

In theory the values of *N* parameters that characterise the canopy reflectance models can be inferred from a set of *N* independent reflectance measurements over the canopy. In practice, such measures are difficult to obtain. Only three or four spectral bands are sufficiently independent for canopy parameter inference, therefore, these must be increased by multi-angle measurements.

Satellite measurements from LANDSAT TM and NOAA AVHRR autonomous measurements of canopy reflectance can only be obtained using multiple satellite acquisitions. Given the cloud cover frequencies, even three cloud free looks are unlikely within a 10-day period when the canopy can be considered relatively unchanged.

These practical difficulties usually requires the knowledge of the free parameters in the radiative transfer (e. g. leaf optical properties, canopy structure parameters etc.), with only one parameter subject to estimation.

At any rate, field studies over homogeneous crop canopies using the inversion techniques, where only leaf area index was the free parameter, resulted in errors varying between ± 10% and ± 20%, where at least four observation angle were available (*Hall et al., 1995*).

2.c. Soil-Vegetation-Atmosphere Transfer (SVAT) models

Many SVAT models have been developed. Among them, we focused on models available in Europe and took care of encompassing a large range of model complexity:

- Simple models: mono-layer energy-balance formulation combined with a simple soil description, as: ISBA (*Noilhan and Planton 1989*), ISBA-Ags (*Calvet et al. 1998*) and MAGRET (*Lagouarde 1991*);
- Intermediate models: with two energy balances, one for the soil surface and one for the vegetation layer, and a simple soil description, as CETP (*Taconet et al. 1986*) and CESBIO (*Lo Seen et al. 1997*);
- Complex models: with a detailed soil description and a two layer energy balance as: SiSPAT (*Braud et al. 1995*), SOIL (*Jansson 1998*) and TEC (*Witono and Bruckler 1989*), (this last model only describing the soil processes).

2.c.1. Simple Monolayer models

2.c.1.1. ISBA

The ISBA scheme simulates the surface fluxes and predicts the evolution of the surface state variables using the equations of the force-restore method from *Deardorff (1978*). Five variables (surface temperature, mean surface temperature, surface soil volumetric moisture, total soil moisture and the canopy interception reservoir) are obtained through prognostic equations.

The surface soil moisture is computed to estimate the evaporation from the soil surface, where the transfer water is extracted from the total soil moisture. Evaporation and transpiration are weighted to compute LE by means of the vegetation cover (veg). The description of the surface fluxes Rn, H, and LE is detailed in *Noilhan and Planton (1989*). The main surface parameters involved in the flux calculation are: canopy albedo (α) and canopy emissivity (εs), which are considered as constant, the momentum (z0) and thermal roughness (z0h), the displacement height (d), the vegetation LAI and the stomatal resistance, which depends on a minimal leaf value (rsmin) the LAI, and the product of reduction functions depending on soil moisture incident radiation, air temperature and vapour pressure deficit. Soil parameters (in temperature and moisture equations from *Deardorff*) are computed from soil texture (*Manzi, 1993*). The ground heat flux (G) is the residual of the energy balance equation, and its value is employed in the *Deardorff* equation for the surface temperature, weighted by a thermal coefficient including a vegetation term (Cw) and the vegetation cover (veg). Meteorological forcing includes air temperature and humidity above the canopy, wind speed, solar and atmospheric radiations.

2.c.1.2. **MAGRET**

The MAGRET (Lagouarde 1991, Courault et al. 1996) model is in many ways similar to ISBA. In particular, the meteorological and the vegetation components are similar.

Differences arise from the way evapotranspiration and soil moisture are computed. Conversely to ISBA, bare soil evaporation and soil evaporation are not distinguished and the total canopy evapotranspiration is obtained using a bulk canopy resistance including vegetation structure resistances, a resistance to soil evaporation related to the dryness of the top soil layers, and the stomatal resistance. This later resistance is calculated in the same way as in ISBA.

Concerning soil moisture, a two-reservoir system is used; each reservoir corresponds to a layer of wetted soil, the thickness of which vary according to the computed loss or gain (rainfall) of water. Another difference concerns the calculation of the ground heat flux G and the effect of vegetation. In MAGRET, G is computed from the temperature gradient at the surface (Fourier equation, solved by combination with the heat conservation equation) and an exponential attenuation term depending on the LAI and an extinction coefficient δ.

2.c.2. **Complex multi-layer models**

2.c.2.1. **SiSPAT**

In this model, the transfers in the soil are described in more detail the vertical heterogeneity of the soil structure and texture may be accounted for, and a root distribution must be prescribed.

Coupled transfers of moisture and heat in a partially saturated soil are described using the approach of *Philip and De Vries (1957*) as modified by *Milly (1982*). The soil prognostic variables are the vertical profiles of temperature and soil matric water potential. This approach requires more complex information on the soil characteristics such as retention curves and hydraulic conductivity as a function of soil moisture.

The effect of vegetation above the ground is based on the solution of two energy budgets, one for the ground surface and another one for the vegetation layer.

Basic radiative transfer calculations are done inside of the canopy in allowing the partition of energy between the soil surface and the vegetation layer (using an attenuation coefficient). They require separately an albedo and an emissivity values for the vegetation layer and for the soil surface, the latter depending on the surface soil moisture.

Calculation of turbulent heat fluxes follows the scheme used by *Daamen and Simmonds (1994)* , which depends on a displacement height and momentum roughness length (conversely to previous uses of the **SiSPAT** model, no thermal roughness length was used in this study). The circulation of water from the soil to the atmosphere through the plants and the soil water uptake by the roots follow an electrical analogue model as proposed by *Federer (1979*). The stomatal conductance is described as a function of vapor pressure deficit, leaf temperature, incident radiation and leaf water potential.

The **SiSPAT** model can be used in two ways, considering either a vertically heterogeneous soil or a homogeneous soil column.

2.c.2.2. **SOIL***(Jansson 1998, Lewan 1993)*

As in **SiSPAT**, the vertical variations of soil texture and structure, as well as root density are taken into account. Water flows are described using *Richards' equation* and heat transfers accounts for the effects of water flows. Net radiation is splitted into vegetation and soil components by means of the *Beer law*. Plant transpiration is computed by means of *Penman-Monteith equation* and a function for the dependence of canopy resistance to vapor pressure deficit and radiation (*Lohammar* equation). The effect of soil water deficit is taken into account by a reduction function affecting root water uptake as a function of soil water potential at each soil layer.

2.c.3. **Land SAF project and SVAT models**

All the **SVAT** models used in this study required:

1. Meteorological data including:
- air humidity and wind speed at some level above the canopy;
- air temperature
- global solar radiation and atmospheric incident radiation;

2. Vegetation data including:
- LAI
- evolution of air-dynamical parameters (roughness length and displacement height);

3. Vegetation parameters related to optical properties;

4. Soil parameters describing physical properties such as thermal conductivity, hydraulic conductivity and water retention;

5. Boundary conditions at the bottom of the simulated soil layer (soil temperature, soil moisture, water tension, or water and heat fluxes);

6. Initial conditions for simulated soil variables (surface and soil temperatures).

<u>Observations</u>

Values at maximum LAI must be used for defining albedo vegetation or canopy albedo (wheat: 0.22; sunflower: 0.21; alfalfa: 0.24). For bare soil, an albedo of 0.23 could be used in dry conditions (soil moisture in the 0-5 cm layer lower than 0.05 m/m) and of 0.08 for wet conditions (soil moisture in the 0-5 cm layer higher than 0.32 m/m).

Classical values of albedo: 0.23 for vegetation (e.g. *Ortega et al. 2000*), 0.10 for wet soil (soil moisture in the 0-5 cm layer higher than 0.3 m/m) and 0.25 for dry soil (soil moisture in the 0-5 cm layer lower than 0.10 m/m, (e.g. *Olioso 1992*) can also be used.

Values of emissivities classically used in the different models are: 0.98 for vegetation and 0.96 for soil.

Some other vegetation variables may be necessary to run some models, as for example the fraction of vegetation cover in ISBA. It was calculated as a function of LAI: Veg = 1 – exp(-δLAI), with δ=0.6)

Veg is used in **ISBA** for partitioning latent heat flux and conduction heat flux between vegetation and soil. Actually, the other models also used such parameter for partitioning net radiation (**SOIL**, **SiSPAT**) or ground heat flux (**MAGRET**) but the extinction coefficient had different values (0.2 in **MAGRET**, 0.4 in **SiSPAT**).

Soil Moisture retrieval is expected to be based on a physical approach basically consisting in forcing a SVAT module with Land SAF vegetation and radiation parameters together with land use information and a Digital Elevation Model (DEM) as well as with forecasted values of 2m meteorological parameters. products to force a SVAT module. The early morning temperature rise as obtained from Land SAF generated Land Surface Temperature product will then be compared to the simulated values from the SVAT. SM will then be adjusted until best coincidence is obtained in terms of a pre-defined cost function. A statistical approach will also be used as a fall-back method.

Evapotranspiration (ET) retrieval will also follow a physical approach based on the works of Norman et al. (1995) , *Kustas and Norman (1999)*, and *Norman et al. (2000) ,* with extensions by *Anderson et al. (1997)* and *Mecikalski et al. (1999).* The model can best be described as a largely simplified SVAT module without explicit soil modelling. ET is basically determined as the residuum of radiation fluxes, turbulent heat flux and ground flux without explicitly taking into account soil hydrology. As in the case of a SVAT module, the approach needs surface air meteorological parameters and the radiation parameters from the lower Land SAF layer products.

It has not yet been decided, which SVAT will be used. Possible SVATs are ISBA, the ECMWF-module Tessel, or the SVAT-module of the hydrological model TOPLATS currently in use at MIUB. The possible use of an Artificial Neural Network, representing the factors with specific weights instead of the SVAT model will be evaluated with respect to data needs, quality of output, and simplicity and effectiveness of algorithm.

2.c.4. **Estimation of real evapotranspiration (ETR)**

The Knowledge of the amount water used by plants in every moment of their development is particularly important to agriculture, for crop growth monitoring under different and anthropogenetic environments, mostly under thermic and hydric stress associated to drought conditions, so as for yield forecast and irrigation monitoring.

Nowadays more models and algorithms are available for the determination of real ETR, based on data obtained from agrometeorological stations which allows punctual estimations of this parameter in operative flux.

Based on the new Remote Sensing technological developments, the use of multispectral satellite data is able to ensure the improvement of the classical determination methods for the agrometeorological parameters of interest–ETR included. The most important advantages, are related with the improvement of the spatial resolution in the range of meters to kilometers, as well as for data updating at time intervals that may vary from hours to seasons.

Actually, NOAA satellites are best adapted for thermal studies on the vegetation due to remarkable representativity (one image at 14.00 LT allows to obtain surface temperatures associated to maximum temperatures) and the availability of the two thermal channels alllowing atmospheric correction and emissivity effects of surface temperature.

Remote sensing observations in the thermal IR part of the spectrum (TIR) provide suitable measures of surface temperature. Remotely sensed surface temperatures (i.e., radiative surface temperatures) have been widely used in estimating spatially distributed energy balance equation components. Because surface temperature is a state variable resulting from incoming and outgoing energy fluxes, can be used to estimate surface energy fluxes, the partitioning of net available energy from incoming short and long wave radiation is governed largely by available soil moisture. On wet surfaces available energy is consumed by evaporation of water, leaving little energy for surface heating . On dry surfaces more energy is used for heating thus resulting in relatively high surface temperatures.

The general approach consists on the estimation of the sensitive heat flux and available energy from micrometeorological and optical/thermal infrared remotely sensed data. Actual evapotranspiration is then derived as the residual term of the one-dimensional energy balance equation. This approach has been found to be successful over surfaces with near full canopy cover with unstressed transpiration. A more exact quantification is a complex procedure because ETR is determined by other factors as well, such as surface roughness, vegetation cover and vapour pressure deficit.

2.c.4. **SEBAL method** *(Bastiaanssen and Visser, 1996)*

The Surface Energy Balance Algorithm for Land Surfaces (SEBAL) determines the ETR rate through the energy balance equation. SEBAL solves the surface energy balance pixel-by-pixel according to micro-meteorological theories without crop classification. Based on the use of medium resolution images, three derived remote sensing products are used:

- surface reflectance of visible and NIR radiation, ρ_0;
- surface temperature, T_0;
- NDVI.

The energy balance equation in its most simplistic form stands:

Net radiation = soil heat flux + sensible heat flux + latent heat flux

$$Q^x - G_0 - H - \lambda E = 0 \qquad (1)$$

where: Q^x – is the net radiation-energy available at the ground,
G_0 – is the soil heat flux-energy lost into the ground,
H – is the sensible heat flux-energy transfer to the medium in form of heat,
λE – is the latent heat flux-energy transfer to the medium in form of vapour.

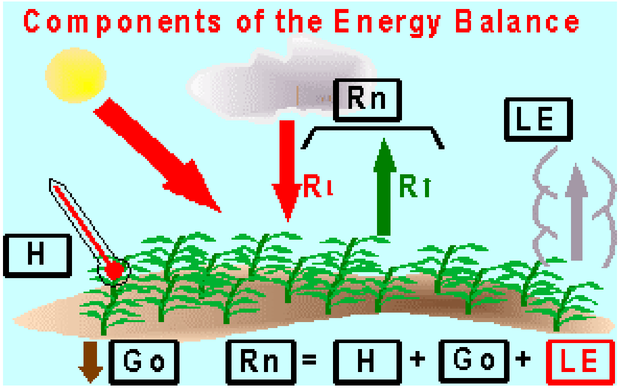

Fig 3 – Components of the Energy Balance- (Source ASTIMWR Project)

The energy coming from the sun and atmosphere in form of short and long wave radiation is dissipated on the ground. The total available energy is transformed and used for several purposes:

- heat up the soil (soil heat flux).
- heat up the surface environment (sensible heat flux).
- transform water into vapour (latent heat flux).

Soil heat flux (G)

The instantaneous soil heat flux is difficult to quantify. Areas fully covered with vegetation might have a soil heat flux equal to zero. Bare soil areas might have values between 30 to 40% of the net radiation. From the practical point of view the soil heat flux is energy that is lost away from the system, so areas having high soil heat flux will have less energy available for the process of evaporation and heating of the surface.

Sensible heat flux (H)

Part of the energy available for the process as measured by the net radiation, is used to heat up the surface and not to evaporate. Convection processes transfer this energy into the atmosphere. This portion of the energy is called sensible heat flux. Vegetated areas having relatively high sensible heat flux are probably suffering of a certain degree of water stress. Those having relatively low values, might be well watered..

Latent heat flux (lambda E)

The energy required to transform liquid water into water vapour is known as latent heat flux, who is related to wetness of the land and by consequence to irrigation. Areas having recent rainfall will also have higher latent heat flux values.
The detection of an increase of latent heat flux for a certain period might indicate that some sort of irrigation scheme started for the area or rainfall was received.

Net radiation (NR)

Part of the incoming energy reaching the ground from the sun and atmosphere is reflected back to the atmosphere (both in the longwave and shortwave radiation). The incoming minus the outgoing radiation is the remaining available energy in the process: the net radiation.

Potential evapotranspiration (PET)

Reference evapotranspiration (RET) is the amount of water which, if readily available, would be removed from the soil and plant surfaces of a reference crop per unit time.
The following relation exists between the PET and the RET in which Kc is the crop factor and is dependent on the crop type and development stage.

$$PET = Kc * RET \qquad (2)$$

The potential evapotranspiration is a maximum evapotranspiration rate compatible with certain crop and its' stage at specific climatic conditions. Potential evapotranspiration is the evapotranspiration rate at which maximal crop growth is achieved.

Evaporative fraction (EF)

The evaporative fraction is the amount of energy used for the evaporation process divided by the total amount of energy available for the evaporation process represented by the equation:

$$EF = \lambda E / (\lambda E + H) = \lambda E / (NR-G) \qquad (3)$$

Although the sensible (H) and latent heat (lambda E) fluxes fluctuates strongly on daily basis, the evaporative fraction behaves steady during daytime.

Actual evapotranspiration (AET)

The actual evapotranspiration (AET) is a real amount of water that is consumed by the crops, depending on climatological factors, type of crops and its' stage and the amount of water available for consumption in the soil root zone.

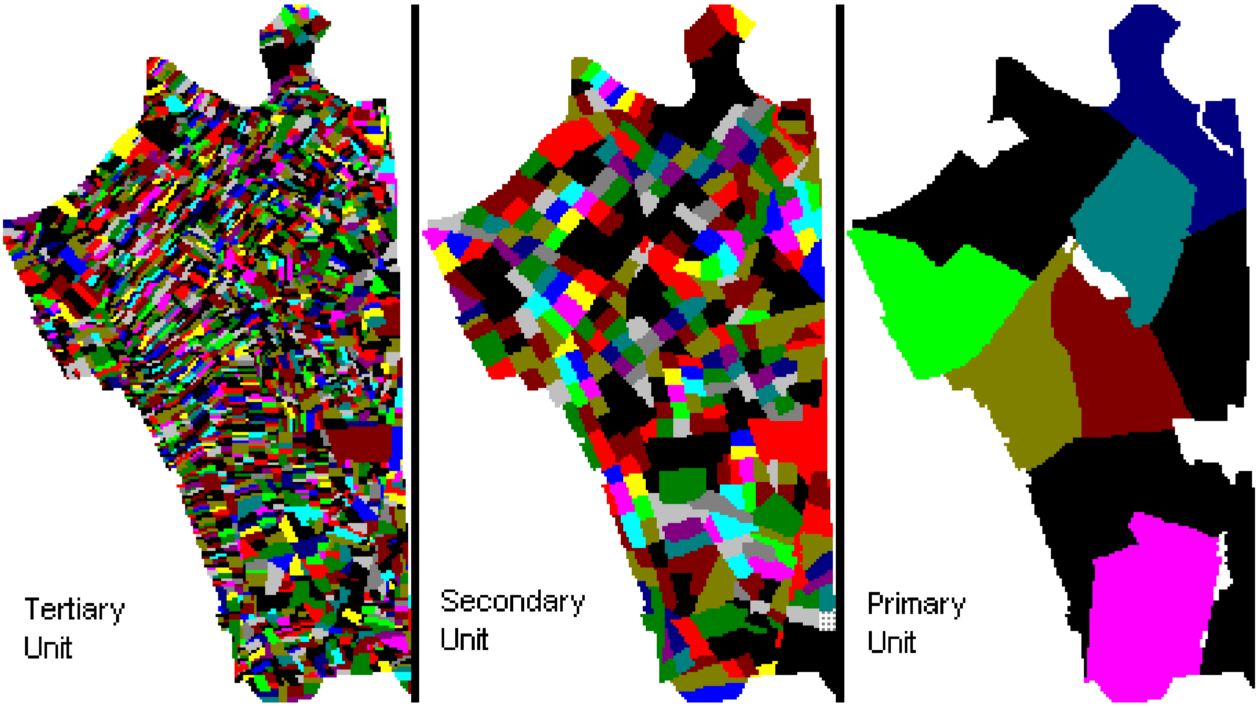

Fig 4- Application of the SEBAL Model to Irrigation Performance Inventory – Paestum Area in Italy (Source ASTIMWR 1999)

The surface temperature is interpreted in energy studies as being the result of partitioning of net energy between latent heat and sensible heat. In the SEBAL algorithm the difference between surface and air temperature ($T_a - T_0$) is coupled linearly to surface temperature and is obtained by inversion of the equation for sensible heat transfer after solving it for two extreme situations: one where H = 0 (wet) and one where λ*E = 0 (dry). These extreme situations can be derived from the relationship between T_0 and ρ_0.

The evaporative fraction reflects the ratio between the available energy for heating of the surface and for evapotranspiration of water (H, λE). This ratio (Λ) is assumed constant over the day and can be used for the calculation of the actual daily evapotranspiration (ETa), expressed in mm/day.

This calculation procedure results in ETa maps reflecting the actual evapotranspiration on a pixel basis for the processed date of recording. The pixel size can vary from detailed (20 metres) to global (several kilometres), depending on the Remote Sensing platform used.

Potential evapotranspiration is similar to the available energy for latent heat flux under many different climatological conditions:

$$\lambda E_{pot} = Q^x - G_0 \qquad (4)$$

In combination with the energy balance equation, the fraction of actual over potential evaporation can be defined as the evaporation fraction of the available energy Λ:

$$\Lambda = \lambda E/(Qx - G0) \qquad (5)$$

It was shown that the instantaneous evaporative fraction and the 24 hours evaporative fraction are similar (*Bastiaanssen et al, 1996*) therefore daily total available energy and the evaporative fractions derived from instantaneous measurements can be combined to obtain the 24 h actual ETR rate:

$$E_{24h} = \Lambda \int_{0}^{86400} (Q^{x} - G0)/(\lambda \rho w) \quad (6)$$

ETR derived from remotely sensed data can be compared with simulated ETR. Under crops with complete soil cover, soil evaporation can be neglected and ETR consists mainly of crop transpiration.

Crop evapotranspiration maps, as derived from high resolution satellite data, supply detailed spatial information on crop water status.

A comparison was made of ETR derived from remotely sensed data and simulated ETR. The results varied according to crop conditions (irrigated or rainfed) and the soil physical conditions.

2.c.6. **Soil water model (SWAP)**

A soil water model (SWAP), have been used to calculate the actual evapotranspiration (AET) of the irrigation district of Paestum (Italy). This model assumes a one dimensional soil column and its' different in and out outputs over a certain period of time, simulating the soil water balance according to the following basic formula:

$$(R + I) - (AET + BF) = \Delta S \quad (7)$$

In which:

R = Rainfall
I = Irrigation applied
AET = Actual evapotranspiration
BF = Bottom flux (e.g. percolation; capillary rise)
ΔS = difference in storage (increase or decrease of soil moisture content)

All terms are calculated in mm per unit of time considered. The time step taken in this model is one day i.e. for each day the soil water balance is calculated and the result is used for the next day.

In this model the needed input data are the rainfall, reference evapotranspiration, irrigation water applied, soil characteristics (water retention and hydraulic conductivity curves at different depths in the soil column) the crops and its' characteristics (depth of the root zone, root characteristics, surface albedo, leaf area index, soil cover) and the Bottom flux. With these data the model simulates the water balance over a certain time period e.g. an irrigation season. It gives as output actual evapotranspiration, soil moisture content, amount of irrigation water (V_{sim}) applied and the bottom flux. The **Simodin** model simulates the soil water model for every tertiary unit in an irrigation district. The output of **Simodin** are maps of all the input variables, Soil, Crop, Leaf area index and surface albedo maps, obtained from satellite images and soil data integrated in a GIS from which **Simodin** calculates the soil water balance. To calculate IP3 two simulation runs of **Simodin** are done. One time the soil water balance is simulated for an irrigation season without irrigation applied. The second time the soil water balance is simulated with an amount of irrigation water applied which is as close as possible to the real amount applied (V_{sim}□V_i)

2.d. **Other Methods**

2.d.1. **Based on the adaptation of the Marchand model**

The method is based on adapting the *Marchand, 1988* model, based on the water balance at the interface atmosphere-plant-soil, which allows to obtain daily and decade values, as well as data by phenological stages for the wheat and maize crops.

In this sense it is necessary to select the input parameters in spatial format for the studied area and the agrometeorological stations, which can provide the parameters, required by the model:

- the meteorological parameters: precipitation amount, mean air temperature, air humidity, mean wind speed, sunshine duration – daily values;
- the phenological parameters: length of phenological stages (50%), the pedological ones (100 cm Available Water Capacity, Moisture content and those values at the sowing date)
- the crop parameters: crop coefficients and root growing speed

Spatialisation algorithms are required for the input parameters as maps with isolines. The classical interpolation and extrapolation methods (Kriging, inverse of distance, power weighted by the inverse of distance) presents results especially in the case of quasi-homogeneous fields, associated to the meteorological parameters, such as: precipitation, mean air temperature, mean air humidity and sunshine duration. Best results are obtained using the Kringing method.

Soil parameters depend on the knowledge of the spatial distribution soil type, structure and texture which requires. Also the spatialisation of the useful–water filling capacity at a depth of 100 cm using the data obtained from the agrometeorological stations measurements, or of the Water Availability at sowing date, measured through the gravimetric method can be achieved using the GIS.

Using NOAA-AVHRR data, land classification and survey of the areas occupied by different crops can be obtained with a resolution of about 1 Km^2.

The adapted model could be applied to each crop–type for defined homogeneous areas as related with the pedological characteristics and meteorological parameters are concerned.

2.d.2. **Based on the energy balance of the surface**

The method used for the computation of daily AE, AEj, is based on the energy balance of the surface expressed in a simplified from. The method uses the connection between AE, net radiation and the difference between surface (T_S) and air (T_a) temperature measured around 1400 hrs. LT – the time of the satellite coverage.

The air temperature around local noon is well approximated by the daily air temperature maximum ($T_{a_{max}}$). A simplified linear relationship is used of the form:

$$\text{AEj} - \text{Rnj} = A - B\times(T_S - T_{a\max}) \quad (8)$$

where:

Rnj is the daily net radiation; A, B are coefficients which depend on the surface type and the daily mean wind speed.

Coefficients *A* and *B* could be determined either analytically, on the basis of the relationships given by *Lagouarde and Brunet (1991)* or statistically.

The daily net radiation is computed as:

$$\text{Rnj} = \text{Rgj}\ (1 - a) + \varepsilon\times\text{Raj} - \varepsilon\ \text{Rsj} \quad (9)$$

where: Rnj = daily global radiation (W/m^2);

Raj = mean daily atmospheric radiation (W/m^2);
ε = emissivity
a = surface albedo
Rsj = radiation emitted by the terrestrial surface in one day.

The radiation emitted by the surface at daily scale may be determined through the *Lagouarde & Brunet, 1991*, method, based on the relation:

$$\text{Rsj} = \sigma\ \text{Tamin4}\ .(c\times D + \tau) \quad (10)$$

where: τ = 24 h;
*T*amin = minimum air temperature (°K)
D = day duration as hours
$c = (3/8) \times r^4 + (16/3\ \pi) \times r^3 + 3 \times r^2 + (8/\pi) \times r$

with: $r = g\ (\Delta T/T_a\text{min})$; $g = 1.13$;
$\Delta T = T_S - T_a\text{min}$

The mean daily atmospheric radiation (W/m^2) is determined with the formula:

$$\text{Raj} = 1.24\ s\ T_{a\text{med}}{}^4 \times (\text{ea}/\ T_{a\text{med}})^{1/7} \quad (11)$$

where: *ea* = vapour pressure expressed as mb;
$T_{a\text{med}}$ = mean daily air temperature expressed as °K.

The daily global radiation may be inferred from direct measurements effected at the actinometric stations or with the help of certain analytic computation relations. The following computation relation can be considered (*Supit, 1994*):

$$\text{Rgj} = A_1\times G \times[(T_{a\max} - T_{a\min})^{1/2} + A_2(1 - FN/8)^{1/2}] + A_3 \quad (12)$$

Where: *G* = the Agnot radiation (MJ/m^2.day);
FN = sky coverage degree (octas);

A_1, A_2, A_3 are parameters obtained through statistical regressions;

The Agnot radiation is the short-wave solar radiation in the absence of the atmosphere, whose daily values (practically constant for a geographic site and a moment of the year) are tabled for various latitudes.

Parameters A_1, A_2, A_3 from the computation relation were determined within the European Program of Applied Remote Sensing for Statistics in agriculture, for more continental areas.

Thus, the following relation must be considered:

$$Rgj = 0.087 \times G \times [(T_{a\max} - T_{a\min})^{1/2} + 4.3(1 - FN/8)^{1/2}] \quad (13)$$

The $T_{a\max}$, $T_{a\min}$, and FN parameters are determined on the basis of the data obtained from the meteorological stations and from the NOAA–AVHRR data.

Owing to the establishment of coefficients A and B through statistical analysis, it is necessary to determine parameters AE, R_n, T_s and T_a max. Having in view the highly erroneous daily values, it was decided to establish correlations between the 10-day values of the mentioned parameters was preferred.

In this sense, AE is able to be computed for the agro-meteorological stations, using the *Marchand , 1988* algorithm.

Given the soil's large thermal inertia, the heat flux exchanged through conduction between soil and atmosphere may be neglected and the simplified computation relationship of real ETR becomes:

$$TRj = Rnj - B' \times (T_s - T_{amax}) \quad (14)$$

with: $B' = 0.0253 + [1.0016 / \log^2(2/z_h)] \times v$

where: v is the mean daily wind speed and z_h is given by the relationship:

$$zh = [1 - \exp(-LAI)] \times [\exp(-LAI/2)] \quad (15)$$

where: z_h is the vegetal cover roughness;

LAI – leaf area index.

For wheat, LAI varies according to the vegetation phenological stage and the agroclimatic conditions, between 0.2 – 4.5.

Fig. 5 presents the AE over the main plains of Romania, determined from the NOAA-AVHRR data (5.07.2000), using the *Marchand , 1988* model.

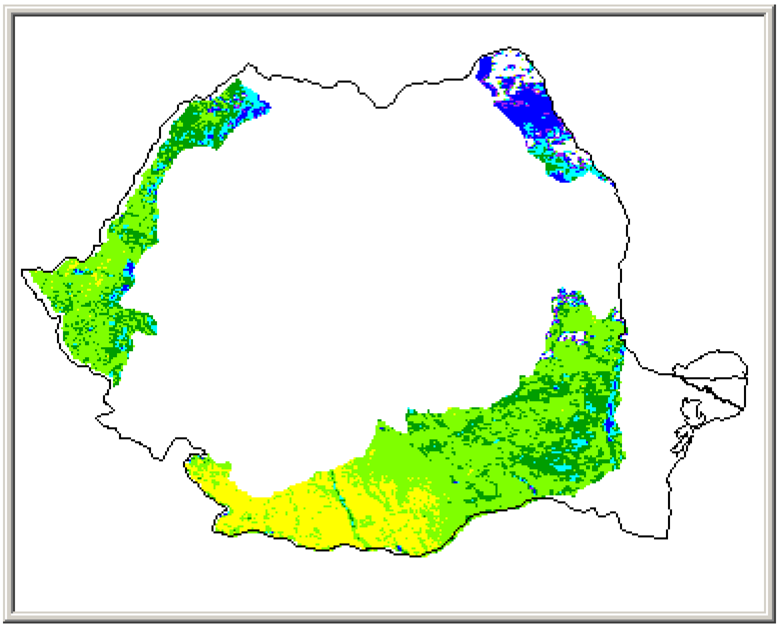

Fig.5. AE over the Romanian plain areas, determined with the *Marchand , 1988* model

2.d.3. **Estimation of AE over sparsely vegetated surfaces (in arid and semi-arid)**

In arid regions evapotranspiration is a significant and often dominant water flux leaving the Earth´s land surface, nearly all the inputs in the form of rain are lost trough evapotranspiration therefore the importance of this parameter for controlling irrigation schedule and determining crops productivity.

In arid and semi-arid regions, characterised by heterogeneous surfaces, a problem is that remotely sensed surface temperature cannot be assimilated to aerodynamic surface temperature, which is the quantity needed to formulate convective flux. One operational solution is to relate empirically remotely sensed radiative surface temperature to aerodynamic surface temperature. This solution is limited by the fact that it is site-specific.

2.d.4. **Model of Chehbouni et al., 1997**

The use of IR satellite data for the evaluation of the energy balance components can be considered as successful over surfaces with near full vegetation cover. This approach rises problems over sparsely vegetated surface because over partial cover conditions, the assumption that consists of assimilating aerodynamic surface temperature to remotely sensed surface temperature is not valid. Over such surfaces, the difference between radiative and aerodynamic temperatures can reach 10 to 15oC (*Chehbouni et al., 1996*).

2.d.4.1. **Short description of the model**

2.d.4.1.a. **Available energy**

Net radiation (Rn), which represents the balance of short and long wave radiation reaching and leaving the surface can be expressed as:

$$Rn = (1 - \alpha)R_s + \varepsilon_s(\varepsilon_a \sigma T_a^4 - \sigma T_r^4) \qquad (16)$$

Where: R_s is the incoming short-wave radiation;

σ is the Stephan-Boltzmann constant ($Wm^{-2}\ K^{-4}$);

ε_s is the surface emissivity;

ε_a is the sky emissivity defined as:

$$\varepsilon_a = 1.24(e_a/T_a)^{1/7} \qquad (17)$$

Where: e_a and T_a are air vapour pressure and air temperature respectively.

T_r is radiative surface temperature

α is the surface albedo which was derived from red and NIR surface reflectance as:

$$\alpha = 0.526\ \text{red} + 0.474\ \text{NIR} \qquad (18)$$

Where: red is the surface reflectance in the red band

NIR is the surface reflectance in the near-infrared band.

The soil heat flux (G) is a significant component of net radiation in arid and semi-arid region. For bare soil, the relationship between R_n and G depends on the surface soil moisture, while for vegetated surface, the ratio G/R_n can be obtained from visible and near-infrared reflectance. In this analysis G was formulated in terms of the **Modified Soil Vegetation Index** (**MSAVI**) as:

$$G/Rn = 0.50\ \exp(-2.13\text{MSAVI}) \qquad (19)$$

Where: **MSAVI** is defined as:

$$\text{MSAVI} = [(\text{red} - \text{NIR})/(\text{red} + \text{NIR} + A)](1 + A) \qquad (20)$$

Where: A is a self-adjusting factor defined to adapt the soil noise correction to the proportion of soil seen by the sensor. A is given by the expression:

$$A = 1 - [2(\text{NIR} - \text{red})/(\text{NIR} + \text{red})](\text{red} - 1.06\text{NIR}) \qquad (21)$$

MSAVI could be considered as the vegetation index to use since it was found to be less sensitive to soil brightness variations including shadows than other spectral vegetation indices.

This must be considered as an importance since the contribution of bare soil to scene reflectance is very significant for partially covered surfaces.

2.d.4.1.b. **Sensible and latent heat flux**

From a theoretical viewpoint, sensible heat flux should be expressed in terms of aerodynamic surface temperature , tacking in account that this parameter determines the loss of sensible heat flux from a surface. Aerodynamic surface temperature is defined as the extrapolation of air temperature profile down to an effective height within the canopy at which the vegetation components of sensible and latent heat flux arise.

Sensible heat flux can be then formulated as:

$$H = p^*c_p\,[(T_0 - T_a)/r_a] \qquad (22)$$

Where: p is the air density (kg m^{-2}),

c_p the specific heat of air at constant pressure (J kg^{-1} K^{-1}),
r_a (sm^{-1}) is the aerodynamic resistance, calculated between the level of the apparent sink for momentum and the reference height.
T_a (°C) is the air temperature at a reference height (z) above the surface,
T_0 (°C) is the aerodynamic surface temperature defined above.

Since aerodynamic temperature cannot be directly measured, it is often replaced by radiative temperature (T_r) in the formulation of sensible heat flux. Under dense canopy, the difference between aerodynamic and radiative surface temperatures is very small, which leads to small errors in heat flux prediction. Over sparsely vegetated surfaces, the difference can exceed 10 °C, resulting in overestimating the sensible heat flux.
The approach suggested by *Chehbouni et al. (1996)* consists on the setting-up of a relationship between aerodynamic and radiative surface temperature, and by defining the coefficient β as:

$$\beta = (T_0 - T_a)/(T_r - T_a) \quad (23)$$

Numerical simulations have shown that the multitemporal behaviour of the coefficient β through the growing season is compared to the variation of the LAI which leads to a parameterisation of the β coefficient with respect to LAI as:

$$\beta = 1/[\exp(L/(L - LAI)) - 1] \quad (24)$$

Where: L is an empirical factor that was set by least squares regression to a value of 1.5 .

Previous studies have indicated that a modified Beer's law expression can accurately describe the general relationship between vegetation index and LAI (*Asrar et al., 1984*). In this study, an exponential type relationship was used to obtain LAI from remotely sensed MSAVI as:

$$MSAVI = 0.88 - 0.78\exp(-0.6LAI) \quad (25)$$

By combining the last three equations, sensible heat flux can be expressed in terms of one remotely sensed surface temperature, MSAVI, and air temperature.
Finally latent heat flux can be formulated as the residual term of the energy balance equation as:

$$LE = Rn - G - H \quad (26)$$

Reflectances have used to compute short wave albedo, and the vegetation index.

2.d.4.2. **Results**

In general, remotely sensed net radiation estimations fit well with the observations (RMSE of about 50 Wm^{-2}). However, a slight discrepancy was noted which may be due to the limitation of the expression used to estimate incoming long wave radiation under cloudy sky conditions (*Brutseart, 1975*).

It must be emphasized however that the expression between R_n and G was developed only for clear sky conditions. Furthermore, this expression does not take into account the time lag between G and R_n (*Moran et al., 1994*). Additionally, it may be possible that the relationship between net radiation and soil heat flux does not depend only the type of surface (bare versus vegetated surface) but depends also on the distribution of the vegetation within the surface These reasons may explain the scatter between measured and remotely sensed soil heat flux.

This model tends to understimate H when measured values ranged from 50 to 150Wm^{-2}. This may be due to the error associated with the formulation of β coefficient or with the estimation of LAI from MSAVI which does not take into account the effect of solar angle variation. However, the root mean square error (RMSE) between observed and simulated sensible heat was about 44 Wm^{-2} for measured values ranged between 0 to 300 Wm^{-2}. The model estimates of latent heat flux are reasonable, the RMSE is about 54 Wm^{-2}.

Additional studies are needed to test the universality of parameterisation, and to investigate how the L parameter changes with vegetation type and structure.

2.d.4.3. **Conclusions**

The simplicity of the *Chehbouni et al, 1997* approach combined with the availability of remotely data, makes it very attractive for operational monitoring of surface fluxes in arid and semi-arid areas.

The major problem with this approach concerns the relationship between remotely sensed variables and the required process formulation are empirical and site specific.

One alternative approach for the use of remotely sensed data for quantitative purposes could be to combine SVAT type model with radiative transfer model. The principle of this method is to use the SVAT output such as surface temperature and soil moisture as input to radiative transfer models. The radiative transfer models will simulate in a given waveband the spectral signature of the surface as a remote sensor can observe it. By minimising the differences between measured and simulated remote sensing variable, it can assumed that the resulting surface fluxes are correct. This approach is certainly more robust, but it needs accurate SVAT and radiative transfer models, which are not readily available at this time.

2.d.5. **Model of Hurtado and Artigao, 1997**

2.d.5.1. **Short presentation of the method**

The determination of energy transport in sparsely vegetated areas requires methods that assumes

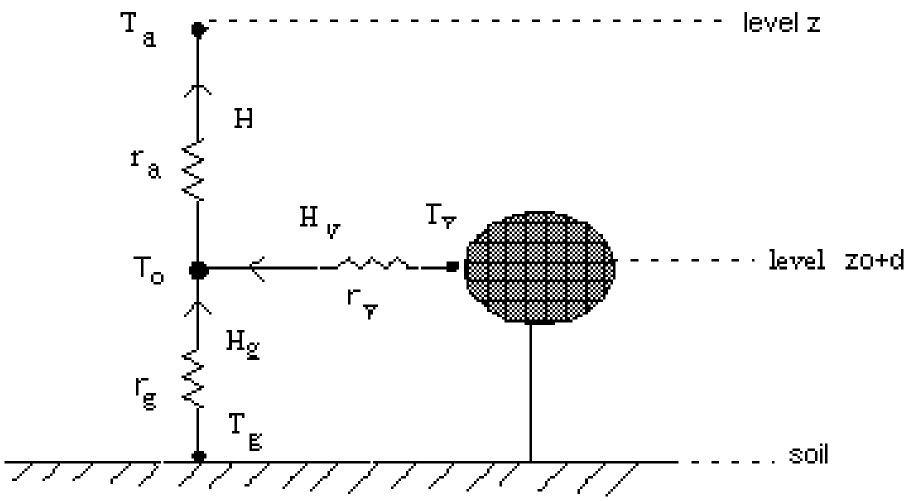

Fig.6. Two-layer model

the soil and canopy as separate sources or sinks for latent and sensible heat fluxes.

In these models the soil and canopy each are considered as a separate source (or sink) of energy which involves the assignation of temperatures and humidities for each one of the sources (or sinks) and for the atmosphere.

The presented model is a two-layer model (fig.6), where T_v and T_g are the surface temperature of the leaves and ground surface respectively. T_a is the air temperature at screen level and T_0 is the canopy-air system temperature at level $z = z_0 + d$, i.e. the level of the sources/sinks of sensible heat, or of the hypothetical canopy airflow. H is the sensible heat flux. If the canopy covers completely the soil a single layer model can be used.

The total radiation absorbed by the vegetation/soil system is:

$$R_n = R_{nv} + R_{ng}. \qquad (27)$$

The division of R_n between latent and sensible components gives:

$$R_{nv} = LE_v + H_v \text{ and } R_{ng} = LE_g + H_g + G \qquad (28)$$

And:

$$T_g - T_0 = (r_g / r_a)(T_0 - T_a) - (r_g / r_v)(T_v - T_0) \qquad (29)$$

where: r_a, r_v and r_g are the appropriate aerodynamic resistances.

The expression for the T_0 is:

$$T_0 = (r_a r_g T_v + r_a r_v Tg + r_v r_g T_a)/(r_a r_g + r_a r_v + r_v r_g) \qquad (30)$$

If a_g is the fractional ground area, observed from the nadir, the measured infrared surface temperature Ts may be expressed as:

$$T_s = T_g a_g + (1 - a_g) T_v \qquad (31)$$

and:

$$T_s - T_a = (T_0 - T_a) + a_g (T_g - T_0) + (T_v - T_0)(1 - a_g) \qquad (32)$$

Finally the following expression results:

$$T_s - T_a = T_0 - T_a + a_g [(r_g/r_a)(T_0 - T_a) - (r_g/r_v)(T_v - T_0)] + (1 - a_g)(T_v - T_0) \qquad (33)$$

For bare soil $a_g = 1$ and $r_v \approx \propto$ and thus:

$$T_s - T_a = (1 + r_g/r_a)(T_0 - T_a) \qquad (34)$$

If the canopy is fully closed, ag = 0 and this yields:

$$T_s - T_a = (T_0 - T_a) + (T_v - T_0) \qquad (35)$$

The measured surface temperature T_s is equal to the foliage temperature T_v, but T_v is not necessarily equal to T_0.

Daily AE_d (in mm) can be obtained from the expression:

$$AE_d = R_{nd}^* - B\,(T_s - T_a) \qquad (36)$$

Where: $R_n^* = R_n/L$ is the net radiation expressed in mm of water
$(T_s\text{-}T_a)$ is the temperature difference between crop surface and air (K).
The subscripts d and i indicate daily and instantaneous at midday values respectively.
B is a semiempirical coefficient, which mean value is given by:

$$B = (R_{nd} / R_{ni}) < pCp / ra^* > \qquad (37)$$

With: p the air density (kgm^{-3})
Cp the specific heat of air at constant pressure ($Jkg^{-1}K^{-1}$),
ra* is the equivalent resistance of the ground-vegetation-atmosphere system (sm^{-1})

L the latent heat of vaporisation of water (JK^{-1}).

The symbol <> means the average value over the growing season of the crop.

The ratio R_{nd}/R_{ni} is reasonably constant for clear days.

AE is estimated from net radiation measured at a meteorological station and $(T_s - T_a)_i$.

T_s is obtained from the satellite overpass (NOAA) coinciding with the approximate time of daily maximum temperature, i.e., at about 13.00-14.00 solar time, and T_a from the daily maximum value.

For operative application the B values must be determined previously using climatic parameters (R_{nd}/R_{ni}), crops parameters (h, LAI,), and handheld radiometric surfaces temperatures (T_v, T_a, T_g). From these values and using a crop map elaborated from high resolution images (SPOT, IRS, LANDSAT) by means of a classification technique, the B map can be obtain. The temperature obtained from the satellite sensor is transformed into ground surface temperature by applying atmospheric and emissivity corrections by means of a split-window method.

2.d.5.2. **Results**

This methodology has been applied to 2 test areas in Spain; one with irrigated crops which cover completely the soil and one with sparse crops. In both zones AE have been obtained with reasonable precision (0.8 and 0.9$mmday^{-1}$).

2.d.6. **Model of TESSEL to be used in the Land SAF project**

Two methods are expected to be tested on the frame of the LANDSAF project:

2.d.6.1. **First version of the algorithm**

The computation of ET is carried out on each pixel independently, without coupling between them. Every pixel is composed of tiles, each of them representing a particular type of surface. The vegetation tiles are furthermore parameterised to include the nature of the vegetation. The relative proportion of the tiles composing a pixel is directly related to the heterogeneous nature of the pixel. Along with parameters defining its behaviour, each tile is also characterised by a 'skin' temperature. This temperature is associated to the interface layer between soil surface and the atmosphere. The 'skin layer' corresponds to the vegetation cover or litter (on bare soil). It is represented as a zero heat capacity layer.

As ET assessment is our main concern, and because we limit ourselves to the clear sky pixels, it is expected to be used, a dramatically simplified TESSEL scheme. The main major simplification is that nor surface water budget nor subsoil moisture transport are accounted for. As a consequence, the amount of precipitation per pixel between two satellite pictures is not needed. The interception reservoir is also removed. This is justified by the fact that this reservoir content is quite small (it is limited to 0.8 mm in TESSEL), and that, in the absence of precipitation, it only accounts for dew condensation or evaporation. Note that neglecting dew is fairly common in radiative methods to assess ET. Neglecting the interception reservoir removes also the need of the interception tile. For the time being, as justified below, pixels covered by snow are also not considered, allowing us to neglect the two snow tiles.

The energy budget at the tile level can be described as

$$(1-\alpha_i)(1-f_{S_\downarrow,i})S_\downarrow + \varepsilon(L_\downarrow - \sigma T_{sk,i}^4) = H_i + L_v E_i + G_i \,. \tag{38}$$

In the equation, index *i* refers to the tile type, $S_\downarrow$ and $L_\downarrow$ are, respectively, the downward short- and long-wave radiation flux, H_i the sensible heat flux, $L_v E_i$ the latent heat flux (L_v being the water evaporation latent heat), G_i the conduction heat into the soil and $T_{sk,i}$ the tile skin temperature. $S_\downarrow$, $L_\downarrow$ and G_i (resp. H_i, $L_v E_i$) are positive for downward (upward) fluxes. Parameters σ, $f_{S_\downarrow,i}$, α_i and ε are respectively the Stefan-Boltzmann constant, the fraction of short-wave radiation reaching directly the first layer of subsoil, the surface albedo and the emissivity (common for all tiles).

The sensible, latent and ground fluxes are given by, respectively,

$$H_i = \frac{\rho_a}{r_{a,i}}\left[c_p(T_{sk,i} - T_a) - g z_a\right], \tag{39}$$

$$L_v E_i = \frac{L_v \rho_a}{r_{a,i} + r_{c,i}}\left[q_{sat}(T_{sk,i}) - q_a\right], \tag{40}$$

and

$$G_i = \Lambda_{sk,i}(T_{sk,i} - T_{1,i}) + (1-\alpha_i) f_{S_\downarrow,i} S_\downarrow \,, \tag{41}$$

with ρ_a is the air density, T_a the air temperature, q_a the air humidity, q_{sat} the air humidity at saturation, z_a the height at which T_a and q_a are measured, c_p the dry air heat capacity, L_v the latent heat of evaporation, $r_{a,i}$ the momentum aerodynamic resistance, $r_{c,i}$ the additional canopy resistance (only for vegetation tiles) to evaporation, g the gravity acceleration, $T_{1,i}$ the temperature of the top ground layer below tile i and $\Lambda_{sk,i}$ the heat conductivity between the skin layer and this top ground layer.

For snow-free pixels, the original TESSEL subsoil is divided into four layers that exchange heat via Fourier-based relations. However, computing these subsoil fluxes requires the knowledge of the soil moisture vertical distribution, which in turn requires to account for the water budget and the subsoil moisture transport that have been eliminated. Also, the TESSEL subsoil model can bewe replace by a simple force-restore model:

$$\frac{dT_{1,i}}{dt} = -\frac{G_i}{\rho_s C_s} + 2\pi \frac{T_{2,i} - T_{1,i}}{\tau_{day}}, \tag{42}$$

$$\frac{dT_{2,i}}{dt} = \frac{T_{1,i} - T_{2,i}}{\tau_{day}}, \tag{43}$$

with $T_{2,i}$ the temperature of the deep soil bulk, ρ_s the soil density, C_s the soil heat capacity and τ_{day} the duration of a single day, i.e. 24 hours.

Assessing the surface and subsoil heat flux for tiles covered by snow is more complex than for snow-free tiles in TESSEL. Indeed, a new snow layer is dynamically added between the skin layer and the first subsoil layer. Snow precipitation increases the height of that layer, while melting (due to a rise in temperature in the snow layer) and evaporation reduces it.

The fluxes at the pixel level are obtained by aggregation of the corresponding fluxes at the tile level:

$$H = \sum C_i H_i \,,\; E = \sum C_i E_i \text{ and } G = \sum C_i G_i \,, \tag{44}$$

with C_i being the fraction of the tile *i* in the pixel.

The relations form a closed system of non linear equations whose unknowns are $T_{sk,i}$, H_i, E_i, G_i, $T_{1,i}$ and $T_{2,i}$. The system is driven by the radiative fluxes $S_\downarrow$ and $L_\downarrow$ (provided internally by the Land SAF). Other driven terms are the air temperature T_a and air specific humidity q_a, as well as wind speed (U_a) and root zone soil moisture θ_{rz} (for computing $r_{a,i}$ and $r_{c,i}$). These last parameters will be obtained via the ECMWF database.

From an algorithm point of view, the method we propose here is very simple. Indeed, in a first step the external data have to be obtained from the other Land SAF product and from ECMWF data. Then, a non linear equation solver is used to solve Eqs. (38)-(39). Total evapotranspiration for the pixel is obtained with eq. (44).

2.d.6.2. **Second version of the algorithm using radiative temperature** T_{rad}

As the radiative surface temperature T_{rad} is a Land SAF product which will be calculated several times a day, it is available and could be used to improve the method outputs. For instance, T_{rad} could be compared to an aggregated skin temperature:

$$T_{rad}^4 = \sum C_i T_{sk,i}^4 \,. \tag{45}$$

It should be noted that radiative (T_{rad}) and aerodynamic temperature ($T_{sk,i}$) can display a few degree difference. Mixing them, as it is done in Eq. (45), thus introduces a source of error. Eq.

(45) introduces a new constraint that turns the system of eqs. (38)-(39) overestimated, and, as a consequence, a new degree of freedom has to be added for the system to have a solution.

One way to achieve this is to remove one of the equation from the system (38)-(44). For instance, eq. (45) is used whilst the bare ground latent flux is determined as a residue. However, the major drawback with this approach is that all error sources (i.e. model and measures) are laundered through this residue.

Another way is to distribute the effect of all errors source over the main computed fluxes. This is for instance achieved by scaling the sensible and latent fluxes by a common error factor χ :

$$H_i = \chi \frac{\rho_a}{r_{a,i}} \left[c_p (T_{sk,i} - T_a) - g z_a \right], \tag{46.a}$$

$$LE_i = \chi \frac{L \rho_a}{r_{a,i} + r_{c,i}} \left[q_{sat}(T_{sk,i}) - q_a \right], \tag{46.b}$$

$$G_i = \chi \left[\Lambda_{sk,i} (T_{sk,i} - T_{1,i}) + (1 - \alpha_i) f_{S_\downarrow,i} S_\downarrow \right]. \tag{46.c}$$

The idea behind this approach is to constrain the computed fluxes such that the energy conservation eq. (1) holds simultaneously with the radiative temperature aggregation eq. (45). Because H_i, $L_i E_i$ and G_i are scaled by a common factor, their relative proportion is, on first approximation, unchanged compared to the simpler version of the model that does no account for T_{rad}. A feature of this approach is that χ gives also an implicit measure of the quality of the produced outputs. Indeed, if relations (38)-(45) were exact and if all parameters were precisely determined, χ would be equal to unity. Departure from unity is thus a measure of the errors in the modelling approach or in the measurements.

The algorithm corresponding to this version is similar to the one of the previous version. The only difference is that T_{rad} is needed from layer IB and that eq. (45) is included in the solver, while Eqs. (46a,b,c) replace Eqs. (39)-(41).

A flowchart of the proposed ET algorithm is given in Figure 7

Input data include AL, LST, EM, DSSF, DSLF calculated internally the Land SAF. Standard meteorological data are also needed: screen air temperature and humidity, wind speed. These data will be extracted from ECMWF numerical model analysis and short-term forecasts. The parameters (*e.g.* $T_{sk,i}$ and $f_{S\downarrow}$ in equation (40)) linked to the land cover type and soil properties (tile parameters) will be taken from the ECMWF database. As the land surface temperature (LST) can not be remotely measured for cloudy pixel, the ET algorithm will only process for clear sky ones; a cloud mask is therefore needed and could be provided by the NWC SAF.

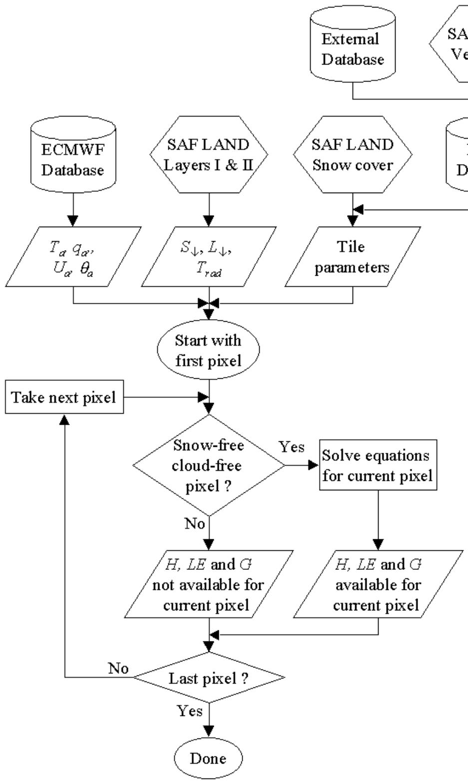

Fig 7 - Flow diagram for the ET product

2.d.7. **Estimation of LAI**

The LAI is the surface of leaves per surface of ground, and is viewed as an important variable of vegetation function. The LAI measures the surface involved in radiation absorption and turbulent transfers between vegetation and the atmosphere. The LAI is a controlling parameter for air-surface exchange processes associated with the canopies.

This variable is a key variable for models of evapotranspiration and photosynthesis at the regional and global levels. The LAI and surface optical properties such as soil and leaf reflectances are also important variables in the study of radiation processes involving the surface albedo and radiation budget. As the LAI shows high variability even within a vegetation type, it is therefore difficult to prescribe a priori values for the different biomass.

Remote Sensing provides an opportunity to estimate the absorption of photosynthetically active radiation (PAR) and, to some extent, LAI (*Sellers et al., 1996*). However, predictive capabilities are required for prognostic modeling.

2.d.7.1 **Inverting optical reflectance to estimate LAI**

2.d.7.1.1. **Introduction**

Observations of spectral reflectance provide an opportunity to describe quantitatively the characteristics of the terrestrial vegetation canopy. The spectral reflectance is a function of surface biophysical and optical properties. Parameters used to describe the surface biophysical and optical properties vary among different radiation models, but they usually include canopy LAI, leaf angle distribution index, leaf reflectance and transmittance and soil reflectance.

Numerous efforts have been made to develop algorithms deriving surface properties from remotely sensed spectral reflectances or their products. These have included both empirical schemes, such as the spectral vegetation index (*Asrar et al. 1984, Sellers 1985, Clevers and van Leenmen 1996) and model inversion (Pinty et al., 1990, Privette et al., 1995, Gao and Lesht, 1995*). Although model inversion is theoretically more objective than empirical schemes (being capable of accounting for bi-directional effects of surface reflectance) the development of adequate inversion algorithms is far for complete.

By inverting a bi-directional reflectance model, the scheme has the potential of retrieving several independent surface parameters such as LAI, soil reflectance, leaf reflectance and transmittance etc. Manipulation of these retrieved parameters allows the calculation of other surface-state variables such as spectral albedo. The inversion method can retrieve soil and canopy parameters with reasonable accuracy in most cases but the retrieval of LAI from satellite data sometimes involves significant errors (*Privette et al. 1994*). Multi-point averaging can greatly reduce the noise level and the error in the retrieved parameters (*Gao and Lesht, 1995*). Further work is necessary before model inversion can be used in an operational scheme.

2.d.7.1.2. **Model of Qiu et al., 1998**

The bi-directional reflectance model used in the inversion scheme is based on a simple approach (*Gao, 1993*) to describe the first-order scattering and multiple scattering of solar radiation within a plant canopy and the interaction of the canopy scattering with the reflectance from the soil surface. The model assumes a horizontally uniform plant canopy and allows for fast computation of directional reflectance, which is important in processing large satellite images. The model provides results that are in accordance with measurements. The vertical dimension is defined by:

$$d_z = dL(z)/L \qquad (47)$$

where: L(z) is the LAI of an infinitesimal layer at the height of z and takes the values of zero and L_T at the top and bottom of the canopy respectively.

The modelled reflectance, R depends on several parameters as:

$$R = R\ (Q_s, Q_r, \varphi_r, LAI, \rho_c, \rho_s, \tau, n) \qquad (48)$$

where: Q_s, Q_r, φ_r, are the solar zenith angle, the view zenith angle and the relative azimuth angle, respectively.

The parameter "n" is the index for the leaf angle distribution, which is related to the leaf angle distribution function; n = 0 represents a canopy with a spherical leaf angle distribution index:

n > 0 represents a canopy with mostly vertical leaves.
n < 0 represents a canopy with mostly horizontal leaves.

In order to invert the bi-directional model and retrieve the parameters to surface properties a multidimensional optimisation scheme was employed. In this scheme, the surface parameters values are adjusted in a series of iteration steps until the differences between the measured and modelled reflectances are minimised.

2.d.7.1.3. **Results**

After the examination of the model inversion scheme the conclusion was that the retrieved LAI values were excellent for LAI below 5.0. The errors at larger LAI probably resulted from the fact that the reflectance tends to "saturate" as the LAI increases to above 5.0. Despite the deviations in retrieved LAI, in this case, the retrieved optical properties and leaf angle distribution index n were quite reasonable.

The results indicate that the model inversion scheme is self-consistent and that it is capable of retrieving LAI over a large range with high accuracy.

2.d.7.1.4. **Observations**

Although the effects of various initial values of τ on ρ_e, ρ_s and n are minimal, the retrieved value of LAI is much more sensitive to the initial τ than to initial ρ_t values. Therefore the inversion must be initialised with a good estimate of leaf transmittance. Under these circumstances green leaves have a leaf reflectance and transmittance in a fairly narrow range of 0.44-0.5. To retrieve LAI for green canopies, a reasonably setting up will be in the middle of the ρ_t and τ typical ranges ($\approx$ 0.47).

The variation of initial ρ_s, did not greatly affect ρ_l, τ and n, but it did influence the retrieved LAI. When no information is available on ρ_s, a good initial guess would be 0.25 (most of the time the soil reflectance in the NIR band is in the range 0.2-0.3).

The inversion “is” must be sensitive to the initial value of leaf angle distribution index, “n”. When initial "n" is different from its tree value, errors in the retrieved values of both LAI and “n” are large.

In summary, ρ_l, ρ_s, τ and n are independent of each other and the initial value of any one parameter will have a minimal effect on the retrieved value of the other parameters. Although the initial value of every parameter influences the retrieved LAI, having the largest effect, a good guess of the initial value of these parameters improves the inversion and speeds convergence.

2.d.7.1.5. **Application to satellite data**

The inversion scheme could be applied to satellite data to retrieve the temporal and spatial variation in surface properties of a vegetation canopy. Because of the retrieval accuracy is the highest in NIR channel reflectance, application to satellite data have to be concentrated on the channel 2 NIR of the AVHRR or the channel 4 NIR in LANDSAT TM data.

The initial value of LAI can be arbitrarily set to 2.0, the midpoint of the range of 0-4 and the initial values of leaf reflectance and transmittance set to 0.47, which is appropriate for green leaves. Soil reflectance can be arbitrarily set to 0.25, within the normal range 0.2-0.3. The leaf angle distribution index, n = 2.0.

The authors reported that the retrieved LAI agrees reasonably well with the values of the canopy LAI.

Although n is not retrievable, LAI is also independent of n which means that even without the knowledge of n it is possible to retrieve LAI with reasonable accuracy by using AVHRR observations.

2.d.7.1.6. **Conclusions**

The success of the inversion is dependent on the initial guess for the model parameters and is must sensitive to the initial estimate of leaf angle distribution index. The independence of each parameter from the others is an important factor that affects the invertibility of the inversion scheme, because coupling between any two or more parameters will cause non-unique inversion results.

2.d.8. **Estimation of Fraction of Photosynthetic Active Radiation absorbed (FPAR)**

The estimation of the Fraction of Photosynthetic Active Radiation absorbed by green part of vegetation (FPAR) is an essential variable for the calculation of photosynthesis, and the energy and water exchange between the Earth's surface (in particular of vegetation) and the lower boundary layer of the atmosphere. It also serves as an intermediate variable to calculate Leaf area index (LAI), Roughness length (Z0), green fraction of total leaves (greenness) and albedo (*Sellers et al 1994*, *1995*). Note that FPAR refers to the fraction of PAR absorbed by the green portion only of the canopy.

The derivation of FPAR fields depends on a near-linear relationship between FPAR and Simple Ratio (a transformation of the NDVI) that was found in theoretical studies by e.g. *Sellers (1985)* for a vegetation canopy over a dark soil background. This near-linear relationship was confirmed in studies during the FIFE field campaign for a grassland (*Hall et al 1992*).

The FPAR - SR relationship is driven by different optical properties of green leaves in the red (high absorption) and infrared (high reflection) bands. SR or NDVI relates less well to the FPAR of the total canopy, the relationship is fairly strong for the "green" FPAR. In some cases (bright soil background), the NDVI - FPAR relationship was shown to be near-linear, rather than the SR-FPAR relationship. Results from large remote sensing experiments will requier further information concerning this relationship.

For this calculation a linear relationship between SR and FPAR could be assumed. It must also be considered that the 98 percentile of the NDVI distribution of a vegetation type reflects fully "green" conditions, and an FPAR value close to maximum (0.95). For certain types of green cover, in general the vegetation classes, are not enough to make this assumptions, because these classes occur in environments that are sub-optimal for maximum vegetation development.

2.d.8.1. **Processing Steps**

Two data sets are necessary for the calculation of FPAR: an NDVI data set and a land cover classification. For the FPAR determination the following formula is used:

$$FPAR = (0.95-0.001)(SR - SR02)/(SR98 - SR02) + 0.001 \quad (49)$$

Where: SR = (1+NDVI)/(1-NDVI)
SR98 = 98 % SR of a particular land cover class for overhead sun
SR02 = 2 % SR of desert (bare soil) for overhead sun

SR98 and SR02 values are calculate from NDVI 98% and 02%
The sources of errors are:

1. Errors inherited from other data sets

2. Errors in classification.

3. Assumption that 2% and 98% values for a vegetation type represent conditions with FPAR of 0.001 and 0.95.

4. Assumption that SR and FPAR relationship is linear, this linear relationship is supported by model studies that use a dark soil background. For a light soil background, it is the relationship between NDVI and FPAR that appears to be more linear, rather than the SR–PAR relationship.

2.d.9. **Land SAF project vegetation parameters estimation**

The level and the state of vegetation covering the Earth surface play a primary role in global scale processes. Vegetation may heavily influence climate in terms of energy balance and, at the same time, it represents a sensitive indicator of the effects of climate change and anthropogenic pressure. Remote sensing techniques have been developed and tested to derive indicators related to vegetation biophysical parameters.

Has as main objective to derive an algorithm for the extraction of vegetation parameters related to LAI from MSG SEVIRI sensor measured canopy reflectance data and adapted to the satellite characteristics. Under investigation is the possibility to derive other vegetation parameters useful for SVAT schemes inside other NWP models (e.g. ECMWF, ARPEGE, ALADIN, HIRLAM).

So, the objective is to derive the **Leaf Area Index** (LAI), and the extraction of a vegetation index the **SEVIRI Vegetation Index** (SVI), related to LAI, and adjusted to MSG SEVIRI sensor.

Such index shall be calculated on appropriate spatial domain as that seen from a geostationary satellite. For this reason, a physically based retrieving strategy will be adopted, in order to take into account the variability of the observed surface conditions not strictly connected with the parameter of interest, such as soil albedo influence (e.g. *Verstraete and Pinty, 1996*).

Others Vegetation Parameters can also be extracted and distributed if the user community can find an appropriate use to their own proposes as vegetation biophysical parameters such as the **fraction of Absorbed Photosynthetic Active Radiation** (f_{APAR}) or the **Fraction of Green Vegetation** (FGV). Close contacts with the user community will be established and maintained during all project phases in order to clarify which are the vegetation parameters to be included and distributed.

The vegetation parameters to be included are at the moment being analysed taking into consideration the user needs and the quality access to be progressively included in the products list.

REFERENCES

Aber, J.D., Federer, C.A., A generalised, lumped-parameter model of photosynthesis, evapotranspiration and net primary production in temperate and boreal forest ecosystems. Oecologia 92: 463–474, 1992.

Anderson M. C., Norman J. M., Diak G. R., Kustas W. P., Mecikalski J. R., 1997, A two-source time-integrated model for estimating surface fluxes using thermal infrared remote sensing, Rem. Sens. Env. 60, 195-216.

Asrar, G., Fuchs, M., Kanemasu, E.T. and Hatfield, J.L., Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agro. J. 76: 300-306, 1984.

ASTIMwR-Application of Space Techniques to the Integrated Management of river basin Water Resources-Contract nº ENV-CT96-0366-Environment Programme-Final Report-Montesinos&Castaño; DL:AB-62-2000; ISBN-84-605-9867-5; 1999

Braud, I., Dantas Antonino, A., Vauclin, M., Thony, J., and Ruelle, P., A Simple Soil Plant Atmosphere Transfer model (SiSPAT) development and field verification, *Journal of Hydrolog*y, *16*6: 213–250, 1995.

Bastiaanssen, W.G.M. (1995). Regionalization of surface flux densities and moisture indicators in composite terrain. PH.D. Thesis, Wageningen Agricultural University (appeared also as Report 109,DLO-Winand Staring Centre), Wageningen, The Netherlands, pp.273

Bastiaanssen W. G. M., Menenti M., Feddes R. A., Holtslag A. A. M., 1998a, A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. J. Hydrol. 212-213, 198-212.

Bastiaanssen W. G. M., Pelgrum H., Wang J., Ma Y., Moreno J.F., Roerink G.J., van der Wal T., 1998b, A remote sensing surface energy balance algorithm for land (SEBAL). 2. Validation. J. Hydrol. 212-213, 213-229.

Bastiaanssen, W, T. van der Wal and Visser, T., "Diagnosis of regional evaporation by remote sensing to support irrigation performance assessment" Irrigation and Drainage System, 10: 1 – 23, 1996.

Brutseart, W., On a derivable formula for long-wave radiation from clear skies. Water Resour. Res. 11: 742-744, 1975.

Calvet, J. C., Noilhan, J., Roujean, J. L., Bessemoulin, P., Cabelguenne, M., Olioso, A., and Wigneron, J.-P., An interactive vegetation SVAT model tested against data from six contrasting sites, *Agricultural and Forest Meteorolog*y, *9*2: 73–95, 1998.

Caselle, V. and J. A. SOBRINO (1989), Determination of frosts in orange groves from NOAA-9 AVHRR data, SER 29: 135-146.

Chehbouni, A., Lo Seen, D., Njoku, E.G. and Monteny, B., A Coupled Hydrological and Ecological modelling Approach to examine the Relationship between Radiative and Aerodynamic Surface Temperature over Sparsely Vegetated Surfaces. Remote Sensing Environment, 1996.

Chehbouni, J. Qi, Lo Seen, D., Y.H. Kerr and G. Dedieu, S. Moran, M. Daubas and B.M. Monteny, Remote sensing and water resources, Proceedings of the International Workshop, Montpellier, France, 1997.

Clevers, J.G.P.W.and van Leeuwen, H.J., 1996. Combined use of optical and microwave remote sensing data for crop growth monitoring. Remote Sensing of Environment, vol. 56, p. 42-51.

Courault, D., Lagouarde, J. P., and Aloui, B., Evaporation for maritime catchment combining a meteorological model with vegetation information and airborne surface temperatures, *Agricultural and Forest Meteorolog*y, *8*2: 93–117, 1996.

Daamen, C. and Simmonds, L., SWEAT, a numerical model of water and energy fluxes in soil profiles and sparse canopies, Tech. rep., Department of Soil Science, University of Reading, UK, 1994.

Daughtry, C.S.T., W.P. Kustas, M.S. Moran, P.J. Pinter, R.D. Jackson, P.W. Brown, W.D. Nichols and L.W. Gay (1990). Spectral estimates of net radiation and soil heat flux, Rem. Sens. Of Env. 32: 111-124.

Deardorff, J., Efficient prediction of ground surface temperature and moisture, with inclusion of a layer of vegetation, *Journal of Geophysical Researc*h, *8*3: 1889–1903, 1978.

D'Urso, G., E.P. Querner and J. A. Morábito (1992)-Integration of hydrological simulation models with remotely sensed data: na application to irrigation management. In: J. Feyen et al. (eds), Advances in planning design and management of irrigation systems as related to sustainable land use. Volume 2. Katolieke Universtiteit Leuven, Belgium, pp 463-472.

Federer, C., A soil-plant-atmosphere model for transpiration and availability of soil water, *Water Re-sources Researc*h, *1*5: 555–562, 1979.

Gao, W. and Lesht, B.M., 1997. Model inversion of satellite-measured reflectances to obtain surface biophysical and bi-directional reflectance characteristics of grassland. Remote sensing of Environment, vol. 59, p. 461 – 471.

Gholz, H.L., 1982. Environmental limits on aboveground net primary production, leaf area, and biomass in vegetation zones of the pacific Northwest. Ecology 63 (2), 469–481.

Goel, N.S., Models of vegetation canopy reflectance and their use in estimating of biophysical parameters from reflectance data, Remote Sens. Rev. 4: 1 – 212, 1988.

Goel, N.S., Inversion of canopy reflectance models for estimation of biophysical parameters from reflectance data in: Theory and application of optical remote sensing (John Wiley, New York), 1989.

Goel, N.S., From artificial life to real life: Computer simulation of plant growth, Int. J. of general systems, General Systems Journal, 18 (4): 283 – 285, 1991.

Govaerts, Y., 2000: "Exploitation and evaluation of retrieval algorithms for geostationary satellite data processing: Current and future systems". In Verstraete *et al.* (eds.), 2000, pp. 77-89.

Gutman, G.G., 1989: "On the relationship between monthly mean and maximum-value composite vegetation indices". *Int. J. Remote Sensing*, vol. 10, pp. 1317-1325.

Hall, F.G, Huemmrich, K.F., Goward, S. N., Use of narrow – band spectra to estimate fraction of photosynthetically active radiation, *Remote Sens. Environ.* 32: (1) 47 – 55, 1990.

Hall, F.G, Huemmrich, K.F., Goetz, S.J., Sellers, P.J., Nickeson, J.E., Satellite remote sensing of surface energy balance: Successes, failures and unresolved issues in FIFE*, J. Geophysical Res.* 97(D17): 19061-19090, 1992.

Hall, F.G., Townshend, J.R. and Engman, E. T., Status of Remote Sensing Algorithms for Estimation of Land Surface State Parameters, Remote Sens. Env. 51: 138 – 156, 1995.

Huete, A., Justice, C., and Liu, H., Development of vegetation and soil indices for MODIS – EOS, *Remote Sens. Environ.* (in press), 1994.

Hurtado, E. and Artigao, M.M., Remote sensing and water resources, Proc. of the Intern. Workshop, Montpellier, France, 1997. http://www.fao.org/docrep/W7320B/w7320b27.htm

Jansson, P. E., Simulating model for soil water and heat conditions. Description of the SOIL model, Tech. rep., Swedish University of Agricultural Sciences, Uppsala, Sverige, 1998.

Kaufman, Y. J. and Tanre, D., Atmospherically Resistant Vegetation Index (ARVI) for EOS – MODIS, *IEEE Trans. Geoscience Remote Sens.* 30: 261 – 270, 1992.

Kustas W. P., Norman J. M., 1999, Evaluation of soil and vegetation heat flux predictions using a simple two-source model with radiometric temperatures for partial canopy cover, Agr. Forest Meteorol., 94, 13-29.

Laguarde, J.P., Brunet, Y., A simple model for estimating the daily upward longwave surface radiations from NOAA-AVHRR data. *International Journal of Remote Sensing,* 1991.

Lagouarde, J.-P., Use of NOAA AVHRR data combined with an agrometeorological model for evaporation mapping, *International Journal of Remote Sensin*g, *1*2: 1853–1864, 1991.

Land SAF Team, Land SAF User Requirement Document. Land SAF project internal documentation, Portuguese Institute of Meteorology 2001.

Land SAF Team, Land SAF Science Plan. Land SAF project internal documentation, Portuguese Institute of Meteorology 2001.

Lewan, E., Evaporation and discharge from arable land with cropped or bare soils during winter. Measurements and simulations, *Agricultural and Forest Meteorolog*y, *6*4: 131–159, 1993.

Li, X. and Strahler, A. H., Geometric – optical modeling for a connifer forest canopy, *IEEE Trans. Geoscience Remote Sens.* GE – 23: 705 – 721, 1985.

Lo Seen, D., Chehbouni, A., Njoku, E., Saatchi, S., Mougin, E., and Monteny, B., An approach to couple vegetation functioning and soil-vegetation-atmosphere-transfer models for semiarid grasslands during the HAPEX-Sahel experiment, *Agricultural and Forest Meteorolog*y, *8*3: 49–74, 1997.

Manzi, A., Introduction d'un schéma des transferts sol-végétation-atmosphère dans un modèle de circulation générale et application à la simulation de la déforestation amazonienne, Thése de doctorat, Université Paul Sabatier, Toulouse, 1993.

Marchand D., Modélisation fonctionnelle du bilan hydrique sur sol cultivé: approche déterministe ou stochastique. Thèse doctorat soutenu à l'Université Joseph Fourier – Grenoble 1, Spécialité: Mecanique. Inp/Grenoble, 246p, 1988.

Mecikalski J.R., Diak G.R., Anderson M.C., Norman J.M., 1999, Estimating fluxes on continental scales using remotely sensed data in an atmospheric-land exchange model, J. Appl. Meteorol. 38, 1352-1369.

Milly, P., Moisture and heat transport in hysteretic inhomogeneous porous media: a matric head-based formulation and a numerical model, *Water Resources Researc*h, *1*8: 489–498, 1982.

Moran, M.S., Clarke, T.R., Kustas, W.P., Weltz, M. and Amer, S.A., Evaluation of hydrologic parameters in semiarid rangeland using remotely sensed spectral data, Water Resour. Res. 30: 1287-1298, 1994a.

Moran, M.S., Kustas, W.P., Vidal, A., Stannard, D.I., Blanford, J.H. and Nichols, W.D., Use of ground-based remotely sensed data for surface energy balance evaluation of a semiarid range-land, Water Resour. Res. 30: 1339-1350, 1994b.

Noilhan, J. and Planton, S., A simple parameterisation of land surface processes for meteorological mod-els, *Monthly Weather Revie*w, *11*7: 536–549, 1989.

Noilhan, J. and Mahfouf, J. F., The ISBA land surface parameterization scheme, *Global Planetary Chang*e, *1*3: 145–159, 1996.

Norman J.M., Kustas W.P., Humes K.S., 1995, Source approach for estimating soil and vegetation energy fluxes in observations directional radiometric surface temperature, Agr. Forest Meteorol. 77, 263-293.

Norman J. M., Divakarla M., Goel N. S., 1995, Algorithms for extracting information from remote thermal-IR observations of the Earth's surface, Rem. Sens. Env. 51, 157-168.

Norman J. M., Kustas W. P., Prueger J. H., and Diak G. R., 2000: Surface flux estimation using radiometric temperature: a dual-temperature-difference method to minimise measurements errors. Water Res. Research, 36(8), 2263-2274.

Olioso, A., Simulation des échanges d'énergie et de masse d'un couvert végétal, dans le but de relier la transpiration et la photosynthèse aux mesures de réflectance et de température de surface, Thèse de doctorat, Université Montpellier II, 1992.

Olioso, A., Braud, I., Chanzy, A., Courault, D., Demarty, J., Kergoat, L., Lewan, L., Ottlé, C., Prévot, L., Zhao, W., Calvet, J. C., Cayrol, P., Jongschaap, R., Moulin, S., Noilhan, J. and Pigneron, J., Physics and Chemistry of the Earth, Soil-Vegetation-Atmosphere Transfer (SVAT) models, 2000.

Ortega-Farias, S., Antonioletti, R., and Olioso, A., Net radiation model evaluation at an hourly time step for Mediterranean conditions, *Agronomi*e, *2*0: 157–164, 2000.

Pelgrum,H., 1992. Mapping areal surface energy balances, during daytime using METEOSAT data, Technical Note 195, DLO The Winand Staing Centre, Wageningen, The Netherlands: 50 pp.

Pinty, B., M.M. Verstraete, si R. E. Dickinson (1990). A physical model of the bidirectional reflectance of vegetation canopies. *J. of Geophysical Res*., vol. 95, p. 11 767 - 11 775.

Philip, J. and De Vries, D., Moisture movement in porous materials under temperature gradients, *Trans. Am. Geophys. Unio*n, *3*8: 222–232, 1957.

J.L. Privette, Myneni, R. B.,Tucker, C.J. and EmeryW.J., 1994. Invertibility of a 1-D discrete ordinates canopy reflectance model. Remote Sensing of Envir., vol. 48, p. 89 – 105.

J.L. Privette, Myneni, R. B., Emery, W.J. and Pinty, B., 1995. Inversion of a Soil Bi-directional Reflectance Model For use with vegetation reflectance models. Journal of geophysical research, vol. 100, p. 25 497 – 25 508.

J. Qiu, W. Gao, B.M. Lesht, 1998. Inverting optical reflectance to estimate surface properties of vegetation canopies., Int. J. Remote Sensing, p. 642 – 656

Roujean, J.-L., M. Leroy, and P.Y. Deschamps, 1992, *A bi-directional reflectance model of the Earth's surface for the correction of remote sensing data*. Journal of Geophysical Research, 97, 20,455-20,468.

Sellers, P.J., Canopy reflectance, photosynthesis and transpiration. *International Journal of Remote Sensing,* 16:1335-1372, 1985.

Sellers, P.J., Los, S.O., Tucker, C.J., Justice, C.O., Dazlich, D.A., Collatz, G.J. and Randall, D.A., A global 1 by 1 degree NDVI data set for climate studies. Part 2: The generation of global fields of terrestrial biophysical parameters from the NDVI. *International Journal of Remote Sensing,* 15(17): 3519-3545, 1994.

Sellers, P.J., Los, S.O., Tucker, C.J., Justice, C.O., Dazlich, D.A., Collatz, G.J. and Randall, D.A., A revised land surface parameterisation (SiB2) for atmospheric GCMs. Part 2: The generation of global fields of terrestrial biophysical parameters from satellite data. *Journal of Climate*, 1995.

Sellers, P.J., Los, S., Tucker, C.J., Justice, C.O., Dazlitch, D.A., Collatz, G.J., Randall, D.A., 1996. A revised land surface para-meterization (SiB2) for atmospheric GCMs. Part 2. The generation of global fields of terrestrial biophysical parameters from satellite data. Journal of Climate 9, 706–737.

Somma G., C.J. de Zeeww, Z.Su and M. Meneti (1998):Application of space techniques to derive energy fluxes for water management in arid zones. EARSel symposium proceedings, 11-15 may 1998.

Suits, G. H., The calculation of the directional reflectance of vegetative canopy. *Remote Sens. of Environ*., 22: 117 – 125, 1972.

Supit, I., Global radiation. *Joint Research Centre*, EUR 15745 EN, pp. 13-21, 1994.

Taconet, O., Bernard, R. and Vidal-Madjar, D., Evapotranspiration over an agricultural region using a surface flux/temperature model based on NOAA-AVHRR data, *Journal of Climate and Applied Meteorolog*y, *2*5: 284–307, 1986.

Valor,E. and V. Caseles 1996).Mapping land surface emissivity from NDVI: Application to European, African, and South American areas. Remote Sens. Environ. 57:167-184.

Verhoef, W., Light scattering by leaf layers with application to canopy reflectance modeling: The SAIL model, *Remote Sens. Environ.,* 16: 125 – 141, 1984.

Witono, H. and Bruckler, L., Use of remotely sensed soil moisture content as boundary conditions in soil atmosphere water transport modelling. 1. field validation of a water flow model, *Water Resources Researc*h, *2*5: 2423–2435, 1989.