# Identification of Priestley-Taylor transpiration Parameters used in TSEB model by Genetic Algorithm

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#### Abstract

The accuracy degree of extracted canopy latent heat from canopy net radiation is depending extremely to the proposed Priestley-Taylor approximation. This extracting canopy latent heat is an initial approximation to compute iteratively partitioned energy components to soil and vegetation using in Two Source Energy Balance (TSEB) Model. This approximation is using a Priestley-Taylor coefficient (ap) and fractional of Leaf Area Index (fg) that is green. The standard values are 1.26 and 1 for respectively (ap) and (fg). This study is focused to identify these two transpiration parameters (ap) and (fg) by Genetic Algorithm method to accurately predict patterns of turbulent energy fluxes by TSEB Model (Norman et al. 1995), over irrigated olive orchard in semi-arid area (Marrakech, Morocco). The (ap) and (fg) are depending on local climatic characteristics and data measurements accuracy for different periods of the year 2003. In summer 2003, the GA gives optimal values for (ap=0.93) and (fg=0.61). Ten runs of GA computing have been applied to guaranty stability of the optimization process. In fact, the simulation of latent heat becomes improved as presented as below, since comparison to ground measurements shows acceptable representativeness in summer 2003 with enhancement of TSEB Model performance assuming correlation to (0.45), bias is to (+15 W.m-2), and the root mean square have been improved to (63 W.m-2). Thus, the results obtained here show the most important support of Genetic Algorithm through the calibration and optimization processes.

**Keywords:** Genetic algorithm, Optimization, Fitness function, Cost function, TSEB Model.

# 1. Introduction

Many methods have been used to estimate canopy evapotranspiration from regions using standard climate data. Priestley-Taylor approximation suggest one of these based on physical argument about processes in the whole of turbulent planetary boundary layer, and their arguments were concerned the relative sizes of advective and radiant energy inputs to land areas of local size (Priestley-Taylor, 1972; McNaughton et al 1991).

They were forced to proceed empirically, and asked whether it was still a principal component of evaporation from a wet region. They looked that a value of coefficient  $(\alpha p = 1.26)$  was found to fit data from several sources especially for wet regions. The TSEB Model uses either this formula adding another coefficient (fg=1) which is a fractional of Leaf Area Index that is green (Norman et al, 1995; Kustas et al 1999). Several studies are also proposed values of  $(\alpha p)$  and (fg) ranging respectively from 0.5 to 3 and 0 up to 1(Castellvi et al, 2001; Kustas et Norman et al, 1999a, Agam et al. 2010). In this study, for a semi-arid areas, we suggest to use stochastic method as Genetic algorithms (GAs) to identify Priestley-Taylor transpiration Parameters over olive irrigated area (in wet and dry conditions). GAs approach are used for solving parameters estimation for its independency to problem types, such as non linear, multimodal and/or nondifferentiable functions (Holland, J. H, 1975; Goldberg, David E, 1989). GAs are a way of addressing hard search and optimization problems which provides a good solution although it requires large execution time.

In section 2 we present study area and data collection, while section 3 describe the

Priestley-Taylor approximation of transpiration used in TSEB Model. The section 4 highlights GAs theoretical bases and implementation. In section 5 we show results but conclusion is presented in section 6.



# 2. Study area and data collection

# 2.1 Site description

The study site was located in the 275 hectare Agdal olive (Olea europaea L.) orchard in the southern side of Marrakech City, Morocco (31,601 N; 07,974 W). It is characterized by low and irregular rainfall (annual average of about 240 mm, but 263.4 mm has been collected in 2003). The climate is typically Mediterranean semi arid; precipitation falls mainly during winter and spring, from November to April. The atmosphere is very dry with an average humidity of 56% and the evaporative demand is very high (1600mm per year), greatly exceeding the annual rainfall. The orchard was periodically surface irrigated through level basin flood irrigation, with water supplies of about 100 mm every each irrigation event. We have approximately 3 irrigation events during summer 2003. Each tree was occupied over 45 m2, and bordered by small earthen levy (about 30 cm) retained irrigation water (Williams et al, 2004). Plant spacing was about (6.5x6.5 m); the trees had an average leaf area index (LAI) of 3. Mean tree height was 6 m and ground cover was 55% (Ezzahar, 2007).

# 2.2 Measurements

Measurements were acquired at a sampling frequency of 20 Hz and passed through a low-pass filter to compute 30min flux averages. Intensive data were collected in Agdal site. Vertical fluxes of heat and water vapor at 9.2 m height were registered on twelve month of 2003 and are measured by an Eddy-Covariance (EC) system (Ezzahar et al, 2007). Finally, the resulting dataset of sensible and latent heat fluxes were available for the 2003 growing seasons, with missing data for few days due to power supply troubles. Almost 6247 hourly observations, during daytime, everyday along the year 2003 without any exclusion related to season or climatic conditions, were used to run and evaluate TSEB model output.

A 3D sonic anemometer (CSAT3, Campbell Scientific, Logan, UT) measured the fluctuations in the wind velocity components and temperature. An open-path infrared gas analyzer (LI7500, LiCor, Inc., Lincoln, NE) measured concentrations of water vapour. The wind speed and concentration measurements were made at 20 Hz on CR23X dataloggers (Campbell Scientific, Logan, UT) and on-site portable computers to enable the storage of large raw data files. Air temperature and humidity were measured at 8.8 and 3.7 m heights on the tower with Vaisala HMP45C probes. Total shortwave irradiance was measured at 9.25 m height with a BF2 Delta T radiometer. Net radiation was measured with a Kipp and Zonen CNR1 net radiometer placed over the olive canopy at 8 m height.

Soil temperature was recorded at 5 cm depth at two locations approximately 30 m from the tower. Three heat flux plates continuously monitored changes in soil heat storage at the tower site. In addition, five point measurements of soil moisture variables were located throughout the site. Each point contained a pair of steel rods for time domain reflectometry (TDR) measurements at 40, 30, 20, 10 and 5 cm depths to estimate volumetric water content. Olive transpiration was measured by sap flow method following the procedure of Williams et al., 2003. Soil evaporation was computed as the difference between evapotranspiration measured by sap flow method.

# 3. Priestley-Taylor transpiration in TSEB Model

The Priestley-Taylor equation is only an initial approximation of canopy latent heat simulated by TSEB Model. TSEB is based on energy balance closure using surface radiometric temperature, vegetation parameters and climatic data. TSEB outputs surface turbulent fluxes, and temperatures of canopy and soil. The version implemented in this study basically follows what is described in appendix A as the "parallel resistance network". As such, the model implemented is described in detail in (Norman et al. 1995, Kustas and Norman 1999). The canopy latent heat LEc is given by Priestly-Taylor approximation (Priestly-Taylor. 1972).

LEc = Rnc. 
$$\alpha p$$
 .fg.  $\frac{\Delta}{\Delta + \Gamma}$  (1)

where  $\alpha p$  is the Priestly-Taylor constant, which is initially set to 1.26 (Priestley-Taylor, 1972; Norman et al 1995; Agam et al 2010), fg is the fraction of the LAI that is green,  $\Delta$  is the slope of saturation vapour pressure versus temperature curve,  $\Gamma$  is the psychrometer constant (e.g: 0.066 kPa C<sup>-1</sup>). If no information is available on fg, then it is assumed to be near unity.

# 4. Genetic algorithms method

# 4.1 Overview

Genetic Algorithms (GAs) are an optimization algorithms based on techniques derived from the genetic and the Darwin's theory of evolution in selection, crossover, mutation, generation, parent, children, etc (Goldberg 1989; Holland 1975). As a considerable development in the computing systems, GAs has shown a significant



improvement by using stochastic and mathematic methods which has been applied into many domains such as ecologies, biology and even economy, in order to experiment it for understanding natural systems, and modelling it to optimize (or at least improve) the performance of the system.

## 4.2 GAs theoretical bases and implementation

Genetic algorithms have been used to solve difficult problems with objective functions that do not possess some properties such as continuity, differentiability, satisfaction of the Lipschitz Condition, etc (Michalewicz 1994; Goldberg 1989; Holland 1975).

GAs search extremum of function defined in space data. These algorithms maintain and manipulate a family, or population, of solutions and implement a "survival of fittest" strategy in their search for better solutions. GAs have shown their advantages in dealing with the highly non-linear search spaces that result from noisy and multimodal functions.

The genetic algorithm works as follows:

- Initialization of parent population randomly
- Evaluation (fitness function)
- Selection

- Recombination of possible solutions (Crossover and Mutation)

- Evaluate child and go to step 3 until termination criteria satisfies.

## 4.2.1 Solution representation

The chromosome (individual) chosen to represent a solution is a vector coded of floating number representing

$$K = <\alpha p, fg >$$
(2)

The ranges of a parameters are a and b. The  $\alpha$ p is the Priestly-Taylor constant, and fg is the fraction of the LAI that is green. The real-valued representation moves the problem closer to the problem representation which offers higher precision with more consistent results across replications (Michalewicz 1992).

### 4.2.2 Initialization, Termination and Evaluation

The most common method providing an initial population is to randomly generate solutions for the entire population such as:

$$K = a + (b - a) * rend(2, N)$$
 (3)

where N is the dimension of population, such that each element of array contains a possible value of parameters; and rand (2,N) returns a pseudorandom vector value are drawn from a uniform distribution on the unit interval.

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The GA moves from generation to generation selecting and reproducing parents until a termination criterion is met. The most frequently used stopping criterion is a specified maximum number of generations.

Fitness in biological sense is a quality value which is a measure of the reproductive efficiency of chromosomes (Goldberg, 1989). In genetic algorithm, individuals are evaluated with it fitness function which is a measure of goodness to be selected.

The evaluation is calculated at each TSEB run through the fitness function  $\Phi(K)$  which is equal to

$$\Phi(K) = \left[\frac{1}{1 + \frac{1}{2}\int_{0}^{T} \left[LE_{sim}(t, K) - LE_{abs}(t)\right]^{2}}\right]$$
(4)

where (t) is the instant of observed latent heat  $LE_{obs}(t)$  and  $LE_{sim}(t,K)$  is the simulated latent heat.

The cost function to minimize is represented by a practical evaluation of  $\Im(K)$  where

$$\Im(K) = \frac{1}{2} \int_{0}^{T} [LE_{sin}(t, K) - LE_{sis}(t)]^{2}$$
(5)

where T is the time period.

#### 4.2.3 Genetic Operators

Genetic algorithm uses some operators to create children forming next new generation by parents selected from the current population. The algorithm usually selects a group of individuals that have better fitness values as parents. The genetic operators are as follows:

• Selection: Reproduction (or selection) is usually the first operation applied on a population to breed a new generation. Individual solutions are selected through probability that individual  $_{(K)1 \le i \le N}$  is selected from the ith line of matrix , to be a member of the next generation at each experiment is given by

$$\operatorname{Prob}\{K_{l} \text{ is selected}\} = \frac{\Phi(K_{l})}{\sum_{j=1}^{N} \Phi(K_{j})}$$
(6)

The process is also called roulette wheel parent selection. This selection step is then a spin of the wheel, which in the long run tends to eliminate the least fit population



members. The population will be represented by a slice that is directly proportional to the member's fitness.

• Crossover: A crossover operator is used to recombine pairs of parents to get better children which generate a second generation of solutions. In the case of individual probability is less than 0.5, the son child chromosome will be an average of two times value of father with one value of mother, and vise versa for the daughter child, but if individual probability is great or equal to 0.5, the son and daughter chromosome will stay respectively like father and mother.

• Mutation: Mutation is an operator that introduces diversity in the population to avoid homogeneous generation due to repeated use of reproduction and crossover operators. Mutation proceeds to Gaussian perturbation with deviation equal to 0.5 and probability mutation equal to 0.0001. Mutation adds simply new information in a random way to the genetic search process.

## 4.2.4 Implementation of GAs to TSEB Model

Possible solutions to a problem are evaluated and ordered according to its adaptation (i.e: fitness function). From generation (k) to new one (k+1), then other chromosome populations are produced after selecting candidates as 'parents' and applying mutation or crossover operators which combine chromosome of two parents to produce two children. The new set of candidates is then evaluated, and this cycle continues until an adequate solution is found (figure.1). In all experiments, GA experimental parameters are as follows: the population size is 10, the crossover rate is 0.5, the mutation rate is 0.0001 and we generate population until the 10th generation. The observations used in TSEB Model are taken each 30 minutes. In this optimization we want to minimize the cost function, then we proceed the minimization to find a vector Kopt as follows:

$$\Im(Kopt) = \inf \Im(K)$$
 (7)

where  $K = \langle \alpha p_i f g \rangle$  is the vector of parameters to be controlled, and  $\mathcal{J}(K)$  is the cost function.

The state variable is the simulated latent heat  $LE_{sim}(t,K)$  evolving in the time during summer 2003 between DOY=152 to DOY=243. The cost function is computed by comparing simulated  $LE_{sim}$  and observed latent heat  $LE_{obs}$  during the all period T. The two unknown parameters controlling the Priestley-Taylor transpiration used in TSEB Model are estimated by optimization of the cost function with the evolution strategies algorithm as follow:

-START: Create random population of 10 chromosomes  $K = \langle \alpha \varphi , f \varphi \rangle$  between 0.5 to 2 for  $\alpha p$ , and 0.1 to 1 for fg,

-*Run TSEB:* Calculate the simulated latent heat LEsim(t,K), the bias to measured latent heat LEobs(t) and the function cost  $\Im(K)$ ,

*-FITNESS:* Evaluate the fitness function  $\Phi(K)$  of each chromosome in the population,

## -NEW POPULATION:

\* SELECTION : Based on  $\Phi(K)$ 

\* RECOMBINATION: Cross-over chromosomes

\* *MUTATION* : Mutate chromosomes

\* ACCEPTATION : Reject or accept new one

*-REPLACE* : Replace old with new population as the new generation

-*TEST* : Test problem criterion to indicate the best solution  $K = \langle ap \rangle f \rangle$  minimizing the cost function  $\Im(K)$ , else to turn over to the next generation

LOOP : Continue step 2– 6 until criterion is satisfied.

# 5. Results

Different number of generations (not shown) with ten individuals population have been experimented in order to

optimize values of  $R_{app} \rightarrow ap_i f_{ij} \rightarrow and$  to carry out stability test to GA with showing performance to Priestley-Taylor formulation. The founded parameters by GA are changing with reproduction in generations. The GA start generally with a randomly values of parameters

in the beginning of minimized cost function [ $\Im(K)$ ], but in the absence of stopping criterion to the most minimizing cost function, the GA change choice to selected individuals who decrease Latent heat error to reach its minimum. The GA continues to generate elite chromosomes for computing predicted surface fluxes until stability of Latent heat error (fig.2). The stability error phase is characterized by a little changing in reproductive individual's adaptation. The convergence will be reached during generation when the best individual is founded to the medium one (fig.1). The estimation of Priestley-Taylor formulation has been improved then the TSEB Model performance will come acceptable with best parameters



giving by 10 generations. We proceed in the following to experiment 10 runs of GA to show best parameters changing and test stability reproduction procedure with 10 individuals' population and 10 generations. During error stabilization error process, the 10 runs of GA shows (table.1) changing in parameters value, since  $\alpha p$  is ranging between 0.72 to 1.00 and fg vary from 0.26 to 0.79. These optimized values for ap and fg are less than the standard value ( $\alpha p = 1.26$  and fg=1 for wet conditions), then we can considered them for semi arid area. Optimized values for fg are conforming to irrigated area explaining conditions supporting soil and canopy transpiration. GA gives sometimes optimal parameters corresponding to minimum error before reaching its stabilization, but GA continue computing process since there is no stopping criterion for this case to reduce calculation time. The mean parameters value optimized in 10 previous runs of  $\alpha p$  and fg (table.1) are respectively 0.93 and 0.61. Now let us see the influence of these optimal mean values to TSEB Model. Figures 3 and 4 present the comparison of measured and predicted daily latent heat before and after optimization process. These figures show an improvement of latent heat representativeness. The correlation becomes from (0.43) to (0.45), the bias is reduced from  $(+240 \text{ W.m}^{-2})$  to (+15)W.m<sup>-2</sup>), and the root mean square have been improved from  $(251 \text{ W.m}^{-2})$  to  $(63 \text{ W.m}^{-2})$ . Furthermore the measured and predicted latent heat evolve both in the same direction expect during irrigation event, because soil is submerged by traditional irrigation system water.

# 6. Conclusion

In this comparison of cases studied here, we observe that GA stability is essential to optimize parameters. The results obtained don't change significantly from each 10

runs, then the optimal vector is Kapt = < 0.93, 0.61 >. We have tried to show that genetic algorithm is a powerful method to optimize parameters of Priestley-Taylor approximation of canopy transpiration. Instead of standard

values of ap = 1.20 and fg = 1 for wet regions, which depend on climatic and soil characteristic, GA gives an optimal values as  $< \alpha p=0.93$ , fg=0.61 > for semi-arid area. Stability optimization is essential, furthermore the GA can be identifying another minimum of optimal parameters in the beginning of computation, but the computation continue since there is no stopping criterion other than the final generation.

The results show an improvement of canopy transpiration then also enhance the TSEB Model performance, since correlation, bias and root mean square error become respectively equal 0.45, +15 W.m-2, and 63 W.m-2. Thus, the results obtained in this study show the most important support of Genetic Algorithm in the calibration and optimization processes. This GAs optimization could replace measures terrain and long experiments since it improve results mostly by making use of fitness function and genetic operators such as selection, crossover and mutation. However, the set of canopy transpiration was improved.

## Appendix A

#### **TSEB** Equations

Soil and vegetation temperature contribute to the radiometric surface temperature in proportion to the fraction of the radiometer view that is occupied by each component along with the component temperature. In particular, assuming that the observed radiometric temperature, (Trad) is the combination of soil and canopy temperatures, the TSEB model adds the following relationship (Becker and Li, 1990) to the set of (Eqs 12 and 13):

Trad(
$$\theta$$
) = [f( $\theta$ ). Tc<sup>4</sup> + (1-f( $\theta$ )) . Ts<sup>4</sup>]<sup>1/4</sup>  
(A.1)

where Tc and Ts are vegetation and soil surface temperatures, and  $f(\theta)$  is the vegetation directional fractional cover (Campbell and Norman, 1998).

$$f(\theta) = 1 - \exp(-0.5 \text{ LAI} / \cos(\theta))$$
(A.2)

The simple fractional cover (fc) is as follows:

$$fc = 1 - exp(-0.5 LAI)$$
 (A.3)

LAI is the leaf area index, and the fraction of LAI that is green (fg) is required as an input and may be obtained from knowledge of the phenology of the vegetation.

The total net radiation Rn (Wm-2) is

$$Rn = H + LE + G \tag{A.4}$$

where H (Wm<sup>-2</sup>) is the sensible heat flux, LE (Wm<sup>-2</sup>) is the latent heat, and G (Wm<sup>-2</sup>) is the soil heat flux. The estimation of total net radiation, Rn can be obtained by computing the net available energy considering the rate lost by surface reflection in the short wave  $(0.3/2.5\mu m)$ and emitted in the long wave (6/100 $\mu m$ ):

$$Rn = (1 - \alpha s).SW + \varepsilon s.LW - \varepsilon s.\sigma.Trad4$$
 (A.5)



where SW (Wm-<sup>2</sup>) is the global incoming solar radiation, LW (Wm-<sup>2</sup>) is the terrestrial infrared radiation,  $\alpha s$  is the surface albedo,  $\epsilon s$  is the surface emissivity,  $\sigma$  is the Stefan-Boltzmann constant, Trad (°K) is the radiometric surface temperature.

The estimation of soil net radiation, Rns can be obtained by

$$Rns = Rn \exp(-Ks \, LAI \, / \, \sqrt{2.\cos (t)}$$
(A.6)

where ks is a constant ranging between 0.4 to 0.6 and is the zenithal solar angle.

The Rnc is the canopy net radiation as

$$Rnc=Rn-Rns$$
 (A.7)

where Rn is obtained using (A.4-5) and is the solar zenith angle. The soil heat flux, G (Wm<sup>-2</sup>) can be expressed as a constant fraction cg ( $\approx 0.35$ ) of the net radiation at the soil surface by

$$G = cg Rns$$
 (A.8)

The constant of cg ( $\approx 0.35$ ) is midway between its likely limits of 0.2 and 0.5 (Choudhury et al 1987). The canopy latent heat LEc is given by Priestly-Taylor approximation (Priestly-Taylor. 1972).

LEc = Rnc. 
$$\alpha p$$
 .fg.  $\frac{\Delta}{\Delta + \Gamma}$  (A.9)

where  $\alpha p$  is the Priestly-Taylor constant, which is initially set to 1.26 (Norman et al 1995; Agam et al 2010), fg is the fraction of the LAI that is green,  $\Delta$  is the slope of saturation vapor pressure versus temperature curve,  $\Gamma$  is the psychrometer constant (e.g: 0.066 kPa C<sup>-1</sup>). If no information is available on fg, then it is assumed to be near unity. As will become apparent later (A.9) is only an initial approximation of canopy latent heat.

If in any case  $\text{LEc} \leq 0$ , then LEc is set to zero (i.e. no condensation under daytime convective conditions)

The sum of the contribution of the soil and canopy net radiation, total latent and sensible heat is according to the following equations

$$Rns = Hs + LEs + G$$
(A.10)

$$Rnc=Hc+LEc$$
(A.11)

$$LEt = LEc + LEs \tag{A.12}$$

where the subscript s and c designs soil and canopy.

The TSEB model considers also the contributions from the soil and canopy separately and it uses a few additional parameters to solve for the total sensible heat Ht which is the sum of the contribution of the soil Hs and of the canopy Hc according to the following equations

$$\mathbf{H}_{\mathbf{t}} - \mathbf{H}\mathbf{s} + \mathbf{H}\mathbf{c} \tag{A.13}$$

$$Hc = \rho Cp \begin{bmatrix} Tc - Ta \\ Ra \end{bmatrix}$$
(A.14)

$$Hs - p Cp \left[\frac{Ts - Ta}{Rs + Ra}\right]$$
(A.15)

Where  $\rho$  (Kg.m<sup>-3</sup>) is the air density, Cp is the specific heat of air (JKg-1 K-1), Ta (°K) is the air temperature at certain reference height, which satisfies the bulk resistance formulation for sensible heat transport (Kustas et al, 2007). Ra (sm<sup>-1</sup>) is the aerodynamic resistance to heat transport across the temperature difference that can be evaluated by the following equation (Brutsaert, 1982):

$$Ra = \frac{\ln \left[\frac{[2u-d_0]}{2} - \Psi H\right]}{k_0 V a}$$
(A.16)

Where  $\mathbb{Z}_{\mathbb{H}}$  is the height of air wind measurements,  $\mathbb{V}^{\ast}$  is the wind friction velocity, do (m) is the displacement height, Z0,H is a roughness parameter (m) that can be evaluated as function of the canopy height (Shuttleworth and Wallace, 1985), k is the von Karman's constant ( $\approx 0.4$ ),  $\Psi$ H is the diabatic correction factor for heat is computed (Paulson, 1970):

$$\Psi H = 2 \ln \left[\frac{1+\theta_h^2}{2}\right]$$
(A.17)

where is a universal function for heat defined by: (Brutsaert, 1982; Paulson, 1970)

$$(A.18) \emptyset_{h} = (1 - 16.\xi)^{1/4}$$

The term  $\xi$  is dimensionless variable relating observation height Z, to Monin-Obukhov stability Lmo.

Lmo is approximately the height at which aerodynamic shear, or mechanical, energy is equal to buoyancy energy (i.e: convection caused by an air density gradient). It is determined from IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 3, No. 1, May 2011 ISSN (Online): 1694-0814 www.IJCSI.org

$$Lmo = -\rho \frac{\frac{U e^2}{R}}{k g \left(\frac{H}{ep Ta} + 0.64 \frac{EE}{A}\right)}$$
(A.19)

Where  $\rho$  (Kgm<sup>-3</sup>) is the air density, Cp is the specific heat of air (JKg<sup>-1</sup> K<sup>-1</sup>), Ta (°K) is the air temperature at certain reference height, H is a sensible heat flux, LE is a latent heat flux, and  $\lambda$  is the latent heat.

Friction velocity is a measure of shear stress at the surface, and can be found from the logarithmic wind profile relationship:

$$U *= \frac{k.Ua}{\ln \left[\frac{Z_U - d_0}{Z_0 M} - \Psi M\right]}$$
(A.20)

Where Ua is the wind speed and  $\Psi M$  is the diabatic correction for momentum.

The Rs (sm<sup>-1</sup>) is the soil resistance to the heat transfer (Goudrian, 1977; Norman et al 1995; Sauer et al 1995; Kustas et al, 1999), between the soil surface and a height representing the canopy, and then a reasonable simplified equation is:

$$Rs = \frac{1}{a^{f} + b^{f} N_{s}}$$

(A.21)

Where a' =  $0.004 \text{ (ms}^{-1})$ , b' = 0.012 and Us is the wind speed in (ms<sup>-1</sup>) at a height above the soil surface where the effect of the soil surface roughness is minimal; typically 0.05 to 0.2 m. These coefficients depend on turbulent length scale in the canopy, soil surface roughness and turbulence intensity in the canopy and are discussed by (Sauer et al. 1995). If soil temperature is great than air temperature the constant a' becomes a'=c .(Ts-Tc)<sup>(1/3)</sup> with c=0.004

Us is the wind speed just above the soil surface as described by (Goudriaan 1977):

$$U_{s} = Uc \cdot \exp\left[-a \cdot \left(1 - \frac{a \cdot cs}{bc}\right)\right]$$
(A.22)

Where the factor (a) is given by (Goudriaan 1977) as

$$a = 0.28$$
.  $F^{2/3}$ .  $h_{a}^{1/3} \cdot s^{-2/5}$   
(A.23)

The mean leaf size (s) is given by four times the leaf area divided by the perimeter.

**U**c is the wind speed at the top of the canopy, given by:

$$\mathbf{U}_{c} = \mathbf{U}\mathbf{a} \cdot \frac{\ln\left(\frac{\ln c - d}{2M}\right)}{\ln\left(\frac{2u - d}{2M}\right) - \Psi \mathbf{M}} \tag{A.24}$$

Where Ua is the wind speed above the canopy at height Zu and the stability correction at the top of the canopy is assumed negligible due to roughness sublayer effects (Garratt, 1980; Cellier et al, 1992).

#### **TSEB** implementation and algorithm

The TSEB model is run with the use of ground thermal remote sensing and meteorological data of Agdal site during 2003. Some model constant parameters are supposed invariable along time such as the Priestly-Taylor constant  $\alpha p$ , albedo, emissivity, leaf area index (LAI), the fraction of the LAI that is green (fg), leaf size (s), the vegetation height and a constant fraction (cg) of the net radiation at the soil surface. These considerations are certainly some consequences on model results according to seasons. The Priestly-Taylor constant ap is fixed to 1.26 (McNaughton and Spriggs 1987). The albedo, value of 0.11 is an annual averaged measured with CNR1, and a surface emissivity of 0.98, the leaf area index (LAI) is equal to 3 (Ezzahar et al, 2007). The fraction of LAI (fg) that is green is fixed to 90% of vegetation (i.e. 10% of vegetation could be considered no active). The mean leaf size (s), is given by four times the leaf area divided by the perimeter (s=0.01). The average height of the olive trees is 6 meters. The fraction of the net radiation at the soil surface is fixed to cg=0.35.

Sensible and latent heat flux components for soil and vegetation are computed by TSEB, only in the atmospheric surface layer instability. Note that the storage of heat within the canopy and energy for photosynthesis are considered negligible for the instantaneous measurements. The total computed heat flux components are then from equations (A.5-8).

The canopy heat fluxes are solved by first estimating the canopy latent heat flux from the Priestley-Taylor relation (A.9), which provides an initial estimation of the canopy fluxes, and can be overridden if vegetation is under stress (Norman et al., 1995). Outside the positive latent heat situation, two cases of stress occur, when the computed value for canopy (LEc) or soil (LEs) latent heat become negative which are an unrealistic conditions.

In the first case, the normal evaluation procedure is overridden by setting (LEc) to zero and the remaining flux components are balanced by (A. 1-10-11-13-15). But in the second case, (LEs) is recomputed by using specific soil Bowen Ratio determined by =Hs/LEs and flux components are next balanced by (A.1-10-11-13-15).

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In order to solve (A.15) additional computations are needed to determine soil temperature, and the resistance terms Rah and Rs but as will become apparent, they must be solved iteratively. Soil temperature is determined from two equations: one to relate the observed radiometric temperature to the soil and vegetation canopy temperature, and another to determine the vegetation canopy temperature. The composite temperature is related to soil and canopy temperatures by (A.1). The resistance components are determined from (A.16), for Rah and the following equation (Sauer et al., 1995) for Rs (A.18).

To complete the solution of the soil heat flux components, the ground stock heat flux can be computed as a fraction of net radiation at the soil surface (A.8).

Applying energy balance for the two source flux components resolves the surface fluxes, which cannot be reached directly because of the interdependence between atmospheric stability corrections, near surface wind speeds, and surface resistances (A.16-17). In these equations, the

stability correction factors  $\Psi$ <sup>M</sup> and  $\Psi$ H depend upon the surface energy flux components H and LE via the Monin-Obukhov roughness length Lmo.

TSEB computation for solving the surface energy balance by ten primary unknowns and ten associated equations (Table.1), needs an iterative solution process by setting a large negative value to Lmo (i.e: in highly unstable atmospheric conditions). This permits an initial set of stability correction factors  $\Psi$ M and  $\Psi$ H to be computed. Computed iteration is repeated until Lmo converges.

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# References

- Agam et al, "Application of the Priestley-Taylor Approach in Two Source Surface Energy Balance Model", Am Meteo Soc, Journal of Hydrometeorology, Volume 11, 2010, pp. 185-198.
- [2] Becker. F, and Li. Z.L."Temperature independent spectral indices in thermal infrared bands," Remote Sensing of Environment, vol. 32, 1990, pp. 17-33.
- [3] Brutsaert. W, "Evaporation Into The Atmosphere," D. Reidel, Dordrecht. 1982.

- [4] Campbell. G. S, and Norman. J. M, "An Introduction to Environmental Biophysics" (2nd ed.). New York: Springer-Verlag., 1998.
- [5] Castellvi. F, Stockle. C.O, Perez. P.J, Ibanez, M, "Comparison of methods for applying the Priestley–Taylor equation at a regional scale" Hydrol. Process. 15, 2001. pp. 1609–1620.
- [6] Cellier et al, "Flux-gradient relationships above tall plant canopies," Agric. For. Meteorol. 58, 1992. Pp. 93-117.
- [7] Choudhury. B.J, Idso. S.B, and Reginato. R.J, "Analysis of an empirical model for soil heat flux under a growing wheat crop for estimating evaporation by an infrared-temperature based energy balance equation," Agric. For. Meteorol., 39, 1987. pp. 283-297.
- [8] Ezzahar. J, "Spatialisation des flux d'énergie et de masse à l'interface Biosphère-Atmosphère dans les régions semiarides en utilisant la méthode de scintillation", Ph.D. Thesis University Cadi Ayyad, Marrakech, Morocco, 2007.
- [9] Garratt et al, "Momentum, heat and water vapor transfer to and from natural and artificial surfaces,". Q. J. R. Meteorol. Sot., 99, 1973. pp.680-687.
- [10] Goldberg et al. "A Comparative Analysis of Selection Schemes Used in Genetic Algorithms", Foundations of Genetic Algorithms, G.Rawlins, ed. Morgan-Kaufmann. Pp 69-93
- [11] Goudriaan. J, "Crop Micrometeorology: A Simulation Study", Center for Agricultural Publications and Documentation, Wageningen. 1977.
- [12] Holland. J, "Adaptation In Natural and Artificial Systems" University of Michigan Press. 1975.
- [13] Kustas. W.P, Norman. J.M, "Evaluation of soil and vegetation heat flux predictions using a simple two-source model with radiometric temperatures for partial canopy cover", Agric. For. Meteorol. 94, 1999a, pp. 75–94.
- [14] Kustas. W. P, & Norman. J. M, "A two-source energy balance approach using directional radiometric temperature observations for sparse canopy covered surfaces", Agronomy Journal, 92, 2000. Pp. 847-854.
- [15] Kustas et al, "Utility of radiometric-aerodynammic temperature relations for heat flux estimation", Bound.-Lay. Meteorol., 122, 2007. pp.167–187,
- [16] McNaughton. K. G, and T. W. Spriggs, "An evaluation of the Piestley and Taylor equation and the complimentary relationship using results from a mixed-layer model of the convective boundary layer", T. A. Black, D. L, 1987. pp. 89-104
- [17] McNaughton. K. G, & Jarvis. P. G, "Effects of spatial scale on stomatal control of transpiration", Agricultural and Forest Meteorology, 54, 1991. pp. 269-301.
- [18] Michalewicz. Z, "Genetic Algorithms and Data Structures", Evolutionary Programs, Springer-Verlag, AI Series, New York. 1992.
- [19] Norman et al, "Source approach for estimating soil and vegetation energy fluxes in observations of directional radiometric surface temperature", Agricultural and Forest Meteorology 77, 1995. pp. 263-293.
- [20] Priestley. C. H. B, & Taylor. R. J, "On the assessment of surface heat flux and evaporation using large-scale parameters", Monthly Weather Review, 100, 1972. pp. 81-92.

- [21] Paulson. C.A, "The mathematical representation of wind speed and temperature profiles in the unstable atmospheric surface layer", J. Appl. Meteorol, 9, 1970. pp. 857-861.
- [22] Sauer et al, "Measurement of heat and vapor transfer at the soil surface beneath a maize canopy using source plates", Agric. For. Meteorol., 75, 1995. pp. 161-189.
- [23] Shuttleworth. W.J, and Wallace. J.S, "Evaporation from sparse canopies-an energy combination theory", Q. J. R. Meteorol. Sot., 111, 1985. pp. 839-855.

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Fig.1: Iterative Procedure of a Genetic Algorithm to TSEB Model

Fig. 1 Iterative procedure of a Genetic Algorithm to TSEB Model



Fig. 2 Error evolution during genetic algorithm with 10 generations and 10 individual's population



Fig. 3 Comparison between predicted and measured latent heat before optimization with Standard values of K=<  $\alpha$ p=1.26, fg=1 >



# Figures

Table 1: Results of Ten Runs genetic algorithm			
Runs	Error Stabilization		
	αρ	fg	R(K)
1	0.75	0.65	66.4
2	0.72	0.59	71.1
3	1.9	0.26	67.0
4	1.00	0.78	85.2
5	0.82	0.71	78.2
6	0.72	0.49	77.1
7	0.94	0.61	84.7
8	0.76	0.79	69.9
9	0.95	0.55	66.4
10	0.78	0.73	85.1

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Fig. 4 Comparison between predicted and measured latent heat after optimization with optimal values of K=<  $\alpha p$ =0.93,fg=0.61 >