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USING OPTICAL-MICROWAVE SYNERGY FOR ESTIMATING SURFACE ENERGY FLUXES OVER SEMI-ARID RANGELAND

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ABSTRACT

This study reports the first results of the Walnut Gulch' 92 experiment concerning the combined use of radar backscattering (ERS-1) and thermal infrared (Landsat TM) data to estimate surface sensible heat flux. The first step investigates the potential use of ERS-1 SAR images for surface soil moisture monitoring of the watershed using five calibrated images acquired during the year 1992 (dry to wet conditions). Results show that despite the typical low level of biomass of semi-arid rangeland, an attenuation of the soil backscatter (up to 2 dB) can occur during the rainy season mainly due to the vegetation characteristics. A statistical relationship is then used to retrieve the volumetric surface soil moisture from ERS-1 backscattering (sensitivity of 0.23 dB / % moisture) with a resulting RMSE of 1.3% of soil moisture. In a second step a semi-empirical approach based on energy balance relates soil temperature Ts to this estimated surface soil moisture. Vegetation temperature is then deduced from Ts and Landsat TM composite temperature in order to estimate sensible heat flux according to a two-layer type model providing an RMSE of 29 W/m^2.

Keywords: ERS-1 SAR images, soil moisture, thermal-microwave synergy, sensible heat flux, two-layer model.

1. INTRODUCTION

Estimation of distributed surface fluxes over heterogeneous terrain and surface cover is of great interest to most agricultural, hydrologic and climatological studies as it is a required first step for aggregation or upscaling to produce regional-scale flux estimates. Remote sensing techniques for estimation of surface fluxes provides one of the few, if only, viable methods for large area flux estimation (Seguin et al., 1991). Unfortunately, when considering remotely sensed estimation of sensible and latent heat flux with optical data (mainly visible, near infrared (NIR) and thermal infrared data), it appears that operational methods are currently applied only to agricultural fields with quite homogeneous surfaces.

In the case of sparse vegetation, such as immature crops or semi-arid rangelands, two-layer models, accounting for the specific contributions of soil and vegetation to fluxes, have proved to describe quite well surface energy exchanges of heterogeneous surfaces with only a few controlling parameters and variables (Lhomme et al., 1994; Choudhury, 1989). Nevertheless, one of the limiting aspects of these models when run with remote sensing data is the need of the specific soil and vegetation temperatures since thermal observation from space provides only a composite signal of these two components. A multi-sensor approach can then be designed to retrieve components temperature using microwaves sensitivity to surface soil moisture (related to its temperature), surface thermal emission and spectral vegetation indices (vegetation cover).

The study presented here will focus at first on the possibility of using radar ERS-1 products to monitor the near surface soil moisture (0-5 cm) over mixed grass and bush rangeland of a semi-arid watershed in Arizona (Walnut Gulch). The second part will then propose a way of combining the resulting estimated soil moisture with thermal infrared data to improve sensible heat flux estimation with the use of a two-layer type model.

2. EXPERIMENTAL DESIGN

2.1. The Walnut Gulch 92 (WG' 92) experiment:

To investigate the use of combined optical-microwave remote sensing, an experiment was conducted during the 1992 dry and monsoon (wet) seasons in the USDA-ARS Walnut Gulch experimental watershed (southeastern Arizona). Rainfall typically ranges from 250 to 500 mm/year in this region with almost 2/3 occuring during the summer "Monsoon" season in July and August. Nine Landsat TM scenes, three SPOT HRV scenes and five ERS-1 SAR images were acquired to monitor the seasonal surface changes. Eight subsites (METFLUX 1 to 8) were selected within the watershed to assess the spatial variability of vegetation, soil and meteorological properties, with a particular monitoring of METFLUX 1 (Lucky Hills) and 5 (Kendall). For each of the METFLUX (MF) sites, a 5x3 TM pixels target (150x90 m) was defined and used for ground based spectral measurements as well as for vegetation and soil measurements. The vegetation is basically composed of grass and bushes in variable proportions as shown in the table below:

sites	dry biomass (g/m2)	% shrub biomass	litter (g/m2)	vegetation cover (%)	rock surface cover (%)
MF1	228.7	99	96.8	28	46
MF2	289.9	72	94.8	51	48
MF3	228.0	89	32.3	42	45
MF4	224.8	24	48.6	62	59
MF5	102.3	33	57.4	44	54
MF6	458.6	92	57.1	38	52
MF7	140.2	67	155.2	32	10
MF8	1033.0	99	95.8	40	58

Table 1: mean surface characteristics of the eight metflux sites

Systematic gravimetric surface soil moisture samples (0-5 cm) were collected throughout the monsoon season at four representative metflux sites (1,3,5,6) with some additional sites depending on satellite overpasses and continuous TDR and tensiometric cubes measurements at Kendall and Lucky Hills. Volumetric soil moisture were then deduced from bulk density measurements. This volumetric soil moisture will be later expressed in percent soil moisture (% sm).

2.2. ERS-1 images

Five ERS-1 scenes were obtained during the experiment around 18h00 UT (11h00 local): days of year (DOY) 135, 170, 240, 275, 310 (35 days repeat orbit) covering only a west part of the watershed (MF 1,2,3,7,8). The characteristics of this spaceborne Synthetic Aperture Radar (SAR) are 5.3 GHz (C band), VV polarization, 23° incidence and 2.5 dB radiometric resolution at -18 dB. We used the standard PRI products provided by the European Space Agency (ESA) that is amplitude images processed as 3-looks (reduced noise) ground range (equal size pixels of 12.5x12.5 m) calibrated digital images.

The images were georeferenced using 1:5000 scale orthophotos of the US Department of Agriculture-Agricultural Research Service. Because of the speckle effect, it was sometimes difficult to define enough ground control points, or to locate them, to perform accurate geometrical rectification. However final transformation RMS error was around 2 pixels (i.e. 25 m) which was quite satisfactory to locate the MF targets. A multitemporal SAR image has thus been produced, showing contrasted pattern in terms of dry to wet conditions evolution. Backscattering coefficients σ^o were then extracted on each of the images for all the 150x90m targets using the formulation below:

$$\sigma^o(dB) = 10 \log \langle DN^2 \rangle - K + \beta \quad (1)$$

$$\beta = 10 \log \frac{\sin \alpha_{\mathrm{loc}}}{\sin \alpha_{\mathrm{ref}}} \quad (2)$$

where $<DN^2>$ is the average value of squared digital numbers DN of the site, K a calibration constant given by the ERS-1 tape header and β the incidence correction over the scene, depending on the satellite incidence angle for the center of the image (α_{ref}=23°) and for the central pixel of the plot (α_{inc}).

3. USE OF ERS-1 SAR DATA FOR SOIL MOISTURE MONITORING

Most of the radar studies conducted till today within hydrological framework focused on observation over agricultural fields in controlled conditions with either ground based sensor (Bertuzzi & Bruckler, 1991), airborne scatterometer (AGRISCATT'88 campaign: Prevot et al., 1993b) or more recently spaceborn SAR (NAIZIN watershed pilot experiment: Loumagne et al., 1994; Le Toan et al. 1993). These studies demonstrated the strong dependence of σ^o upon soil surface properties, mainly moisture and roughness. But they demonstrated too that vegetation layer can significantly affect the signal, as expected from general radar backscatter expression derived from radiative transfer theory (Attema & Ulaby, 1978):

$$\sigma^o = \sigma^o_v + \tau^2 \sigma^o_s + \sigma^o_{sv} \qquad (3)$$

where σ^o_v represents the scattering contribution by vegetation volume, σ^o_s the direct soil surface contribution, τ^2 the two-way attenuation through the vegetation layer and σ^o_{sv} interactions between soil surface and vegetation volume. From above studies, the observed vegetation effects were mainly due to attenuation (τ^2 term) (Le Toan et al. 1993), even in the case of grass covered areas as biomass approaches and exceeds 1 kg/m2 (Dobson et al., 1992). The specific volume scattering ($\sigma^o v$ term) was observed only at higher level of biomass (dense crops). Consequently we can expect that, concerning semi-arid conditions, the low amount of biomass (< 1 kg/m2, *Tab. 1*) is a great advantage to monitor soil moisture as attenuation should be the only vegetation effect to take into account, if significant.

3.1. σ_o sensitivity to soil moisture and roughness and to vegetation properties

Fig.1 shows that the temporal trend of radar backscattering σ^o on four selected MF sites seems to follow quite well rainfall events and the mean surface soil moisture of the watershed. However, when considering σ^o dependence upon soil moisture site by site (*Fig. 2*), the relation appears to be weaker than expected.

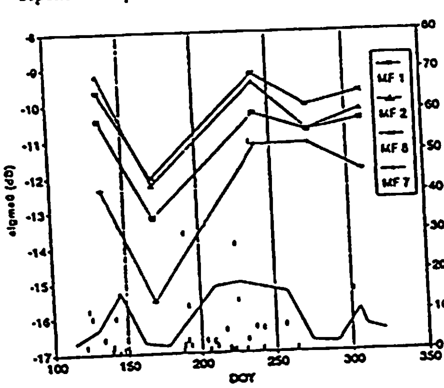


Fig.1: temporal trend of SAR ERS-1 σ^o on MF sites. Dots stand for rainfall events (mm) and solid line for mean volumetric surface soil moisture (0-5cm) observed in the waterhed (% sm).

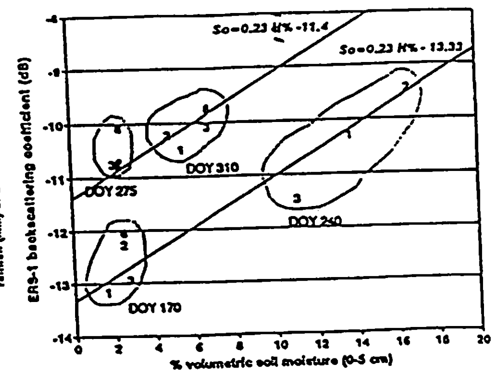


Fig. 2: radar backscattering vs volumetric soil moisture, for 4 different dates. Numbers correspond to metflux sites.

To explain this behavior, we must stress first of all the small range of soil moisture compared to values encountered under temperate climate (like those related in the studies mentioned above) and which makes difficult the detection of σ^o evolution with soil moisture. In fact these low values do not result directly from the particular semi-arid climate but from the typical sandy-loam soils of these regions (about 20% loam and 70% sand here) for which volumetric moisture can hardly exceed 20-25 % sm (field capacity) whatever the rainfalls amount.

Second point is roughness effects that proved to be of significant importance on soil backscatter at C band (Beaudoin et al., 1990). In view of MF 7 on *Fig. 1* (no soil moisture available for *Fig. 2*) we can point out an expected downward shift of σ^o compared to other MF sites (1-2 dB), as the roughness is smaller for this site due to the lower rock surface cover reported in *Tab. 1*. Therefore, roughness effects can explain partly the level of backscatter temporal curves in *Fig. 1* and the dispersion within backscatter values for each date in *Fig. 2*.

In addition to roughness effects, the vegetation effects on backscatter must be addressed. Contribution from volume scattering can be neglected considering low biomass levels and the small size of leaves compared to C-band wavelength (5.6 cm). Therefore, only attenuation effects should be accounted for. Variable attenuation effects can be obtained due to temporal/spatial changes in water content, biomass and structure of grass and bushes. It is expected that attenuation properties in time should be mainly affected by water content changes with respect to season. According to this hypothesis, MF 1 to 3, which have similar soil roughness and biomass characteristics, are showing on *Fig. 2* quite good dependence upon soil moisture respectively for drying period (DOY 170 & DOY 240) and wet period (DOY 275 & DOY 310) but significant difference between these periods. Therefore, this temporal difference can be attributed to soil backscatter attenuation from fully developped vegetation compared to dry one. During the wet season, mean water content values of 0.15-0.2 kg/m2 were measured in 90 on these sites, whereas water content can drop down to 0.02 kg/m2 during dry season. In a first approximation, we can then estimate the resulting attenuation factor (τ^2) according to the cloud model formulation as given by Attema & Ulaby (1978):

$$\tau^2 = \exp\left(\frac{-2.B.m_v}{\cos\alpha_{inc}}\right) \qquad (4)$$

where m_v is this total amount of water contained in the vegetation layer (kg/m^2) and B an unknown constant, function of the canopy type/structure for a given radar configuration. At C band, most of the studies (Bertuzzi & Bruckler, 1991, Jackson et Schmugge, 1991, Prevot et al., 1993b) reported B values for various crops between 0.1 and 0.5. However, Jackson & Schmugge (1991) reported larger B values (up to 2) for short and tall grass covers. This difference from crops could be explained by the presence of stubble and detritus matter, in addition to structure. As few B values are available for rangeland, we can consider in a first approximation a B range from 0.5 to 2, leading an attenuation factor ranging from 0.6 to 2.5 using (4), in which falls observed values around 2dB.

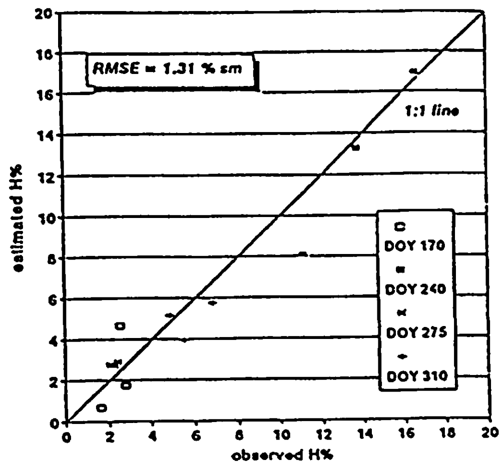
Further investigation will be done to study attenuation properties of the vegetation, taking into account the evolution in structure and moisture content. At this step, a statistical approach was designed to relate σ^o to soil moisture.

3.2. soil moisture estimation from σ^o

As it has been shown previously, the period of measurement during the year is greatly responsible for the change in backscattering relation to soil moisture because of the evolution of vegetation characteristics, both water content and structure. Two sets of data have thus been marked off corresponding to two different vegetation conditions. The first set (DOYS 170-240) corresponds to full development and well water supplied vegetation during the monsoon period while the second one (DOYS 275-310) concerns the drying season.

A linear relationship was then deduced for the first set of data (*Fig. 2*, R=0.98) considering only MF 1 to 3 (similar roughness and vegetation characteristics). Since the vegetation attenuation acts as a translation of the σ^o curve when expressed in dB units, the second linear model was adjusted simply by changing the constant value. The resulting radar sensitivity to soil moisture (0.23 dB / % sm) is in good agreement with other studies (Bertuzzi & Bruckler, 1991; Prevot et al., 1993b) and the direct estimate of soil moisture from σ^o (*Fig. 3*) provides a root mean square error (RMSE) of only 1.31% sm. Even though it gives quite accurate estimate of soil moisture on most test sites representative of the watershed, in terms of roughness and vegetation conditions, further semi-empirical model development is needed. This model should take into account the vegetation attenuation effect through the use of a relevant and simple vegetation parameter. For soil moisture inversion, this parameter could be obtained either from other remote sensing data (VIS for example) or a priori knowledge of the temporal behavior of this parameter for this type of ecosystem.

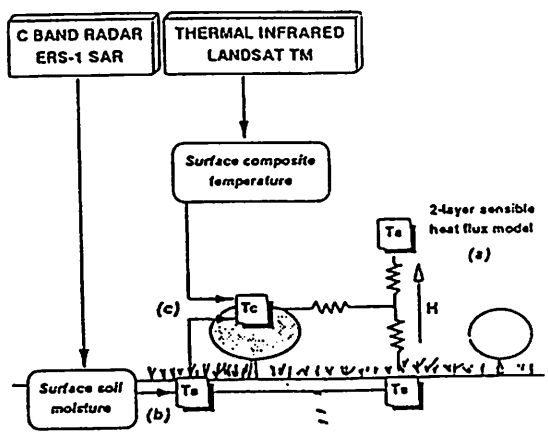
Fig. 3: accuracy of soil moisture estimation from ERS-1 σ° backscattering coefficient.



4. COMBINE USE OF RADAR AND THERMAL DATA

4.1. Theory and method

Fig. 4: general scheme of the approach. The letters (a), (b) and (c) refer to the three models described below.



4.1.1 Sensible heat flux model: as shown in *Fig. 4 (a)*, the sensible heat flux is estimated here according to a two-layer formulation model as proposed by Shuttleworth and Wallace (1985), since the classical one layer approach is not designed to take into account aerodynamic exchanges between soil and vegetation over sparse canopy unless some extra-modelling (kB-1 method, Prevot et al., 1993a). This model is based on a system of temperatures and resistances between soil, vegetation and air mass, controlling sensible heat fluxes between each component:

$$H = \rho c_p \frac{\frac{T_c - T_a}{r_c} + \frac{T_s - T_a}{r_s}}{1 + \frac{r_a}{r_c} + \frac{r_a}{r_s}} \qquad (\mathrm{W/m^2}) \qquad (5)$$

where *a*, *c* and *s* indices correspond respectively to air, canopy and soil temperatures and *T* and *r* stand for temperature and aerodynamic resistance. In addition to these input variables, aerodynamic resistances calculation needs wind speed values and some classical vegetation properties concerning roughness estimates: mean height, LAI and fraction cover.

4.1.2 Soil temperature model: (*Fig. 4 part (b)*) numerous studies demonstrated the strong dependence of the actual to potential soil evaporation ratio (E/Ep) upon soil surface resistance or more simply upon top surface soil moisture (Deardorff, 1977; Chanzy et al., 1993). Moreover, soil temperature is linearly related to this ratio through the concept of Crop Water Stress Index (Jackson et al., 1981) initially designed for crop monitoring but also valid for bare soil and sparse vegetation (Moran et al., 1994a):

$$\frac{E}{E_p} = 1 - CWSI = 1 - \frac{T_s - T_{s\,min}}{T_{s\,max} - T_{s\,min}} \tag{6}$$

where Ts is surface temperature and *min and max* correspond respectively to potential and no evaporation. We can assume in a first approximation that T_{Smin} equals air temperature T_a and that T_{Smax} can be easily infered from energy balance equation (E=0):

$$T_{s\,max} - T_a = \frac{r_a(Rn - G)}{\rho c_p} \tag{7}$$

where Rn is the net radiation (W/m²), G the soil heat flux (assumed to be 30% of Rn on bare soil, Clothier et al., 1986), and r_a aerodynamic resistance of bare soil. The only additional input variables needed here is thus net radiation.

4.1.3. Vegetation temperature model (*Fig. 4 part (c)*): as a first approximation, the surface radiometric temperature observed from space over sparse vegetation can be considered as the area weighted mean of vegetation and soil temperatures. However, when using Landsat TM data acquired around 10h00 local, the shaded part of the soil must be acounted for because of the low solar elevation. Indices *sh* and *sl* corresponding to shaded and sunlit soil respectively and assuming that *Tsl=Ts* and *Tsh=(Tc+Tsl)/2* we can write:

$$Tr = fc.Tc + fsl.Tsl + fsh.Tsh = (fc + fsh/2).Tc + (fsl + fsh/2).Ts \tag{8}$$

fsh and *fsl* are computed according to the Jasinsky model (Jasinski & Eagleson, 1990) as a function of solar elevation, vegetation cover and mean shrub height and diameter.

4.2. Results

Infrared bare soil temperature collected at MF 5 were used to adjust the model of eq. (6) & (7). Results are reported on *Fig. 5* and show a good fit to an exponential law. The different parameterizations encountered in litterature range in fact from simple linear model (Deardorff, 1977) to more complex sigmoïde shape (Chanzy et al., 1993) but these works demonstrated above all that the relationship between E/Ep and soil moisture depends essentially on soil texture. Since the texture is nearly similar on the whole watershed this model will thus be used on other sites.

Concerning the Jasinski model, it was run on MF 1 at 10h00 local and it provided estimated shaded soil portion ranging from 20% to 50% depending on the day from the beginning to the end of the rainy season. Not accounting for this shaded portion in eq. (8) leads here to vegetation temperature sometimes lower of more than 15 degrees.

Two Landsat images (DOY 162, 274) and three additionnal aircraft flights (DOY 290,291,310) were finally selected in the dataset close to ERS-1 overpasses (respectively DOY 170, 275 for TM and DOY 275,310 for aircraft). Estimating soil moisture from σ^o (mainly dry conditions on these dates), input variables Ts and Tc were then computed at the time of satellite/aircraft overpass (between 10h00 and 11h00 local) according to eq. (6) to (8). The resulting sensible heat fluxes derived from eq. (5) on MF 1 are plotted on *Fig. 6* and display an overall RMSE around 29 W/m² corresponding to a slight overestimation. This is to be compared with previous modelling approach on Walnut Gulch with one layer models (Moran et al., 1994b) which provided RMSE between 40 and 50 W/m². Nevertheless, this quite good agreement between ERS-1/TM estimated and observed fluxes doesn't mean a complete validation of the method because of the limited number of points. Particularly wider range of moisture conditions should have better demonstrated the interest of ERS-1 SAR data to improve fluxes estimation.

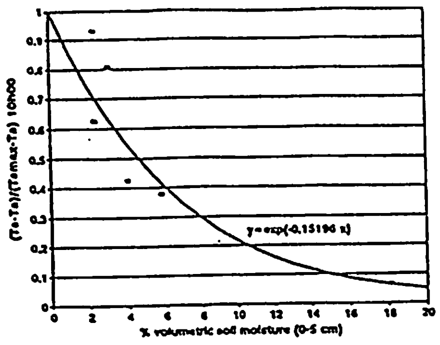


Fig. 5: Adjustment of (Ts-Ta)/(Tsmax-Ta) to the volumetric soil moisture. Soil temperatures were measured with a hand-held thermo-radiometer on Kendall site (MF 5).

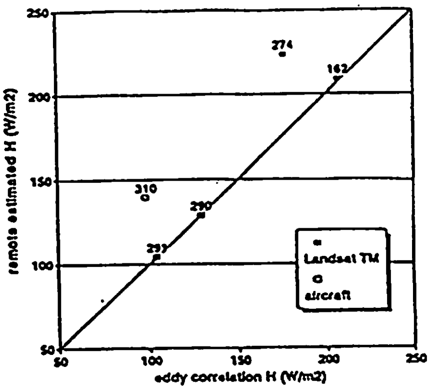


Fig. 6: comparison between remote estimate of sensible heat flux (ERS-1/TM) and eddy correlation measurements on Lucky Hills site (MF 1).

5. CONCLUSION

This study has presented a multi-sensor scheme, combining radar and thermal data, to retrieve the main driving variables of two-layer model suited to sparse vegetation of semi-arid areas. The use of ERS-1 SAR images was *a priori* a powerful means to monitor soil moisture on these areas considering the generally low development of vegetation biomass and the resulting low vegetation effects on σ^o. The results has shown in fact that the particular structure of this vegetation, particularly dead material buildup characteristic of semi-arid rangeland, plays a major role on backscattering behavior and thus that the amount of vegetation biomass was not the main driving variable. Moreover the evolution in time of this structure makes difficult the multidate use of these images without a modelling approach. At last soil roughness spatial variability has appeared as a dispersion factor if not accounted for.

However a statistical model has been designed with simple assumptions about vegetation biomass and provided good estimate of soil moisture that can be used in conjunction with thermal data for sensible heat flux modeling. The proposed approach needs yet further validation with various vegetation and moisture conditions to be fully operational.

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