SHORT COMMUNICATION

COMPARATIVE ANALYSIS OF SPLIT-WINDOW ALGORITHMS FOR ESTIMATING SOIL TEMPERATURE

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ABSTRACT

The ability to estimate soil temperature (Ts) from satellite information is highly useful, since this is one of the main input variables in various models designed for estimating biophysical parameters. A comparative analysis is made of various Split-Window algorithms used to estimate soil temperature from data provided by the Advanced Very High Resolution Radiometer (AVHRR) sensor on board of satellites of the National Oceanic and Atmospheric Administration (NOAA). The algorithms compared are those proposed by: Prata and Platt (1991); Uliveri *et al*. (1992); Sobrino *et al*. (1993); Caselles *et al*. (1997); Sobrino and Raissouni (2000). The temperature estimates were validated with data of the soil temperature *in situ* recorded in a data logger installed in a meteorological station belonging to La Araucanía Region, Chile. The results showed that the algorithm proposed by Sobrino and Raissouni (2000) come the closest to the in situ data. However, there are no statistically significant differences between the different algorithms evaluated.

Keywords: AVHRR-NOAA Sensor, meteorological station.

INTRODUCTION

Obtaining soil temperature (Ts) is of great use as an equilibrium indicator in soil-atmosphere system and other biophysical parameters. Normally, the soil temperature is measured by using thermistors, but the cost of evaluating large geographical areas is usually high and time-consuming. The solution for these drawbacks arises with the development of infrared technology and later use on board artificial satellites.

However, one of the biggest problems measurements of soil temperature from satellites is the combined action of perturbations due to atmospheric water vapor and the variability in the emissivities of different soil coverings (Morales and Parra, 2002).

The need to implement algorithms to correct this effect introduced by the earth's emissivity and the water vapour in the atmosphere has led to the development of various methodologies, where Split-Window method has been one of the best-validated (Sobrino *et al*., 1993; Caselles *et al*., 1997; Sobrino and Raissouni, 2000; Sobrino *et al*., 2004).

The objective of the present communication is to apply and compare different Split-Window algorithms to estimate soil temperature from data provided by the AVHRR sensor on board the NOAA satellite, in order to find the best fit with data generated *in situ*.

MATERIALS AND METHODS

Soil temperature measurement

The soil temperature measurements were taken at hourly intervals, using one thermistor LI-COR buried at a depth of one centimeter and calibrated in the range -10 to 50 ºC (mean squared error of 0.06 ºC). The thermistor was connected to a meteorological station located in the Institute of Agricultural Research-Carillanca, Chile (INIA-Carillanca) (38°41’ S; 72°25’ W; 200 m.a.s.l), between October 2003 and January 2004. The data were registered in a data logger LI-1000 (LI-COR Inc., USA).

The study zone is characterized by a temperate climate (Rouanet, 1983), flat topography (slopes of 0 - 25 %) and soils derived from modern volcanic ash (Andisol), Vilcún soil Serie (Tosso, 1985).

Obtaining and selecting NOAA images

Images were used from the NOAA 16 satellite in the visible and thermal infra-red spectrum bands, obtained at not cost from the Comprehensive Large Array-data Stewardship System (CLASS). The data base of images was chosen because it coincided with the dates of the field measurements (October 2003 and January 2004). Images were selected only for cloudless days in order to avoid image perturbation. A total of 62 images were reviewed, from which 18 were selected and subjected to a geo-referencing process. The identified pixel (size is 1 km^2) corresponded to INIA-Carillanca meteorological station location.

Algorithms implementation

The Split-Window algorithms selected correspond to those proposed by: Prata and Platt (1991), Uliveri *et al.* (1992), Sobrino *et al.* (1993), Caselles *et al.* (1997) and Sobrino and Raissouni (2000) (Table 1).

The implementation of the various algorithms assumes the availability of the following information: brightness temperatures in bands 4 and 5, mean emissivity, spectrum variation of emissivity, and water vapour content. All these variables are associated to the pixel where the thermistor is located.

Radiometric temperatures in bands 4 and 5 of the AVHRR were obtained using the Calibrate Data module of the ENVI programme (version 4.0). Mean emissivity and spectrum variation were estimated by application of the threshold method, as described by Carlson and Ripley (1997). Finally, data from atmospheric water vapor were obtained from Morales and Parra (2002).

Statistical analysis

To compare the soil temperature data measured in situ with those obtained by each of the Split-Window algorithms, a linear regression equation was calculated between the observed (X) and simulated (Y) values. The parameters of these equations were evaluated by proposing simultaneous hypothesis tests for the

Table 1. Split-Window algorithms. T_4 and T_5 are brightness temperatures (ºK) in bands 4 (10.3 - 11.3 µm) and 5 (11.5 - 12.5 µm); $\varepsilon = (\varepsilon_4 + \varepsilon_5)/2$ and $\Delta\varepsilon = \varepsilon_4 - \varepsilon_5$ are the mean emissivity and spectrum variation of emissivity in bands 4 and 5 of the AVHRR-NOAA sensor; W is the water vapour content (g cm^{-2}).

Authors	**Split-Window algorithm**
Prata and Platt, 1991. (P)*	$T_s = 3.45\frac{(T_4 - T_0)}{\varepsilon_4} - 2.45\frac{(T_5 - T_0)}{\varepsilon_5} + 40\frac{(1-\varepsilon_4)}{\varepsilon_4} + 273$
Ulivieri *et al.,* 1992. (U) *	$T_s = T_4 + 1.8\,(T_4 - T_5) + 48\,(1-\varepsilon) - 75\,\Delta\varepsilon$
Sobrino *et al.*, 1993. (S1)*	$T_s = T_4 + \left[1.06 + 0.46\,(T_4 - T_{5)}\right](T_4 - T_5) + 53\,(1-\varepsilon_4) - 53\,\Delta\varepsilon$
Caselles *et al.,* 1997. (C) *	$T_s = T_4 + \left[1 + 0{,}58\,(T_4 - T_5)\right](T_4 - T_5) + C\,(1-\varepsilon) - D\,(\Delta\varepsilon) + 0{,}51$ $C = (0{,}190\,W - 0{,}103)\,T_4 - 67\,W + 107$ $D = (0{,}100\,W + 1{,}118)\,T_4 - 68\,W - 163$
Sobrino and Raissouni, 2000. (S2) *	$T_s = T_4 + \left[1{,}40 + 0{,}32\,(T_4 - T_5)\right](T_4 - T_5) + C\,(1-\varepsilon) - D\,(\Delta\varepsilon) + 0{,}83$ $C = 57 - 5\,W$ $D = 161 - 30\,W$

* Indicates the abbreviation used subsequently for each algorithm

intercept (Ho: a = 0) and the slope (Ho: b = 1) using Student's "t" test and a P-value ≤ 0.05 (Steel and Torrie, 1988). In addition, the root mean squared error (RMSE) of the prediction was calculated with the result being expressed in percentage units of the average value obtained in the real observations (Rabat, 1995).

RESULTS

Figure 1 shows modeled and measured data in order to evaluate algorithms performance. When the ratio between the estimated Ts (°C) and the T *in situ* (°C) is calculated, a significant equation is obtained ($P < 0.00001$) at a confidence level of 99%, with a mean standard error of 2.57 ºC.

When we carry out hypothesis tests on the values of the intercept and the slope in the algorithms for each case, we were able to conclude that these do not differ from the values zero and one, respectively. Table 2 shows the results of the regression equations obtained and the main statistics associated, which are: b = intercept; m = slope; r^2 = coefficient of determination adjusted from the regression; RMSE = root mean squared error of the prediction in percentage terms; and P = level of significance.

The variance analysis of the means comparison test shows a P-value of 0.9413, which is greater than 0.05, indicating that the differences between the means of the algorithms used are not statistically significant, with 95 % confidence.

DISCUSSION

It is well known that the superficial soil temperature retrieval from satellite observations has been ongoing for

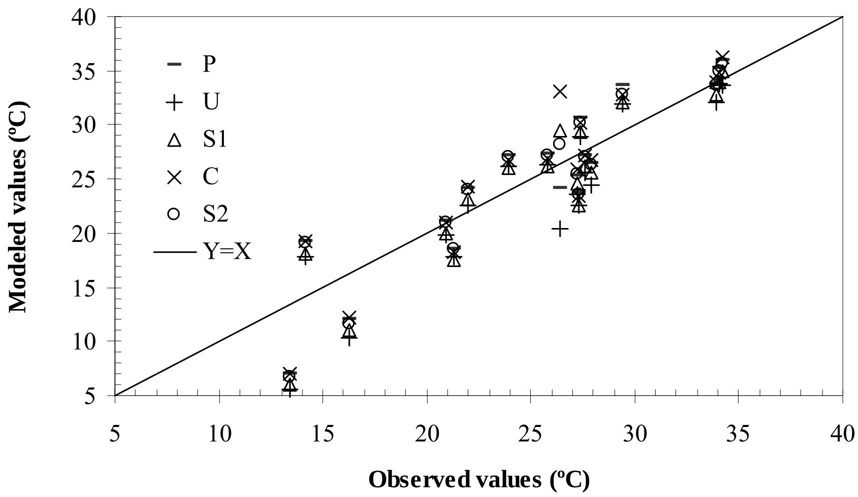

Figure 1. Modeled and measured soil temperature data. Solid line represents 1:1 ratio.

Table 2. Regression equations ($T_{in\ situ}$ = m T_s + b) obtained between the values measured ($T_{in\ situ}$) and estimated (T_s) for the soil temperature for each of the Split-Window algorithms.

Algorithm	b	m	r^2	RMSE (%)	P
P	-3.31	1.13	0.8465	1.0182	0.0000
U	-4.35	1.10	0.8254	1.1977	0.0000
S1	-4.30	1.14	0.8486	1.0551	0.0000
C	-3.30	1.14	0.8319	1.1005	0.0000
S2	-3.45	1.13	0.8548	0.9959	0.0000

decades. Several methods have been proposed. However, Split Window algorithms have the advantage to show a simple mathematical structure and, in many cases, only need the information from satellite.

The coefficients adjusted from the linear regression enable us to explain on 82.54% of the soil temperature variability. Algorithms used exhibit mean squared errors greater than 1 %, while that of Sobrino and Raissouni (2000) is 0.9959 %. This error indicates the degree of over- or under-estimation produced by the algorithm with respect to the average of the observed values (Rabat, 1995). Nevertheless, errors observed, are consistent with those reported by Galve *et al.* (2007) to compare different Split-Windows algorithms.

In our research, the corrections for water vapor tend to be irrelevant in statistical terms, although the importance of this parameter has been reported in other studies (Parra *et al.,* 2006).

The used method has been validated by other authors from NOAA satellite images (Price, 1984; Sobrino and Raussoni, 2000), but data estimation is very sensitive to changes in soil coverage, so that these algorithms require that coverage uniform within the pixel soil as occurred in this application.

CONCLUSIONS

The analyses carried out show that the five studied algorithms generate results with no significant differences, either in the estimate or in the mean squared error. However, in terms of absolute values, the algorithm of Sobrino and Raissouni (2000) presents the lowest errors.

The results are satisfactory, although it is necessary to use more thermistors in order to better pixel representation and algorithms validation.

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