FIRE DANGER AND FUEL MOISTURE CONTENT ESTIMATION FROM REMOTELY SENSED DATA

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ABSTRACT

Fuel moisture content (FMC) for Mediterranean species was measured and correlated with NOAA-AVHRR and Landsat-T M images. The best variable related to FMC was the quotient between the Normalized Difference Vegetation Index and Surface Temperature (NDVI/ST). Two other indices derived from Landsat's SWIR bands also showed good correlation. Two multiple regression equations to derive a synthetic FMC for grassland and shrubs are presented, with r^2 values of 0.61.

Keywords: Remote Sensing, Fire Danger, Fuel Moisture Content.

INTRODUCTION

The estimation of plant water content is critical for various applications such as predicting agricultural yields, appraising regional evapotranspiration and determining fire risk conditions. In order to apply remote sensing techniques to carry out this estimation it is first necessary to study in detail the effects of water on leaf and plant reflectance.

In the context of fire danger rating, Fuel moisture content (FMC) is estimated from meteorological danger indices, which try to account for the effect of weather variations on water availability for plants. The relation of weather variables (air temperature, relative humidity, wind, etc.) with FMC has been proved with some dead fuels since they are very dependent on the atmospheric conditions. However, there is little experience regarding live fuels, which are more related to water availability in the soil and to their own physiological mechanisms of minimizing water loss. Consequently, the estimation of FMC from meteorological indices may be rather imprecise.

The other conventional method to estimate FMC would be the direct measurement of FMC in the field, which is very costly and time consuming. Therefore, satellite imagery may be a reasonable alternative to derive FMC information. Satellite data cover the whole territory and are directly related to the vegetation status. However, the application of satellite data to FMC can only be used once the relationship between this variable and the spectral characteristics of vegetation covers has been derived. For instance, it ought to prove that FMC changes the way plants reflect or emit electromagnetic energy, with enough clarity to make it distinguishable from other sources of spectral variation (leaf area index, soil background, atmospheric disturbances, etc.). The issue is therefore, whether or not current satellite systems provide the necessary spatial, spectral and temporal resolution for the operational use of these data in real fire management.

Data from high and low-resolution sensors have been used to compare both sources of information.

FUEL MOISTURE CONTENT ESTIMATION

Remote Sensing of plant water content has been attempted using mainly optical and thermal wavelengths, although microwave data are also promising in this field (Gogineni, S. et al. 1991). Most of the experiences were performed in laboratory analyses, and commonly at leaf level. These studies have shown that leaf water content is most clearly related to short-wave infrared reflectance (SWIR), ranging from 1.4 to 2.0 µm (Bowman, W. D. 1989; Cohen, W. B. 1991; Hunt, E. R. et al. 1987; Jackson, R. D. and Ezra, C. E. 1985; Tucker, C. J. 1980). It is well known that these wavelengths present a high absorption of water, and therefore SWIR reflectance is negatively related to leaf water content.

Regarding near-infrared (NIR) reflectance (0.8 - 1.1 µm), conclusions obtained from different studies do not completely agree. Some authors find a small increment as the leaf dries (Bowman, W. D. 1989; Hunt, E. R. and Rock, B. N. 1989; Hunt, E. R. et al. 1987; Thomas, J. R. et al. 1971), which may be caused by the increase in the refractive index of the mesophyll layer when water is replaced by air. Other authors do not find a significant change in NIR reflectance for leaf drying (Carter, G. A. 1991), while some others measure a decrease in reflectance (Westman, W. E. and Price, C. V. 1988). This reduction may be caused by the indirect effects of leaf dryness, such as the decrease in leaf area index or shadowing due to leaf curling (Jackson, R. D. and Ezra, C. E. 1985; Westman, W. E. and Price, C. V. 1988).

Finally, the visible domain does not appear to have enough sensitivity to estimate leaf water content, at least in absolute terms. On the one hand, the chlorophyll reduction after drying increases reflectance, while on the other hand, the decline in water decreases it. Some authors, though, found that the red band is sensitive to water content (Jackson, R. D. and Ezra, C. E. 1985; Ripple, W. J. 1986), while others did not observe significant changes (Bowman, W. D. 1989 Thomas, J. R. et al. 1971).

When these laboratory studies are applied to remote sensing image analysis, models to extrapolate from leaf to canopy's reflectance are required. Some authors emphasize the difficulties in estimating plant water content, since they consider that the contribution of leaf water to the whole canopy reflectance is too weak in comparison with other factors: leaf geometry, shadows, soils, etc. (Carter, G. A. 1991; Cohen, W. B. 1991). However, other authors have found high a correlation between leaf water content and canopy reflectance (Cibula, W. G. et al. 1992; Hunt, E. R. and Rock, B. N. 1989; Hunt, E. R. et al. 1987 Westman, W. E. and Price, C. V. 1988). Their conclusions were based on hand-held spectro-radiometry and not on actual satellite images.

Experiences with satellite data are somewhat scarce. The most consistent results were found when estimating temporal evolution of FMC for grassland (Chladil, M. A. and Nunez, M. 1995; Paltridge, G. W. and Barber, J. 1988; Paltridge, G. W. and Mitchell, R. M. 1990), whereas FMC for shrubland showed weaker relationships with satellite data (Alonso, M. et al. 1996; Deshayes, M. et al. 1998).

An alternative to determining canopy water content is the analysis of plant thermal dynamics. When the plant is well watered the increase in air temperature causes evapotranspiration to rise also, which will increase latent heat loss and reduce sensitive heat loss, and consequently, leaf temperature will decrease. On the contrary, when the plant dries, transpiration is reduced and consequently latent heat loss is reduced and sensitive heat loss increases. As a result of this relation, the difference between air and surface temperature is related to evapotranspiration, and indirectly to water content and water stress. Several indices have been proposed based on this difference and additional weather variables (net radiation, air humidity, wind data, etc.). The most currently used are the Stress Degree Day (SDD) (Jackson, R. D. 1986), the Crop Water Stress index (CWSI) (Jackson, R. D. et al. 1981) and the Water Deficit Index (WDI) (Moran, M. S. et al. 1994). The WDI has been successfully tested as a predictor of fire danger with both NOAA-AVHRR and Landsat-TM data (Vidal, A. and Devaux-Ros, C. 1995; Vidal, A. et al. 1994).

Samples were composed of terminal leaves for shrubs and trees, whereas the whole plant was extracted for pastures. Approximately, 100 grams per sample were introduced in an envelope, which was then sealed and weighed with on a field balance (precision ±0.1-gram). Then, the envelopes with the samples were dried in an oven during 48 hours at 60º Celsius, and weighed again with the same balance. The weight of the envelopes was subtracted to compute the moisture content. Among the different criteria to measure moisture content, a simple relation of wet over dry weight was used in this work, as follows:

$$FMC(\%) = \left(\frac{W_f - W_d}{W_d}\right) * 100 \tag{1}$$

where Wf is the fresh weight of the leaves (the one measured each time it was taken out of the oven) and Wd is the dry weight (the one obtained at the end of the process). The result is expressed as a percentage of the dry weight.

SATELLITE DATA INTERPRETATION

Low-resolution AVHRR Data

The Advanced Very High Resolution Radiometer (AVHRR) on board the NOAA satellite series has been the most commonly used sensor in fire danger estimation, since it provides an adequate temporal resolution (12 hours) for operational danger management. However, it presents several difficulties for FMC estimation, especially its low spatial resolution (1.21 km² at nadir), poor radiometric quality, and lack of a channel in the SWIR, which is the most sensitive band for water content assessment. In this work the afternoon pass of NOAA-14 satellite has been used to estimate FMC, since it is close to the period of maximum temperature and therefore shows most dangerous conditions from a fire management point of view.

Within the European Union Megafires project, two years of satellite data were compared with field measurements of FMC in three Mediterranean countries (Spain, France and Greece). The following variables were derived from AVHRR images: Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI); Global Environmental Monitoring Index (GEMI); Surface Temperature (ST); Difference between Surface Temperature and Air Temperature (ST-AT); and the quotient between the NDVI and ST (NDVI/ST). Relative Greenness (RGRE) and Absolute Greenness (AGRE) (Burgan, R. E. and Hartford, R. A. 1993) were also computed for comparison among the different plots. Validation of the satellite-derived indices was based on the measurements of foliage moisture content of different species carried out during 2 years on four networks of test land plots situated in three Mediterranean countries. From a methodological point of view, NOAA-AVHRR-derived indices proved to be useful for monitoring FMC as significant correlations have been obtained on the four test land plots (Chuvieco, E. et al. 1999; Deshayes, M. et al. 1998). Depending on the test land plot, different indices obtained the best results: for example, ST and ST-linked indices (ST – AT, NDVI/ST) for Cabañeros (Spain), but ARND and multitemporal-NDVI ones for the Les Maures area (France). It should be clarified that the former used spring and summer data, while the latter only summer measurements and consequently, a much narrower range of FMC values was found. The object of using daily or maximum value composites (MVC) was more precisely studied at Les Maures. The analysis with daily images has, however, suffered from the small number of cloudless days, due to the unusually rainy ’96 and ’97 summers. The analysis with MVC data, that, to a certain extent, provides clear data during cloudy periods, has shown good potential, with significant correlations, especially when considering several land plots together. Some aspects, brought to light by the project, such as the problem of “change of scale” between the size of field plots (100x100 m) and the size of NOAA pixel (1x1 km) or even the NOAA 3x3-pixel window (3x3 km), should now be investigated.

From an operational point of view, the Megafires project showed that NOAA-AVHRR images contain information that could be used to monitor and provide some mapping of FMC. This would give information on a parameter that is considered important by fire fighting authorities, but that up to now could not be monitored conveniently. This parameter when assessed from space, together with other parameters such as meteorological ones, could be used for an improved estimation of short-term fire risk.

One step further in the Megafires project was to derive a synthetic estimation of FMC from AVHRR data, in order to propose a single index that could be used operationally for FMC estimation. For doing this, several correlation analyses were performed: both considering spring and summer data or just the latter. These tests were focused on the study area of Cabañeros National Park, in Central Spain (200 km south of Madrid). Field sampling was carried out in this area every 8 days from early April to the end of September, from 1996 up to the present. The study area includes very good examples of Mediterranean type vegetation. Plots were located in the central valley of the Park, which has very gentle slopes. Species collected were grassland (3 plots of several types of herbaceous plants), shrubs (2 plots of *Cistus ladanifer*, *Erica australis*, and *Rosmarinus officinalis*), all of which are very common in Mediterranean areas. Three samples of FMC were taken for each species and plot.

Average FMC values of grassland for the three plots sampled on the field were computed. Similarly, average FMC shrub values were computed for the two plots sampled. *C. ladanifer*, *R. officinalis* and *E. australis* samples were averaged as a whole, in order to derive a single value for the FMC estimation of shrub. The tendencies observed may be summarized as follows:

- Correlation of satellite data and FMC is consistent for grassland when spring and summer trends are included. The most significant variables found were NDVI/ST, RGRE and AGRE, with r^2 values higher than 0.84 (although the first variable accounts for 90 % of the variance).

- Correlation of satellite data and FMC for shrubs is lower, but still significant, with r^2 values of 0.66. The most significant variables in this case are NDVI/ST, NDVI and ARND.

- A set of three satellite variables provides adequate multiple regression values with both grassland and shrubland these being, NDVI/ST, RGRE and ST. For the spring and summer period, they account for 0.83 of the total variance in grassland and 0.51 in shrubland.

- If we only consider the summer time (mid June to the end of September), much lower correlations are found, since the range of FMC values is also much lower. The most significant associations were found for RGRE in the case of grassland, and NDVI/ST for shrubland. The r^2 values decrease down to 0.4 for grassland and 0.23 for shrubland.

Consequently with the previous results, two lines of application for generating a synthetic fire danger index that could be used operationally are proposed. The first one is based on a direct estimation of FMC from satellite data, while the second on an indirect method, which would derive FMC from correlations of satellite data and meteorological danger indices. Both methods are based on the analysis of NOAA-14 afternoon passes (14.30 h. approximately).

Using images from spring season: Although most fire managers are focused on summer conditions, which are the riskiest, to include spring data in the estimation of FMC provides a wider range of FMC conditions, and makes it possible to better analyze relative changes in FMC among the species. After the analysis of field sampled FMC and satellite-derived indices for the spring and summer season of 1996 and 1997 in the Cabañeros study area, several simple and multiple regression analysis were performed. As said before, different agreements were found for grassland and shrub species. However, in order to propose a synthetic index that could be used operationally for the forest managers, a final regression analysis was applied after mixing together grassland and shrub samples. Consequently, a synthetic fuel moisture content (SFMC) values may be estimated as follows:

$$SFMC = -106.95 + 14.87*NDVI/TS + 7.18*AGRE - 1.50*RGRE \qquad (2)$$

A determination coefficient (r^2) of 0.62 was found for the samples collected on the field. A scattered plot of the observed versus predicted value of FMC is shown in figure 1.

The satellite variables would be computed as follows:

$$NDVI / ST = ((NDVI + 1)*125) / ST \text{ (in } ^\circ \text{C)} \qquad (3)$$

$$AGRE = (100*(NDVI-0.05))/0.66 \qquad (4)$$

$$RGRE = \frac{NDVImin}{NDVImax - NDVImin} *100 \qquad (5)$$

where NDVImax and NDVImin, are the maximum and minimum NDVI values of that pixel.

AGRE and RGRE are closely related to NDVI, but they are more easily compared in time and space. A previous suggestion to use these indices in operational fire risk estimation was included in the Fire Potential Index (PFI) by Burgan, R. E. et al. 1998.

SMFC values are estimations of FMC (considering mixed the values of grass and shrub species), and therefore are measured in percentage of dry weight. Coefficients should be tuned up to different vegetation types. The ones proposed are averaged over grassland and shrubland over two years of field measurements.

SFMC values might be converted into danger classes after comparing them with the maximum and minimum values found for a historical series of data. Once the limits of SFMC variation for each pixel were found, a relative danger index (RDI) may be computed as:

$$RDI = \frac{SFMCi - SFMCmin}{SFMCmax - SFMCmin} *100 \qquad (6)$$

Then, a quantification of danger may be proposed as follows:

Extreme danger: Below 10 %
High-danger: 10-20 %
Medium-danger: 20-50 %
Low-danger: Above 50 %.

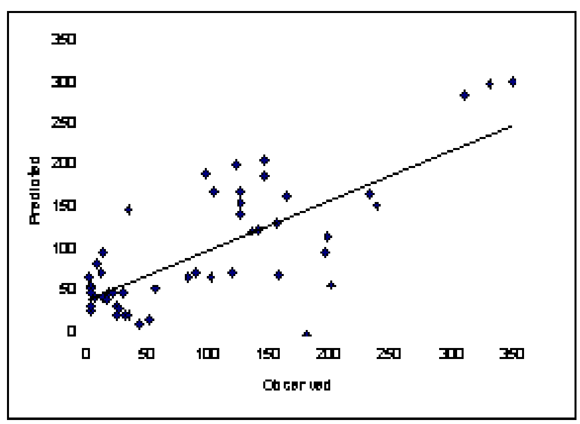

Figure 1. Predicted versus Observed FMC values of shrub species and grassland (Spring and Summer data)

Without images from the spring season: In this case, only images from the middle of June to the end of September would be available. In this case, the model would become:

$$SFMC = -4.587 + 2.387*NDVI/TS - 4.062*AGRE + 4.029*RGRE \quad (7)$$

In this case the r^2 value is slightly reduced (0.61).

The satellite variables would be generated similarly as with images from spring season. The maximum and minimum SFMC values to compute the RDI would be derived from the analysis of 1998 images. Danger levels would be also computed as with images from spring season.

High-resolution Landsat-TM Data

In spite of its high cost and its 16 day temporal resolution, which is rather low for operational fire danger estimation (daily predictions are usually required by fire managers), Landsat-TM data analysis has two advantages over NOAA-AVHRR images. Firstly, it provides images from the SWIR band (band 5 and 7), which is more clearly related to water content than visible or NIR bands. Secondly, it reduces the uncertainty in correlating field measurements and satellite data, since Landsat's higher spatial resolution makes it much easier to locate target plots than in AVHRR images.

Three Landsat-TM images were acquired for this project. They correspond to dates in which field measurements were available: April 16, July 21 and September 23, all of them in 1997. Besides calculating the indices mentioned, in the case of NOAA-AVHRR images, two other indices were computed: the NDII5 and the NDII7. Both are similar to the NDVI but instead of using band 4 and 3 of the sensor, corresponding to the NIR and Red, they use bands 4-5 and 4-7, respectively, being the 5 and 7 in the SWIR). Also the ratio between the NDII5 and the ST and the Water Deficit Index (WDI) were calculated. Correlations were consistent with expected tendencies, showing the vegetation indices based on the SWIR bands the highest sensitivity to FMC Chuvieco, E. et al. 1999.

For the most significant correlation, several fitting models were computed to explore the presence of nonlinear trends, but since there were few data available no definitive conclusions could be reached.

COMPARISON OF SATELLITE ESTIMATIONS OF FMC

In an effort to combine results from the two data sources analyzed in the previous section, the following table may be useful for a preliminary assessment of the differences in FMC estimation depending on which source is used. Table 1 shows correlation coefficients between FMC obtained in the 1997 field campaign, and a selection of vegetation indices derived from satellite data.

Data Source	Species	Vegetation Indexes			
		NDII5	NDII7	NDVI	NDVI/ST
AVHRR	*C. ladanifer*			0.49	0.62
TM	*C. ladanifer*	0.88	0.90	0.72	0.68
AVHRR	Shrubs			0.49	0.58
TM	Shrubs	0.90	0.92	0.74	0.69
AVHRR	Grasslands			0.56	0.79
TM	Grasslands	0.96	0.94	0.96	0.97

Table 1. Pearson R values computed between Landsat-TM and AVHRR variables and FMC of grassland, average shrub and *C. ladanifer*.

NDII5 and NDII7, derived from Landsat TM, perform very well with all the species. In the case of NDVI/ST, the higher spatial resolution the Landsat TM provides, compared to the NOAA-AVHRR, does not seem to be an advantage for correlation with the *C. ladanifer*. AVHRR data correlation with NDVI/ST improves considerably with respect to NDVI, especially in the case of grassland. This may prove to be a useful index for this sensor in the future.

CONCLUSIONS

The possibility of comparing FMC results from several data sources is now more feasible. The use of standard and derived vegetation indices can link information gathered from fieldwork and both high and low resolution sensors.

The new NOAA 15, which includes a band in the SWIR, ought to help these comparative studies further, especially for significant indices such as the NDII5 and NDII7 derived from Landsat TM.

Meanwhile, the NOAA-AVHRR remains the most operational data source for fire danger management, in spite of its drawbacks (mainly noise). The most suitable variable for FMC appraisal that can be obtained from the AVHRR is the NDVI/ST.

RDI or any other danger index need to be validated for other test sites in order to better asses the relationship between FMC, satellite images and fire danger.

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