ESTIMATING TEMPORAL DYNAMICS OF FUEL MOISTURE CONTENT OF MEDITERRANEAN SPECIES FROM NOAA-AVHRR DATA

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1. THE ESTIMATION OF FIRE DANGER FROM REMOTE SENSING

Forest fires are a natural process in Mediterranean ecosystems. However, in recent years, changes in traditional patterns of land use have implied an increasing number of fires and the extension of burnt areas. The consequences of forest fires in such a fragile ecosystem as the Mediterranean are widely known: increasing soil erosion, changes in the hydrological cycle, loss of landscape attractiveness, reduction in timber profits and human casualties. The importance of these effects are severe enough as to reinforce the research on this field.

This paper presents the first results of a test study being developed under the European project Minerve-2 with partial funding by the Spanish Forest Service. It tries to improve current methods of fire danger estimation by using near-real time information gathered by NOAA satellites. As it is well known, fire danger is related to several factors, among which vegetation status (i.e. fuel moisture) and meteorological conditions (wind speed, temperature, relative humidity) are the most critical. Currently, fire danger indices are computed from meteorological observations, for two reasons. First, because it is very costly to obtain field measures of vegetation moisture content, and secondly, because it is assumed that meteorological data may be a good surrogate of vegetation status. However, in most cases weather stations are located far from forested areas, thus the spatial extrapolation of data might be very inaccurate for determining the actual risk of those areas. On the other hand, the relationship between weather data and fuel moisture of live vegetation may widely change according to plant physiology.

Satellite images can complement meteorological data in fire danger estimation, since they provide critical and updated information about the status of live vegetation. Fire danger rating requires frequent data for short-term periods, since fire prevention measures need to be taken timely. This requirement is currently only fulfilled by meteorological satellites. Among them, the NOAA system offers a good trade-off between spatial, spectral and temporal resolution, which makes it convenient for fire danger estimation over regional areas. The AVHRR sensor have been used for mapping burnt areas (Kasischke *et al.*, 1993), estimating fire danger (Chuvieco and Martín, 1994a), detecting hot spots (Setzer and Pereira, 1991), mapping fuel types (Werth *et al.*, 1985), and monitoring the spatial growth of large fires (Chuvieco and Martín, 1994b).

In fire danger applications, it is critical to estimate the vegetation water stress in order to detect those areas and periods where fires can more easily start. The most common approach to the estimation of vegetation stress has been the analysis of NDVI multitemporal series. NDVI provides a good indication of vegetation health. Decreases in NDVI are related to reduction of plant vigour and greenness, which are related to vegetation moisture content. Multitemporal NDVI composites have been successfully correlated to accumulated evapotranspiration, rainfall and crop moisture indices (Walsh, 1987; Kerr *et al.*, 1989; Deblonde and Cihlar, 1993). One of the best known vegetation indices is the NDVI (Normalized Difference Vegetation Index), that can be defined as:

$$\mathrm{NDVI} = \frac{\rho_{IR} - \rho_R}{\rho_{IR} + \rho_R}$$

where ρ_{IR} and ρ_R are respectively the reflectances of near infrared and red channels.

Relation between vegetation indices and plant living parameters has been proven by different authors. Sellers (1989) established a theoretic model to explain the relations between plants spectral behaviour and some plant physiological variables. He demonstrated that there was a linear correlation between vegetation indices and evapotranspiration, chlorophyll content of the plant, intercepted photosynthetically active radiation (IPAR) and absorbed photosynthetically active radiation (APAR) as far as the plants are not stressed. This author also showed that the relationships between leaf area index (LAI) and vegetation indices are only strong for low values of LAI. NDVI is saturated for LAI values from 3 to 5 in the case of crops, and from 4 to 6 for forested areas. Above these values, an increase in LAI does not affect the NDVI value.

Some experimental works have proven these theoretical developments. They show strong correlation between vegetation indices and chlorophyll content of the plant (Running and Nemani, 1988), evapotranspiration indices (Cihlar *et al.*, 1991) and absorbed photosyntetically active radiation (APAR) (Baret and Guyot, 1991). The APAR is related to vegetation productivity, and therefore it is possible to build biomass models by analysing time series of vegetation indices (Goward *et al.*, 1985; Box *et al.*, 1989). However, there are two important problems of using AVHRR-NOAA data to estimate physiological parameters:

- AVHRR pixels cover areas of about 1 sq. km at nadir. Thus, the signal received by the sensor represent a mean value for this area, which is vast enough to receive influences of a great variability of factors (i.e. different slopes, aspects and land covers).
- Calibration and atmospheric correction of AVHRR data are quite complex (Kaufman and Holben, 1993) and therefore there are severe difficulties to derive absolute models of vegetation status.

In fire danger applications good results in estimating vegetation stress had been obtained in grasslands areas (Sadowsky and Westover, 1986; Paltridge and Barber, 1988). In a pilot study conducted in Victoria State, Australia, good correlation between a modification of NDVI and fuel moisture content were found. In this work, the authors also analyse the relation between temporal variation in fuel moisture and NDVI value of November, the month with highest physiological activity (Paltridge and Barber, 1988; Paltridge and Mitchell, 1990).

It is possible to analyse the NDVI temporal variation with meteorological variables in order to calculate a fire danger index better adjusted to local conditions. This is the subject of a work developed in Nebraska, Kansas, North Dakota and South Dakota, in which the authors built a weekly fire danger index based on AVHRR-NOAA images and on certain meteorological variables (Eideshink *et al.*, 1989). The U.S. Forest Service is now using the absolute and relative temporal variation of NDVI to improve current fire danger rating systems (Burgan and Hartford, 1993; Burgan, 1995).

The temporal evolution of NDVI images has been used to estimate fire risk areas in the Mediterranean forest. Close relationships were found between the decrements of NDVI and fire incidence (López *et al.*, 1991; Illera *et al.*, 1994). High correlations have also been measured between NDVI and surface temperature with potential evapotranspiration (Martín *et al.*, 1994) and fire incidence (Prosper-Laget *et al.*, 1994).

An alternative to the use of NDVI series for vegetation moisture estimation is to follow the thermal dynamics of the vegetation cover. Vegetation moisture stress can be measured as the ratio of actual and potential evapotranspiration (ET/PET). ET has proven to be linearly related to net radiation and to the difference between air and surface temperature (T_s - T_a). Over long term periods and at regional scales, correlation coefficients of r = 0.99 have been measured between accumulated values of T_s - T_a and $\sum(ET - R_n)$ (Seguin *et al.*, 1991). This relationship has proven to be very useful for fire danger rating (Vidal *et al.*, 1994).

2. OBJECTIVES

The general objective of this project is to test the suitability of NOAA-AVHRR images to estimate fire danger. More specifically, we are studying the relationships between the information supplied by satellite images and the main variables which determine the ignition or spread of forest fires: live and dead fuel moisture content, meteorological danger indices and fire occurrence. This article summarises the first results obtained in computing correlation coefficients between NOAA-AVHRR derived variables and fuel moisture content measured on the field, for some Mediterranean species. The study area selected for this work is the Andalusian region (87,200 sq. km.), located at the South of Spain. The intense fire occurrence in this area and the collaboration provided by the Regional Government of Andalucía for accessing fire and meteorological statistics leaded us to choose this region for this project. Present results cover the period from July 1 to September 10, 1994, which agrees with the fire season in Mediterranean countries (in fact, fire season ends on September 30th but, as it is known, NOAA-11 satellite stopped sending data on September 10th 1994).

3. METHODOLOGY

3.1 Collecting fuel moisture data

Fuel moisture content (FMC) can be defined as the amount of water a plant holds, and it is expressed as:

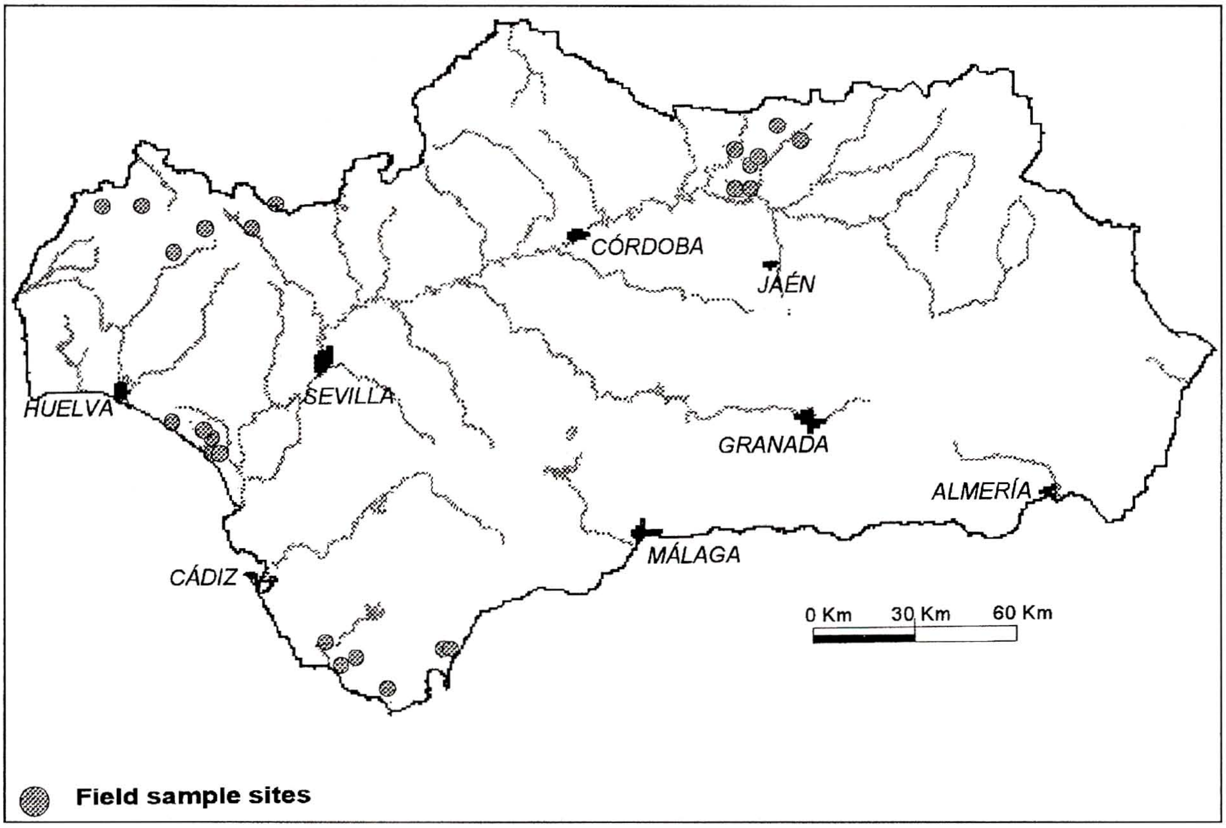

Figure 1 - Location of field samples

$$\mathrm{FMC} = \left(\frac{\mathrm{W_f} - \mathrm{W_d}}{\mathrm{W_d}} \right) \times 100$$

where W_f is the weight of fresh fuel and W_d the weight of dry fuel. The result is expressed in percentage. To apply the expression shown above, the first step is to collect fresh fuel samples in the field, in a certain number of sample sites. It is quite critical to carefully select the location of these sample parcels, considering AVHRR sensor characteristics. In this case, the following criteria were established for the selection of sample parcels:

(i) Homogeneous fuel type area of about 9 sq. kilometres size.

(ii) They should be clustered in different sectors of the study area, since field sampling needed to be performed around satellite acquisition time (from 12,00 to 16,00 h.) and therefore the parcels needed to be fairly close together.

(iii) The parcels should be located close to weather stations, in order to complement and correlate fuel moisture measurements with meteorological data.

(iv) All sample sites had to be located in smooth terrain to avoid illumination.

To select sample parcels, we overlaid the location of all the existing weather stations in the study area to a digital land-cover map provided by the Environmental Agency of Andalucía (De la Rosa and Moreira, 1987).

Those areas with large homogeneous patches were visited in the field. The most suitable 24 parcels were finally selected (figure 1). Fuel moisture measures were collected every 10 days in each parcel (from July, 1 to September, 10). Three samples per parcel were taken, either of litter, pasture, shrub or tree leaves according to the parcel composition. The samples were weighted in the field with a "Kern 466-45" scale (error: ± 0.1 g; maximum weight allowed: 250 g.). Each sample should weight more than 100 grams, in order to obtain a measurement accuracy of $\pm 5\%$.

The samples were collected according to morphological characteristics of each plant species. In the case of trees (*Quercus ilex*, *Quercus suber*, *Quercus faginea*, pine trees) an certain species of shrub (*Cistus ladanifer*, *Pistacia lentiscus*, and *Halimium halimifolium*) only leaves were taken. For shrubs like *Erica arborea* and *Arthrocnemum* *glaucum*, the end part of the branches were collected. Pasture was simply rooted out and cleaned up from topsoil, and litter (dead fuel) was collected from the upper layer of the soil.

Samples were dried up in an oven ("Selecta 2000"; stability: ± 0.75%; volume: 80 l.). Afterwards, samples were weighted again in the same scale to obtain the weight of dry fuel. Fuel moisture was obtained from the relation between both weights, and expressed in percentage of dry fuel weight, as previously shown.

3.2. NOAA-AVHRR images processing

NOAA-AVHRR images used for this project were acquired by the Valladolid University receiving station from NOAA-11 satellite (all images were taken around 15,00 h.). Images cover the period from March to September 1994. Spring images

(from March to June) were acquired for obtaining information about the maximum vegetation vigour of each pixel. In this case, only the last 10 days of each month were acquired, while for the summer period (from July 1 to September 10) daily images were used. After solving reception and cloud cover problems, 72 images were finally processed.

All images were geometrically corrected by using an orbital model (Ho and Asem, 1986) to the UTM projection (zone 30, extended along the western border). This is the one used for all the auxiliary information included in this project. After navigating the image, an image-to-image registration using ground control points was applied to insure consistency in the multitemporal analysis.

Each NDVI image was computed from albedo using the calibration coefficients proposed by Kaufman and Holben (1993). Theoretical NDVI values range from -1 to +1, but since typical land covers range between -0.05 to +0.8, these values were used as thresholds to apply a linear contrast stretch to expand the NDVI values range to 0-255 (8-bit integer number scale).

A cloud mask was applied to each image for preventing atmospheric absorption effects. To avoid distortions caused by atmospheric scattering and view-angle conditions 10-day Maximum Value Composites (MVC) were generated from March to September (March 21-31, April 21-30, May 21-31, June, 21-30, July, 1-10, July 11-20, July 21-30, July 31-August 9, August 10-19, August 20-29, August 30-September 8: figure 2). We expected to find positive correlation between NDVI values and FMC, because an increase in NDVI values implies an increase in vegetation vigour and a decrease in water stress.

From the NDVI values, two new variables were derived:

(i) Relative greenness, which accounts for the temporal dynamics of vegetation vigour, since it relates the NDVI of each period to the maximum and minimum NDVI for each pixel:

$$\mathrm{GREENNESS}_i = \frac{\mathrm{NDVI}_i - \mathrm{NDVI}_{min}}{\mathrm{NDVI}_{max} - \mathrm{NDVI}_{min}}$$

where $NDVI_i$ is the NDVI value for the period y, $NDVI_{max}$ and $NDVI_{min}$ are respectively the maximum and minimum NDVI values from all the 10-day-period images processed (from March to September) for each pixel. Correlation between greenness and FMC should be positive, since greenness expresses the relation of the current vegetation vigour of each pixel to its potential limits (Burgan and Hartford, 1993).

(ii) Cumulative NDVI change, which was calculated as:

$$\Delta\mathrm{NDVI}_i = \mathrm{NDVI}_i - \mathrm{NDVI}_{i-1} + \Delta\mathrm{NDVI}_{i-1}$$

where $\Delta NDVI_i$ is the change in the NDVI value between the period i and the previous one (i-1). Correlation with FMC should also be positive, because a high change value implies an increase in NDVI and, therefore, in plant vigour respect to previous periods.

Surface temperatures (ST) were calculated using a modified split-window algorithm (Coll *et al.*, 1994). This algorithm has been found to provide errors less than 1°C in a dry atmosphere, and less than 2°C in a humid one for Mediterranean environments, when the emissivity is well known. ST calculation required the brightness temperature of bands 4 and 5 of AVHRR sensor, and the pixel emissivities in both bands. Surface temperature was calculated as follows:

$$ST = T4 + 2.13(T_4 - T_5) + 0.18 + 40(1 - \bar{\varepsilon}) - 75\Delta\varepsilon$$

where ST is the surface temperature in a certain pixel, T_4 and T_5 are respectively the brightness temperatures of NOAA channels 4 and 5, $\bar{\varepsilon}$ is the average emissivity of channels 4 and 5, and $\Delta\varepsilon$ the difference in emissivity in these two channels. Brightness temperatures were calculated by the receiving station.

Since emissivities depend on the land cover, which is not always available, we derive the emmissivity correction from the method proposed by Kerr *et al.* (1992). This method is based on calculating the proportion of each pixel that is covered by vegetation. A simple way to obtain this information is to relate each pixel's NDVI value to a standard reference of NDVI values considered to be a fully vegetated pixel and bare soil pixel. A percent green cover is then generated as follows:

$$PGC_i = \frac{NDVI_i - MIN}{MAX - MIN} \times 100$$

where PCG_i is the percent green cover of a certain pixel for the period y, $NDVI_i$ is the NDVI (MVC) value for that period, and MAX and MIN are the maximum and minimum values of NDVI for all periods and all pixels. In our case, MAX = 0.76 (value located in an irrigated area in the Guadalquivir Valley) and MIN = 0.16 (value which corresponds to a desert area in the South-east of Andalucía).

Sobrino el al. (1993) have given the following formulas to calculate emissivities in AVHRR channels 4 and 5 for each pixel:

$$\varepsilon_4 = 0.982 PGC_i + 0.956(1 - PGC_i)$$
$$\varepsilon_5 = 0.986 PGC_i + 0.967(1 - PGC_i)$$

With these emissivity values, we could calculate the difference in the emissivities as:

$$\Delta\varepsilon = \varepsilon_4 - \varepsilon_5$$

Trends in surface temperature over the study period are complementary to what was shown on the NDVI values (figure 3). Higher temperatures appear in Guadalquivir valley (mainly crop-covered) in July and August, while the forested areas (located at higher elevations) show cooler temperatures.

Similarly to the variables generated from the NDVI (equations 3 and 4), two new variables were calculated from the surface temperature : relative ST and ST change (ΔST). We expected negative correlation between all variables derived from ST and FMC, since an increase on vegetation activity reduced surface temperature.

The last variable generated was a synthetic one, a ratio of NDVI and ST . Both variables offer complementary information, because the higher the vegetation vigour, the higher the NDVI and the lower the surface temperature (since evapotranspiration implies heat release). So we expected positive correlation between this variable and fuel moisture.

To compute the correlation between satellite variables and fuel moisture, we extracted from the images the median value of a 3 x 3 pixel window around each sample site. In doing so, the effects of inaccurate AVHRR cartographic correction may be reduced. Median instead of mean values were used, because of the median is more robust to boundary effects since it is less influenced by extreme values. For the fuel moisture measurements, we also calculate the median value in those sample sites where 3 samples of the same species were collected.

4. RESULTS

We present in this paper results from the temporal correlation between satellite variables and FMC. Temporal correlation means the relation between the temporal dynamics of the two parameters (AVHRR variables and FMC). To each species and parcel, the Pearson linear correlation coefficient has been calculated for the seven summer periods, when both variables were available.

Before discussing the results, we must take into account that the FMC samples collected on the field try to characterise the water content of such vast areas as 9 sq. km., which in fact are never homogeneous. Therefore, these measurements may not be representative enough as a consequence of the geographic variability (local topography, various cover densities, landscape fragmentation, etc.) of each AVHRR pixel. This problem is very difficult to solve, since an exhaustive spatial sampling of large parcels is unapproachable. Therefore, an important amount of "*noise*" is expected, specially when the fuel moisture data have been collected from different sample sites. In other words, the field sampling procedure may introduce inconsistency in the fuel moisture measurements and consequently more systematic and longer sampling data should be obtained to derive final conclusions.

Temporal correlations for each species were calculated using two different datasets:

(i) FMC median values of each species. They were computed as the median value of all parcels where samples of the same species were taken. With this method, we have seven values per species to compute the Pearson r coefficient (one value in each period).

(ii) Raw FMC values for each species. In this case, all parcels and periods collected per species were taken into account. This method increase the number of values used to compute the r coefficient proportionally to the number of parcels per species collected on the field.

The first dataset eliminates "*noise*" from raw data, but the statistical significance of the correlation values is low because of the few number of observations involved. Table 1 shows the correlation coefficient, following the first dataset, for each variable in 13 different sampled species. The results are more encouraging for shrub species, being poor for trees and pasture. Among the shrubs, the species which show the best correlation between FMC and the satellite variables are the rosemary (*Rosmarinus officinalis*) and the rose gum (*Cistus ladanifer*), which show correlation coefficients above 0.7 for the variables derived from NDVI and the ratio NDVI/ST, and slightly lower values for those derived from surface temperature (figures 4 and 5), probably because of the low variation of the surface temperature along the summer. The signs of the correlation coefficients are consistent with what should be expected. *Halimium halimifolium* and *Pistacia lentiscus* provide lower correlations than rose gum and rosemary, though they maintain the consistency of the signs since the NDVI and its derived variables show positive correlation coefficients while surface temperature and its derived variables negative. Heather (Erica arborea) is the worst correlated shrub species among the ones sampled, showing no significant values with NDVI and its derived variables, although it presents consistency of the signs (figure 6).

Regarding the tree species, the measurements refer mainly to evergreen oaks (*Quercus ilex*, *Quercus suber*), which regularly appear in sparse canopies, and pine trees (*Pinus pinea*). In Andalucia, as well as in many other areas of Spain, evergreen oaks are associated to cereal crops and pastures, a mixed system of land use called "dehesa". This mixture implies that the contribution of the soil to the signal received by the sensor is of great significance (note the high positive correlation between *Quercus ilex's* moisture content and surface temperature).

Correlations with the FMC of grasslands do not present the expected trend because the values measured on the field at the beginning of July were lower than 10% (in practice, they could be consider as litter, dead fuel) and they hardly varied through the summer. In other words, pastures were almost dry at the beginning of the sampling period and they do not offer enough variation to be registered by satellite data. For this reason, these correlation need to be extended to the Spring season, in order to consider higher values of FMC too.

Results considering raw data increase the noise of the median values, but they show similar trends (figure 7). In this case, all sampled parcels for each species have been considered. For some of them, several parcels were sampled each period and, therefore, more data are available for the correlation. Table 2 shows the r values, number of observations available and the significance value for the correlation. As in the case of median values, correlation of FMC and satellite variables is rather poor for forested species (quercus and pine trees), as well as pasture and litter. However for these last two fuel types, surface temperature is much better correlated to FMC than NDVI, which shows the influence of soil temperature in satellite signal. Shrub species show again the best correlation, specially *Cistus ladanifer* and *Hallimium Halimifolium*, being *Erica Arborea* more poorly related.

5. DISCUSSION

This project is in progress. Satellite and field data for 1995 and 1996 are now being processed. Therefore, final conclusions cannot be still derived. From the analysis carried out in this paper, a good correlation between FMC of some Mediterranean shrub species and the variables obtained from NOAA-AVHRR images have been observed. Considering the high level of noise, "good correlation" means consistency of the signs with our original hypothesis, not necessarily high r values. Nevertheless, there are some questions left in relation with the sampling strategy followed to measure FMC. Some doubts remain about the significance of extrapolating fuel moisture data from the field to the vast area covered in a AVHRR pixel. For this reason, the development of this work in 1996 will include satellite data with higher spatial resolution (Landsat TM) to complement the results obtained with NOAA-AVHRR.

The development of future research aims to answer some of these questions. First, the evolution of FMC through the Spring season will be taken into account, since the lack of correlation observed for some species might be due to the severe drought that affected Spain in the summer of 1994. This drought severely reduced the range of variation in the moisture content of some species. Secondly, the measurements will be repeated on homogeneous sample sites, avoiding the association between evergreen oaks and pasture. Finally, meteorological danger indices are now being incorporated into the analysis of both FMC and satellite variables, in order to include meteorological indices to compute multivariate relationships.

Table 1 - Temporal correlation between FMC and NOAA-AVHRR satellite variables. Median values for each species.

		NDVI	ST	Relative Greenness	Relative TS	NDVI change	TS change	NDVI/ TS
Quercus ilex	**r**	**0,2685**	0,9213	**0,4614**	0,7610	**0,0221**	0,7982	-0,5441
	# data	7	7	7	7	7	7	7
	Significance level	0,560	0,003	0,297	0,047	0,962	0,031	0,207
Quercus suber	**r**	**0,3827**	**-0,2258**	**0,3851**	**-0,2258**	**0,3827**	**-0,2258**	**0,4575**
	# data	6	6	6	6	6	6	6
	Significance level	0,454	0,667	0,451	0,667	0,454	0,667	0,362
Quercus faginea	**r**	**0,1037**	**-0,5844**	**0,1097**	**-0,5844**	**0,1037**	**-0,5844**	**0,2659**
	# data	6	6	6	6	6	6	6
	Significance level	0,845	0,223	0,836	0,223	0,845	0,223	0,611
Pinus pinea	**r**	**0,1072**	0,4601	**0,1187**	0,5415	**0,0941**	0,5374	-0,2784
	# data	7	7	7	7	7	7	7
	Significance level	0,819	0,299	0,800	0,209	0,841	0,213	0,545
Cistus ladanifer	**r**	**0,7804**	**-0,3895**	**0,7657**	**-0,5027**	**0,7948**	**-0,5076**	**0,7281**
	# data	7	7	7	7	7	7	7
	Significance level	0,038	0,388	0,045	0,250	0,033	0,245	0,064
Erica arborea	**r**	**0,1034**	**-0,4884**	**0,0231**	**-0,5304**	**0,1473**	**-0,5240**	**0,4158**
	# data	7	7	7	7	7	7	7
	Significance level	0,825	0,266	0,961	0,221	0,753	0,227	0,354
Halimium Halimifolium	**r**	**0,6038**	**-0,6372**	**0,6528**	**-0,6490**	**0,5995**	**-0,6866**	**0,8658**
	# data	7	7	7	7	7	7	7
	Significance level	0,151	0,124	0,112	0,115	0,155	0,088	0,012
Rosmarinus officinalis	**r**	**0,7808**	**-0,4313**	**0,8029**	**-0,4602**	**0,7235**	**-0,4833**	**0,7886**
	# data	7	7	7	7	7	7	7
	Significance level	0,038	0,334	0,030	0,299	0,066	0,272	0,035
Pistacia lentiscus	**r**	**0,2459**	**-0,2056**	**0,3205**	**-0,1216**	**0,2132**	**-0.1713**	**0,2424**
	# data	6	6	6	6	6	6	6
	Significance level	0,639	0,696	0,536	0,818	0,685	0,746	0,643
Pasture	**r**	-0,5573	0,2586	-0,2319	0,2617	-0,3423	0,3849	-0,6568
	# data	7	7	7	7	7	7	7
	Significance level	0,194	0,575	0,617	0,571	0,452	0,394	0,109
Dead pine leaves	**r**	**0,7409**	**-0,5383**	**0,7251**	**-0,5680**	**0,7400**	**-0,6461**	**0,7664**
	# data	6	6	6	6	6	6	6
	Significance level	0,092	0,271	0,103	0,240	0,093	0,166	0,075
Litter	**r**	-0,3619	**-0,0600**	-0,3279	**-0,1173**	-0,4425	**-0,0145**	-0,1770
	# data	6	6	6	6	6	6	6
	Significance level	0,481	0,910	0,526	0,825	0,380	0,978	0,737

Bold type remarks the consistency of the signs.

Table 2 - Temporal correlation between FMC and NOAA-AVHRR satellite variables. Raw values for each species.

		NDVI	ST	Relative Greenness	Relative TS	NDVI change	TS change	NDVI/ TS
Quercus ilex	**r**	-0.2371	**-0.0139**	-0.1530	0.0355	-0.5164	0.4619	-0.1941
	# data	40	40	40	40	40	40	40
	Significance level	0.141	0.932	0.346	0.828	0.001	0.003	0.230
Pinus pinea	**r**	-0.3647	0.4207	**0.1588**	0.2258	**0.3185**	0.3258	-0.5012
	# data	21	21	21	21	21	21	21
	Significance level	0.104	0.058	0.492	0.325	0.159	0.150	0.021
Cistus ladanifer	**r**	**0.4154**	**-0.2121**	**0.4239**	0.0079	**0.4680**	**-0.1795**	**0.4105**
	# data	37	37	37	37	37	37	37
	Significance level	0.011	0.208	0.009	0.963	0.003	0.288	0.012
Erica arborea	**r**	**0.2640**	**-0.1612**	**0.0156**	**-0.2527**	**0.3135**	**-0.4368**	**0.3677**
	# data	14	14	14	14	14	14	14
	Significance level	0.362	0.582	0.958	0.383	0.275	0.118	0.196
Halimium Halimifolium	**r**	**0.4083**	**-0.3785**	**0.4186**	**-0.4059**	**0.3927**	**-0.3905**	**0.5293**
	# data	14	14	14	14	14	14	14
	Significance level	0.147	0.182	0.136	0.150	0.165	0.167	0.052
Pasture	**r**	-0.4099	**-0.2767**	**0.1609**	**-0.1747**	**0.1189**	**-0.2911**	-0.2280
	N° data	72	72	72	72	72	72	72
	Significance level	0	0.019	0.177	0.142	0.320	0.013	0.054
Dead pine leaves	**r**	**0.4324**	**-0.4002**	**0.2155**	**-0.3369**	**0.1902**	**-0.3416**	**0.4991**
	# data	18	18	18	18	18	18	18
	Significance level	0.073	0.100	0.390	0.172	0.450	0.165	0.035
Litter	**r**	-0.5934	**-0.6902**	**0.5006**	**-0.5334**	**0.6683**	**-0.7206**	**0.0904**
	# data	10	10	10	10	10	10	10
	Significance level	0.071	0.027	0.141	0.112	0.035	0.019	0.804

Bold type remarks the consistency of the signs.

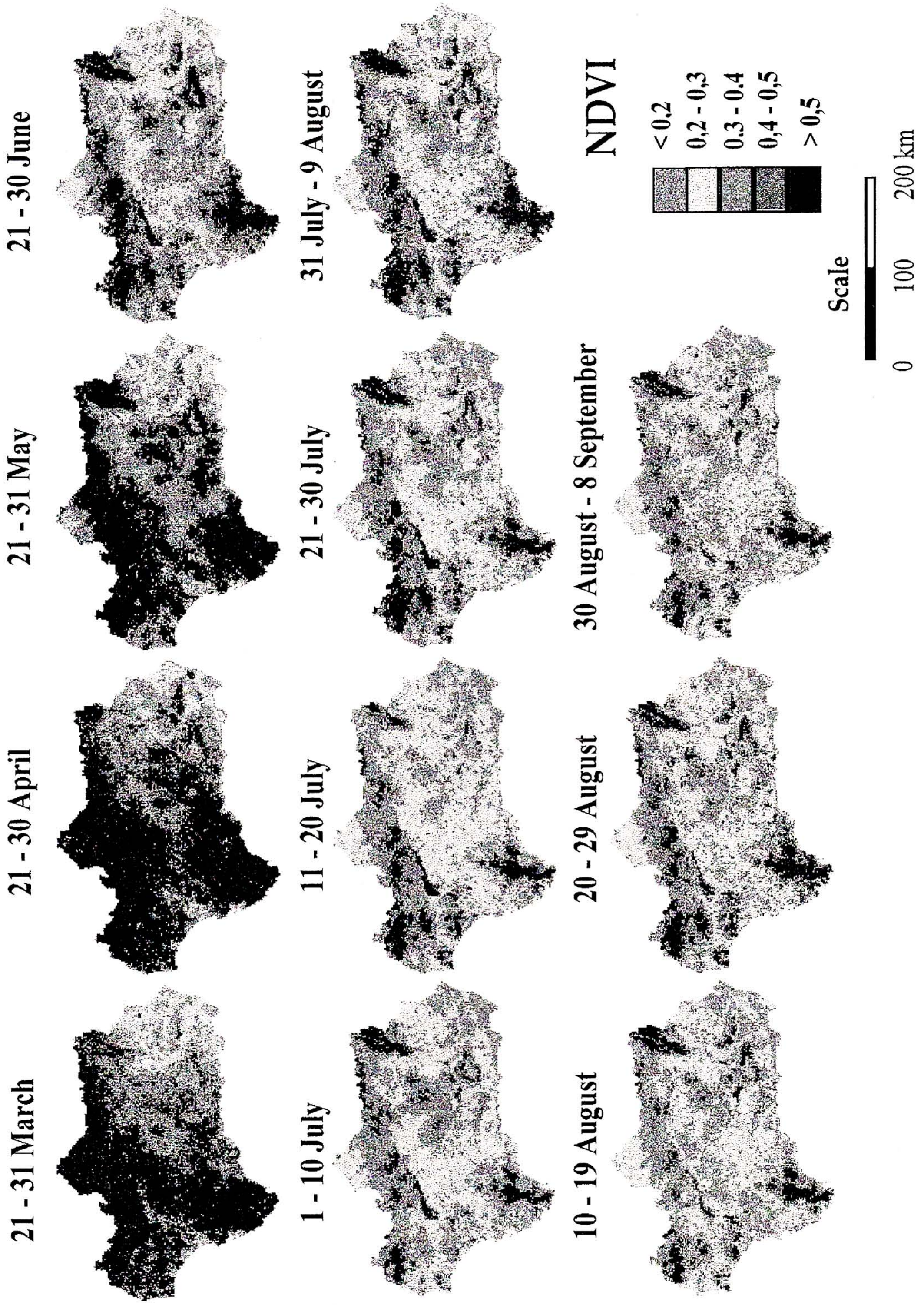

Figure 2 - Evolution of NDVI values

See plate III at end of volume

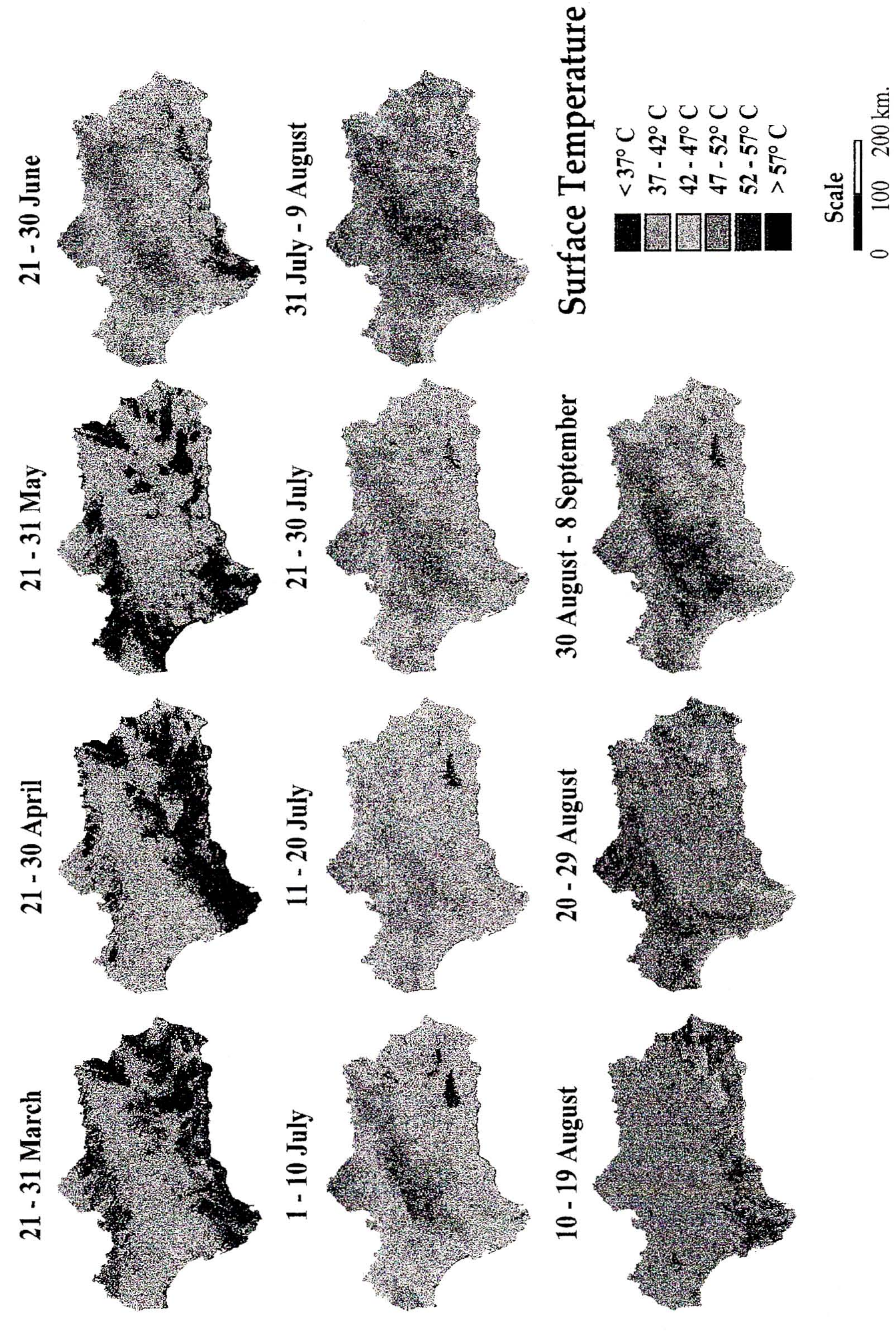

Figure 3 - Evolution of Surface Temperature

See plate IV at end of volume

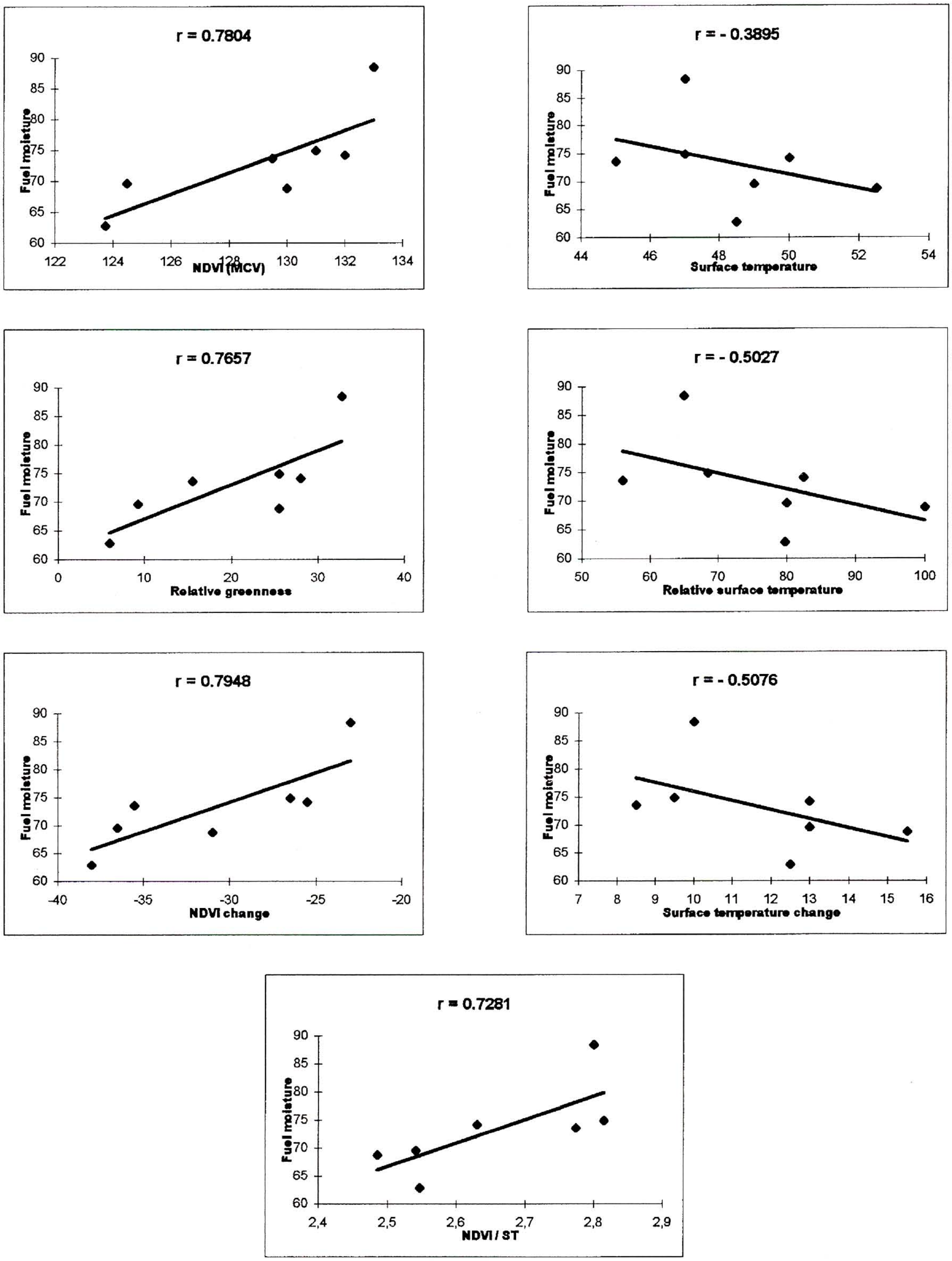

Figure 4 - Cistus ladanifer. *Fuel moisture vs. Satellite variables scattergrams and correlation coffficient. Mediam values*

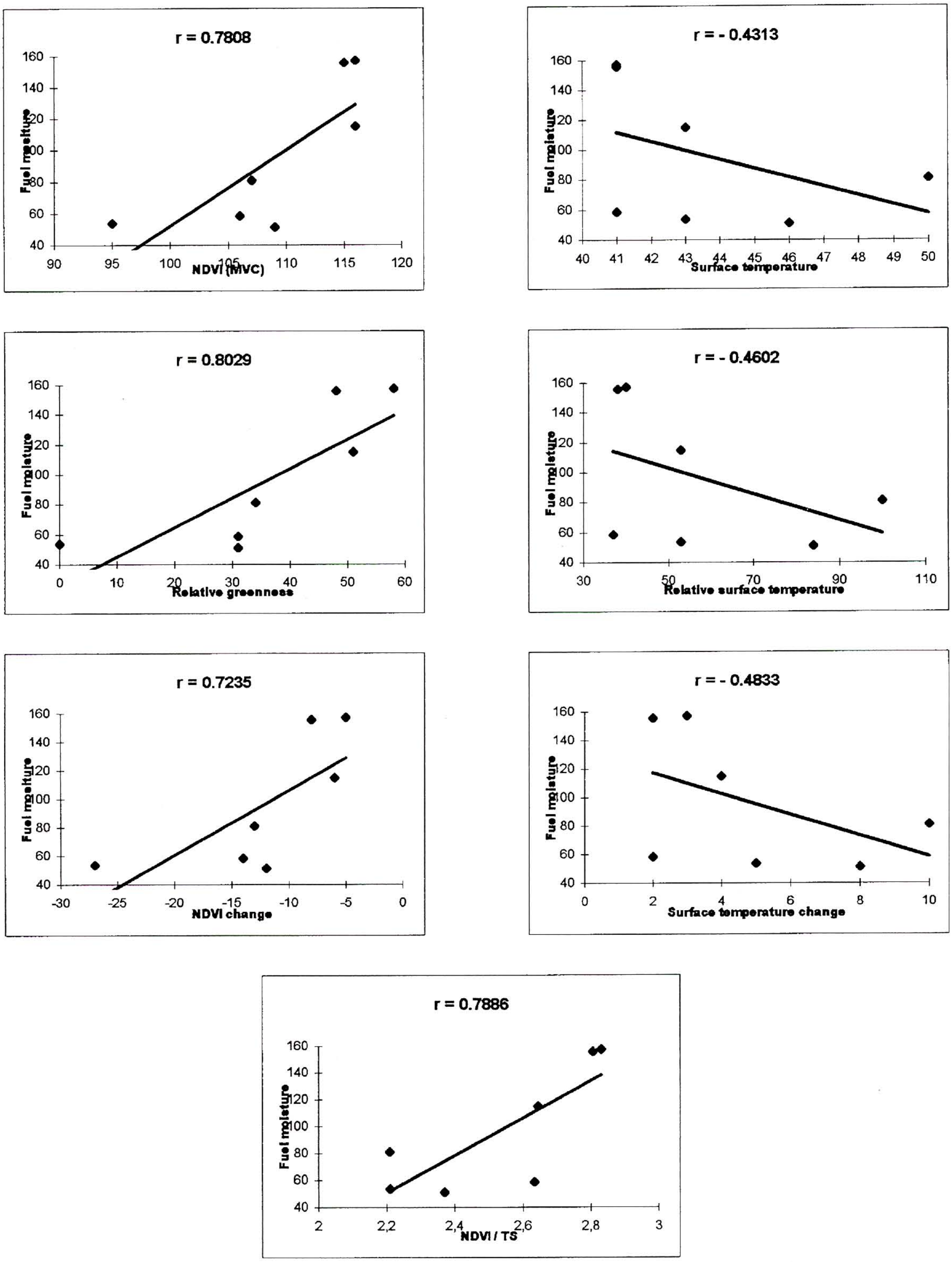

Figure 5 - Rosmarinus officinalis. *Fuel moisture vs. Satellite variables scattergrams and correlation coefficients. Median values.*

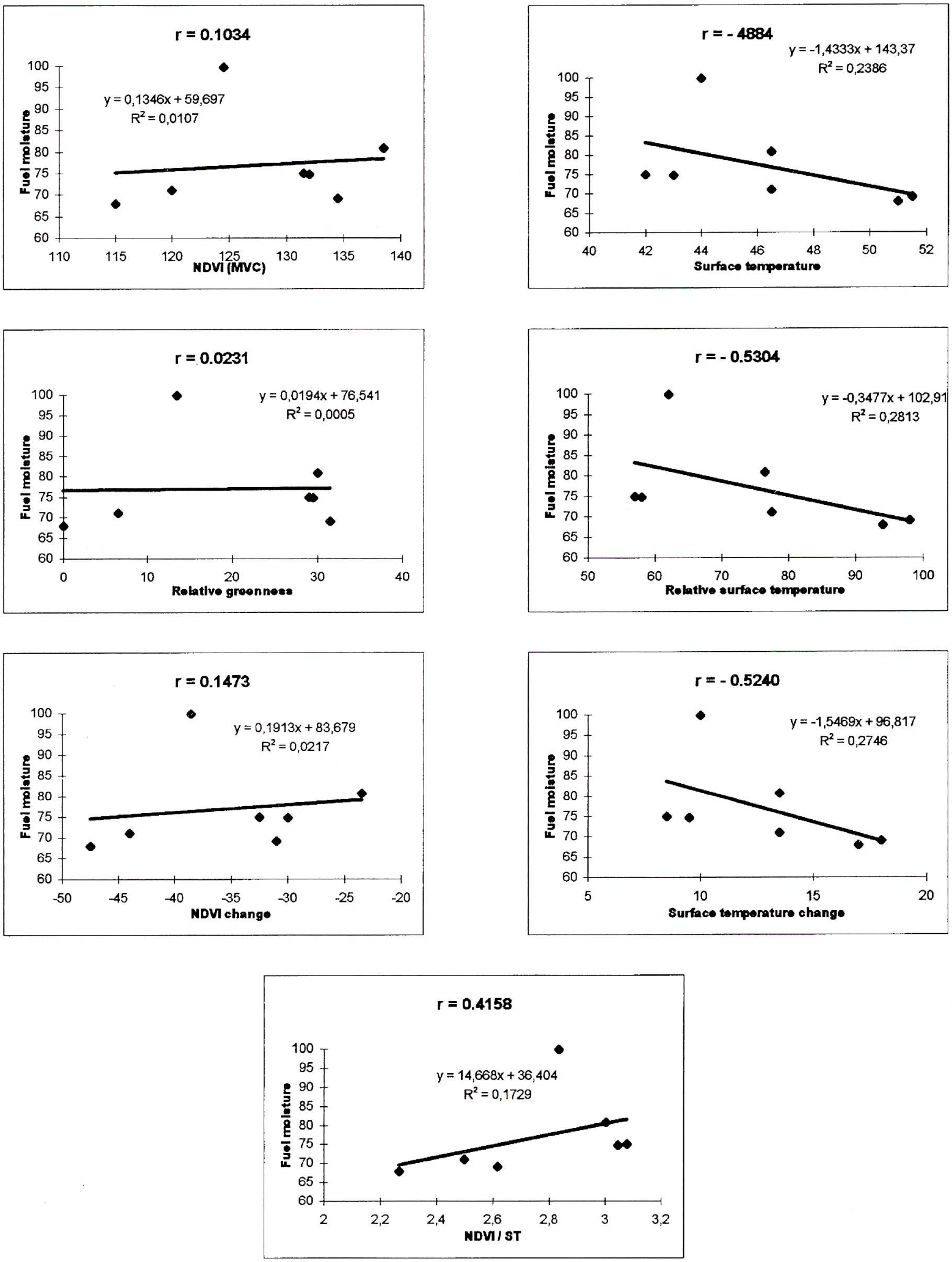

Figure 6 - Erica arborea. *Fuel moisture vs. Satellite variables scattergrams and correlation coefficients. Median values.*

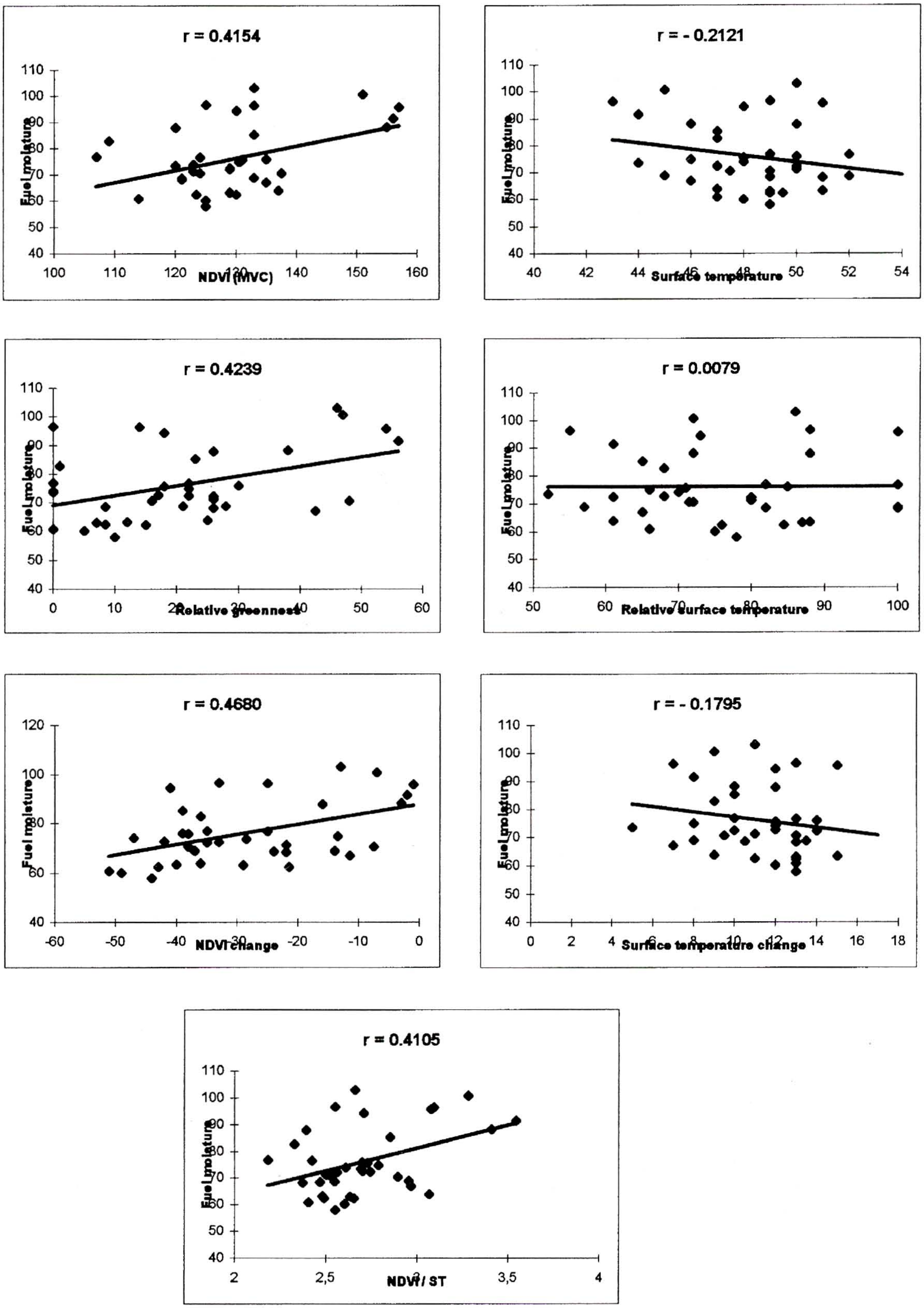

Figure 7 - Cistus ladanifer. *FMC vs. Satellite variables (Raw data)*

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