Extension of Climate Parameters Over the Land Surface by the Use of NOAA-AVHRR and Ancillary Data

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Abstract
Climatic estimates relative to the land surface between ground stations are of utmost importance to many agricultural and forestry activities. In the present paper, two methods are tested for extending the most important parameters for a climatic classification (mean annual temperature and length of the arid and cold seasons) over a complex region in central Italy (Tuscany). The first method is based on conventional multivariate regressions applied to the environmental factors most influential on climate variability (elevation, distance from the sea, and latitude). The second relies on the extraction of the climatic information from an integrated NOAA-AVHRR data set composed of NDVI profiles and thermal infrared images of two growing seasons. In this latter case, a more flexible approach based on a fuzzy classification was adopted. The two methods yielded similar results, with some differences explainable by environmental considerations. A statistical procedure is applied for the optimal merging of the climatic estimates from the two methods. It is finally concluded that the information derived from suitably processed NOAA-AVHRR data can supplement that from more conventional sources for the extension of fundamental climatic parameters over large land surfaces.

Introduction
Climatic classifications are of great utility for territorial planning and, in particular, for optimizing the management of agricultural and forestry resources (Thornthwaite, 1933; Pinna, 1977). This is particularly the case in developing countries, where such resources are generally limited and often threatened by various hazards (deforestation, desertification, pollution, etc.). Climatic classifications are commonly generated by extrapolating from or interpolating between local measurements, commonly taken at meteorological stations. Unfortunately, the process of extending point estimates on the land surface is often complex and nearly impossible in very irregular terrain (Conese *et al.*, 1989).

Recent works have demonstrated that data taken by the Advanced Very High Resolution Radiometer (AVHRR) mounted onboard National Oceanic and Atmospheric Administration (NOAA) satellites are useful for eco-climatic classifications, thanks to the abundant environmental information contained in the Normalized Difference Vegetation Index (NDVI) and in thermal infrared images (Derrien *et al.*, 1992; Gaston *et al.*, 1994; Benedetti *et al.*, 1994; Maselli *et al.*, 1996). The extent to which these data can be used to directly estimate the most important parameters for the climatic zonation of complex areas is, however, mostly unknown. In particular, it has not been clearly established how the images can assist in extending the main mean climatic parameters computed at some ground stations (temperatures, lengths of growing and arid seasons, etc.) over the land surface.

The present work aims to address this issue with reference to a region in central Italy with complex environmental characteristics (Tuscany). The performance of NOAA-AVHRR and ancillary data are first compared for the extension of these parameters using an independent climatic classification as a reference for the training and the testing phases. In particular, appropriate environmental information layers are treated by usual multivariate regression procedures while a methodology recently proposed based on a fuzzy classification approach (Maselli *et al.*, 1995) is utilized for the processing of the remotely sensed data. Finally, a method is applied to statistically combine the results of the two procedures in order to optimize the extension process of the study climate parameters.

Study Area and Data

Environmental Features
Tuscany is situated in central Italy between 9° and 12° east longitude and 44° and 42° north latitude (Figure 1). From an environmental point of view, Tuscany is peculiar for its extremely heterogeneous morphological and climatic features. The topography ranges from flat areas near the coastline and along the principal river valleys to hilly and mountainous zones towards the Appennine chain. Approximately two-thirds of the region is covered by hilly areas, one-fifth by mountains, and only one-tenth by plains and valleys.

From a climatic viewpoint, Tuscany is influenced by its complex orographic structure and by the direction of the prevalent air flows (from the west-northwest). As a result, the climate ranges from typically Mediterranean to temperate warm or cool according to the altitudinal and latitudinal gradients and the distance from the sea (Rapetti and Vittorini, 1995). The land use is predominantly agricultural where the land is flat and mixed agricultural and forestry in the hilly and mountainous areas. The main agricultural cover types are cereal crops in the plains and olive groves and vineyards on the hills. The upper mountain zones are almost completely covered by pastures and forests.

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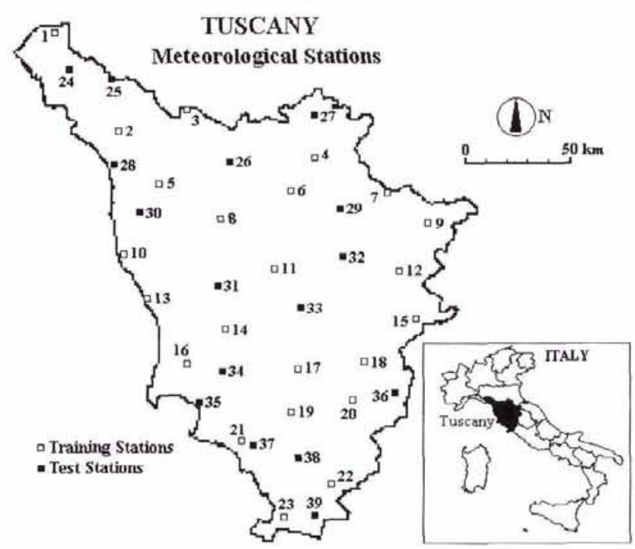


Figure 1. Geographical position of the study region and locations of the meteorological stations.

Reference Climatic Classification

For the present study, the climatic classification of Tuscany produced by Rapetti and Vittorini (1995) was used as a reference. This classification, at a 1:250,000 spatial scale, is based on the composition of maps of the main climatic parameters which were derived from the analysis of a historical series of meteorological data taken at about 40 stations over approximately 30 years. The principal parameters of the climatic classification are mean annual temperature (AT), mean length of the arid season (AS), and mean length of the cold season (CS), divided respectively into eight levels (from 6 to 17°C), four levels (from 0 to 4 months), and four levels (from 0.5 to 6.5 months) (Table 1). These three parameters were the most appropriate for the classification of the region because they expressed all climatic trends previously mentioned (Rapetti and Vittorini, 1995). The extension of the parameters over the region was mainly based on consideration of thermal and humidity gradients. In general, mean temperature and the number of arid months increase going from the medium-high mountains towards the coast line and the principal valleys, while the opposite trend is visible for the number of cold months. The number of arid months is also influenced by other factors partly related to geomorphological, soil, and land-use characteristics (Rapetti and Vittorini, 1995).

Satellite Data

The NOAA-AVHRR data set consisted of monthly NDVI Maximum Value Composites (MVC) and of four surface temperature (ST) images taken over two years (1989–1990), all at the original 1.1-km resolution. The MVCs were considered because they reported information about vegetation dynamics in the region, while the ST images were related to land temperatures in different seasons.

The NDVI data were recovered from the Telespazio (Rome) archives already in the form of vegetation index (NDVI) images. Some preprocessing operations (radiometric calibration, geometric rectification, ten-day Maximum Value Compositing) had already been performed on the data (Rossini *et al.*, 1994). Thus, only monthly compositing was necessary for these images. This operation was carried out in order to eliminate possible residual atmospheric influence and cloud contamination which might remain in the ten-day composites. Unfortunately, only a few NDVI images were available for the winter months, which were insufficient to produce reliable composites. Only seven monthly MVCs for each year covering the growing season (March through September) were therefore finally obtained, projected into the Universal Transverse Mercator (UTM) system.

The ST images were derived from calibrated bands 4 and 5 AVHRR data bought from ESA (Rome). Among the midday scenes available for the two study years (about 40), only six appeared from a visual examination to be completely cloud-free and practically unaffected by atmospheric variations throughout the entire region. From these six dates, four were selected as representative of different seasons (09 May 1989, 05 October 1989, 04 March 1990, and 21 July 1990). The scenes were first georeferenced to the same coordinate system as above using a third-degree polynomial transformation function and nearest-neighbor resampling algorithm trained on ground control points. A mean error of about 1 AVHRR pixel was obtained for both the X and Y axes. Because the data were in Sharp 2A format (brightness temperature in channels 4 and 5), it was sufficient to apply the split-window algorithm of McClain *et al.* to derive surface temperature data (ESA User Guide, 1992). No correction for variations in surface emissivity was made at this stage.

Table 1. Meteorological Stations Used in the Research with Values of the Three Climate Parameters Derived from the Classification of Rapetti and Vittorini (1995).

	Meteorological Station	Mean Temperature (C°)	Length of the Arid Season (month)	Length of the Cold Season (month)
	Training Stations			
1	Montelungo	10	0	4.5
2	Campagrina	10	0	2.5
3	Boscolungo	6	0	6.5
4	B.S. Lorenzo	13.5	1	2.5
5	Lucca	14.5	1	0.5
6	Firenze	14.5	1	0.5
7	Camaldoli	10	0	6.5
8	S. Miniato	15.5	3	0.5
9	P.S. Stefano	12	1	4.5
10	Livorno	15.5	3	0.5
11	Poggibonsi	14.5	2	0.5
12	Arezzo	14.5	1	2.5
13	Vada	15.5	3	0.5
14	Larderello	13.5	1	2.5
15	Cortona	13.5	1	2.5
16	Suvereto	15.5	3	0.5
17	Pari	14.5	2	2.5
18	Pienza	12	2	2.5
19	Campagnatico	14.5	2	0.5
20	Vivo d'Orcia	14.5	1	2.5
21	S. Leopoldo	15.5	4	0.5
22	Manciano	13.5	3	2.5
23	Orbetello	16.5	3	0.5
	Test Stations			
24	Bagnone	12	0	2.5
25	P.sso Cerreto	8	0	6.5
26	Pistoia	14.5	1	2.5
27	Firenzuola	12	1	4.5
28	Viareggio	15.5	1	0.5
29	Vallombrosa	10	0	4.5
30	Pisa	15.5	1	0.5
31	Volterra	13.5	1	2.5
32	Montevarchi	14.5	1	2.5
33	Siena	13.5	2	2.5
34	Massa maritt.	13.5	1	2.5
35	Follonica	15.5	3	0.5
36	Spineta	12	1	4.5
37	Grosseto	15.5	3	0.5
38	Scansano	13.5	2	2.5
39	Capalbio	14.5	3	0.5

Data Analysis

The data processing was carried out on a Digital Microvax 3100 computer system utilizing FORTRAN 77 and C programs and Genstat 5 procedures (Genstat, 1993) written in house. The various steps of the processing chain are described in the following sections.

Extraction of Climatic Parameters from the Reference Map

As mentioned previously, the climatic information content of the NOAA-AVHRR data set in the study region was evaluated by comparison to the climatic classification of Rapetti and Vittorini (1995). In particular, the three most important climate parameters estimated at 39 meteorological stations were considered. The values of mean annual temperature (AT), mean length of the arid season (AS), and mean length of the cold season (CS) were identified for all 39 reference stations (Table 1). As can be seen, only rounded values could be derived from the maps. The study stations were then divided into two groups, the first for training (23 stations) and the second for testing (16 stations). The number and positions of the stations were selected so as to obtain two groups which were homogeneously distributed in the region, with a slight prevalence of the training group which had to cover all the possible environmental situations (Figure 1). The selection of the stations was not random to ensure that both the training and test sets would be representative of most variability in the region.

Regression Analysis on Environmental Factors

A first analysis was conducted to extrapolate the three climate parameters studied on the basis of the environmental factors most influential on climatic variations. Elevation, latitude, and distance from the sea are known to exert a dominant effect on climate (Pinna, 1977), and they were taken into consideration in the present analysis.

A digital elevation model (DEM) of the region with a pixel size of 1.1 by 1.1 km was generated by digitizing and processing the contour lines every 100 m taken from 1:100,000-scale geographic maps of the Istituto Geografico Militare Italiano (IGMI). Two digital images with a north-south gradient and distance from the Tyrrhenian Sea were also produced by FORTRAN programs.

The values of the three factors (i.e., elevation, latitude, and distance from the sea) corresponding to the training station pixels were extracted from the digital images and used in a conventional multivariate linear regression model with respect to each climate parameter (i.e., AT, AS, and CS) (Anderson, 1984). The use of linear regressions to relate mean climate parameters to geomorphological features dates back to classical authors (Spreen, 1947; Burns, 1953). Even if now partly superseded by more recent methodologies, this approach was chosen in the present case to produce a reference set related only to the main climate driving factors with the ultimate purpose of evaluating the additional spatial information provided by the satellite data. The models found were then applied to the whole region and the relevant values for the test station pixels were determined. The performance of the three models was evaluated by the coefficient of determination (r^2) and the root-mean-square error (RMSE) of these estimates with respect to the values derived from the Rapetti and Vittorini climatic classification.

Fuzzy Classification of NOAA-AVHRR Data

As is well known, climatic factors strongly affect vegetation dynamics, which are reflected in NOAA-AVHRR NDVI multitemporal profiles at a 1.1-km pixel scale. Also, the distribution of air temperature is a major driving variable in determining the thermal infrared signal of NOAA-AVHRR bands 4 and 5 (Petkov *et al.*, 1996). Accordingly, it was possible to formulate a working hypothesis that the study data set from NOAA-AVHRR imagery (NDVI profiles of two growing seasons and four surface temperature images) is informative regarding the spatial distribution of the three climate parameters considered.

On the other hand, it had to be expected that the useful information contained in these data is related to the climate parameters in a complex, non-linear manner, because vegetation in temperate areas responds to environmental factors in a complex way and is also sensitive to human influences (agricultural and forestry practices, urbanization processes, etc.). In effect, recent studies have demonstrated that NDVI data are linearly related to a main climate factor only in homogeneous areas where this factor is strongly limiting for vegetation development (Hielkema *et al.*, 1986; Maselli *et al.*, 1994). The usual regression techniques would therefore be ineffective for the processing of these data, due to the relevant rigid statistical constraints. A suitable alternative would have to be based on a more flexible identification of spectral similarities among pixels. This being the case, a fuzzy logic approach was deemed the most appropriate. In particular, a methodology was followed which had recently been developed by our research group for the estimation of forest parameters in complex terrain from Landsat TM data (Maselli *et al.*, 1995).

As described by Zadeh (1965), each element in a fuzzy set is characterized by a series of fuzzy membership grades which express the extent to which the element belongs to a series of classes. In the current approach, the image pixels are the fuzzy elements and each training entity (corresponding to the pixels of a meteorological station) is treated as an individual class. Fuzzy probabilities of attribution of all pixels to each entity are consequently obtained by a softened maximum-likelihood classification of the remotely sensed data (Wang, 1990a; Wang, 1990b). These probabilities are finally used to estimate the study parameters for each pixel through a weighted average strategy as follows:

$$Xe = \sum_{i=1}^{NC} Pr_i \cdot Xm_i \tag{1}$$

where

Xe is the estimated value for the pixel considered,
NC is the number of classes (stations),
Pr_i is the pixel fuzzy probability of attribution to class (station) i, and
Xm_i is the measured value of class (station) i.

The approach is conceptually similar to that used in geostatistics, where the weights for Equation 1 are derived from spatial covariances instead of spectral similarities (Davis, 1973). In the present case, the AVHRR data were first subjected to mean filtering with a 3 by 3 moving window in order to reduce the effects of misregistration errors and excessive spatial irregularities. A Principal Component Transformation (PCT) was then applied to each study year (seven monthly NDVI MVCs) so as to compress these markedly redundant data and reduce the time for subsequent processing. For each year four Principal Components contained over 98 percent of the total variance and were therefore retained. No statistical transformation was applied to the ST images, which, taken in different seasons, were generally not strongly correlated. Next, the spectral signatures of the nine pixels around each training station were computed for the subsequent classification (mean vectors and variance-covariance matrices). These signatures were used to generate probability images by a softened maximum-likelihood classification (Wang, 1990a; Wang, 1990b; Maselli *et al.*, 1995). Equation 1 was then applied for the estimation of AT, AS, and CS over

TABLE 2. CORRELATION COEFFICIENTS BETWEEN THE THREE ENVIRONMENTAL FACTORS CONSIDERED (ELEVATION, LATITUDE, AND DISTANCE FROM THE SEA) AND THE THREE STUDY CLIMATE PARAMETERS (MEAN ANNUAL TEMPERATURE (AT) AND LENGTHS OF THE ARID AND COLD SEASONS (AS AND CS)) FOUND IN CORRESPONDENCE WITH THE 23 TRAINING STATIONS (* = SIGNIFICANT CORRELATION, $P < 0.05$; ** = HIGHLY SIGNIFICANT CORRELATION, $P < 0.01$).

r	Elevation	Latitude	Distance from the Sea
AT	−0.913**	−0.613**	−0.250
AS	−0.706**	−0.759**	−0.502*
CS	0.874**	0.449*	0.486*

TABLE 3. RESULTS OF THE STATISTICAL COMPARISONS BETWEEN THE CLIMATE PARAMETERS IN THE 16 TEST STATIONS AND THE CORRESPONDING ESTIMATES FROM THE TWO METHODS (MULTIVARIATE REGRESSION ON ENVIRONMENTAL FACTORS AND FUZZY CLASSIFICATION OF NOAA-AVHRR DATA) (ALL CORRELATIONS ARE HIGHLY SIGNIFICANT, $P < 0.01$).

	AT		AS		CS	
	r^2	RMSE (C°)	r^2	RMSE (month)	r^2	RMSE (month)
Multiv. Regr.	0.891	0.822	0.672	0.675	0.874	0.829
Fuzzy Class.	0.888	0.781	0.708	0.555	0.691	1.179

the whole region. The three images produced were finally subjected to another 3 by 3 mean filtering in order to completely remove high frequency spatial variability related to land-use changes. The performance of the procedure was evaluated by use of the same statistics as for the multivariate regression method (r^2 and RMSE).

Statistical Merging of the Estimates from the Two Sources

Because the estimates of the three climate parameters were derived from two sources which could be considered independent, they could be combined to produce relatively "optimum" estimates. According to Gelb (1974), if two independent measurements of the same variable X are available, the combined optimal estimate $\hat{X}$ can be found as

$$\hat{X} = \left(\frac{1}{V_1} + \frac{1}{V_2}\right)^{-1} \left(\frac{X_1}{V_1} + \frac{X_2}{V_2}\right) \tag{2}$$

where

X_1, X_2 are independent measurements of X, and
V_1, V_2 are error variances of the two measurements.

To use this formula, the values of the two error variances are needed, which, in the present case, had to be derived from the training pixels. This was not a problem for the multivariate regression models, because the error variances could be approximated from the relevant mean square errors. The underestimation of the error variances due to the use of the same points as for the regression training was deemed almost uninfluential (see also below). The same method could not be applied to the fuzzy estimation procedure which, by its nature, tends to reduce the errors at the training points almost completely. In this case, a leave-one-out method was therefore utilized, merely excluding the extreme points of the training data in such a way as not to lose their complete representativeness of the different environmental situations. The slight reduction of the estimated errors deriving from this exclusion was considered to substantially counterbalance the error underestimation from the regression method.

Results

Regression Analysis on Environmental Factors

The three environmental factors considered were strongly correlated to the study climate parameters. From the correlation coefficients reported in Table 2, it can be seen that elevation was the most influential factor for AT and CS, followed by latitude in the case of AT and by distance from the sea in the case of CS. Latitude was most influential for AS, followed by elevation. All factors had a negative influence on AT and AS, and a positive influence on CS.

As a result of these strong correlations, the multivariate regression analysis on the environmental factors produced reasonably good results. The following models were found for the three parameters:

$$\text{AT} = 17.41 - 0.0056\,\text{E} - 0.0101\,\text{L} - 0.0021\,\text{D} \qquad r^2 = 0.859$$
$$\text{AS} = 4.18 - 0.0013\,\text{E} - 0.0100\,\text{L} - 0.0245\,\text{D} \qquad r^2 = 0.780$$
$$\text{CS} = -0.97 + 0.0043\,\text{E} - 0.0001\,\text{L} - 0.0418\,\text{D} \qquad r^2 = 0.829$$

where

E = elevation (above mean sea level),
L = latitude (km from the region origin), and
D = distance from the sea (km).

When applied to the estimation of the climate values of the test stations, these three models gave relatively satisfactory accuracies, especially for AT and CS (Table 3). In both cases, a coefficient of determination close to 0.9 was reached with quite low RMSEs (0.822°C and 0.829 months over ranges of 7.5°C and six months, respectively). A slightly lower accuracy was achieved for AS ($r^2 = 0.672$ and RMSE = 0.675 months over a range of three months). As indicated in Table 3, all the correlations were highly significant, as was the case for the following testings.

Fuzzy Classification of NOAA-AVHRR Data

The fuzzy estimation methods based on the use of the NOAA-AVHRR data set produced results with accuracy levels similar to those of the multivariate regression procedures. From the statistical comparison with the test data (Table 3), it can be seen that the estimation of the AT was substantially as accurate as in the previous case ($r^2 = 0.888$ and RMSE = 0.781°C), while a higher accuracy was obtained for AS ($r^2 = 0.708$ and RMSE = 0.555 months) and lower accuracy for CS ($r^2 = 0.691$ and RMSE = 1.179 months).

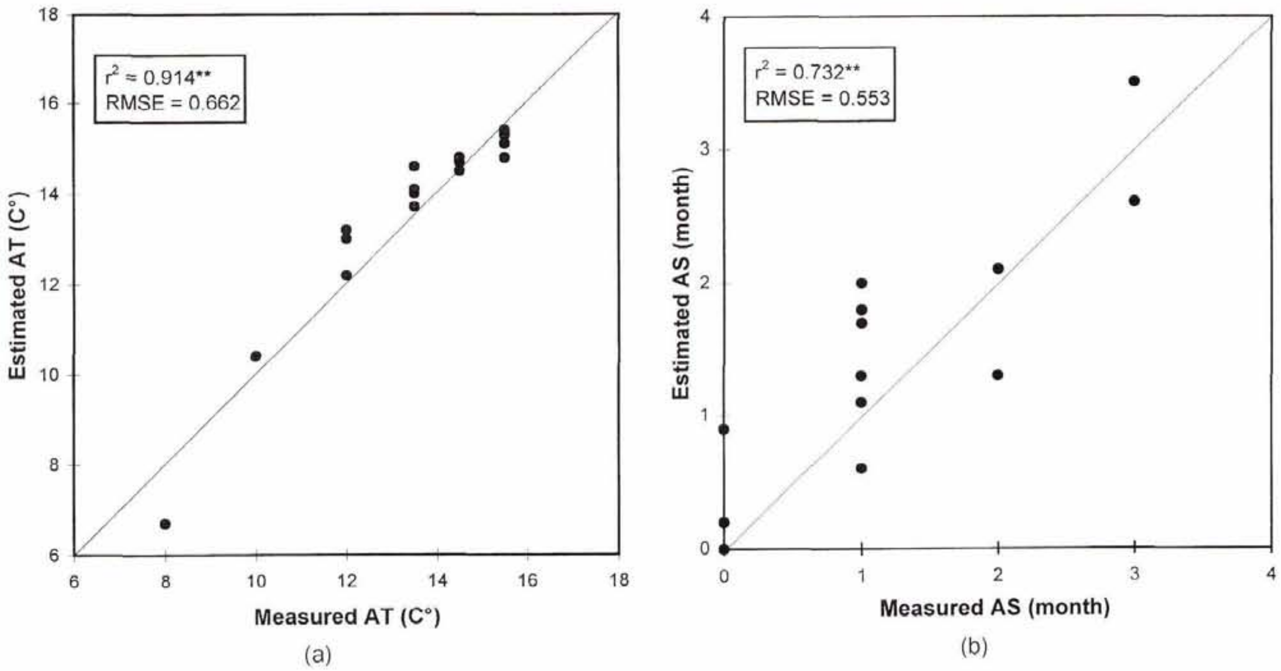
By a visual examination of the estimated parameters, it can be noted that, even if generally similar, the estimates from the fuzzy procedure had spatial structures different from the previous ones. They were more heterogeneous and reported information apparently related not only to the main driving factors, but also to landscape variations (land-use, soil, and vegetation differences).

Statistical Merging of the Estimates from the Two Sources

By the statistical merging of the two data sources based on Equation 2 and the error variances of Table 4, relatively optimal estimates of the three study parameters were obtained. In this case, the comparisons between the measured and esti-

TABLE 4. ERROR VARIANCES OF THE TWO ESTIMATION METHODS FOR THE THREE CLIMATE PARAMETERS DERIVED FROM THE 23 TRAINING STATION POINTS (SEE TEXT).

	AT ($C^{\circ 2}$)	AS (month^2)	CS (month^2)
Multiv. Regr.	0.761	0.353	0.532
Fuzzy Class.	0.727	0.223	1.440



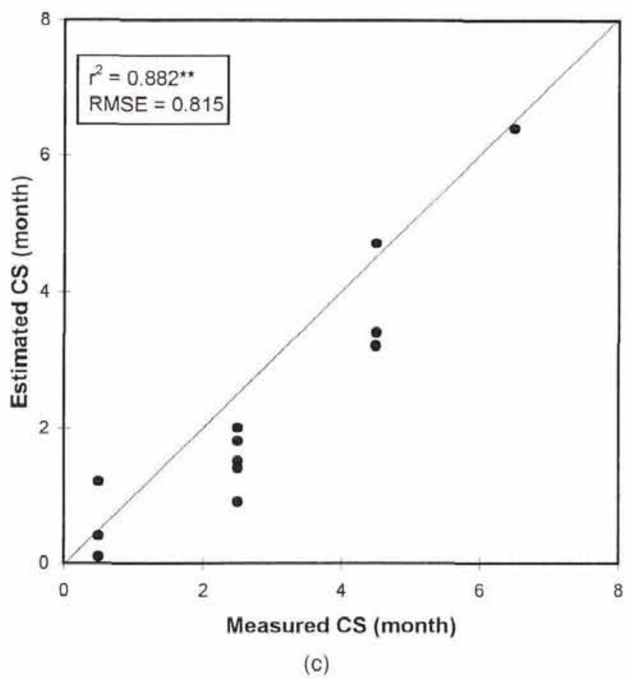


Figure 2. Statistical comparisons between the values of the three climate parameters measured and estimated by the merging approach in correspondence to the test stations (** = *highly significant correlation*, $P < 0.01$). (a) Estimated AT versus measured AT. (b) Estimated AS versus measured AS. (c) Estimated CS versus measured CS.

mated parameters are summarized in Figures 2a, 2b, and 2c. As can be seen, the estimation accuracy of the three parameters was higher than in the previous cases. In particular, good results were obtained for AS and CS, which were poorly estimated by the multivariate regression and fuzzy classification procedures, respectively.

These results indicated that the two data sources contained at least partly non redundant, useful information about the study parameters and that the statistical merging method used was effective in combining this information. The final products of the merging procedure, shown in Figures 3a, 3b, and 3c, were also visually compared to the classification of Rapetti and Vittorini (1995). Notable similarities existed, but a higher spatial variability was present in the new product, which was reasonably related to the more abundant spatial details originating from the NOAA-AVHRR images.

Discussion

The present investigation has raised several issues which are worth briefly discussing. First of all, some problems derived from the use of the Rapetti and Vittorini (1995) classification as a reference for the extraction of the training and test values of the study parameters. This choice was motivated by

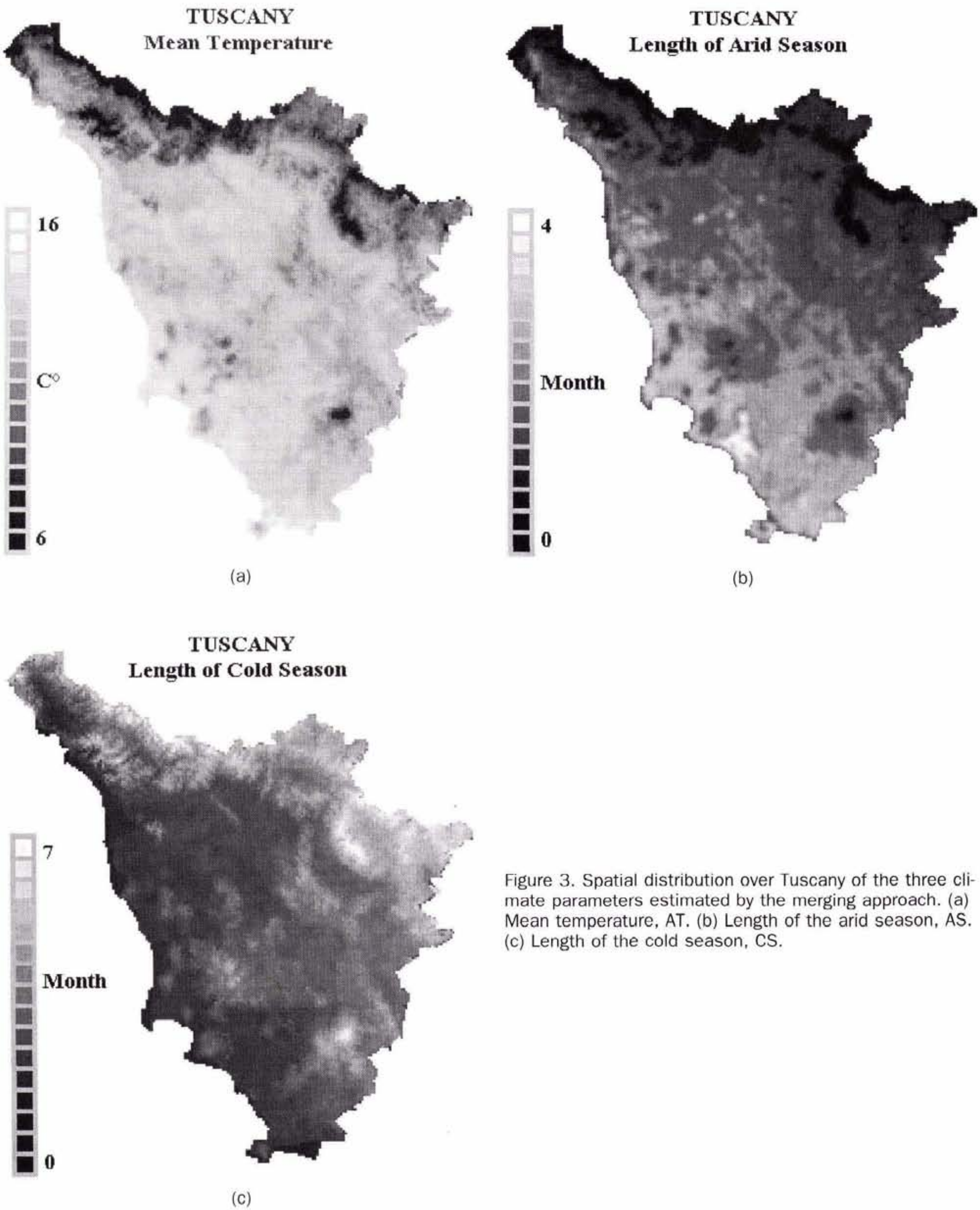


Figure 3. Spatial distribution over Tuscany of the three climate parameters estimated by the merging approach. (a) Mean temperature, AT. (b) Length of the arid season, AS. (c) Length of the cold season, CS.

the need for independently generated reference information about the climate of the region; in fact, the use of that classification allowed a simple evaluation of average climate parameters for many meteorological stations, which would otherwise have required intensive and complex processing of long meteorological data time series. On the other hand, this use only permitted the extraction of climatic parameters with a certain rounding, depending on the map representation. In practice, this led to approximation in the values extracted for training and testing of about half a degree for temperature, half a month for the arid period, and one month for the cold period. This approximation may have led to an underestimation of the absolute accuracy of the study procedures.

The multivariate regression method was only applied to the three environmental factors which were deemed most influential on climate and at the same time which were easily obtainable. The inclusion of other factors could improve the fit of the models, but this improvement would probably be marginal and could only be achieved at the expense of the simplicity of the method. Most of the correlations obtained were actually to be expected on the basis of climatic considerations. For example, it is well known that elevation and latitude exert a strong influnce on all climatic parameters, while distance from the sea is especially influential on the length of the arid and cold seasons. In any case, the results of such a regression analysis must be considered to apply only in the particular geographical study context.

Another limitation of the present study lies in the fact that it considered satellite data from only two years. It can reasonably be supposed that NDVI profiles and thermal infrared images from more seasons would characterize the environmental features of the study region more completely. As previously explained, this choice was necessitated by the lack of a longer time series of AVHRR data, but it could easily be avoided in other works if images from more years were available. Conversely, the inclusion of thermal infrared images in the data set is an important characteristic of the study, because the value of these data for the discrimination of different landscapes had already been demonstrated in previous works (Lee, 1992; Lambin and Strahler, 1994; Maselli *et al.*, 1996).

The most important considerations must be made on the differences in estimation accuracy reached by the two basic methods for the three climate parameters. As previously seen, the regression model yielded good performances for the estimation of mean temperatures and the cold period, but less so for the estimation of the arid period. The latter is, in effect, the parameter most directly controlled by rainfall events, which are driven also by environmental factors other than those considered in the regression analyses, such as prevalent directions of the air flows and orientation, size, and shape of the valleys. Actually, the interpolation of rainfall by classical methods is known to be less accurate than that of temperature, owing to the higher spatial and temporal variability of the former variable (Pinna, 1977).

On the other hand, the length of the arid season was estimated better by the fuzzy strategy, which works on information relating to vegetation types and conditions. Both these features are, in fact, strongly affected by rainfall, especially during the long Mediterranean arid season. By the fuzzy method, the estimation accuracy of mean temperature was substantially the same as by the multivariate regression, while a lower performance was obtained for the length of the cold season. This can be explained by keeping in mind the time span of the AVHRR images considered. Both the NDVI profiles and the thermal infrared images were, in fact, taken during two growing seasons (from March to September-October). Because the cold season of most areas in Tuscany goes from November to March, the time coverage of the satellite data was not the most appropriate for its estimation.

Conclusions

The fuzzy strategy used for the processing of the NOAA-AVHRR study data is actually a modification of a methodology successfully applied to Landsat TM data for the estimation of forest parameters (Maselli *et al.*, 1995). As in that case, a necessary assumption for its correct working is that the remotely sensed signal is informationally related to the parameters to be extrapolated. In the present situation, it is known that climate is the main agent in controlling vegetation dynamics, which, in turn, determines NDVI variations. Consequently, NDVI profiles and surface temperature images surely contain information on the mean thermal regime and the mean arid and cold periods in a region. On the other hand, no assumption was strictly necessary for the shape of the relationships between the remotely sensed data and the estimated parameters, which is clearly a fundamental advantage of the fuzzy approach. Actually, the results obtained in the current experiment support these considerations.

Other comments need to be made about the combination method used to merge independent estimates of the same parameters, which always produced the most accurate results. This was a definitive confirmation that NOAA-AVHRR data bring information which *is not* redundant to that of the three study environmental factors and therefore useful for climatic classifications. In practice, such a merging method could be widely applicable in other remote sensing studies when diverse estimates of environmental parameters are available, for example, from multi-temporal or multi-source data processing techniques.

The final product of the methodology proposed are three maps which are highly informative on the study parameters, showing a density of estimation points (one every 1.1 by 1.1 km) which could probably never be reached by traditional ground measurements. In this case study, a relatively high number of training stations were necessary to cover most of the variability in terrain and land-use features of Tuscany. A lower number of reference points would probably be sufficient in more homogeneous areas. In effect, the method proposed could find its greatest utility for the eco-climatic characterization of developing countries, where the existing knowledge of the territory is usually scarce and the density of reliable meteorological stations is often very low.

The methodology could also be applied to the extension over the land surface of environmental parameters variable in time, such as estimates of annual crop productivity derived from agro-meteorological models. In this case, it would have to be assumed that inter-year fluctuations are identified by the point (station) measurements, while the extension process would be based on more temporally stable environmental similarities reflected in NDVI profiles. Because vegetation features would be involved, the informative value of NDVI data could be hypothesized even more safely. Research in these directions is presently underway within the framework of international collaborative projects.

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References

Anderson, T.W., 1984. *An Introduction to Multivariate Statistical Analysis*, John Wiley & Sons, New York.

Benedetti, R., P. Rossini, and R. Taddei, 1994. Vegetation classification in the middle Mediterranean area by satellite data, *International Journal of Remote Sensing*, 15:583–596.

Burns, J.I., 1953. Small-scale topographic effects on precipitation distribution in San Dimas Experimental Forest, *Transations of American Geophysical Union*, 34:761–768.

Conese, C., G. Maracchi, F. Maselli, F. Miglietta, and M. Romani, 1989. ISAP: Integrated system for the evaluation of agriculture productivity: A case study in the Mugello Region, *Proceedings of the Conference on the Application of Remote Sensing to Agricultural Statistics*, Villa Ponti, VA, Italy, 10–11 October, pp. 269–278.

Davis, J.C., 1973. *Statistics and Data Analysis in Geology*, John Wiley & Sons, New York.

Derrien, M., B. Farki, H. Legleau, and A. Sairouni, 1992. Vegetation cover mapping over France using NOAA-11/AVHRR, *International Journal of Remote Sensing*, 13:1787–1795.

ESA User Guide, 1992. *Sharp Level 2A*, Earthnet Programme Office, Rome.

Gaston, G.G., P.L. Jackson, T.S. Vinson, T.P. Kolchugina, M. Botch, and K. Kobak, 1994. Identification of carbon quantifiable regions in the former Soviet Union using unsupervised classification of AVHRR global vegetation index images, *International Journal of Remote Sensing*, 15:3199–3221.

Gelb, A. (editor), 1974. *Applied Optimal Estimation*, The MIT Press, Cambridge, Massachusetts.

Genstat, 1993. *Genstat 5 Reference Manual*, Oxford Science Publications.

Hielkema, J.U., S.D. Prince, and W.L. Astle, 1986. Rainfall and vegetation monitoring in the Savanna zone of the Democratic Republic of Sudan using the NOAA advanced Very High Resolution Radiometer, *International Journal of Remote Sensing*, 7:1499–1513.

Lambin, E.F., and A.H. Strahler, 1994. Indicator of land cover change from change-vector analysis in multitemporal space at coarse spatial scales, *International Journal of Remote Sensing*, 15:2099–2119.

Lee, J., 1992. *Integration of Vegetation Indices and Thermal Measurements for Ecosystem Modeling*, Ph.D. Dissertation, University of Arizona, Tucson, 219 p.

Maselli, F., C. Conese, L. Petkov, and M.A. Gilabert, 1994. Environmental monitoring and crop forecasting in the Sahel through the use of NOAA NDVI data. A case study: Niger 1986–89, *International Journal of Remote Sensing*, 14:3471–3487.

Maselli, F., C. Conese, T. De Filippis, and S. Norcini, 1995. Estimation of forest parameters through fuzzy classification of TM data, *IEEE Transactions on Geoscience and Remote Sensing*, 33:77–84.

Maselli, F., C. Conese, L. Petkov, and G. Maracchi, 1996. Eco-climatic classification of Tuscany through NOAA-AVHRR data, *International Journal of Remote Sensing*, 17:2369–2384.

Petkov, L., M. Pieri, F. Maselli, and G. Maracchi, 1996. Study and modelling of temperature spatial variability by NOAA-AVHRR thermal imagery, *ISPRS Journal of Photogrammetry and Remote Sensing*, 51:127–136.

Pinna, M., 1977. *Climatologia*, UTET, Torino, Italy, 302 p.

Rapetti, F., and S. Vittorini, 1995. *Carta climatica della Toscana*, Pacini Editore, Pisa, Italy.

Rossini, P., L. Bottai, M. Frezzotti, G. Pandiscia, and R. Taddei, 1994. Nuova Telespazio Contribution to Annual Progress Report of EFEDA-Phase II, *EFEDA Group V, Remote Sensing and Radiometric Properties of the Surface: Assessment of Desertification from Space*, Coordinator H.J. Bolle, Berlin, November.

Spreen, W.C., 1947. A determination of the effect of topography upon precipitation, *Transations of American Geophysical Union*, 28:285–290.

Thornthwaite, C., 1933. The climates of the earth, *Geographical Review*, 23:433–440.

Wang, F., 1990a. Fuzzy supervised classification of remote sensing images, *IEEE Transactions on Geoscience and Remote Sensing*, 28:194–201.

———, 1990b. Improving remote sensing image analysis through fuzzy information representation, *Photogrammetric Engineering & Remote Sensing*, 56:1163–1169.

Zadeh, L.A., 1965. Fuzzy sets, *Information and Control*, 8:338–353.

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