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ESTIMATING SUB-PIXEL TO REGIONAL WINTER CROP AREAS USING NEURAL NETS

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ABSTRACT:

The work aimed at testing a methodology which can be applied to low spatial resolution satellite data to assess inter-annual crop area variations on sub-pixel to regional scales. The methodology is based on the assumption that within mixed pixels land cover variations are reflected by changes in the related hyper-temporal profiles of the Normalised Difference Vegetation Index (NDVI). We evaluated if changes in the fractional winter crop coverage are reflected in changing shapes of annual NDVI profiles and can be detected by using neural networks. The neural nets were trained on reference data obtained from high resolution Landsat TM/ETM images. The proposed methodology was applied in a study region in central Italy to estimate winter crop areas between 1988 and 2002 from 1 km resolution NOAA-AVHRR profiles and additional ancillary data readily available (CORINE land cover). The accuracy of the estimates was assessed by comparison to official agricultural statistics using a bootstrap approach. The method showed promise for estimating crop area variation on sub-pixel level (cross-validated R^2 between 0.7 and 0.8) to regional scales (normalized RMSE: 10%). The network based approach proved to have a significantly higher forecast capability than other methods used previously for the same study area.

1. INTRODUCTION

There is a growing concern for large-scale environmental issues such as global warming, loss of biodiversity and food security. Remote sensing is the only practical source of environmental data with global coverage. Moderate to coarse spatial resolution satellite sensors such as NOAA-AVHRR or SPOT VGT provide synoptic information at a high temporal resolution while the amount of data is still manageable. Due to their coarse resolution, however, most pixels contain a mixture of land cover classes, referred to as sub-pixel mixing (Atkinson et al., 1997).

Knowledge of the spatial distribution of crop types is important for land management and trade decisions, and is needed to regularize the inversion of radiative transfer models for mapping crop biophysical and biochemical variables (Atzberger, 2004; Richter et al. 2009). However, in regional to global agricultural studies, mixed spectral signatures are common (Lobell & Asner, 2004). For example, small field sizes (1 - 10 ha) are typical for many agricultural systems in the developing world, but also in Europe. Thus, methods are required that allow the mapping of fractional coverages from coarse resolution imagery (Foody et al., 1997). If suitable methods could be developed, the analysis of archived images would also allow tracing back the development of the landscapes to the early eighties, when the first global data sets became available.

To un-mix coarse resolution imagery, many studies rely on the assumption of a linear relationship between end-member signatures and the composite signature (e.g. Quarmby, 1992). However, mixing is often non-linear and end-member spectra are sometimes difficult to obtain.

To overcome these problems, Foody et al. (1997) proposed an un-mixing approach based on neural nets. The approach makes no assumptions about the nature of the mixing and does not require end-member spectra. Relative to a conventional classification oriented approach, the areal extent of classes was generally more accurately estimated from (single date) AVHRR data after the application of the unmixing procedure.

Neural networks (NN) were also used together with mixture modelling and fuzzy classification by Atkinson et al. (1997) for mapping sub-pixel proportions of land cover classes in U.K. Again, it was found that neural networking was the most accurate technique, but its successful implementation depended on accurate co-registration of the 5 band AVHRR image with a high resolution SPOT HRV image. The availability of an accurate training data set was also very important.

A probabilistic temporal unmixing (PBU) using MODIS reflectance data was proposed by Asner & Lobell (2004). Landsat data was used to identify pure pixels for the extraction of temporal endmembers. Sub-pixel fractions of crop area were modeled by using linear un-mixing. Performance of the mixture model varied from 50 to 80 % depending on the scale of comparison.

NDVI time series from NOAA-AVHRR was used successfully by Remold & Maselli (2004; 2006) for estimating inter-annual crop area changes in Tuscany (Italy). The study used an approach based on the Spectral Angular Mapping (SAM). For model calibration, test data derived from high resolution Landsat TM and ETM was used. Albeit relatively accurate inter-annual crop area changes could be achieved, the results were strongly dependent on the quality of the satellite images. Useful results for winter crops

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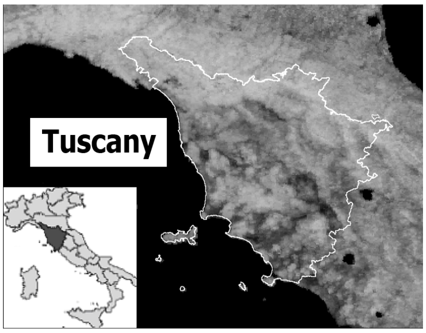

Figure 1. Study area Tuscany, Italy. The sample image is from AVHRR (top left: 44° 42'-8° 19', lower right: 42° 00'-13° 21')

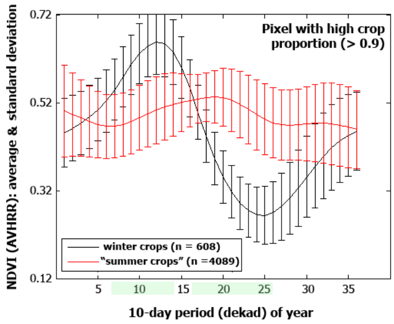

Figure 2. NDVI profiles of pure winter and "summer crops". The dekads used for modelling are shown in green

could be provided only by end of September, reducing considerably the timeliness of the area change information.

The use of neural nets for estimating sub-pixel land cover from temporal signatures was investigated by Verbeiren et al. (2008). Monthly MVC of SPOT-VGT (between March and October) were used to model the area fraction images (AFI) of eight classes in 2003 for Belgium. Relatively good results were obtained especially if the initial (pixel-based) results were aggregated to higher regional levels. The portability of the trained networks across growing seasons was investigated by Bossyns et al. (2007) in an accompanying paper on the same data set. The NNs were trained on data of one growing season and than applied to SPOT-VGT of the training year and three other seasons. High and stable accuracies of the estimated AFI's were obtained when the trained network was applied on the imagery of the training year. For example, at regional level, the R^2 for winter wheat was ~0.8 (0.67-0.87) for the training years. However, on average, this values decreased by 0.45 units when the trained networks were applied to different seasons, probably because of a too high inter-annual variability of the temporal signatures.

The objectives of the present study were:

- to test if NNs can be used with low resolution NOAA-AVHRR imagery and additional ancillary information to accurately estimate winter crop surfaces at sub-pixel to regional scales between 1988 and 2002
- to evaluate the impact of ancillary land use information (CORINE) on the estimation accuracy as well as the influence of an improved smoothing of the AVHRR time series
- to determine the optimum prediction dates for early-season forecasts of winter crop surfaces

2. MATERIAL

The methodology was tested using data for the Tuscany region in Central Italy. The choice was driven mainly by the availability of both satellite imagery and agricultural statistics. The region is covered by a consistent NOAA-AVHRR data time series taken in the period from 1986 to 2003, when also several Landsat TM/ETM+ scenes were acquired. An area frame sampling method has been regularly applied since 1988 to measure the extent of the main crops in Tuscany (Carfagna et al. 1998).

2.1 Geography and environmental features of the study area

Tuscany is situated between 9°- 12° East longitude and 44°- 42° North latitude, covering circa 2 x 10^6 hectares (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 coast-line and along the principal river valleys to hilly and mountainous zones towards the Apennine chain. The climate in Tuscany ranges from typically Mediterranean to temperate warm or cool according to the altitudinal and latitudinal gradients and the distance from the sea.

The land use of Tuscany 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. Cropland is spread over the coastal zones and the inner plain and hilly areas cover approximately 25% of the land surface. The prevalent cereal is durum wheat, with an average planted area of 112 000 ha and with a mean growing cycle from November to the end of June (figure 2).

2.2 Data

2.2.1 Reference information on winter crop areas: The land cover classification of Tuscany produced by the CORINE project was used as reference map (Annoni & Perdigao, 1997). Wheat area estimates for the period 1988-2002 were obtained from the AGRIT project (Consorzio ITA, 1987). These statistics are produced annually through an area frame sampling method, which guarantees high estimation accuracy (error < 10 %) at the regional scale (Carfagna et al., 1998). From the available data, 1994 has been excluded because of the insufficient quality of the AVHRR data. In what follows, we use the term "winter crop area" as a synonym for the wheat area.

2.2.2 High resolution images: The high resolution images were necessary to spatialize the statistical information provided by the AGRIT statistics (2.2.1). The high resolution data set consisted of 8 Landsat frames (192/30), 6 taken by the Thematic Mapper (TM) (1988, 1991, 1992, 1995, 1997 and 1998) and 2 by the Enhanced Thematic Mapper (ETM+) (2000, 2001). All of them were acquired during the month of August and were cloud free over the main agricultural areas. The Landsat TM/ETM+ scenes were first geo-referenced by a nearest neighbor resampling algorithm using

	Total winter crop surface (Tuscany)		Sub-pixel winter crop surfaces, i.e. spatialization	
Year	AGRIT [ha]	NNcv [ha]	RMSEcv (RMSE)	R^2cv (R^2)
1988	133795	147543	9,6 (8,8)	0,70 (0,80)
1991	184024	152491	10,8 (8,8)	0,79 (0,78)
1992	112450	96053	8,3 (9,0)	0,71 (0,79)
1995	145999	170981	8,8 (8,9)	0,81 (0,79)
1997	167000	136426	10,3 (8,8)	0,72 (0,80)
1998	174296	168462	9,0 (8,8)	0,79 (0,79)
2000	183356	183569	9,8 (8,9)	0,82 (0,77)
2001	154510	201407	10,6 (8,9)	0,77 (0,79)
X_{med}	160755	160477	9,4 (8,9)	0,79 (0,79)

Table 3. Cross-validated results obtained with the neural network for the eight years for which reference information was available. The results for the training data are given in parentheses

about 120 control points selected on a CORINE-based land/water mask. Bands 4 (nIR) and 3 (Red) were corrected for atmospheric effects and converted into reflectances from which high resolution NDVI images for every training year were calculated.

2.2.3 Low resolution images: JRC-MARS owns the most elaborate archive of NOAA-AVHRR 1km data over the pan-European continent. In 2008, all historical data were re-processed with new procedures, which resulted in an unique archive of 27 years. For this study, the AVHRR time series from 1988 to 2002 was used, fully encompassing the years for which high resolution TM/ETM data was available (2.2.2).

3. METHODS

3.1 Generation of reference abundance maps

In a first step the CORINE land cover classes were grouped into five environmentally meaningful categories (summing up to unity) with more or less similar NDVI profiles. Besides the “arable land” class, four other categories were derived: forests, pastures, tree plantations and urban areas (Maselli, 2001). We assumed that the broad land cover was stable between 1988 and 2002. In a second step, the CORINE “arable land” class was split into winter crops and summer crops using the available TM/ETM+ images of the eight training years (2.2.2). For this purpose, each high resolution NDVI image was thresholded. The threshold was determined so that the summed high resolution winter crop surfaces equal the AGRIT statistic (2.2.1). This operation was possible as winter crop fields are almost bare in August, while other fields with summer crops (maize, sunflower, etc.) but also fallows and pastoral areas are in a “green” phase. This also implies that the class “summer crop” is a mixture of typical summer crops with other classes. Although the thresholding resulted in two masks per image (one for the winter crops, the other showing the distribution of summer crops), the latter was not further used.

The five categories identified in the eight training dates (four CORINE categories plus winter crops) were spatially degraded by pixel averaging to produce abundance images (i.e., AFI) with the same spatial resolution as the AVHRR images. Of course, out of these images only the winter crop abundance maps were different for each date. Hence, only the variations within the CORINE “arable land” category were analyzed, without considering any changes within the other categories.

	Total winter crop surface for Tuscany		
	Nobs	R^2	nRMSE
training years	8	0.77	7.9
validation years	6	0.35	12.4
pooled data	14	0.57	10.7

Table 4. Results obtained with the neural network trained on the eight years for which reference information was available

3.2 Smoothing of low resolution AVHRR data

Time series from AVHRR require a careful filtering/smoothing before they can be applied within quantitative studies (Beck et al., 2006). The standard maximum value compositing (MVC) only corrects for major disturbances. To eliminate the negatively biased noise typical for coarse resolution time series, the modified Whittaker smoother was used (Atzberger & Eilers, 2010a; 2010b). The filter was chosen because it is very fast, interpolates easily and optimizes its smoothness parameter automatically.

3.3 Neural networking

A simple net with one hidden layer was used to map the winter crop fraction from the profiles of coarse resolution NDVI images and the ancillary data (e.g. five AFI related to arable land, forests, tree plantations, urban areas and pastures). The output layer represented the winter crop area fraction and had thus only one neuron. In the standard setting, the number of input neurons was 21. This allowed to simultaneously input the 5 (inter-annually constant) abundance values derived from the CORINE data plus 16 neurons describing the temporal NDVI profile (dekads 7 to 25, excluding dekads 14 to 16). The three dekads were excluded because winter and summer crop signatures strongly overlap during this period (figure 2). The number of neurons in the hidden layer was set to 3, resulting in a compact 21-3-1 network architecture. For network training the resilient backpropagation algorithm was used. To improve generalization of the net and to prevent overfitting, the early stopping technique was applied (Atkinson & Tatnall, 1997; Farifteh et al. 2007). For this purpose, the training samples were split into three subsets with 50 % (training), 25 % (test) and 25 % (validation) of the total available pattern. Only the training set was used for computing the gradient and up-dating the weights and biases. The training was stopped automatically when the test error started to rise and the actual weights were returned. To keep the methodology simple, other more elaborated training strategies were not investigated.

4. RESULTS AND DISCUSSION

4.1 Spatio-temporal distribution of winter crops

To derive statistically sound results, a jacknife procedure was selected. This means that 8 different training sessions were run, each time using only 7 out of the available 8 years. The left-out sample was than predicted by the trained network. The resulting

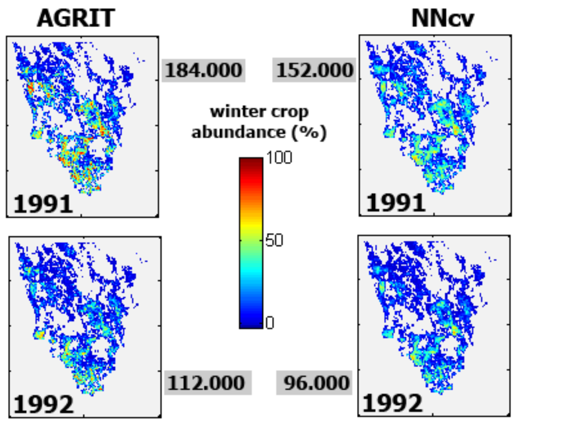

Figure 5. Reference (left) and cross-validated NN-derived (right) spatial distribution of winter crop surfaces for 2 contrasting years

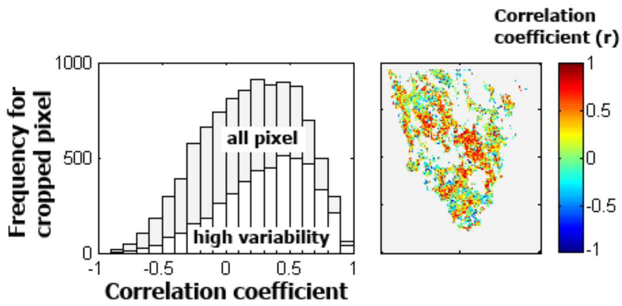

Figure 6. Spatial distribution of the cross-validated correlation coefficient (r) between AGRIT reference information and the modeled results (right). The corresponding frequency distribution is shown on the left. The histogram gives the frequency for all pixels (in gray) and for those having a high inter-annual winter crop area variability (in white)

winter crop surfaces for Tuscany are reported in table 3. The table also lists two statistics describing the accuracy with which the (spatial distribution) of the abundance images was modeled, distinguishing between cross-validated results and training data.

On average, 79 percent of the observed spatial variability of the (sub-pixel) winter crop area was explained by the net. However, we also observe large variations from year to year with R^2cv ranging between 0.70 (1988) and 0.82 (2000). In general, the cross-validated RMSE values of winter crop areas were around 10 %. As expected, cross-validated RMSE were higher than those obtained on the training sample (< 9 %). Together, this indicates that the spatial distribution of winter crops was quite well modeled, however, with sometimes some significant offset.

Spatialized winter crop abundances are shown in figure 5 for the two most contrasting years of the data set (1991 and 1992). A high winter crop surface was reported for 1991. In 1992, the winter crop surface dropped by almost 40 % as a reaction of new European policies. The NN well depicted this general tendency. The spatial distribution of winter crop surfaces was also well modeled (figure 5) with, however, a noticeable bias.

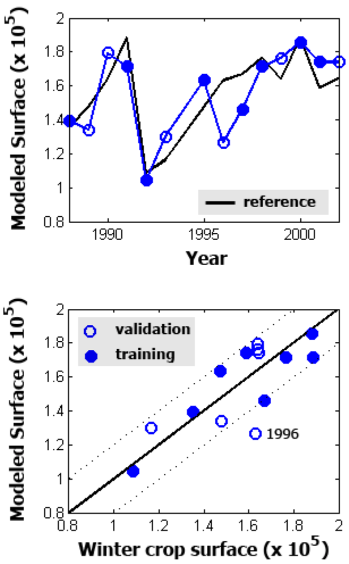

Figure 7. Total winter crop area (1988-2002; 1994 excluded) for Tuscany modeled by the NN against reference data (AGRIT). The eight training years (filled circles) were used for network training

The cross-validated correlation coefficient (r) between reference winter crop fraction (AGRIT) and the modeled value is shown in figure 6 (right) for each AVHRR pixel for which CORINE indicated at least 2 percent arable land. Two frequency distributions are shown as well (left): (i) for all pixels with arable land, and (ii) excluding those pixels having a low inter-annual variability in winter crop area (STD < 5%). The figure shows that the NN often performed well to estimate the inter-annual variability of winter crop areas at this high dis-aggregation level. The amount of inter-annual variance explained by the net increased when stable pixels were excluded. However, low (or even negative) correlations were frequently obtained in the plains of Tuscany (blue colors). The net probably failed because the "summer crop" signatures were too variable from year to year in these areas.

We tested if an increased number of neurons in the hidden layer could improve the results. This was not the case (Atzberger & Rembold, 2009). Albeit it was possible to increase the accuracy within the training set, the net could not generalize this improvement for yielding better predictions on the left-out samples.

4.2 Regional winter crop area estimates 1988-2002

To evaluate the capacity of the net to predict regional winter crop surfaces of Tuscany for the entire AVHRR time series, the NN was trained with all 8 years for which reference information was available. The trained net was next applied to the full time series (1988 to 2002). The results are shown in table 4 and figure 7.

Overall, the regional winter crop area was well modeled with a normalized RMSE of around 10 percent. Noticeable, however, is the strong decrease in performance for the six years not included in the training set. For this data, only 35 percent of the inter-

	Assessment of CORINE and filtering impact		
	Dataset 1 (“standard”)	Dataset 2 (“no ancillary”)	Dataset 3 (“no filtering)
CORINE	Yes	No	No
Filtering	Yes	Yes	No
Inputs	21	16	16
R^2	0.60	0.52	0.40
nRMSE	10.0	14.4	14.1
Nobs	14	14	14

Table 8. Statistics obtained on the pooled data set (14 years of data – 1994 excluded) from which 8 years where used for network training. The three data sets differ in the amount of ancillary information (CORINE land cover) and the pre-processing applied to the NOAA-AVHRR data. The statistics refer to the accuracy with which the regional winter crop surfaces were modeled

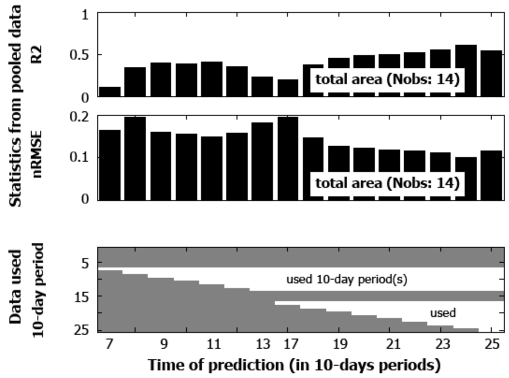

Figure 9. Accuracy of the net to predict regional winter crop areas (pooled data set; Nobs: 14). The two bar charts display the statistical information. The third chart indicates which images were used (left: early predictions; right: late predictions)

annual variance was explained by the NN (compared to 79 percent of the training years), mainly because 1996 was seriously underestimated. This year was also not well modeled in the precursor study using SAM (Rembold & Maselli, 2006). Until now we were unable to indentify the exact reasons that led to this outlier.

4.3 Impact of CORINE data and the smoothing of AVHRR data

One of the study objectives was to evaluate the impact of the ancillary data (CORINE) and the filtering of the AVHRR data. Table 8 reports the main results referring to the regional winter crop surfaces of the 14 years 1988-2002. The (positive) impact of the CORINE data was strong. The R^2 decreases from 0.60 to 0.52 when the five CORINE abundance maps were not used. At the same time the normalized RMSE increased from 10 to more than 14 %. The R^2 value further decreased if the original (unfiltered) NDVI data were used instead of the filtered images.

4.4 Within-season predictions

Early (within-season) predictions of crop surfaces are of upmost importance in any agricultural monitoring system such as MARS (Lobell & Asner, 2004). To evaluate the possibility to estimate the winter crop area of Tuscany already early in the season, 16 different nets were trained on the 8 reference years and applied to the pooled data set (14 years). The nets solely differed by the number of low resolution NDVI images used as network input. Figure 9 summarizes the results, where the plot on the bottom specifies the used (and excluded) NDVI data. The two bar charts indicate the statistics obtained more or less early in the growing season. Not surprisingly, the best results were obtained if NDVI data from the full winter crop cycle (e.g., up to dekad 25) was used for the modelling ($R^2 > 0.5$, nRMSE < 11%). But already by March-April some relatively accurate first predictions of winter crop (and potential summer crop) areas were achieved. The accuracy was substantially lower compared to the predictions made at the end of the winter growing season, but could possibly be useful. It has also to be noted that the analyzed data set still contained the data from 2006 which was previously identified as problematic (4.2).

5. CONCLUSIONS

The study evaluated the performance of neural networks to map (1) the spatial distribution of winter crops, and (2) the inter-annual variation in regional winter crop surfaces. The nets were fed by low resolution (NOAA-AVHRR) imagery and ancillary information (CORINE). Reasonable results were obtained with a compact standard backpropagation network (21 inputs, 3 hidden neurons). The results were better than those obtained in a previous study with the same data set using the SAM of temporal NDVI profiles (Rembold & Maselli, 2006). Albeit the performance of the net decreesed when applied to different growing seasons, the drop in accuracy was not as strong as in Bossyns et al. (2007). Hence, the network generalized comparatively well. Considering the spatialization of the winter crops, it has to be noted that the accuracy of the reference (TM/ETM) images is unknown. Errors in these reference maps will automatically deteriorate the training process and fudge the accuracy assessment.

Using the same data set, the neural net gave relatively good results much earlier than in our previous work (Rembold & Maselli, 2006). In the precursor study reasonable results were only obtained after August, whereas in the present study first reasonable results could already been achieved end of March, making the proposed method more interesting for in-season crop monitoring and area estimation.

The research clearly demonstrated the positive impact of using ancillary information (CORINE) in the modelling. With the help of this information (albeit known not to be perfect), the neural net was able to better ‘learn’ the relation between the temporal signatures and the corresponding area fraction images (AFI) of the winter crops. This result looks plausible, as the proportion and composition of non-arable classes within a pixel can vary significantly. This will inevitably affect the resulting NDVI profile. By providing the NN with ancillary information, more specific mapping functions can be developed.

The main limitation of the proposed approach relates to the variability of signatures which are not winter crops (e.g., the “summer crops"). Indeed, an analysis of pixels with >90% arable land and labeled as "summer crop" revealed signatures that were highly variable in space and time (not shown). The consequences were clearly seen in several plains of Tuscany where it is known that the proportion, composition and phenology of summer crops have a high inter-annual and spatial variability. To tackle this problem, a follow-up study will try to "normalize" the NDVI profiles by taking meteorological indicators and DTM information into account. Likewise, one could try to improve network generalization by providing the net with an additional output variable indicating the area fraction of summer crops.

1996 was the year presenting the highest problems for winter crop area estimation (figure 7). Further investigation is needed to understand exactly what makes 1996 different from the other years. The additional research should address both the quality of the AGRIT statistics for this particular year and possible climatic or agronomic factors. It is curious however to observe that the same year was also the worst estimate in the precursor study, indicating that independently from the methodology used, it is difficult to explain Tuscany's winter crop area of 1996 by using low resolution NDVI data.

Considering the promising results obtained, it would be of interest to test the proposed methodology for its robustness in other geographical areas and larger regions as well as by using other low or medium resolution NDVI time series such as SPOT VGT or MODIS. The main requirements for further investigations in this sense are the availability of:

- training data for the discrimination between winter and summer crops, either based on high resolution data analysis or on existing agricultural databases (e.g. high resolution land use classifications or cadastral data; Verbeiren et al., 2008);

- reliable crop area statistics for model validation, possibly based on a high accuracy area frame sampling approach, such as the one of the AGRIT project (Consorzio ITA, 1987) at provincial or national level.

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