A methodology for a combined use of normalised difference vegetation index and CORINE land cover data for crop yield monitoring and forecasting. A case study on Spain

Giampiero Genovese, C. Vignolles, T. Nègre, G. Passera

Agronomie 21 (2001) 91–111

Original article

A methodology for a combined use of normalised difference vegetation index and CORINE land cover data for crop yield monitoring and forecasting. A case study on Spain

Giampiero GENOVESE[a]*, C. VIGNOLLES[a], T. NÈGRE[a], G. PASSERA[b]

[a] Joint Research Centre, SAI-ARIS, TP 262, 21020 Ispra (VA), Italy
[b] Terma Elektronik SRL, via Milano 9, 21023 Besozzo (VA), Italy

(Received 11 January 2000; revised 19 September 2000; accepted 3 October 2000)

Abstract – The objective of the experience described in the paper consists of extracting crop yield indicators from a combined use of land cover data, CORINE (CO-ordination of INformation on the Environment), and NOAA-AVHHR/NDVI data on a regional scale. First, the paper describes the methodology used to integrate the NDVI and the CORINE data. Then, a case study on Spain for a four year span between 1995 and 1998 is presented in the paper. The methodology thus developed allows a better exploitation of the NDVI time series by partly reducing the problem of mixed values. The use of an independent land cover can increase the information content of the extracted time series of NDVI. It is shown in this experience that indicators based on the CNDVI (CORINE-NDVI) time profiles can be more closely related to crop yield performances than indicators based on simple NDVI. The advantages of the approach are confirmed by the case study: good results in terms of crop yield forecast modelling, good discrimination of annual crop cycles, good desaggregation of average regional NDVI profiles. The application and the results fit the objective of the MARS (Monitoring Agriculture with Remote Sensing) Crop Yield Forecasting System of the EC, within which the experience was conducted. The objective of this system is to contribute to an independent, reliable and timely production forecasts EC system.

vegetation index / land cover / yield indicator / CORINE / MARS project / remote sensing

Communicated by Gérard Guyot (Avignon, France)

* Correspondence and reprints
giampiero.genovese@jrc.it

Résumé – Méthodologie pour l'utilisation conjointe des données de NDVI et de CORINE land cover pour le suivi des cultures et la prévision des rendements. Application au cas de l'Espagne. L'objectif de l'expérience décrite dans cet article consiste à extraire des indicateurs de rendement en utilisant conjointement les données de NDVI (Normalized Difference Vegetation Index) issues de NOAA-AVHRR et la couverture d'occupation du sol "CORINE land cover" (COordination of INformation on the Environment), à une échelle régionale. Dans un premier temps, l'article présente la méthodologie utilisée pour intégrer les données NDVI et CORINE. Ensuite, une étude de cas pour l'Espagne entre 1995 et 1998 est proposée. La méthodologie développée permet une meilleure exploitation des séries temporelles de NDVI en réduisant partiellement le problème des valeurs mixtes. L'utilisation d'une cartographie d'occupation du sol indépendante des données de télédétection de NOAA-AVHRR permet d'accroître le contenu informatif des séries temporelles de NDVI. Il est montré dans cette expérience que les indicateurs issus des profils temporels CNDVI (CORINE-NDVI) peuvent avoir un lien plus étroit avec le rendement des cultures que les indicateurs issus de simples profils temporels NDVI. Les avantages de cette approche sont confirmés par l'étude de cas : bons résultats en ce qui concerne le modèle prévisionnel d'estimation des rendements, reconnaissance du cycle annuel des cultures, bonne décomposition du profil NDVI moyen régional en profils spécifiques correspondant à des classes de végétation. L'application et les résultats correspondent aux objectifs d'indépendance et de fiabilité du système d'estimation des rendements des cultures du projet MARS (Monitoring Agriculture with Remote Sensing) de la Commission européenne dans le cadre duquel l'étude a été réalisée.

indice de végétation / occupation du sol / indicateur de rendement / CORINE / projet MARS / télédétection

1. Introduction

In the framework of the "Monitoring Agriculture with Remote Sensing" (MARS) project of the European Commission (EC), satellite-derived information is largely used to derive information and indicators for national crop production assessment [1, 3, 7, 18, 20].

Among the different data sets available at the MARS project, some indicators on vegetation status are derived from daily NOAA-AVHRR data. The NDVI (Normalised Difference Vegetation Index) is the most frequently used within agrometeorological analysis. It is defined as:

$$\mathrm{NDVI} = \frac{\rho 1 - \rho 2}{\rho 1 + \rho 2} \qquad (1)$$

$\rho 2$ and $\rho 1$ are respectively the reflectance (%) in the near infrared and in the red channels.

A description of the physical characteristics and the link with the vegetation behaviour is given by Tucker et al. [21].

Some efforts have been recently made within MARS to extract information from the NDVI, which can be linked to crops. In this framework two major lines are being followed: the derivation of growth parameters through energy balance models [14] and the derivation of indicators to fit statistical models [3, 8, 18, 20, 25]. A challenge in both the approaches is the decomposition of the NDVI vegetation mixed values into more reliable values for single vegetation targets.

In this study, the way chosen to predict yields with remote sensing data is an empirical way. It consists of directly linking the crop production to radiometric measurements combined in vegetation indices as explained by Guérif [10]. In this, lots of works have set up strong correlation between them for various crops [2, 5, 11, 19, 21, 22]. Other ways are also to combine semi-empirical or mechanistic crop models with remote sensing data. Different methods [4] have been tested. An overview of these different methodologies is done by Vignolles [24] and by Moulin et al. [15].

The main goals of this study are to exploit more effectively the time series of NDVI, linking them as much as possible to crop growing conditions, extracting indicators which can be related more closely to crop yield performances and fitting forecasting models. More precisely, the final objective is to find an indicator built from the NDVI profiles, which can be related to administrative yield statistics. To achieve these objectives, the vegetation

indicator must be re-calibrated to a crop indicator. The use of an independent land cover can increase the information content of the extracted NDVI profiles in such a way that the information is closer to crop behaviour than a simple mixed vegetation profile. In this context the use of CORINE land cover data as a stratification layer is introduced and a case study is presented.

2. Description of the data used

2.1. NOAA-AVHRR data

The data available at the MARS project is acquired using a receiving station placed at the Joint Research Centre in Ispra (Italy). Data is pre-processed using the JRC SPACE software (unpublished data) and then composed and re-sampled in a daily mosaic to obtain a contemporary picture which covers all of Europe (including Russia, other eastern countries and northern Maghreb). The final data obtained is daily European 1.1×1.1 km^2 pixel data (called level 3 format).

2.2. CORINE land cover data

CORINE land cover has been derived by high-resolution satellite data (SPOT-HRV, Landsat-TM), through techniques of photo-interpretation [12, 16]. The data has been validated using local cartography and ground surveys [12, 16]. The resulting map covers, at the moment, the EU-15 countries, the Central European Countries and part of the Maghreb, with 100×100 km^2 sheets at a nominal geographic scale of 1:100 000.

The classes of interest within this application are the agricultural areas (class 2 of the CORINE legend), which are sub-divided into:

21 Arable land

211 Non-irrigated arable land
212 Permanently irrigated arable land
213 Rice fields

22 Permanent crops

221 Vineyards
222 Fruit trees and berry plantation
223 Olive groves

23 Pastures

231 Pastures

24 Heterogeneous agricultural areas

241 Annual crops associated with permanent crops
242 Complex cultivation pattern
243 Land principally occupied by agriculture with significant areas of natural vegetation
244 Agro-forestry areas.

A full description of the nomenclature is given in the CORINE technical guide [12]. Other issues related to the accuracy and precision of the CORINE data can be found in [6] and [16].

3. The methodology for data integration

3.1. First step of the methodology: obtaining CORINE class NDVI profiles

3.1.1. The calculation of a simple average NDVI profile

During the image pre-processing phase, the angle of view information is associated with each pixel. Previous studies showed that the channel values are not independent from angle of view [26]. Off nadir area pixels reach a maximum size of 6.79 km^2 at the edge of the swath, resulting in mixed non-consolidated pixels. To compensate for this effect and a not perfect absolute geometric reference of the image, a re-sampling of the image at 4.4×4.4 km^2 has been chosen empirically for this application [26]. The value of the new pixel is given by an average of the 16 pixels composing the 4.4×4.4 km^2 window using equation (2):

$$\overline{NDVI} = \frac{\left(\sum_i^k \rho 2_i - \sum_i^k \rho 1_i \right)}{\left(\sum_i^k \rho 2_i + \sum_i^k \rho 1_i \right)}. \qquad (2)$$

The index i refers to the pixels in the re-sampling method. Equation (2) is only valid if at least 8 out of 16 pixels k are cloud free or water free or are not missing data. Otherwise the window of 16 pixels is considered to be a single missing value. This selection method is based on empirical choices of the MARS project.

Before or after the NDVI data is calculated at 4.4×4.4 km^2 pixel level, some options are available to enhance the information, or to reduce the noise which is still present:

- Channels re-processing using filtering techniques based on physical environmental characteristics (atmospheric and soil effects). We will call it ex-ante filtering. Examples in the MARS project are the GEMI [23] and the SMART algorithm (unpublished data).
- Applications of filtering techniques on the NDVI are mainly based on empirical assumptions and analysis of the final results. We will call it ex-post filtering. Examples of ex-post filters are the mvc (Maximum Value Composite) technique [13], and mathematical smoothing on curve profiles. Basically these algorithms depend on parameters defined by the observation of the raw initial profiles, such as the time lag of application, and are used empirically.

Within this experience NDVI profiles were built by applying a maximum value composite technique for a ten-day period followed by mathematical smoothing. Smoothing consisted of a moving average procedure with lag 3 applied after elimination of isolated negative picks according to an empirical distance threshold.

3.1.2. The integration of the CORINE land cover

The two starting data sets consist of:

- MARS SPACE II - NDVI data, with pixel size of 4.4×4.4 km^2, averaged as described by equation (2), reassembled into a mosaic at European level, in the Albers Equal Area projection (unpublished data), and to which a ten-day mvc technique has been applied.
- CORINE land cover data set release December 1997 EEA (European Environment Agency) version, scale 1:100 000 (raster version, pixel size of 100×100 m^2), Lambert Azimuthal Equal Area projection.

The approach for the integration consists of calculating the percentage of land cover of each CORINE class within each new NOAA-AVHRR pixel of 4.4×4.4 km^2 (see Fig. 1). This percentage (p^c) is called CORINE incidence for class c. Each pixel NOAA-AVHRR contains 1936 pixels

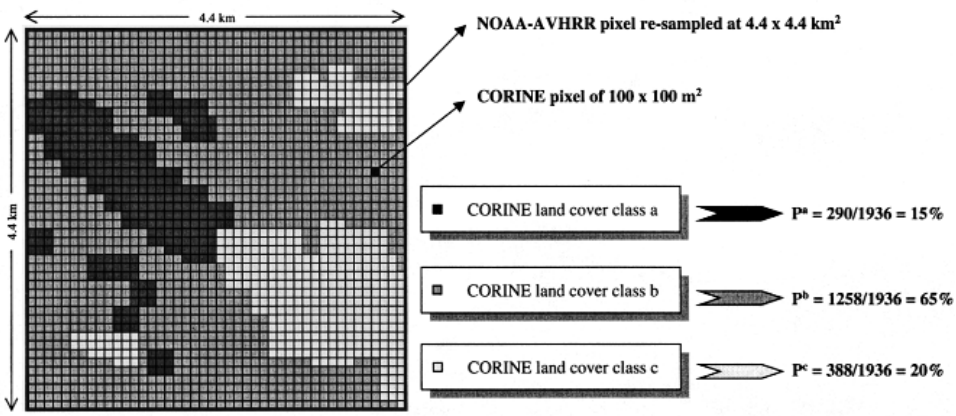

Figure 1. Example of incidence of CORINE classes on one pixel re-sampled.

CORINE of 100 × 100 m^2. The class incidence is obtained by calculation of a simple ratio as shown by equation (3):

$$p^c = n^c / \mathrm{N}. \tag{3}$$

With n^c = number of pixels CORINE ∈ class of interest c and N is the total population of land cover pixels within each re-sampled NOAA-AVHRR pixel. It is a fixed number and in our case N = 1936.

To achieve the objective, CORINE was re-projected using an Albers geographic reference. Then the ratio p^c of each CORINE class for each NOAA-AVHRR pixel was computed.

3.1.3. Definition of a weighted average mvcNDVI profile for the CORINE classes

The definition of the calculation for an average NDVI for a given CORINE class was made by area of interest (AoI). In the specific case the AoI coincides with the regions NUTS level 2 (Nomenclature Unités Territoriales Statistiques), which are EU regions of the GISCO database available from the Statistical Office of the European Commission (EUROSTAT). The choice of the NUTS level 2 as AoI was steered by the final objective, which is to get NDVI indicators related to administrative yield statistics.

The CORINE incidence p^c was used as a base to obtain a weighted average value of mvcNDVI per CORINE class. As a consequence of the variability linked to cloud conditions and more generally to the image acquisition environment, and to the dimension of the AoI, not all the set of existing pixels can be observed or acquired regularly. It means that in order to obtain an average mvcNDVI for the AoI the p^c cannot always be applied to the observed pixels just because the pixels can be missing values. However, the p^c can be seen as a system of weights in the hypothesis that all the population is observed. A system, which calculates the weight w of each observed pixel within the AoI on the basis of the actually available pixels, was defined as follows.

Given a CORINE class $c \in$ C (the set of the all CORINE classes, which is a partition of the territory). Given a region r (or Area of Interest, AoI) ∈ R (the set of all regions, for instance administrative, which constitute a partition of the territory). Given a period of the year $t \in$ T (the set of periods, which can constitute a partition of the time, for instance t can be a ten-day period).

We define an index j on the given m 4.4 × 4.4 km^2 available (cloud free) pixels in the image and belonging to the area r. The ws are then defined as:

$$w_j^{c,r,t} = \frac{p_j^{c,r,t}}{\sum_{j=1}^{m} p_j^{c,r,t}} = \frac{n_j^{c,r,t}}{\sum_{j=1}^{m} n_j^{c,r,t}}. \tag{4}$$

The ws are such that

(a) $0 < w_j^{c,r,t} < 1 \ \forall$ pixel j available $\in r$

(b) $\sum_{j=1}^{m} w_j^{c,r,t} = 1$.

The resulting mvcNDVI weighted average for a given CORINE class c on the region r, is called CNDVI (CORINE Normalised Difference Vegetation Index), and is given by:

$$\mathrm{CNDVI} = \hat{\mu}^{c,r,t} = \sum_{j=1}^{m} mvcNDVI_j^{c,r,t} w_j^{c,r,t}. \tag{5}$$

The μ value is here estimated by sampled observations within the AoI. Thus, using equation (5), the average true μ value is considered to be an estimation obtained by the CNDVI.

This estimation can be repeated varying the CORINE class c, the region r (NUTS2), and for each ten-day period t of the year. The result is a CNDVI profile for the fixed parameters. It is stressed here that, the number of pixels m actually used within the selected region r, is a function of the image cloud conditions, and then m is principally variable at the variation of t . The ws are then re-calculated for each image acquisition on the time lag t to guarantee conditions (a) and (b).

Considerations of the consistency of calculations and the class representativeness of the points of the profiles are postponed to further communications. More details on *m* will be given later.

The methodology described here can be applied to any country and any land cover available. For the following steps, specific explanations will be given for the particular context of this study: at a first stage all experiments were done on the Iberian Peninsula with the objective of forecasting yields of two crops, namely wheat and barley. To achieve this goal, the CORINE class *c* studied was the "non-irrigated arable land" class in which all the main annual crops are included. Currently other studies are under way using profiles on other CORINE classes and other AoI.

3.2. Second step of the methodology: conditions on pixels and regions

Over time, production of CNDVI on regions makes it possible to build profiles, which can be used to monitor the class-dominant-vegetation conditions to detect possible stresses during the year. However, a more quantitative use of the information is sought here. In order to use profiles with a better relation to the target agricultural classes, and decrease the measurement error, two directions have been tested. The first is a series of conditions on the pixels, the second is a series of conditions on the regions (AoI).

3.2.1. Conditions of keeping the pixels

First, conditions on the choice of the pixels affect the number *m* of observations used for the CNDVI estimates. The first parameter to be set is the angle of view (θ) just after the pre-processing phase. For the application an angle threshold of ± 30° is chosen to keep information as homogeneous as possible. This means that only the pixels with an average angle of view $-30° \leq \theta \leq +30°$ are kept.

The next parameter *t* to be set is the time unit for the composition of the mvc (Maximum Value Composite) image. The time lag within the experiment was fixed as a unit of 10 days. This is a reasonable period in which to obtain good results south of the 45° parallel north. In the northern areas this period could be revised to a larger size. Holben [13] has shown that the use of this technique minimises different effects due to variable atmospheric conditions, view and illumination geometry.

In equation (5) the number *m*, which can be assumed to be a sample size for the estimate of the regional NDVI for a given CORINE class, is then a function of the cloud conditions, the angle of view and the time of acquisition *t*:

$m = f(cc, \theta, t)$

cc = cloud conditions

θ = angle of view

t = time lag of acquisition or period of observation.

We observe that while *cc* and θ are limiting conditions on the size of *m*, the bigger *t* is the more straightened the observed sample is.

Besides, *m* can also be constrained by other conditions:

m can be fixed according to criteria of sampling representativeness for the target class and on the sampling design. In this context it is worthwhile for the application to know if the number of hectares for the target class *c*, in the regions (AoI), covered by the available *m* guarantees a certain theoretical precision and accuracy of the indicator derived from the CNDVI estimate. Are we really observing class *c* pixels sufficiently to have a sound description of the class *c* vegetation behaviour? This simple and reasonable question involves many issues such as error measurement, error propagation and definition of a sampling plan. As a consequence *m* could also vary according to the degree of precision required. At this stage, and within this experience, the only answer is given by the good fit of the final forecasting model obtained as compared to the observed reference official regional crop yield data.

Moreover, we have to reflect on the purity of the signal. Spectrally the NDVI values by 4.4 × 4.4 km^2 pixels are dominated by the main land-covering class. How much of the NDVI can be purely related to the target land cover class? Thresholds on the minimum level of incidence for

the CORINE class (here referred to as TD, threshold of dominance) can be established a priori per pixel. Thus, the pixels are included in the sample if the CORINE incidence (p^c) is higher than a certain threshold (TD). The use of thresholds implies the inclusion/exclusion in the calculations of many pixels and so influences the *m* number of observations. Within the experience *m* becomes a function of

$$m = f(cc, \theta, t, \mathrm{TD}).$$

TD is normally accepted to be the maximum level of p^c given a minimum level of representativeness. The level is calculated per region (AoI). Explanations on the use of thresholds are that indicators can be linked to the degree of concentration of the target crop in the area. The more a crop covers an area the more the NDVI value is dominated by the crop reflectance. In other terms, the more the crop covers the area of observation, the more it spectrally dominates the vegetation response. In the hypothesis of large crop cover this allows a decrease of TD, thus a higher *m*. In this situation TD can also be increased resulting in a lower *m* but not necessarily in a degraded estimation of NDVI as shown later. In this study, different TD were tested thus CORINE class NDVI profiles were built for the following thresholds: 5%, 10%, 20%, 30%, 40%.

Figure 2 shows the steps of the methodology.

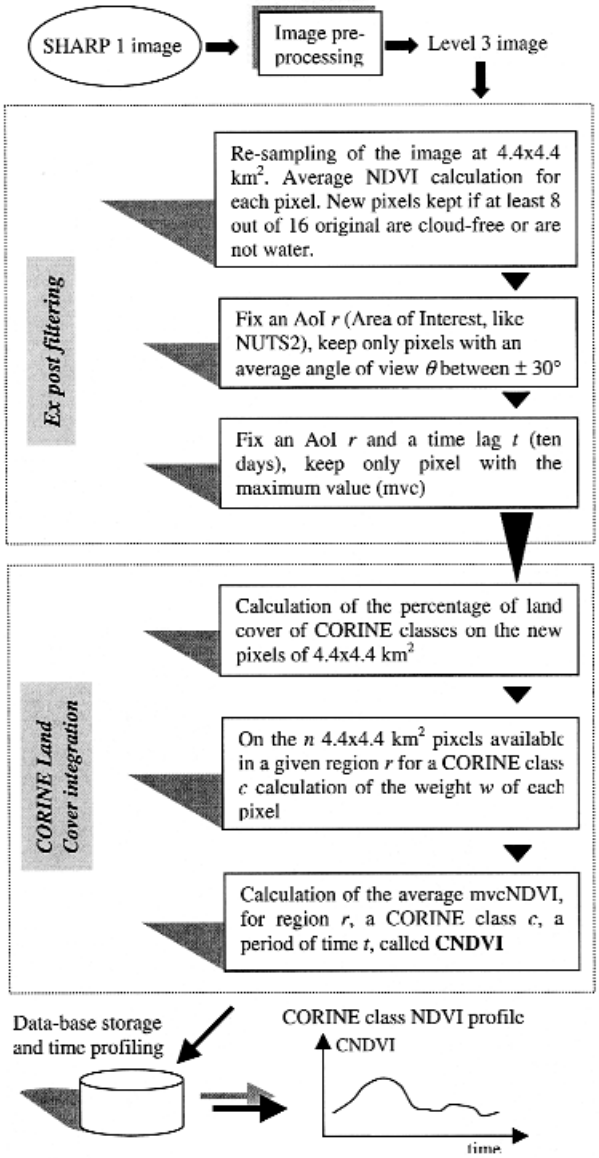

Figure 2. Flow charts on the average mvcNDVI calculation by CORINE classes.

3.2.2. Conditions of keeping the regions (AoI)

Looking at the relationship between the CNDVI estimates and the observed regional crop yields, some further conditions were tested to include or exclude regions in order to improve model performance.

– *Condition 1*: all the regions for which a profile can be built have been retained;

– *Condition 2*: a region is accepted as AoI if the crop area represents 10% or more of the arable land area;

– *Condition 3*: a region is kept as AoI if the Utilised Agricultural Area (UAA) is predominant in the total area and if the arable land area is predominant in the UAA;

– *Condition 4*: the region is kept as AoI if the condition 3 is realised and if the crop area represents strictly more than 10% of the arable land area.

3.3. Third step of the methodology: extraction of the yield indicators

The indicators extracted from the CORINE class NDVI profiles to fit statistical models are based on a hypothesis of crop dominance. The integral of the profile on different periods of the reckoned cycle is used. For instance, between the stem elongation and the anthesis period for wheat as suggested by Tucker et al. [21], and between flowering and ripening as suggested by Benedetti and Rossini [1]. Some studies have also shown that the maximum value reached as suggested by Cabezon and Taylor [3] could be used. It has been shown that the percentage of land cover of the class of interest could also influence the result [1].

In this paper, a case study on Spain is presented. Simple linear regressions were calculated by testing several periods of CNDVI integrated at regional level versus regional crop yield data. Regional crop yield data for wheat and barley in Spain is provided by the Spanish Ministry of Agriculture. For wheat, crop regression analyses were performed in a three year span between 1995 and 1997. For barley, data from 1998 was available and then regressions were realised for four years between 1995 and 1998. For wheat crop, six periods of integration were tested. Therefore, the sum of CNDVI values was calculated:

– between flowering and ripening *(Period of Integration 1)*,
– over six decades after reaching the maximum NDVI *(PI 2)*,
– between shooting and ripening *(PI 3)*,
– between shooting and flowering *(PI 4)*,
– between ear emergence and flowering *(PI 5)*,
– between ear emergence and ripening *(PI 6)*.

For barley, the phenological calendar available at JRC only allowed the sum of CNDVI values between ear emergence and ripening dates. All the dates of these phenological stages were provided by K.U. Leuven Research and Development [27]. In the work of Leuven, average cropping calendar data (sowing and harvesting) and flowering dates were collected through ground observations and literature, then using a crop thermal calendar the other phenological stages were estimated. Tables I and II show the corresponding dates for both the

Table I. Phenological calendar for wheat.

NUTS2 name	NUTS2 code	Sowing date	Emergence date	Tillering date	Shooting date	Ear emergence date	Flowering date	Ripening date
Galicia	ES11	291	305	305	55	106	118	204
P. Asturias	ES12	290	303	349	47	99	112	202
Cantabria	ES13	290	302	346	46	99	112	203
País Vasco	ES21	289	302	345	46	99	112	201
C. Navarra	ES22	290	302	348	54	103	114	200
La Rioja	ES23	289	300	345	53	101	112	202
Aragón	ES24	290	302	350	59	106	117	201
C. Madrid	ES3	289	300	339	78	97	109	209
Castillon y León	ES41	290	301	309	60	103	114	207
Castilla la Mancha	ES42	293	304	332	56	96	107	205
Extremadura	ES43	297	309	327	47	93	104	206
Cataluña	ES51	291	304	307	71	119	129	201
C. Valenciana	ES52	292	305	334	51	101	114	199
Islas Baleares	ES53	290	304	349	46	103	116	197
Andalucía	ES61	319	332	80	50	85	94	183
Región di Murcia	ES62	310	324	184	54	95	105	193

Table II. Phenological calendar for barley.

NUTS2 name	NUTS2 code	Sowing date	Emergence date	Asumed end of initial stage date	Ear emergence date	Ripening date
Galicia	ES11	33	72	109	150	211
P. Asturias	ES12	32	65	99	141	206
Cantabria	ES13	30	62	96	137	202
País Vasco	ES21	34	65	98	138	200
C. Navarra	ES22	49	78	108	143	197
La Rioja	ES23	40	74	107	144	198
Aragón	ES24	53	82	111	145	196
C. Madrid	ES3	30	74	109	147	200
Castillon y León	ES41	31	70	106	145	201
Castilla la Mancha	ES42	35	73	108	145	199
Extremadura	ES43	*	*	*	*	*
Cataluña	ES51	55	88	115	146	195
C. Valenciana	ES52	52	80	108	142	196
Islas Baleares	ES53	58	81	108	141	195
Andalucía	ES61	*	*	*	*	*
Región di Murcia	ES62	*	*	*	*	*

* No data.

crops. They are given in Julian days for each AoI (NUTS2 regions).

4. Results

4.1. Results on the integration of the CORINE land cover

In order to show the usefulness of the integration of CORINE land cover data, comparisons between simple average mvcNDVI profiles and CORINE integrated profiles have been realised. Figure 3 represents profiles for average mvcNDVI and profiles obtained on different CORINE classes between 1995 and 1998 in Andalucia (Spain). It shows that CORINE class NDVI profiles present better dynamics and that clear vegetation cycles can be recognised when annual crops are present. In addition, it could be seen that on the Y-axes a higher variability of the NDVI can possibly be associated with vegetation conditions. Figure 3 shows for example that the 1995 low data can be interpreted as low crop performances. In fact we know from meteorological data that the area during that period was affected by a severe drought.

Condition 4 of paragraph 3.2.2. on the AoI was tested running linear regressions of regional crop yield data versus sum of CNDVI values between the flowering and ripening dates and versus average NDVI on the same regions (AoI). As shown, under condition 4, all the regression indicators improve using the CNDVI (see Fig. 4). Condition 4 is considered the strictest in terms of crop presence in the AoI. Under this condition acceptable results can be obtained without any use of a land cover. However it is shown here that even in the most favourable conditions for using NDVI, the integration of a land cover can improve the results (an increase of the correlation coefficient is shown). Nevertheless, it also has to be noticed that this increase can be not significant. In the example the coefficient of determination (R^2) goes up from 0.751 to 0.884 (increase of 17.7%) while the standard error goes down to 0.315 t/ha (decrease of 31.7%).

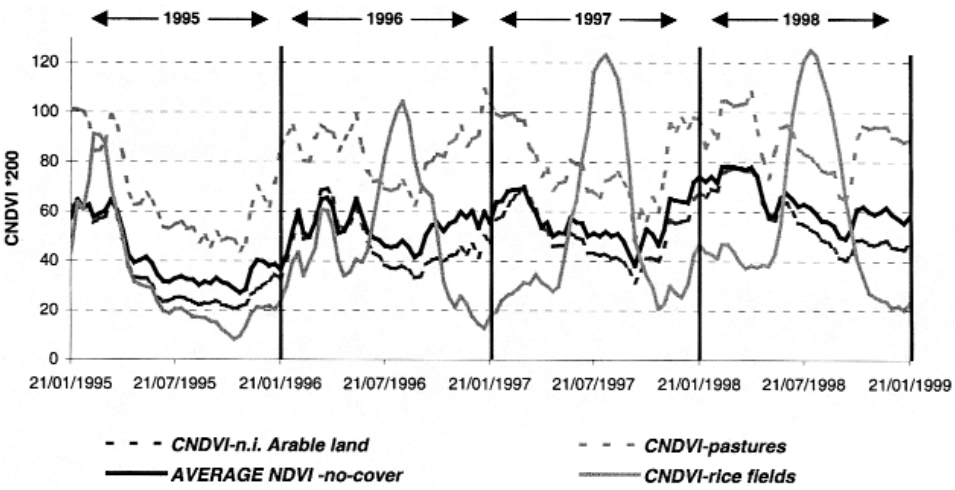

Figure 3. CORINE class NDVI profiles for different classes (CNDVI) compared to a simply averaged NDVI (AVERAGE NDVI – no-cover) for the region of Andalucia between 1995 and 1998. The NDVI values are re-scaled with a factor of 200 for a better legibility.

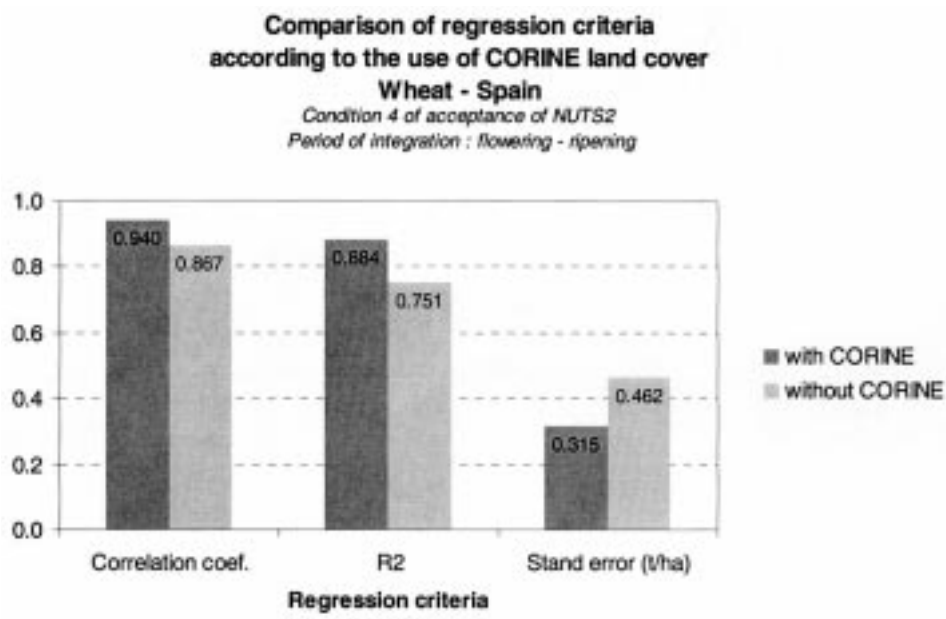

Figure 4. Regression criteria: CNDVI vs. observed crop yields and NDVI (no use of CORINE) vs. observed crop yields.

4.2. Results using the four conditions on the AoI

4.2.1. For wheat

As explained before, several conditions to accept, or not, a region as AoI have been tested. These conditions are based on indexes (ratios) like crop area against total arable land area, arable land area against UAA (Utilised Agricultural Area) and UAA against total area of the NUTS2 (see Sect. 3.2.2.). Simple linear regressions were made using only two of the six periods of integration to test these four conditions. The two periods of integration selected were *PI 1* and *PI 2*. Table III shows the results. In the table, the number of observations is given. It is the number of statistical units (CNDVI indicators on the regions) used in

Table III. Results of the simple linear regressions testing the four conditions to accept or reject the areas of interest for wheat between 1995 and 1997.

	Condition 1		Condition 2		Condition 3		Condition 4	
	PI 1	PI2	PI 1	PI2	PI 1	PI2	PI 1	PI2
Correlation coefficient (R)	0.447	0.422	0.814	0.677	0.787	0.520	0.940	0.838
Determination coefficient (R^2)	0.200	0.178	0.662	0.459	0.620	0.270	0.884	0.702
Stand error (t/ha)	1.024	1.037	0.720	0.912	0.572	0.792	0.315	0.506
Number of observations	48	48	27	27	27	27	15	15

Table IV. List of regions NUTS2 (areas of interest) according to the acceptance/rejection conditions of the region for wheat and barley.

NUTS2		Wheat				Barley			
Name	Code	Under condition							
		1	*2*	*3*	*4*	*1*	*2*	*3*	*4*
Galicia	ES11	1	0	0	0	1	0	0	0
Principado de Asturias	ES12	1	0	0	0	0	0	0	0
Cantabria	ES13	1	0	0	0	1	0	0	0
País Vasco	ES21	1	1	0	0	1	1	0	0
Comunidad F. Navarra	ES22	1	1	1	1	1	1	1	1
La Rioja	ES23	1	1	0	0	1	1	0	0
Aragón	ES24	1	1	1	1	1	1	1	1
Comunidad de Madrid	ES3	1	1	1	1	1	1	1	1
Castilla y León	ES41	1	1	1	1	1	1	1	1
Castilla la Mancha	ES42	1	0	1	0	1	1	1	1
Extremadura	ES43	1	1	1	0	0	0	0	0
Cataluña	ES51	1	1	0	0	1	1	0	0
Comunidad Valenciana	ES52	1	0	0	0	1	1	0	0
Islas Baleares	ES53	1	0	1	0	1	0	1	0
Andalucía	ES61	1	1	1	1	0	0	0	0
Región de Murcia	ES62	1	0	1	0	0	0	0	0

1 for region accepted and 0 for region rejected.

the regression, taking into account the number of years and the number of areas of interest retained. For instance, under condition 1, the 48 observations used in the regression correspond to the 16 regions NUTS 2 on three years (1995, 1996 and 1997). Table IV shows the acceptance/rejection of NUTS2 regions under the four conditions. Results show that whatever the period of integration retained, the regression criteria are better under the fourth acceptance/rejection condition. It means that the results increase when the arable land area is prevalent against the UAA and when the wheat area is more than 10% of the total arable land area. Similar results showing the importance to have a certain representiveness of the crop of interest in the area studied have already been obtained by Benedetti and Rossini [1] in Emilia Romagna (Italy) on wheat.

4.2.2. For barley

The same type of experiment was realised for barley. Table IV shows the number of regions

Table V. Results of the simple linear regressions testing the four conditions to accept or reject the areas of interest for barley between 1995 and 1998.

	Condition 1	Condition 2	Condition 3	Condition 4
Correlation coefficient (R)	0.342	0.727	0.717	0.88
Determination coefficient (R^2)	0.117	0.528	0.513	0.775
Stand error (t/ha)	0.967	0.700	0.638	0.416
Number of observations	48	36	24	20

retained under each acceptance/rejection condition. Under condition 1 (where normally all the regions are kept), the number of regions is different than for wheat. It is due to the non-presence of barley in the region of Asturias and to the non-availability of crop calendar data for the regions of Extremadura, Andalucia and Murcia. Table V gives results of the regression analysis. The conclusions are the same as for wheat: the best regression performances are obtained under condition 4.

4.3. Results on different indicators extracted from CNDVI

Simple linear regressions were done to test the six periods of integration mentioned before (see Sect. 3.3). Regression analyses were realised under condition 4 and by using regional wheat yield data. Results are given in Figure 5. Except for the two periods ear emergence – flowering and shooting – flowering, the coefficient of determination (R^2) obtained is higher than 60%. Best results are yielded when the sum of the CNDVI values is made during the flowering – ripening period. Benedetti and Rossini [1] and Rossini and Terpessi [18] have found similar results. This result is not surprising because in the process of wheat yield formation, the main substance accumulation in storage organs is realised between the flowering and the wax ripeness stages [1].

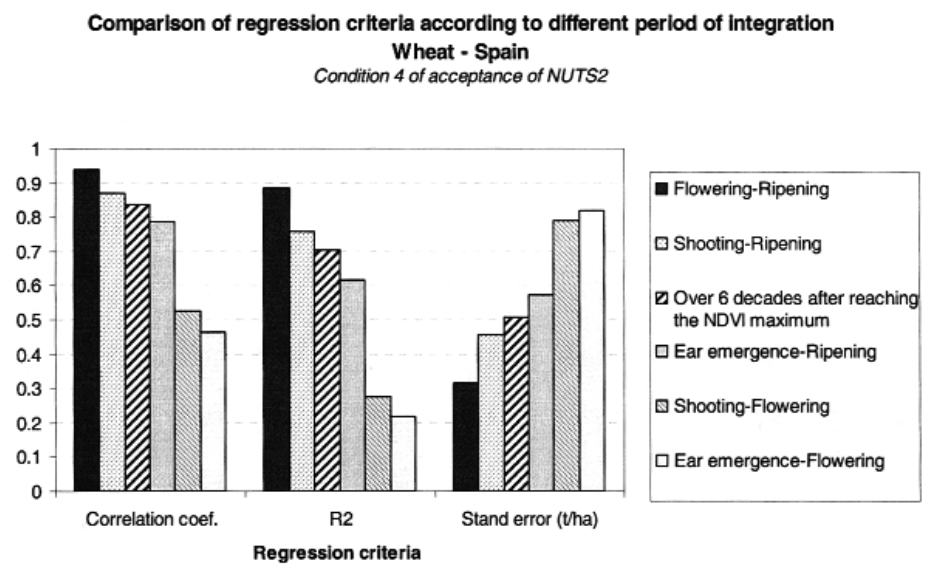

Figure 5. Results of simple linear regressions by testing different periods of integration.

4.4. Results using land cover percentage thresholds

Finally, the experiment on the land cover class threshold of dominance (TD) to keep or reject a pixel *j* within a region *r*, was made.

Comparisons of CNDVI profiles at different TD for the non-irrigated arable land class were made. Some examples are given in Figure 6. On the one hand, whatever the area of interest and the year, a difference between CNDVI values at different thresholds can be noticed. On the other hand, a similar dynamics over time is shown with some differences in terms of time lag. A mean absolute difference in percentage between CNDVI values calculated at different TD and CNDVI values with no TD was calculated for each year and AoI. As shown in Figure 7 the difference increases when TD increases. The difference between CNDVI values with a threshold of 5% and CNDVI values without threshold is very low. It is always lower than 2% except for the region NUTS2 ES53 (Islas baleares) where the difference is at 2.42% (1995 value). When TD = 40%, then the differences increase without reaching 14% except for the region NUTS2 ES52 (Valenciana) with a value of 22.31% in 1995. Table VI sums up the mean absolute differences between CNDVI values obtained by using a threshold of 40% and the values obtained without the use of a threshold. It is hypothesised that the kind of spatial concentration of the class of interest (non-irrigated arable land) within the regions has an effect on the level of CNDVI. However, this effect is not regular and further studies are necessary to explain the differences observed among the regions. The experience has shown that most of the time, with a high threshold the resulting profiles of CNDVI are well separated from those obtained without threshold. The question now is whether this difference is an improvement of the profiles: are the profiles better related to the non-irrigated arable land class? In other terms, could this difference with a high threshold lead to a better separation among CORINE classes? To analyse the effect of a selection on pixels by using different levels of TD on the final crop yield forecasts linear regressions were calculated for each of the respective indicators extracted. The experience was realised for wheat crop. The sum of the CNDVI values on the first two periods of integration selected (*PI 1* and *PI 2*) were used as indicators. The regressions were performed also crossing the four conditions of region acceptance. It is shown that in general, independently from the threshold retained, the best fittings are obtained when condition 4 for a region is applied and when the NDVI is integrated between the flowering and ripening dates (*PI 1*). Within this case, the effect of a selection on pixels by using thresholds of dominance on the CORINE class percentage p^c has been analysed. Figure 8 shows the results. A small degradation of the regression performances is shown when the threshold increases, but it is not significant. In this case, the selection of a pixel according to its percentage of land cover does not improve the results.

Table VI. Mean absolute differences (%) between CNDVI values with a threshold of 40% and CNDVI values without threshold.

NUTS2 name	NUTS2 code	1995	1996	1997
País Vasco	ES21	8.06	7.89	10.69
Comunidad F. Navarra	ES22	11.06	8.63	8.23
La Rioja	ES23	2.99	3.30	3.74
Aragón	ES24	12.60	10.21	6.88
Comunidad de Madrid	ES3	3.44	3.28	3.70
Castilla y León	ES41	5.48	6.08	5.59
Castilla la Mancha	ES42	5.37	5.22	5.09
Extremadura	ES43	12.97	8.66	7.50
Cataluña	ES51	9.36	7.37	7.07
Comunidad Valenciana	ES52	22.31	11.56	13.34
Islas Baleares	ES53	13.34	6.19	4.03
Andalucía	ES61	8.28	5.33	4.98
Región de Murcia	ES62	3.00	4.03	3.19

Nevertheless, if the same type of results is observed without selection of the regions (condition 1), that is, in a condition when no further crop information is available, a different conclusion can be drawn (see Fig. 9).

Despite the regression, results are worse than the ones obtained by adding condition 4 to the

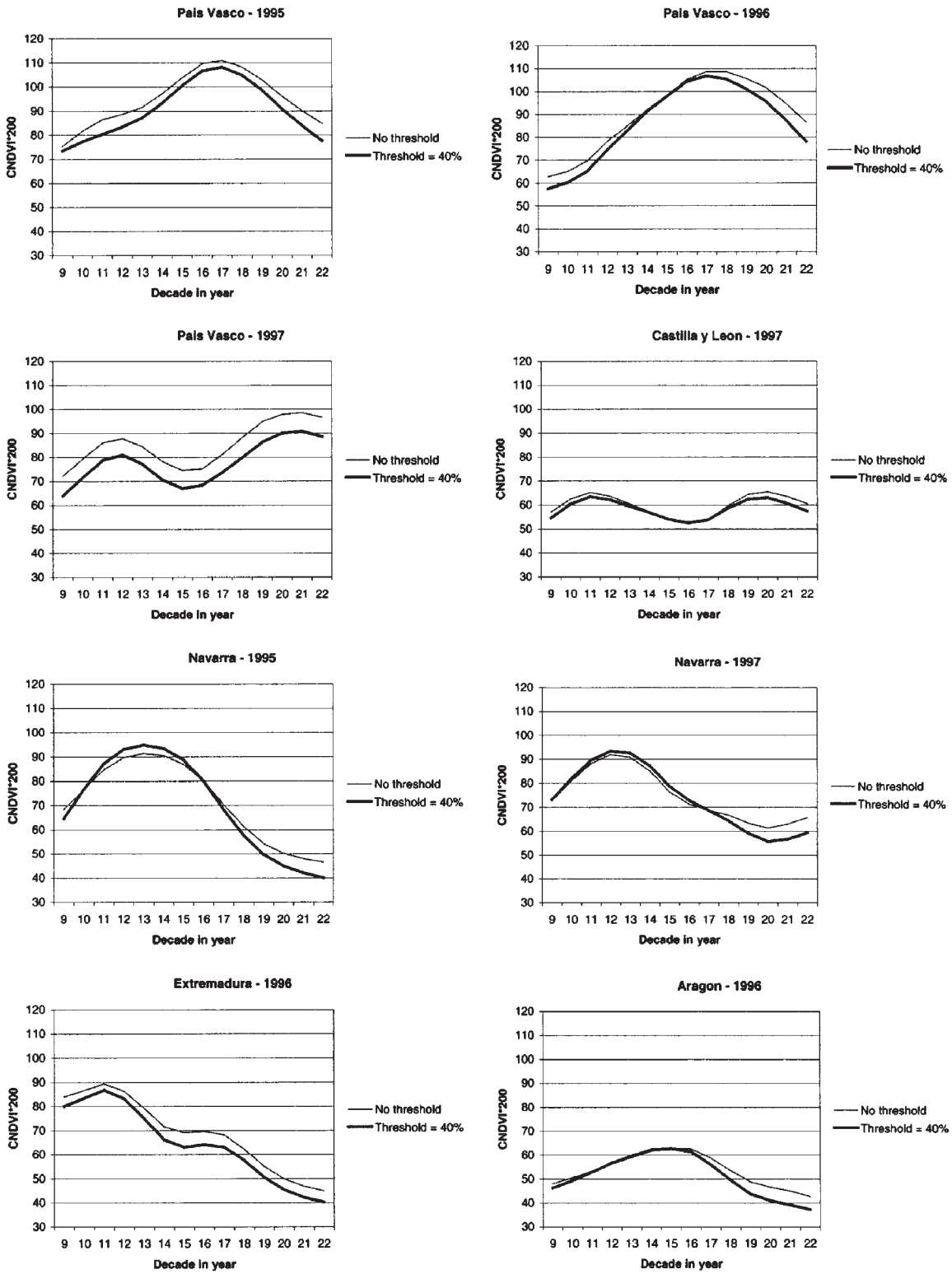

Figure 6. Comparison of CNDVI values at different thresholds of dominance for different regions and several years.

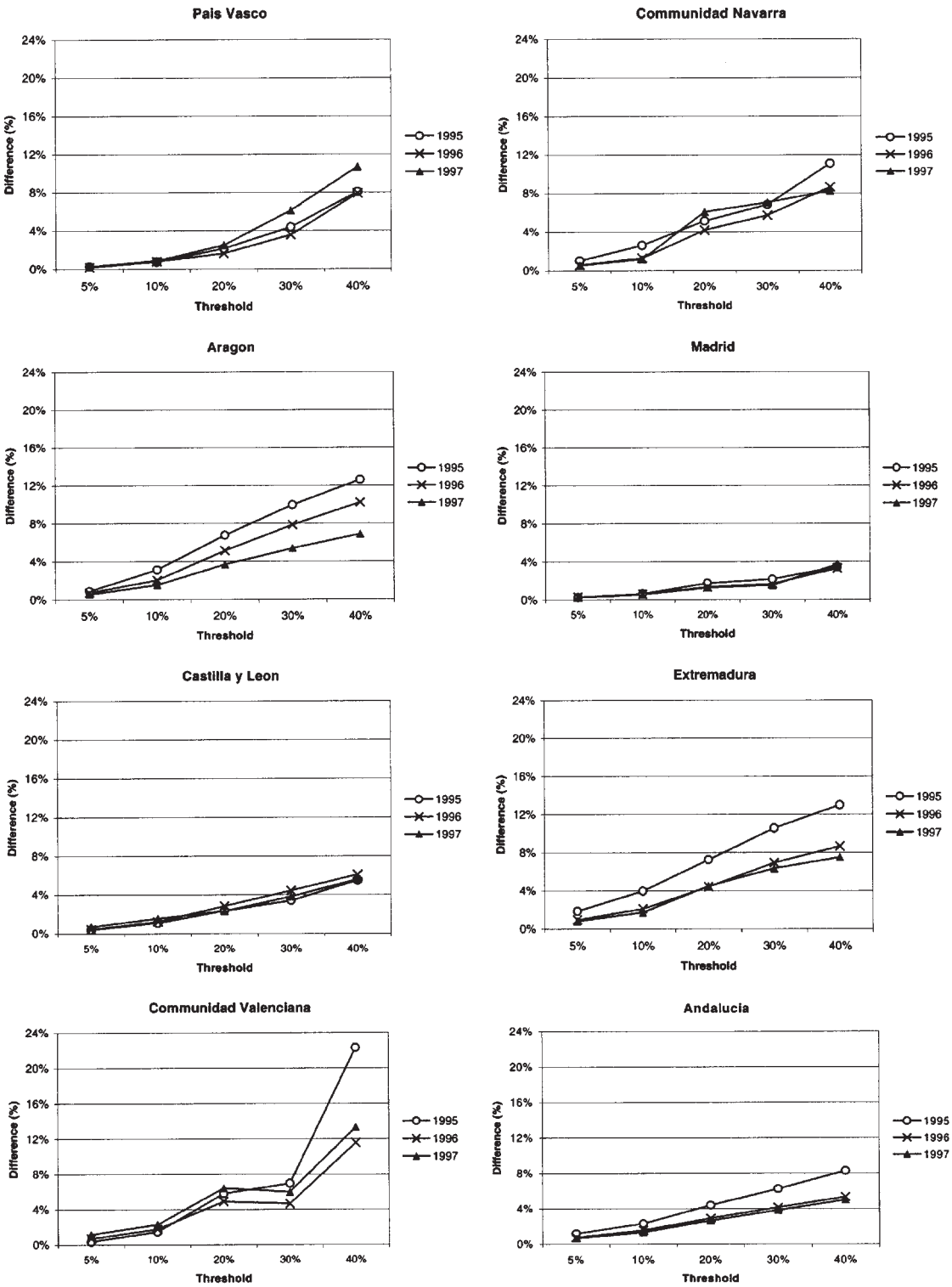

Figure 7. Mean absolute difference (%) per year, between CNDVI values at different thresholds of dominance and CNDVI values without threshold for different regions.

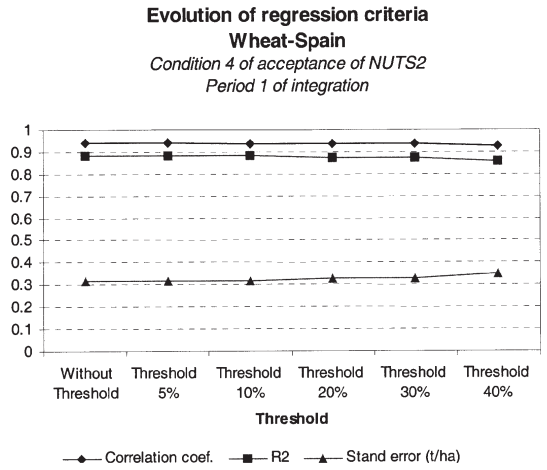

Figure 8. CNDVI vs. observed crop yields. Results of regressions by testing different land cover class thresholds under the condition 4.

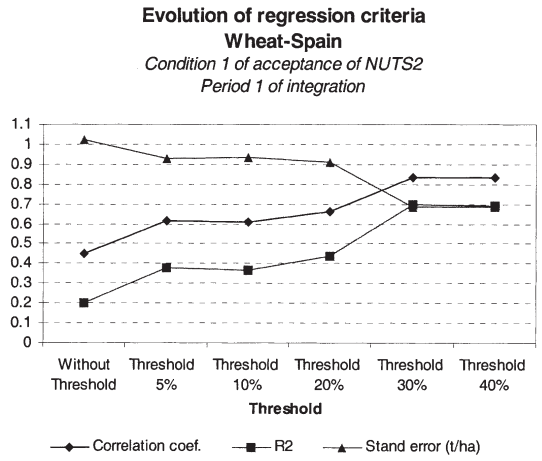

Figure 9. CNDVI vs. observed crop yields. Results of regressions by testing different land cover class thresholds under the condition 1.

experience; an improvement of the results can be seen when the TD used increases up to 30%. The coefficient of determination (R^2) goes up from 20% to 69.8% and the standard error decreases from 1.024 to 0.683 t/ha. The role of the selection on pixels to obtain CNDVI profiles related to the target vegetation class is shown clearly in this case. It is likely that the geometric accuracy of the NOAA-AVHRR data could affect this result. In fact the choices mentioned in Section 3.1.1. should reduce this effect but not completely.

As a conclusion we can say that a selection based on the AoI can get better regression results than a selection based on TD. However, the first situation implies further information available on target crops areas.

4.5. Crop yield estimations

In order to go for a national forecast, we stress that we calibrated a model using only the significant regions based on the conditions of Section 3.2.2.

4.5.1. Wheat yield estimation for the significant regions

A yield estimation model was obtained through simple linear regression analysis. Various models were tested using different sets of observations/indicators. The one for which the determination coefficient (R^2) and the correlation coefficient were the highest and the standard error the lowest was selected as the best predicting one. The best simple linear regression model combines 1995, 1996 and 1997, under condition 4 and integrate CNDVI profiles between flowering and ripening (*PI 1*). Under condition 4, only five AoI were kept, namely Communidad F. Navarra (ES22), Aragón (ES24), Communidad di Madrid (ES3), Castilla y León (ES41) and Andalucia (ES61). The R^2 was 88.4%, the coefficient correlation was 94% and the standard error was 0.315 t/ha. The model obtained for wheat using the observed yields in the Spanish regions (NUTS 2 level) is the following:

$$Y = -3.26 + 9.36 \times 10^{-3} \sum_{P/1} CNDVI. \qquad (6)$$

The crop calendar of each region [27], (see Sect. 3.3.), was used to sum the CNDVI between flowering and ripening. The results (see Tabs. VII and VIII) are quite satisfying except for the region of Madrid for which in 1996 and in 1998, the percentage prediction error is above 30%. In most cases, there is similarity between official yields and estimated ones. The 1998 data not included in the regression, and used to validate the prediction, also shows good results.

A final comparison of the regional estimated wheat yields with the official data is given in Figure 10. The figure shows a good linear relation between the modelled and the official data with a determination coefficient reaching 76.5%. As a first approach we considered the linear relationship to be a reference. Non-linear relations are to be taken into account in further studies.

4.5.2. Wheat yield estimation at a national level

Using the regional estimated wheat yields ($\hat{Y}_r^d$) and the regional wheat areas (S_r^d), an estimated production for all the five kept regions ($\hat{P}_R^d$) has been calculated per year. The regional official statistics (yields, productions and areas) were provided by the Spanish Ministry of Agriculture.

$$\hat{P}_R^d = \sum_{r=1}^{5} \hat{Y}_r^d S_r^d \tag{7}$$

where d represents the year.

Considering that the production of the five AoI retained to build the simple linear yield estimation model represents respectively for the four years 73.8%, 75.7%, 75.4% and 70.1% of the Spanish production, it was possible to estimate a national production (P_N^d) per year.

$$\hat{P}_N^d = \frac{\hat{P}_R^d}{Q_R^d} \tag{8}$$

where Q_R^d corresponds to the ratio between the wheat production of the kept regions and the total wheat production of Spain.

Then the national estimated yield ($\hat{Y}_N^d$) per year was obtained by dividing the national estimated

Table VII. Wheat yields estimation at regional level for 1997 and 1998.

NUTS2		1998			1997		
Code	Name	Estimated Y	Reported Y	Error (%)	Estimated Y	Reported Y	Error (%)
ES22	Navarra	3.36	3.45	–2.55%	3.07	3.34	–8.11%
ES24	Aragon	2.55	2.29	11.56%	2.27	2.12	6.98%
ES3	Madrid	3.73	2.36	58.03%	1.76	1.75	0.37%
ES41	Castilla Leon	4.10	3.61	13.45%	2.30	2.65	–12.97%
ES61	Andalucia	3.15	2.46	27.82%	1.91	1.88	1.31%

Table VIII. Wheat yields estimation at regional level for 1995 and 1996.

NUTS2		1996			1995		
Code	Name	Estimated Y	Reported Y	Error (%)	Estimated Y	Reported Y	Error (%)
ES22	Navarra	3.35	3.53	–4.83%	3.06	2.98	2.45%
ES24	Aragon	1.94	2.21	–12.14%	1.16	1.20	–3.45%
ES3	Madrid	2.49	1.91	30.42%	1.00	1.05	–4.32%
ES41	Castilla Leon	3.63	3.43	5.99%	2.54	2.04	24.53%
ES61	Andalucia	2.51	3.07	–18.32%	0.83	0.67	24.48%

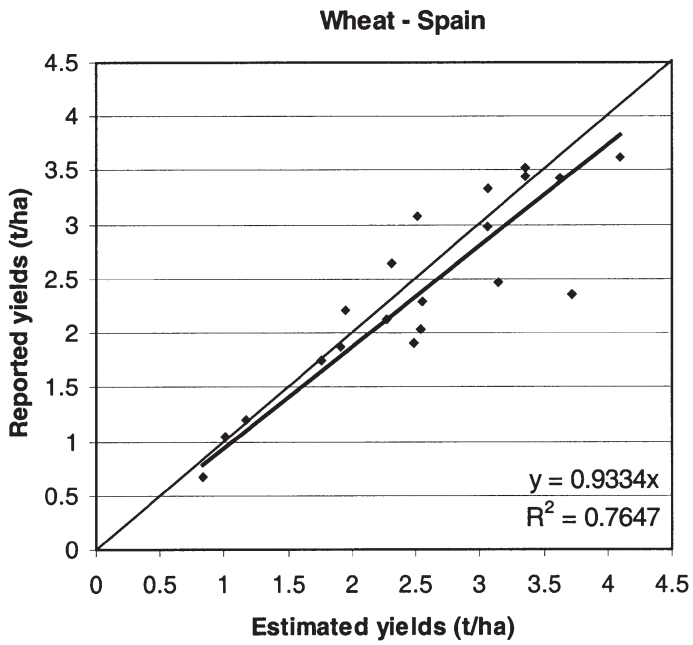

Figure 10. Comparison between regional official yields and regional estimated yields.

production ($\hat{P}_N^d$) by the total wheat area (S_T^d). The national official statistics (yields, productions and areas) were provided by EUROSTAT (CRONOS database).

Finally, the national predictions ($\hat{P}_N^d$ and $\hat{Y}_N^d$) were compared to the national official statistics. Table IX shows the results. For 1996 and 1997, the difference with the official "observed" data is lower than 6%. For 1995 and 1998, the difference is higher than 6% but remains lower than 18%. These results are encouraging for a country like Spain where the inter-annual wheat yield variability, even at national aggregated level, can be very high (40% in average) and difficult to predict with low margins of error. This also shows the potentiality of the methodology to obtain acceptable national forecasts in an operational and independent way. This is confirmed by the 1998 predictions formulated with this approach. Besides, it is shown in Figure 11 that the annual dynamics of the forecasts obtained follows the same pattern as the reference data.

5. Conclusions and further developments

Many advantages and improvements have been shown by integrating NOAA-AVHRR profiling on a given land cover in terms of:

- Desaggregation of the average profiles;
- Better discrimination of annual crop cycles;
- Extraction of indicators better related to crop yield performances, thus good forecasting models for national crop yield. However, limited benefit is drawn when the region is already well covered by the target crop. In that case a regional average NDVI with no land cover integration gives similar results to using the CNDVI technique.

Further directions of investigation, which can be further developed starting from these results, is within pixel signal decomposition studies.

As far as crop yield forecasts are concerned, a further step to prove the validity of this approach is to extend the application to other countries, crops and to more years of observations. Other models

Table IX. Wheat production and yield estimations at national level.

	1995	1996	1997	1998
Estimated produtions all Spain (t)	3700586.029	5703828.599	4381664.876	6222638.838
Estimated yields for all Spain (t/ha)	1.74	2.84	2.11	3.32
Official productions all Spain (t)	3138711	6040454	4643300	5347000
Official yields for all Spain (t/ha)	1.48	3.00	2.23	2.85
% Error	17.9	–5.6	–5.6	16.4

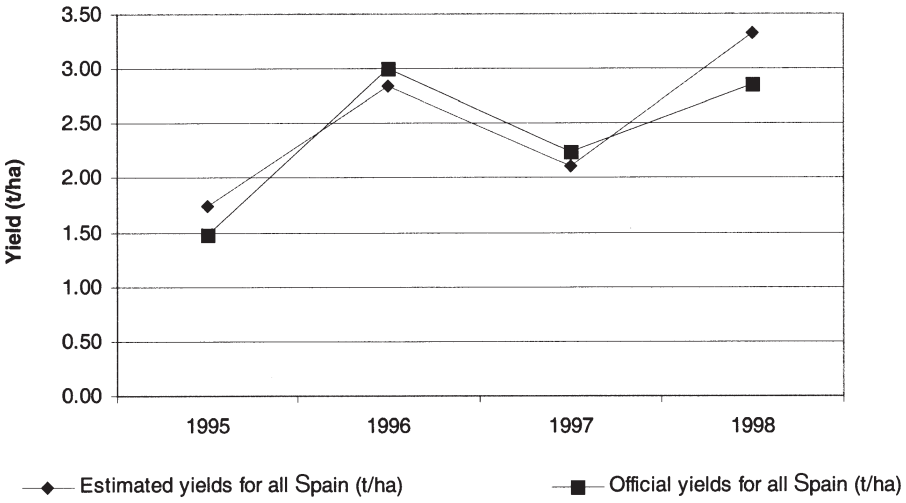

Figure 11. Comparison of dynamics between official and estimated national yields.

than simple linear ones are being tested. The experience is progressing to test multiple linear regressions taking into account several indicators based on CNDVI, like the integrated CNDVI, the maximum CNDVI, the decade when the maximum CNDVI occurs, the regionally averaged rainfall, the latitude of regions. Indeed, Cabezon and Taylor [3], Groten [9], Quarmby et al. [17] and Ruddorf and Batista [19] have shown the usefulness of the integration of meteorological parameters to improve the prediction of yields.

Acknowledgements: The authors would like to thank M. S. Peedel and M. P. Schiphorst of JRC and M. I. Cerrani of Object Way who contributed to realising the CNDVI preparation and extraction.

References

[1] Benedetti R., Rossini P., On the use of NDVI profiles as a tool for agricultural statistics: the case study of wheat yield estimate and forecast in Emilia Romagna, Remote Sens. Environ. 45 (1993) 311–326.

[2] Boissard P., Pointel J.G., Leterme Ph., Belluomo P., Renard D., Estimation du rendement du blé en Beauce à partir de données SPOT multidates, Bull. S.F.P.T. 114 (1989) 45–48.

[3] Cabezon M.P., Taylor J.C., Modèle de Prévision des rendements de blé et d'orge en Andalousie, in: Proceedings of the Yield Forecasting Seminar, Villefranche-Sur-Mer, France (Eurostat-JRC-DGVI-FAO, 24–27 October 1994), 1994, pp. 469–478.

[4] Delécolle R., Baret F., Guérif M., Maas S.J., L'utilisation conjointe de la télédétection et des modèles

d'estimation des productions agricoles : tendances actuelles, in: Proceedings of the 5th International Colloquium – Physical Measurements and signatures in Remote Sensing, Courchevel, France, 14–18 January 1991, pp. 529–534.

[5] Doraiswamy P.C., Cook P.W., Spring wheat yield assessment using NOAA AVHRR data, Can. J. Remote Sens. 21 (1995) 43–51.

[6] ETC-LC - European Topic Centre on Land Cover, Workshop on land Cover Applications, Needs and Use, Proc. Eur. Environ. Agency, Copenhagen, 1997.

[7] Genovese G., The methodology and the results of the MARS bulletin: an integrated crop production assessment and forecast bulletin, in Agrometeorological Applications for regional crop monitoring and production assessment, Vossen-Rijks-Terres editors, EUR 17735 EN, 1998, Chap. 5, pp. 67–116.

[8] Genovese G., Vignolles C., Nègre T., Passera G., NOAA-AVHRR/NDVI profiling on CORINE land cover classes, in: Proceedings of IGARSS'99, Hamburg, Germany, 28 June–2 July 1999, pp. 2345–2347.

[9] Groten S.M.E., NDVI-crop monitoring and early assessment of Burkina Faso, Int. J. Remote Sens. 14 (1993) 1493–1515.

[10] Guérif M., Utilisation des indices de végétation issus de données SPOT pour estimer la biomasse et le rendement de cultures de blé dur, Bull. S.F.P.T. 114 (1989) 49–52.

[11] Hatfield J.L., Remote sensing estimators of potential and actual crop yield, Remote Sens. Environ. 13 (1983) 301–311.

[12] Heymann Y., CORINE land cover technical guide, European Commission, Luxembourg: Office for Official Publications of the European Communities, ISBN 92-826-2578-8, 1994.

[13] Holben B.N., Characteristics of maximum-value composite images from temporal AVHRR data, Int. J. Remote Sens. 7 (1986) 1417–1434.

[14] Laguette S., Vidal A., Vossen P., Using satellite into productivity model, in: Proceedings of IGARSS'95, Firenze, Italy, July 1995, pp. 1465–1467.

[15] Moulin S., Bondeau A., Delécolle R., Combining agricultural crop models and satellite observations: from field to regional scales, Int. J. Remote Sens. 19 (1998) 1021–1036.

[16] Perdigao V., Annoni A., Technical and methodological guide for updating CORINE land cover data base, Publication of the European Commission JRC-EEA, EUR 172888 EN, Brussels, 1997.

[17] Quarmby N.A., Milnes M., Hindle T.L., Silleos N., The use of multi-temporal NDVI measurements from AVHRR data for crop yield estimation and prediction, Int. J. Remote Sens. 14 (1993) 199–210.

[18] Rossini P., Terpessi C., Utilisation des données NDVI/AVHRR pour la prévision du rendement du blé dans l'Italie du Sud, in: Proceedings of Méthodes de Prévision de Rendements Agricoles, Villefranche-Sur-Mer, France, (Eurostat-JRC-DGVI-FAO, 24-27 October 1994), 1994, pp. 439–445.

[19] Rudorff B.E.T., Batista G.T., Wheat yield estimation at the farm level using TM Landsat and agrometeorological data, Int. J. Remote Sens. 12 (1991) 2477–2484.

[20] Taylor J.C., D'Souza G., Coleman V.R., Vegetation conditions and yield indicators in England and Wales using NOAA-AVHRR data, in: Proceedings of the Conference on the application of remote sensing to agricultural statistics, Belgirate, Italy, (EUR 14262 EN, 26-27 November 1991), 1991, pp. 249–256.

[21] Tucker C.J., Holben B.N., Elgin J.H., McMurtrey III J.E., Relationship of spectral data to grain yield variation, Photogrammetric Eng. Remote Sens. 46 (1980) 657–666.

[22] Tucker C.J., Vanpraet C.L., Sharman M.J., Van Ittersum G., Satellite remote sensing of total herbaceous biomass production in the Senegalese Sahel: 1980-1984, Remote Sens. Environ. 17 (1985) 233–249.

[23] Verstraete M., Pinty B., Designing Optimal Spectral Indexes for Remote Sensing Applications, IEEE Trans. Geosci. Remote Sens. 34 (1996) 1254–1264.

[24] Vignolles C., Modélisation de la production agricole à moyenne échelle – Apport du couplage des mesures par satellite à haute résolution spatiale et à haute fréquence temporelle, thèse de Doctorat, Université Paul Sabatier, Toulouse, France, 1996, pp. 29–48.

[25] Vignolles C., Genovese G., Nègre T., On the use of CORINE land cover and NOAA-AVHRR/NDVI profiles for crop yield forecasting, in: Proceedings of

International Symposium Modelling Cropping Systems, Lleida, Spain, 21–23 June 1999, pp. 83–84.

[26] Vogt J., The use of low-resolution satellite data for crop states monitoring. Possibilites and limitations, in: Proceedings of the workshop for Central and Eastern Europe on Agro-meteorological models: Theory and Applications in the MARS project (EUR 160008 EN), 1994, pp. 223–240.

[27] Willekens A., Orshoven J.V., Feyen J., Estimation of the phenological calendar, Kc-curve and temperature sums for cereals, sugar beet, potato, sunflower and rapeseed across Pan Europe, Turkey and the Maghreb countries by means of transfer procedures, Volume 1: Project Report, Ground for GIS, Katholicke Universitet Leuven Research and Development, 1997, 61 p.