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# Use of SPOT<sub>4</sub>-VEGETATION satellite data to improve pasture production simulated by STICS included in the ISOP French system

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**Abstract** – In France, pastures represent a significant land-cover type, which mainly sustains husbandry production. For this reason, it is of great benefit to develop real-time monitoring of pasture biomass production, taking into account its spatial and temporal variability. The absence of low-cost methods applicable to large regions has oriented French stakeholders to the use of growth simulation models adequately informed through spatialised databases (such as the ISOP system). Remote-sensing data may be considered a potential tool to improve simulations by objective observations in a real-time framework and the aim of this work was to evaluate this potential role of remote sensing. Thirteen forage regions (administrative partitioning of the French territory for pastures and grasslands) were selected in France, differing by their soil, climatic and land-cover characteristics. SPOT<sub>4</sub>-VEGETATION satellite images (1 km<sup>2</sup> resolution) were used to provide the spectral signature corresponding to pure pasture, using subpixel estimation methods. This information was then related to growth variables calculated by the STICS-pasture model (included in the ISOP system). We found that the best relations were obtained between a middle infrared-based vegetation index (SWVI) calculated from the elementary reflectance bands of the satellite, and the leaf area index (LAI) calculated from STICS. The use of these relations first showed the ability of satellite data to provide real-time estimations of growth status variables. Second, the comparison between both types of data showed that spatial and temporal differences existed between satellite and model information, mainly during the harvesting periods. This result could contribute to improving the model evaluations on a regional scale.

**pastures / remote sensing / vegetation index / biomass production / STICS / regional scale**

## 1. INTRODUCTION

The monitoring of pasture has a strategic impact on a national scale. For instance, it can allow the organisation of forage transfers between regions submitted to various drought conditions or the giving of objective elements for applying subsidy policies after extreme climatic events such as drought (the year 2003 is a good example). In fact, this kind of preoccupation is typical of national or European institutions (for example, the Central Service of Investigations and Statistical Studies in France-SCEES or the Joint Research Centre at the European Union level-JRC). However, the high spatial and temporal variability of pasture conditions, the small amount of readily available information, and the absence of forage economical traceability through specific markets, make it difficult to apply real-time alert systems to prairie production.

Some research groups are developing different methods to establish biomass production of pastures in a precise, economic and fast way. Biomass cutting is a simple method for estimating biomass production [54, 61] but this technique is limited by being time-consuming and costly, all the more because the amount of required measurements to produce a reliable evaluation at a national level is high. For these reasons, it is of great

benefit to develop indirect techniques to estimate functional prairie features, such as biomass, net primary productivity (NPP) or leaf area index (LAI).

In recent years, growth simulation models have allowed methodological and operational progress in this domain. Pasture modelling has been the objective of different research groups [1, 18, 39, 47, 56, 62]. The STICS model developed at INRA [11] was adapted to pasture conditions by adding specific functions to simulate pasture characteristics [50]. The ISOP system (*Information et Suivi Objectif des Prairies*) was developed thanks to collaboration between INRA and Meteo-France with the financial support of the SCEES. It consists of the STICS-pasture model properly connected to soil, climate and technical databases through a Geographical Information System. The ISOP system aims at estimating pasture growth variables, taking into account water and nitrogen budgets in order to identify water-deficient years as early as possible in the season as compared with a 16-year average. Current problems come less from the reliability of the model than from the input data variability to inform the forage regions or FR [16, 49, 51]. No actual validation has been possible because of the lack of existing ground truth data on this scale.

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Remote sensing offers interesting perspectives to enhance the achievements of simulation models, particularly the use of spatial and repetitive information provided by sensors with different spatial resolution. The use of remote sensing for prairie monitoring has been focused mainly on species and plant community identification [6, 15, 26, 33, 36, 55] and on surveying their geographical distribution [3, 22, 33, 42]. Also, several investigations have demonstrated the existence of a strong relationship between satellite information (principally from the NOAA-AVHRR satellite) and biomass or net primary productivity (NPP) for different regions and ecosystems worldwide [10, 12, 23, 27, 40, 41, 43, 53, 63]. Other studies have tried to identify drought periods or dry zones [57]. The major benefit of remote-sensing data lies in the possibility of getting spatially continuous information with a reasonable time period and cost. It also appears to be a unique tool for obtaining actual observations of crop status while models only offer a virtual estimation of it. It was decided to use VEGETATION sensor data (launched in April 1998 on the SPOT<sub>4</sub> platform) in combination with outputs from the ISOP system to propose a national pasture survey in France. Therefore, the present work consists of exploring the possibilities of improving pasture productivity estimation at a regional resolution, by associating measurements provided by remote sensing and simulation results. In a first stage, we estimated pure pasture spectral responses from the radiometric information of pure pasture pixel at the resolution of 1 km<sup>2</sup>. After obtaining the spectral response of pure prairie for different dates and regions we submitted the satellite indicators of some biophysical variables, such as LAI or biomass, to estimation from the ISOP system using the STICS growth model. Finally, we analysed the possibilities offered by coupling the model and remote-sensing data.

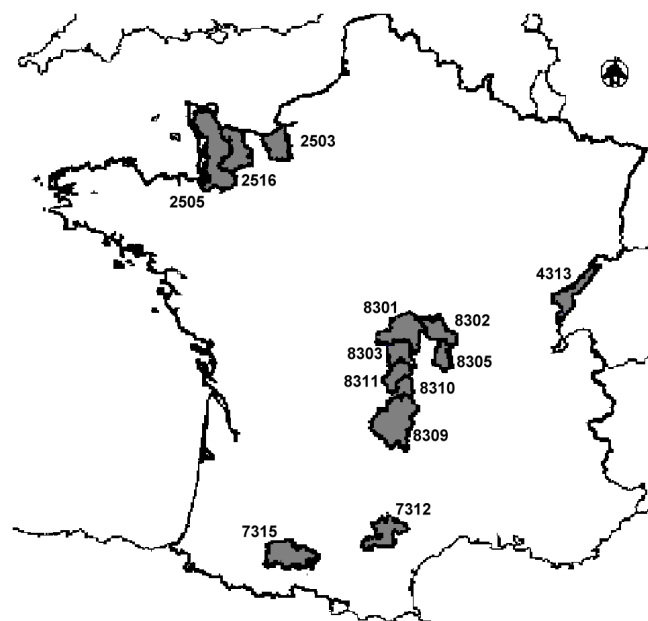
## 2. MATERIALS AND METHODS

### 2.1. Study areas

The spatial resolution used in the ISOP system, also used in this work as the elementary model resolution, comes from an administrative partitioning of the French territory: the Forage Region (FR). In order to limit the work volume (the whole territory is covered by 200 FRs), we chose FRs representing most of the pasture production, climate and topography conditions (Fig. 1): 2503, 2505 and 2516 (Normandy Region); 4313 (High Jura Region); 7312 and 7315 (Southern France Pyrenees Region) and 8301, 8302, 8303, 8305, 8309, 8310 and 8311 (Central Plains Region). As far as remote-sensing resolution is concerned, each FR is characterised by a window of 25 km<sup>2</sup> (5 × 5 pixels of 1 km<sup>2</sup>), and each window (pasture proportion and accompanying crop) is described in Table I.

### 2.2. Satellite data and the subpixel estimation

We used SPOT<sub>4</sub>-VEGETATION sensor data acquired during 1999 and 2000. All these images were geo-referenced and co-registered in latitude/longitude projection. The data were received as S products (integrating available atmospheric corrections as 10-day synthetic data) [7, 45]. All images were received in HDF format (16 bits) and transformed into radio-



**Figure 1.** Thirteen forage regions (FR) selected as study areas in France.

**Table I.** Window characteristics inside each one of the selected FRs. PP = pasture proportion.

FR	PP (%)	Accompanying Crop / (%)
2503	80	Cultures complexes / 7
2505	96	Turbe / 2
2516	85	Complex Crops / 11
4313	57	Conifer Forests / 20
7312	50	Forests / 26
7315	41	Complex Crops / 35
8301	69	Complex Crops / 13
8302	60	Complex Crops / 16
8303	54	Complex Crops / 15
8305	55	Complex Crops / 17
8309	85	Agriculture / 7
8310	59	Conifer Forests / 15
8311	60	Agriculture / 15

metric values, coded on 8 bits (0–255) (© ENVI 3.1). This treatment allowed us to reduce the file size and computing time as well. However, this transformation altered the original reflectance values while keeping the whole spatial and temporal dynamics.

In a SPOT<sub>4</sub>-VEGETATION image, every pixel integrates the spectral signatures of each land-cover type included in a pixel (1 km<sup>2</sup>). For the particular case of the VEGETATION sensor, this integration corresponds to a mean reflectance value in the blue (B<sub>0</sub>), red (B<sub>2</sub>), near-infrared (B<sub>3</sub> or NIR) and middle infrared (B<sub>4</sub> or MIR) bands from the electromagnetic spectrum. This integration results in a mixed value representing many land-cover types. To recover the spectral response of a specific

land-cover type, it is recommended to apply subpixel techniques, as described by several authors [8, 29, 44]. In France, Fischer [20] studied the temporal evolution of NDVI for pure cultures from mixed pixels while using an empiric model for all land use, assuming a double logistical function for the NDVI evolution. From the mixed spectral values and land use, it is possible to recover every double logistic parameter. Later, Kerdiles and Grondona [31] and Faivre and Fischer [19] assumed that the spectral variability within the mixed pixels was only due to land use. Using a linear model, every pure response was derived from the mixed reflectance, considering that the reflectance of a mixed pixel is the linear combination of the reflectance of each elementary pixel multiplied by its respective proportions within the pixel.

In order to achieve the pixel decomposition data from the SPOT<sub>4</sub>-VEGETATION sensor data (1 km × 1 km), corresponding to the window area, we adapted the model developed by Faivre and Fischer [19] with a specific programming format (© Matlab). This model requires two types of input data to get pure spectral responses of every land-cover type inside a pixel of 1 km<sup>2</sup>: (a) the proportion of each land-cover type per pixel, and (b) the reflectance values of mixed pixels in the different bands. Thus, for the 25 pixels selected from each FR (window), we firstly calculated the proportion of every land-cover type in the pixel, using the Corine Land Cover database (1989–1994). Secondly, for each pixel and date, we extracted the spectral data: B<sub>0</sub>, B<sub>1</sub>, B<sub>2</sub>, B<sub>3</sub> and B<sub>4</sub>. We generated the mean reflectance value for the different land uses in the pixel and the corresponding estimated variance as from these data, applying the subpixel estimation methodology, for every date and spectral band.

We tested the performance of several vegetation indices, using the spectral response of pure grassland estimations, as vegetation indices are not all as good for explaining structural and functional features of vegetation, such as green biomass and LAI [4, 9, 21, 25, 35, 58, 65] as well as net primary productivity [34, 41]. Those indices are the NDVI, the SAVI (Soil Adjusted Vegetation Index, [28]) or PVI (Perpendicular Vegetation Index, [46]) that takes into account soil effects, and the SWVI (Middle Infrared-based NDVI, [13]) or the ARVI (Atmospherically Resistant Vegetation Index, [30]) that reduces the effects of atmospheric absorption (Tab. II). Linear and exponential-type relationships between the best index and the simulated LAI were then tested.

### 2.3. STICS-pasture model and the ISOP system

The ISOP system provides pasture productivity estimates on the Forage Region (FR) scale using the STICS simulation model [51] which simulates daily values of Leaf Area Index (LAI) in m<sup>2</sup> leaf m<sup>-2</sup> soil, standing biomass (MSEC), in g dry matter m<sup>-2</sup> and dry matter Productivity (DMSEC) in kg ha<sup>-1</sup> day<sup>-1</sup> as growth variables of the system. Some stress indicators are also available as model output, such as the available soil water storage (RES) in mm, and water and nitrogen-stress indices (TURFAC) and INNS as defined in [11]. The STICS model estimated those variables for the possible pasture management variables, fertilisation levels and soil types. The simulated value corresponding to each FR resulted from weighting all possible combinations considering their relative importance to the FR.

**Table II.** Vegetation Indices generated from the different spectral bands. B<sub>0</sub> = blue band, B<sub>2</sub> = red band, B<sub>3</sub> = near-infrared band and B<sub>4</sub> = middle infrared band.

Index	Formula	Reference
NDVI		[48]
Normalised Difference Vegetation Index	$NDVI = \frac{B_3 - B_2}{B_3 + B_2}$	
PVI	$PVI = \frac{(B_3 - B_2 \times 1.2)}{\sqrt{1 + 1.2^2}}$	[46]
Perpendicular Vegetation Index		
SAVI	$SAVI = \frac{(B_3 - B_2)}{(B_3 + B_2 + 0.5)}(1.5)$	[28]
Soil Adjusted Vegetation Index		
SWVI	$SWVI = \frac{B_3 - B_4}{B_3 + B_4}$	[13]
Middle Infrared-based NDVI		
ARVI	$ARVI = \frac{B_3 - B_0}{B_3 + B_0}$	[30]
Atmospherically Resistant Vegetation Index	If the atmospheric factor is 1	

### 2.4. Assimilation data

The Monteith model [37] is one of the simplest and most popular models for assimilating remote-sensing data. In our study, this model, based on the concept of radiation-use efficiency, will allow the estimation of biomass productivity using different data sources: LAI provided by the STICS-pasture model or LAI estimated by remote-sensing data [2]. In this way, to estimate dry matter production for the day *j* (DMS<sub>*j*</sub> in g·m<sup>-2</sup>), we used the following algorithm (Fig. 2):

$$\Delta MS_j = \varepsilon_b \times \varepsilon_{ij} \times \varepsilon_c \times GR_j$$

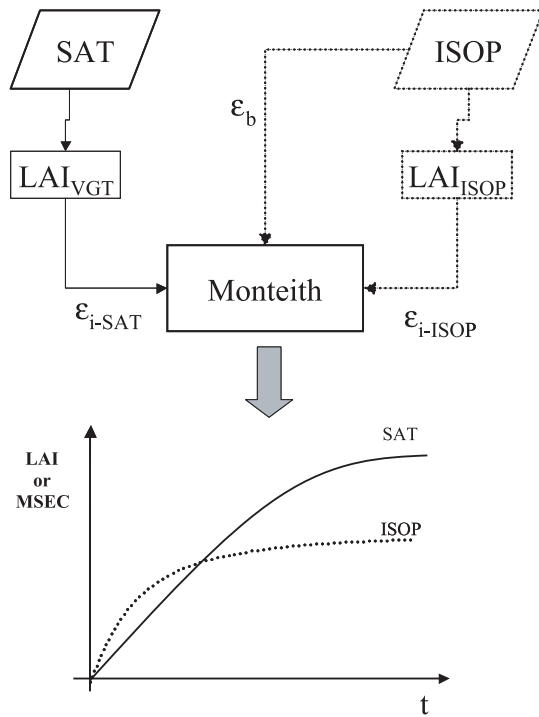
where  $GR_j$  is the global radiation (MJ·m<sup>-2</sup>),  $\varepsilon_c$  stands for climatic efficiency (no units),  $\varepsilon_b$  is the growth efficiency (g·MJ<sup>-1</sup>) and ( $\varepsilon_{ij}$ ) is the intercepted radiation efficiency (no units). GR was obtained directly from meteorological weather stations reported by Meteo-France and interpolated to the FR scale for 1999 and 2000. The climatic efficiency value was fixed to 0.48 [64]. Growth efficiency, that was considered constant for long periods of time (season) and in non-limiting soil conditions [32], was set to 1.8 (g/MJPAR) for the whole growing season (February–October) [5, 17]. Finally, the intercepted radiation efficiency was indirectly estimated using LAI with a Beer-law-type relationship [38]:

$$\varepsilon_{ij} = \varepsilon_{i\max} (1 - e^{-kLAI_j})$$

where  $\varepsilon_{ij}$  is the intercepted radiation,  $\varepsilon_{i\max}$  is the maximal interception of  $\varepsilon_{ij}$  (no units),  $k$  is the extinction coefficient (0.55) and  $LAI$  is the Leaf Area Index. In our case, the  $LAI$  will be provided either by the STICS model ( $LAI_{isop}$ ) or by inversion of reflectance data ( $LAI_{vgt}$ ).

## 3. RESULTS

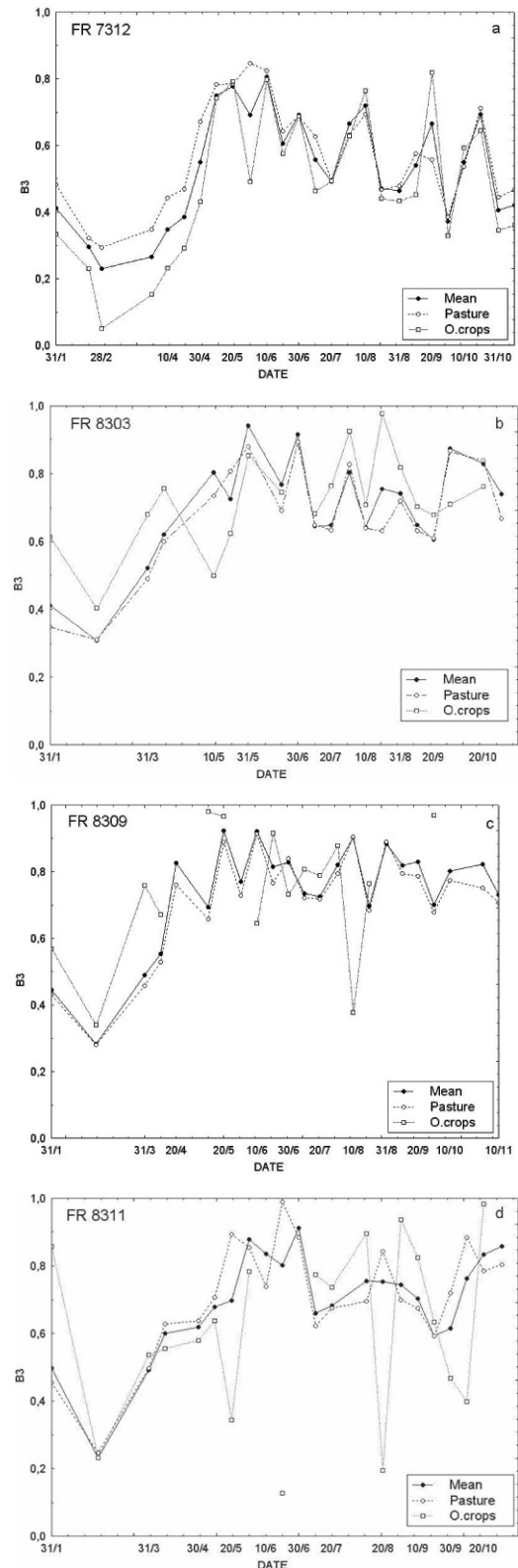
We obtained the spectral response corresponding to pure pasture conditions inside each pixel (Fig. 3) using the subpixel



**Figure 2.** Schedule of assimilation procedure using remote-sensing data (SAT) or simulated growth data (ISOP).

model [19], for every FR and date. Comparing the different FRs, it is possible to evaluate the influence of prairie proportion and the type of accompanying crop inside each pixel. In general terms, all FRs showed a good correspondence in the temporal evolution of radiometric values of  $B_3$  between mean pixel values and those corresponding to the pure prairie estimations. However, depending on pasture proportion or the accompanying crops in the pixel, the subpixel estimations resulted in different seasonal spectral values.

Once we obtained the pure pasture conditions, and considering the set of variables obtained from the STICS-pasture simulation model, we found that LAI and MSEC were the best correlated to most satellite indices (Tab. III). These results, in agreement with Sellers [60], showed the potentiality of vegetation indices to describe vegetation status and, mainly, to join them to fluxes such as photosynthesis or net primary productivity. The SWVI vegetation index was the best correlated to growth estimations. The relationship of SWVI with LAI presented a correlation coefficient of 0.55, and with MSEC of 0.40, for a total of 594 cases, that showed the benefit of the MIR spectral band. This band not only corresponds to a sensible portion of water content in leaves, but also to dry matter content and leaf internal structure [14], showing (as a result) that SWVI is less sensitive than the NDVI to atmospheric effects. Another explanation could also be the one described by Guérif [24]. In that work, based upon the PVI, the  $PVI_{mir}$  calculated from the MIR band resulted in a better estimation of the LAI as compared with the PVI, calculated from the visible band ( $PVI_{vis}$ ). The



**Figure 3.** Evolution of the infrared values (digital counts) ( $B_3$ ) during January–October 1999 for four forage regions (a: FR 7312; b: FR 8303; c: FR 8309 and d: FR 8311). (●) Mean values of the 25 pixels in each pilot zone; (○) pasture values estimated from the subpixel model; and (□) main accompanying crop.

**Table III.** Correlation coefficients between satellite and production variables during the 1999 and 2000 experiments.

SAT. / ISOP.	LAI	MSEC	RES	TURFAC	INNS	DMsec
B0	.1772	.0114	-.0568	-.0793	.0242	-.0548
B2	.1581	.0015	-.1093	-.1163	-.0086	-.0832
B3	.4190	.2299	-.0673	-.0667	-.1261	.0622
B4	-.0417	-.1146	-.0539	-.1041	-.0293	-.0699
NDVI	.0608	.1626	.1334	.1130	-.0435	.1923
SWVI	.5540	.4041	-.0544	.0060	-.1208	.1498
B3DB4	.4289	.3409	.0107	.0540	-.1569	.0977
SAVI	.3649	.2633	.0272	-.0067	-.1211	.1494
PVI	.4283	.2862	-.0184	-.0134	-.1523	.1276
ARVI	-.0253	.1160	.1231	.1047	-.0581	.1403

authors found that the  $PVI_{vis}$  is considerably influenced by differences observed in chlorophyll concentration in the leaves.

After having established that the *SWVI* vegetation index is the best descriptor of the biophysical variables characterising prairie production (LAI or MSEC), a general linear regression between *SWVI* and *DMLAI* allowed the establishment of the following linear function (Standard Deviation = 1.85,  $P < 0.005$ ,  $R^2 = 0.32$ ):

$$LAI = 3.256 + 6.141 \times SWVI$$

which allows the derivation of LAI values from *VEGETATION* data. The comparison with LAI values produced by the *ISOP* model displayed an underestimation of lower values and an overestimation of higher ones. In order to improve this first attempt, an exponential relationship between vegetation indices and LAI was considered [25, 52, 59]. In a first approach, we defined a basic relation as:

$$SWVI = SWVI_{\max} + (SWVI_{\min} - SWVI_{\max})e^{-kLAI}$$

considering, for the first time, a  $k$  value of 0.55,  $SWVI_{\min}$  of -0.357 and  $SWVI_{\max}$  of 0.828 (obtained from the database).

After using an iterative procedure to reduce the mean quadratic error for a total of 7005 cases during March–October 1999 and 2000, and keeping a maximal value for the  $LAI_{isop}$  of 8 and *SWVI* between 0.828 and -0.357, we calculated the  $k$  value that minimises the sum of quadratic errors between  $LAI_{vgt}$  and  $LAI_{isop}$  (Initial  $k$  of 0.55). The  $k$  value determined by this optimisation procedure ( $k = 0.215$ ) was therefore kept for the *SWVI* relation =  $f(LAI)$ . The application of this relation allowed the improvement of the linear relationship by increasing the internal data dynamics and decreasing the minimal LAI value during the winter period for the satellite values. In detail, it is also possible to observe, in the first place, that  $LAI_{vgt}$  is different in both growing seasons; while this is not observed for the  $LAI_{isop}$  (Fig. 4). For both studied years and different FRs, the agreement between LAI estimations is highly variable (Fig. 4). At the beginning of the growing season, the LAI is underestimated by *ISOP* in Normandie (FR 2503) and Piémont Pyrénéen (FR 7315), and overestimated in one small area of the Central Plains (FR 8310). In the middle of spring (March to May), before the first cuts, the agreement is quite good. From June to September,

the cuts do not occur exactly on the same date with both methods. Finally, by the year's end, especially in 1999, *ISOP* values are higher than those derived from satellite data. At the beginning of the growing season, the *ISOP* system assigned the same LAI values for all the areas, whatever the local climate. In this case, *VEGETATION* images can supply information to vary initial growth conditions between FRs.

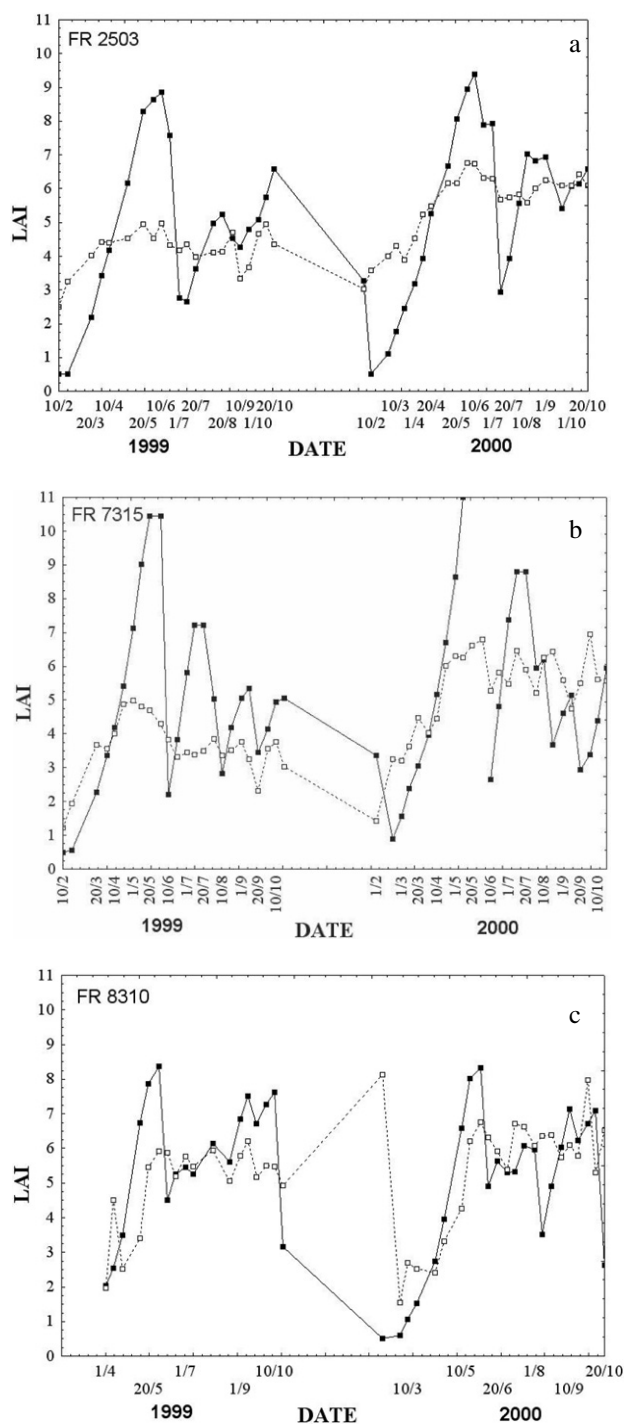
Satellite information can also be useful to establish cutting dates, especially in areas smaller than the FR. In the *ISOP* system, these dates are only estimated as from grass management systems (e.g. hay and silage) and growing degree days between successive cuts, without taking into account rainy events delaying harvest, or local technical changes.

As from the established relation, it was possible to try a simple assimilation approach. LAI calculated from satellite data and the LAI values in the *ISOP* procedure were assimilated into the Monteith model. As a result, the daily production of MSEC was calculated for every FR and date during 2000. Figure 5 presents the difference between MSEC calculated from satellite data ( $MSEC_{vgt}$ ) and MSEC obtained from the *STICS* model within the *ISOP* system ( $MSEC_{isop}$ ). This result confirmed that the *SWVI/LAI* relation could be applied to introduce the satellite information when it appears significant. While analysing the evolution of the differences between  $MSEC_{vgt}$  and  $MSEC_{isop}$  values for the different FRs, there is a period in June with large differences in plain zones, especially in the Piémont Pyrénéen (FR 7315) and in mid-July, in the mountain zones (FR 8310 – Fig. 5). The *ISOP* underestimation can proceed from poor attribution of pastures to soil types.

#### 4. CONCLUSIONS

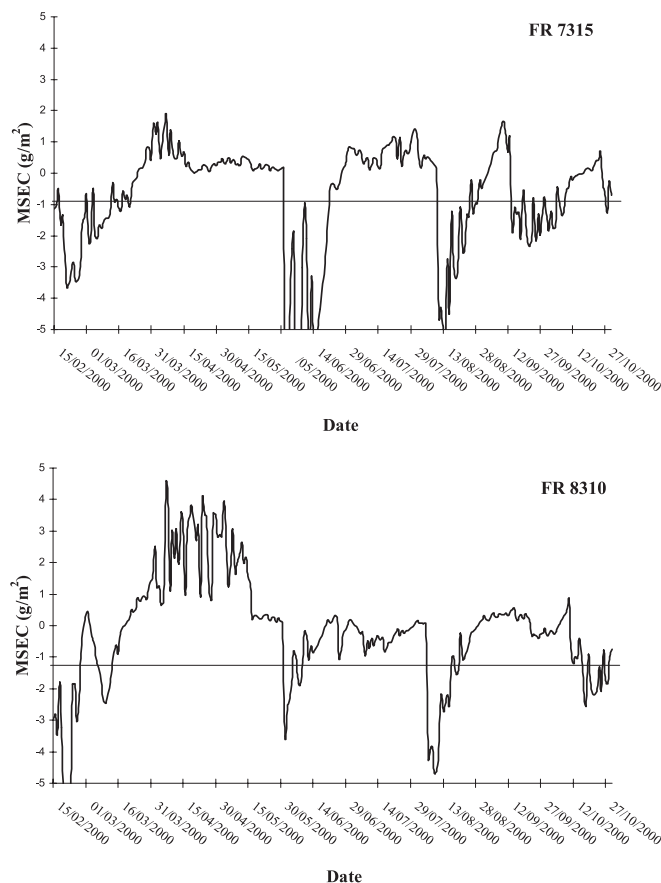
With the objective of elaborating an evaluation tool for grassland production, adapted to a regional scale, it was confirmed that the use of low spatial resolution sensors, such as *VEGETATION*, is promising. They deliver significant aggregated information with a high temporal resolution. The model developed by Faivre and Fischer [19], and adapted for the objectives of this work, proved to be a very useful and accurate tool for obtaining spectral responses, while taking into account the big spatial variability of information captured in the different wavelengths. It is important to notice that the usefulness of





**Figure 4.** Temporal evolution of LAI estimated from satellite data (LAI<sub>VGT</sub>-dashed line) and LAI simulated by the STICS-pasture model (LAI<sub>ISOP</sub>-continued line) for 1999 and 2000 for the FRs 2503, 7315 and 8303.

VEGETATION could be enhanced by the possibility of getting the same spectral information at high spatial resolution (10 metres with the HRV-SPOT sensor). This characteristic, which confers upon the VEGETATION sensor a unique advantage over other available sensors, was not tested in our study, but it could



**Figure 5.** Temporal evolution of the difference between dry matter (MSEC) simulated in the ISOP system (MSEC<sub>ISOP</sub>) and estimated from VEGETATION data (MSEC<sub>VGT</sub>), only for the year 2000, for the FRs 7315 and 8310.

undoubtedly greatly increase the validity of pure pasture signatures.

Disaggregated information in the near-infrared and middle infrared bands corresponding to pure pasture conditions showed an acceptable correspondence with the temporary evolution of some productive variables such as the LAI and dry matter. This correspondence was improved appreciably by the calculation of vegetation indices, through band combination and normalisation of the strips that compose them (for example, SWVI). These interrelationships were significantly improved by applying an exponential function and selecting periods where temporary discordances do not exist within the model.

Satellite information, through its relationship to biophysical variables such as the LAI, gives a unique measure of the true dynamics of plant cover. Evaluations from satellite data agree with the model evaluations; however, some differences highlight some of the limits of a real-time framework. The forcing assimilation methods used in this paper allow the achievement of a real complementarity between remote sensing and the simulation model, and in the representation of annual dynamics (cutting and beginning of growth dates' representation). Also, more sophisticated methods, such as re-standardisation, would

permit the estimation, region by region, of some STICS parameters using remote-sensing data, specially for the variables involving winter or cuts' re-growth (initial LAI), or the determination of cutting dates (sum of temperatures). Some divergences from the ISOP evaluations in relation to remote sensing could probably be attributed to the evaluation of some input variables (for example, soil water reserve).

Finally, it is important to highlight that even if remote sensing could not be considered as a direct reference for validation, the results obtained make the usefulness of this kind of information evident on a local scale, as well as the potentialities for the development of a combination method between the model and remote-sensing data.

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