

## AGROPHENOLOGY INDICATORS FROM REMOTE SENSING: STATE OF THE ART

Y. Curnel and R. Oger

CRA-W, Walloon Agricultural Research Centre, 9 rue de Liroux, 5030 Gembloux, Belgium –  
(curnel, oger)[@cra.wallonie.be](mailto:)

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### ABSTRACT:

Monitoring phenology at a regional, national or at a global scale is recognized by the scientific community as very important for many practical applications and notably for climate change studies. Phenological observations are classically realised for specific plant species in botanical garden or in small study areas or fields all over the world and sometimes date back to the 19<sup>th</sup> century. Although these observations are very interesting for studying the trends in phenology over time and their drivers, they are punctual and provide therefore only little information on its spatial variability. In this context, remote sensing information and especially low resolution sensors through their broad spatial resolution can provide additional information on phenology and allow creating dynamic maps of vegetation development. Different remote-sensed indicators for assessing vegetation phenology, for the most part based on smoothed NDVI curves, have already been proposed in various studies. These indicators are computed on moving averages, NDVI thresholds, logistic curves or maximum rate of changes. The phenological metrics directly derived from RS information are generally the start and the end of the growing season and also the moment of maximum greenness. Other RS phenological indicators are often derived from these metrics as, for example, the length of the growing season. RS phenological metrics can also be used as input variables in dynamic simulation models. These models unfortunately failed in non-optimal conditions (e.g. in case of damaging frost, hail, drought...). Remote sensing data could possibly be used to re-calibrate and re-adjust these models.

### 1. INTRODUCTION

Monitoring phenology at a regional, national or at a global scale is recognized by the scientific community as very important for many practical applications and notably for climate change studies. Analysis of spatial and temporal variations in the beginning and the end of the growing season can be used for example to determine regional variations and trends of the change in temperature and precipitation regimes. In agriculture, the accurate monitoring of crop development patterns represents an important component of farm management since it allows assessing if the most critical stages of growth occur during periods of favourable weather conditions.

Phenological observations are classically realised for specific plant species in botanical garden, in small study areas or fields all over the world and sometimes date back to the 19<sup>th</sup> century. Although these observations are very interesting for studying the trends in phenology over time and their driving factors, they are punctual and provide therefore only little information on the spatial variability.

In this context, remote sensing information can provide valuable information on phenology and allow creating dynamic maps of vegetation development.

Monitoring phenology through remote sensing is not a novelty. The idea was already suggested more than 25 years ago by Tucker *et al.* (1979). Since that time, different techniques have been proposed in literature. These different techniques can be arbitrarily classified in different categories. A distinction can be indeed made between techniques based on thresholds (Justice *et al.*, 1985; Runtunuwu & Komdoh, 200; White *et al.*, 2002; Wang & Tenhunen, 2004), derivatives (Kaduk & Heiman, 1996; Xin *et al.*, 2002; Viña *et al.*, 2004) logistic curves (Badhwar,

1984; Zhang *et al.*, 2003), moving averages (Reed *et al.*, 1994; Brown *et al.*, 2002; Schwartz *et al.*, 2002) and empirical equations (Moulin *et al.*, 1997).

These different techniques derived from literature are based, for the most part, on NDVI time series (Swets *et al.* 1999). These NDVI time series needs to be smoothed prior to the use of these techniques in order to reduce at the most the remaining noises in remote sensing products.

The aforementioned techniques have been applied for different vegetation types as field crops (Xin *et al.*, 2002; Viña *et al.*, 2004), forests (Zhang *et al.*, 2003; Schwartz *et al.*, 2002) or as savannah, shrublands... (Runtunuwu & Komdoh, 2001; Wang & Tenhunen, 2004).

This paper will present first of all briefly the different possible techniques used to smooth vegetation index (VI) time series (mainly NDVI). The different indicators that can be derived from these time series in order to monitor will be then presented as well as the different techniques proposed in literature to derive these indicators.

### 2. SMOOTHING METHODS TO REDUCE NOISE IN NDVI TIME SERIES

There are many complications, limitations and causes of error associated with satellite data, including sensor resolution and calibration, digital quantization errors, ground and atmospheric conditions as well as orbital and sensor degradation. NDVI data sets are generally well-documented and quality-controlled data sources that have been pre-processed to reduce many of these problems.

However, some noise is still present in the remote sensing data sets and, therefore, NDVI time-series need to be smoothed

before being exploitable. Such noise is mainly due to remnant cloud cover, water, snow, or shadow. These sources of errors tend to decrease the NDVI values. False highs, although much less frequent, can also occur at high solar or scan angles (in which case the numerator and denominator in the NDVI ratio are both near zero) or because of transmission errors, such as line drop-out. To minimize the problem of false highs, the remote-sensed products are generally based on low-angle observations wherever possible.

Most errors thus tend to decrease NDVI values. This unusual error structure, with high NDVI values being more trustworthy than low ones, breaks the assumptions of many standard statistical approaches. Further complications can arise because the error structure can vary in time and space (Pettorelli *et al.*, 2005).

Different smoothing methods exist to reduce noise in NDVI data. Some of these techniques are presented below.

#### *Maximum value compositing (MVC) method*

The maximum value compositing method (Holben, 1986) is certainly the easiest one. NDVI value for a compositing period is the highest NDVI value observed during this period (generally 1 decade or 1 month). The time period is a trade-off: a longer period decreases the amount of cloud interference, but it means missing short-term variations.

This method minimises data gaps in any particular composite image due to cloud interference or missing data and overcomes some of the systematic errors that reduce the index value. However, the procedure would be biased by a single false high (Pettorelli *et al.*, 2005)

#### *Curve-fitting method*

The curve-fitting method, initially developed by van Dijk *et al.* (1985), aims at fitting a polynomial or Fourier function to the NDVI time-series. The shortcoming of the polynomial and Fourier smoothers is that they only determine the general shape of the curve, rather than pinpointing particular cycles. The Fourier series smoother must also be rerun over the entire time series each time a new data point is added.

#### *Step-wise logistic regression method*

This method was initially developed by Zhang *et al.* (2003). These authors pretend that the bell-shaped NDVI curves can be represented using a series of piecewise logistic functions of time.

#### *Best Index Slope Extraction (BISE) method*

Initially developed by Viovy *et al.* (1992), this method is based on the slope of increasing and decreasing data values referred to as the “best index slope extraction”. The method accepts a point if it has a higher value than the previous observation. Where the NDVI value decreases, the decrease is only accepted if there is no point within the next  $n$  periods with a value greater than 20 percent of the difference between the first low value and the previous high value.

The method is dependent on both the 20 percent threshold and the predefined period of time (i.e.  $n$ ). The resulting profiles tend to lose some of the nuances of the NDVI profile and, in some cases, appear to be insensitive to the timing of NDVI increases.

#### *Weighted least-squares linear regression*

This method was developed by Swets *et al.* (1999). This approach uses a moving window operating on temporal NDVI to calculate a regression line. The window is moved one period at a time, resulting in a family of regression lines associated with each point; this family of lines is then averaged at each point and interpolated between points to provide a continuous temporal NDVI signal. Also, since the factors that cause contamination usually serve to reduce NDVI values, the system applies a weighting factor that favors peak points over sloping or valley points. A final operation assures that all peak NDVI values are retained.

#### *Savitzky-Golay smoothing method*

This time-domain method of smoothing is based on least squares polynomial fitting across a moving window within the data. The method was originally designed to preserve the higher moments within time-domain spectral data.

Savitzky-Golay smoothing filters, also called least-squares or DISPO (digital smoothing polynomial) filter are particular types of low-pass filters, well-adapted for data smoothing. Rather than having their properties defined in the Fourier domain, and then translated to the time-domain, Savitzky-Golay filters derive directly from a particular formulation of the data smoothing problem in the time domain (Press *et al.*, 1992).

#### *4253H, twice smoothing method*

The 4253H, twice (or T4253H) smoothing method (Tukey, 1977; Velleman & Hoaglin, 1981) belongs to a family of smoothers based on the use of running medians to summarize overlapping segments. Indeed, as the fitted curves are intended to be robust to any outlying observations in the sequence, techniques as T4253H make use of medians rather than means.

The 4253H, twice smoothing method consists of a running median of 4, then 2, then 5, then 3. This is then followed by a method known as “Hanning”. Hanning is a running weighted mean, the weights being  $\frac{1}{4}$ ,  $\frac{1}{2}$  and  $\frac{1}{4}$ . The result of this smoothing is then ‘reroughed’. This involves computing residuals from the smoothed curve, applying the same smoother to the residuals and adding the result to the smooth of the first pass (NAG, 2005).

#### *5RX, twice and 7RY, twice smoothing methods*

These two smoothing methods have been proposed by Ladiray & Roth (1987) and are in a way an adaptation of the smoothing techniques proposed by Tukey (1977) and Velleman & Hoaglin (1981) and are notably based on iterative processes. Indeed, for moving medians of odd order (only), Tukey had proposed to use a smoother as much as necessary until the moment when the smoothed series become invariant to the smoothing procedure. In many situations (Ladiray & Roth, 1987), convergence is reached quite rapidly (after 4 or 5 iterations).

Ladiray & Roth (1987) propose to run median of 5 (5RX) or 7 (7RY) using this iterative process and to use then a method similar to “Hanning” except that the weights are here  $(1/8, 1/4, 1/4, 1/4, 1/8)$  and  $(1/8, 1/8, 1/8, 1/4, 1/8, 1/8, 1/8)$  respectively for 5RX and 7RY.

The result of this iterative smoothing is afterwards “reroughed” (see “4253H, twice” smoothing method).

According to Ladiray & Roth (1987), these 2 smoothing methods (5RX and 7RY) are more efficient than 4253H smoothing method in many situations. However, the iterative process lead to a loss of data at the end of the series especially if the smoothing order is high and if the iterative process has difficult to convergence.

However, for many purposes, the choice of smoothing method might not be crucial. For example, in a recent ecological study, similar estimates of spring phenology were obtained using either locally weighted regressions or a simple cumulative maximum throughout the season (Loe *et al.*, 2005).

### 3. PHENOLOGICAL KEY INDICATORS DERIVED FROM REMOTE SENSING

Different key phenological events can be derived from NDVI or more generally from Vegetation Index (VI) time series. Whatever the technique used, three phenological key indicators called "basic" can be derived from vegetation index time series, as aforementioned most of time NDVI time series (Figure 1): the onset and the end of greenness and the maximum NDVI value. Let's note that the onset/end of greenness is not necessarily linked to the beginning/end of the growing season especially if VI time series monitor two crops during the same growing season.

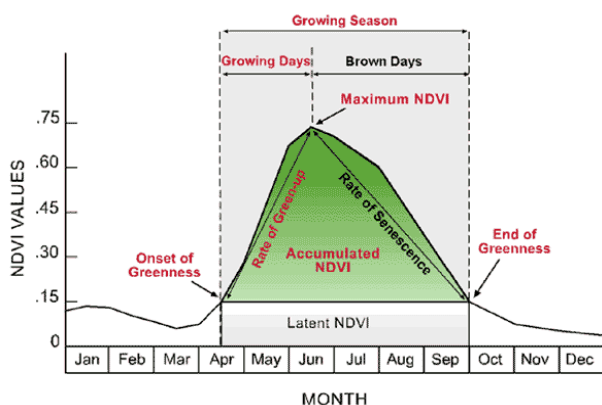


Figure 1. Phenological metrics derived from a NDVI curve (From <http://www.terrametricsag.com/DataSets.html>)

According to the spatial resolution and under some site-specific conditions (as the possibility to have pure pixels), phenological metrics could be associated to species-specific events or not.

For example, Xin *et al.* (2002) working in the Huang-Huai-Huai plain (China) with NOAA-AVHRR images have linked on the basis of field data the peak of greenness (maximum of NDVI value) to heading of winter wheat and tasseling of summer maize. In the same way, Thiruvengadachari and Sakthivadivel (1997) consider that the peak of greenness of a seasonal NDVI profile (for pure pixels in rice) corresponds to heading stage of rice. For Schwartz *et al.* (2002), the onset of greenness can be, to a certain extent, associated in deciduous American forest to bud-break.

From these basic phenological key events, other phenological indicators (figure 1) can be derived as for example the length of the growing (LOG) and brown (LOB) days i.e. the time between the moment of maximum (ND)VI and respectively the onset and the end of greenness, the rates of green-up (ROG) and

senescence (ROS) i.e. the rate of VI increase during respectively the growing and the brown days or the length of the growing season (LOS) corresponding to the time between the onset and the end of greenness ( $LOS = LOG + LOB$ ).

### 4. TECHNIQUES TO DERIVE PHENOLOGICAL KEY EVENTS FROM REMOTE SENSING

#### Techniques based on thresholds

These techniques are certainly the most simplistic. The philosophy of these approaches is based on the definition of a VI threshold. The onset/end of greenness is defined as the moment when the VI values become higher/lower than the defined threshold

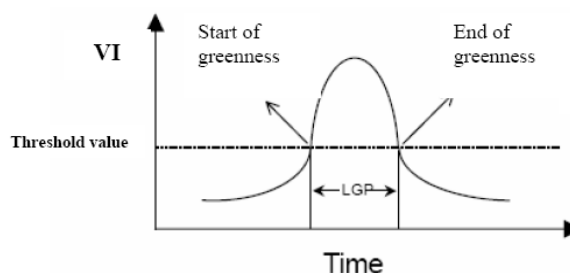


Figure 2. Determination of the start and the end of greenness based on VI threshold.

Different threshold values have been proposed in literature e.g. 0.17 (Fischer, 1994), 0.09 (Markon *et al.*, 1995) or 0.099 (Lloyd, 1990). These values are however specific to a given vegetation type and/or to a given area.

The seasonal midpoint NDVI (SMN) methodology is another method, more complex, based on threshold. This method was initially developed by White *et al.* (1997) and subsequently modified by White *et al.* (1999) and White *et al.* (2002).

In the SMN methodology, the annual cloud-screened minimum and maximum NDVI are selected and the midpoint (average) between them is computed. This operation is repeated for  $X$  years of the NDVI time series. The average of the  $X$  midpoint NDVI values (SMN value) is finally computed and used as a threshold to identify the start and the end of the growing season.

Parameters derived from this SMN method has been shown to be related to initial leaf expansion of the broad leaf forest overstory in New England (White *et al.*, 1997) and deciduous forests in France (Bondeau *et al.*, 2000).

According to Schwartz *et al.* (2002), the SMN method has the advantage to be sensitive to site-specific NDVI amplitude but, with its dependence on a time-constant NDVI threshold, an additional sensitivity to time-dependent drift in sensor calibration.

#### Techniques based on moving averages

This category of techniques involves applying a moving average filter to the VI time series which essentially creates a new time series with a time lag. The moving average time-series (MATS) then can serve as a predicted VI based on the  $n$  previous observations. When the actual (smoothed) values are greater than the value predicted by the MATS, then a trend change (onset of greenness) is occurring (Figure 3). The end of

greenness can be found similarly except that the moving average runs in the opposite direction. The number  $n$  of previous observations to select in order to compute delayed moving averages is user-defined. For example, Brown *et al.* (2002) suggest 5 periods.

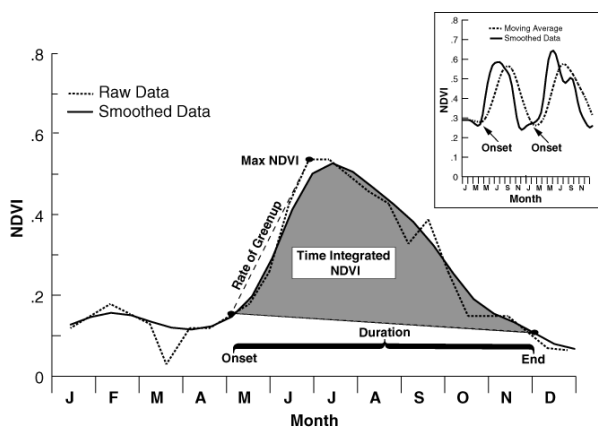


Figure 3. Illustration of a delayed moving average (DMA) approach (from Reed and Saylor, 1997)

*Techniques based on first derivatives*

In many situations and especially for annual species and broadleaved trees, vegetation indices as NDVI presents a bell shape as the one presented in figure 1.

With the first derivatives of the vegetation indices, it can be therefore possible to identify the onset and the end of greenness considering that these moments correspond to inflexions points. This category of techniques aims therefore to identify precisely the moment when the VI time series start increasing or stop decreasing.

In other words, according to these techniques, the onset of greenness is signalled by the  $x$  (generally 1 or 2) first positive VI increments in a given possible time window in which the event is supposed to occur. Similarly, the end of greenness is signalled by the  $x$  last consecutive decrements also in a given time window.

At the beginning of the growing season (which can be different from the onset of greenness), small increases and decreases of the signal simply due to residual noise are sometimes observed. In order to make the distinction between true onset of vegetation and these signal variations due to residual noise, a threshold of acceptable VI increase is used. As far as the end of the growing season is concerned, different studies (e.g. Xin *et al.*, 2002 ; De Wit & Su, 2004) have demonstrated that this event is generally poorly defined. In order to overcome this problem, a threshold corresponding to the VI value at the onset of greenness is used. The end of the growing season is then defined as the time step (for example the decade or the week) below or above this threshold.

Some practical applications of this category of techniques can be found for example in Xin *et al.* (2002) or Viña *et al.* (2004).

Variants in these techniques exist. For example, Zhang *et al.* (2003) have represented their NDVI time series by a series of piecewise logistic functions of time (figure 4). Periods of sustained VI increase or decrease are identified through the use

of a moving window by a change from positive to negative slope and vice-versa.

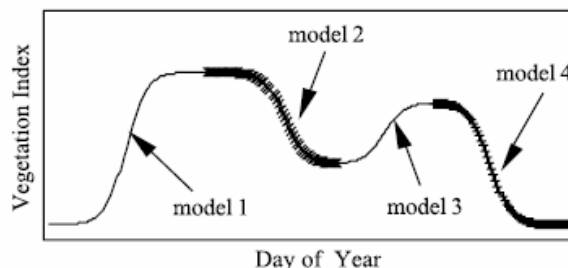


Figure 4. An idealized trajectory of vegetation index values with multiple growth periods described using several logistic models (from Zhang *et al.*, 2003)

Zhang *et al.* (2003) have afterwards identified what they have called transitions dates on the basis of the rate of change in the curvature of the fitted logistic models. Transition dates corresponds to the onset/end of greenness but also here the onset/end of the maximum of NDVI value (linked in their study to the maximum of leaf area index).

These transition dates correspond to the times at which the rate of change in the curvature presents local minima and maxima (black dots in figure 5).

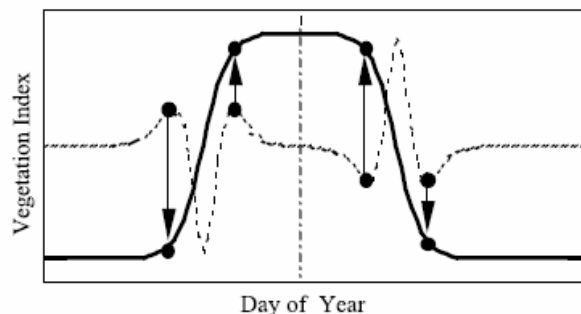


Figure 5. Schematic representation of how transition dates are estimated using time series of VI data (the solid line is a time series of vegetation index data and the dash line is the rate of change in curvature from the VI data).

*Techniques based on empirical equations*

Approaches based on empirical equations are certainly the most complex ones. An example of algorithm is for example provided in Moulin *et al.* (1997). In this study, the authors have used an algorithm in order to detect three transition dates (beginning, maximum and end of the vegetation cycle) through the analysis of NDVI temporal series.

With this algorithm, Moulin *et al.* (1997) does not determine an instantaneous phenological stage of the vegetation but rather the timing of the change from one state to the other that they call transition dates.

Determination of the start and end dates is done by finding the minimum of two criteria  $b$  and  $e$  computed for every week (Figure 6). The determination of the maximum of the vegetation cycle corresponds, once again, to the date of maximum value of NDVI time series.

The criterion  $b_i$  used to determine the beginning of the cycle ( $b\_date$ ) is based on the following considerations: (i) NDVI

value is close to a value of bare soil; (ii) the time derivative before  $b\_date$  (left derivative) should be zero or close to zero, NDVI being almost constant; and (iii) on the opposite, the time derivative after  $b\_date$  should be positive as the signal increases when the vegetation appears. For smoothing purposes, left and right time derivatives were computed with  $x_{i+2}$ ,  $x_{i-2}$  and not  $x_{i+1}$ ,  $x_{i-1}$ , such that

$$b_i = |x_i - x_0| - \lambda[(x_{i+2} - x_i) - |x_{i-2} - x_i|] \quad (\text{Eq. 1})$$

where  $b_i$  is  $b\_date$  criterion for week  $i$  (from week 5 to week 50),  $x_i$  is radiometric signal value for the date  $i$ , and  $x_0$  and  $\lambda$  are empirical parameters. As the beginning of the time series cannot be filtered (boundary effect), the first two values are not significant, so the detection begins on week 5 instead of week 3.

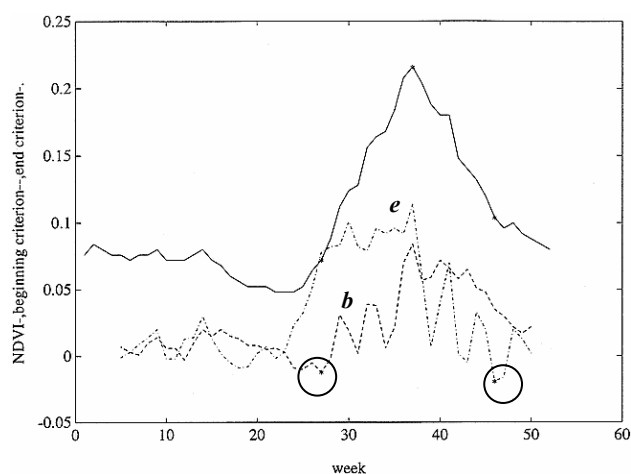


Figure 6. Detection algorithm of transition dates: NDVI time profile (solid), time profiles of criteria  $b$  and  $e$  allowing respectively the detection of start (dash-dash) and end (dash-dot) dates. Start and end dates (\* circled in black) were obtained when criteria time profiles are minima (from Moulin *et al.*, 1997)

The date at which vegetation cycle ends is calculated similarly to the beginning date. The NDVI value must be close to the soil threshold, and the left derivative is negative as the signal decreases during the senescence phase and equals zero on right, such that

$$e_i = |x_i - x_0| + \gamma[|x_{i+2} - x_i| - (x_{i-2} - x_i)] \quad (\text{Eq. 2})$$

where  $e_i$  is  $e\_date$  criterion for week  $i$ .

Each equation includes a term accounting for the mean level of the signal (“mean term”) and a term accounting for the shape of the signal (“derivative term”). A soil threshold ( $x_0$ ) is used in the mean term of the equation, whereas a slope coefficient ( $\lambda$  or  $\gamma$ ) is used in the derivative term. Thresholds and coefficients used in the algorithm were empirically set.

With the mean term, variations of soil color and texture can induce variations of NDVI even if there is no vegetation. Among two dates leading to the same derivative term, the mean term helps the algorithm to select the one that has the lowest value (i.e., which is the closest to the soil or constant green background). For pixels covered with bare soil during a part of the year, the mean term in Eq. 1 allows to detect the beginning date of the cycle when the NDVI is close to bare soil threshold. For pixels with a constant background vegetation (and then a constant level of NDVI always above the soil threshold), the

algorithm also detects the beginning of the cycle (when the NDVI level is close to, but larger than, the background level). In Moulin *et al.* (1997),  $x_0$  corresponds to NDVI values observed for the Matthews (1983) desert class.

For the derivative term, the factors  $\lambda$  and  $\gamma$  weight the derivative term of Eqs. 1 and 2. Hence, if  $\lambda$  and  $\gamma$  are too large, the algorithm may fail for pixels with a large part of the year with no vegetation (i.e., arid or cold regions). Indeed, in that case, the detection may be confused by short-term signal variations due to residual noise (e.g., soil color, directional effects). On the other hand, if the values are small, the algorithm may fail for pixels, which remain partly green during the year. According to this,  $\lambda$  and  $\gamma$  were empirically set to 3 and 5 in Moulin *et al.* (1997), respectively, in order to obtain a compromise between the two terms (mean and derivative). Due to the shape of seasonal profiles, the factor  $\gamma$  is larger than  $\lambda$  in Moulin *et al.* (1997). In fact, for a large number of grid cells, the decrease of the radiometric signal is slower than the increase. So, the weight of the derivative term must be amplified to detect the ending date.

An other example of algorithm can be found in Kaduk & Heiman, (1996).

## 5. CONCLUSIONS AND DISCUSSIONS

Different techniques aiming to derive agrophenology indicators from remote sensing information have been presented in this paper.

It would be unwise however to pretend that one method is better than the other. None of them are really ideal.

Indeed some of them, as the ones based simply on thresholds, are clearly specific to certain area and/or to certain species or vegetation types. In the same way, in techniques based empirical equations, proposed coefficients are always specific to the study conditions.

These methods, based mainly on NDVI time series, present also some restrictions. For example in boreal regions, it is well known that snow melting tend to increase NDVI values. Considering that in these regions the onset of vegetation and snow melting occurs globally at the same period, there is therefore a risk of confusion between an increase of NDVI due to snow melting and an increase of NDVI due the onset of vegetation, which is the event that must be detected. In other words, It is difficult in these conditions to distinguish, especially with the methods based on first derivatives or delayed moving average, the part of the NDVI increase due to snow melting from the NDVI increase due to the vegetation greening-up. Same kind of problems occurs of course also at the end of the growing season when snow reappears. Detection of the different key phenological indicators is however improved by using other VI as the Normalized Difference Water Index NDWI instead of NDVI (Delbart *et al.*, 2005).

These techniques are not also very efficient in situations as equatorial evergreen forests. Indeed the small magnitude of the vegetation cycles compared to the effects of the important cloud contamination over these regions make the interpretation of the NDVI time profile very difficult (Moulin *et al.*, 1997).

It seems also that the end of growing season is often poorly defined.

An other important point to consider is that these techniques and methodologies proposed in literature are not always validated with ground control observations. Questions also remain on some parameters used as for example the ideal size of the moving window used in techniques as the delayed moving average techniques.

There is therefore a need for compromise and it seems obvious that these different techniques should be adapted according to the context/situation.

Concerning the final uses of these phenological key indicators derived from remote sensing imagery, they are numerous.

First of all, considering that these phenological indicators are derived from RS information, it allows a global coverage of the different phenological events and provide more information on the spatial variability of the phenological events. It will be therefore possible to map and monitor phenology on a large area as Europe for example with a view to detect possible trends in phenology that can be linked to climate changes. This kind of study is underway in the frame of COST action 725 ([www.cost725.org](http://www.cost725.org)). In this kind of study, long time series are needed. Moreover, trends in phenology are generally not monitored for a particular species (which should be ubiquitous in order to be monitored on a large area) but for global vegetation or a vegetation class according to the size of the area monitored. Therefore in this kind study, low resolution images are generally preferred.

Phenological information derived from satellite could be also very useful to recalibrate / readjust crop growth models (as CGMS or B-CGMS) which tend to fail in non optimal conditions (low models sensitivity to LAI evolution...). Remote sensing information could be therefore used to recalibrate/readjust some of the parameters of these models. As these models are crop specific, extraction of phenological parameters should be done on pure pixels and therefore in this case (very-) high resolution images are needed.

The choice of the images spatial resolution is therefore linked to the targeted objectives.

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