Identification of contaminated pixels in AVHRR composite images for studies of land biosphere

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ABSTRACT

The objective of this study was to develop a robust method for identifying contaminated pixels from AVHRR composite data sets intended for biospheric studies. Of particular interest were land pixels partially contaminated by clouds, smoke or other atmospheric aerosols, as well as pixels with partial snow or ice cover. The method developed for this purpose, dubbed CECANT (Cloud Elimination from Composites using Albedo and NDVI Trend), uses channel 1 surface reflectance to identify fully cloud-, snow- , and ice-covered pixels; and two parameters (R, Z) to distinguish bright (in channel 1), clear-sky pixels from intrinsically darker but partly contaminated pixels. R and Z are based on the seasonal NDVI trajectory. Three thresholds are required to apply this approach; they are obtained from the histograms of channel 1, R and Z. The thresholds are adjusted separately for each compositing period. Tests with multidate histograms and single-date images indicated the consistency and robustness of the method in an area where most seasonal NDVI trajectories have a single peak. An application of the CECANT procedure to AVHRR composites over Canada for 1993 showed that an average 51% of the land pixels were fully or partly contaminated (37%±5% in the June to August period), with a range from 31% (mid-summer) to 91% (October). The method should be applicable to other geographic regions where seasonal AVHRR composite data sets (minimum is channel 1 and NDVI for each composite period) are available.

1. INTRODUCTION

Medium resolution satellite optical sensors have become a fundamentally important tool for the monitoring of the changing land surface conditions on a global basis. The initial success applications of the NOAA Advanced Very High Resolution Radiometer (AVHRR) on various continents (Justice et al., 1985; Goward et al., 1987; Goward and Dye, 1987), led to the specification of similar sensors for the late 1990s such as the Moderate-Resolution Imaging Spectroradiometer and the Medium-Resolution Imaging Spectrometer. Because most land areas on images obtained by these sensors are obscured by clouds, image compositing over periods of 5-30 days is usually carried out as a pre-processing step (Gatlin et al., 1984; Holben, 1986; Allison et al., 1989; D'Iorio et al, 1991; Townshend et al., 1994). The maximum value of the normalized difference vegetation index (NDVI) has most often been used as a compositing criterion (Cihlar et al., 1994; Townshend et al., 1994). The reason is that NDVI is reduced by most atmospheric and bidirectional effects which modify the land surface reflectance in AVHRR channels 1 and 2 (Holben, 1986; Holben et al., 1986; Lee and Kaufman, 1986; Cihlar and Huang, 1994). Although various studies indicated the shortcomings of this approach (Qi and Kerr, 1994; Cihlar et al., 1994; Gutman, 1991) no superior alternative has yet been found. The compositing process thus provides partial cloud screening. However, in practice the resulting composites may still contain substantial residual clouds, either when no cloud-free pixels were available during the compositing period or as subpixel clouds which are not easily discerned within the pixel (e.g., Cihlar and Howarth, 1994). As an example, Figure 1 shows several NDVI curves from the boreal coniferous forest in central Canada for 1993. The observed features include frequent single-period dips, occasional multiple-period dips, multiple-period suppressed increases, and an occasional large rise between periods. These are related to various sources of noise in the data: mostly clouds (thick to thin or sub-pixel), snow, or land ice but also pixel misregistration (which can result in sharp NDVI increase or decrease), and likely small effects of bidirectional reflectance variations. The composite product does not contain explicit information as to which pixels are contaminated or the degree of contamination.

Various cloud screening methods have been developed (e.g., Simpson, 1994). Most of these operate on single date images using multispectral analysis, spectral differencing or other transforms, spatial coherence or texture, clustering, and thresholds of in individual channels or channel combinations. Single-date approaches present substantial challenge over land because of the temporal and spatial variability of the background surface, and ingenious solutions have been designed in cloud screening software packages to overcome these (Saunders and Kriebel, 1988, Stowe et al., 1990; Gallaudet and Simpson, 1991). However, because of the complexity of cloud identification and the operational implications of the cloud screening procedures developed so far, most present operational programs concerned with the preparation of AVHRR data for land studies do not rely on cloud screening during preprocessing. Rather, the compositing approach is used to implicitly screen out cloudy pixels (Robertson et al., 1992; Townshend et al., 1994; Anonymous, 1994; Smith, 1994). Thus, given the unavoidable residual contamination of the composite images, cloud masks are an important ancillary data set for the analysis of these composites over land. The basic reason is that the contaminated pixels need to be flagged or excluded from further processing of NDVI or of individual channels.

In a noisy composite data set, the problem is identifying pixels/periods which are unacceptable because of excessive contamination. Two approaches have recently been developed which make use of the fact that in most instances vegetated land surfaces are typified by monotonic NDVI profiles, increasing before the growing season peak and decreasing thereafter. Sellers et al. (1994) and Los et al. (1994) used an average NDVI curve, calculated as the best fit through all the measured NDVI points during the season, and a statistical measure based on multiple fractions of the median difference between measured and predicted values as a measure of pixel contamination. This method can detect deviations from the expected average NDVI value. Since it applies one threshold for the whole season, it is sensitive to the average contamination of the pixel but not to the time-specific variability of the measured NDVI. It also does not employ directly the information on the expected monotonic relationship between adjacent periods for the same pixel.

Cihlar and Howarth (1994) proposed an algorithm which tracks the change in NDVI between successive periods. They assumed that whenever NDVI decreases (increases) before (after) the seasonal peak, the pixel is contaminated. This approach can locate pixels with single-period and multiple-period decreases. It cannot find pixels with small NDVI increases between successive periods which may still be contaminated (Figure 1), without making arbitrary assumptions about a minimum necessary increase for an uncontaminated pixel. Qi and Kerr (1994) proposed a variation of the same principle for AVHRR compositing. - Although this approach is very sensitive to detecting anomalies in the temporal trend, it is unforgiving to individual measurements in that it does not accept even small decreases in NDVI, such as might be caused by bidirectional effects.

For biospheric studies employing AVHRR composites over land there is a need for a screening method which can detect partial contamination by clouds, smoke, etc. in individual pixels with various clear-sky reflectance and at different times in the growing season. Secondly, there is a need to detect partial contamination by snow or land ice because of its strong effect on reflectance and NDVI. This is especially important at northern latitudes where snow/ice cover infringes on the growing season. For vegetation studies, both effects can be treated as undesirable. This is useful because although snow-cloud separation has been demonstrated (e.g., Li and Leighton, 1991) its sensitivity to subpixel contamination remains in question until more spectrally appropriate data become available (e.g., a 1.6 ÿm channel). Thirdly, change in the size of the original pixel (due to viewing angle differences) or spatial misregistration during geocoding may also introduce undesirable noise in the composite images.

The purpose of this paper is to describe a simple and robust method for the detection of such contaminated pixels which could be routinely applied to AVHRR composites in studies of vegetation dynamics over large land areas. Specifically, the objective is to detect pixels which should be excluded from further analysis because of atmospheric or snow/ice contamination or pixel misregistration, but to retain pixels with 'acceptable' noise caused by these or other (e.g., bidirectional reflectance) effects.

2. RATIONALE and ALGORITHM

In land composites, completely cloud- or snow/ice-covered pixels are readily evident from the high albedo, and can be easily identified using a threshold value. Although both visible and thermal AVHRR channels can be employed to identify such pixels (e.g., Saunders and Kriebel, 1988), the use of the reflected radiation is preferable because it avoids the sensitivity of the measured satellite signal to surface and cloud temperatures which in turn require threshold adjustments or ancillary information (e.g., Derrien et al., 1993; Loudjani et al., 1994; Smith, 1994). As the proportion of cloud/snow within the pixel decreases and/or the clear-sky albedo increases (e.g., bare sand), it becomes increasingly more difficult to find a clear demarkation line between the two trends. The method described here, dubbed CECANT (Cloud Elimination from Composites using Albedo and NDVI Trend), therefore employs surface reflectance and temporal consistency requirements for a composite land pixel to be considered uncontaminated. Three features of the annual surface reflectance trend are used: the high contrast between the albedo (represented by AVHRR channel 1) of land, especially when fully covered by green vegetation, and clouds or snow/ice; the average NDVI value (expected value for that pixel and period); and the monotonic trend in NDVI. The procedure builds on algorithms developed by Sellers et al. (1994) and Cihlar and Howarth (1994), respectively. It is based on the following assumptions:

1. For a given pixel, at least some compositing periods during the growing season contain uncontaminated pixels.
2. The first peak in the AVHRR channel 1 histogram (corresponding to surface reflectance below about 0.20) contains clear-sky, snow/ice-free, land pixels.
3. NDVI values for a given pixel increase monotonically from the beginning of the growing season until they reach the seasonal peak green (maximum NDVI) for that pixel.
4. The shapes of the average and the ideal NDVI curves can be calculated.

The development of the procedure is detailed in the following sections. Figure 9 summarizes the steps involved in the derivation and application of the decision criteria.

2.1 R criterion

Assuming that most images in the temporal sequence were correctly registered, the NDVI value calculated for a pixel (i,j) at compositing period t, by fitting an average curve through all the measured NDVI values, represents the best estimate of the *expected average* NDVI value for that location and period. The magnitude of the decrease of the measured NDVI(i,j,t) below the estimated average value NDVI$_a$(i,j,t) is therefore a measure of the degree of contamination of the pixel. The criterion is defined as

R(i,j,t) = ÿNDVI(i,j,t)/M(i,j), (1)

ÿNDVI(i,j,t)=NDVI(i,j,t)-NDVI$_a$(i,j,t), (2)

where M(i,j) is the median for the set |ÿNDVI(i,j,t)| for all values of t.

R thus measures the deviation of NDVI(i,j,t) from the expected average value in units of 'average scatter' around the seasonal curve. The median is chosen because it is less sensitive to large deviations from the average curve than other measures of central tendency (see also Loss et al., 1994).

The histogram of R values for all pixels (i,j) and a given period t and the geographic area of interest can be visualized as a distribution of R values orthogonal to the time axis (parallel to the NDVI axis in Figure 1 and placed in the time period t), where low (high) R represents a pixel much below (above) its respective average curve NDVI$_a$(i,j,t). The lower foot of the R histogram contains pixels which are most likely contaminated for that period. 'Most likely' is determined from the deviation ÿNDVI(i,j,t) and the average scatter is represented by the median difference. A high R is a result of high ÿNDVI(i,j,t) or low M(i,j). The likelihood of contamination is thus determined in R through a comparison to the same pixel during the rest of the growing season. As R(i,j,t) increases, the likelihood of a pixel being contaminated decreases until near the peak of the R histogram there is no evidence (by this criterion) that the pixel is contaminated. If the pixel is fully cloud- or snow/ice-covered in all periods both ÿNDVI(i,j,t) and M(i,j) will be small but R could be high or low due to the variability in the data. Since frequent large ÿNDVI(i,j,t) variations produce higher M(i,j), R values for such pixels will tend to be lower compared to otherwise similar pixels with only occasionally high ÿNDVI(i,j,t).

The high-end tail of the R histogram contains pixels with NDVI(i,j,t) much above the NDVI$_a$(i,j,t) for that period. These should be the most likely correct NDVI values, uncontaminated by other effects (e.g., Holben, 1986; Los et al., 1994). The most probable exception is due to pixel misregistration, e.g. because of topographic displacement or to inaccuracies in the geometric transformation used.

2.2 Z criterion

NDVI$_a$ is not an optimal estimate of the *original* NDVI value because the various sources of noise in satellite measurements decrease the computed NDVI. For this reason, a more meaningful estimate is the upper envelope bounding the measured values, and substantial decreases below this envelope therefore also imply the presence of contamination. A second measure Z(i,j,t) is used to test the magnitude of the decrease:

$$\mathbf{Z(i,j,t) = (NDVI_{max}(i,j,t) - NDVI(i,j,t))/NDVI_{max}(i,j,t),} \qquad (3)$$

where $NDVI_{max}$ is the value of the upper envelope for (i,j,t).

Z tests for the monotonic behaviour of the seasonal NDVI profile. It implies that a decrease in NDVI below the value expected by the monotonic trend is caused by pixel contamination. Conceptually, Z is similar to the Cihlar and Howarth's (1994) test [NDVI(i,j,t-1) - NDVI(i,j,t)] < 0 (for the first part of the growing season) and [NDVI(i,j,t-1) - NDVI(i,j,t)] > 0 (after seasonal peak). Ideally, Z would range between 0 and 1 but in practice the range may be greater, depending on the accuracy of estimating $NDVI_{max}$. For example, negative Z shows that the measured value was higher than $NDVI_{max}$, and high positive value could indicate poor fit by the model of the upper envelope of the NDVI curve.

In the optimum case when there are no residual clouds, snow/ice or other noise in the data over land during the growing season, $NDVI=NDVI_{max}$, R=0, and Z=0. As the deviations from the average curve increase, R will increase (decrease) as well but only for anomalously high (low) NDVI, the magnitude of the anomaly being compared to the same pixel in other periods. Similarly, as NDVI decreases below $NDVI_{max}$, Z will increase and a limit will be reached beyond which the noise is not acceptable and the pixel should be eliminated. This happens e.g. prior to peak green when the NDVI(i,j,t) value suddenly drops below (NDVI(i,j,t-1), or when it remains constant or even gradually increases over several time periods but at a slower rate (Figure 1).

2.3 C1 criterion

Although R and Z respond to short-term pixel contamination, they are not likely to detect all cloud- and snow/ice-covered pixels. If a pixel has consistently (constant or slowly varying) high albedo then R and Z may be low because $NDVI_a$ and $NDVI_{max}$ will follow the same trend. However, for land vegetation studies (other than snow or ice) these pixels represent noise and should be eliminated. This can be achieved by using an albedo threshold, represented in CECANT by AVHRR channel 1 (C1). This threshold should be sufficiently high to ensure that no clear-sky land pixels with high albedo are eliminated.

The three parameters (C1, R, Z) are used in combination to separate pixels with a relatively high albedo which could nevertheless be caused by intrinsically high surface reflectance, from pixels with a similar albedo caused by a mixture of a dark surface and cloud/snow/ice. They therefore operate in the trailing edge of the first peak in the AVHRR channel 1 histogram, as discussed below. The challenge is to establish the limits for C1, R and Z. Four thresholds are required in CECANT to identify partially contaminated pixels:

C1: the maximum channel 1 reflectance of a clear-sky, snow- or ice-free land pixel in the data set.

R_{min}: the maximum acceptable deviation of the measured value NDVI(i,j,t) *below* the estimated $NDVI_a$(i,j,t). Pixels with lower NDVI are considered contaminated by atmospheric components (clouds, aerosols) or snow/ice.

R_{max}: the maximum acceptable deviation of the measured value NDVI(i,j,t) *above* the estimated $NDVI_a$(i,j,t). Pixels with R values higher than R_{max} represent anomalously high NDVI.

Z_{max}: the maximum acceptable deviation of the measured value NDVI(i,j,t) *below* the estimated $NDVI_{max}$(i,j,t). Pixels with lower NDVI are considered unacceptable even if $NDVI > NDVI_a$, pixel misregistration being one example.

Note that a Z_{min} could also be used to further constrain the anomalously high NDVI values but this does not appear necessary because R_{max} provides that limit. The C1, R and Z criteria are self-calibrating because the thresholds can be chosen individually for each compositing period. This partly compensates for inaccuracies in $NDVI_a$ and $NDVI_{max}$ estimation.

3. DATA AND METHODOLOGY

An AVHRR composite data set of NOAA-11 ascending passes was prepared by the Manitoba Remote Sensing Centre using the GEOCOMP system (Robertson et al., 1992). Briefly, GEOCOMP performs sensor calibration, orbital modelling, and precise geometric registration with Landsat image chips, and image resampling of daily images over the North America north of 42^{o} N. Sensor calibration coefficients given by Cihlar and Teillet (1995) were used. Resampling was performed using Kaiser window damped 16-point (sinx)/x algorithm (Friedel, 1992). Composite images were created every 10 days between 11 April and 31 October, 1993 using the maximum value of NDVI as the compositing criterion. Viewing geometry-dependent atmospheric correction of the composites was then carried out using the SMAC algorithm (Rahman and Dedieu, 1994). The atmospherically corrected NDVI values were further corrected for solar zenith angle effects, using the empirical coefficients derived by Sellers et al. (1994) for a global

AVHRR data set. No bidirectional reflectance corrections were carried out on channels 1 or 2. The procedures are described in more detail elsewhere (Cihlar et al., in preparation). The result of the preprocessing was a sequence of 20 composite NDVI images calculated from surface reflectance values. Since each single channel GEOCOMP image is 55 MB in size, the data set was subsampled every 6th line and 6th pixel to produce a subset of 247,960 pixels for analysis.

The average $NDVI_a(i,j,t)$ curves were calculated using the FASIR method which employs third-order Fourier transform (Sellers et al., 1994). First, NDVI=0 values were substituted for any missing value among the 20 periods and two NDVI=0 values were added at each end of the growing season to better accommodate the cyclical nature of the model. The Fourier series were then fitted through the data using least squares method:

$$([F]^T * [F]) * [c] = [F]^T * [Y], \qquad (4)$$

where [Y] are the measured NDVI values, [c] are the Fourier constants to be found, and [F] are the values of $\cos((j-1)ÿ_t)$ and $\sin((j-1)ÿ_t)$ corresponding to each period t. This calculation produces Fourier coefficients which can be used to compute the average NDVI curve, $NDVI_a$. $NDVI_a$ computed in this way was found to provide a good average fit of the measured NDVI(i,j,t) points through visual inspection of randomly selected pixels. The median values M(i,j) were also saved in a separate file.

The next step in the FASIR method is the calculation of the $NDVI_{max}$ by using empirical weights. These weights are computed from functions which vary with (i,j,t) depending on the difference between NDVI and $NDVI_a$ (Sellers et al., 1994). Essentially, the computed weights are near 0 for NDVI values much below $NDVI_a$, near 1.0 when NDVI~$NDVI_a$, and up to 10 or more when NDVI is much above $NDVI_a$. This step produces $NDVI_{max}(i,j,t)$ for all periods t.

A land mask based on the World Data Bank data (U.S. Department of Commerce, 1977), subsampled similarly as the satellite data, was used to eliminate most open water. Because of the spatial resolution of this water mask or of AVHRR, many water bodies could not be eliminated and the final data set therefore includes some pixels with water, open or covered with ice. Fortunately, the compositing procedure typically selects cloudy pixels over open water bodies and these, along with ice, can be eliminated using the albedo criterion.

The $NDVI_a$, $NDVI_{max}$, and M data were used to compute R and Z for all land pixels (i,j,t) of the GEOCOMP data set (Figure 9). The histograms were then prepared for each period and used to select threshold values for contaminated pixels as described below.

4. RESULTS AND DISCUSSION

4.1 DERIVATION OF THRESHOLDS

Figure 2 shows examples of channel 1 histograms for four periods from the 1993 GEOCOMP data. In April (period 2), a large part of the Canada's land surface was covered by snow/ice and the histogram shows a strong bimodal distribution. The values above 1.0 result from the conversion of satellite measurements to surface reflectance for very high solar zenith angles. These values are not acceptable but can be easily eliminated by the albedo (C1) threshold or by choosing a maximum acceptable solar zenith angle.

Of particular interest for land biospheric studies is the first peak in Figure 2 histograms which contains data for vegetated (and other dark) surfaces. This peak is typically narrow and falls off rapidly as the reflectance increases. The width of the peak decreases and the rate of fall-off increases as the growing season progresses (compare periods 2 and 11). Pixels well within this peak can be considered cloud- (including haze) and snow/ice-free. On the other extreme, pixels with high reflectance are contaminated and can be excluded using C1 threshold. Partly contaminated or otherwise doubtfully useful pixels are adjacent to the descending foot of the first histogram peak. This region contains uncontaminated pixels representing bright targets as well as darker pixels with partial cloud contamination. The overall channel 1 reflectance in a given period can be identical in the two cases. Their separation is possible because the bright cloud-free pixel will appear bright in other periods (thus having lower M, lower R and higher Z) while the contaminated pixel is likely to be darker and will have higher R and lower Z for the period of interest. The pixels adjacent to the first histogram peak of channel 1 must therefore be examined in more detail to determine if their channel 1 value is due to partial contamination or to inherently high surface reflectance.

To determine appropriate R and Z thresholds, four C1 thresholds with progressively higher reflectance values were determined for each of the 20 periods using channel 1 histograms of the GEOCOMP data set:

- T1: C1 value obtained by a linear extension of the descending branch of the first histogram peak to zero frequency of observations.

- T2: C1 values at the foot of the descending branch of the first histogram peak, i.e. the point where a fixed decrease in C1 is accompanied by the highest increase in the number of pixels;
- T3: C1 value where the histogram levelled off following the first peak;
- T4: the maximum C1 value observed (i.e., no threshold);

In addition, a fixed threshold C1ÿ0.3 was used.

As channel 1 reflectance decreases from T3 to T1, the number of the remaining contaminated pixels also decreases. Since these pixels have lower R and lower Z values, they may be singled out if appropriate R and Z thresholds are used. R and Z thresholds were thus derived for the 1993 GEOCOMP data by calculating $NDVI_a(i,j,t)$, M(i,j), and $NDVI_{max}(i,j,t)$ (Equation 4) for each pixel and period (see also Figure 9). Histogram curves were then plotted for each period, separately for pixels below each of the four channel 1 threshold criteria.

Figure 3 shows the resulting R histograms for four periods in 1993. Although specific values differ, the trend is consistent in all cases. First, many pixels were eliminated by the weakest threshold T3. These bright pixels (including open water for which the maximum NDVI compositing criterion tends to select cloudy pixels; snow/ice; clouds) had the full range of R values but the change is particularly noticeable near R=0 where $NDVI=NDVI_a$. Such pixels could not be eliminated using R but a C1 criterion can be very effective. Second, the progressively more stringent C1 thresholds had a diminishing effect on the number of eliminated pixels. The magnitude of this effect varies between periods, as does its distribution with respect to the R axis (compare Figure 3a, 3b, 3c). Third, the values near the extremes of the histograms represent pixels with NDVI much above or below the expected average value $NDVI_a$. Pixels much below are highly likely cloud contaminated and should be eliminated. Pixels much above may also be suspect, not because of contamination but because they are so different from the remainder of the seasonal series; misregistration is the most obvious reason. Fourth, the R histogram does not consistently peak at R=0, thus indicating that $NDVI_{(i,j,t)}$'s are not always uniformly distributed around $NDVI_a$. This could be due to the inaccuracies in $NDVI_a(i,j,t)$ estimation or the more pervasive cloudiness in period t. Since most R mean values (R_{mean}; 16 out of 20 for the C1ÿ0.3 threshold for 1993) were positive, the model mismatch appears to be the major cause of the fluctuation. These observations lead to using R_{min} and R_{max} to trim the wings of the R histogram, while accounting for the displacement of the R histogram peak from R_{mean}=0.

The actual thresholds for R are necessarily somewhat arbitrary since the distributions are continuous. After examining various options, the following thresholds were adopted:

$$\mathbf{R_{min}(t)=R_{mean}(t)-1;} \qquad [5]$$

$$\mathbf{R_{max}(t)=R_{mean}(t)+4,} \qquad [6]$$

where R_{mean} is computed only for pixels with C1ÿ0.3.

Since R values are normalized by M(i,j), the above thresholds correspond to 1*M(i,j) below and 4*M(i,j) above $R_{mean}(t)$. For R_{min}, the threshold cutoff was found to fall consistently adjacent to the main peak in the R histogram. For example, the R_{min} values for the four dates in Figure 3 were -0.51 (Figure 3a), -0.68 (3b), -0.32(3c), and -0.33(3d; see also Figure 5). The value of R_{max} was chosen to minimize the possibility of eliminating a cloud-free pixel; this could result in retaining some misregistered pixels. In Figure 3, R_{max} was 4.49 (3a), 4.32 (3b), 4.68 (3c), and 4.67 (3d) - in all cases in the tail of the R histogram.

The histograms for Z are shown in Figure 4 for the same four periods. For most composites in early and late seasons there is a smaller second peak when all pixels are considered (no C1 threshold), also visible in periods 2(4a), 6(4b), and 16(4d). The peak disappeared during the summer (periods 9-13) and in all cases where a C1 threshold was used (including Figure 4a-4d). Since high Z values correspond to low NDVI values, the valley between the two peaks separates pixels with large NDVI decreases below $NDVI_{max}$ (refer also to Figure 5). The pixels in the secondary peak are therefore not acceptable, even though their R values might be. The Z value for the valley was stable and could be approximated by

$$\mathbf{Z_{max}(t)=Z_{mean}(t)+2*|Z_{mean}(t)|,} \qquad [7]$$

where Z_{mean} is computed only for pixels with C1ÿ0.3.

The Z_{max} threshold was close to the observed valley for all dates; for example, the values were 0.53 (Figure 4a), 0.51 (4b), 0.29 (4c), and 0.59 (4d) which are consistent with the position of the valley. The threshold for Z is thus specified in units of 'average contamination' and, because of the use of Z_{mean}, it also accounts for the imperfect fit of $NDVI_{max}$.

Figure 5 shows R vs. Z contour plots for the same periods as Figure 3 and 4. There is generally a weak relationship between R and Z which varies with the period. The correlation coefficient r between R and Z was -0.1 (Figure 5a), -0.17 (5b), -0.1 (5c), and -0.07 (5d). Among all the dates, the r values were all negative; 17 were between -0.01 and -0.24, and the highest r was -0.45 (period 12). Note that in all cases, the threshold R values computed using Eq. 5 and 6 separated the small secondary peak corresponding to contaminated pixels near the lower tail of the R histogram (it is distinct in Figure 5c and 5d, and implied by the contours in Figure 5a and 5b). The weak correlation between R and Z indicates that the two measures capture different aspects of the NDVI trajectory as intended. Figure 5 also suggests that while separate R and Z thresholds may not be as optimal as using a linear combination of the two, the error is relatively small.

The above results indicate that C1, R and Z thresholds consistently separated the contaminated pixels in a statistical sense. An additional assessment was performed by using single-date AVHRR images where the cloud structure is more readily visible. To this end, a one-day composite AVHRR image was prepared over Canada for 95/07/06. The data were corrected for atmospheric effects and NDVI(i,j) was computed. The R(i,j) and Z(i,j) images were prepared using Equations 1 and 3. The cloud mask for 95/07/06 was produced using Equations 4-7 in which the $R_{min}(t)$, $R_{max}(t)$, $Z_{max}(t)$, $NDVI_a(i,j,t)$ and $NDVI_{max}(i,j,t)$ were those determined (using the seasonal data) for period 9. A constant threshold of C1ÿ0.3 was employed. The resulting cloud mask (Figure 6) consistently identified all visible clouds of various types. Figure 6a shows that visible clouds were clearly detected but also identifies as contaminated pixels which could not be visually considered cloudy in AVHRR channels 1 and 2 as well as in NDVI. They include pixels obtained at different viewing directions (note the image seam in Figure 6a) and pixels sufficiently far from cloud structures which would visually be considered cloudfree. Figure 6b shows that the pixels labelled as contaminated had in most cases lower NDVI than the NDVI of the corresponding composite (period 9). For a 1000x1000km area (of which Figure 6b is a subset) 22.12% pixels were labelled clear while in 76.27% pixels the NDVI(i,j,93/07/1-10) was higher than NDVI(i,j,95/07/06). These pixels were thus correctly identified as contaminated by definition since their NDVI values were lower than those from other dates in the same period.

Although the above discussion refers to limited periods of the growing season, the same trend was observed on other dates. The same procedure (Figure 9) was also applied to 1994 data over the same area and found similar characteristics of R and Z and their thresholds. The described behaviour may therefore be considered representative of data sets collected at northern latitudes. It is also evident that the C1, R and Z criteria may overlap and therefore a given pixel eliminated by more than one. This is in fact it is preferable because it strengthens the justification for eliminating that pixel.

5.2 APPLICATION OF THRESHOLDS

Figure 7 shows examples of pixels from the 1993 GEOCOMP data set after applying the CECANT procedure. In general, pixels with high channel 1, low NDVI, temporary decrease in NDVI, or pixels with increasing NDVI between dates but below the expected value, were identified. As expected, pixels near the $NDVI_{max}$ envelope passed as uncontaminated. The complementary value of C1 is evident in cases where NDVI alone does not provide sufficient discrimination, especially near the end of the growing season when the low NDVI is caused by snow cover. Figure 7 also shows that the $NDVI_{max}$ for coniferous forest had a tendency to two peaks. In many cases this was consistent with the data but at times the second peak value was much higher than justified by the seasonal trend (e.g., Figure 7a, 7d); in these cases, possibly cloud-free pixels are screened out by the Z_{max} criterion. This suggests a need for refining Equation 4 to provide a better match for pixels with a broad plateau in the NDVI curve. The results for pixels with a narrower NDVI peak were very good, virtually without exception (Figure 7e-7h). Figure 7e illustrates the high sensitivity of the procedure in cases where the small deviations from the expected trend occur, resulting in low M and high R values.

Figure 8 shows results of applying the above procedure to the 1993 GEOCOMP data set. The C1 criteria retained similar proportions of pixels (Figure 8a), especially for T2, T3 and 0.300. Threshold T1 differed significantly from the others, suggesting that it might go too far by eliminating possibly cloud-free pixels. The constant C1ÿ0.3 tends to pass more pixels than other thresholds and appears thus to be a good conservative choice. The pronounced seasonal trend in Figure 8a indicates the presence of snow at these latitudes. The decrease between periods 1 and 2 is due to the missing coverage of some Arctic islands during period 1 which led to a higher proportion of pixels being snow/ice-free; if present in the composites, these pixels would have been snow/ice-covered and thus eliminated by the C1 criterion. On the average, C1ÿ0.3 threshold eliminated 32% (standard deviation 23%) of all land pixels. Figure 8a also shows that at these latitudes, a large fraction of pixels will have missing data (except for mid-summer) when one is interested in the surface itself (as opposed to snow). Interpolation or assimilation techniques will therefore be necessary to effectively use such data sets.

Figure 8b shows the proportions of pixels passing the R thresholds. The number of pixels eliminated by R_{min} was relatively stable during the growing season but increased at the extremes, especially in the fall. The reason for this trend is not clear but may be related to the number of non-cloudy images used in the compositing process. Relatively few pixels were eliminated by R_{max}. The reason for using R_{max} is to identify misregistered pixels, especially near water bodies, whose number is expected to be larger than identified by the R_{max} threshold used (1.5% on the average for the data set). It is thus possible that the R_{max} threshold (Equation 6) was too high or, alternatively, that such pixels are misregistered frequently and thus have high M(i,j) values. It may be possible to improve the definition of R_{max}, especially for the cases where misregistered pixels are in highly contrasting neighbourhoods. Overall, the two R criteria eliminated 38±13% pixels. - Pixels retained by the Z threshold are shown in Figure 8c. The Z threshold histograms showed seasonal trend, somewhat similar to the R histograms, with 25 ±12% pixels eliminated on the average.

Combined R and Z criteria are given in Figure 8d. The seasonal trend resembles those of R and Z. On the average, 57±11% pixels passed both R and Z thresholds, while 82±10% pixels passed one or the other. This indicates the complementarity of the two criteria and confirms the low correlation between them. Combining all the criteria (Figure 8e) shows the complementary functions of C1 and R, Z. In mid-summer, most of the pixels are eliminated by R+Z, although some of these are also identified by C1. This is evident by comparing the fractions of retained pixels for periods 8-13 in Figure 8e (C1+R+Z) with those for R+Z (8d). At the ends of the growing season, C1 is the more active criterion due to the effect of snow cover (compare 8e with 8a). With the combination of C1+R+Z the resulting data sets are thus much reduced, with an average 51±17% pixels labelled as contaminated; the proportion of clear pixels ranged from 9% (period 20) to 69% (period 10).

Figure 9 summarizes the steps in CECANT when applied to a data set. Given a multitemporal composite (minimum set is channel 1 or equivalent and NDVI or equivalent), values $NDVI_a$ and $NDVI_{max}$ are computed (Equation 4) for each pixel (i,j) and all periods t, followed by computation of R (Equation 1) and Z (Equation 3). From R and Z images, $R_{mean}(t)$, ($Z_{mean}(t)$ and thresholds $R_{min}(t)$ (Equation 5), $R_{max}(t)$ (Equation 6) and ($Z_{max}(t)$ (Equation 7) are determined. A simple decision rule is then applied to decide if a pixel (i,j,t) is contaminated.

5. 3 COMMENTS

The high proportions of contaminated pixels testify to the residual noise in the AVHRR composites for biospheric studies, especially at northern latitudes. This is mainly due to the presence of snow/ice in the spring and fall seasons but residual clouds are also significant. For example, in the June-August time frame (periods 6-14) 37±5% pixels were labelled as contaminated. The residual clouds could be partly eliminated by using longer compositing intervals but this approach does not consistently or fully compensate for residual clouds, and it has the additional disadvantage of decreasing the temporal resolution of the rapid seasonal vegetation changes at northern latitudes (Cihlar and Howarth, 1994).

The above results show that the CECANT procedure can be effective in identifying contaminated land pixels in AVHRR composite images for the purpose of biospheric studies. The accuracies of estimating $NDVI_a$ and $NDVI_{max}$ are very important, although the procedure does allow to compensate for systematic bias in the estimation of these values in different periods. The Fourier series approach to computing $NDVI_{max}$ seems flexible enough to approximate various shapes of the NDVI seasonal trajectory, e.g. double-peak, thus providing the possibility of applying this method in various managed ecosystems. However, $NDVI_{max}$ trajectories for pixels with a broad seasonal peak tend to be overestimated through this method, thus introducing errors in the calculation of Z.

CECANT assumes regular behaviour of the seasonal NDVI trajectory. As described here, it may therefore be confused by vegetation that burns during the season. The likelihood of confusion depends on the deviation of the NDVI values after the burn from the expected nominal trend (i.e., type of fire, degree of combustion, etc.). Such pixels should have high M(i,j) values (unless the fire took place very early in the season) and both spatial and temporal contiguity; it may thus be possible to devise detection algorithms to deal specifically with these. - As pointed out above, CECANT is also not able to deal with permanent ice/snow fields on land. This is not a problem in biospheric studies but presents problems e.g. for land cover mapping. As in the case of burns, special algorithms would be required here. For example, ice/snow covered pixels would have consistently high C1, low NDVI, and low M(i,j).

Although the procedure described has been designed to detect cloud- and snow- free land pixels, it could also be used to identify temporarily snow-covered pixels provided that clouds and snow can be differentiated in this subset. This may be possible using data from other AVHRR channels (e.g., Stowe et al., 1991).

6. CONCLUSIONS

A new method, dubbed 'Cloud Elimination from Composites using Albedo and NDVI Trend' (CECANT) was developed for the elimination of contaminated pixels from AVHRR composite images. The procedure aims to identify land pixels that are unsuitable for the study of biosphere dynamics due to residual clouds or other atmospheric contamination (e.g., smoke, aerosols), intermittent snow/ice, or pixel misregistration. It employs thresholds of three parameters, one for albedo (C1, channel 1 reflectance) and two (R, Z) representing the NDVI trend. While the C1 threshold need not vary with time, composite period-specific R and Z thresholds should be chosen. An application of this procedure to 1993 composite data over a part of North America north of 42^o showed that close to 50% of all the land pixels were contaminated in early spring and late fall, and about 35% during the peak green season. The procedure is easily adaptable to other geographic areas, subject to the estimation of average and maximum NDVI values.

Collectively, the C1, R and Z criteria explicitly account for possible interactions between atmosphere/snow/ice contamination, geographic location/surface cover, and season.

Compared to other procedures previously developed, CECANT covers two dimensions. First, it considers the temporal trend individually for each pixel (for the whole season through R and for adjacent periods through Z). Second, it considers the variations among all pixels in a given composite period (through period-specific thresholds). It does not dynamically set the thresholds for each pixel and each period. In this respect it is similar to other cloud screening methods, including those designed to work with single-period images.

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(93/07/1-10): 6a) clear pixels are masked out; 6b) the mask covers pixels for which NDVI(93/07/06)<NDVI(93/07/1-10). See text for discussion.

Figure 7. Examples of NDVI (heavy line), $NDVI_{max}$ (light solid line), $NDVI_a$ (broken line), and channel 1 surface reflectance (broken dotted line) for selected coniferous (6a-6d) and cropland/rangeland (6e-6h) pixels from the 1993 GEOCOMP data set. Pixels identified as contaminated are marked by rectangles.

Figure 8. Proportions of pixels labelled as cloud-free in 1993 GEOCOMP data for Canada on the basis of various thresholds: 7a) channel 1; 7b) R; 7c) Z; 7d) R plus Z; 7e) channel 1 plus R plus Z.

Figure 9. Flowchart summarizing steps in CECANT processing.

1. Input (minimum set):

composite images of C1, NDVI

2. Determination of thresholds:

2.1 For each pixel (i,j,t):

Calculate $NDVI_a$(i,j,t), $NDVI_{max}$(i,j,t) ***(E. 4)***

Calculate R(i,j,t), Z(i,j,t) ***(Eqs. 1,3)***

2.2 For each period t:

Calculate R_{mean}(t), Z_{mean}(t)

Calculate R_{min}(t), R_{max}(t), Z_{max}(t) ***(Eqs. 5,6,7)***

3. Derivation of contamination mask:

For each pixel (i,j,t):

IF [C1(i,j,t)ÿ0.3 and <R_{min}(t)<R(i,j,t)ÿR_{max}(t)> and Z(i,j,t)ÿZ_{max}(t)] then clear
ELSE contaminated.