A Temporal-BRDF Model-Based Approach to Change Detection

L.Rebelo and P. Lewis
Department of Geography
University College London
WC1H 0AP, UK
Email: lrebelo@geog.ucl.ac.uk

D.P.Roy
Department of Geography
University of Maryland and
Goddard Space Flight Centre
Code 922 (B32), Greenbelt, MD 20771
USA

Abstract—Remote Sensing provides the only practical means to monitor changes over large areas. This paper describes the development of a generic algorithm designed to map the temporal occurrence and spatial extent of areas exhibiting sudden change. The algorithm is demonstrated here applied to the problem of mapping fire affected areas. The research further develops the work of [1], which implemented a bi-directional reflectance (BRDF) model-based change detection algorithm to map the approximate day and location of burning, using daily 500m MODIS surface reflectance data. An original algorithm assumption is that the surface state remains static prior to the changes of interest. This is problematic in the presence of underlying change (for example, due to vegetation phenology) especially when there are missing and/or cloudy data. In an attempt to deal with this issue, an additional kernel has been added to the BRDF model in the form of a cubic function of time. In addition, a step function kernel has been introduced in order to more robustly detect step-like changes. These modifications and preliminary results over southern Africa using daily MODIS land surface reflectance data are presented.

I. INTRODUCTION

The remote sensing of changes taking place on the earth's surface forms an extremely active research field, with results forming an input to models of the global climate, biogeochemical and hydrological cycles. Vegetation fires have an impact on these cycles, and the identification and delineation of fire affected areas may be seen as a change detection problem. A number of change detection methods have been proposed based upon statistical classification approaches. With the availability of well calibrated and geo-located satellite data more physically based approaches are being developed. The research described develops the algorithm of [1] who implemented a new, generic approach to change detection. A model describing the anisotropic nature of surface reflectance was inverted over a time series of MODIS reflectance data for an area of southern Africa, and the resulting model parameters were used to provide a subsequent prediction of reflectance. Areas of surface change are identified as large discrepancies between the observed and predicted reflectances. Different types of changes may be separated using a temporal consistency threshold, as well as by examining the magnitude and the sign difference of potential 'change' pixels. Although results indicate that this algorithm is successful in mapping both the location and the approximate day of burning, problems

occur in the presence of underlying phenological changes and various heuristics are required to separate changes of interest (i.e. burning) from these changes.

II. METHODOLOGY

It is widely accepted that the reflectance of solar radiation from the earth's surface is highly anisotropic. This variation in reflectance as a function of the geometry at which the surface is illuminated at and viewed from may be described by a Bi-Directional Reflectance Distribution (BRDF) model. The model used in the current research and that of [1] is the semi-empirical kernel driven approach of [2]. The surface BRDF is modeled as a linear combination of kernels which are functions of illumination and viewing angles only. Three kernels have been shown to describe sufficiently the BRDF shapes of most naturally occurring surfaces [3]. These typically consist of i) an isotropic kernel to describe isotropic scattering from the surface, ii) a volumetric kernel which provides a single scattering approximation to radiative transfer, and iii) a geometric kernel to account for shadowing effects. The model thus takes the form of Equation 1.

$$\rho(\lambda, \Omega, \Omega') = f_{iso}(\lambda) + f_{vol}(\lambda)k_{vol}(\Omega, \Omega') + f_{geo}(\lambda)k_{geo}(\Omega, \Omega') \quad (1)$$

where ρ is the spectral reflectance, Ω and Ω' represent the viewing and illumination vectors respectively, and k_{vol} and k_{geo} are the kernels. These are geometric expressions of BRDF shapes and are functions of viewing and illumination geometry only. f_{iso} , f_{vol} , and f_{geo} are the kernel weights which describe the relative contribution of each type of scattering.

In the original implementation of the change detection algorithm [1] the model was inverted over a 16 day sliding window. An assumption of this approach is that the surface state remains invariant over the size of the window. With too large a window the results may be smoothed and the probability of underlying change occurring increased, while a small window size may result in larger uncertainties. Either of these may be problematic when looking for sudden changes.

In order to address this issue a polynomial temporal model has been introduced to the isotropic term of the BRDF model (Equation 1), as a cubic function of time. A major assumption of this approach is that the BRDF shape parameters remain

constant over the time period of the inversion. The model now takes the form of Equation 2.

$$\rho(\lambda, \Omega, \Omega') = f_{iso(0)}(\lambda) + f_{iso(1)}(\lambda)t + f_{iso(2)}(\lambda)t^2 + f_{iso(3)}(\lambda)t^3 + f_{vol}(\lambda)k_{vol}(\Omega, \Omega') + f_{geo}(\lambda)k_{geo}(\Omega, \Omega') \quad (2)$$

Previously the model parameters were updated for each new observation of reflectance (calculated from the previous 16 days of observations). For the temporal model however (Equation 2), only the three parameters $f_{iso}(\lambda)t$, $f_{iso}(\lambda)t^2$ and $f_{iso}(\lambda)t^3$ are allowed to vary as a function of time. Over the time period of the inversion the BRDF shape parameters ($f_{vol}(\lambda)$, $f_{geo}(\lambda)$) thus remain constant.

III. STEP DETECTION

The occurrence of a fire typically results in a sudden decrease in MODIS band 2 (841-876nm), band 5 (1230-1250nm) and band 6 (1628-1652nm) reflectances [1]. In order to model such changes, a 'step function kernel' has been incorporated into the model by the introduction of an additional parameter (Equation 3).

$$a(\lambda, t) = s(\lambda)H_c(t) \quad (3)$$

$a(\lambda, t)$ represents the change in brightness, $s(\lambda)$ the magnitude of the change, and $H_c(t)$ is a heaviside function, defined in Equation 4, and c is a non-linear parameter representing the day of the step change.

$$H_c(t) = \begin{cases} 0 & : t < c \\ 0.5 & : t = c \\ 1 & : t > c \end{cases} \quad (4)$$

Parameter c is inverted by stepping through each possible value of c (each observation within the time series) and the remaining linear parameters are inverted using the method of least squares. For a generic change detection approach the 'best fit' value for c may be found by selecting the value which gives the lowest error in model fit. The method used to select the most appropriate value of c may be refined according to the changes of interest. In this case a measure has been defined to specifically locate 'burn type' changes (i.e. a step like drop in reflectance). This is discussed in more detail in section V.

IV. CLOUD FILTERING

Residual cloud and sub-pixel clouds are occasionally found in the MODIS 500m land surface reflectance data which have not been identified in the product quality assessment (QA) bits. If these are not removed from the temporal sequence then they will contribute to subsequent predictions of reflectance. A chi type measure is defined to investigate the probability of a new observation belonging to the same set as that used in the model inversion (Equation 5);

$$Z = \frac{\rho_{observed}(\lambda, \Omega, \Omega') - \rho_{predicted}(\lambda, \Omega, \Omega')}{\varepsilon} \quad (5)$$

Fig. 1. Modeled and measured band 5 reflectance

where $\rho_{observed}(\lambda, \Omega, \Omega')$ is the observed reflectance, $\rho_{predicted}(\lambda, \Omega, \Omega')$ is the model predicted reflectance and ε is the error in model prediction. This is calculated as;

$$\varepsilon = e\sqrt{1 + \frac{1}{w}} \quad (6)$$

where e is the expectation of error in an observation and $\frac{1}{w}$ is the 'weight of determination' [4]. The latter is defined as;

$$\frac{1}{w} = [U]^T [M]^{-1} [U] \quad (7)$$

where $[U]$ is the parameter vector and $[M]^{-1}$ is the inverse matrix, and T denotes the transpose operation. e is approximated from the residuals (Equation 8) where m is the number of observations and $m - 7$ the degrees of freedom.

$$e^2 = \frac{1}{m - 7} \sum_{i=1}^m (\rho_{observed}(\lambda_i \Omega_i \Omega'_i) - \rho_{predicted}(\lambda_i \Omega_i \Omega'_i))^2 \quad (8)$$

Multiple iterations are performed and isolated spikes (high positive values) are removed at each pass using the best knowledge of the parameter estimation and noise in the data at each iteration. Figure 1 shows the modeled and measured band 5 reflectance for a single pixel which burned on day of year 225. The inversion has been performed over a time series of 105 days. The sequence contains a spike on day 257 which is probably a cloud that has not been flagged by the product QA bits. The model clearly fits the observed reflectances well, with the minimum of the rmse (0.011) occurring on day 226. The isolated spike is identified by its high chi value (Equation 5), and does not contribute to the subsequent predictions of reflectance.

V. IDENTIFYING FIRE AFFECTED AREAS

With the increase in cloud cover over parts of southern Africa towards the end of the year, and a decrease in the confidence of predicting a step at the ends of the temporal sequence, it is necessary to incorporate some measure relating to the confidence with which a step may be predicted at a certain point based on the sampling. The weight of determination (Equation 7) provides an indication of the uncertainty in prediction as a result of the angular and temporal sampling

Fig. 2. Uncertainty in prediction of step

Fig. 3. Significance of step

[4]. This is shown for a temporal sequence of a single pixel in Figure 2. A ten day buffer is applied at either end of the sequence. Although observations within the buffers will contribute to the inversions, a step is not looked for within this period as there are too few samples to robustly determine both parameters $a(\lambda, t)$ and $s(\lambda, t)$ (see Equation 3).

A measure is therefore defined which takes into account this uncertainty in prediction and thus the confidence associated with the identification of a step change within the time series at a particular point. This is defined in Equation 9, where $s(\lambda)$ is the magnitude of the step, and $e(\lambda)$ is the error in model fit for a particular waveband, assumed to be a measure of noise within the data.

$$M(\lambda) = \frac{s(\lambda)}{(\frac{1}{w}) * e(\lambda)} \quad (9)$$

$\frac{1}{w}$ is the 'weight of determination' [4] defined in Equation 7.

In order to separate changes which occur to vegetated surfaces as a result of a fire from those that occur due to other causes, a filter is applied to the burn measure described (Equation 9). The presence of a fire in a MODIS pixel generally results in a decrease in reflectance in bands 2, 5 and 6, and little change in band 7 [1]. Changes which take place in the remaining MODIS 500m wavebands are dependent on factors including the vegetation type and condition, atmospheric properties and the stability of the atmospheric correction. Figure 3 displays the significance of the step ($M(\lambda)$) for a single pixel which burned on day 246 for each of the seven MODIS land surface reflectance bands [6]. The filter used to

separate burn pixels from those which have not been affected by fire incorporates this information and involves the three conditions defined below.

- 1) $M_{(band2)} < 0$ and $M_{(band5)} < 0$
- 2) $M_{(band1)} > M_{(band2)}$ and $M_{(band1)} > M_{(band5)}$
- 3) $M_{(band7)} > M_{(band2)}$ and $M_{(band7)} > M_{(band5)}$

If these three conditions are met then the pixel is labelled as a potential burn. The day of burning is located as the point in the temporal sequence at which the minimum value of M occurs in either of bands 2 and 5.

VI. RESULTS

Results are presented for a 250km by 250km area over the Okavango Delta, Botswana. The burn scar detection algorithm has been applied to a time series of daily MODIS 500m reflectance data for the period of 29th July to 8th October 2003. Pixels which fit the criteria described above are represented by the dark areas in Figure 4(a). Figure 4(b) shows all 1km pixels which have been identified as containing an active fire during this period as documented in the MODIS Thermal Anomalies product, as well as the output from the model. These results show a 91% agreement between the location of a 'burn pixel', and the location of an active fire. It should, however, be noted that the MODIS Thermal anomalies product only documents fires which occur at the time of the satellite overpass, while the burn scar detection algorithm identifies changes which have taken place between each consecutive cloudfree MODIS observation. Figure 5(a) shows the day of the burn as output from the burn scar detection algorithm, and the day of the active fire detection (Figure 5(b)) between the 8th August (blue) and the 28th September (red) 2003. 94% of the detected burn pixels are located within seven days of the active fire detections.

VII. CONCLUSION

A generic change detection algorithm is presented which identifies the location within a time series of daily MODIS 500m data at which a step-like change has occurred. The model improves on [1] by the incorporation of an empirical temporal model in the form of a cubic function of time. With this temporal BRDF model (Equation 2) it is possible to fit to much longer time periods than the 'static' version of [1]. A step function 'kernel' has also been incorporated which allows for the explicit detection of sudden changes in the surface reflectance. An additional filter is applied to separate changes which have taken place as a result of a fire, from changes which have occurred due to other causes. As with [1] an initial comparison with the MODIS Thermal Anomalies product shows a high agreement between the location of 1km active fires, and the location of 500m burn pixels. However, this comparison is not ideal as burning may not coincide with the satellite overpass and therefore errors of omission may be large. As multitemporal Landsat imagery is available over the study area, the next stage in the research will involve a more detailed validation approach using the high resolution Landsat data to locate burning. Further work is planned on the wider

(a) Fire affected areas

(b) Active fire pixels and burned areas

Fig. 4. Location of active fires and area affected by fire

(a) Day of burn

(b) Day of active fire

Fig. 5. Temporal location of fires

applicability of this method to different types of change, and a comparison with a more recent version of the MODIS burned area algorithm [5] will be investigated.

REFERENCES

- [1] D. Roy, P. Lewis and C. Justice, (2002) *Burned area mapping using multi-temporal moderate spatial resolution data - a bi-directional reflectance model-based expectation approach*, Remote Sensing of Environment(83), 263-286
- [2] L.J. Roujean, M. Leroy and P.Y. Deschamps, (1992) *A bi-directional reflectance model of the Earth's surface for the correction of remote sensing data*, Journal of Geophysical Research(97), 20455-20468
- [3] W. Lucht and J.L. Roujean, (2000) *Considerations in the parametric modelling of BRDF and albedo from multiangular satellite sensor observations*, Remote Sensing Reviews(18), 343-379
- [4] W. Lucht and P. Lewis, (2000) *Theoretical noise sensitivity of BRDF and albedo retrieval from the EOS-MODIS and MISR sensors with respect to angular sampling*, International Journal of Remote Sensing(21), 81-98
- [5] D. Roy, Y. Yin, P. Lewis and C.O. Justice *Prototyping a global algorithm for systematic fire-affected area mapping using MODIS time series data*, In preparation
- [6] E.F. Vermote, N.Z.El Saleous and C.O. Justice (2002) *Operational atmospheric correction of the MODIS data in the visible to middle infrared: first results*, Remote Sensing of Environment(83), 97-111