A SPATIO-TEMPORAL APPROACH TO DETECTING LAND COVER CHANGE USING AN EXTENDED KALMAN FILTER ON MODIS TIME SERIES DATA

†*W. Kleynhans, †‡J.C. Olivier, †*B.P. Salmon, *K.J. Wessels, *F. van den Bergh

† Electrical, Electronic and Computer Engineering University of Pretoria, South Africa

*Remote Sensing Research Unit Meraka Institute, CSIR, Pretoria, South Africa

‡Defense, Peace, Safety and Security, CSIR, Pretoria, South Africa

ABSTRACT

A method for detecting land cover change using NDVI time-series data derived from MODerate-resolution Imaging Spectroradiometer (MODIS) satellite data is proposed. The algorithm acts as a per pixel change alarm and takes as input the NDVI time-series of a 3x3 grid of MODIS pixels. An Extended Kalman Filter was used to estimate a series of parameters related to each NDVI signal. A spatial comparison between the center pixel of the the 3x3 grid and each of its neighboring pixels' parameters was done to calculate a change metric which compared to a threshold yielded a change or no-change decision. The method was tested on real change examples in the study area and results indicate 90% detection of new settlements occurring in naturally vegetated areas.

1. INTRODUCTION

Anthropogenic land cover change has a major impact on hydrology, climate and ecology [1]. Remote sensing satellite data provide researchers with an effective way to monitor and evaluate land cover changes. Automated change detection reduces human interaction and enables large datasets to potentially be processed in a fraction of the time. Fully supervised change detection methods using temporal satellite data have shown potential, but require a considerable amount of change and no-change examples to be useful [2, 3, 4]. Only a limited number of these examples are typically available. The dearth of regional land cover training data makes unsupervised change detection a more attractive solution.

In this paper, unsupervised change detection using a NDVI time-series with a high temporal frequency (1 sample every 8 days) is considered. Each pixel's NDVI time-series is modeled as a single but triply modulated cosine function, where the mean μ, amplitude α and the phase ϕ values are a function of time. The parameters of the triply modulated cosine function are estimated using a non-linear extended Kalman filter (EKF) [5]. The change metric is then calculated by means of spatial comparison of the EKF parameter sequence of any given pixel with that of its neighboring pixels. The objective is to demonstrate that by making use of the spatial EKF derived change metric and a threshold selection method based on simulated land cover change, an unsupervised change detection method can be formulated. This method was applied to detecting new settlement formations in the Limpopo province of South Africa.

Making use of a simulated or synthetic data is not a new concept in the remote sensing community [6, 7, 8]. In this study, the use of simulated change as a preliminary step in the evaluation of the proposed algorithm is twofold. Firstly, to properly evaluate the performance of the algorithm, a large number of known change pixels have to be available. This requirement is often not achievable as regional land cover change in most cases is a rare event [9]. This holds true for our study region where the most pervasive form of land cover change, namely settlement expansion, is infrequently mapped on an ad hoc basis and amounts to a relatively small number of MODIS pixels. Simulating a change from natural vegetation to settlement substantially increases the number of change examples that could be used in the development and evaluation of a change detection method. The second reason is that the start date and the rate of change in actual examples is unknown, however by simulating a land cover transition, the start and rate of the land cover change can be controlled.

2. DATA DESCRIPTION

The Limpopo province is located in northern South Africa and is mostly covered by natural vegetation. A large number of informal settlements are however rapidly expanding throughout the province. The study area covers an approximate 25000 km^2 having an upper left coordinate of ($23^\circ 20' 12.09''$S ; $28^\circ 35' 25.18''$E) and a lower right coordinate of ($25^\circ 00' 14.59''$S ; $30^\circ 06' 58.30''$E). NDVI time series data was derived from 8 daily composite MCD43 bidirectional reflectance distribution function (BRDF)-corrected, MODIS data with a spatial resolution of 500m [10] for the period 2001/01 to 2008/01. A large simulated change dataset was generated to evaluate and optimize the change detection method. This was done by linearly blending a natural

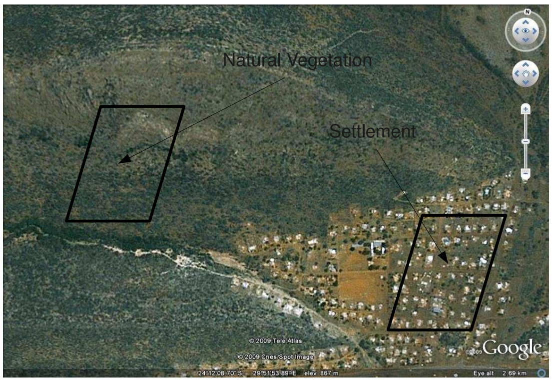

Fig. 1. 500m MODIS Pixel covering Natural Vegetation and Settlement land cover in close proximity (courtesy of Google™Earth)

vegetation time-series with that of a settlement time-series in close proximity ensuring that the rainfall, soil type and local climate were similar [11]. Figure 1 shows a typical 500m MODIS pixel covering natural vegetation and settlement in close proximity. As will be described in section 3, the algorithm uses a 3x3 pixel grid with the center pixel being compared to all neighboring pixels. It is not realistic to assume that only the center pixel has changed with all neighboring pixels remaining unchanged. For this reason, the center pixel together with a range of neighboring pixels (zero to four) where subject to a simulated land cover change. The simulated change for each of the neighboring pixels was done in a similar manner ensuring that the settlement pixel with which the blend is done is unique and in close proximity. Real change areas were identified by means of visual interpretation of two high resolution SPOT images in 2000 and 2006 respectively. All settlements identified in 2006 were referenced back to the same area in 2000 and all the new settlement polygons were mapped and the corresponding MODIS pixels were identified.

3. METHODOLOGY

3.1. EKF framework

The NDVI time series for a given pixel was modeled by a triply modulated cosine function given as

$$y_k = \mu_k + \alpha_k \cos(\omega k + \phi_k) + v_k, \tag{1}$$

where y_k denotes the observed value of the NDVI time series at time k, and v_k is the noise sample at time k. The values of μ_k, α_k and ϕ_k are functions of time, and must be estimated given y_k for $k \in 1, \ldots, N$ [5]. An EKF was used to estimate these parameters for every increment of k. The estimated values for $\mathbf{x}_k = [\mu_k \; \alpha_k \; \phi_k]^T$ over time k effectively results in a time series for each of the three parameters.

3.2. Change Detection Method

Having the parameter sequence for μ_k, α_k and ϕ_k for $k \in 1, \ldots, N$ for a given pixel, a change detection method was formulated by comparing the parameter sequences of the pixel with that of its direct neighboring pixels. This effectively means focusing on the center pixel of a 3×3 grid of pixels and examining each neighboring pixel's EKF parameter sequence relative to the center pixel. It was previously established that the ϕ parameter sequence does not yield any significant separability between natural vegetation and settlement land cover types, and consequently only the μ and α parameter sequence was considered [5, 12].

Figure 2 shows the μ parameter sequence for a 3x3 pixel grid with the center pixel gradually changing to settlement over a 6 month period. It is clear that the μ parameter sequence for the center pixel becomes less correlated with that of its neighboring pixels as time passes. The μ and α parameter sequence difference between the center pixel and an arbitrary neighboring pixel at time k can be written as

$$D^k_{\mu(n)} = |\mu_k - \mu^n_k| \qquad n \in 1, \ldots, 8, \tag{2}$$

$$D^k_{\alpha(n)} = |\alpha_k - \alpha^n_k| \qquad n \in 1, \ldots, 8, \tag{3}$$

where $D^k_{\mu(n)}$ is the distance between the μ parameter sequence of a selected pixel (μ_k) with its n'th neighboring pixel (μ^n_k) at time k. $D^k_{\alpha(n)}$ is the distance between the α parameter streams of a selected pixel (α_k) with its n'th neighboring pixel (α^n_k) at time k. Equation 2 and 3 can be combined as

$$D^k_n = D^k_{\mu(n)} + D^k_{\alpha(n)} \qquad n \in 1, \ldots, 8. \tag{4}$$

Having obtained a distance relative to each of the neighboring pixels, these could be combined at time k by simply adding all the values of D^k_n $n \in 1, \ldots, 8$ at time k

$$D^k = \sum_{n=1}^{8} D^k_n \qquad k \in 1, \ldots, N. \tag{5}$$

Having vector $\mathbf{D} = [D^1 \; D^2 \; D^3 \; \ldots \; D^N]$, a change metric was derived by firstly determining how the relative distance between the center pixel and its neighboring pixel changes through time. This was done by differentiating the vector D. A single change metric was then derived by summing all the values of the differentiated D vector to yield

$$\delta = \sum_{k=2}^{N} |D^k - D^{k-1}|, \tag{6}$$

where δ is a single valued change metric for the center pixel of the 3x3 pixel grid. The change metric for each of the pixels in the study area was thus calculated by sliding a 3x3 pixel grid over the entire study area and calculating δ for the center pixel in each case.

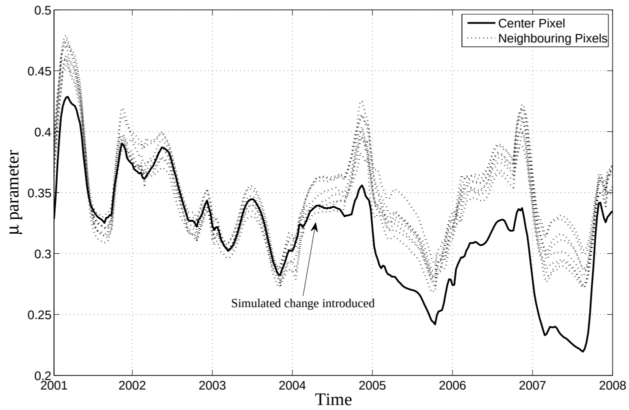

Fig. 2. Mean parameter sequence comparison of a 3x3 pixel grid with simulated natural vegetation to settlement change introduced to the center pixel.

Table 1. Confusion Matrix - Land cover change detection where the simulated change had a 6 month blending period

# of pixels changed in 3 x 3 grid	Change introduced	No Change introduced	δ^*
1 pixel change			1.68
Change Detected	91.71%	7.75%	
No Change Detected	8.29%	92.25%	
2 pixel change			1.66
Change Detected	92.45%	8.16%	
No Change Detected	7.55%	91.84%	
3 pixel change			1.65
Change Detected	92.38%	8.42%	
No Change Detected	7.62%	91.58%	
4 pixel change			1.63
Change Detected	92.38%	9.09%	
No Change Detected	7.62%	90.91%	

4. RESULTS AND DISCUSSION

4.1. Simulated change

The algorithm was run on the examples of natural vegetation pixels known not to have changed within the seven year study period. The value of δ as calculated in Equation 6 was recorded for each pixel. Next, the algorithm was run on the simulated changed pixels as described in section 2. The value of δ was again calculated and recorded for each pixel. The Bayesian decision error in the form of a confusion matrix is given in table 1. The value of δ^* is the optimal decision threshold and is also shown for each case in table 1. It is evident that the overall accuracy of the algorithm decreases as the number of changed pixels within the 3x3 grid increases. This is to be expected as the spectral signature of settlement pixels in close proximity (i.e the final state of all the changed pixels in the 3x3 grid), is very similar. The pixels subjected to change within the 3x3 pixel grid would thus be correlated. This implies that the average distance between the center and neighboring pixel's parameter stream would reduce, effectively reducing the value of δ.

4.2. Real Change

As is the problem with most unsupervised change detection methods, the selection of a suitable threshold is not an arbitrary task [13]. As was shown in the simulated change experiment results (table 1), the optimal threshold δ^* varied between 1.63 and 1.68 depending on the rate of change, as well as the number of pixels changing in the 3x3 pixel grid. By lowering the threshold, the change detection rate increases at the cost of increasing the number of false alarms. The approach in selecting the threshold for real change detection was to firstly determine the range of the threshold by anticipating the rate and area of change that is characteristic of the type of change that is expected. In the case of settlement formation, new settlement formations are mostly between 0.25 and 1 km^2 which relates to between one and four MODIS pixels. Figure 3 shows the distribution of the number of of MODIS pixels that changed for each instance of new settlement formations in the study area based on SPOT multi-date images. It is evident that 90% of the recorded new settlement formations affected an area of four or fewer MODIS pixels. The rate of change is very difficult to determine having only two SPOT images (2000 and 2006). From simulation results shown in table 1, the optimal threshold ranged between 1.68 for a one pixel change with a land cover transition of 6 months and 1.63 for a four pixel change. The best change detection rate will be achieved when selecting the lower threshold with the trade-off being a higher false alarm rate. Thus the approach was to select the lower range threshold and upwardly adjusting the threshold until the false alarm rate is at an acceptable level. In our case, a false alarm rate of 13% was selected and the corresponding threshold value ($\delta = 1.52$) was used. New settlement formation in naturally vegetated areas are very well suited to the proposed change detection method. In this type of settlement formation, no form of existing settlements are within the direct vicinity of existing settlements. The new settlement is developed within an area that is otherwise in an undisturbed naturally vegetated state. In accordance with the simulated land cover change experiment, the change detection accuracy that was achieved for new settlement formations was 90.48% with a false alarm rate of 13%.

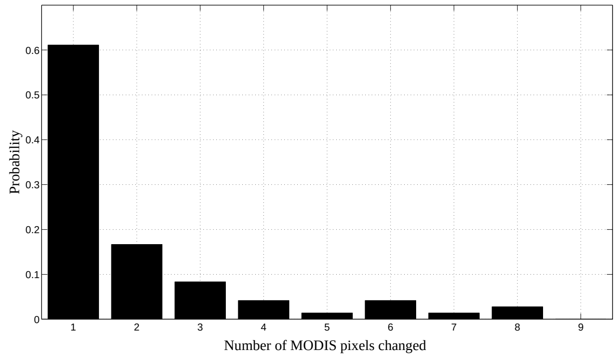

Fig. 3. Distribution of the number of contiguous MODIS pixels affected by actual new settlement formations in the study area.

5. CONCLUSION

In this paper, a land cover change detection method is proposed. The method models an NDVI time series as a triply modulated cosine function and estimates the mean, amplitude and phase for each time increment using an EKF. A change index was derived by comparing each pixel's mean and amplitude parameters with that of its neighboring pixels. Because the parameters of the EKF are updated for each increment of the time series (i.e. every eight days), changes can be detected in near real time. The threshold that determined whether the change index associated with each pixel should be classified as change or no-change was determined by means of land cover change simulation. The algorithm was tested for new settlement developments where no form of existing settlements were present within the direct vicinity of the new settlement and the surrounding area was mostly in an undisturbed naturally vegetated state. The change detection algorithm was particularly well suited to this type of change as the land cover change transition from natural vegetation to settlement was very similar to the blended simulated change that was used for threshold selection. A change detection accuracy of 90.48% with a 13% false alarm rate was achieved.

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