

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

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## 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  $\mu$ , amplitude  $\alpha$  and the phase  $\phi$  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. METHODOLOGY

### 2.1. EKF framework

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

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

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  $\mu_k$ ,  $\alpha_k$  and  $\phi_k$  are functions of time, and must be estimated given  $y_k$  for  $k \in 1, \dots, N$  [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.

### 2.2. Change Detection Method

Having the parameter sequence for  $\mu_k$ ,  $\alpha_k$  and  $\phi_k$  for  $k \in 1, \dots, N$  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  $3 \times 3$  grid of pixels and examining each neighboring pixel's EKF parameter sequence relative to the center pixel. It was previously established that the  $\phi$  parameter sequence does not yield any significant separability between natural vegetation and settlement land cover types and consequently only the  $\mu$  and  $\alpha$  parameter sequence was considered [5]. The  $\mu$  and  $\alpha$  parameter sequence difference between the center pixel and an arbitrary neighboring pixel at time  $k$  can be written as

$$D_{\mu(n)}^k = |\mu_k - \mu_k^n| \quad n \in 1, \dots, 8, \quad (2)$$

$$D_{\alpha(n)}^k = |\alpha_k - \alpha_k^n| \quad n \in 1, \dots, 8, \quad (3)$$

where  $D_{\mu(n)}^k$  is the distance between the  $\mu$  parameter sequence of a selected pixel ( $\mu_k$ ) with its  $n$ 'th neighboring pixel ( $\mu_k^n$ ) at time  $k$ .  $D_{\alpha(n)}^k$  is the distance between the  $\alpha$  parameter streams of a selected pixel ( $\alpha_k$ ) with its  $n$ 'th neighboring pixel ( $\alpha_k^n$ ) at time  $k$ . Equation 2 and 3 can be combined as

$$D_n^k = D_{\mu(n)}^k + D_{\alpha(n)}^k \quad n \in 1, \dots, 8. \quad (4)$$

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  $D_n^k$   $n \in 1, \dots, 8$  at time  $k$

$$D^k = \sum_{n=1}^8 D_n^k \quad k \in 1, \dots, N. \quad (5)$$

Having vector  $\mathbf{D} = [D^1 \ D^2 \ D^3 \ \dots \ D^N]$ , 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

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

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

### 3. CONCLUSION

The proposed 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 is 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.

### 4. REFERENCES

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