# Detection of land cover change using an Artificial Neural Network on a time-series of MODIS satellite data

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## Abstract

An Artificial Neural Network (ANN) is proposed to detect human-induced land cover change using a sliding window through a time-series of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite surface reflectance pixel values. Training of the ANN is performed on data from two pairs of different, but adjacent areas: (i) degraded vs. non-degraded and (ii) urban settlements vs. natural grasslands. The close proximity of the sites limited natural variability in rainfall, soils and vegetation type. It was therefore assumed that the ANN based its classification decisions on human modifications of the land cover, specifically in the form of land degradation and urban expansion. Numerical results are presented for locations in the Limpopo and Mpumalanga provinces, where the non-degraded class was located inside the Kruger National Park. It was found that some 80% of the pixels were correctly classified, and simulations demonstrated that change from non-degraded to degraded could be detected reliably. In Gauteng 87% of pixels were correctly classified as either urban settlements and natural grasslands and the ANN would be able to accurately detect urban expansion.

## 1. Introduction

Land cover is the physical material that covers the surface of the earth and include grass, asphalt, trees, bare ground, water, etc. Human activities alter this land cover through deforestation, urban expansion and land degradation. With the use of satellite imagery insight into the effects of these activities at a global scale has increased. State of the art image processing is however unable to detect the effect of these complex activities from a single image of most of the current satelite products. However, there is more than twenty years of library data of coarse resolution satelite reading of Earth currently available. Coarse resolution satellite remote sensing has been successfully used to monitor land cover change over very large areas, on a continuous basis [1]. The development of an effective methodology to analyse the multi-temporal data is one of the most important challenges facing the remote sensing community [2]

Land degradation is defined as a reduction in the biological productivity of the land due to human impacts [3]. The detection of human induced land degradation is a complex problem since natural effects such as inter-annual rainfall variation, varying soil types, vegetation types and land use changes tend to obscure the human impact [4]. Human-induced land degradation is a serious environmental problem, and is directly responsible for placing the lives of some 1 billion people worldwide at risk. To combat land degradation, environmental agencies and governments need spatial monitoring systems that are able to detect change in the environment due to human activity and can distinguish these from natural processes such as rainfall variability [3].

Urban expansion is currently the most prevalent and obvious form of land cover change in South Africa. Spatial information on formal and informal urban expansion is essential for effective service delivery (e.g. water and electricity supply). The automated change detection of urban expansion with coarse resolution image could guide the acquisition of expensive high resolution satellite imagery for detailed urban mapping over specific target areas.

A number of different time-series analysis methods have been used to monitor land cover change with satellite data. Markov chain models with genetic algorithms have been used to study urban change based on rapidly changing urban landscapes in China [5]. Statistical similarity measures were applied by measuring the evolution of local statistics over time using the Kullbac-Leibler divergence [6]. Artificial Neural Networks (ANN) were applied using MODIS data in the Amazon region where the combination of high resolution and moderate resolution data was studied to detect human induced change [7]. ANN's were used to detect change on floodplains in Africa, and results obtained there made clear the ANN's ability to detect change in MODIS time-series data [8]. Linear trends in remotely sensed estimates of vegetation production per unit rainfall have been used to detect land degradation with some success in South Africa [4], however, ANN may to be better suited to unravelling the non-linear, complex changes involved in the process of land degradation.

In this paper we apply ANN's to time-series data of selected pixels extracted from 8-day 500m MODIS composite images [9]. Using a 3-year sliding window through time, an ANN was trained to recognise a typical signal within the sliding window of each time-series of the selected pixels, and then change is detected when the ANN classifier changes states over time from one class to the other. The objective of this paper is to evaluate the use of Artificial Neural Networks (ANN) in detecting human induced land cover change (land degradation or urban expansion) with a time-series (2000 to 2007) of MODIS satellite data.

The paper is organised as follows. Section 2 provides an overview of the MODIS data, while Section 3 introduces the finite time series window based ANN classifier used for change detection. Section 4 provides numerical results on actual MODIS data, and Section 5 presents conclusions.

## 2. MODIS remote sensing data

MODIS data are recorded on board the Terra and Aqua satellites as part of NASA's Earth Observing System (EOS) Data and Information System (EOSDIS) initiative [9]. Since 2000, the MODIS sensor has been recording daily reflectance data (500m resolution) for the entire globe which are processed to 8-day composites images to remove clouds and restrict view angles [10].

The MODIS surface reflectance MOD 09 V004 product (MODIS/Terra 8-Day 500m Surface Reflectance) is the input for product generation for several of the land products: Vegetation Indices (VIs), Thermal Anomalies, Land-cover and Snow/Ice Cover. It is an estimate of the surface spectral reflectance for each of the seven frequency bands as it would have been measured at ground level if there were no atmospheric scattering or absorption. There are 7 frequency bands that are sensitive to a specific land surface properties (bands 1, 2, 3, 4, 5, 6, and 7 are centered at 648 nm, 858 nm, 470 nm, 555 nm, 1240 nm, 1640 nm, and 2130 nm, respectively). This product is used in this paper.

For each band the surface reflectance data are available as well as quality flags indicating reliability of each pixel's data based on cloudiness, aerosol loading and view angle [10]. We used the quality flags to reject unreliable data that are then replaced by interpolated data in the time series used by the ANN.

## 3. The ANN change detector

Denote by $x_i^j[n] \, \forall \, n \in \{1, \cdots, N\}$ a time series containing the surface reflectance data for pixel $i$ and band $j$. For the MOD 09 data the sample rate is 8 days, and there are data for 7 years starting from 2000. We select a subset of data from $\mathbf{x}_i^j$ which we call a window denoted by $x_i^j[n_s, n_s + M]$ where $n_s$ indicates the start sample and the window contains $M + 1$ values. The window may be moved through the time-series $\mathbf{x}_i^j$ by varying $n_s$. Here a three year moving window was used to accommodate the inter-annual seasonal variability in the reflectance signals of the different land cover classes.

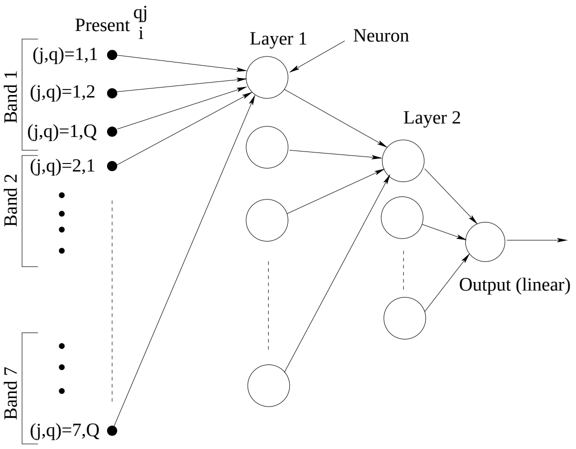


Figure 1: The ANN used for classification.

The next step is to identify areas where two different land cover classes are located in close proximity to each other. In South Africa the National Land Cover (NLC) map [11] provide detailed data for identifying degraded land located next to non-degraded land that are equivalent in all other respects, including soil type, local climate, rainfall, and topography[1]. Degraded land cover area is denoted as Class 1, and the undegraded area as Class 2. An ANN [12] (depicted in Figure 1) may be trained to recognise a pixel with its associated 7 sets of data $x_i^j[n_s, n_s + M] \, \forall j \in \{1, \cdots, 7\}$ as belonging to either Class 1 or 2. The training is performed by moving the window through the entire time series. The training is performed on a a subset of all the pixels available, and then the ANN is tested on the remaining pixels that were excluded during training. Figure 2 depicts the siding window concept.

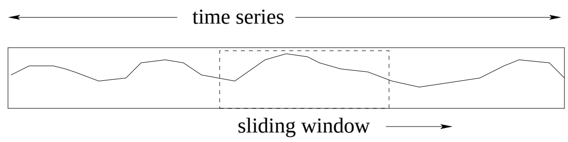


Figure 2: The concept of the sliding window used for training the ANN.

The data contained in window $(j, i)$ is transformed from the time-domain into frequency-domain using Discrete Fourier transformed by applying the FFT algorithm given by

$$X_i^j[1, \cdots, M] = \mathcal{F}\left(x_i^j[n_s, n_s + M]\right). \qquad (1)$$

The ANN is then presented with information from all the 7 bands for each pixel $i$ and window position as indicated in Figure 1. For each band $j$ and pixel $i$ in the training set the $Q$ first entries of $\mathbf{X}_i^j$ are used, given by

$$\text{Present}_i^{qj} = |X_i^{qj}| \times \text{angle}(X_i^{qj}) \, \forall \, q \in \{1, \cdots, Q\}. \qquad (2)$$

Using the Fourier domain data for input to the ANN has the additional advantage of rejecting noise which typically does not constitute the largest values of the FFT.

By combining the Fourier domain information of each band for input to the ANN (see Figure 1), the ANN is able to select optimally weights associated with each band in order to achieve the highest possible classification rate on the training data. It is not known *a priori* how the 7 bands should be combined to detect different kinds of change. The ANN is therefore allowed to choose the optimal combinations due to the lack of *a priori* information.

After training the ANN, land cover change can be detected by applying the ANN to a time-series using a sliding window. If change is occurring in the pixel, the most recent data points entering the window will take on characteristics of the opposite class and the ANN output will gradually change until it classifies the window as now belonging to the opposite class. At that point, change detection has been accomplished. Drought over an extended period of time may mimic change, but then the drought has to last for a period longer or comparable to the window length, which is not a common event if the window spans multiple years. The close proximity of the compared areas should further limit the spatial variability in rainfall so that it can be assumed that they received the same amount of rainfall for any given period.

[1] In mountainous areas this may not be possible since rainfall and land cover may vary drastically within just a few kilometers

# 4. Numerical results

## 4.1. Land degradation

Based on the NLC maps two areas were identified where non-degraded and degraded land cover occur in close proximity. Degraded sites in the Limpopo and Mpumalanga provinces near the border of Kruger National Park were compared to adjacent areas inside the park where human impacts were assumed to be minimal. At both locations 1600 pixels at 500m resolution were sampled, representing approximately $400\ km^2$ per class.

For the ANN 100 layer 1 and 10 layer 2 neurons were initially used and it was found that moderate variations in these choices had little effect on performance. A validation set can be used to prevent overvitting, while the remaining data were used for training and testing respectively. The vectors presented to the ANN contained 35 values since the choice for $Q$ was $Q = 5$. It was found that larger Q values yielded identical results. Gradient descend back-propagation was used with 800 epochs to complete training. Performance on the testing sets are shown in Table 1 below. A 3 year sliding window was used.

Table 1: *Percentile of pixels correctly classified on four locations, two near the Kruger national park and two in Gauteng.*

| Change Type | Location | Classification accuracy |
|---|---|---|
| Land degradation | Limpopo | 81% |
| | Mpumalanga | 77% |
| Urban expansion | Evaton | 91% |
| | Soshanguve | 83% |

It was found that pixels that were misclassified were in fact mostly pixels in one class that resembled the time series signatures of the opposite class. This implies that there are pixels in areas mapped as degraded by the NLC that appear to be non-degraded. Experiments were conducted by eliminating some bands in the vectors presented to the ANN. Generally results degraded with the elimination of each band, while bands 1 and 2 were found to have larger impact than the others. This is in-line with previous remote sensing research that most vegetation indices calculation is mainly based on these two bands. Bands 1 and 2 without the aid of the other bands however only yield some 64% classification accuracy, indicating that the other bands do play an important part. Overall best performance is obtained when all 7 bands are used, since the ANN has the greatest amount of information at its disposal.

## 4.2. Urban expansion

Two areas in the Gauteng province were identified where a combination of informal and Reconstruction and Development (RDP) settlements exist next to highveld grasslands. The first is near Evaton with the grassland separated from the settlements by the a freeway. The second site was near Soshanguve north of Pretoria. Of the two sites Evaton was more densely populated and contained little vegetation, while Soshanguva contained some open land. The urban settlements and nearby natural grasslands were selected as 2 classes and the ANN trained to recognise windows periods obtained from each class. The ANN was applied according to the specifications described in the previous section. The results obtained with this ANN also shown in Table 1. In this case, classification accuracy is higher (especially for Evaton where the density of dwellings is higher) and it is clear that fewer pixels resemble the opposite class than is the case for land degradation.

## 4.3. Change detection

As field validated examples of land cover change were not yet available, “space-for-time substitution” was applied so that change was simulated by concatenating the two time series of the contrasting land cover classes together to form a longer time series. The detection of change was tested on a random pixels that were classified correctly in their initial state. Time series data from adjacent correctly classified pixels belonging to opposite land cover classes was concatenated. The sliding window was used on the concatenated time series and the trained ANN was used to classify the window period as a function of time. The results for the Limpopo site is shown in Figure 3, and for Evaton in Figure 4. It is clear that the ANN output starts moving in the direction of class 2 as the data from class 2 starts entering the sliding window. When the window has its first half filled with class 1 data and the other half with class 2 data the ANN outputs approaches 0, since it is uncertain of the class. As the sliding window forward in time window is filled with more class 2 data and the ANN classifies the pixel as class 2. Change detection has thus occurred. For Figure 4 the results seem to suggest that urban expansion may be relatively easily detected using ANNs. The results depicted in Figure 3 and Figure 4 are typical for pixels that were correctly classified. Finally using more than one pixel (neighbouring pixels) with an ANN operating on each independently and then combing the results is expected to improve the classification accuracy, but that was not performed in this paper.

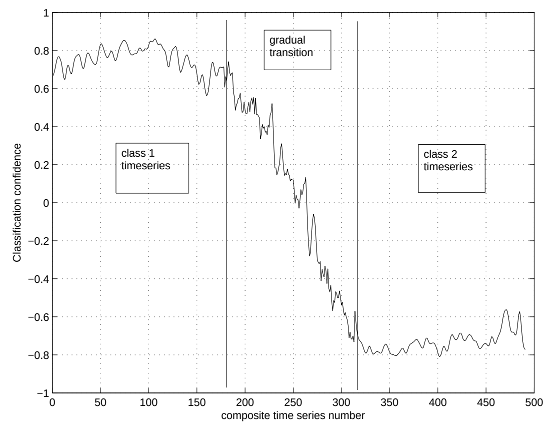


Figure 3: Classification confidence as a method for change detection from a non-degraded (class 1) to degraded (class 2) state in a concatenated time series extracted from the Limpopo province.

# 5. Conclusions

The results suggest that land cover change in the form of land degradation and urban expansion may be detected using an ANN in conjunction with a sliding window on a time series of MODIS pixel data. All 7 bands of the MOD 09 surface reflectance data were shown to be important in obtaining the best possible results. This was accomplished by letting the ANN

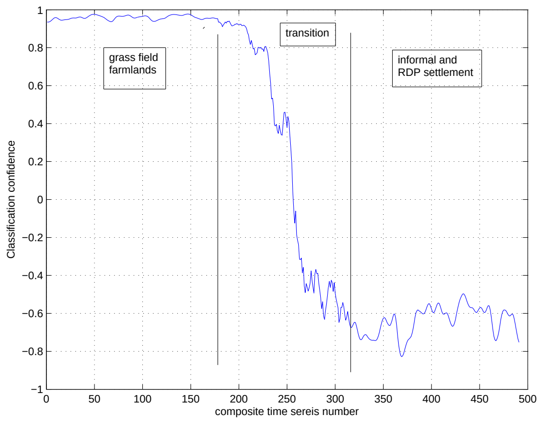


Figure 4: Classification confidence as a method for change detection from natural grasslands (class 1) to urban settlements (class 2) state in a concatenated time series extracted from the Gauteng province (Evaton)

choose the optimum combining weights between all 7 bands. Numerical results obtained from degraded land in the Limpopo and Mpumalanga provinces showed that classification rates of some 80% or better is achievable. In densely populated RDP and informal settlements classification rates of approximately 90% are achievable. The ANN was also successful at identifying the land cover changes simulated by concatenating the time series of contrasting land cover classes. This research is the first step in the development of an automated land cover (land use) change detection system capable of processing data for the entire South Africa in near real-time.

## 6. Acknowledgement

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