

CHAPTER SEVEN

CONCLUSION AND FUTURE RESEARCH

7.1 CONCLUDING REMARKS

The most pervasive form of land cover change in South Africa is informal human settlement expansion. It was shown in chapter 1 that determining where and when new informal settlements occur is beneficial from both an ecological as well as a social development perspective. The problem, however, is that these settlements are infrequently mapped in South Africa and that there exists a need to determine the location of these settlements in a timely and cost-effective manner. The primary objective of this thesis was to develop and test an automated change detection framework that is able to detect the transformation of natural vegetation to human settlement which could be adapted to consider many other types of land cover change as part of an ongoing endeavor towards developing a global or regional automated land cover change detection method. Two novel change detection methods were formulated to solve the aforementioned problem. Both of these methods utilize the hyper-temporal time-series data that are available from coarse resolution imagery. The novelty of these methods is underpinned by the fact that the temporal dimension of the time-series is considered as a highly sampled (relative to the natural phenological variation) data-sequence, and change classification is done by combining standard signal processing based methods for feature extraction with machine learning methods for change classification.

Human operator-dependent change mapping was found to be very time consuming and resource intensive. It follows that for large areas to be processed, a need exists to detect new settlement developments in an automated way. It was proposed in this thesis that a remote sensing approach be used to detect the formation of new settlements. Coarse resolution remotely-sensed data were found to provide an effective manner to monitor large areas on a frequent basis as the wide swath-width of coarse resolution sensors enables the same area to be observed at a very high temporal sampling rate

(hyper-temporal) as opposed to the lower revisit frequency typically associated with high resolution imagery.

When considering current change detection methods in literature, it was found that the majority of methods are based on multi-date high resolution data (in most cases only two images are used) for change detection [14, 15]. In the case where hyper-temporal data were used, change metrics were derived, giving an indication of the change intensity [16, 17, 19, 80]. A threshold-based approach was mostly used, i.e. the change metric is compared to a pre-defined threshold to infer a change or no-change decision. It was found that the change metric that is used by most of these methods is based on the annual statistics of the underlying hyper-temporal time-series and effectively reduced the hyper-temporal time-series to only a few observations. This approach fails to exploit the valuable temporal components (e.g. phase or frequency modulation, etc.) of the signal which is driven by seasonal changes in land surface phenology. The threshold selection procedure that is usually used is based on expert *a-priori* knowledge of the area. In addition, many of these methods identify large-scale ecosystem disturbances as opposed to the relatively small spatial extent of a new settlement development (resulting in but a few contiguous MODIS pixels). It follows that a novel change detection strategy had to be formulated for detecting new settlement developments using hyper-temporal satellite time-series data. When considering the objective of this thesis, the NDVI differencing method, with its statistical threshold selection methodology [17] (Section 2.7.1) was found to be the most comparable method in current literature and was consequently used for comparison with the novel change detection methods proposed in this thesis.

One of the major challenges in formulating a novel change detection method for new settlement detection was the lack of change examples, which results from the fact that regional anthropogenic land cover change is a relatively rare event in a regional landscape and that settlements are infrequently mapped in South Africa. An intuitive solution is to opt for a fully unsupervised approach which does not require any ground truth. The problem, however, is selecting suitable thresholds. The saying: “*just because everything is different doesn’t mean anything has changed – Irene Peter*”, is very relevant when considering this change detection problem. Differentiating real change from natural variations in the spectral signature using a completely unsupervised approach proved to be a very difficult task as there are still no operational MODIS land-cover change detection products available, even though more than a decade has passed since the launch of MODIS. A more practical solution is to use all ground truth, even in the absence of real change examples. This forces one to look at the specific problem from another angle. The fact that anthropogenic change is a rare event in a regional landscape

implies that no-change is a very common event in a regional landscape. It follows that obtaining no-change examples is a simple task. To address this problem, change examples were simulated by blending a time-series from a natural vegetation to a settlement state using representative time-series examples of each of these land cover types.

The objective that was set out at the beginning of this thesis was to make use of coarse resolution satellite data to infer the location of new settlement developments in an automated manner by employing machine-learning methods and subsequently two novel change detection methods were presented. The first method is based on a spatial comparison of parameter sequences derived using an EKF framework. The EKF change detection method was used to detect new settlement developments in the Limpopo and Gauteng provinces of South Africa (section 6.3.1 and 6.4.1). The second method that was proposed was the temporal ACF change detection method where the temporal ACF was used to exploit the non-stationarity of change pixels relative to no-change pixels by using the correlation coefficient of a pre-determined band and lag combination as a change metric. The method was also used to detect new settlement developments in both provinces (section 6.3.2 and 6.4.2). Both methods were compared to a recently published change detection method that uses NDVI differencing to detect land cover change. The performance of this method is also given for both provinces (section 6.3.3 and 6.4.3) where it was found that the EKF change detection method performed best in the Limpopo province (89% change detection accuracy with a false alarm rate of 13%) whereas the temporal ACF change detection method had the best performance in the Gauteng province (92% change detection accuracy with a false alarm rate of 15%). Both the proposed methods performed well when compared to the NDVI differencing method proposed in [17].

Although some MODIS change detection products do exist (such as MODIS burn-scar detection [82]), there are currently no operational MODIS products available specifically for land cover change detection, even though land cover change detection was one of the primary objectives of the MODIS mission [48]. Two previous attempts to implement an automated MODIS land cover change product as an operational system [12, 83] was not very successful, making automated land change detection using MODIS data an ongoing endeavor.

When considering the methodology for creating an automated MODIS land cover change detection framework there are a few considerations. In light of this study, it is the view of the author that unsupervised threshold based large scale land cover change detection using a completely unsupervised approach is not feasible. To illustrate this, one only has to consider the threshold values corresponding

to a similar false alarm rate for both methods in the two study areas. For example, the threshold value selected for the EKF method corresponding to a false alarm rate of 13% in Limpopo was 1.5 whereas the threshold corresponding to a similar false alarm rate in Gauteng was 1.97. Although it was shown that the threshold value produced a stable false alarm rate in a 70 km radius from the study area center, this does not imply that the threshold value will be valid over large areas spanning multiple bio-regions. The difference in the false alarm rate for the aforementioned example relates to the inherent difference in natural vegetation in both study areas which implies that blindly running the method in both regions without taking into consideration representative no-change examples is not advisable.

A better approach is to determine the most applicable land cover changes to be detected and select the appropriate system parameters to detect these specific changes. This is in line with the change detection philosophy adopted in this thesis. The two proposed methods lend themselves to operational viability by determining appropriate parameters for specific land cover change events. This is accomplished by making use of no-change examples of the two land cover types involved in the land cover change and simulating the corresponding land cover change.

When considering the operational viability of the two methods presented in this thesis a few interesting conclusions can be made. When practically implementing the EKF method, it is important that the following be taken into consideration. The EKF method utilizes a 3×3 pixel grid when determining the change metric. The advantage of this approach is that in the case of a homogeneous area and changes in the order of less than 4 contiguous MODIS pixels (see tables 6.4–6.4), the method effectively exploits the information from neighboring pixels in calculating the change metric. It was also found that, although the duration of the change does influence the method's performance (see tables 6.4–6.4), the exact change date does not. This implies that a change can be determined as soon as a significant difference in the parameter sequences of the center pixel and neighboring pixels are detected. The disadvantage of the EKF method is that when neighboring pixels are no longer correlated with the center pixel the performance of the method deteriorates, as was found to be the case in the Gauteng study area. The method should thus operate well in homogeneous areas where a simultaneous change is typically in the order of less than 4 contiguous MODIS pixels and where representative “no-change” examples of the land cover types in question are available.

In the case of practical implementation of the ACF method, the following should be taken into consideration. The advantage of the ACF method is that the method is a per pixel change detection

method and is thus not sensitive to the correlation to neighboring pixels. This implies that the homogeneity of the area will not affect the method in the same way as was found to be case for the EKF method. The ACF method utilizes all of the MODIS land bands when determining the optimal detection parameters. This makes the method more versatile than the EKF method, which only utilizes NDVI. The disadvantage of the method, however, is that the start of change date does influence the performance of the method as the change detection performance increases when the change date moves towards the center of the time-series (see table 6.17). When practically implementing the ACF method, it is advisable that the anticipated start of change date be taken into consideration when determining the time-series length of the study period. However, even when there is no *a-priori* knowledge of the start of change date and a random start of change date is assumed, the method should still perform acceptably, as was found in the simulated change experiments and real change detection performance in Limpopo.

7.2 FUTURE RESEARCH

Based on the findings of this thesis, the following areas were identified that could potentially be explored in subsequent studies.

- Currently, the distribution of the change metrics derived using the EKF and ACF change detection methods in the case of simulated change and no-change respectively is estimated by means of the Parzen-Rosenblatt window method using Gaussian kernels (see section 6.2.2). The corresponding optimal threshold is then determined by making use of these estimated distributions. An alternative approach to determining the optimal threshold could be to use a supervised classifier for example a Neural Network (NN) or Support Vector Machine (SVM) by using the change metric as input features. The use of other features as input to the aforementioned classifiers can also be investigated. For example, a selected subset of bands and lags of the ACF functions shown in section 5.3 can be used as input features to the classifier.
- The EKF change detection method currently uses a triply modulated cosine function to model the NDVI time-series and uses the non-linear EKF to track the model parameters for each time step (see section 5.2). The EKF change detection method can be adapted to use as input all seven bands. Although this would require a representative observation model to be formulated for each band, the resulting increase of tracked parameters could produce a higher change detection accuracy as the increase in usable features could produce a higher separability between change and no-change when used with a non-linear classifier, as mentioned in the previous point.

- As suggested in section 6.5.1, changes other than settlement expansion (for example deforestation) can be considered using the same methodology proposed in this thesis. Using no-change examples of representative land cover types (for example, forested and deforested regions if the aim is to determine areas affected by deforestation), the EKF change method can be adapted to detect a host of possible change events.
- An analysis could be done to determine the correlation between specific land cover types and typical false alarm rates using each of the change detection methods presented in this thesis, using this information, no-change land cover types, prone to being flagged as false alarms (for example agriculture or water), could be masked out if the algorithm is run over large areas.
- Currently, the EKF change detection method only makes use of NDVI data as input. The effect of using other vegetation indices, such as Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), as input to the algorithm can also be investigated.