CHAPTER NINE
CONCLUSION

9.1 CONCLUDING REMARKS

The importance of reliable land cover monitoring and detection of land cover change was discussed in chapter 1, and has been shown to be of great benefit to the global community [11]. Each country or region faces its own challenges in monitoring the land; in South Africa the transformation of natural vegetation to new human settlements is the most pervasive form of land cover change [7].

South Africa's National Land Cover (NLC) was mapped in 1995–1997 using manual photo interpretation [225] of Landsat imagery, while the NLC of 2000 was based on digital classification of Landsat images by regional experts [226]. Both of these took a number of years to complete. Subsequently land cover has been mapped by provincial governments on an ad hoc basis through private companies using a variety of methods. Since the methods have not been standardised through time and space, reliable land cover change data cannot be generated from successive national land cover data sets. The Landsat-based land cover mapping efforts furthermore relied on single date imagery, which resulted in neighbouring images being acquired on widely varying dates containing seasonal effects that hampered multi-spectral land cover classification. The hyper-temporal, time-series analysis approach described here capitalises on seasonal dynamics to characterise land cover and land cover change in a repeatable, standardised method that can be applied over large areas.

The satellite images used in this thesis were acquired by the MODIS sensor. The MODIS sensor is used to produce a hyper-temporal, multi-spectral medium spatial resolution land surface reflectance data product. This sequence of images is used to construct a time series, which can be analysed with a change detection algorithm to detect the formation of newly developed human settlements. A post-classification change detection framework was developed to detect land cover change occurring in time series. The framework classifies the geographical area for each time index and declares change if a permanent transition in class label is observed. Two novel hyper-temporal feature extraction methods were proposed in this thesis, which are used in the post-classification change detection framework. The two types of features extracted with these novel feature extraction methods are:

- the Seasonal Fourier Features (SFF), and
- the Extended Kalman Filter (EKF) features optimised using the Bias-Variance Equilibrium Point (BVEP) criterion.

The SFF is a hyper-temporal feature vector that extracts information from multiple spectral bands, which exploits the seasonal spectral signature in the temporal dimension of a geographical area. SFF is the first type of novel hyper-temporal feature in this thesis that incorporates temporal information, allowing the analysis of seasonal surface reflectance variations of different land cover classes. SFF (extracted from the MODIS time series) allows the post-classification change detection framework to be sensitive enough to detect new human settlements as small as 0.25 km^2.

The second novel hyper-temporal feature extraction method is an improvement on the method proposed by Kleynhans *et al.* [30]. The first contribution made to this method is the extension to higher dimensions, which improves the land cover change detection accuracies. This contribution is supported by all the experiments conducted in chapter 8. The second contribution made to the method proposed by Kleynhans *et al.* [30] is the definition of the novel BVEP criterion, which defines the condition that improves the tracking of time series, while simultaneously improving the internal stability of the EKF.

This criterion allows the evaluation of the EKF performance in an unsupervised fashion. The drawback with the method proposed by Kleynhans *et al.* is that it requires an offline optimisation phase, which must be performed by an operator with a training set. This drawback is overcome by defining a scoring function such as the Bias-Variance Score (BVS) to evaluate how well a particular set of parameters satisfy the BVEP criterion. The EKF parameters are adjusted using a search algorithm such as the Bias-Variance Search Algorithm (BVSA) in an attempt to best satisfy the BVEP criterion. This led to another contribution, namely the development of the BVSA; the BVSA is an unsupervised search algorithm that can effectively optimise the BVS using the BVEP criterion for optimal EKF performance. It was found in chapter 8 that the BVSA performed similarly to other popular search algorithms, but had the advantage of having a faster convergence time. All these contributions led to the full automation of the method proposed by Kleynhans *et al.* [30]. The BVS optimised using the BVEP criterion provides statistical information on the phenological growth cycle, which could also be used to provide vital insight to environmental dynamics [31, 32].

The post-classification change detection framework uses a machine learning method to classify a geographical area at each time index and can be either a supervised or an unsupervised classifier. In chapter 8 the ability of the hyper-temporal features to separate different land cover classes was investigated. A classification experiment was used to evaluate class separation; a Multilayer Perceptron (MLP) was used to represent supervised classifiers. Unsupervised methods were represented by a selection of clustering methods. The supervised classifier performed significantly better than the unsupervised methods, but it requires labelled examples derived from commercial high resolution satellite imagery, making the unsuperivsed methods more attractive for operational implementation.

A range of experiments were conducted for different combinations of spectral bands: NDVI, first two MODIS spectral bands, and all seven MODIS spectral bands. It was observed that the experiments using the first two spectral bands yielded better results than the experiments using NDVI. This is a well-known property in the machine learning community, that better separation is usually obtained in higher dimensions [130, Ch. 1 p. 4]. This was supported by classification experiments in chapter 8, where the MLP reported general improvements with an increase in the number of spectral bands. The performance of the unsupervised methods improved when going from two-dimensional features (NDVI) to four-dimensional features (first two spectral bands), but the performance deteriorated when going to 14-dimensional features (all seven spectral bands), suggesting that complex decision boundaries are required to maximise performance in 14-dimensions.

The goal for this thesis was the development of a novel land cover change detection method. The method had to be sufficiently near automated with minimal human interaction. A post-classification change detection framework was used to evaluate two features extraction methods to improve land cover separability, which in turn improved the land cover change detection. The SFF is a novel introduced feature and was compared to the EKF feature presented by Kleynhans *et al.* [30]. The EKF features were improved using the novel BVEP criterion, which resulted in an optimised EKF that gave the best performance. The downside was that the EKF features could only provide better results if the BVEP criterion was used in the optimisation phase. These improvements over the SFF features were small when compared to the computational requirement of the optimisation phase. Therefore, it was concluded that the SFF is more practical for operational applications.

9.2 FUTURE RECOMMENDATIONS

In this section a brief overview is given of potential future research that could stem from the work presented in this thesis.

- **Spatial information analysis:** In chapter 2 it was discussed that algorithms are usually designed to provide acceptable performance for an application in a particular geographical area. This is caused by the inherent differences between geographical areas. The BVEP criterion can be used to analyse a particular geographical area by studying the statistical parameters derived, such as the standard deviation of model parameters. This information can be used in a statistical test to determine whether a region of the study area can be expanded to cover a larger area. An example of such a test is the use of the Aikaike Information criterion (AIC) to determine if the size of the current study area is acceptable. The AIC is given as

$$\mathrm{AIC} = \ln(K) - 2\ln(L), \tag{9.1}$$

where K is the number of model parameters and L is the likelihood of the model which incorporates the standard deviation. The criterion is used to balance the cost of increased complexity (more small regions) against the loss of performance when using fewer, larger regions.

- **Spectral band selection criterion:** In chapter 4 it was discussed that proper domain knowledge leads to proper definition of feature vectors. Feature selection is always a relevant topic in remote sensing, as new sensors are continually being developed with more sophisticated capabilities. In chapter 3, an approach to training a neural network was presented which was proposed by Caruana *et al.* [168]. The training algorithm starts by mapping all the linear regions in the feature space and then progresses to map more complex non-linear regions. In a neural network architecture context, input nodes that contribute to the output nodes are assigned larger synaptic weights, while input nodes that contribute little information to the output nodes are assigned smaller synaptic weights. The distribution of the synaptic weights can be used to infer a spectral band selection criterion.

- **Internal covariance matrix analysis:** In the computation of the BVS, it is assumed that the internal covariance matrix $\mathfrak{P}_{(i|i)}$ (equation 5.38) is set to the identity matrix. The matrix will then converge to a stable internal covariance matrix $\mathfrak{P}_{(\mathcal{I}_T|\mathcal{I}_T)}$ at time $\mathcal{I}_T$ if the Riccati condition holds and enough observation vectors are supplied. This convergence should be almost constant and can be expressed as

$$\left\| \frac{\mathrm{d}^2\mathfrak{P}_{(i|i)}}{\mathrm{d}i^2} \right\| \leq \varepsilon, \tag{9.2}$$

where $\|\cdot\|$ is a suitable matrix norm, e.g. induced norm or Frobenius norm. An in-depth study is proposed on the behaviour of the EKF's internal covariance matrix $\mathfrak{P}_{(i|i)}$ with regards to land cover change. The internal covariance matrix $\mathfrak{P}_{(i|i)}$ should fluctuate when experiencing a non-stationary process such as land cover change. These fluctuations can be used to define a change threshold $T_{\mathfrak{P}}$ that flags a change when

$$\left\| \frac{\mathrm{d}^2 \mathfrak{P}_{(i|i)}}{\mathrm{d}i^2} \right\| > T_{\mathfrak{P}}. \tag{9.3}$$

- **Complex model design:** In chapter 5 the emphasis was placed on using a triply modulated cosine model to describe the MODIS time series. The next phase is to explore more complex models, which could be used to model the time series. For example, the triply modulated cosine model given in equation (5.44) can be expanded to incorporate multiple models as

$$x_i = \sum_{m}^{M} \mathbf{h}_m(\vec{W}_i) + v_i, \tag{9.4}$$

with measurement function defined as

$$\mathbf{h}_m(\vec{W}_i) = W_{i,\mu,m} + W_{i,\alpha,m} \cos(2\pi f_{\mathrm{samp}} i + W_{i,\theta,m}). \tag{9.5}$$

Another proposed expansion to the SFF feature is to consider more Fourier components for analysis. The sinusoidal behaviour is not a true representation of all different land cover classes, which motivates a further exploration of new models.