

**GIS and Remote Sensing based land cover change detection,
prediction modeling and assessment of change on
biodiversity using time-series data**

Priyakant Sinha

BSc (H). Vinoba Bhave University
M.Tech. Birla Institute of Technology

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Abstract

Various anthropogenic transformations and modifications have continuously modified and/or changed the land cover for centuries for different forms of human productions. These ultimately impacted or changed the biodiversity, nutrient and hydrological cycles as well as global environment and climate, especially in the developing world. Australia has a great variety of native vegetation ranging from rainforests, alpine habitats, wetlands, grasslands, eucalypt forests and woodlands reflecting the diversity of species, habitats and ecosystems found across the country. The destruction of habitat due to native vegetation clearing has been identified as the greatest single threat to biodiversity in New South Wales (NSW), Australia. The clearing has mainly taken place in grassy woodlands areas for pasture improvement by the application of fertilizers, ploughing and the sowing of introduced grasses and clovers. This research explored the potential of a range of remote sensing and modelling techniques to assist in the investigation of suitability of land cover mapping in terms of time-period, methods, and seasonal and long term land cover change in the north-eastern parts of NSW, Australia. The overall aim of this research was to investigate the potential of remote sensing, GIS and modelling techniques in detailed investigations of seasonal and nearly four decadal land cover change analysis and assessment of long term pattern of land cover change for future change predictions. The research also aimed at assessing the impact of land cover change on terrestrial habitat configurations.

The importance of considering seasonal variations in land cover classifications was considered since accuracies can vary seasonally within and between years and the selection of a particular season can have a large impact on the accuracy and reliability of the resulting classification. The study investigated the issue of selection of the most appropriate season for land cover mapping by studying the spectral response of land cover categories in different seasons. The highest accuracy was obtained with a mid-summer (January) image and the lowest with an early spring (September) image. The superiority of mid-summer images in generating highly accurate land-cover classifications was demonstrated by the analysis of additional images under varying rainfall conditions in different years. Investigation of class-wise land cover classification accuracies in different seasons provided a scope of selection of most suitable season or month for mapping of individual classes. This was done using conditional Kappa () coefficient which

further confirmed that most of the classes showed 100% agreement with the January classification.

Considering the need for information on land cover change in short intervals and understanding the usefulness of binary change images for such assessment, the study identified the requirements of highlighting the areas where land cover features' brightness values had increased or decreased (mostly due to change in vegetation density), or remained unchanged and also the issues related to traditional means of threshold determination for change/no-change identification. The study proposed a new method for optimal threshold value determination by considering the left and right parts of a histogram from mean separately and computing the two separate mean and standard deviation for spectrally decreased and spectrally increased parts. The issue of asymmetrical nature of distribution histogram for the two sides was tested by comparing the results from the proposed with other techniques.

Investigations of the relative performance of object-based and pixel-based analysis in land cover classification and in change identification was carried out over a 37-year period. The results showed that the object-based classification had an improvement in overall accuracy compared to results from maximum likelihood classifier (MLC).

This study considered the importance of evaluation of landscape metrics with respect to remote sensing data characteristics and also difficulties associated in the selection of appropriate and effective metrics for change identification. The study proposed a new rank-based metric selection process through the computation of four difference-based indices using a Max–Min/Max normalization approach. The method was found simple and straightforward, capable of highlighting change in two contrasting landscapes.

Modelling the change process using time series satellite data using Markov chain model (MCM) provided an opportunity of detailed land cover change pattern investigation and also helped in projecting the probability of temporal change developments into future land cover change. The study addressed two major issues associated with the use of Markov models in land cover change predictions: the issues of stationarity of change and the impact of neighbouring cells on change areas. The model was considered suitable for predicting land cover change for future years. The land cover prediction ten years into the future indicated that future land cover changes would

continue to affect the natural vegetation, which would continue to decrease over the years by being converted to agricultural lands. According to the report on BCASR (2002), the main driving force of land cover changes in this region was identified as vegetation clearing. Extensive logging has reduced the original tree size classes in forests on basalt soils on the Liverpool Range, while biologically significant dry rainforests were vulnerable to fire, grazing from feral animals, including goats and rabbits, and invasion by exotic plant species. The succession of droughts over the three decades was an additional factor of change in the natural vegetation areas in combination with land use extensification (BCASR, 2002). The remote sensing analysis reveals, however, that land cover changes have increased in recent years compared to the seventies and eighties when the annual rate of land cover change was more than 10%.

Analysis of the impact of land cover change on habitat configuration by automated mapping of habitat linkages in the landscape using the concept of metapopulation and the least cost path algorithm indicated that there was a significant loss in the terrestrial habitat in the region. The loss was more in the slopes on the southern side that had been developed for pasture or crop production, but on the northern slopes the forests were mostly still present. The use of time series land cover data provided an opportunity to evaluate the pattern of change in vegetation situation over time along with the threatening process responsible for change, if it existed. The identification of clearing as a major threat in EHA decline, particularly after the year 1993, supported this fact, which otherwise would not have been identified in case of normal change detection process

Overall, the research demonstrated the potential of various image processing techniques for improved land cover mapping and change identification and also modelling land cover change for future change. The outcome from long term change analysis and modelling future change results will provide a scope for land managers and policy makers in the region for better understanding the amount and pattern of change that happened in the past and their future predictions. These understandings will help them in better policy formulation for effective and sustainable land management in the region.

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Note to Examiners

This thesis has been written in journal-article-format. I have attempted to minimize the duplication of material between chapters. However, some repetition remains, particularly in the methodology sections of the articles as these were independent publications.

Although effort has been made to ensure consistency in the format for the purposes of this thesis, I acknowledge that some inconsistencies remain because of the requirements of each of the journals to which the separate papers were submitted.

Contents

CHAPTER 1 Introduction	1–19
1.1 Definition of problem	1
1.2 Distribution of major land use types in NSW	3
1.3 Native vegetation – biodiversity	4
1.4 Land use/land cover and vegetation change detection techniques	5
1.4.1 Image differencing and image ratioing – algebra	6
1.4.2 Transformation	6
1.4.3 Classification	7
1.4.4 Land use/land cover change using spatial pattern metrics	8
1.5 Applications of time series data in land use/land cover change and predictive Modelling.	9
1.5.1 Markov transition probability modelling	10
1.6 Use of land cover change in habitat configuration assessment	11
1.7 General aims	14
1.8 Description of study area	15
1.9 Format of thesis	17
CHAPTER 2 Seasonal variation in land cover classification accuracy in a diverse region	20–44
2.1 Introduction	21
2.2 Study region	24
2.2.1 Location	24
2.2.2 LULC identified in the region	25
2.3 Materials and methods	25
2.3.1 Image acquisition and pre-processing	25
2.3.2 Image transformation	27
2.3.2.1 NDVI	27
2.3.2.2 TC	28
2.3.2.3 PCA	28
2.3.3 Image classification	29
2.3.4 Accuracy assessment	30
2.3.5 Multi-year LULC classification	31
2.4 Results and discussion	33
2.4.1 NDVI	33
2.4.2 PCA	34
2.4.3 LULC classification: comparison of accuracy	35
2.5 Conclusions	40
CHAPTER 3 Three-date Landsat TM composite in seasonal land cover change identification in a mid-latitudinal region of diverse climate and land use	45–72
3.1 Introduction	46
3.2 Study region	48
3.2.1 Location	48
3.2.2 LULC identified in the region	49

3.3	Materials and methods	50
3.3.1	Remote sensing data	50
3.3.2	Image normalization	51
3.3.3	Image transformation	52
3.3.4	Land cover classification	53
3.3.5	Density slicing	54
3.3.6	Mapping seasonal variations in LULC	55
3.3.7	RGB–NDVI and RGB–TC2 classifications	56
3.3.8	GIS integration of classifications for LULC change analysis	57
3.3.9	Accuracy assessment	57
3.3.10	Referential refinement and aggregation	59
3.3.11	LULC classification in summers of different years	59
3.4	Results and discussion	60
3.4.1	LULC classification	60
3.4.2	Seasonal variations in LULC	65
3.4.3	LULC aggregation	69
3.5	Conclusions	70
 CHAPTER 4 Binary images in seasonal land-cover change identification: a comparative study in parts of New South Wales, Australia		 73–103
4.1	Introduction	75
4.2	Study region	76
4.3	Materials and methods	78
4.3.1	Image acquisition and pre-processing	78
4.3.2	Reference data	80
4.3.3	Change detection analysis	82
4.3.4	Determination of thresholds	85
4.3.5	Accuracy assessment	89
4.4	Results	90
4.5	Discussion and Conclusion	96
 CHAPTER 5 Independent two-step thresholding of binary images in inter-annual land cover change/no-change identification		 104–134
5.1	Introduction	105
5.2	Study region	108
5.3	Materials and methods	110
5.3.1	Image acquisition and pre-processing	110
5.3.2	NDVI differencing	113
5.3.3	Reference data	114
5.3.4	Determination of thresholds	116
5.3.5	Accuracy assessment	120
5.4	Results	121
5.5	Discussion and Conclusion	127

CHAPTER 6 Comparison of pixel and object based land cover changes over a 37-year period in parts of Brigalow Belt South Bioregions (BBSB) of NSW, Australia 135–165

6.1	Introduction	137
6.2	Methodology	140
6.2.1	Description of study area	140
6.2.2	Satellite data and fieldwork	141
6.2.3	Image Segmentation	145
6.2.4	Training Data for <i>k</i> -nearest neighbor (<i>k</i> -NN) classifier	147
6.2.5	Supervised Classification	148
6.2.6	Accuracy Assessment	149
6.2.7	Temporal analyses of land cover change	150
6.3	Results and discussion	151
6.3.1	Pixel vs object-based classification accuracy	151
6.3.2	Temporal change analysis: overall LULC change	155
6.3.3	Province wise change analysis	161
6.4	Conclusions	162

CHAPTER 7 Rank-based method for selection of landscape metrics for land cover pattern change detection 166–195

7.1	Introduction	167
7.1.1	Traditional techniques	168
7.1.2	Selection of pattern metrics for land cover change identification	169
7.2	Study area	170
7.2.1	Land cover classification	172
7.3	Methodology	172
7.3.1	Pattern metrics to measure landscape attributes	172
7.3.2	Capability of metrics to capture change in landscape pattern	178
7.3.3	Sensitivity of metrics to spatial resolution of remote sensing data	179
7.3.4	Sensitivity of metrics to a changing number of classes	179
7.3.5	Statistical analysis	180
7.4	Results and discussion	181
7.4.1	Cluster analysis	181
7.4.2	Analysis of scores of metrics to capture landscape pattern change	182
7.4.3	Sensitivity of metrics to spatial resolution of remote sensing data	184
7.4.4	Sensitivity of metrics to thematic changes	186
7.4.5	Selection of landscape metrics	187
7.4.6	Change analysis using the two study sites	188
7.5	Conclusions	192

CHAPTER 8 Markov land cover change modelling using multiple pairs of time-series satellite images 196–224

8.1	Introduction	197
8.1.1	Land cover change prediction - Markov Chain Modeling (MCM)	199

8.1.2	Issues in MCM land cover change	199
8.1.3	Cellular Automata Markovian Model	201
8.2	Materials and methods	202
8.2.1	Study area	202
8.2.2	Land cover classification	202
8.2.3	MCM	204
8.2.4	CA-MCM	206
8.2.5	Model Validation	207
8.3	Results and discussion	207
8.3.1	Summary of land cover change	207
8.3.1.1	Gains and losses in land cover types	208
8.3.1.2	Spatial pattern of land cover change	209
8.3.2	Land cover change projections	211
8.3.2.1	Components of agreements and disagreement	212
8.4	Conclusions	220
CHAPTER 9 Effective habitat area modeling using cost-benefit raster based technique in time series		225–246
9.1	Introduction	226
9.1.1	Effective Habitat Area (EHA)	228
9.1.2	Habitat condition, fragmentation and EHA	229
9.2	Materials and methods	231
9.2.1	Study area	231
9.2.2	Land cover classification	232
9.2.3	Effective Habitat Area Modeling	233
9.2.3.1	Cost-benefit approach	233
9.3	Results and discussion	236
9.3.1	Cost and benefit grids	236
9.3.2	Effective habitat area modeling (EHA)	237
9.4	Conclusion	243
CHAPTER 10 Conclusions		247–267
10.1	Introduction	247
10.2	Summary of main findings	248
10.2.1	Remote sensing based seasonal and long term land cover change	248
10.2.2	Landscape characterization, modeling land cover change and habitat configuration	251
10.3	Main conclusions	252
10.4	Implications of the Study	253
10.5	Synthesis of study	254
10.6	Limitations and recommendations	255
Bibliography		257

List of Tables

Table 2.1: LULC identified in the study region and their descriptions (BRS, 2006)	26
Table 2.2: LULC classification accuracy assessment performed on different sets of band combinations	31
Table 2.3: Results of the Kappa analysis tests for comparison between error matrices for B1–4 vs other combinations	37
Table 2.4: LULC classification accuracies using the B1–4 combination in each season (note that sample sizes are given as the minimum and maximum number of polygons, since data was collected in different seasons and the number of samples varied depending on availability and spread)	38
Table 2.5: McNemar's test for comparison of summer 2010 (normal) with other summer and winter classifications under different environmental conditions. (refer Foody (2004) for details)	39
Table 3.1: Three-Date LULC change detection scheme for the study region	56
Table 3.2: Logical aggregation of January, August and November classifications to generate aggregate LULC map (based on Hill et al. (1999)	61
Table 3.3: LULC classification accuracies using the supB1–4 combination in each month obtained by comparing the classifications with reference data (see section 3.2.2 for LULC descriptions)	62
Table 3.4: Conditional Kappa (of each LULC class in different months and corresponding Z-values for the classes when was less than 1. The values reflect the relative accuracy obtained for each class on different dates. Value approaching 1 indicates higher accuracy	63
Table 3.5: Z-statistics for comparison of the conditional Kappa of each LULC class taking January as a reference and comparing the corresponding LULC class in other months (see section 3.2.2 for LULC description)	64
Table 3.6: Test statistic (Z) for pair-wise comparison of RGB–NDVI with respect to other methods	66
Table 3.7: Percent area of LULC change for each of the three-date composites using RGB–NDVI method	67
Table 4.1: Linear regression equations computed from NDVI image pairs	80
Table 4.2: Example of three-date (January, March and May) land-cover change detection scheme for the study region. Similar classes on two consecutive dates were merged to get two-date (January–March and March–May) change/no-change reference data (e.g. code YYN was merged as YY (i.e. no change between date1 and date2 as ‘no change’) and	81

YN (i.e. vegetation cover to no-vegetation cover as ‘negative change’ between date2 and date3). Similarly, code YNY was merged as YN (i.e. vegetation to no-vegetation as ‘negative change’ between date1 and date2) and NY (no-vegetation to vegetation as ‘positive change’ between date2 and date3) and so on.

Table 4.3: Sample points used for change/no change accuracy assessment for different change period	82
Table 4.4: Change Detection techniques used in this study	83–84
Table 4.5: The skewness statistics and results of the test of normality of distribution of histograms of NDVI difference images	87
Table 4.6: Accuracy comparison of image differencing based change detection methods for different change periods(see Table 4.4 for method descriptions)	91
Table 4.7: Accuracy comparison of image ratio based change detection methods (see Table 4.4 for method descriptions)	93
Table 4.8: Accuracy comparison of PCA based change detection methods (see Table 4.4 for method descriptions)	94
Table 4.9: McNemar's test for comparison of vegetation index change images in different change periods	95
Table 4.10: Percentage change due to spectral decrease and spectral increase in pixel brightness values and also percentage area that remained unchanged between two date change periods based on NDVI_Diff images	99
Table 5.1: Example of three-date (January, March and May) land-cover change detection scheme for the study region. Similar classes on two consecutive dates were merged to get two-date (Jan–Mar and Mar–May) change/no-change reference data (e.g. code YYN was merged as YY (i.e. no change between date1 and date2 as ‘no change’) and YN (i.e. vegetation cover to no-vegetation cover as ‘negative change’ between date2 and date3). Similarly, code YNY was merged as YN (i.e. vegetation to no-vegetation as ‘negative change’ between date1 and date2) and NY (no-vegetation to vegetation as ‘positive change’ between date2 and date3) and so on	116
Table 5.2: Sample points used for change/no-change accuracy assessment for different change periods	116
Table 5.3: The <i>skewness</i> statistics and results of the test of normality of distribution of histograms of NDVI difference images	118
Table 5.4: Regression equation of NDVI image pairs	121
Table 5.5: Change/no-change accuracy comparison for different thresholding techniques for selected change periods. It can be seen that accuracy varies significantly for asymmetrical distributions between existing and the proposed method	124

Table 5.6: Accuracy of NDVI differencing images for different change periods	125
Table 5.7: Percentage change due to spectral decrease and spectral increase in pixel brightness values and also percentage area that remained unchanged between two date change periods based on NDVI_Diff images	130
Table 6.1: Provinces of the Brigalow Belt South Bioregion (BBSB) (Morgan and Terrey 1992)	141
Table 6.2: Description of remote sensing data used in this study	142
Table 6.3: Relative atmospheric correction of image mosaic of different change periods with respect to 2009-10 image mosaic	144
Table 6.4: Sample points used for training and accuracy evaluation in each change period by MLC and OBC methods	146
Table 6.5: LULC classification accuracy in different change years from MLC classification	154
Table 6.6: LULC classification accuracy in different change years from OBC classification	154
Table 6.7a: LULC change statistics using MLC technique	156
Table 6.7b: LULC change statistics using OBC technique	156
Table 7.1 List of landscape metrics used in this study (MacGarigal and Marks, 1994).	189
Table 8.1: Markov transition probability (A) and proportion of area change (B) in land cover types during different change periods.	214
Table 9.1: lookup table linking land use codes to $1/\alpha$ and habitat condition values	234

List of Figures

Figure 1.1: Location of study area.	16
Figure 2.1: Location of the study region.	24
Figure 2.2: Monthly average rainfall for (a) summer and (b) winter 1990–2010.	32
Figure 2.3: Mean NDVI for land cover classes for all dates (see Table 1 for LULC codes).	33
Figure 2.4: Comparison of overall classification accuracies taking B1–4 as the reference with (a) three original and derived bands, (b) four original bands, (c) four mixed original and derived bands, and (d) five original bands.	36
Figure 2.5: Overall accuracy obtained under variable rainfall conditions in January/February and September using the B1–4 combination.	39
Figure 3.1: Location of the study region.	49
Figure 3.2: Flow chart explaining various image processing and statistical analysis steps carried out in this study.	52
Figure 3.3: Comparison of overall accuracy in LULC class change with different methods and three date composites.	66
Figure 3.4: Seasonal variation in LULC using the RGB–NDVI method in Jan–Mar–May, May–Aug–Sept and Sept–Nov–Jan composites (refer to Table 3.2 for code descriptions).	68
Figure 3.5: LULC aggregate map of a part of the study region generated by aggregating January, August and November classifications and referential refinement processes (refer to Table 3.2 for class code descriptions).	69
Figure 4.1: Location of the study region.	77
Figure 4.2: Histogram of NDVI difference image (a) Jan NDVI – Mar NDVI (b) Mar NDVI – May NDVI (c) May NDVI – Aug NDVI (d) Aug NDVI – Sept NDVI (e) Sept NDVI – Nov NDVI and (f) Nov NDVI – Jan NDVI.	86
Figure 4.3: Probability density functions of NDVI differencing image. Data present in the two sides from mean are assumed to be normally distributed to compute means (M_L and M_R) and standard deviations (SD_L and SD_R) for spectrally decrease and spectrally increase parts respectively (Pu et al. 2008). C-value can be determined by an optimal Kappa or other accuracy indices (Fung and LeDrew, 1988).	88
Figure 4.4: Optimal change/no-change thresholds (C-value) determined by Kappa value or overall accuracy (OA). The figure shows that an optimal Kappa value can be at -1 , $-$	88

1.2 or -1.4 C-values for NDVI difference image for January-March period. Thus, when $M_L = 0.05$, $SD_L = 0.08$ and $M_R = 0.3$, $SD_R = 0.08$, at $C = -1.2$, threshold values $< -0.04 =$ negative change, values between -0.04 and $0.4 =$ no change and value $> 0.4 =$ positive change, see Figure 4.3).

Figure 5.1: Location of the study region. 109

Figure 5.2: Flow chart showing different methodology steps followed in the study. 112

Figure 5.3: Histogram of NDVI difference image (a) Mar NDVI– May NDVI (*left skewed*) (b) Aug NDVI–Sept NDVI (*nearly symmetrical*) (c) Sept NDVI – Nov NDVI (*right skewed*). 117

Figure 5.4: Probability density functions of NDVI differencing image. Data present in the two sides from mean are assumed to be normally distributed to compute means (M_L and M_R) and standard deviations (SD_L and SD_R) for spectrally decrease and spectrally increase parts respectively. C-value can be determined by an optimal kappa or other accuracy indices (Fung and LeDrew, 1988). 119

Figure 5.5a: Change/no-change thresholds based on $\text{Mean} \pm C * \text{SD}$ (Method 1) at different C-values for Mar–May, Aug–Sept and Sept–Nov change periods. The optimal threshold values were determined by highest Kappa value or overall accuracy (OA). The figure shows that an optimal C-value for Mar–May, Aug–Sept and Sept–Nov can be at 2.0, 1.6 and 1.8, respectively. 122

Figure 5.5b: Change/no-change thresholds based on two step $\text{Mean} \pm C * \text{SD}$ (Method 2) at different C-values by masking opposite part (Mas, 1999). Data present at the two sides from mean are treated independently. Mask applied on right part while change/no-change thresholding of left part is carried out and vice versa. The optimal threshold value (C-value) was determined by highest Kappa or overall accuracy (OA) of left and right part of histogram separately. Based on optimal Kappa identified at a given C-value for left and right part separately, overall change/no-change areas are identified. For example, for Mar-May period C-value can be 2.0 and 2.2 for left and right parts, respectively, and if $\text{Mean} = 0.18$ and $\text{SD} = 0.15$, pixel values less than -0.12 and pixel values greater than 0.51 are identified as change and pixel values falling in between these two values are no-change areas. Similarly, the range for change/no-change classification for Aug–Sept and Sept–Nov periods can be determined at 1.8 (left part) and 2.0 (right part) and overall change/no-change classification can be done based on these two values as described earlier. 123

Figure 5.5c: Change/no-change thresholds using proposed Independent Two-step thresholding technique (Proposed Method) at different C-values. The optimal threshold value (C-value) was determined by highest Kappa or overall accuracy (OA). Data present at the two sides from mean are treated independently to compute means (M_L and M_R) and standard deviations (SD_L and SD_R) for spectrally decrease and spectrally increase parts, respectively. For example, for Mar–May period C-value can be -1.4 , and if $M_L = 0.04$, 123

$SD_L = 0.06$ and $M_R = 0.3$, $SD_R = 0.08$, at $C = -1.4$, pixel values < -0.044 = negative change, values between -0.044 and 0.412 = no change and values > 0.412 = positive change, see Figure 3. Similarly, the range for change/no-change classification for Aug–Sept and Sept–Nov periods can be determined at -2.0 and -1.2 C-values, respectively.

Figure 5.6: Change/no-change in Site 1 in the study area where results from the two existing methods (Method 1 and Method 2) differ from the Proposed Method in different change periods. 126

Figure 5.7. Change/no-change in Site 2 in the study area where results from the two existing methods (Method 1 and Method 2) differ from the Proposed Method in different change periods. 127

Figure 6.1: Location of Brigalow Belt South Bioregion (BBSB) and its provinces. 141

Figure 6.2: Percentage LULC area statistics and their changing pattern from 1972-73 to 2009-10 from MLC (A) and OBC (B). 153

Figure 7.1: Location of Liverpool Plains and Liverpool provinces in Brigalow Belt South Bioregion (BBSBR), NSW, Australia 171

Figure 7.2: Proportion of native vegetation cleared in each province from 1995 to 2000 of a total of vegetation cleared (BCASR, 2002). 171

Figure 7.3: Land cover classification in different years for the Liverpool Plains and Liverpool Range provinces (refer section 7.2.1 for class descriptions). 173

Figure 7.4: Dendrogram of the hierarchal clustering of metrics. 181

Figure 7.5: β -score of landscape metrics ranked in descending order in different years 183

Figure 7.6 γ -score of landscape metrics ranked in descending order in the two provinces 184

Figure 7.7: ξ -score of landscape metrics ranked in ascending order for the Liverpool Range. 185

Figure 7.8: ξ -score of landscape metrics ranked in ascending order for the Liverpool Plains. 186

Figure 7.9: θ -score of landscape metrics for the Liverpool Range in different years. 187

Figure 7.10: θ -score of landscape metrics for the Liverpool Plains in different years. 187

Figure 7.11: Metrics change pattern in different years for the Liverpool Plains and the Liverpool Range.	191
Figure 7.12: Land cover change area (ha) from 1972-73 to 2009-10 in (a) Liverpool Range (b) Liverpool Plains.	192
Figure 8.1: Location of Liverpool Range provinces in Brigalow Belt South Bioregion (BBSBR), NSW, Australia.	204
Figure 8.2: Land cover class area percentage from 1972 to 2009 in Liverpool Range (a); change in land cover area in different observation years between 1972-2009. (AL, Agriculture land; IP, Improved pasture; NP, Natural pasture; EFWL, Evergreen forest and woodland).	208
Figure 8.3: The patterns and trends of changes that occurred in different land covers between 1972-09 periods. Spatial trend of change provides a means of generalizing the pattern of change.	210
Figure 8.4: The Markovian conditional probability images aggregated to make one single land cover map using stochastic choice decision model for short term transition periods (a) Land cover predicted for 1993 from 1972-1987 matrix, (b) Land cover predicted for 1999 from 1987-1993 matrix, and (c) Land cover predicted for 2009 from 1993-99 matrix.	213
Figure 8.5: MCM validation for short term transition simulation.	214
Figure 8.6: Suitability maps for the land cover class for the year 1999 and also for the spatial factors on the same continuous suitability scale (0–255).	215
Figure 8.7: Predicted land cover map of 2009 by MCM and CA-MCM.	215
Figure 8.8: Model validation for 2009 simulated years for allocation and quantity agreements between MCM and CA-MCM.	216
Figure 8.9: Simulation of the evolution of the analyzed land cover classes within the study area under four future scenarios. The scenarios are based on a markovian models of land cover change between different change periods.	217
Figure 8.10: Simulation of the evolution of the natural pasture (a) and evergreen forest and woodland (b) under four future scenarios based on a markovian models of land cover change between different change periods.	218
Figure 9.1: Biodiversity configuration in a given landscape based on land cover as a surrogate.	229
Figure 9.2: The decay in link permeability as link length decrease where the uniform curve shows decay in homogenous condition and the un-uniform curve shows decay under variable condition. (Drielsma et al., 2007).	230

Figure 9.3: Location of Liverpool Range provinces in Brigalow Belt South Bioregion (BBSBR), NSW, Australia.	231
Figure 9.4: Different steps involved in cost and benefit grids generation taking example of the calculation of the neighbourhood effect for a focal cell (shaded) based on a neighbourhood of 5 x 5 cells.	235
Figure 9.5: Graph showing the effect of changing $1/\alpha$ parameter on permeability at different distances for six land cover categories (BS, $1/\alpha = 1000\text{m}$; CL, $1/\alpha = 2000\text{m}$, IP, $1/\alpha = 3500\text{m}$, NP, $1/\alpha = 4000\text{m}$ and EF and EWL, $1/\alpha = 5000\text{m}$) from a focal cell. The pattern of curve reflects a homogenous condition designed for generic specie movement.	237
Figure 9.6: Habitat conditions in different change years.	238
Figure 9.7: The permeability cost grids in different years.	239
Figure 9.8: Neighbourhood Habitat Area (NHA) as a measure of spatial configuration in different change years.	240
Figure 9.9: The EHA for each grid-cell under a given scenario between 1972 and 2009.	241
Figure 9.10: Amount of clearing and fragmentation that occurred along with habitat conditions and effective habitat areas in the study region in different change years (a) Habitat configuration as a proportion of total habitat area, (b) pattern of change in habitat configurations from 1972 to 2009.	242