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Monitoring urban green spaces using geospatial technologies- A case study of Hobart, Tasmania, Australia

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Abstract

Urban vegetation management has become an important issue because of rapid urban development and urban green space (UGS) is an important component of sustainable urban planning. Unless we measure and quantify tree cover, we cannot manage it sustainably. The present study aimed at exploring the urban green space of Hobart city between 2003 and 2013 by using very high-resolution data that includes IKONOS (2003) and Worldview-2(2013) satellite data. The extraction of urban green space was done using object-based image analysis (OBIA) with very high accuracy and the results were exported to ArcGIS for change detection. Since the available satellite imageries do not cover the Tasmanian cities completely, the study was designed as experimental design 1 and 2 for UGS analysis at various scales. The experimental design 1 was designed at parcel level (part of the city of Hobart) to study the decadal changes and the experimental design 2 included 3 subsets (2km x 2km) of Great Hobart regions, the Central business district area of Hobart municipal council, suburban area and residential area of a part of Glenorchy city council area. The study revealed that there are positive as well as negative changes in the urban green space of Greater Hobart between 2003 and 2013 with an overall growth of 3.43%. Recent suburban development is responsible for some negative changes in the suburban area while the initiatives taken by the local government encouraged positive growth. The forested areas also showed minor changes because of the extension of road activities. The study also showcases the efficacy of OBIA in extracting urban green cover with a simplified ruleset. The results will be useful for urban local bodies for sustainable urban management and also strengthen the Australian Government Vision 2020.

Keywords: *Urban Green Space; OBIA; WorldView-2 data; Ikonos data; Greater Hobart, Urban Management*

Introduction

Urbanization in the future has to face many ecological and social changes as it takes new forms and functions, at different rates and scales (Romolini et al., 2013). Urban green space (UGS) is an essential component of a sustainable environment, and knowledge about existing urban green space is crucial for green infrastructure development, conserving the ecosystem and sustainable urban development policy-making (Schwab et al., 1995; Feng, 2005; Marvin Bauer,2011; Roy et al., 2012; Pearce et al., 2013; Razieh shojanoori, 2016). UGS includes the tree canopy, grass, shrubs, lawns and other grass-covered areas found in parks, golf courses and playgrounds (Bauer et al., 2011). Urban tree canopy – a key indicator of green space in the cities can be defined as “the layer of leaves, branches, and stems of trees that cover the ground when viewed from above” (Raciti et al., 2006). Trees can enhance the quality of air by filtering pollutants; they moderate the heat-island effect and they are an essential part of the global carbon cycle, serving as a carbon sink (O’Neil-Dunne et al., 2014; Dong Chen, 2013). Green space helps in promoting the physical and mental health of urban residents by providing pollution-free spaces and fresh air for physical activities and improving their psychological well-being (Wolch et al., 2014). Quantifying urban tree canopy cover is indispensable for managing urban forests and assessing the environmental benefits provided by them (Small and Lu, 2006; King and Locke, 2013).

The urban forest ecosystem is involved with a variety of species and due to variations in their tree crowns, it is difficult to quantify and monitor their spatial extent (Moskal et al., 2011). Accessing all urban trees by field surveys is not possible as some are in private properties, and the exercise would be very time-consuming (Razieh Shojanoori, 2016). Detailed vegetation maps are required for efficient assessment of biodiversity of an urban area (Mathieu et al., 2007) and that demands an updated spatial technology.

Urban areas have mixed land use and land cover and have intra-class variability (Moskal, Styers et al., 2011). In a complex urban scene, as the number of object classes increases, the degree of within-class variability also increases (Sridharan and Qiu 2013). Therefore, there is a need for remotely sensed high resolution data for accurate mapping (Zhou and Troy 2008; Tsai et al., 2011). Classifying such high-resolution data requires improved image classification techniques and analysis (Herold and Scepan, 2002; Liau, 2014). The interpretation of urban features from remote sensing data remains a conceptual and technical challenge (Myint et al., 2013). It requires new tools and techniques (Niebergall et al., 2007). The object-oriented (also known as object-based) image classification provides a better way of classifying very high-resolution satellite data, since it integrates both spectral and spatial information in image classification (Weiqi Zhou and Morgan Grove, 2006; Moskal et al., 2011). Object-based techniques are based on the idea that single pixels do not provide relevant information and contextual relations as image objects (Mathieu et al., 2007; Matikainen and Karila 2011). The present study tries to explore the efficiency of OBIA using WorldView-2 and IKONOS data in urban green space management.

Urban vegetation mapping in Australian cities

The beginning of urban green governance in Australia has given due importance to urban green space by recognizing their role in achieving sustainable smart cities (Kirkpatrick et al., 2013). The inter-relationship between trees and urban dwellers is complex (Ivey-Law and Kirkpatrick, 2015). A research article on the ‘attitude syndrome related to planting and removal behaviour of trees in eastern Australian cities,’ had shown that tree management should get tailored to different segments of urban residents according to their attitudes rather than property owners in general (Kirkpatrick et al., 2012). In another article that explores the motives that cause people ‘to plant and remove trees on private land in urban areas in eastern Australia’ including Hobart, the authors could identify the reasons for tree death as prolific property transactions, changes in the individuals' sensibility, and changing trends (Kirkpatrick et al., 2013). A study on secluded urban forests in the suburbs of Melbourne and Hobart revealed that higher level protection of large trees on private land and compensation through tree planting on public land could mitigate environmental impacts (Pearce et al., 2013).

The LGAs (Local Government Area, which means city councils) assessed the tree canopy at the council level, and Tasmania claimed a comparatively high proportion of tree canopy. Of the five LGAs, Hobart and Glenorchy have 59% of the tree canopy. Tree canopy percentages range from 66% in Kingsborough to 31% in Clarence while Launceston has more than 40%. The recent assessment showed that there are also sizable areas of the state that could benefit from potential planting increases (Jacobs et al., 2014). An intensive study on various types of gardens in the suburbs of Hobart to understand the similarity between adjacent gardens and spatially separated gardens lead to a recommendation to the government which resulted in the intervention to create significant changes in private gardens (Kirkpatrick et al., 2009).

Very few studies utilising remote sensing have been carried out to understand the urban vegetation of eastern Australia. Aerial photographs were used to determine the changes in canopy cover of Bay-side reserve between 1970 and 2013 (Ivey-Law and Kirkpatrick, 2015). Land cover class extraction was done for part of Hobart city by using WorldView-2 data in the GEOBIA environment using 'Environmental Spatial-Temporal Ontology' (ESTO) (Aryal et al., 2014b). Similarly, for part of Hobart city, extraction of urban forests was carried out in GEOBIA using WorldView-2 imagery (Aryal et al., 2014a). Thus only a few studies are available concerning Australian cities and also the available vegetation maps do not provide satisfactory details regarding the extent of green cover across metropolitan cities (Jacobs et al., 2014). In the current climate change scenario, to fight against the rising temperature, there is a need for continuous monitoring and improvement of the existing urban green space. Therefore, an effort has been made to understand if there have been any significant changes in the green cover of Hobart between the years, 2003 and 2013? If yes, where in the city's landscape did these changes take place? The present study also aims to develop a simple, OBIA based ruleset, which can help in extracting urban green space in an efficient manner with reasonable accuracy (Blaschke. T, et al., 2010).

In the present case, we have used two different sets of data with high resolution for extracting the green space. The extracted green data used for change analysis in the GIS platform. To exploit the full advantage of available high-resolution data for urban green space management, an attempt has been made to use the latest satellite data for the two different time periods (IKONOS, 2003 and WorldView-2, 2013) for the same study area. It was decided to use the same ruleset with modified threshold values (if necessary) and same training samples for the accuracy assessment. This methodology thus helps in the continuous monitoring of urban green space with the latest available data and acts as a tool for urban green governance. It can be adapted to other data sets and other study

Table 1: Details of Satellite data

Satellite	Bits	Format	Spatial resolution	Spectral Bands	Date of capturing
Ikonos (Launched- Sep 1999)	11bits	Geo TIFF	1m-Pan 4m-MSI	B1-Blue - 445-516 nm B2- Green-506-595 nm B3-Red- 632-698 nm B4-NIR -757-853 nm PAN	22 February 2003
Worldview-2 (Launched- Oct 2009)	11bits	Geo TIFF	50cm-Pan 2m-MSI	B1-Coastal Blue -400-450nm B2-Blue- 450-510 nm B3-Green- 510-580 nm B4-Yellow- 585-625 nm B5-Red- 630-690 nm B6-Red edge- 705-745 nm B7-NIR1- 770-895 nm B8-NIR2 - 860-1040 nm PAN-450-800 nm	28 January 2013

Source: Satellite Imaging Corporation

areas since the rule set is based on spectral characteristics of NIR band and the most used vegetation index i.e., Normalized Difference Vegetation Index (NDVI) (Xue and Baofeng, 2017).

Data

In this study, we used PAN sharpened WorldView-2 (2013) and Ikonos (2003) data (Table 1) to study the decadal changes in urban green cover. The parcel maps from the Land Information System Tasmania (LIST.), the official data provider of Tasmanian state, Australia, were used for GIS analysis. The population data is from the Australia Bureau of Statistics.

Study Area

Urbanization is the process through which city landscapes are experiencing continuous change (Mackenzie and Barnett, 2006). Australia is also undergoing the same. The population of Australia has doubled to almost 24 million in 2016 from 12 million in 1968 and 89% of the population resides in urban areas and is projected to grow to 93% by 2050 (WUP 2014). The present study focuses on urban green spaces of Tasmanian cities. The island state of Tasmania, Australia is separated from its mainland by the Bass Strait. The study area is part of Greater Hobart, the metropolitan area of Tasmania. Greater Hobart consists of three cities, Hobart, Glenorchy, and Clarence. Kingborough and Brighton are the municipalities that come under Greater Hobart. The metropolitan area also includes the suburbs within their limits (figure 1).

Hobart is the capital of Tasmania and one of the nation’s greener urban areas. It has a population of approximately 240,000 (2019) and a population density of 124 persons/km^2. Over 40% of Tasmania’s population lives in this city. Hobart’s population is gradually increasing because of the migration of people to Greater Hobart. Glenorchy has a population of 46,253. It covers the suburbs north of central Hobart on the western shore of the Derwent River.

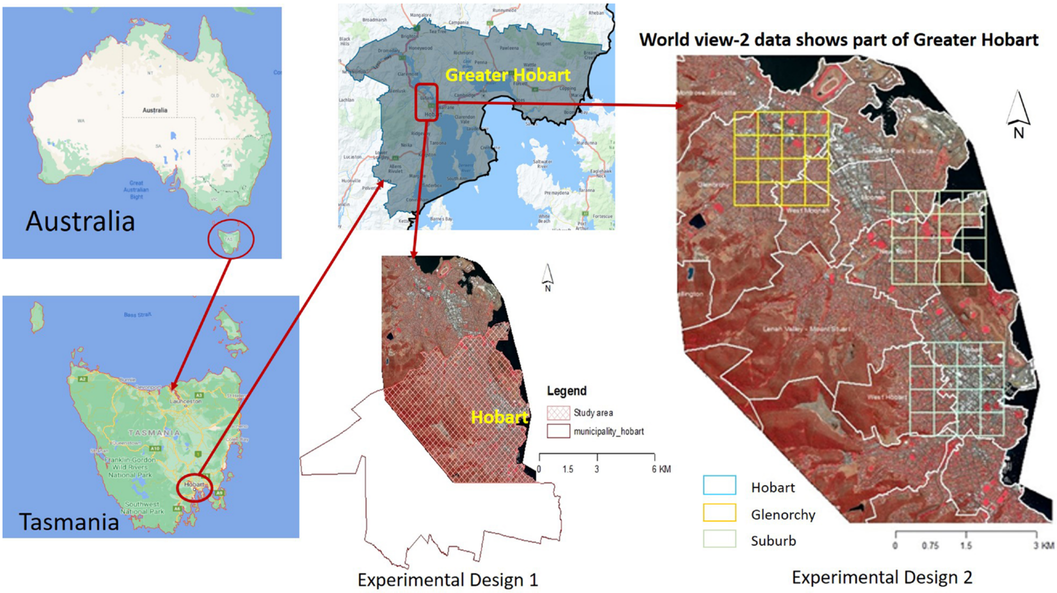

Fig. 1: Study area

The present study has been designed to understand decadal variations in the green space at two levels with the available data. Since the available imagery did not cover the entire Hobart council area, the first one was designed to understand the changes at the parcel level and the second one was designed at subset level (2km x 2km grid). The subsets represented three different categories of land use. The Hobart subset represents the central business district (CBD) area where commercial and institutional land use dominates. The Glenorchy subset represents mostly the residential land use, and the suburb subset representative of sprawled suburban development.

Methodology

The paper primarily aims to extract urban green space using a simple OBIA rule set from the satellite data with very high spatial resolution and study the decadal variations in urban green cover for sustainable urban management. The overall methodology used for achieving the objective is shown in Figure 2. It includes four main processes - image processing, object-based image classification, accuracy assessment, and GIS analysis.

Image processing

At first, essential geo rectification was done to match both image datasets (WorldView-2 and IKONOS) spatially and then multispectral (MS) bands were pan-sharpened using a subtractive resolution merge algorithm to increase their spatial resolution from 2 meters to 0.50 meter for WorldView-2 data and from 4 meters to 1.0 meter for Ikonos data. Since processing very high-resolution data demands very high memory and high-end hardware support (Liau 2014), the constraints of our hardware necessitated the creation of three subsets of 2 x 2 km^2 representing Hobart (CBD), Glenorchy (residential) and the suburb (sprawl development) from

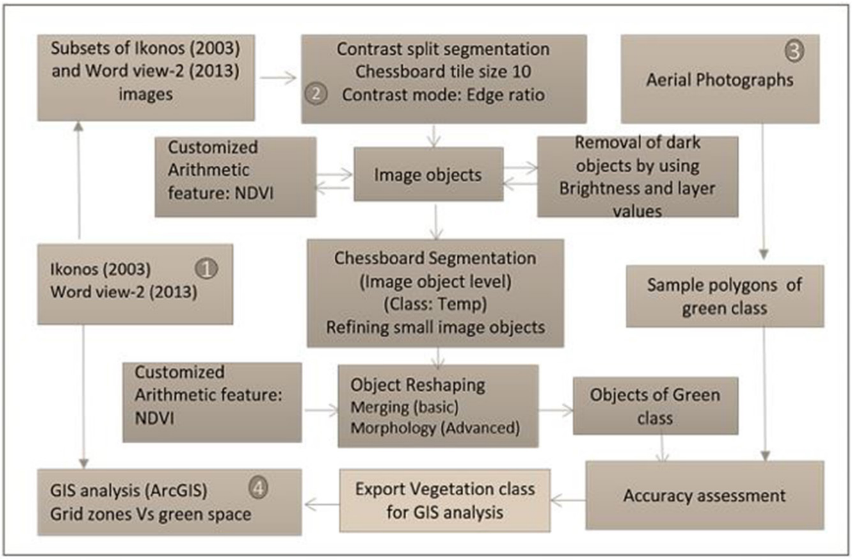

Fig. 2: Work flow

WorldView-2 and Ikonos data. This was done using the subset tool in Erdas Imagine 2014. The analysis of decadal variations in green space was done upon the subsets. To match the spectral characteristics of the datasets, four standard colour bands (blue, green, red, near-IR) with similar spectral characteristics of IKONOS were taken from WorldView-2 satellite data (Table 1) to form the base for the analysis.

Object-Based Image Analysis

Image processing and the geospatial domain are progressively using object-based image analysis (Johansen et al., 2011). The amalgamation of high-resolution satellite data and object-based image analysis solved the problems in urban mapping (O'Neil-Dunne et al., 2014). The OBIA method includes two significant steps (Zou et al., 2016) and the first step is segmenting the image by the grouping of spatially contiguous pixels that share similar spectral characteristics into meaningful objects (Sridharan and Qiu, 2013). Even though estimating scale parameter (ESP) is used to determine the scale for segmenting the image objects, it is difficult to get an optimum object size and a single scale factor may not be suitable for all classes (Myint et al., 2013) and these procedures often have to be combined with domain knowledge for an effective segmentation process (Zaitouna and Aqelb, 2015).

Image Segmentation

Contrast-split segmentation, a top-down method was used to segment the WorldView-2 data and the Ikonos data. The contrast split algorithm works on threshold values. Splitting contrast information from the original image is a useful method (Kok, 2012) for segmentation. The algorithm evaluates the optimal threshold value for each domain object. At first, it executes a chessboard segmentation of a variable scale and then performs the split on each square as a dark and bright image object based on a threshold value that maximizes the contrast between them at the pixel level. The layer of interest (near infrared layer) and the classes (green space) one wants to assign to dark and bright objects are the basic parameters primarily used for segmentation. (eCognition 2014). During the segmentation, the initial chessboard tile size was kept as ten since small-scale segmentation produces higher accuracy (Myint et al., 2015).

Image Classification

Once the segments are formed, the next step is the classification of image objects to assign an appropriate category to these segments using a suitable classifier. Many researchers prefer rule-based classification as it performs better than traditional classifiers (Zaitouna and Aqelb, 2015; Razieh shojanoori, 2016). The rule-based classifier assigns the objects to a particular class using a set of rules derived from domain knowledge using the spatial, spectral, and neighbourhood characteristics summarized at the object level. Rule sets based on fuzzy logic membership functions are transferable and helpful in defining unique object features. Fuzzy description enables urban land use classes to be assigned according to the membership degree rather than crisp threshold values (Hájek, 2005). In this case, vegetation index (NDVI) was used to assign objects to the Green class.

In eCognition Developer 9 software, the two classification algorithms followed a standard structure such as contrast-split segmentation, classification of image objects by using vegetation index, and applying reshaping algorithms. For shaping the objects, basic object reshaping tool, “Merge” was used to merge all green class objects. After cleaning the false positives through visual interpretation (objects classified as green but which were not; example: roofs with dark red tiles), both the image objects were brought under a similar platform for more advanced reshaping of objects. The merged class was further reshaped by using advanced reshaping algorithms such as “Morphology” and finally, the required class was exported as a .shp file for GIS-based analysis.

Urban Green Space extraction using NDVI

Mapping urban vegetation through remotely sensed images involves various procedures and processes. Using the spectral reflectance in the red and near-infrared regions (Xie et al., 2008) are the best ways of delineating the green cover from non-green areas. Near-infrared reflectance is highly suitable for differentiating crown edges and shadows (Karlson et al., 2014).

NDVI is a well-established mechanism for differentiating vegetation and non-vegetation in an urban area (Zhou and Troy 2008). It relies on the principle that chlorophyll in the leaves strongly absorbs visible spectral bands and reflects in near-infrared bands. Therefore, the red band (RED) and the near-infrared band (NIR) are used to calculate the NDVI ratio (Formula 1). This ratio is universally accepted to evaluate forests and monitor crop status and environmental changes (White Paper 2010).

$$NDVI=(NIR-RED)/(NIR+RED) \quad \ldots\ldots (1)$$

A good range of NDVI values from -1 to +1 helps in classifying vegetation classes. In general, the impervious surface that include construction materials that have negative NDVI values (Barnett et al., 2005). Therefore, it is used in the rule set to classify the image objects as green (the area covered by trees, shrubs, and grass (Jacobs, 2014) and non-green (anything other than green space). NDVI value more than 0.3 was used

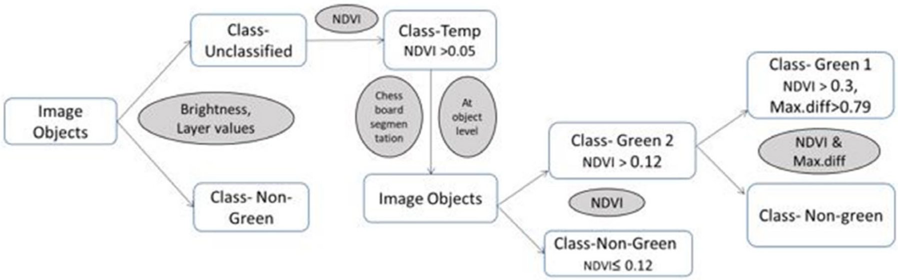

Fig. 3: Classification of Image objects

as a threshold condition to classify the green space (class-Green 1) along with other image parameters (figure 3).

GIS Analysis

The urban green cover analysis of the city of Hobart, the city of Glenorchy, and the suburb of Greater Hobart was studied at two levels in a GIS environment. To understand the temporal changes, the 4 km^2 subset area was further divided into 16 zones of 500m x 500m grid size and these zone maps were prepared in ArcGIS. The green maps (2003 and 2013) were intersected with the parcel map of Hobart council at first and green area per parcel was calculated for both the period. The grid maps were then intersected with subset green maps (2003 and 2013) and the grid zone wise green area was calculated for all the three subsets. The results were tabulated to understand urban green space changes (UGSC) between 2003 and 2013.

The green percentage per grid zone (Gg) was calculated by using the following formula (Formula 2).

$$Gg = \frac{\sum AGi}{Agi} \times 100 \qquad \text{.......(2)}$$

$\sum$AGi= Sum of Green area in grid zone i

Agi= Area of the i^{th} grid zone

Then the decadal variation in the green space was calculated by using the following formula (Formula 3).

$$UGSC = \sum_i^n Gg\,T2 - \sum_i^n Gg\,T1 \qquad \text{........(3)}$$

Gg= Percentage of Green in grid zone i (i = 1…..n)

$\sum$GgT1= Sum of green area in all grids at Time one (the Year 2003)

$\sum$GgT2= Sum of green area in all grids at Time two (the Year 2013)

Results and Discussion

The role of urban greenery in upholding the quality of the city environment is well-known (Feng 2005, Marvin Bauer, 2011; Roy et al., 2012; Razieh shojanoori, 2016; Shekhar and Aryal, 2019). An increase in the urban built-up area due to rapid urban expansion and the impact of climate change in urban areas emphasizes the need for green infrastructure planning and sustainable management.

Urban Green Space classification results

The classification yielded a reasonably high accuracy for the rule sets in WorldView-2 and Ikonos data. The developed rule set has the minimum parameters (O'Neil-Dunne et al.,

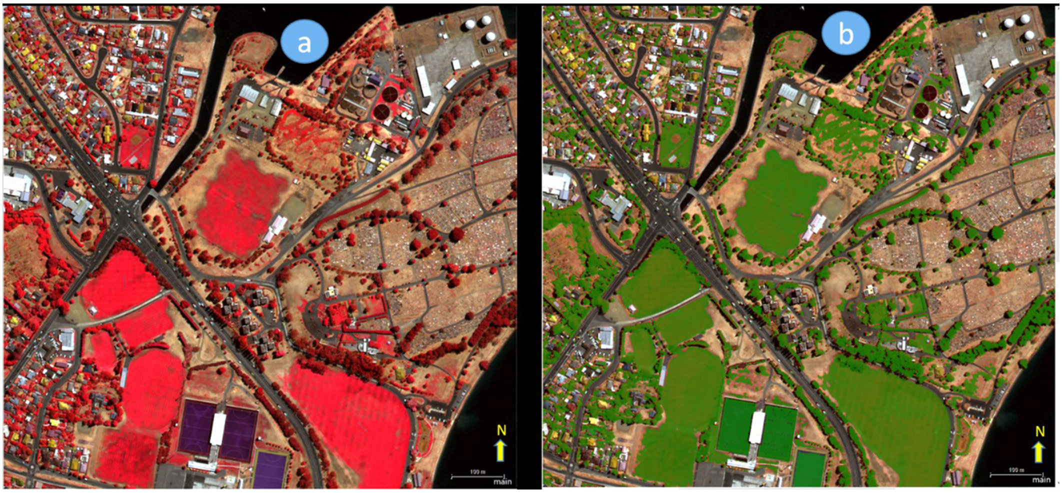

Fig. 4: Classification result of World View-2 data: a) Unclassified false colour composite image b) classified image showing green space

Fig. 5: Classification result of Ikonos data: a) Unclassified false colour composite image b) classified image showing green space

2014), essential for green space extraction and the ruleset is transferable with minimum changes in feature threshold conditions (Demers et al., 2015). The classification results of the WorldView-2 image (figure 4) and Ikonos Image (figure 5) are shown below.

The result of an accuracy assessment is very high. The high accuracy values are typical for vegetation extraction in general. In the present case, the samples taken from the WorldView-2 data had a 99% match with the classification results and proved the same.

Change detection results

Experimental design 1 - Parcel Level

Based on the extent of available imagery,

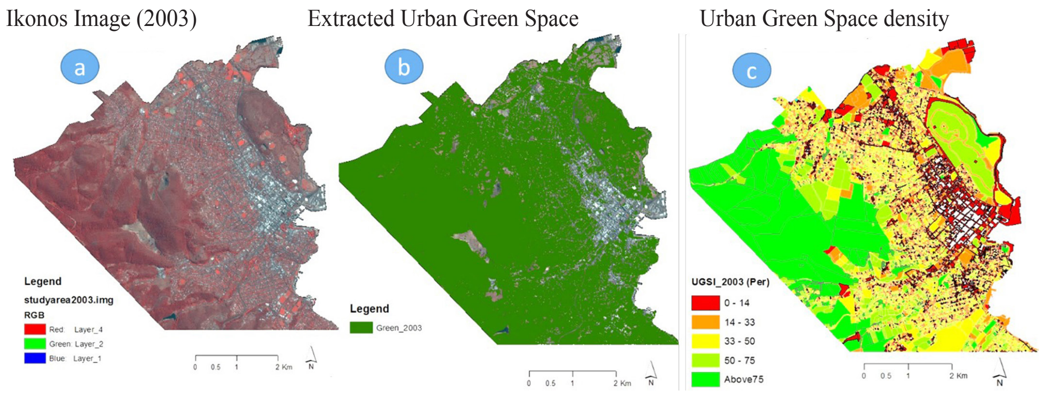

Fig. 6: Urban green space at parcel level -2003: a) Unclassified image b) Classified image with green class C) urban green space density at parcel level

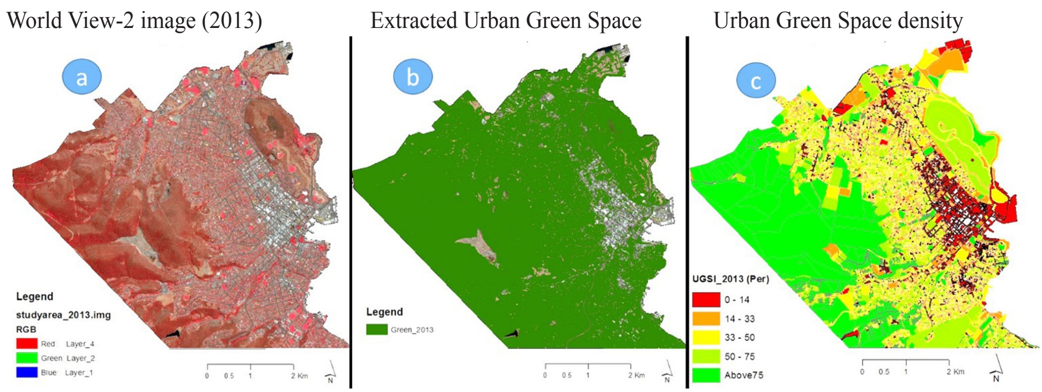

Fig. 7: Urban green space at parcel level -2013: a) Unclassified image b) Classified image with green class C) urban green space density at parcel level

a subset of parcel map has been used in experimental design 1 (Figure 1) and an analysis was carried out. Figures 6 and 7 show the results of the parcel-level study.

Overall, the urban green space had increased from an average of 33.95% in 2003 to 37.38% in 2013. The standard deviation of urban green space in 2003 was 23.79 and in 2013, it was 24.17. The average change in green space per parcel is 5.83 %. The decadal changes varied from less than one percent to more than forty percent in the urban green space at parcel level.

Even though there aren't many changes in the percentage of UGS in general in the forested area, some parcels showed a notable variation due to construction activities. The CBD area dominated by built-up land cover did show some changes even though most of the parcels have a green space of less than 15%. The parcels with a NULL value (Only had roads, building roofs without green space) had a significant reduction from 2003 to 2013. It came down from 6452 parcels to

4932 parcels. The size of the parcels is small in many cases and even a loss of a few trees led to a large percentage change in UGS. The number of parcels having less than 33% of UGS in 2003 was 10,800 out of 27,026 and it became 10,067 parcels in 2013. In the year 2003, only 5186 parcels had more than 50% of UGS, and 1270 parcels had more than 75% of UGS. This has increased to 6348 parcels with more than 50% and 1616 parcels with more than 75% of urban green space.

Experimental design 2 – Grid level

The experimental design 2 has three subsets of satellite data that includes Hobart city (CBD area), Glenorchy city (residential area), and a suburban part of Greater Hobart.

Each subset is a 2 km x 2 km size grid area divided into 16 grid zones of 500m x 500m. The subsets represent major land use categories of an urban area such as CBD, residential zone and suburban area to inform future green planning. The central part of the city where the commercial, institutional and administrative activities dominate will also have a large floating population. Therefore, improving the quality of air in such zones becomes necessary to improve public health. The presence of green cover in a residential

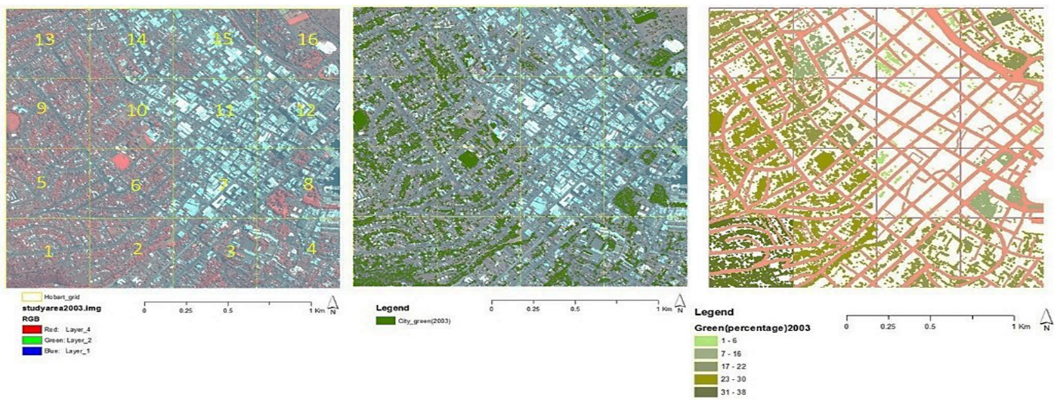

Fig. 8a: Hobart city subset results of grid analysis (2003)

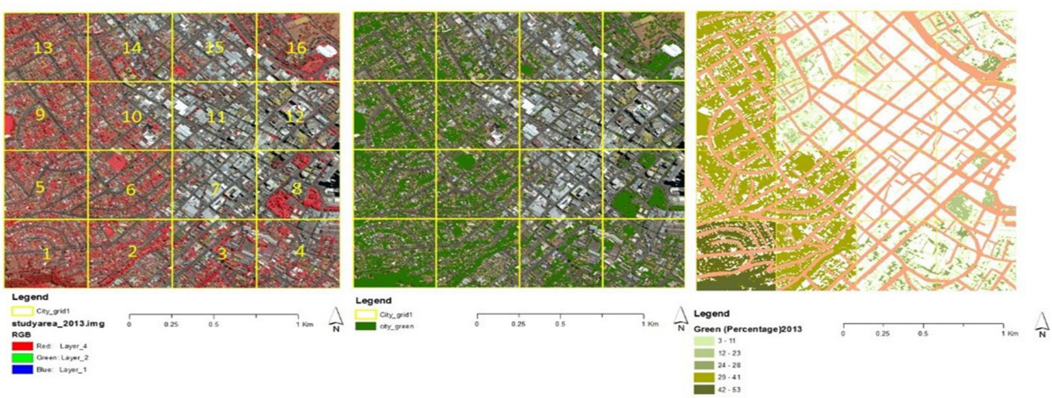

Fig. 8b: Hobart city subset results of grid analysis (2013)

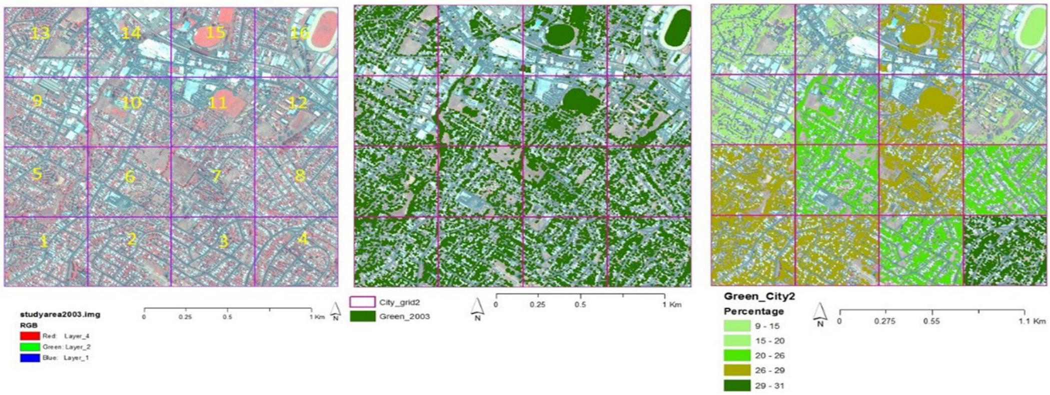

Fig. 9a: Glenorchy city subset results of grid analysis (2003)

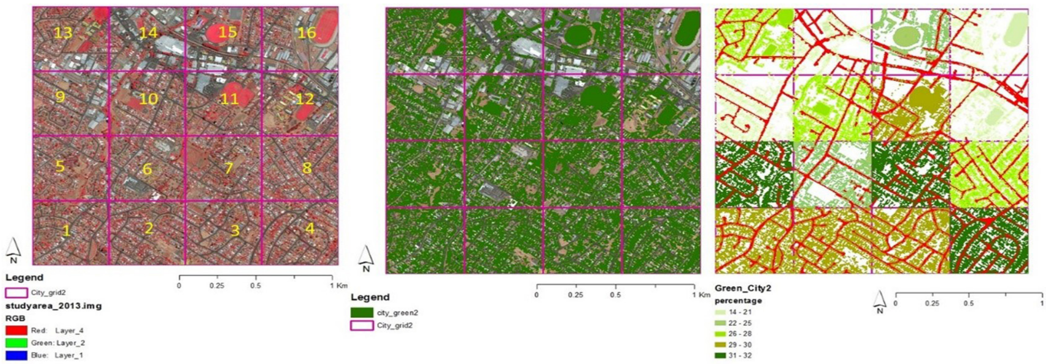

Fig. 9b: Glenorchy city subset results of grid analysis (2013)

area in the form of residential gardens, children's parks and green open areas will certainly contribute to improving the quality of urban life. An organized, planned suburban development is the need of the hour and this will ensure sustainable urban development. After intersecting the zone maps with the green maps, the percentage of green per grid zone was calculated by using formula 2 and the results are shown in figures 8, 9, and 10. Tables 2, 3, and 4 summarize the decadal changes.

Positive and negative changes in Urban Green Space

The three study areas showed a notable difference in urban green space between 2003 and 2013 (Figure 11). The city area of Hobart showed a positive change, with an average increase of 7.58% per grid zone in the green space from 2003 to 2013. The city of Glenorchy showed an adverse change in two grid zones, namely grid zones 4 and 15. The rest of the grid zones of Glenorchy showed a nominal increase of green space with an average increase of 2.58% per grid zone.

The negative changes are also observed in five grid zones of the suburb area. Except for grid zones 4, 5, 6, 10, and 15, all other

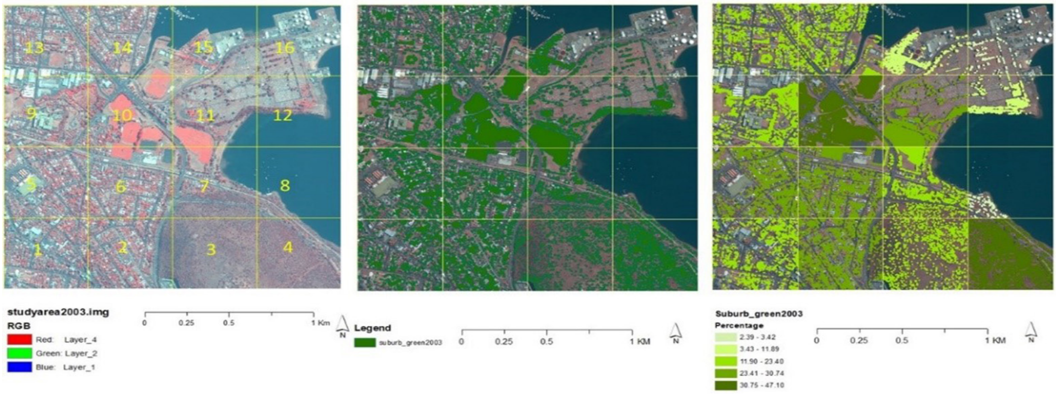

Fig. 10a: Suburb subset results of grid analysis (2003)

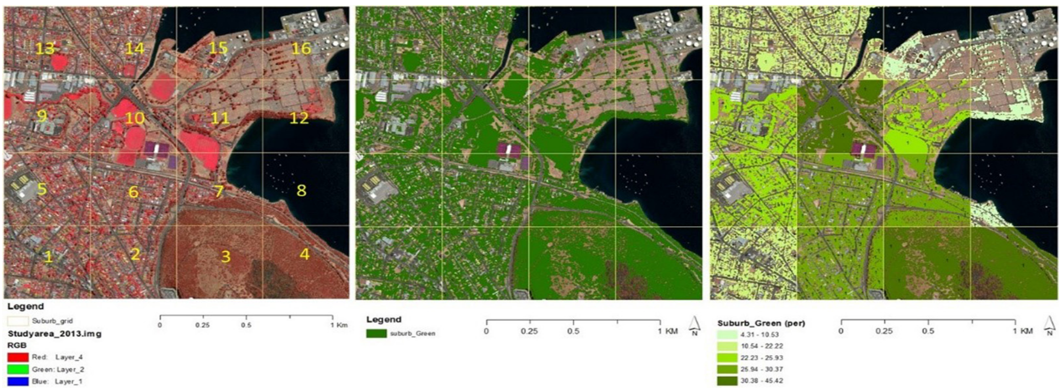

Fig. 10b: Suburb subset results of grid analysis (2013)

grid zones showed a positive change with an average increase of 3.26%. per grid zone.

The negative changes in the grid zones were thoroughly evaluated for the reasons behind the change. The deforested/burnt area in zone 4 has demonstrated its impact on the NDVI values (low) in 2013, and the same area had high NDVI values in 2003. Hence there is a change in the green space in grid 4. Similarly, in the city of Glenorchy, grid zone 15 showed a negative change. The reason for most of its change was change in the play field, and also there were changes in the residential gardens.

The quantity of perfect green (canopy) cover for a green city varies from city to city based on the climate and land use of a particular city. The quantification given by the US Department of Agriculture seems to be applicable for Tasmanian cities as they have low population density. Accordingly, 15% green cover in a CBD, 25% in urban residential and light commercial areas and 50% in suburban residential areas seem to be ideal for a green city. In our case, the Hobart subset which represents the CBD area has seen an increase from 17.9% (2003) to 25.5% (2013). The residential and light

Table 2: Decadal change in UGS of Hobart Subset area

Grid Zone	Grid area (M^2)	Green area in 2003 (M^2)	Green area in 2013 (M^2)	Change in area (M^2)	% green 2003	% green 2013	Change (%)
1	250000.00	96097.86	131649.60	35551.73	38.44	52.66	14.22
2	250000.00	70033.88	100984.38	30950.50	28.01	40.39	12.38
3	250000.00	48532.15	67347.91	18815.77	19.41	26.94	7.53
4	250000.00	44071.29	60451.29	16380.00	17.63	24.18	6.55
5	250000.00	69075.13	98879.33	29804.20	27.63	39.55	11.92
6	250000.00	62403.68	84187.75	21784.07	24.96	33.68	8.71
7	250000.00	5517.05	10466.51	4949.46	2.21	4.19	1.98
8	250000.00	39591.30	50617.90	11026.60	15.84	20.25	4.41
9	250000.00	75834.59	103210.92	27376.33	30.33	41.28	10.95
10	250000.00	47987.07	57376.41	9389.34	19.19	22.95	3.76
11	250000.00	2810.08	7151.67	4341.59	1.12	2.86	1.74
12	250000.00	5843.03	12957.07	7114.04	2.34	5.18	2.85
13	250000.00	54284.94	90325.10	36040.16	21.71	36.13	14.42
14	250000.00	31434.91	47458.63	16023.72	12.57	18.98	6.41
15	250000.00	14733.03	28232.90	13499.87	5.89	11.29	5.40
16	250000.00	49319.52	69385.76	20066.25	19.73	27.75	8.03

Table 3: Decadal change in UGS of Glenorchy Subset area

Grid Zone	Grid area (M^2)	Green area in 2003 (M^2)	Green area in 2013 M^2)	Change in area (M^2)	% green 2003	% green 2013	Change (%)
1	250000.00	71907.85	72676.68	768.83	28.76	29.07	0.31
2	250000.00	72324.21	73827.20	1502.99	28.92	29.53	0.61
3	250000.00	64436.82	70806.54	6369.72	25.77	28.32	2.55
4	250000.00	78654.95	77824.98	-829.96	31.46	31.13	-0.33
5	250000.00	71260.40	78172.58	6912.18	28.50	31.27	2.76
6	250000.00	57106.55	59005.87	1899.32	22.84	23.60	0.76
7	250000.00	72326.38	78838.50	6512.12	28.93	31.54	2.60
8	250000.00	64092.86	69083.06	4990.19	25.64	27.63	2.00
9	250000.00	47751.57	48821.06	1069.50	19.10	19.53	0.43
10	250000.00	57870.58	69191.86	11321.28	23.15	27.68	4.53
11	250000.00	66851.77	75119.00	8267.23	26.74	30.05	3.31
12	250000.00	37161.07	49850.92	12689.86	14.86	19.94	5.08
13	250000.00	50198.04	64806.70	14608.66	20.08	25.92	5.84
14	250000.00	22866.36	34744.37	11878.01	9.15	13.90	4.75
15	250000.00	66350.10	61770.04	-4580.06	26.54	24.71	-1.83
16	250000.00	49630.64	51274.71	1644.07	19.85	20.51	0.66

Table 4: Decadal change in UGS of Suburb Subset area

Grid Zone	Grid area (M^2)	Green area in 2003 (M^2)	Green area in 2013 M^2)	Change in area (M^2)	% green 2003	% green 2013	Change (%)
1	250000.00	52054.41	55556.32	3501.90	20.82	22.22	1.40
2	250000.00	75015.83	75913.66	897.83	30.01	30.37	0.36
3	250000.00	47322.11	95204.58	47882.47	18.93	38.08	19.15
4	250000.00	104694.33	98205.05	-6489.27	41.88	39.28	-2.60
5	250000.00	62874.53	58695.54	-4178.99	25.15	23.48	-1.67
6	250000.00	76858.71	75523.99	-1334.72	30.74	30.21	-0.53
7	250000.00	56571.78	70930.56	14358.78	22.63	28.37	5.74
8	250000.00	5966.58	10783.82	4817.24	2.39	4.31	1.93
9	250000.00	58500.08	63314.45	4814.37	23.40	25.33	1.93
10	250000.00	117761.90	113546.33	-4215.57	47.10	45.42	-1.69
11	250000.00	63496.53	64813.76	1317.22	25.40	25.93	0.53
12	250000.00	23970.24	24205.50	235.26	9.59	9.68	0.09
13	250000.00	47529.98	51814.51	4284.53	19.01	20.73	1.71
14	250000.00	46427.41	50365.45	3938.04	18.57	20.15	1.58
15	250000.00	29724.56	26316.17	-3408.38	11.89	10.53	-1.36
16	250000.00	8538.48	12167.38	3628.90	3.42	4.87	1.45

commercial area of Glenorchy has seen a slight improvement in its green cover and that is from 23.8% (2003) to 25.9% (2013). The suburban area which has more water bodies did not have much area under green cover but also showed a small improvement

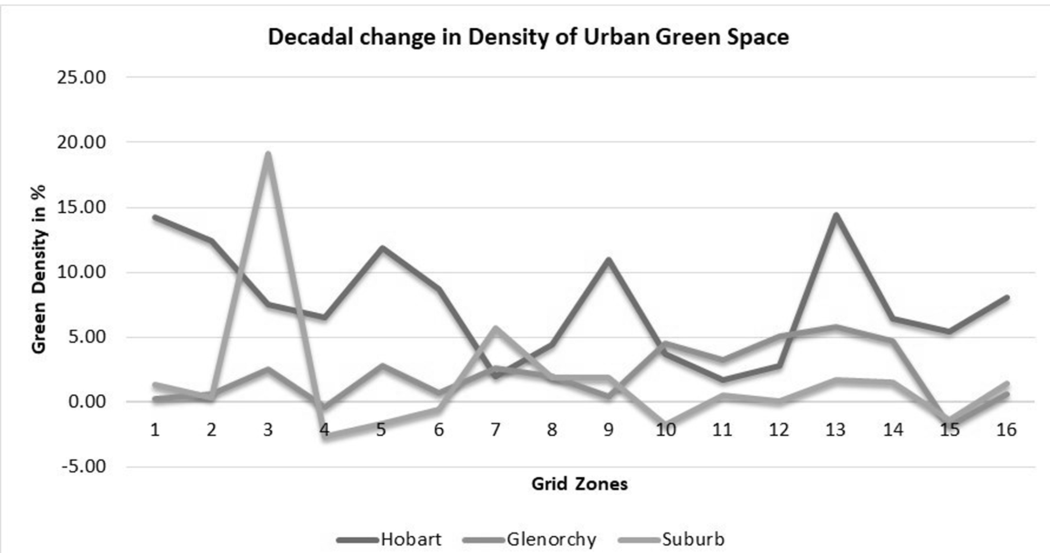

Fig. 11: Decadal change in Urban green space in three study areas

in its green cover i.e., 21.9% (2003) to 23.7% (2013). This shows that the city region has an ideal green cover in major parts of the city and lots of potential to improve its green infrastructure in the future.

Reasons for the change in Urban Green Space

During the period between 2003 and 2013, the city has grown significantly. The recent report shows that Tasmania is now ranked high on relative population growth with a 0.64% annual population growth rate. Greater Hobart is in the middle of a housing boom because of its affordability compared to other capital cities of Australia (https://www.abc.net.au/). Much of Hobart city's green area is within private properties. In general, there are changes in the urban green space due to changes in private residential gardens, which might have arisen due to the sale of residential property and changes in the attitudes of property owners (Kirkpatrick et al., 2012). Due to an increase in the paved area, the city has lost some of its green covers. Therefore, the city plans to control the removal of trees on private gardens and offers protection over specific tree species under green planning schemes.

Limitations

In a temporal data set of high-resolution images, the image objects tend to be different despite no change in the vegetation, and this false change is very common when multi-temporal datasets are used for change analysis (Zhou, Yu et al. 2014). Therefore, the difference in the spatial resolution of the IKONOS image and the WorldView-2 is also, to some extent, responsible for changes in the extracted green cover instead of actual decadal changes.

The selected study area had 27,026 parcels taken from the LIST maps. Therefore, parcel to parcel, the change detection was hard to accomplish and also with the available hardware, it was a challenge to analyze the UGS changes at the individual parcel level. Hence, to get one to one change detection, a comparable structure of grid zones was selected in the experimental design 2. The problems related to the parcel layer (having different projection and topology) to overlay with the green layer also led to some mismatches; hence there were some outliers in the UGS statistics.

Looking for a more transferable ruleset led to limited attributes in the ruleset, hence texture-based measures were not applied in the feature extraction since the texture will vary with sensors as well as species, and thus needs a thorough understanding of both. The drawback of the transferability rule set is that it is not highly technical and focuses more on practicality, so as to be useful to non-experts such as administrators and managers of local urban bodies.

The time for this research was short and did not allow us to perform ground verification of results. The high spatial resolution of the WorldView-2 image was used for accuracy assessment instead of ground samples.

Conclusions

In today's world, everyone is accepting that green areas are critical to building smart and liveable cities (Nadja Kabisch et al., 2016). Spatial information on green space is crucial for green planning and sustainable urban management (Karlson, Reese, et al. 2014).

While field-based techniques are necessary for validating the results, remote sensing remains one of the reliable methods for change detection analysis (Zhou, Yu et al. 2014).

In this study, the changes in the green space of Tasmanian cities were understood using a clear operational definition based on measurable criteria (Lucy Taylor and Dieter F. Hochuli, 2017). The present study contributed by developing and providing a simple rule set to the urban local bodies for extracting urban green space with high accuracy. The decadal change analysis gave a detail at 500m x 500m grid level as well as parcel level, which will be helpful for future planning and effective urban management. It also generated a database of changes in the urban vegetation in Hobart, Glenorchy, and suburb areas, and tried to accommodate the causes/reasons behind those changes. The results reassure the advantages of using high-resolution satellite data and the OBIA method for monitoring and managing the green infrastructure in an urban area. This is an earnest contribution towards achieving the 2020 vision of the Australian government in making Australia's urban areas the greenest in the world.

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