INVESTIGATION AND ANALYSIS OF LAND USE / TREE COVER IN RIVERSIDE, CALIFORNIA

By

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DEDICATION

This is for my wife and children, who in the course of my studies have seen and experienced new things. I know my wife has, as she looked at aerial images of our local neighborhood to see what our neighbors had tucked away behind their fences.

ACKNOWLEDGMENTS

Sincere thanks to Ken Althiser and Nathan Heck from the Information Technology Department, City of Riverside for allowing me to access the city's aerial image archives.

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ABBREVIATIONS

Abbreviation	Description
LC	Land Cover
LU	Land Use
PAN	Panchromatic
MS	Multi-spectral
TC	Tree Cover

ABSTRACT

This investigation and analysis of land use/tree cover was conducted to determine the impact of land-use policy developments in a major city. The City of Riverside was selected as a case study for this investigation because it had the necessary attributes: aerial photos of the study area over two decades, including two different yet comparable areas, one under a form of land use restriction with politically active citizenry interested in preserving their agricultural heritage. The research question is, can land use policy changes be analyzed for effectiveness by analyzing changes in land use and tree cover over time? Land use is defined herein as residential, farmland, or orchards. Aerial imagery covering a 50-year time span was collected and loaded into a GIS system for analysis. The GIS analysis included identification of land use types, imagery analysis of tree cover, and the correlation of the imagery analysis with land use policy using a feature analyst/computer–aided classification system. The research identified a significant reduction in tree cover due to the transition from orchards to residential land use. The results illustrate the land use and tree cover consequences of greenspace conservation policies adopted by the City of Riverside in 1979 and 1987. These results indicate that changes to land use and tree cover can be linked to policy developments in major southern California cities. The challenges in conducting this research included the acquisition of aerial imagery data sets, and analytical tool selection for measuring land use and tree cover which could be accurately associated with local, state and Federal policy development. Remaining questions include the correlation of census and property tax roles to the land use changes that have been identified.

1 INTRODUCTION

The conversion of agricultural land to other land uses — residential, industrial, commercial — has occurred very rapidly in Southern California since the end of World War 2. This thesis investigates changes in the urban landscape that affect the tree cover in the City of Riverside, California in response to these land use changes and policies designed to protect trees. In response to changes in urban character, the city adopted two land-use policies to preserve the area known as the Green Belt of Arlington Heights because it is representative of the City's agricultural heritage. These policies were citizen initiatives that created the Green Belt in 1979 (Measure R) and provided further restriction on land use in 1987 (Measure C).

Any quantifiable land use and tree cover analysis will require geographic data, usually obtained from aerial imagery or remotely sensed data, with a suitable resolution and collected over a sufficiently long period of time (Gillanders et al. 2008, Henebry 2000). Various types of data can be used to track temporal changes by comparing images of various ages of the same area, for example to estimate change in tree cover during a specified time span (Miller and Winer 1984, Ridd 1995). By tracking the landscape changes in a given community, one can attempt to identify the point in time when a change occurred (Sirén and Brondizio 2009). This temporal knowledge of landscape change is the key to interpreting the consequences of policies and events.

1.1 Defining land use and tree cover

This thesis includes the terms *land use*, *landscape*, *tree cover*, and *greenspace*. These terms are general defined to mean:

Land use. The type of human activity taking place at a location (e.g., agricultural or residential). In this report it identifies the following: residential areas, non-residential areas, roads, farmland, and orchards, bodies of water, and undisturbed land or vacant land.

Landscape. The physical surface of the land over a very large area, which is classified as agricultural, urban, etc. Landscapes include many different land use types.

Tree cover. The tree canopy cover in the study area. This includes trees in farmland, plant nurseries, and residential areas.

Greenspace. Area of trees, grasses, and other vegetation.

1.2 Objectives

The goal of this research is to identify the long term effects of the 1974 Measure R and 1984 Measure C land use policies on the Greenbelt area in the Arlington Heights neighborhood of the City of Riverside. Only undisturbed ground or natural ground cover, large bodies of water, orchards, residential, farmland, commercial, and transitional areas are considered. This analysis uses aerial imagery that is currently available from the City of Riverside Planning and Information Technology Department.

1.3 Study Area

The study area is the city of Riverside, located 80 kilometers east of Los Angeles and 144 kilometers north of San Diego, and is contiguous to desert and mountain regions (Figure 1). This distance for many decades served to both protect and isolate Riverside from the urban sprawl that crept outward from Los Angles, engulfing parts of northern and central Orange County. In the 1990s, Riverside elected to develop master plans that would control the urban development that had already begun to breach the Santa Ana Mountains. The question being asked at the time was whether the City could plan for sensible, managed "smarter" growth. According to the Riverside General Plan:

Faced with these and other critical planning challenges, Riversiders embarked upon a visioning process toward a positive future, a vision of a vital and self-contained City that builds upon its strengths rather than lets them erode. This vision calls for a future that focuses new growth along well-established, in-town travel corridors rather than on "paper" streets at the urban fringe. This vision celebrates and enhances Riverside's signature agricultural, hillside, historic and recreational assets (CoR-MP 2010).

Figure 1. Study Area: Greenbelt area located in Arlington Heights, Riverside, CA. (Arlington Heights, California 2011).

The goal of these master plans was to continue providing residents with various choices in their lifestyles.

> *Throughout its history, Riverside has offered lifestyle choices, catering to many different needs and desires. Residents could live in an urban neighborhood within a short distance of stores and services needed every day, or families could opt for suburban neighborhoods with traditional amenities. Riverside also has communities like Downtown, Arlington and the Eastside, with a full complement of urban land uses. In the Arlington Heights and La Sierra Acres neighborhoods, Riversiders experience agricultural and semi-rural residential living environments set amidst orange groves and rolling hills* (CoR-MP 2010).

As a precursor to the Riverside Mater Plan, in the mid-1970s community action began to control the unfettered urban sprawl that the Riversiders saw coming. The community efforts resulted in political action by a segment of the population to preserve Riverside's agricultural heritage. The outcome of the political action was the passage of the two local voter approved measures, R and C mentioned previously aimed at reducing urban sprawl and facilitating preservation of Riverside's citrus and agricultural lands (CoRMP 2010).

Since 1979, the City of Riverside has sought to control the makeup of the city. The results of these efforts are evident in the present day zoning map (Figure 2) and in current land use patterns (Figure 3). Figures 2 and 3 clearly illustrate the desired Greenbelt that is the subject of this investigation.

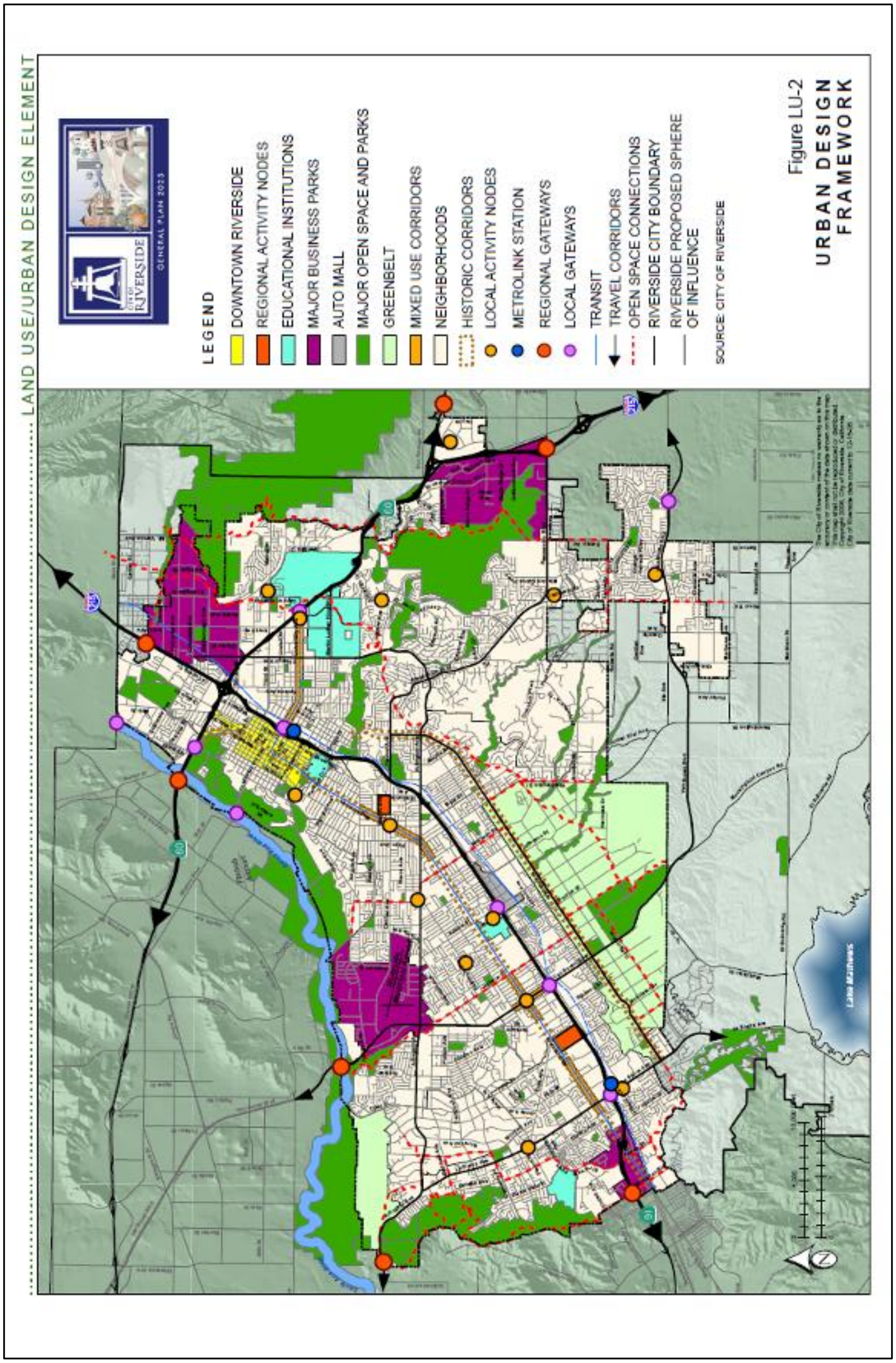


Figure 2. 2010 Urban Design Framework for City of Riverside (CoR-MP 2010).

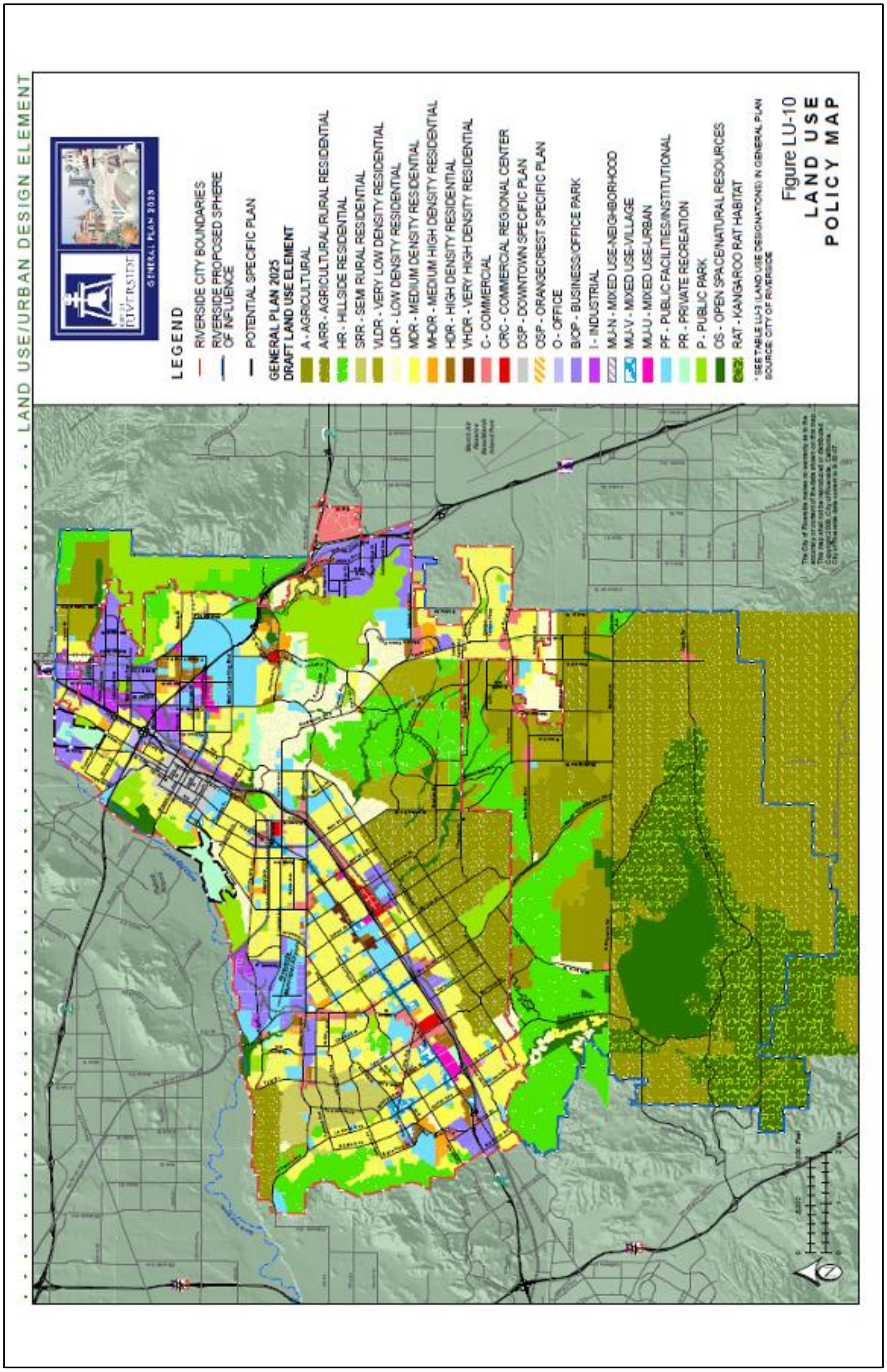


Figure 3. 2010 Land Use Map for the City of Riverside (CoR-MP 2010).

The City of Riverside was selected as the research site as it represents an area that has transitioned from an agricultural community with a small urban area to one that is now wholly suburban/urban in composition in a relativity short period of time. These changes have been documented in aerial imagery over a number of decades and were available for analysis. The main goal of this research is to perform an in depth temporal analysis of the tree cover change in the Greenbelt to determine the status and trajectory of tree cover (increasing or decreasing) within the Greenbelt.

Given on the expressed desire of the City of Riverside to maintain tree cover associated with agricultural lands, this thesis addresses what happened to tree cover during the last fifty years and addresses key questions about the City and its policies:

1. How have these two measures shaped tree cover of the Greenbelt since their passage?
2. What progress has been made in achieving the goals of Measure R and Measure C?

Other pertinent questions that remain to be addressed include:

Can changes to tree cover be identified by monitoring of the ratio of tree cover to urban/suburban area over a temporal period of some number of years?

Can changes in tree cover areas be identified from the type of changes or modifications to the existing housing and commercial building stock or from new construction?

Can changes to the tree cover areas be identified from the approval governmental rules or regulations or the passage of laws affecting the urban tree cover?

Can changes to the tree cover areas be identified from new types of building construction including residential, commercial or infrastructure structures?

Can changes to tree cover areas be identified from changes in land cover, land use or from any other outside influence?

The next chapter of this thesis presents a brief synopsis of the current efforts to utilize aerial imagery to classify land cover, tree cover and landscapes, concentrating on past yet recent studies most relevant to this research.

2 BACKGROUND

Aerial imagery has been around since the first time a camera was utilized to photograph the surface of the earth from an airplane. Aerial imagery is currently available in either film or digital formats. The purpose behind collecting aerial imagery involves the desire to understand the world and to extract quantitative answers to very difficult problems in public policy, urban planning, and environmental studies. This chapter reviews the current uses of high spatial aerial resolution imagery to map land cover, and to identify the temporal changes in land use/tree cover.

2.1 Land cover classification using high spatial resolution imagery

Remote sensing technology is continually improving in the type and quality of collected data for various land monitoring applications. Aerial photography has increased in spatial resolution, and with new sensors capturing the data in digital format, thus eliminating the digital scanning process needed for conversion of hardcopy imagery. One example of this is the use of aerial photography for mapping urban areas (Hester et al., 2008) to determine the growth of impervious surfaces. With high spatial resolution imagery the subsequent analysis of the images becomes more efficient in that an analysis does not have to rely on a person to decipher the image.

2.2 Landscape classification categorization schemes

Landscape analyses can utilize both field and remotely sensed from either aerial or satellite data sources. Typically, a landscape classification scheme based on field sources will extract detailed landscape information within the geographic scope of the research. The limits of the level of landscape classification detail are constrained by the time and labor to perform the data collection. Then one needs to consider the impact of statistical analyses, which are often used to determine the adequacy or the bias of the landscape classification on the sampling design. It is expected that this type of problem may be encountered when using either type of remote sensing source, aerial or satellite imagery or aerial photography. All of these datasets have different output limitations. These limitations include cost, spatial and spectral resolution, and interpretability.

Regardless of data source, selection of category definitions is critical to mapping any landscape. For example, suppose a field inventory looks at highway medians that are rich in information content. Here the analyst can potentially identify and measure any number of parameters which can be statistically relevant. Then there is the potential subjectivity of linking the classification and the objects of interest. So it is particularly important that the user develop a clear classification definition before the data is processed. Once the data have been validated then one can be confident in the output and that future researchers can repeat the categorization effort in a similar application.

The classification process is iterative as it is easier to work with a small number of data types and then expand the classification population once the major types have been identified. Often times a classification set may become so large that it prevents meaningful analysis from being performed due to the inability to discern patterns or statistical relevance. This, however, is easily rectified by condensing the classifications through generalization. Furthermore, generalization may be necessary when the analyst begins to share or present his/her findings because of the amount of information or the type of information of interest to the users of the data. Often these adjustments to class definitions can change the entire study process and visual map output depending on the type of audience receiving the research materials.

2.2.1 Landscape classification and high spatial resolution imagery

High spatial resolution data currently enables analysts to map the urban landscape directly and precludes the need to aggregate it. However, there are challenges due to the possibility of misclassifying either low or high resolution images. The aggregation of landscape features (such as shadows or small features containing one pixel or a combination of pixels) from spatially coarse (low resolution) data may affect landscape mapping results. In the past, several strategies that have been successful in landscape classification for coarse data may not necessarily translate into classification success with spatially fine (high resolution) data (Thomas et al., 2003).

New classification approaches have been developed to mitigate such issues related to aggregation of landscape features. These approaches include:

- Texture features (Johansen and Phinn, 2006), which identifies texture patterns to classify features;
- Morphological (Cablk and Minor 2003), which uses a combination of image processing methods based on principal component analysis and spatial morphological operators; and
- Image segmentation (Carleer et al., 2005), which employs segmentation algorithms on images to classify the features in the image.

These approaches provided the extraction of additional information from either a panchromatic or multispectral image of a given resolution. As image capturing technologies advanced, film technology to electronic sensors, from an image resolution of 1 meter to sub-meter distances, the analytical approaches were able to provide the analyst with the mathematical tools to extract the desired information.

Various spectral-based methods are available to classify land cover. They are, in order of accuracy: Conventional per-pixel classifiers (Table 1), spectral-textural (Puissant et al. 2005), Kettig and Landgrebe's (1976) Extraction and Classification of Homogeneous Objects (ECHO) classification, maximum likelihood classification using the segment mean (Lee and

Warner 2006), segment divergence index or the segment probability density function (PDF) (Lee and Warner 2006) and minimum-distance-to mean algorithms (Hester et al. 2008) (Table 2). These methods were considered by Hester (Hester et al. 2008) to be among the historically dominant approaches to remote sensing-based automated landscape classification. Of these, Hester states that the maximum likelihood classifier is frequently used as a "benchmark" against which novel classification algorithms are evaluated (Song et al. 2005).

Table 1. Accuracy of Various per-pixel Classification Schemes (Hester et. Al 2008).

Highest Accuracy	Classification using the segment PDF
	Classification using the segment mean
	Standard maximum classification (Benchmark) (Song et al. 2005)
	ECHO, a multistage spatial-spectral classifier that has elements of a parametric per-pixel classifier and elements related to texture classification
Lowest Accuracy	Classification using the segment divergence index

Table 2. Urban Landscape Categorization Scheme used by Hester et al. (2008)

Class	Landscape Type	Description
1	Impervious	Manmade impervious surfaces: buildings roads walkways etc.
2	Water	Lakes, ponds, streams, rivers including natural or manmade
3	Bare/Disturbed Soil	Construction sites, landfills, any unpaved non-vegetated surface
4	Deciduous	Trees or shrubs that shed their leaves in winter
5	Evergreen	Trees or shrubs that do not shed their leaves in winter
6	Herbaceous	Urban grasses (yards, playing fields, road medians etc.

These are not the only methods used to classify landscapes. More recent developments include the Multiple Endmember Spectral Mixture Analysis (MESMA) (Franke et al. 2008), which have been used to achieve a 76% classification accuracy for 20 land classification types with a spatial resolution of at least 5 m. As described in Table 3, the classification scheme use is more developed as it uses a schema with 20 classifications.

Table 3. Urban landscape categorization scheme (Franke et al. 2008).

1 Imperviousness	2 Land Cover	3 Dominant	4 Material/Species
Pervious	Vegetation	Trees	European Chestnut
			Linden
			Mixed deciduous
		Grass	Grass
	Bare soil	Bare soil	Soil
	Water body	Water body	River
			Lake/Basin
Impervious	Built up	Road	Asphalt
			Cobblestone
		Roof/	Red-shingle
		Building	Dark-shingle
			Gravel roof
			Corroded metal roof
			Metal roof
			Bitumen roof
			Slated roof
			Glass-roof
			Cardboard roof
			Plastic roof 1
			Plastic roof 2

The application of Franke’s (Franke et. Al. 2008) classification scheme(s) for land cover and landuse provided a starting point for identifying the analytical techniques and procedures which were utilized to address the research questions posed in this study in Chapter 1. The adapation of Franke’s scheme will be explained in further detail in the Methods section.

3 METHODS

In this study, changes in tree cover and land use between 1960 and 2008 were quantified using orthorectified images. The imagery was obtained from the City of Riverside's Information Technology Department and included both photographic aerial images and digital multispectral images (Anthiser 1960, 1974, 1998, 2003, 2008). The resolution of each source varied according to the system the image was recorded with: photographic systems from 1960 to 1998 and digital systems from 2003 to 2008. Information quality also depended on the time of year the photos were taken, as this significantly influenced the amount of tree cover in natural and farmland areas. Classifications were attempted for both panchromatic and multi-spectral images (Table 4).

Table 4 Available Aerial Imagery of Study Area (Althiser 1960, 1974, 1998, 2003, 2008).

Type	Year Available	Resolution
Panchromatic	1960, 1974, 1998	.3 meter
Multi spectral	2003, 2008	.1 meter

The classification schemes commonly used in remote sensing technology are limited by the ability of the analyst or software to discern and match the imagery to an appropriate classification methodology found on the ground. Significant human judgment is needed to correctly identify and then classify the objects in the image. To minimize the amount of human judgment in the identifying tree cover, Overwatch's Feature Analyst 4.2 for ArcGIS was utilized to perform in this particular analysis. Overwatch's Feature Analyst is a third party package used to classify the features identified in the imagery into three categories or classifications: water, tree cover, and natural ground cover because these represent most of the land cover in the greenbelt area.

Overwatch's Feature Analyst extracts object-specific geographic features from all types of GIS imagery. In this study, panchromatic and multispectral images were investigated. The workflow approach adopted to conduct this analysis is illustrated in Figure 4. One important analysis decision branches is the option to choose supervised or unsupervised schemes to classify the objects identified in the images. In a supervised scheme, in the first classification pass the operator has the opportunity to make refinements in the classification parameters and identify pixel patterns for specific classes. This refinement enables the software to classify areas in a second round of analysis that were not classified during the first pass, or exclude areas that were determined to have not classified correctly during this supervised classification effort. The number of supervised classifications passes is dependent on the quality and type of the image. Panchromatic images required up to four passes to process with Overwatch's Feature Analyst. Whereas multispectral images could be classified in a single supervised classification pass. After these refinements were completed the images were processed without further supervised classification. Unsupervised classification means that the operator does not refine the classification parameters after the Feature Analyst software has classified the image. Both supervised and unsupervised classification schemes were utilized in the analysis (Figure 4).

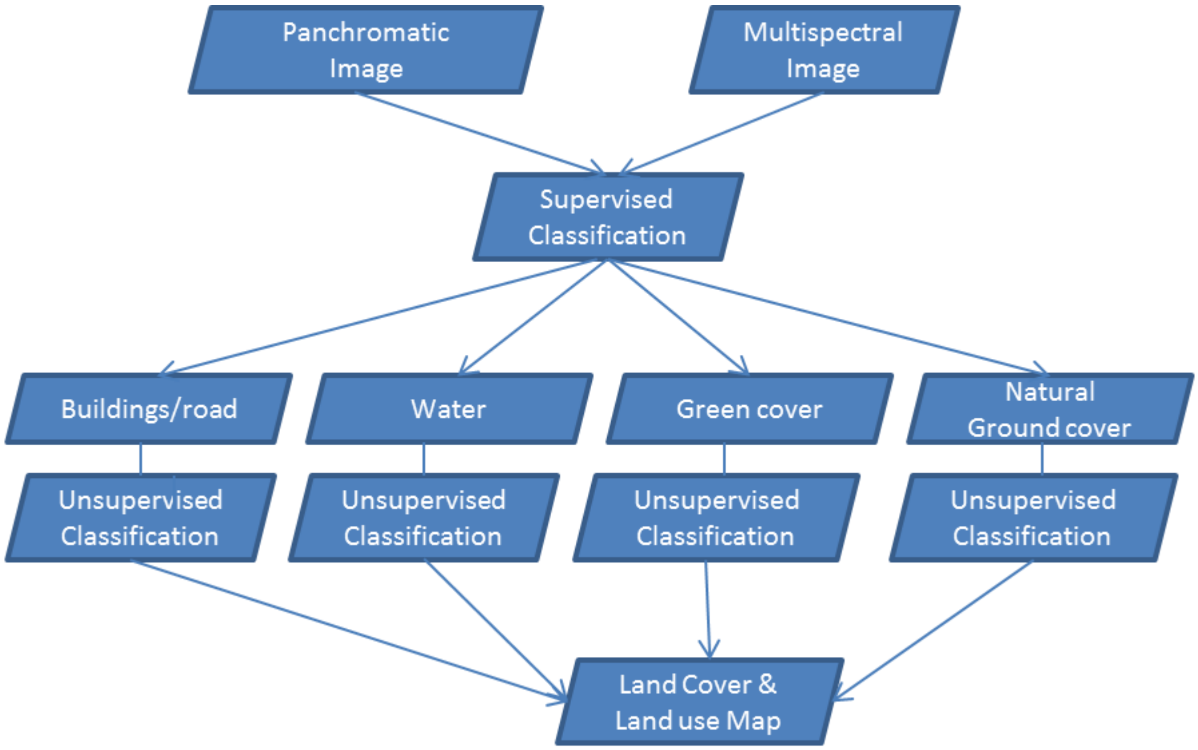


Figure 4. Basic workflow for performing land cover classification.

Images were obtained from the City of Riverside Information Technology Department (Anthiser 1960, 1974, 1998, 2003, 2008) and were scanned in preparation for analysis using ESRI ArcGIS and Overwatch Feature Analyst. For example, polygons encompassing colors recognizable as green vegetation were ultimately extracted. Once these polygons were collected the next step in the analysis involved matching the land use with the tree cover.

3.1 Photo imagery

Panchromatic images were also obtained for the years 1960–1998, natural color images for the year 2003, and multispectral imagery for the year 2008 (Figures 7 and 8). Each image set has a resolution of 0.3 m, but no additional information on the images (i.e. metadata) was available (Table 7). It was not possible to find the camera details or time and date of the image captures to include in the image's metadata. The only confirmed metadata is the year the image data sets were created.

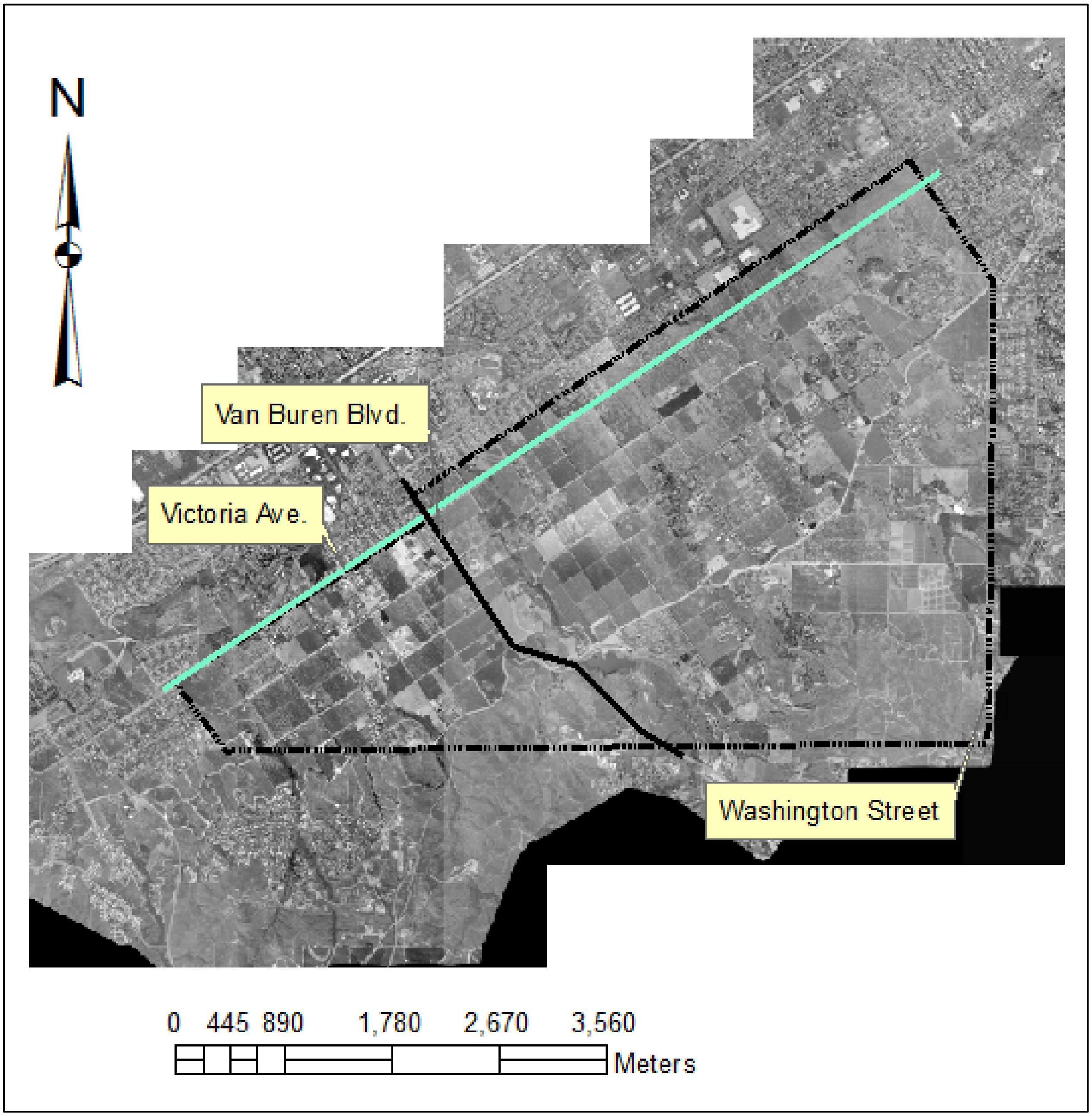


Figure 5. Aerial image of Riverside, 1998 (Althiser 1998).

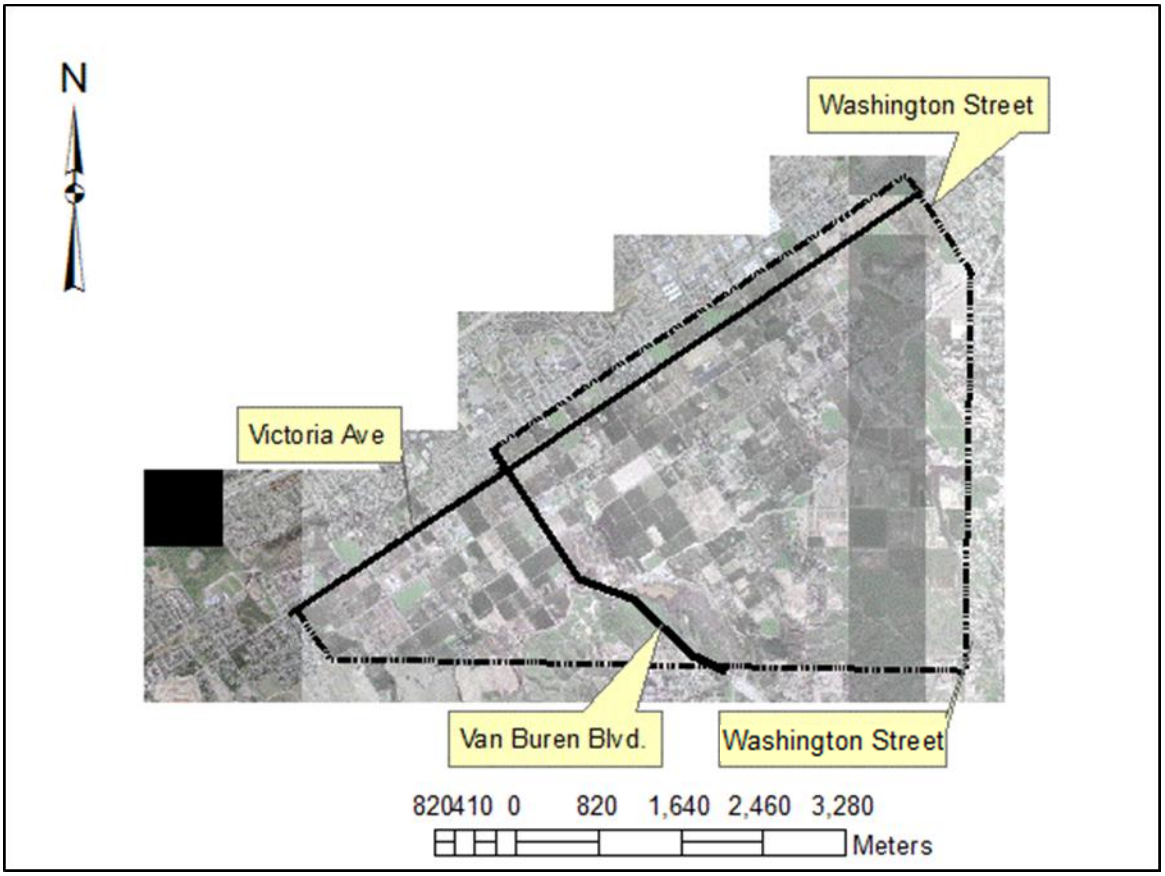


Figure 6. Aerial image of Riverside, 2003 (Althiser 2003).

Table 5. Image source information.

Year	Type	Bands	Resolution	Image Source	Data Source	Method of Digitizing	DPI	Figure Number
2008	Multispectral	3	0.3 m	Aerial	Riverside IT	As imaged	600	14
2003	Multispectral	3	0.3 m	Aerial	Riverside IT	As imaged	600	13
1998	Panchromatic	1	0.3 m	Aerial	Riverside Planning	Scanned	400	12
1974	Panchromatic	1	0.3 m	Aerial	Riverside Planning	Scanned	600	11
1960	Panchromatic	1	0.3 m	Aerial	Riverside Planning	Scanned	600	11

3.2 Image and Data Classification

The feature classification process followed two procedures that are eventually merged to provide the desired information regarding the nature and spatial extent of land cover in each of the years analyzed. These procedures include land cover feature extraction followed by land use classification from the images (Figure 7). Pre-processing steps were carried out because image analysis software cannot discern intent or application of land use, whereas the human mind can. This land cover classification process using both unsupervised and supervised classification steps is presented in more detail in Figure 8.

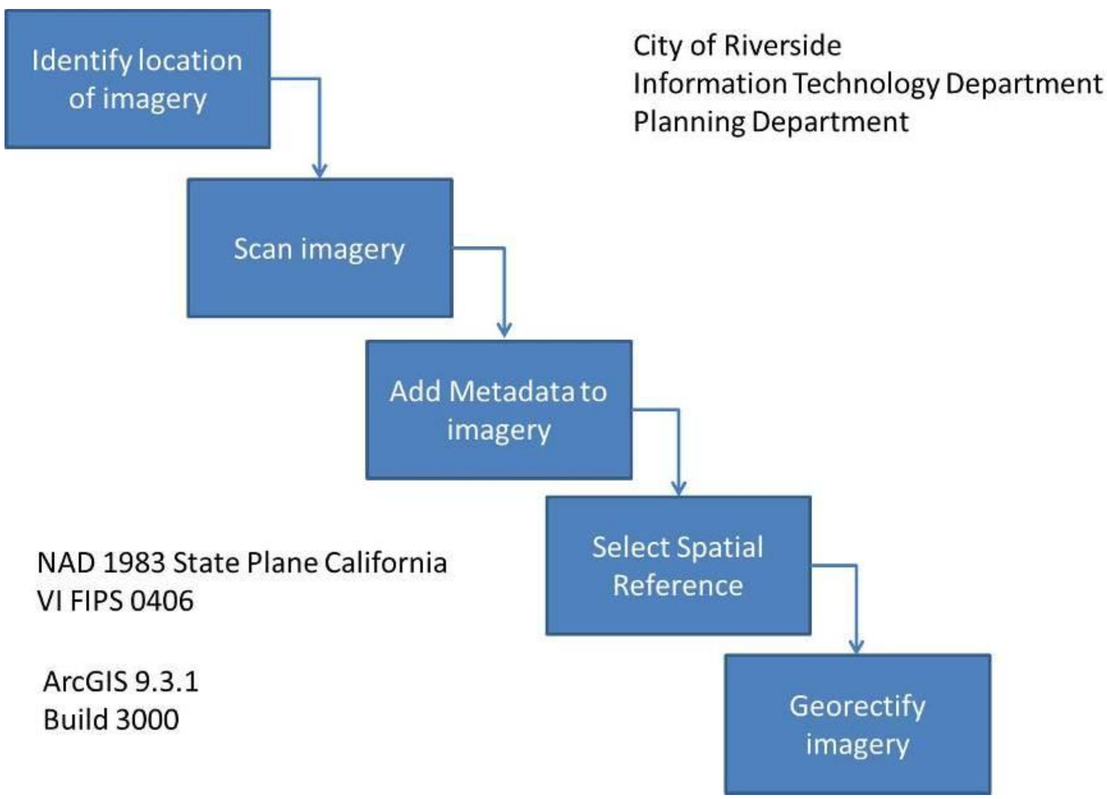


Figure 7. Image collection and analysis pre-processing steps.

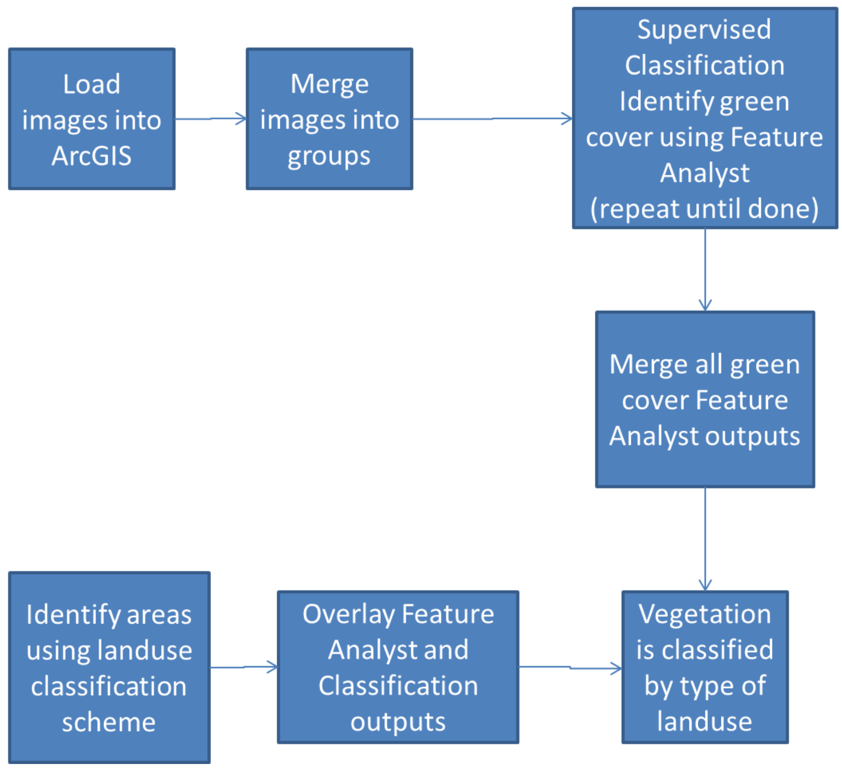


Figure 8. Feature classification process steps.

The process for land cover feature extraction using ESRI ArcMap tools is described as follows: First, this imagery was georectified using NAS 1983 State Plane California VI FIPS 0406. Second, because the number of images for each was rather large, 50–75, blocks of images were merged together into groups of 1–6 blocks to reduce the processing time. This produced strips of images, which allowed easier tracking and reduced the analysis time. Third, land use was digitized manually by looking at the image and applying the rules from the classification scheme. New layers of features extracted representing different types of land use were gradually built and collected as shapefiles overlaid on the images, also as base maps for visual verification of results. The following land use classifications were developed for the project area:

Orchard: Areas where 10 or more fruit bearing trees could be identified were classified as orchards. In some instances the orchards were on small hills where the traditional grid patter could not be maintained, instead the trees followed the terrain contours. This resulted in the creation of some odd shaped orchards. Out buildings and residences were included in the orchards if they were a part of the orchard complex.

Nursery: Consists of vegetation for commercial sale, it has a unique signature in the image and could be easily identified and mapped.

Farmland: Consists of vegetation planted in uniform rows, it has a unique signature in the image and could be easily identified and mapped.

Residential: These areas consisted of a house, grass area and other non-orchard areas. An area was identified as residential if it had fewer than 10 fruit bearing trees. These area included tract homes on with various lot sizes. I discounted the lot size from consideration unless it showed in later images that more than 10 fruit bearing tress were present. There were several cases where new fruit bearing trees could be identified in later images, but not in previous ones.

Transitional: This area was typically vacant land, and included unattended orchards, which could be identified by dead or dying trees. Untended orchards could be identified by various tree sizes throughout the orchard and in color images one could identify dead trees from their grey color.

Natural: Areas where no land improvements could be identified at all. Typically this was in stream beads and towards the outer boundaries of the Green Belt with grasses or exposed rocks and dirt roads.

3.3 Image Analysis Validation

The validation of the tree cover output from the Feature Analysis software was verified by comparing the output with a ground survey. The verification method was performed by visually comparing the analysis output with the tree cover along Victoria Ave. and Van Buren Blvd. Both streets cross the Greenbelt with Victoria Ave. passing through orange groves, farmland, and residential areas. Van Buren Blvd passes by orange groves, residential areas, natural areas, and water reservoirs. During validation, I confirmed earlier assumptions regarding water bodies, in that the green algae in the water would be identified as tree cover.

3.4 Control Area

A control area was also selected where Measures R and C were not implemented to assist in determining if tree cover and land use changes in the Green Belt area were unique. The area known as Hunter Park shared many of the attributes of the Greenbelt (Figure 9).

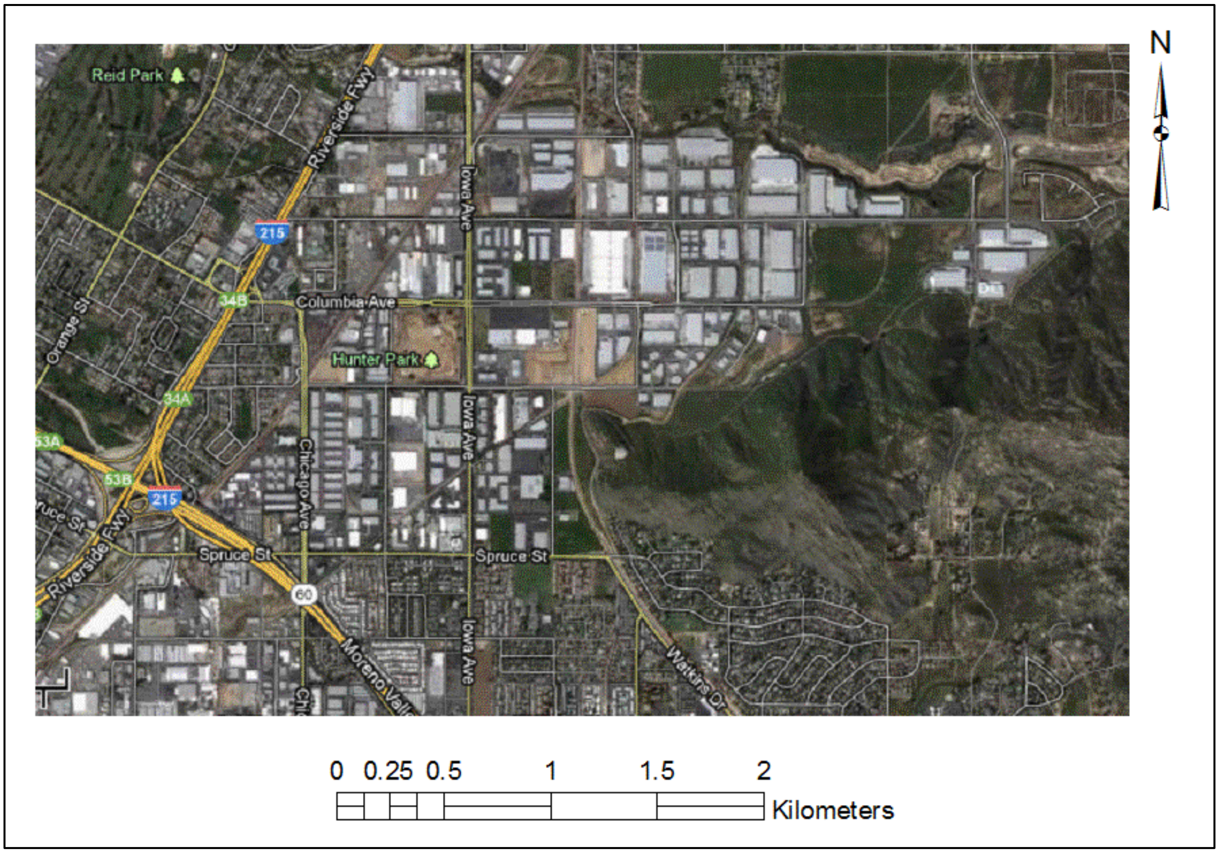


Figure 9. Control Area: Hunter Park, Riverside, CA (Hunter Park, California 2011).

3.5 Feature Analyst Process

The tree cover analysis using Overwatch's Feature Analyst was an important tool in extracting this data from the aerial imagery. Feature required careful setup so meaningful data could be extracted from the imagery. Using a hierarchical learning approach Feature Analyst takes into account correct and incorrect examples from a previously extracted feature set. The basic process was previously described and illustrated in Figure 4 as an overview. A more detailed description of that process is now provided on how the Feature Analyst hierarchical learning approach is used to extract the tree cover area from panchromatic or multi-spectral aerial (Visual Learning Systems 2008).

The first step is to determine which classification approach to take: supervised or unsupervised. For this analysis the supervised classification analysis was used as this provided the fastest way of extracting usable results from Feature Analyst. This is implemented through the software module called the 'Learner', which uses a hierarchical approach in building the classification data sets to identify features from the aerial imagery.

The approach taken by Overwatch's Feature Analyst is based on hierarchical feature extraction, which improves classification results by mitigating clutter (false positives) and retrieving missed features. The overall process repetitively narrows the classification task into sub-problems that are more specific and well-defined. By labeling features from the initial classification as either positive or negative, a clutter removal training set is established. The Learner then classifies additional features using the positive instances from the previous learning pass (Visual Learning Systems 2008).

Learning continues by creating new training sets that select missed features; the remaining unclassified features become the background class, which is used to remove clutter is subsequent analyses. The new learning task is more narrowly defined since the variability of the positives is reduced (Visual Learning Systems 2008).

This analysis used the following workflow steps with Feature Analyst:

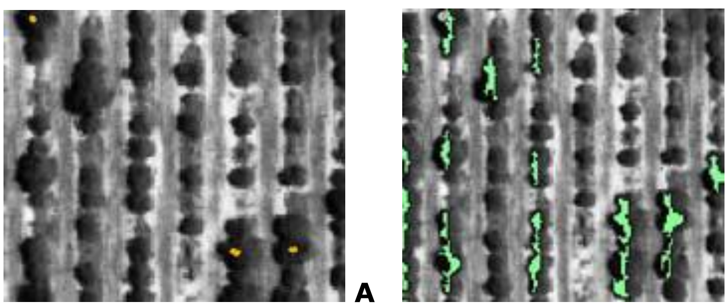
1. Define the initial setup selections for the type of aerial image used: multi-spectral or panchromatic.

   Both required different setups as the data sets contain different data elements. The multi-spectral setup used a predefined feature setup for identifying vegetation patterns. The panchromatic images required a trial and error approach to match the specific tree cover (fruit trees) with an appropriate pixel sampling pattern provided in the feature setup section of Feature Analysis.
2. Define feature target examples for the Learner in a training set.

The Learner is a software module within Feature Analysis that the user trains to identify the desired features from these training examples. This is typical a small area that contains a sample of the desired features the user wants to identify.

3. Run an initial learning pass.
4. Refine the training set, as necessary.

   The user reviews the results and can adjust the training set and setup parameters to produce the best results for the Learner to use. This may require changing the initial parameter setup to assist the Learner in identifying the desired features should the initial pass fail to identify all the features the user is interested in. During this review the user must validate the Learner results with ground truth or other data to insure the Learner setup can be verified. A training set is shown in Figure 10 and 11.



A **B**

Figure 10. Training set does not include edges (A), Poor results (B) (Visual 2008).

If the training polygons are small, then the area identified by the Learner will require additional passes to capture the actual area.

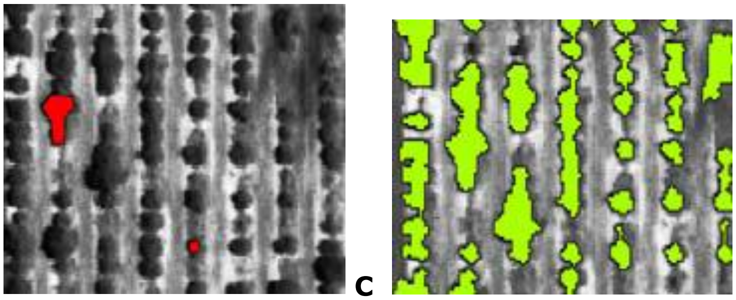


Figure 11. Training set includes edges (C), Good results (D) (Visual 2008).

The training polygons include the edges, then the area identified by the Learner will include these critical boundary regions which reduce the number of passes to capture the actual area.

5. Train the Learner to recognize the targets through a sequence of Hierarchical Learning activities.

   Additional feature target examples are identified and added to the target list; see Figure 12 (Visual Learning Systems 2008). In addition, the user can also identify features that the Learner can exclude from consideration as the user knows that certain feature attributes will provide false positives if not accounted for.

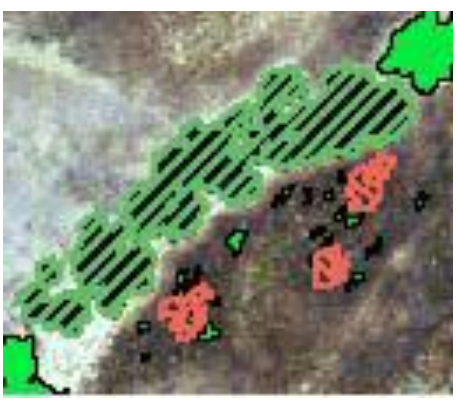


Figure 12. Areas to be added and removed from training set (Visual 2008).

6. Learning passes with adjustments, as necessary, to the input representation.

This step repeats steps 4 and 5 until the user is satisfied that all the features desired have been identified within the aerial imagery sample.

7. Mask out troublesome features, if necessary.

   This step allows the user to remove those features which report false positives. This seems like a repeat of step 5, but it targets larger features which have the desired feature attributes but is not a desired feature to be included in the analysis, see figure 13.

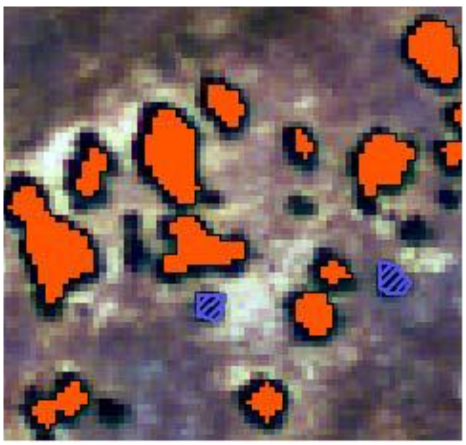
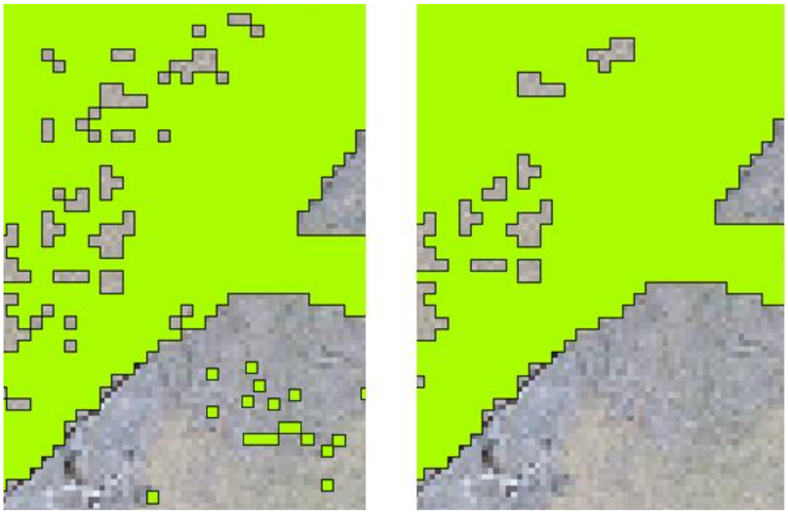


Figure 13. Areas identified undesired features (Visual 2008).

8. Remove clutter (noise) and finding missed features by correcting the Learner through the selection of correct, incorrect, and missed examples. This is another refinement where the user can Learner can aggregate features, see Figure 14 (Visual Learning Systems 2008), fine tune the selection of missing features and remove features that are not relevant to the analysis. One example would be bodies of water with high algae content. This was identified as tree cover until it was masked out.



A B

Figure 14. Aggregation: Before (A) and After (B) (Visual 2008).

9. Repeat the hierarchical learning process until satisfied with results.

The next chapter of this thesis provides a detailed discussion of the analytical results of the procedures presented above.

4 RESULTS

The Greenbelt in Riverside, California underwent a considerable transformation between the years 1974 and 1998. From 1960 to 1974 the tree cover within the orchard land use category was stable at around 13 million square meters. After 1974, several additional land use types, including Transitional and Nursery, were introduced into the Greenbelt area. Residential land use also changed from being oriented toward orchard production to more suburban and ranch style purpose through two paths, direct conversion from orchard to residential or an indirect conversion from orchard to transitional to residential (see Figure 15). The transitional land use consisted of a non-productive state, i.e. vacant land, or a productive state in the form of tree or plant nurseries. The natural areas remained constant until the 2003–2008 periods, during which they show a reduction owing to residential construction in those areas (Figures 17, 19, 21, 23 and 25). To summarize the results of this analysis, there are indications that in 2003 the land use measure implemented through Measures R and C did change as the area of land with the transitional land use classification was reduced.

The land use analysis showed a continuous decrease in orchard land use starting in 1974 and continuing to the present. The nursery land use has the most variability as peaked in 1988 and 2008 (see Figure 16). We can infer from this variability is that nursery land use is an intermediate step between orchard and residential. The progression from the orchard classification appears to be random. Figures 18, 20, 22, 24 and 26 illustrate this progression.

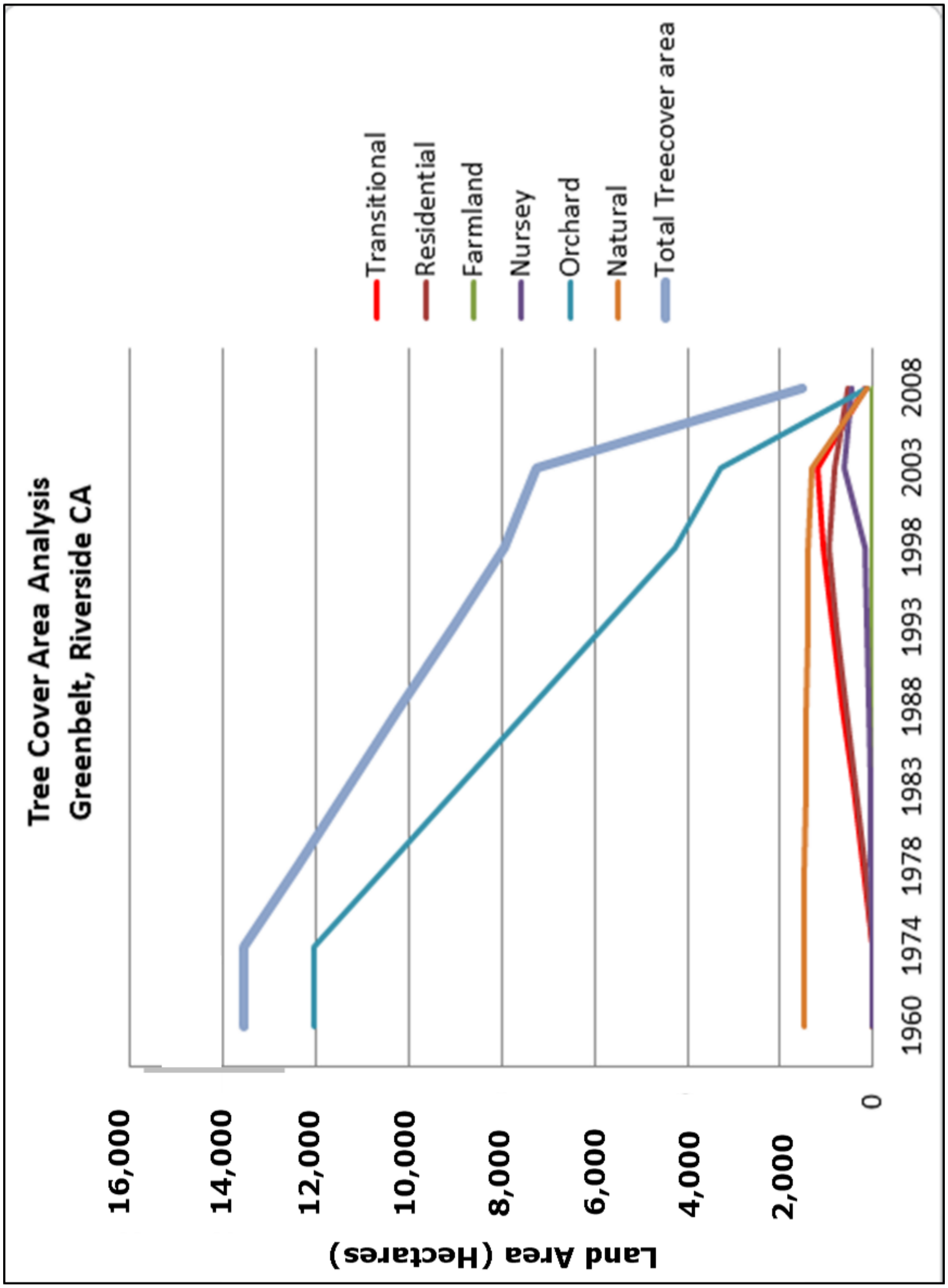


Figure 15. Treecover from 1960 to 2008 in the Arlington Heights Greenbelt, Riverside, California.

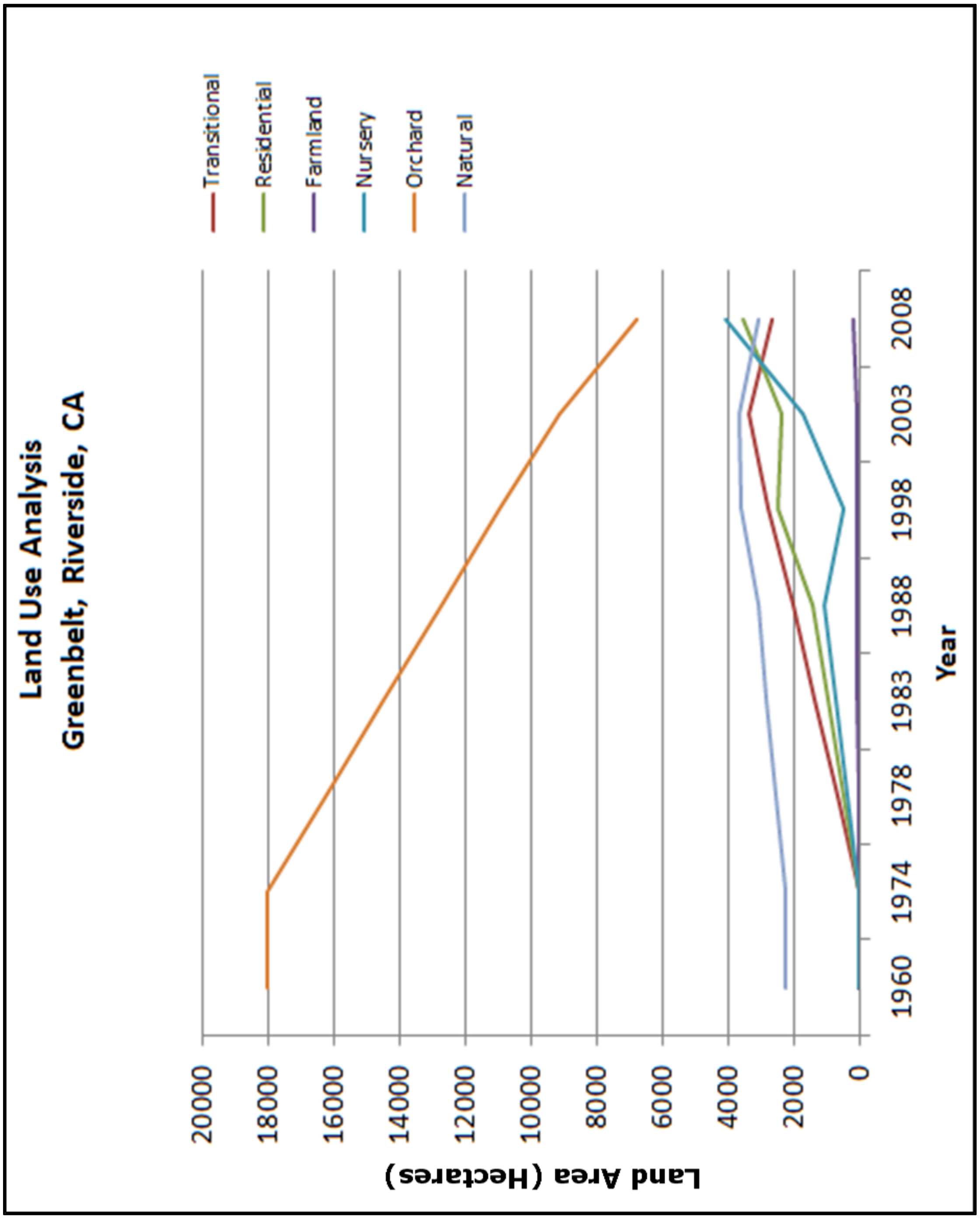


Figure 16. Land Use Trends in the Arlington Heights Greenbelt, Riverside, California, 1960–2008

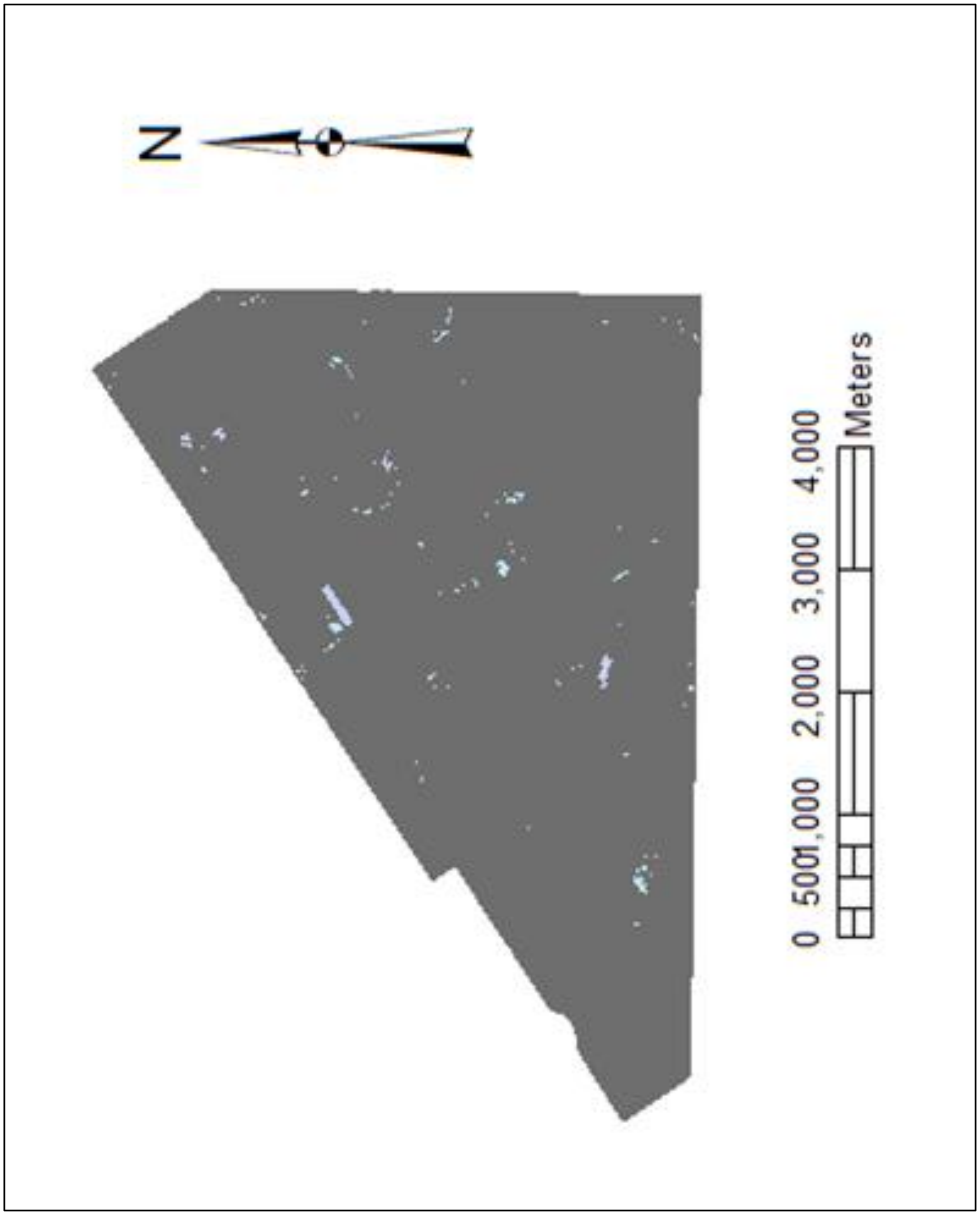


Figure 17. 1960 Tree cover.

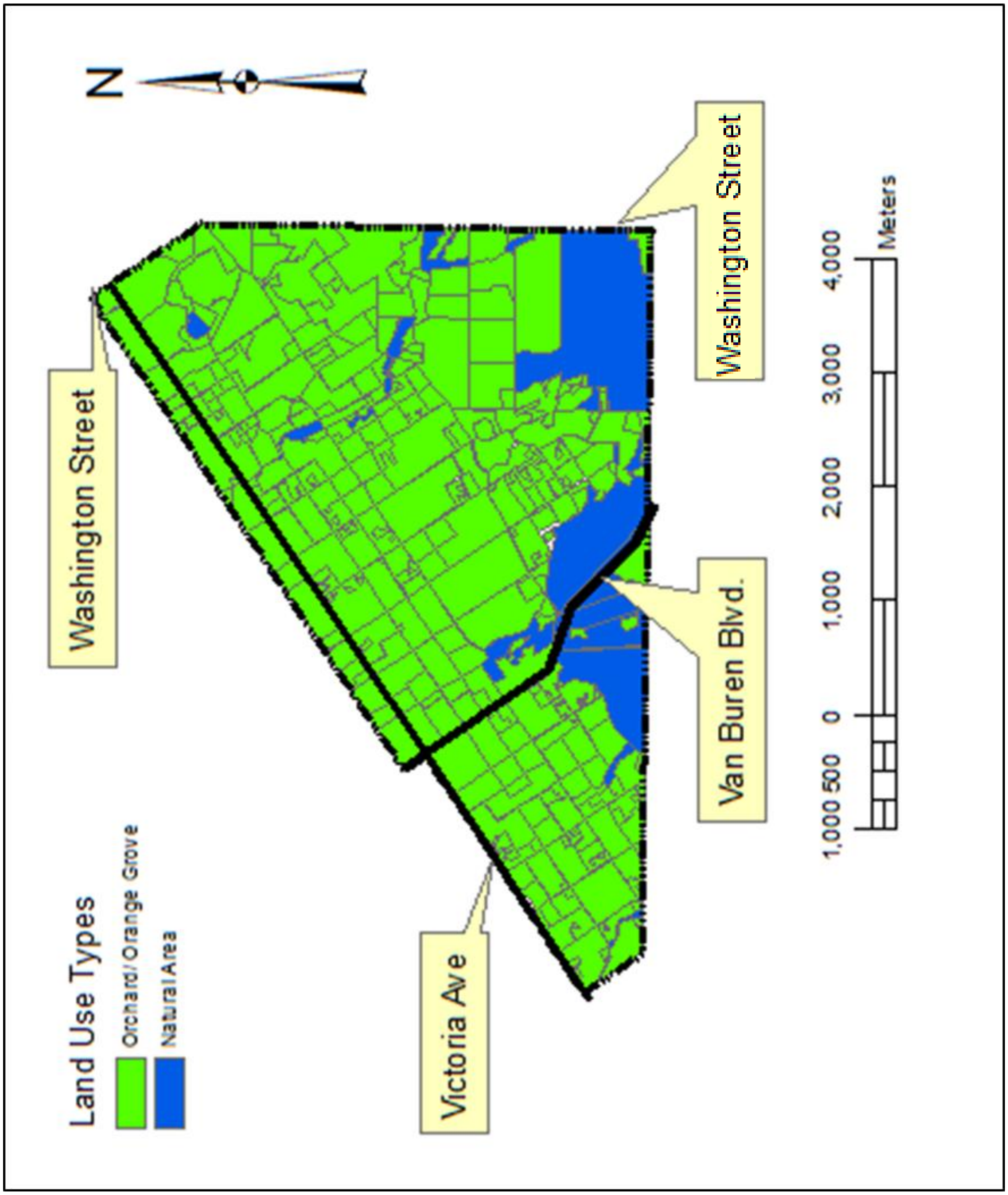


Figure 18. 1960 Green Belt Land Use.

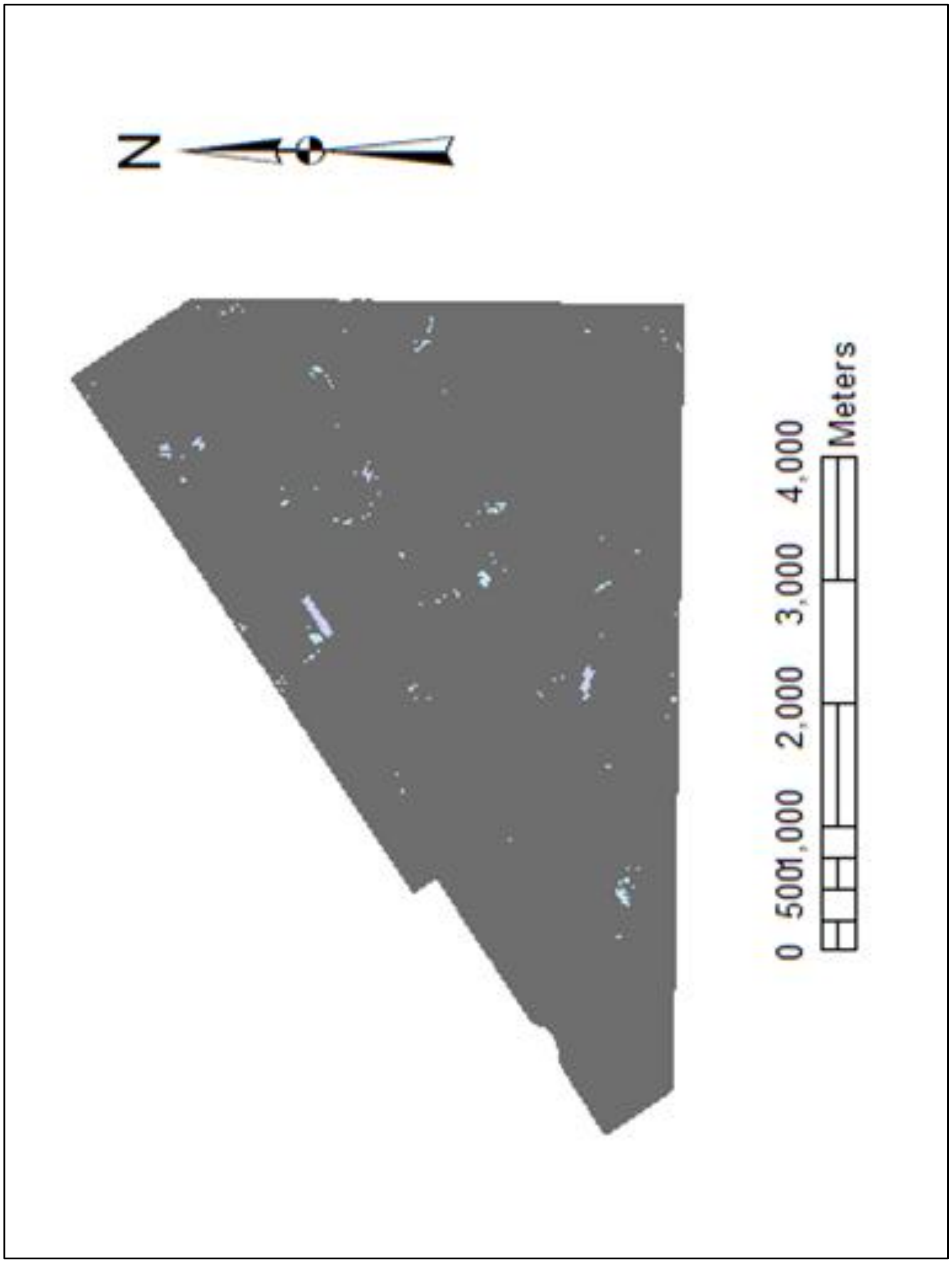


Figure 19. 1974 Tree cover.

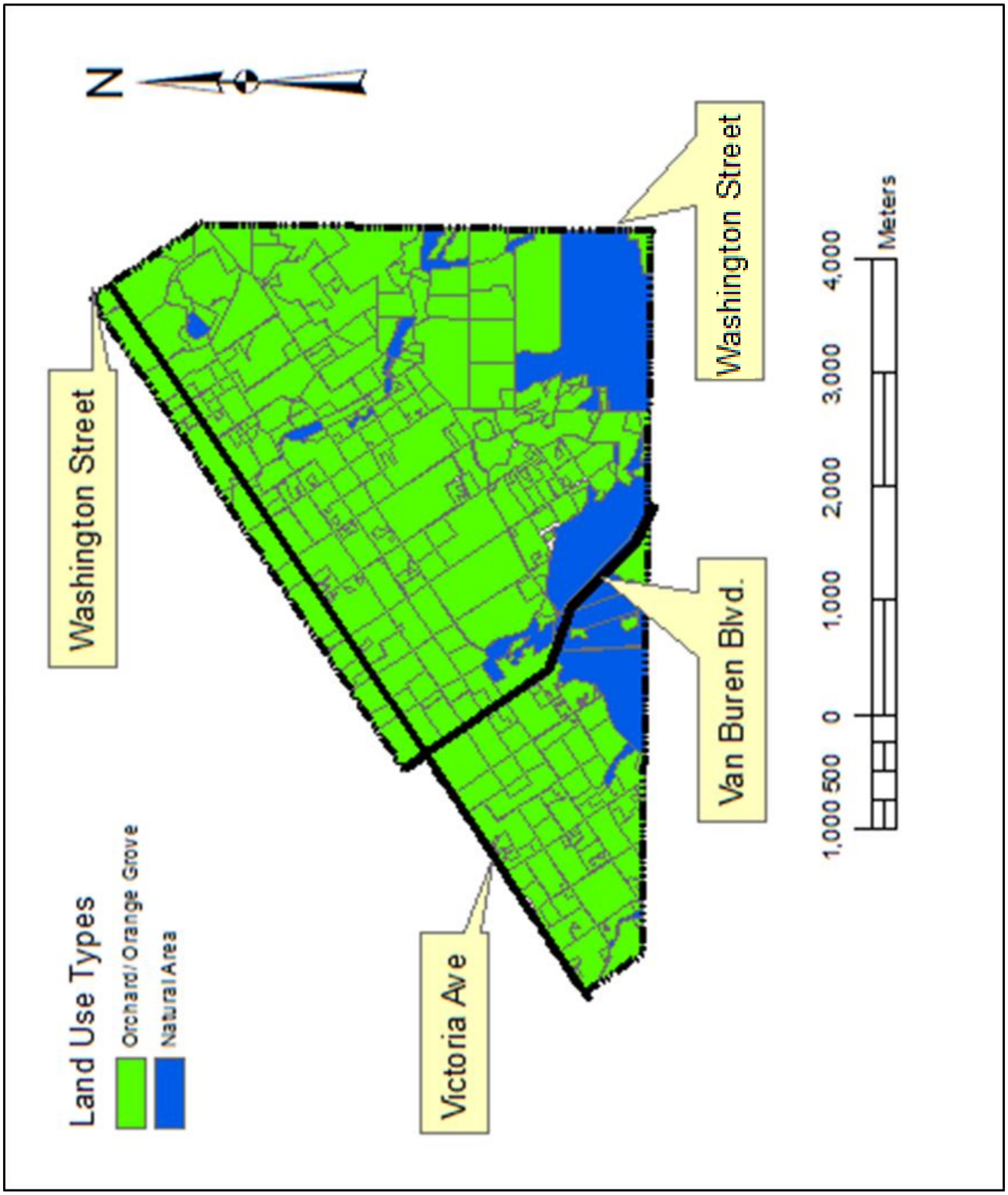


Figure 20. 1974 Green Belt Land Use.

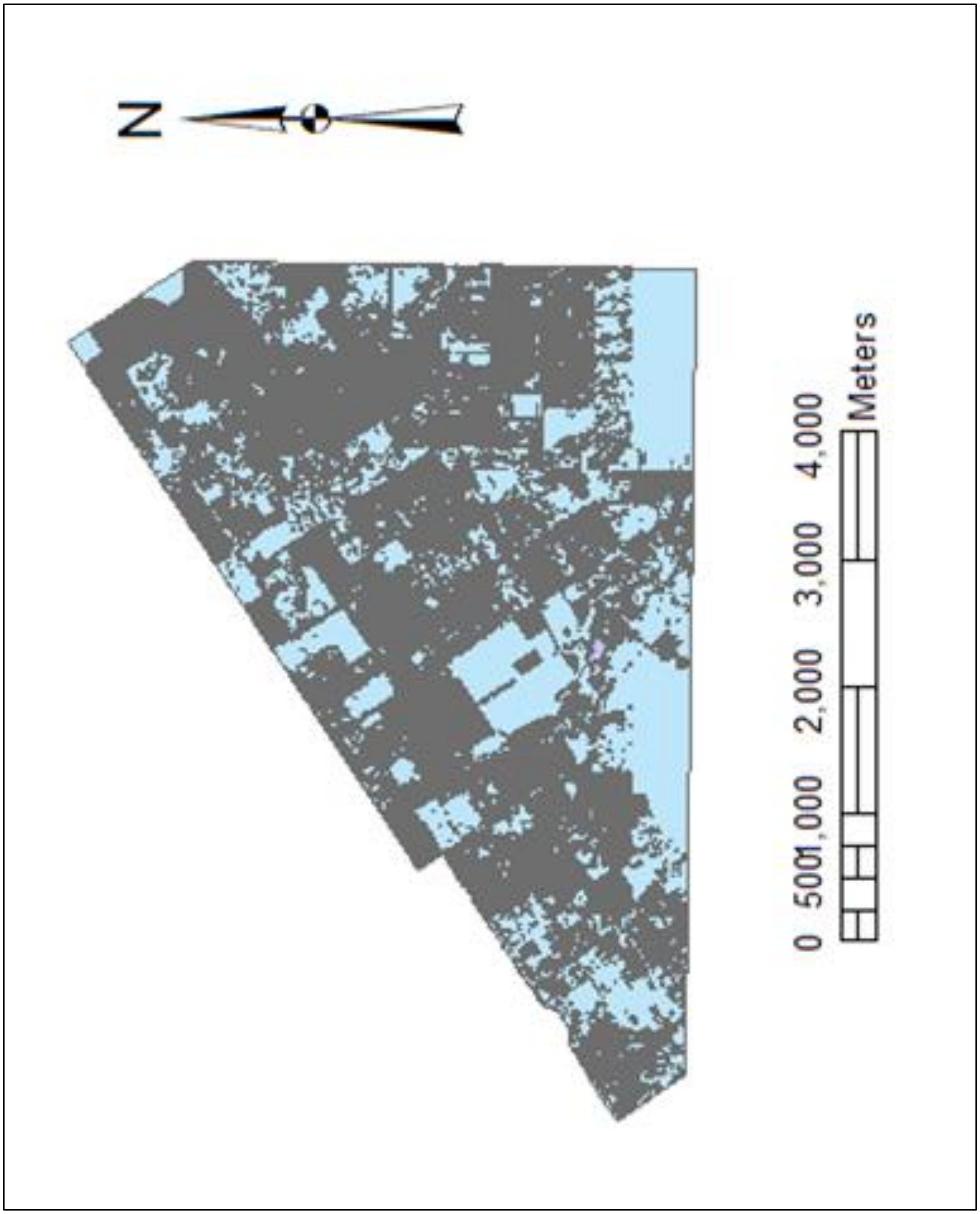


Figure 21. 1998 Tree cover.

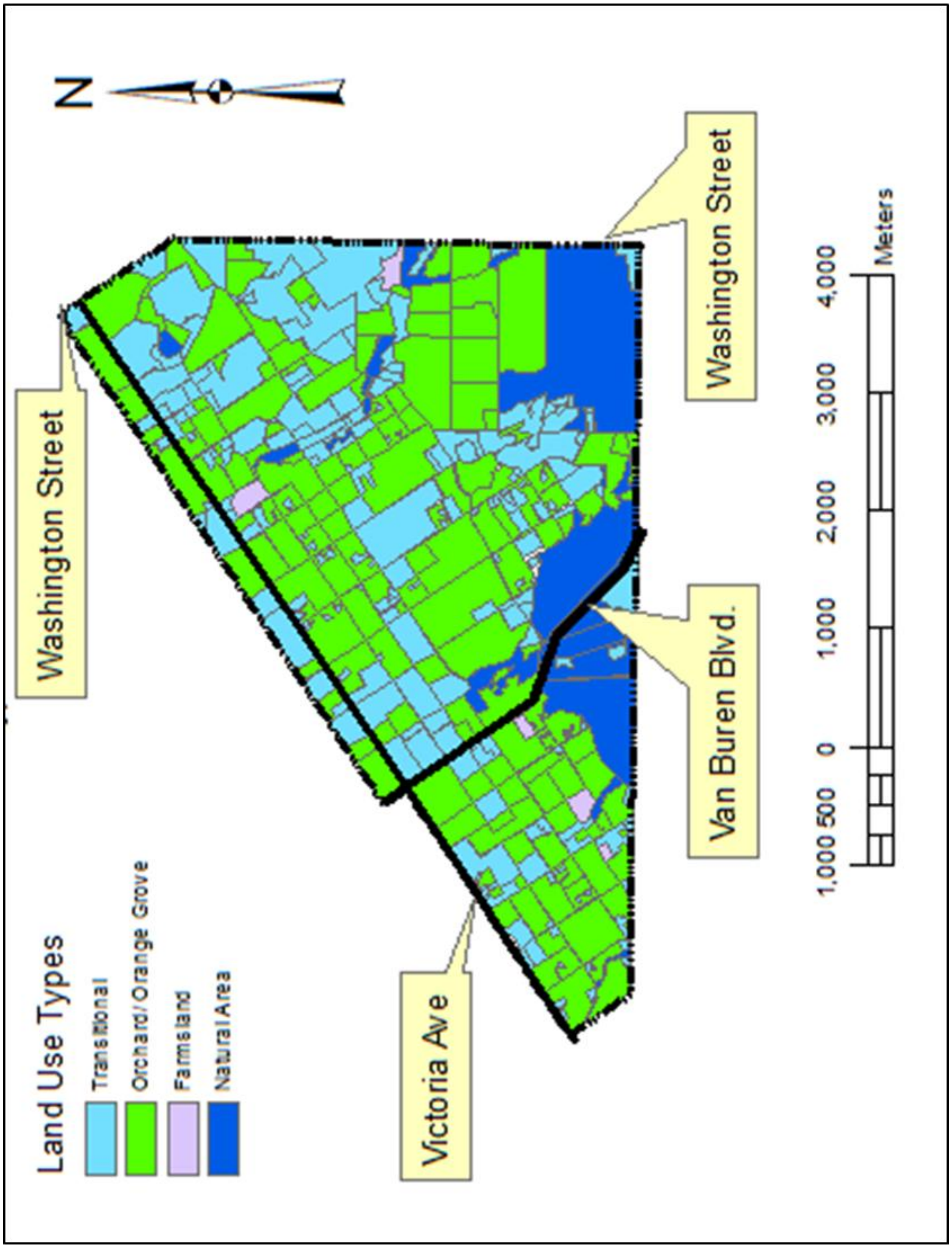


Figure 22. 1998 Green Belt Land Use.

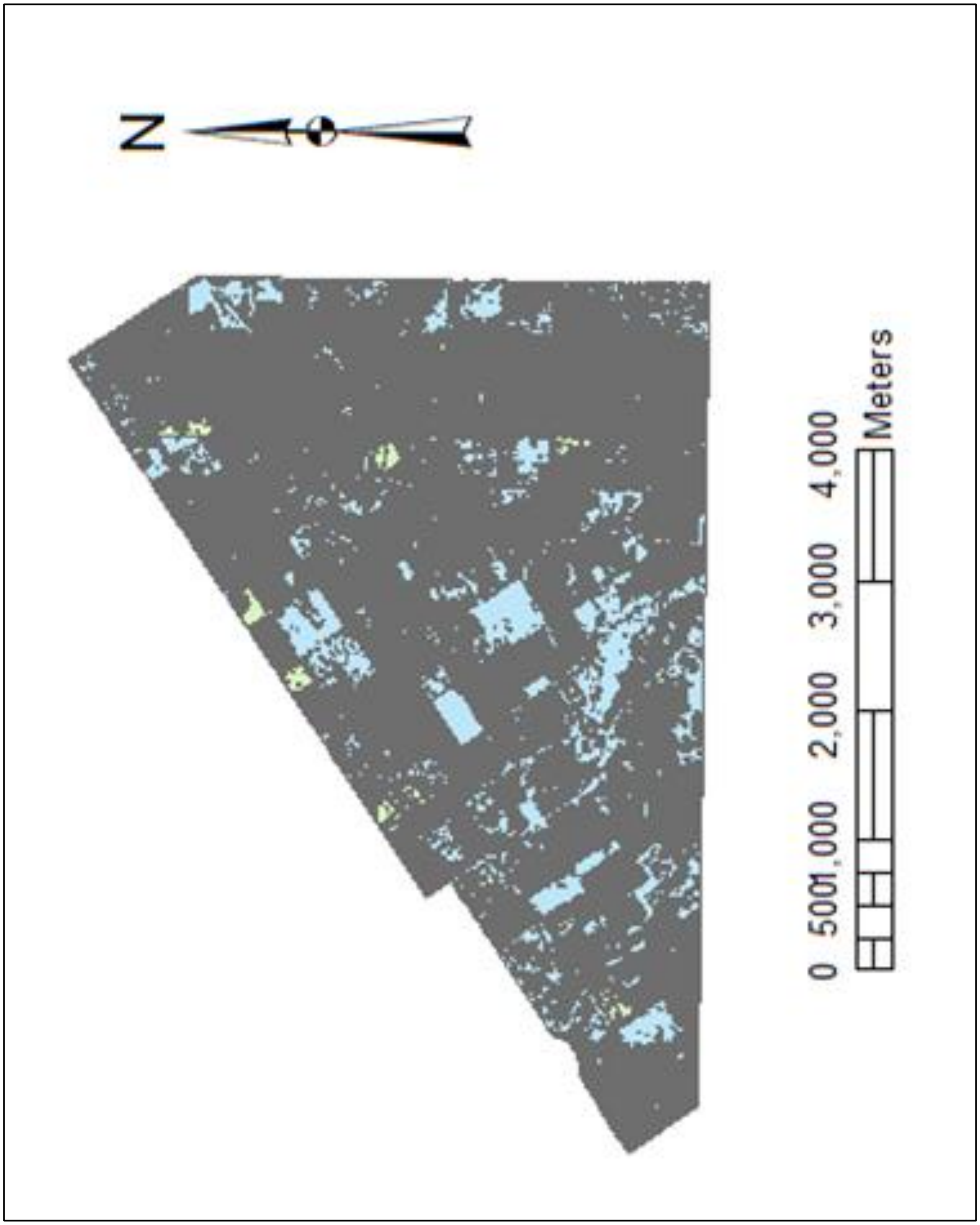


Figure 23. 2003 Tree cover.

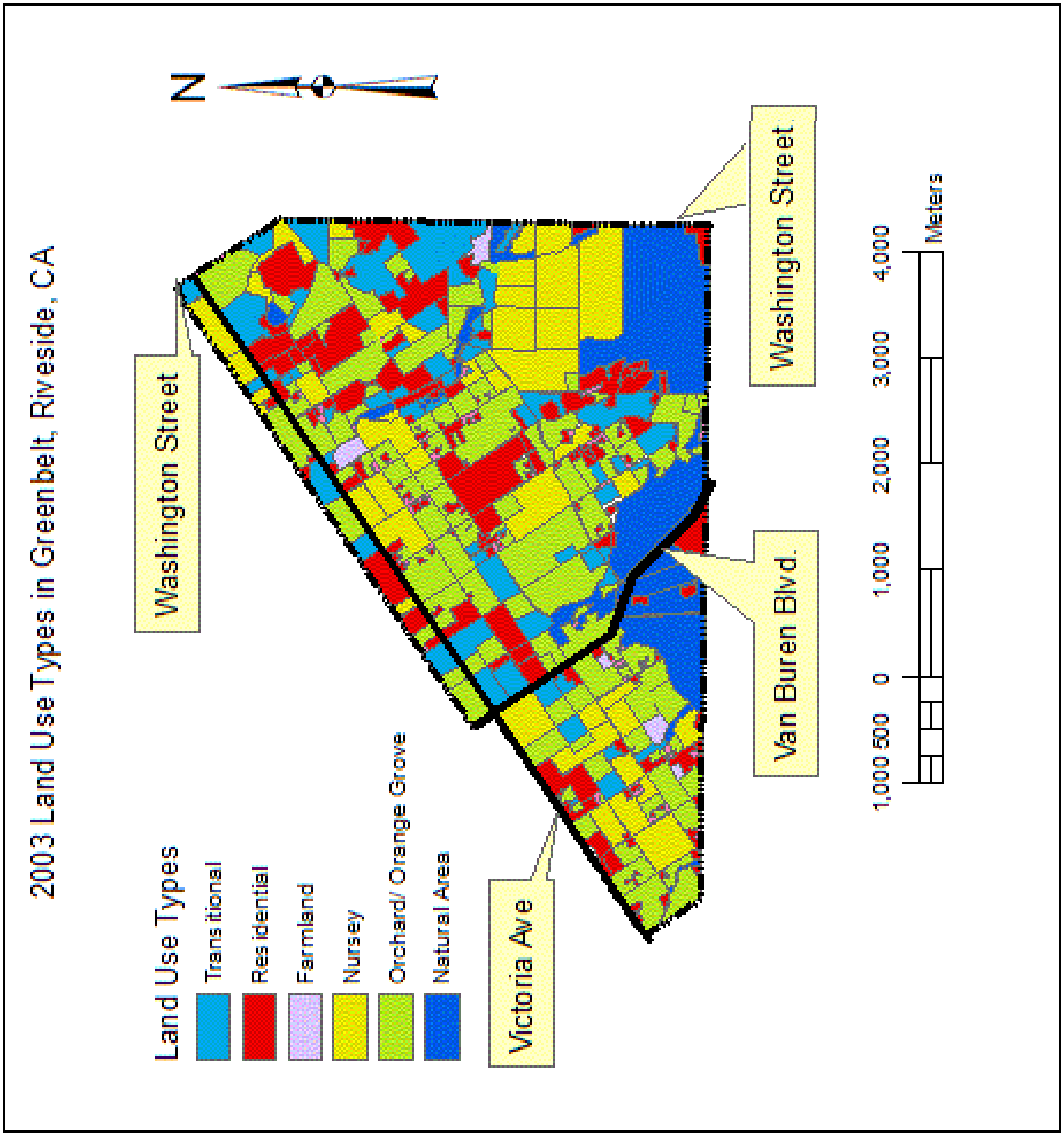


Figure 24. 2003 Green Belt Land Use.

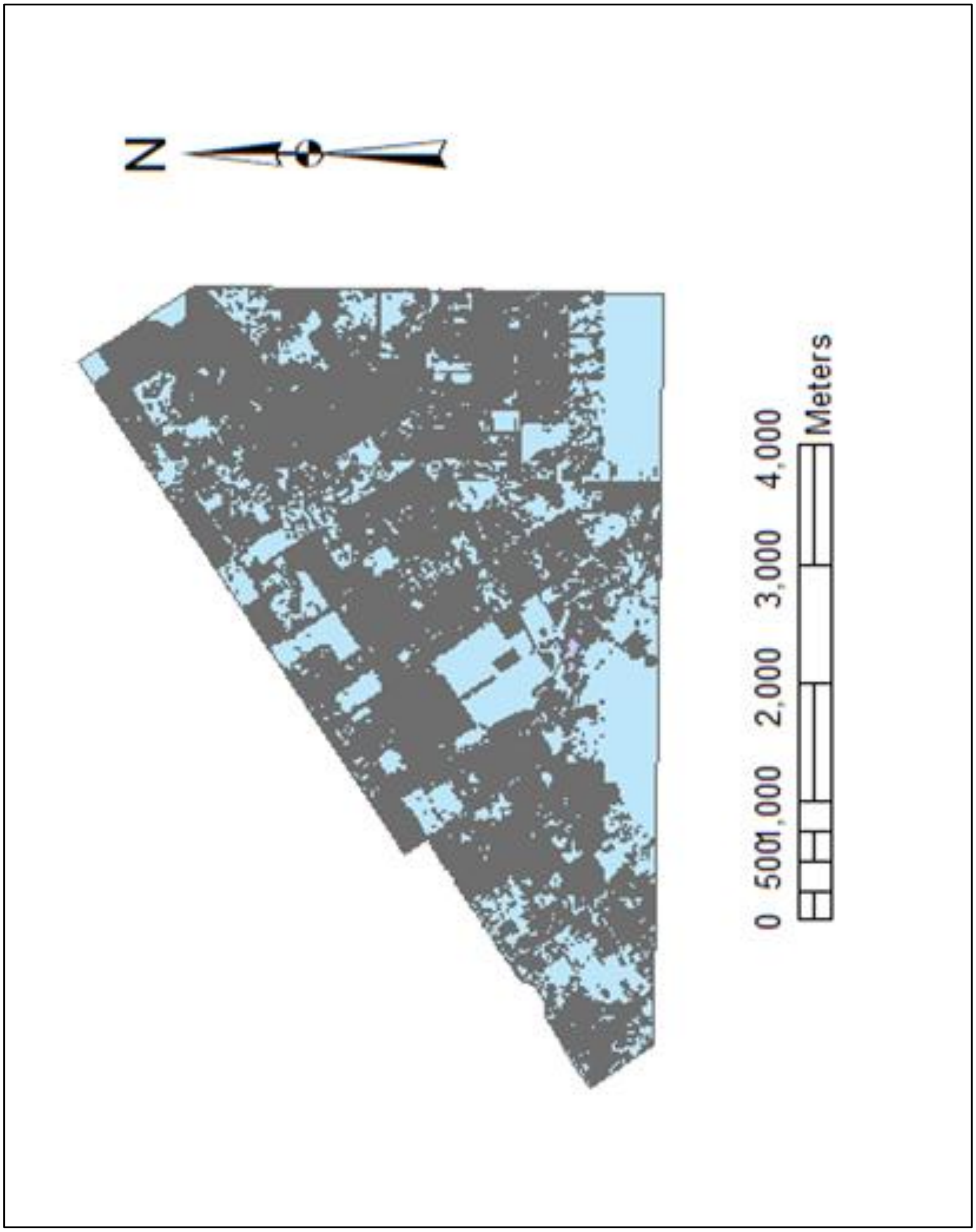


Figure 25. 2008 Tree cover.

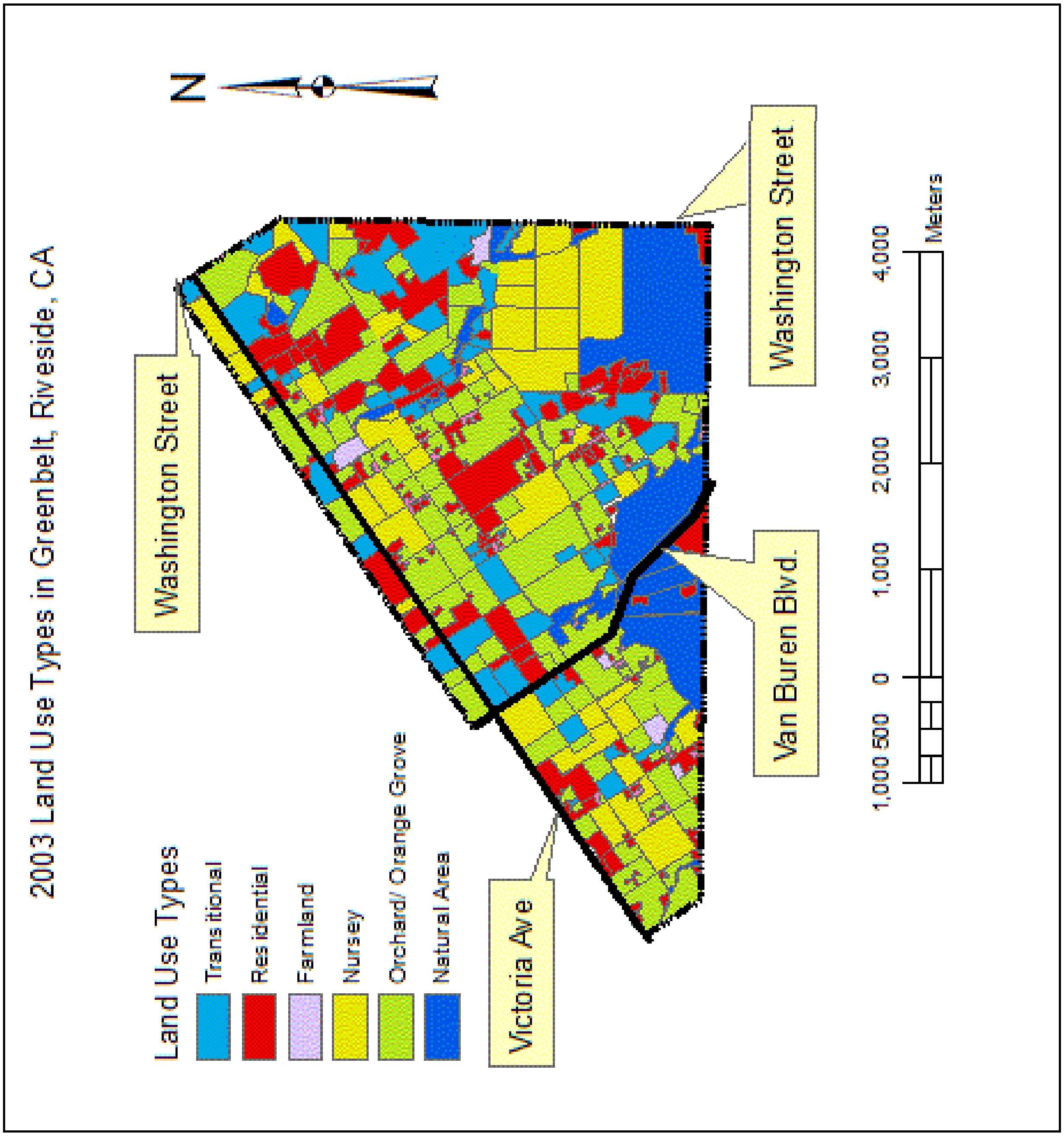


Figure 26. 2008 Green Belt Land Use.

4.1 Orchards

Before 1974 orchards were relatively stable with some minor reductions in area around the fringes of the Greenbelt area. Between the 1974 and 2008, orchards decreased 43% (1,000 hectares). In the 24 years from 1974 to 1998 tree cover in the orchard land use classification decreased 35% (8,000 hectares in orchard land uses. During the next ten years, the losses slowed to 9% of the original cover, a loss of 2 hectares .

4.2 Transitional

The transitional land use is an indicator of farmland and orchards that have been removed or were allowed to go unmaintained. This was verified by reviewing the imagery sets where the condition of the tree cover could be identified. Between 1974 and 2003 the transitional land use areas with tree cover area increased by 14% (1,200 hectares) and then dropped to 4% (200 hectares) by 2008. In reviewing the imagery sets it became apparent that the transitional land use would be transitioned to nursery or low density/estate residential land use.

4.3 Residential

Prior to 1974 residential land use was not present in the Greenbelt. From 1974 to 1998 the conversion of orchards resulted in 2,500 hectares, or 12% of the total trees cover in 1998, of tree cover to be transferred to the residential land use classification. This orchard to residential land use conversion saw each residential lot having some amount of orange trees. From 1998 to 2003 there was a minor reduction of 200 hectares in tree cover due to the removal of some orange trees from the lots due to landscaping changes. Further review of the 2003 and 2008 imagery sets showed that some owners of the estate type residential lots were engaged in planting new orchards. This activity increased the tree cover by 5% (1,200 hectares) and was identified in the 2008 aerial imagery. In the next time period, 2008 to 2013, the tree cover will increase likely as these young trees mature.

4.4 Farmland

Farmland is an indicator of a changing land use because land is put to productive use as a farm while awaiting the conversion to either residential or a nursery land uses. Farmland was nonexistent until the 1998 imagery set where only 300 hectares (<1%) of green cover existed consistently in this land use from 1998 to 2008. Farmland locations were not consistently in the same place. Farms tended to move around the Greenbelt area, which indicates that this is a transitional land use in this region. It should also be noted that farmland consisted only of green cover and not tree cover.

4.5 Nursery

No tree cover was found in a nursery land use in the 1960 or 1974 imagery sets. Nursery land use was first noted in the 1998 image set and accounted for 2% (200 hectares) of the total tree cover. In 2003 this increased to 9% or 1,700 hectares of tree cover. In 2008 the nursery area showed a doubling of the tree cover to 20% representing 4,000 hectares. The nurseries do not produce as much tree cover as an orchard due to the reduced density and young age of the trees in these nurseries. Nurseries are also a transitional land use; some nurseries were converted to residential estates during in 2003 and 2008.

4.6 Natural

The natural land use and corresponding tree cover in natural areas underwent considerable change during the 1960 to 2008 time period. From 1960 to 1974, the natural tree cover was 11% (2,500 hectares) of the total tree cover within the Greenbelt. Between 1998 and 2003 the tree cover within this classification remained constant at 3,600 hectares of tree cover, 18% of the total tree cover for 2003. Whereas in the next time frame, 2003 to 2008, the natural landuse area tree cover were reduced to 15% (6,800 hectares). This resulted from conversion of natural areas to residential and nursery land uses.

4.7 Measure R & C Effects

The effects of Measures R & C are not easy to identify (see only Figure 16). Tree cover areas in each land use changed direction due to, what appear to be external economic influences (Figure 16). Prior to 1998 the conversion of orchards into residential the tree cover remained constant. Basically these residential lots maintained the existing orchards on the property. After 1998 we see residential tree cover being reduced and an increase in the tree cover from plant nurseries. This is due to new landscaping where the residential orchards were removed.

5 CONCLUSION

I proposed several hypotheses that assess whether land use restriction could maintain the Greenbelt tree cover in the City of Riverside, California. The results from my geospatial analysis of the Greenbelt area of Riverside show several trends that would indicate that the passing of specific land use restrictions to preserve the tree cover in the Greenbelt area are having an effect. However the trends that were discovered sometimes contradict original expectations and hypotheses.

The following points summarize the findings of this study, presented in previous chapters.

1. *Can changes to tree cover be identified by the monitoring of the ratio of tree cover to urban/suburban area over a temporal period of some number of years?* Yes, and the results shows that one can identify and quantify these types of changes over time through the use of photo imagery and image analysis.
2. *Can changes in tree cover areas be identified from the type of changes or modifications to the existing housing and commercial building stock or from new construction?* For the changes cannot be discerned from the available data for this study, and additional necessary data was not acquired covering the years this particular analysis was focused on.
3. *Can changes to the tree cover areas be identified from the approval governmental rules or regulations or the passage of laws affecting the urban tree cover?* Considering the Hunter Park area of Riverside as a control area, the results provided an illustrative example. The greenspace area in the Hunter Park area (Figure 4) disappeared from the landscape during the time frame 1998 to 2008. The Hunter Park area was not included in Measures R and C. Except for a large city park, the area in now an industrial zone.

4. *Can changes to the tree cover areas be identified from new types of building construction including residential, commercial or infrastructure structures?* A transition process was discovered from orchard to residential or infrastructure development. This process began with the orchards being allowed to die, with a drop in tree cover. Next a land use transition to farming or nursery would occur. Finally a transition to either residential estate or infrastructure type construction.
5. *The changes to tree cover areas cannot be identified from changes in land cover, land use or from any other outside influence. Such changes are random or are not impacted by the possible changes identified in Hypotheses 1, 2, 3 or 4.* Changes in land use and tree cover can be identified if supplemented with ground investigation which confirms the changes to tree cover over time. These changes are not random but occur within a complex relationship with several outside influences including economic, political and cultural.

Based on the outcome of this analysis it is apparent that land use can be identified from an examination of tree cover from a series of aerial imagery sets if high resolution aerial imagery can be utilized. A sufficient number of aerial images from 1960 to 2008 were collected to determine the temporal land use patterns in the City of Riverside during this time period.

Further interesting research could focus on the impact of "policies" and the housing economy which occurred between the years 1998 and 2008. The real estate dynamics within the Greenbelt has created a unique environment where developers own a large number of transitional lots with no tree cover. These lots will remain as they are until buyers are found for estate type homes. In this economic environment circa 2012, it is doubtful this will occur in the foreseeable future. Until then, Measures R & C will hold this land in a static state unless the land is converted to residential estates.

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