Rome, 15 October 2013 – III *eCognition Day*

Development of land cover map based on object-oriented classifiers

Introduction

Land cover information is generated from remote sensing data through different classification methods, the main approaches to image analysis and classification are usually referred to as pixel-based (P-B) and object-oriented (O-O).

P-B methods are based upon the statistical classification of single pixels in a single digital image [1].

Recent studies indicates that P-B classification methods have a number of shortcomings; for instance they prove less effective compared to O-O ones especially when applied to aerial photograph or to high-resolution imagery [2, 3]. This is due, among other reasons, to their tendency to oversample the scene [4], resulting in a 'pixelized' (salt and pepper) representation of land cover [5, 6].

Introduction

To the contrary, O-O approaches classify images based on objects and **their mutual relations** [7]. Hence, O-O as opposed to P-B classifications may incorporate important semantic information and generate land cover objects that are **uniform and meaningful** from the perspective of the different application domains [8]. For such reasons, the application of O-O approaches as an alternative to P-B analysis has increased in the earth observation community in the last decade [9, 10, 11].

Image segmentation provides the building blocks of O-O image analysis [9]. Thanks to the recent improvements, automated image segmentation is increasingly being used in conjunction with O-O classifiers in the identification of land cover objects [12, 13].

In this perspective, the aim of this study is the generation of land cover classifications from false colour aerial orthophotos using O-O methods combining radiometric and textural image properties as well as vegetation indices.

Methods

The applied methodology integrates textural analysis, vegetation index extraction, multi-resolution segmentation and O-O classification. The procedure can be divided into the following steps:

- Pre-processing of image, including textural analysis and the derivation of a vegetation index;
- Segmentation of the pre-processed images;
- Classification of the segmented images based on radiometric and textural properties and vegetation indices by means of an object oriented classification.

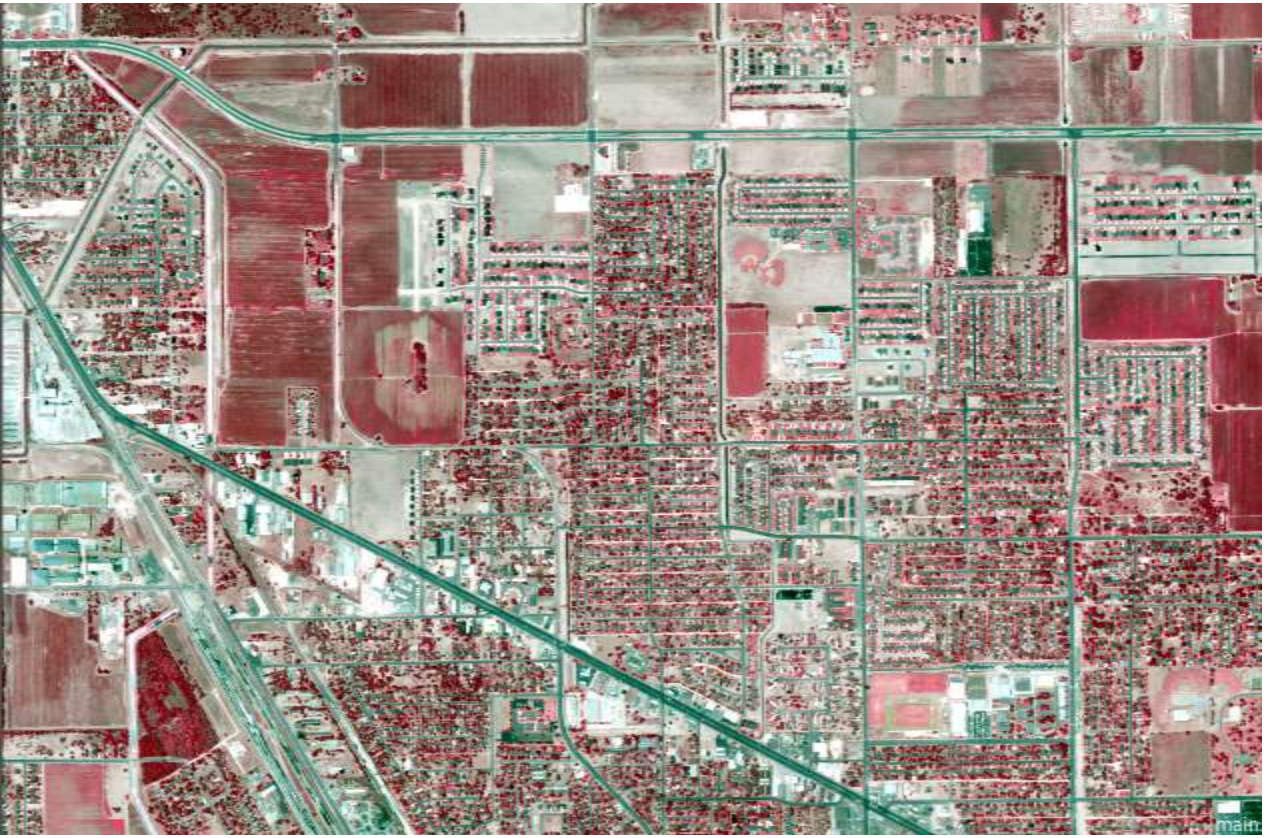
Pre-processing: textural analysis

As discussed for instance by Møller-Jensen [14], Pesaresi and Bianchin [15], Yan [16] and Matinfar [17], a more traditional classification strategy based entirely on the spectral properties of individual pixels is not enough for adequately classifying land cover from satellite images or aerial ortho photo, especially in the case of urban fabric [18].

Many texture measures have been developed [19, 20] that are mainly used for land cover classification [21, 22]. For instance, texture analysis applied to the identification of the urban footprint is grounded on the consideration that urban areas can be defined on the basis of urban elements. Accordingly, a definition of urban texture can be given as the geometrical structure formed by the spatial distribution of urban elements as buildings, roads and green areas [23]. Based on these consideration, in order to improve the classification results, textural analysis was also applied. A number of derivative bands measuring different textural properties were generated from the original data. The texture bands were derived from the application of the convolution filter on the NIR (near infrared) band.

Three different texture measures were computed: Variance, Mean and Contrast [24, 25] and the texture value was assigned to the central pixel of each window location of the 9 pixels involved. As a result, three images were obtained, one for each texture measure.

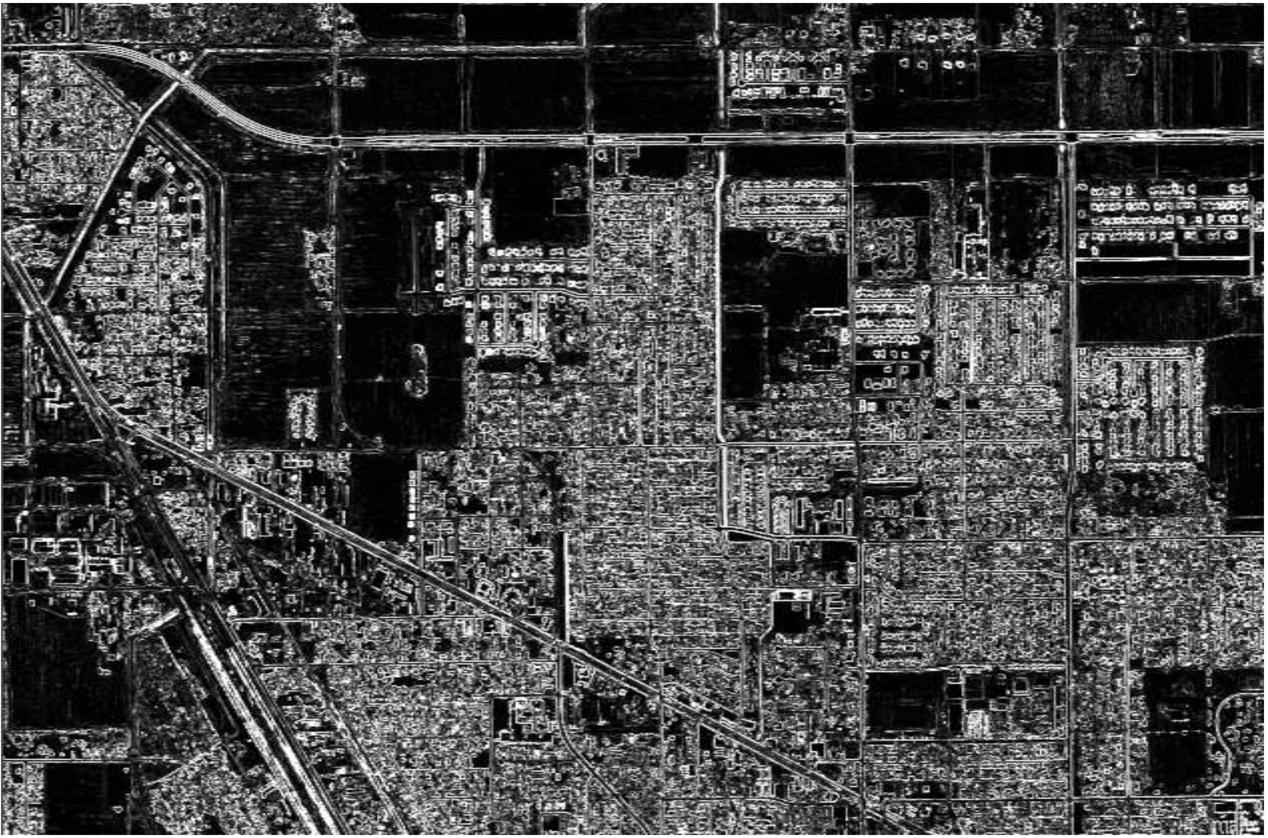
Pre-processing: textural analysis



Original image

- Spatial resolution 2.0 m;
- Spectral resolution 3 bands:
  - Green;
  - Red;
  - Near Infrared (NIR).

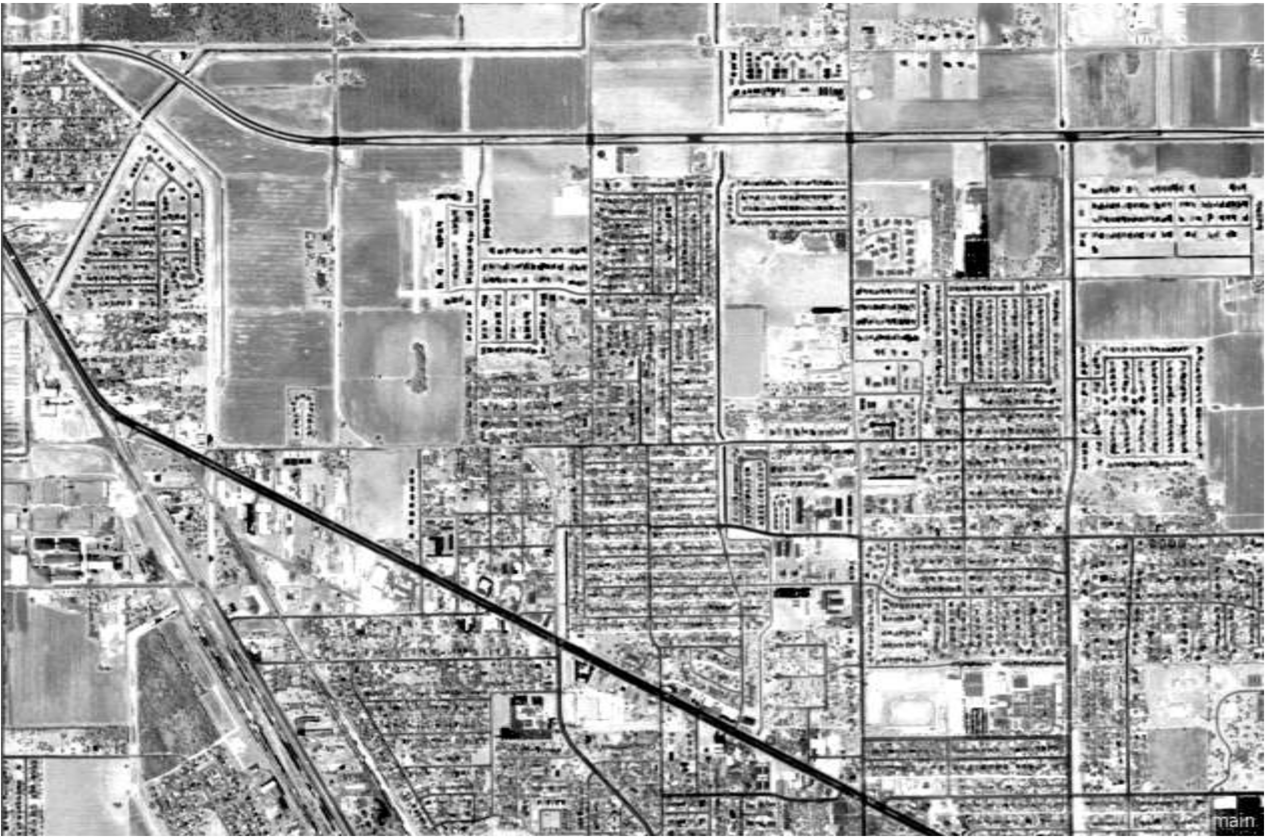
Pre-processing: textural analysis



Texture: variance (GLCM)

While color and brightness are associated with single pixels, texture graininess, is computed from a set of connected pixels.

Pre-processing: textural analysis



Texture: mean (GLCM)

Mean: Average grey level in the local window.

Pre-processing: textural analysis

Texture: contrast (GLCM)

Contrast is a measure of the contrast or amount of local variation present in an image or surface. Contrast is high for contrasted pixels while its homogeneity will be low.

Pre-processing: vegetation indexes

Remote sensing spectral vegetation indices are widely used to characterize the type, amount and condition of the vegetation within the scene [26, 27].

For this purpose, greenness indices such as the N.D.V.I. (Normalized Difference Vegetation Index) are commonly used [28, 29, 30]. The NDVI is computed as the normalized ratio between the reflectance in the Red and Near InfraRed (NIR) spectral bands and ranges from -1 to 1, where the negative values refer to non-vegetated areas, while positive low values indicate sparsely vegetated zones and values close to 1 indicate densely vegetated zones. NDVI is typically used to characterize the phenological state and the seasonal dynamics of vegetation [31, 32] because of its demonstrated direct relation with plant cover activity [32] and biophysical parameters like the fraction of absorbed photo-synthetically active radiation [33].

Pre-processing: vegetation indexes

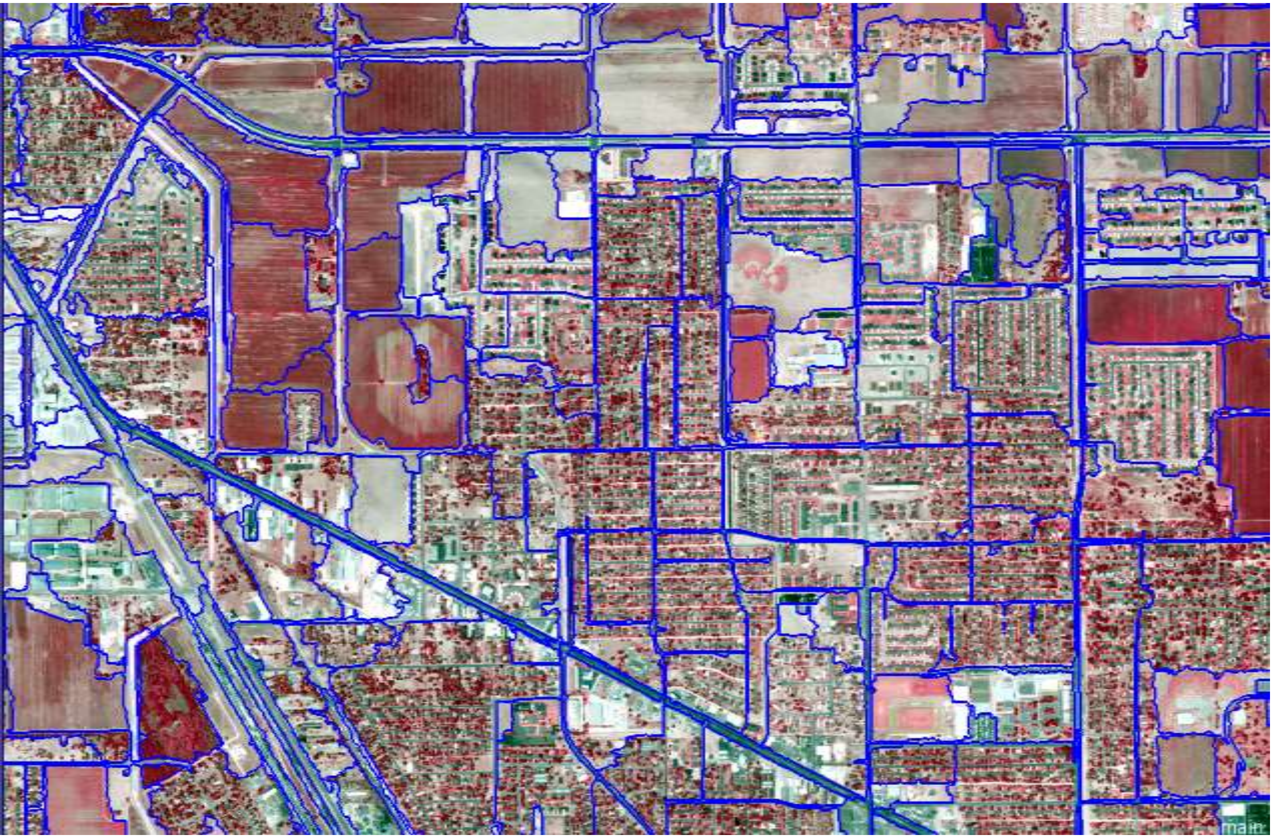
Normalized Difference Vegetation Index (NDVI): *is a simple graphical indicator used to analyze [remote sensing]() measurements whether the target being observed contains live green vegetation or not.*

Segmentation

Image segmentation is the partitioning of raster images into spatially continuous, disjointed and homogeneous regions, i.e. segments, based on pixel values and locations [34]. Pixels having similar feature (textural and spectral) values that are spatially connected are grouped in single segments or objects, minimizing their heterogeneity. In this application , the image segmentation was used as a preliminary step in the integrated classification. **The segmentations were performed based on the software *eCognition*®.**

In order to make the resulting segments as comparable as possible in terms of resolution and to test the repeatability of the procedure to different images, the same method and parameters (scale, color, smoothness) were applied in the generation of samples and in the classification of image objects to both study areas. The multiresolution segmentation was selected as the most appropriate method.

Segmentation



Multiresolution segmentation

The algorithm of segmentation is based on homogeneity definitions in combination with local and global optimization techniques. A scale parameter is used to control the average image object size.

Pixel will be aggregate in objects: information to understand an image is not represented in single pixels but in meaningful image objects and their mutual relations.

Classification

The classification model was developed using the *eCognition*® object-oriented algorithms. The image segmentation, used as a preliminary step to the integrated approach, was based on the following feature variables:

- Original images
- Texture layer
- NDVI

In the this classification, objects originated from the segmentation are evaluated instead of individual pixels. The classification algorithm analyses features in each image object against a list of selected classes and determines its membership value of the basis of class descriptions. The classification adopted was based on fuzzy membership functions acting as class descriptors. Fuzzy membership functions describe intervals of feature values wherein the objects belong to a certain class or not by a certain degree [35]. This is especially relevant when the same value cannot be assigned unambiguously to a class, as it was found to be the case for all the classifiers in the present study. Each class was described combining class descriptors for the different feature variables by means of fuzzy-logic operators and the objects were then grouped and located in the corresponding classes.

Classification

An example of rule-set for the class “Urban areas”, is shown below:

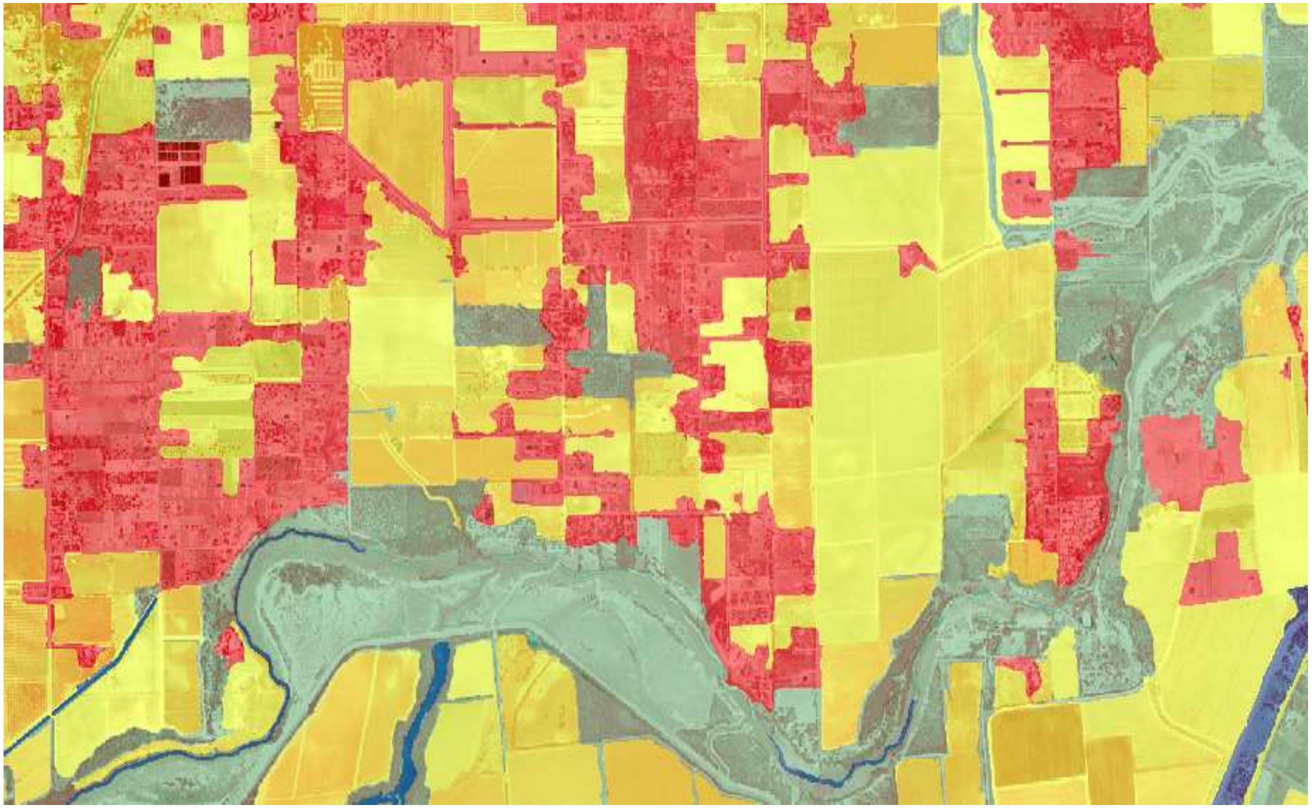
- And (min)
    - Mean GLCM_Contrast
    - Mean GLCM_Variance
    - Standard deviation GLCM_Contrast

In order to be assigned to the class, all the conditions have to be applied (logical operator “and”(min)). Class descriptions were defined based on their capacity of discriminating among the different classes. This was achieved by means of the *eCognition*® “sample editor”, inspecting image values of the samples especially in relation to classes with similar properties. From this analysis it emerged that NDVI and the Mean NearInfrared band were those contributing better to the identification of image objects without vegetation, while texture features (GLCM_Contrast and GLCM_Variance) further helped in discriminating between non-vegetated arable land and “Urban areas”.

The result of classification has been improved by a video interpretation; an expert on image interpretation had verified the geometry and the thematic attributes of map, correcting approximately 15/20% of classified objects.

Results

The object-oriented approach to the classification was performed initially at the first level of the CORINE Land Cover nomenclature, i.e. generating four, more generalized land cover classes.



Land cover map

- Urban areas
- Agricultural areas
- Natural areas
- Water courses

Results

Land cover map

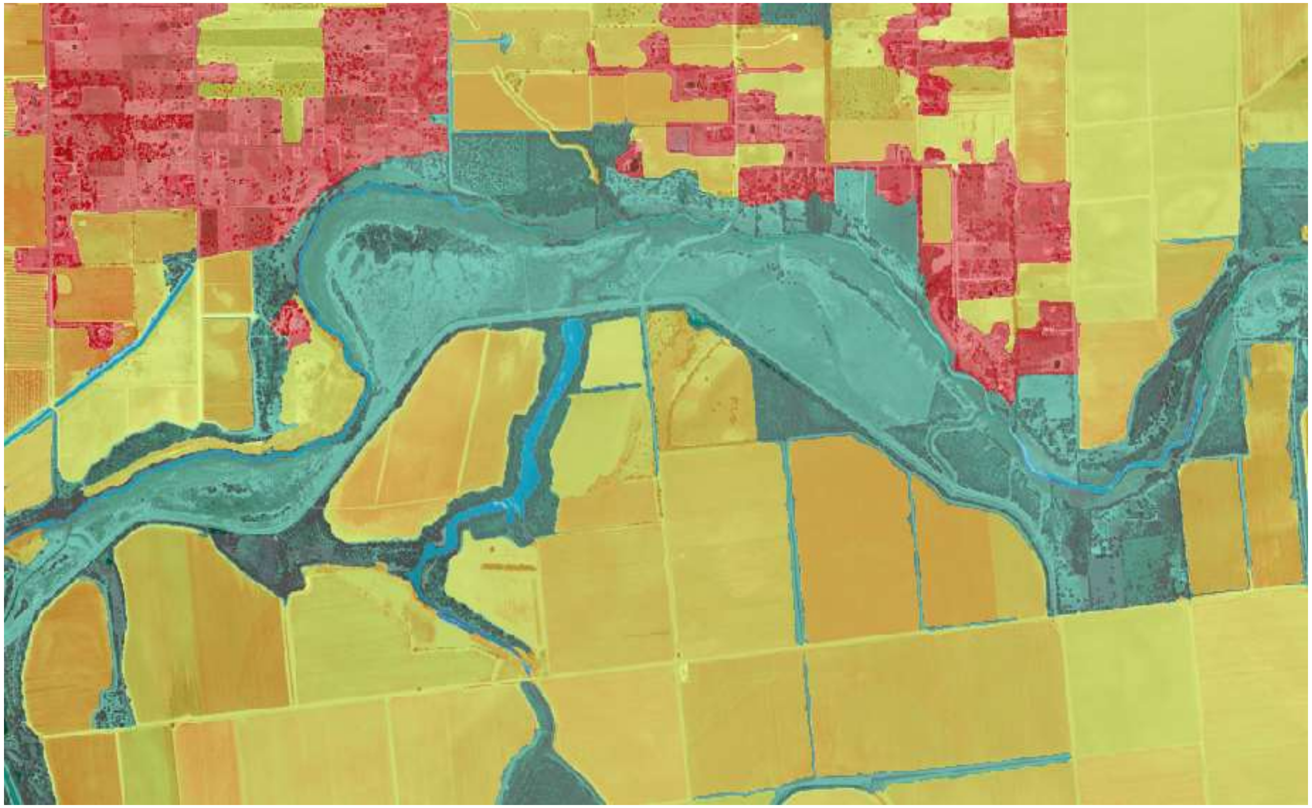
Urban areas

Agricultural areas

Natural areas

Water courses

Results



Land cover map

Urban areas

Agricultural areas

Natural areas

Water courses

Results

Land cover map

Urban areas

Agricultural areas

Natural areas

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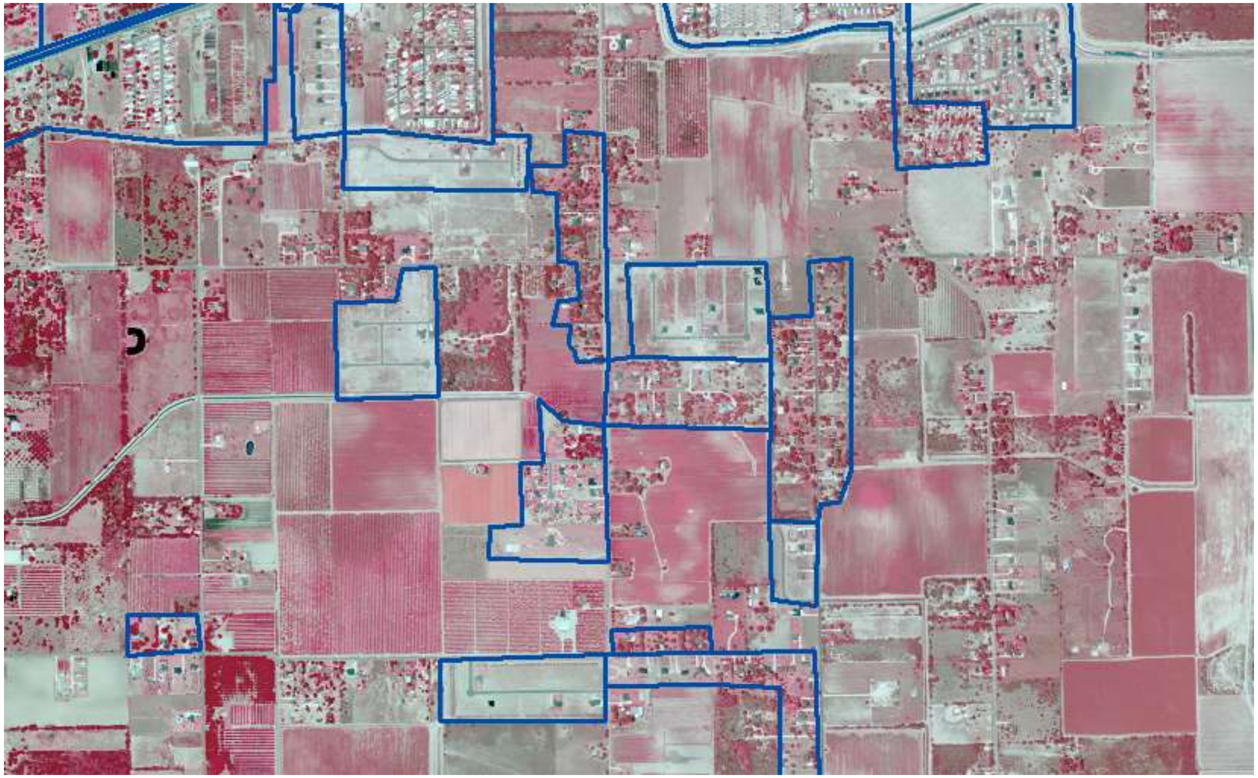
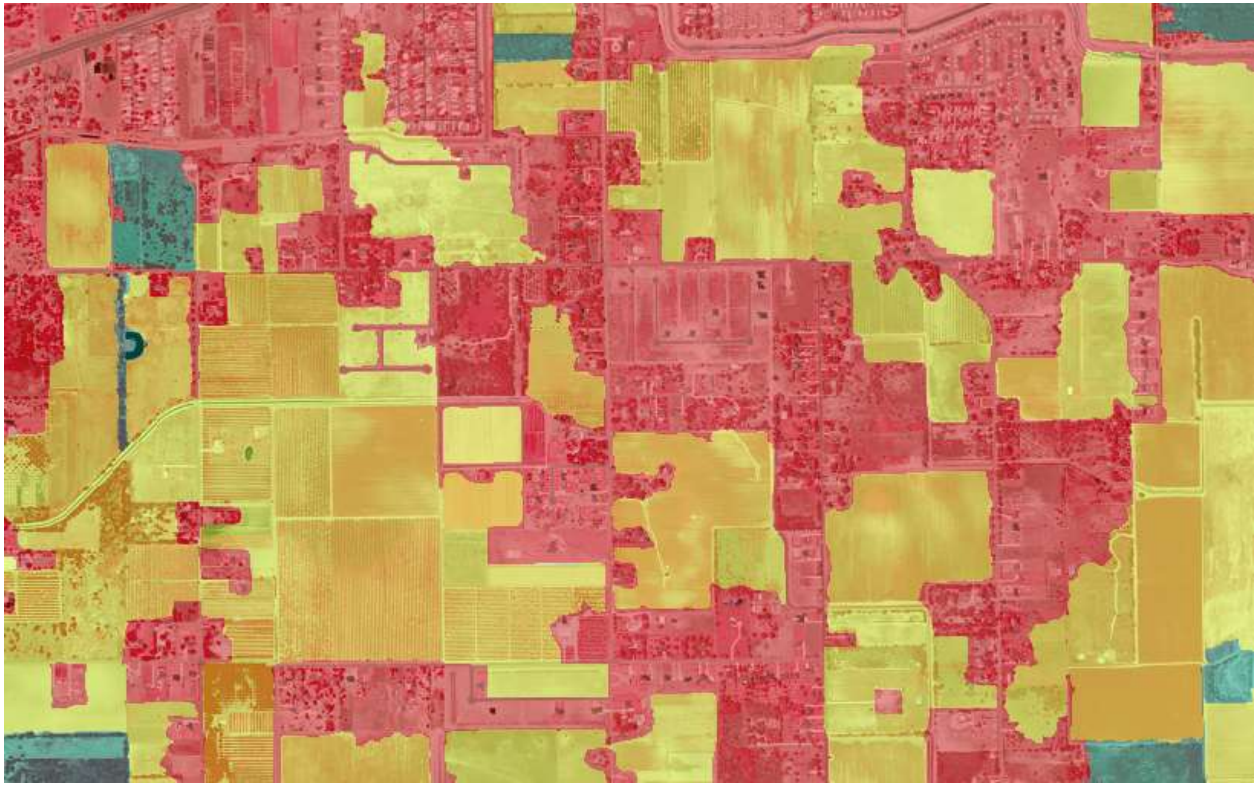
Results



Previous Land cover map

Urban areas

Results



Land cover map

- Urban areas
- Agricultural areas
- Natural areas
- Water courses

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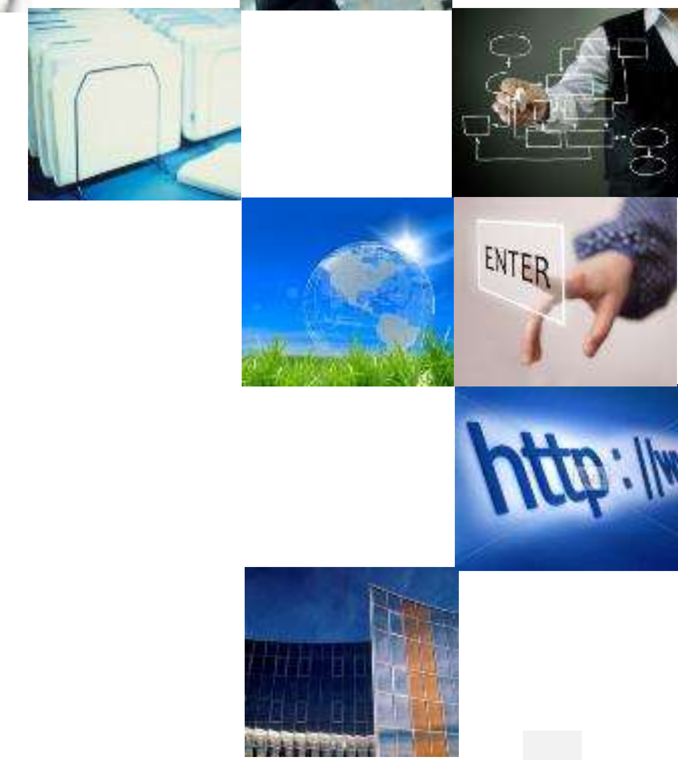

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