

# CHANGE DETECTION AND UNCERTAINTY IN FUZZY TREE CROWN OBJECTS IN AN URBAN ENVIRONMENT

Wietske Bijker, Juan Pablo Ardila, Valentyn A. Tolpekin,

Faculty of Geo-Information Science and Earth Observation (ITC)  
University of Twente  
7500 AA Enschede, The Netherlands  
bijker@itc.nl, ardila14710@itc.nl, tolpekin@itc.nl  
<http://www.boomenbeeld.nl>

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## ABSTRACT:

Municipalities need information on the location and state of the trees in their area, to maintain and manage these resources. Trees defined and handled as objects would therefore better match this information need than raster output. In this study, we detect and compare tree crown objects from two different very high resolution images of Enschede, The Netherlands. Soft classifiers were used to calculate probabilities for each class: for the Quickbird image we used super-resolution mapping and for the aerial image support vector machines. We modelled the probability profiles of single tree crowns or groups of overlapping tree crowns with Gaussian functions, resulting in tree crown objects. By overlaying, tree crown objects extracted from two different images were compared on an object-by-object basis. Where a tree crown object in one image did not find a match in the other image, we recalculated the probabilities for all classes in the image where the tree was missing. If the probability for tree crown was above a threshold, we extracted the tree crown object, even if the probability for another class was higher. This iterative process was applied both to the earlier and to the later image, which increased the accuracy of tree crown mapping at individual dates and the accuracy of the detected changes. The procedure to extract objects based on probabilities allows using images from different spectral and spatial resolution in change detection. Changes in existence could be mapped adequately, while detection of changes in extent of tree crowns shows promising results, but needs further development. The use of probabilities for object-based change detection shows for which objects uncertainty is highest and hence where field verification would be most beneficial.

## 1 INTRODUCTION

In densely populated countries like The Netherlands, a considerable number of the total amount of trees is located outside the forest, in urban and rural areas. These trees contribute to carbon sequestration, filtering of noise and particulate matter, biodiversity and to a better micro-climate, as they provide shade and mitigate the urban heat island effect (McPherson et al., 1994). Furthermore, municipalities need information on the location and status of the trees in the area under their jurisdiction, because they are responsible for maintenance of trees on public land. Furthermore, they are in charge of the permits for removal of large trees on both public and private land. Recent projects to update the tree databases of municipalities have shown that current databases are often incomplete and outdated. Very high resolution (VHR) imagery can help to update these databases and to monitor the existence and state of trees.

While some success has been seen for detection of individual trees in (plantation) forests (Hirschmugl et al., 2007, Leckie et al., 2005, Wolf and Heipke, 2007), detection and mapping of trees in urban areas has remained difficult for several reasons: first of all, the urban context in which the trees grow, is very diverse, with a variety of materials surrounding the trees and high buildings casting shadows, which vary with the time and date of acquisition of the images. Furthermore, the trees themselves are diverse in size, shape and species. Small trees, often encountered in newly built or reconstructed neighborhoods and in private gardens, are difficult to detect in remotely sensed images. In this paper we show how iterative comparison between image classifications of different dates can help to find previously undetected trees in imagery, thus increasing both the accuracy of tree mapping at the individual image dates as well as the accuracy of the detected changes.

For the users of the information on urban trees, the trees should be treated as objects, in mapping as well as in change detection. Knowing the uncertainty in the detection per object and not only for the area as a whole, would help to prioritize field checks by the municipality. Also with regard to detected changes, a measure of uncertainty of the detected change would help to decide which actions to take. Up till now, only few methods exist for object based change detection and even less address uncertainty in object based change detection (Johansen et al., 2007, Hagen, 2003, Stein, 2008). In this paper we formulate a method to use object based tree extraction techniques followed by change detection while including uncertainty at the level of the individual tree crown. This research was part of the "Boom en Beeld" (Tree and Image) project.

## 2 TREE CROWN EXTRACTION

The change detection method presented here combines fuzzy contextual classification of VHR color infrared images followed by tree crown object extraction via fitting of Gaussian functions on the probability images of different dates and iterative cross-verification of these objects between consecutive dates. Figure 1 describes the general workflow. To test our method we selected two images of Bothoven district, a residential area in the city of Enschede, The Netherlands: a 2006 QuickBird image and a 2009 VHR aerial image (iDelft BV, 2010), as shown in Figure 3 (left), with the characteristics presented in Table 1.

Because of the difference in spatial resolution of the input images, we used two different classification approaches, both based on a fuzzy contextual approach combining spectral characteristics with prior knowledge. On the QuickBird 2006 image we applied a super resolution mapping (SRM) classification based

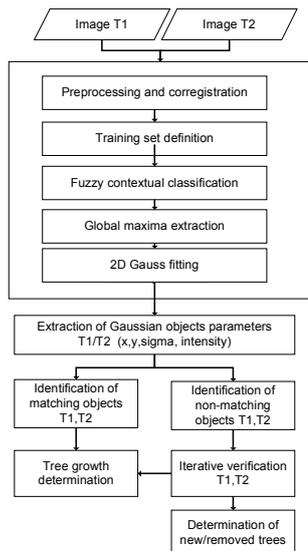


Figure 1: False color composite of Very high resolution with digitized tree crowns objects in yellow

	QuickBird	VHR
Acquisition date	21/09/2006	25/05/2009
Resolution (m)	0.6 (PAN)-2.4 (MS)	0.25
Spectral bands	R,G,B,NIR,Pan	R,G,B,NIR

Table 1: Characteristic of the images used for change detection

on Markov random fields (MRF) to produce a tree crown probability image at 0.6 meters resolution, while for the 2009 VHR aerial image a MRF classification based of Support Vector machine (SVM) was used to produce a tree crown probability image at 0.25 meters as described below.

## 2.1 Super resolution mapping of QuickBird image

We computed the probabilities for tree crown in the QuickBird image using a fuzzy SRM classification approach (Tolpekin et al., 2010). The super resolved tree crown map at 0.6 m resolution was obtained by combining the conditional probabilities for defined land cover classes in multi-spectral and panchromatic bands and the prior probabilities of the spatial distribution of the class labels of spatially adjacent pixels. Spectral properties of classes were computed from training areas collected for the defined land cover classes: tree crown, grassland, shrubs and sealed surface. The pixel labeling was formulated as an energy minimization problem which was solved iteratively with simulated annealing. Optimal parameter values were selected based on the estimated accuracy from error matrix for different trials. While in Tolpekin et al. (2010) only a crisp tree crown map is reported, we also computed a posterior probability image for the tree crown class.

## 2.2 Contextual SVM classification of VHR image

Support Vector Machine (SVM) is an advanced machine learning method which has recently been adopted by the remote sensing community for supervised multivariate image classification, which usually outperforms conventional parametric classification methods. The SVM method defines an optimal separating hyperplane in the feature space between the classes of a training set (Huang et al., 2002, Foody and Mathur, 2004). An advantage of SVM classification is that it supports high dimensional data, which may be useful to find better separating hyperplanes

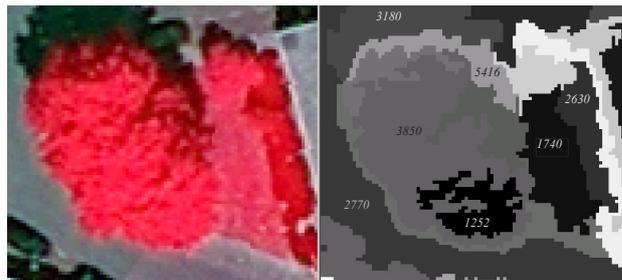


Figure 2: False color infrared composite showing a group of trees, grassland and a row of shrubs (left) with their respective segment-wise standard deviation values computed after segmentation of near infrared band (left).

between spectral classes. To enhance the class separability between tree crowns and other vegetated surfaces such as shrubs and grasslands, the normalized vegetation index (NDVI) and a texture band were computed. For the texture band, we segmented the near infrared band and computed the standard deviation of the pixels inside the segments as shown in Figure 2. The segments were generated using multi-resolution segmentation (Baatz and Schäpe, 2000).

SVM classification was applied after defining a training set of tree crown- and background classes, using a radial basis function with gamma equal to 0.167. Probability images were computed for the tree crown- and for the background classes with the total probability for tree crown  $P_{tc}$  equal to the maximum probability of all spectral sub-classes defined as belonging to tree crown  $P_{tc_n}$  and similarly for the background classes.

$$P_{tc} = \max(P_{tc_1}, P_{tc_2}, \dots, P_{tc_n}) \quad (1)$$

Once the probability images for the tree crown and background classes were computed, we implemented a spatial optimization of those probabilities using a local MRF model which favors the classification of adjacent tree crown pixels within a first order neighborhood and penalizes the tree crown probability of pixels which are isolated or distant from other tree pixels. Graph cuts optimization method (Karimov, 2010, Boykov et al., 2001, Kolmogorov and Zabih, 2002, Boykov and Kolmogorov, 2004) was used to determine the solution for the model. The combination of SVM with contextual optimization described above will be referred to as Contextual SVM (CSVM) in this study.

## 3 OBJECT GENERATION AND CHANGE DETECTION

Inspecting the probability images from SRM and CSVM, we observed that the tree crown resembles a bell-shaped profile. To model size and location of the tree crown as an object we therefore used model-based fitting of a Gaussian function on the probability images using a non-linear square fitting method. The Gaussian equation with rotated axes ( $x', y'$ ) fitted to the image locations ( $x, y$ ) is defined as:

$$F(x, y) = I \exp \left[ -\frac{1}{2} \left( \left( \frac{x'(x, y)}{\sigma_x} \right)^2 + \left( \frac{y'(x, y)}{\sigma_y} \right)^2 \right) \right] \quad (2)$$

where  $I$  is the height of the Gaussian,  $\sigma_x$  and  $\sigma_y$  are the standard deviations along the axes  $x'$  and  $y'$  respectively. The rotation of the axes around the center ( $cx, cy$ ) by the angle  $\theta$  is defined as:

$$x'(x, y) = (x - c_x) \cos \theta - (y - c_y) \sin \theta \quad (3)$$

$$y'(x, y) = (x - c_x) \sin \theta + (y - c_y) \cos \theta \quad (4)$$

Before fitting the data we applied a Gaussian smoothing filter on the data. The kernel sizes were  $9 \times 9$  and  $19 \times 19$  pixels, the standard deviations were 4 and 9 for the images of 2006 and 2009, respectively. The different kernels were applied to accommodate for the difference in spatial resolution of the images. The fit is iteratively computed on the image by locally fitting the Gaussian function around the local maximum. During each iteration, the algorithm fits a region around the global maximum point to the data and subtracts the contribution of the fitted object from the probability image. This procedure was repeated until the global maximum of the remaining image was lower than a defined probability threshold. For each fitted region the location of the Gaussian function ( $c_x, c_y$ ), the standard deviations ( $\sigma_x, \sigma_y$ ) and the rotation angle ( $\theta$ ) were estimated. From these parameters, the position of the Gaussian function ( $c_x, c_y$ ) was interpreted as the approximate center position of tree crown on the ground while the standard deviations of the Gaussian function were translated into the width of tree crown object via an estimated calibration factor of 1.5.

### 3.1 Iterative checking of changes and validation

After fitting Gaussian functions to the probability images of 2006 and 2009, we overlaid the resulting tree crown objects to identify matching and non-matching objects between the two dates. On these differences, an iterative analysis was applied to verify the changes of the preliminary non-matching objects (see Figure 1). In this iterative analysis, we re-estimated the probabilities for tree crown for those pixels where we expected a matching object, but did not detect one. During first classification the probability for tree crown for these pixels could have been substantially larger than zero, but they were classified into another class with a higher probability. This multi-class probability estimate was based on the maximum likelihood classifier and the class statistics calculated from the training areas. If the probability for tree crown was above a threshold for these pixels, we implemented Gaussian fitting over that region to recover the tree crown object. If the probability was below the threshold, we considered the tree crown object missing in the image of that date. This iterative detection of tree crown objects was performed both to previous and to later dates. For validation of the classification results and the detected changes, we used manual digitization of the tree crowns and field data for comparison.

## 4 RESULTS AND DISCUSSION

The images of 2006 and 2009 are shown in Figure 3, along with the tree crown probability images obtained from SRM (2006) and CSVM (2009). For comparison, the digitized tree crowns are overlaid on all images. From the image we can see that in some cases two trees were merged into one tree crown object and that small trees were difficult to detect. In the SRM classification one of the three large trees in the bottom left corner of the 2006 image was not detected. Still, the iterative verification of changes correctly recovered the object as shown in Figure 4. This proves the importance of the iterative verification, as it can reduce false detection of changes due to omission errors in the classification of one of the images.

ID matching objects (2006,2009) (9,3);(7,4);(2,5);(8,7);(6,11);(6;13)
ID non-matching objects (2006) (1,3,4,5,10,11,12,13,14)
ID non-matching objects (2009) (1,2,6,8,9,10,12,14,15,16,17)

Table 2: Overlay analysis of Gaussian functions fitted for 2006 and 2009

ID matching objects (2006,2009) <b>(15,1);(16,2);(9,3);(7,4);(2,5);(8,7);(6,11);</b> <b>(6;13);(3,18);(5,19);(9,3);(10,20);(11,21)</b>
ID non-matching objects (2006) (1,4,12,13,14)
ID non-matching objects (2009) (6,8,9,10,12,14,15,16,17, <b>22</b> )

Table 3: Overlay analysis of Gaussian functions after iterative fitting for 2006 and 2009. In bold type newly generated Gaussian functions after iterative analysis

The result of the fitting of Gaussian functions on the 2006 and the 2009 probability images, followed by tree crown mapping and overlaying can be seen in Figure 4 (left), while Table 2 presents the list of matching and non-matching objects fitted for the two dates using their ID as shown in this figure. The result of the iterative probability analysis is shown in Figure 4 (right) and Table 3. The figure and the table show that for this area, the number of matching objects, i.e. trees present in both images, increased from 6 to 13 after iterative probability analysis between the two images. Figure 5 shows the tree crown objects that were recovered in the 2006 and the 2009 image.

Figure 6 shows the changes in the reference data (manually digitized with field verification) and the changes detected after the iterative probability analysis. The changes had to be made crisp for comparison, since the reference data were crisp. There are two aspects of change in this study: existence and extent. The method works well for detecting changes in existence of trees, for example in the centre of the images, where trees were removed to create parking space, and the two trees along the road in the top left corner of the image. Some further work is needed on groups of trees, such as the group in the top right corner of the images, where differences in the way of merging the individual trees into a group affect the matching of objects between the two dates. A further advantage of our method of object-extraction based on Gaussian fitting, is the fact that it allows to use images from different sources and different resolutions together in change detection, as long as the images contain comparable spectral bands and spatial resolution finer than approximately half of the tree crown diameter.

Figure 6 also shows changes in the extent of the tree crowns, some of which clearly seem to reflect growth of the tree crown. For better understanding of these changes and to maintain the quantification of uncertainty in change detection, we computed the differences in probability, area- and volume of the matching Gaussians after the implementation of the iterative analysis and plotted the result in Figure 7. Changes in probability are small, in most cases probability for the same object is higher in 2009 than in 2006, which can be explained by the better spatial resolution of the 2009 image. With regard to the area covered by the Gaussians, for most objects, areas were found equal or larger in 2006 than in 2009. This surprising result is most likely due to the coarser resolution of the 2006 image and the choice of the parameters in classification and fitting of the Gaussians. Some tree

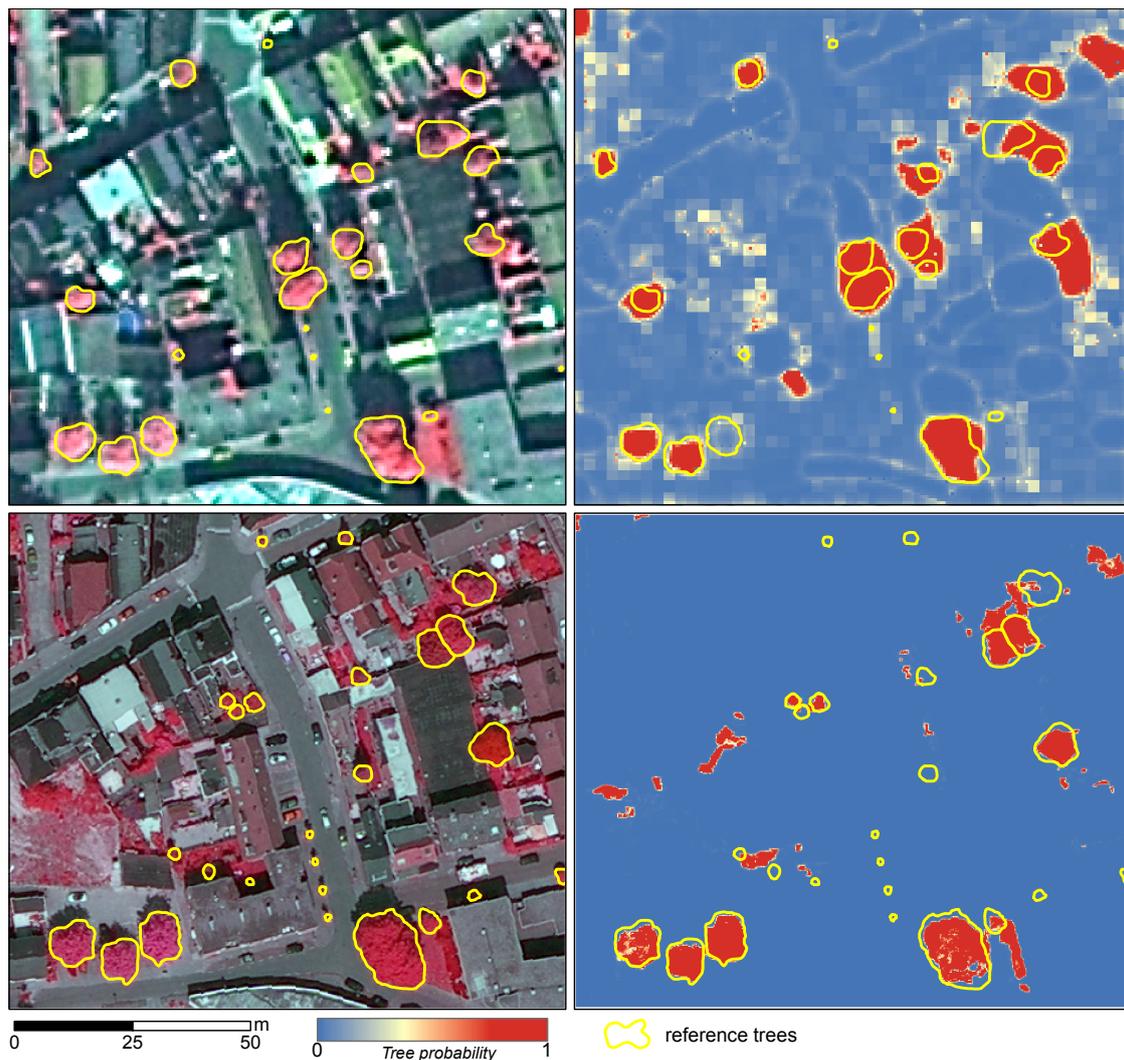


Figure 3: False color composite image of 2006 (top-left) and 2009 (bottom-left) and corresponding tree crown probability image for 2006 (top-right) and 2009 (bottom-right). Reference trees are shown in yellow

group objects became smaller, because of removal of a tree, see Figure 6. Results for the differences in volume covered by the Gaussian functions are similar to the differences in area. From these results it is clear that mapping changes in extent of tree crowns still needs further study, preferably with larger time span between the images, as well as adequate ways of validating the extent of vague objects.

## 5 CONCLUSIONS

In this paper we have shown how change detection can be performed on fuzzy objects, while including the uncertainty, instead of making the objects crisp. We successfully extracted tree crown objects from probability images generated by super resolution mapping or contextual support vector machines, depending on the resolution of the input image. The iterative change detection between images resulted in a higher accuracy (lower omission error) of tree crown detection in the individual images, because trees that were not detected at first, could be detected when prior information from a tree crown object from a later or an earlier image could be used. As a result also the accuracy of change detection improved. An advantage of the method is that it can be used to combine images of different resolution in change detec-

tion. Detection of changes in the extent of the tree crown still needs further research.

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Figure 5: Areas used for Gaussian fitting after iterative classification analysis for 2006 (left) and 2009 (right)

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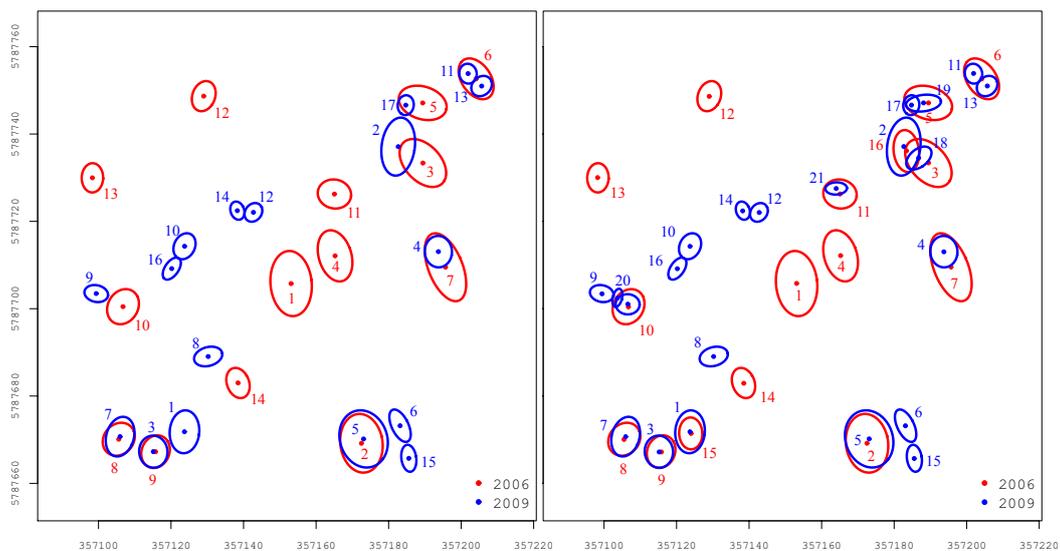


Figure 4: Tree crown objects, results of Gaussian fitting to probability images for 2006 and 2009. Left: after fitting on individual probability images; Right: after iterative analysis

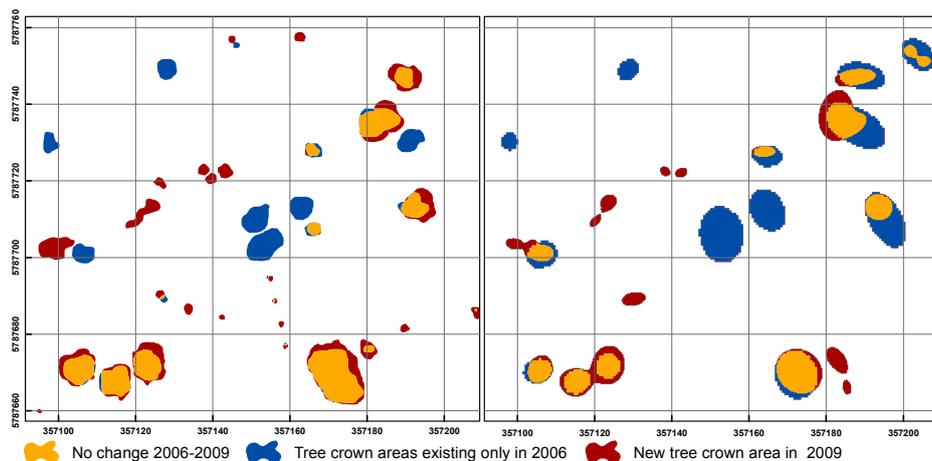


Figure 6: Assessment of changes between 2006 and 2009 for matching objects

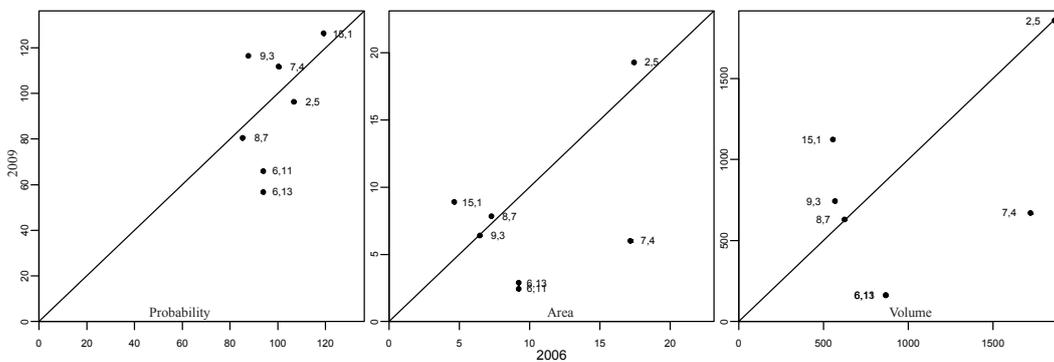


Figure 7: Changes in tree probability, area- and volume of the Gaussian function between 2006 and 2009 for matching objects