VEGETATION FIRE FUELS MAPPING IN THE SAN DIEGO CITY CANYONS – A METHOD COMPARISON

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ABSTRACT:

Fire risk is a major threat to life, property and natural resources in southern California. Recent fire disasters occurred in autumn 2003 and 2007. Fire risk management deals with these hazards, input data are collected, analyzed and evaluated. One of the most important input data is the vegetation density in the endangered areas. Here we describe methods to map vegetation density forming five hazard classes.

The main objective of this study is to explore the benefits of using remote sensed data for the accurate classification of vegetation in San Diego city canyons. Three very high resolution remote sensing data sets (< 1 m) were used in comparison: scanned color infrared film (CIR) airborne, digital multi-spectral airborne (ADS40) and digital multi-spectral satellite imagery (QuickBird).

Different classification approaches (e.g. pixel-based, segment-based and knowledge-based) were tested and analyzed to separate the vegetation into five hazard classes. Accuracy assessment indicated low overall accuracies of 58 % on average. With regard to an optimized classification result in particular unsupervised and segment-based classification can be recommended. The overall accuracy for these two methods reached around 62 %. The use of specially selected reference areas for validation helped to increase the accuracies up to 81 %. Also a separating between three instead of five different hazard classes resulted in accuracies around 80 %. Furthermore it could be shown that all three data sets can be used for successful classification procedures.

The resulting fire risk maps can help to reduce or prevent fire hazards. The maps are a basis for the brush management of the Fire Department to manage sites of high risk next to residential areas (e.g. establish a 30 m fire break around properties concerned).

1. MOTIVATION AND AIM OF THE STUDY

Disastrous wildfires are a major threat to life, property and natural resources in southern California (USA) and represent a risk not to be underestimated. Especially in the region of the San Diego County fire disasters occur periodically – most recently in autumn 2003 and 2007. Additionally, due to the climate change the area is subject to increased warming and aridity. These facts are indicated in the maps of the fourth IPCC report (IPCC, 2007). In consequence the fire risk will rise in the future.

The City of San Diego Fire-Rescue Department (SDFRD) has developed a concept to minimize the risk of fire damage, the so-called brush management. Thus, residents are required to clear or reduce vegetation within a 30 m safety zone between endangered properties and the vegetated areas to reduce the risk. To assess high risk areas detailed information of the vegetation fire fuels that are close to residential areas, the SDFRD seeks to map vegetation density representing different fire hazard classes. Furthermore, a continuous monitoring for the fire risk management is of interest. Until now the vegetation density mapping is based on coarse air-photo interpretation (1:24,000 scale) and outdated (1995) vegetation maps. This study aims to support the efforts of the SDFRD to use high spatial resolution, remotely sensed imagery to generate detailed maps of the vegetation fire fuels within the City canyons and other urban-wildland interfaces.

Remote sensing data are available today differing in the platform used (air-borne/space-borne) and the data format (analogue/digital). A pilot study was completed in 2005 that evaluated multi-spectral/color-infrared airborne and satellite imagery for classifying vegetation fire fuels (Coulter et al., 2005). The suitability of such different multi-spectral remote sensing imagery for mapping vegetation density in the San Diego City Canyons is further analyzed here.

Furthermore, a variety of classification approaches is available today for information extraction. Within this study, the most suitable method for mapping fire hazard classes should is sought.

Additionally, the use of vegetation indices to discriminate some fire hazard classes is one objective of this research. Especially the differentiation of trees from shrub vegetation is necessary to increase risk map quality.

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2. STUDY SITES

San Diego is situated in the state of California in the southwestern USA. The region is bounded by the Pacific in the west and extensive dessert areas in the east. In recent decades the area became one of the most popular residential areas within the US. The costal zones are characterized by valleys, foothills, and mesas. If these valleys and foothills extend into urban areas they are addressed also as City Canyons.

After prior consultation with the SDFRD two typical investigation areas within neighborhoods of the City of San Diego have been defined as study sites. First, the partly dense residential area bordering the southern part of the Mission Trial national park (165 hectares, figure 1), and second, the area around Mt. Soledad in the city district La Jolla (360 hectares, figure 2). The canyons vary a lot in dimension and shape. The average size of these canyons is about 1 km in length and 30 to 50 m width at a depth of max. 50 m.

3. INPUT DATA

Within the study sites three different very high resolution image data sets (<1 m ground resolution) were available:
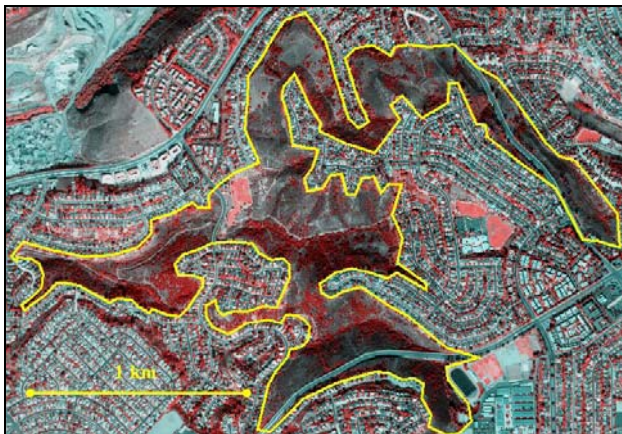

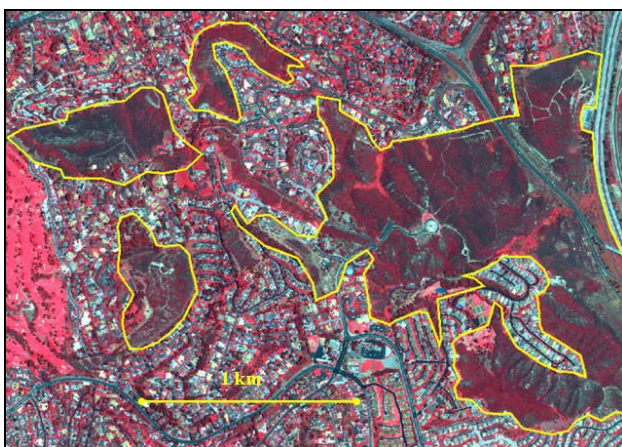Figure 1. Mission Trial study site (source: ADS40 imagery)

Figure 2. Mt. Soledad study site (source QuickBird imagery)

- A scanned false color infrared (CIR) aerial image (figure 3);
- An ADS40 digital aerial image (figure 4, available for the Mission Trial study site only);
- And a QuickBird satellite image (figure 5).

Table 1 characterizes the imagery by showing some key parameters. The different data sources are almost of the same characteristics but differing in the spectral features and the date of acquisition. All images are pre-processed (e.g. geo-referenced). The QuickBird image was pan-sharpened using the Principal Component algorithm.

Parameter	CIR	ADS40	QuickBird
Acquisition date	Juli 2000	November 2003	Juni 2004
Geometric Resolution	0.6 m	0.5 m	0.6 m
Spectral resolution	3 bands (G, R, NIR)	4 bands (B, G, R, NIR)	4 bands (B, G, R, NIR)
Radiometric resolution	8 bit	8 bit	11 bit

Table 1. Key parameter of the input imagery

4. METHODS

4.1 Definitions of the Fire Risk Classes

The SDFRD developed the Wildland Fire Risk/Hazard Severity Assessment model for determining the areas at highest fire risk. This model incorporates information about access, general vegetation (fuel models), topography, roof assemblies, building construction, available fire protection (water source availability, water pressure/volume, and fire response time), utilities, and other rating factors. General fuel models are categorized into five classes in the Wildland Fire Risk/Hazard Severity Assessment model. For image-based classification and assessment, these classes were slightly modified to emphasize the information that could be derived directly through spectral-based classification of remotely sensed imagery (based on the methods of Coulter et al., 2005):

1. None or fire-resistive ornamentals (e.g., ice plant, bare soil, water, rocks, and roads);
2. Light (e.g., grasses, low density ornamentals), burns fast but low (-2.5 m) and not hot;
3. Medium (e.g., coastal sage scrub and other low stature sub-shrubs ≤ 4 ft. high, with some woody material with moderate biomass and some woody material), burns fast and medium-high (-5 m) with high temperatures;
4. Heavy (e.g., trees and shrubs with low to medium density canopies), burns fast and high with high temperatures;
5. Extreme (e.g., trees and shrubs with high density, closed canopies), burns very fast and high (-20 m) with very high temperatures.

The appearance of these fire risk classes is shown in figure 6. For more examples see Coulter and Stow (2007).
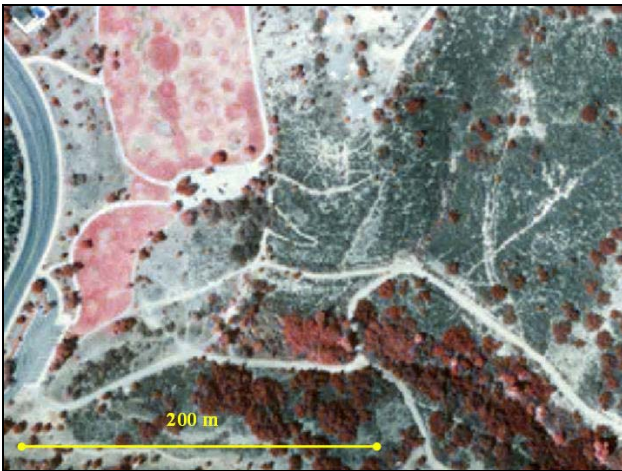
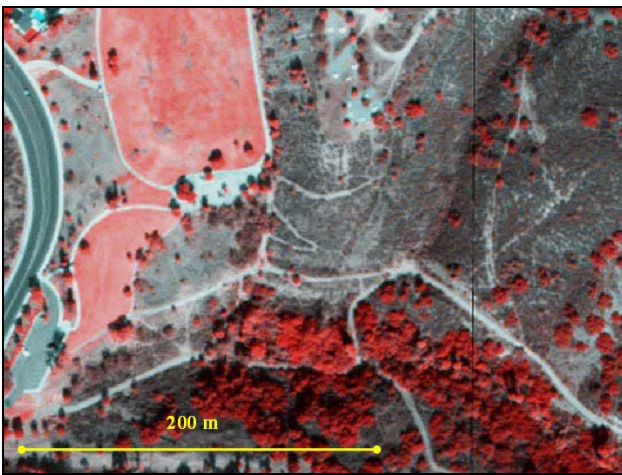Figure 3. Scanned false color infrared (CIR) aerial image
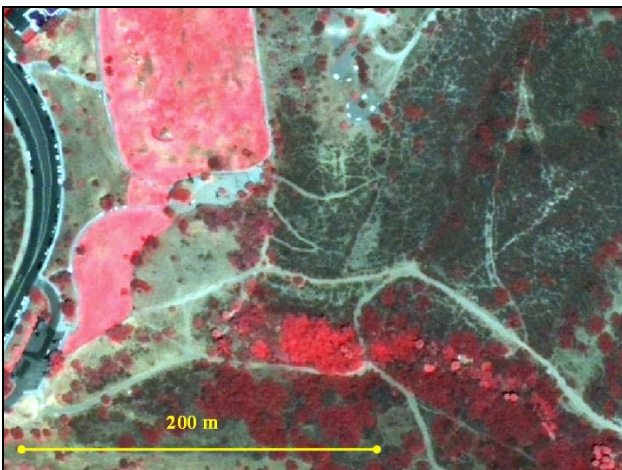

Figure 4. ADS40 digital aerial image

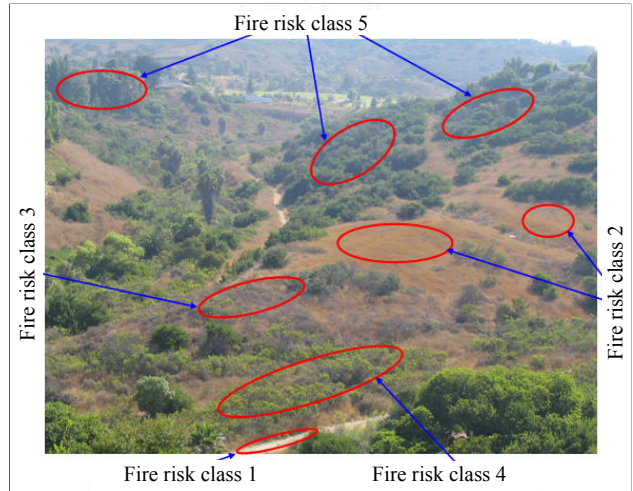Figure 5. QuickBird satellite image

Figure 6. Appearance of the fire risk classes
(Photo: S. Kropp, 2005)

4.2 Reference map

For evaluation and accuracy assessment of the results a reference map was produced by on-site field mapping in cooperation with the SDFRD for both study sites. Polygons corresponding to land cover patches were delineated on hard copy color printouts of the ADS40 imagery. The fire risk level for each polygon was indicated by visual inspection. A digital reference map in raster format was digitized based on the field maps of fire risk level (see figure 7). In addition some specific classes have been introduced to evaluate the classification results regarding areas covered by Ice Plant *(Carpobrotus Edulis)*, turf grass and tree canopies. These classes tend to be misclassified into other risk classes due to spectral similarity.

4.3 Applied classification approaches

To find out which classification approach is most suitable to differentiate the five fire risk classes the following methods have been applied:
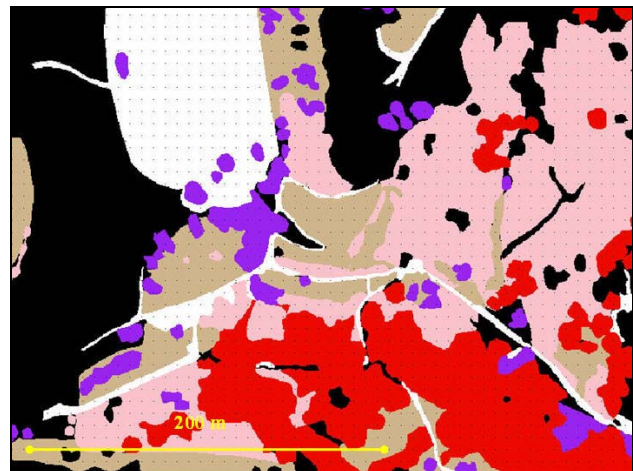
- Unsupervised (ISODATA);

Figure 7. Reference map according to the area displayed in figures 3-5: fire risk classes 1 - white, 2 - light brown, 3 - light red, 4 – purple, and 5 - red, black indicates areas without information

- Supervised (minimum distance, parallelepiped, maximum likelihood);
- Fuzzy-logic;
- Segment-based (Definiens Professional);
- Rule-based (Erdas Imagine Expert Classifier).

Most of the approaches used are implemented in the software Erdas Imagine (cf. ERDAS, 2003; Lillesand and Kiefer, 2004). For segment-based image analysis the Definiens Professional software was applied (cf. Definiens, 2006; Navulur, 2007).

4.4 Comparison of vegetation indices

Different vegetation indices (cf. Lillesand and Kiefer, 2004) have been evaluated regarding their capabilities to increase the accuracy of the classification result (see table 2). These indices were calculated for the three data sets used. A comparison was carried out concerning the ability to separate the five fire risk classes. Thus, thresholds for characterizing these classes were identified using the Erdas Imagine Breakpoint Editor. For better interpretation and comparison the indices have been stretched to a range from 0 till 200 (the numerical value of 1 was added to original values and multiplied by 100).

Name	Formula
Simple-Ratio (SR)	$SR = \dfrac{NIR}{RED}$
Normalized-Difference-Vegetation-Index (NDVI)	$NDVI = \dfrac{NIR - RED}{NIR + RED}$
Green-Normalized-Difference-Vegetation-Index (GNDVI)	$GNDVI = \dfrac{NIR - GREEN}{NIR + GREEN}$
Soil-Adjusted-Vegetation-Index (SAVI)	$SAVI = \left(\dfrac{NIR - RED}{NIR + RED + L} \right) * (1 + L)$

Table 2. Evaluated vegetation indices

4.5 Detection of tree canopies

An additional objective of the study was to develop a method for discriminating tall tree canopies from shrub/brush canopies. Due to a high similarity these classes cannot be separated by spectral or texture information. For this reason the software Feature Analyst, that incorporates spectral and spatial information, was used (Visual Learning Systems, 2006). The advantage of this software is the possibility to define individual search pattern considering the spatial neighborhood. The idea was to distinguish tall trees by identifying the adjacent shadow of the tree. Individual search pattern were created for each image data set due to different shadow occurrence in size and direction (see figure 8). Since the QuickBird image contains minimal shadows the approach is suitable only limited in this case. The intermediate result was optimized by a clutter removing process to minimize classification errors.

5. RESULTS

5.1 Classification accuracy for the different image data sets

Within the accuracy assessment the individual classification results of all approaches for each image data set were compared with the reference map and an error matrix was produced. The overall accuracies of these matrices are shown in table 3.
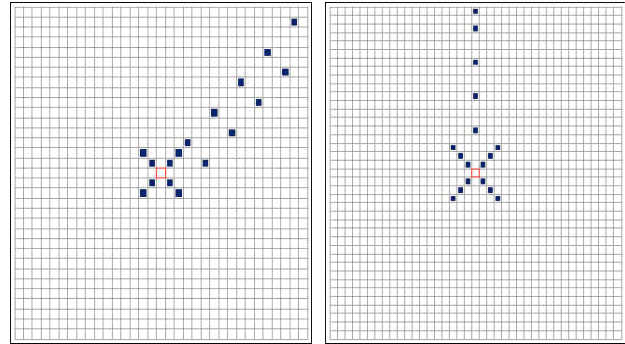

Figure 8. Feature Analyst search pattern according to the different size and direction of shadows in CIR data (left) and ADS 40 data (right)

	CIR	ADS40	QuickBird
ISODATA	58 %	67 %	60 %
Minimum distance	51 %	55 %	57 %
Parallelepiped	52 %	60 %	59 %
Maximum likelihood	52 %	60 %	59 %
Fuzzy-logic	53 %	61 %	62 %
Segment-based	58 %	68 %	61 %
Rule-based	52 %	66 %	57 %

Table 3. Overall classification accuracies of all approaches for each image data set (Mission Trial study site)

All overall accuracy values are within the range from 51 till 68 % (κ = 0.36 - 0.56). The lowest accuracy resulted from the minimum distance method based on CIR data while the highest value was reached by the segment-based approach in combination with ADS40 data (see figure 9 for a graphical representation).

Comparing the results for the different image data sets in average yielded that the accuracy varies slightly between 54 % (CIR, κ = 0.40) and 62 % (ADS40, κ = 0.50). Therefore, ADS40 data turned out to be the most suitable data type for the task. But the decision which data type to use is also determined by other factors, such as availability and costs.

Accuracy variations can also be noticed for the averages of the different classification approaches. Here the range starts with the minimum distance classifier with 54 % (κ = 0.41). The highest average values were obtained by the unsupervised and segment-based approaches with 62 % (κ = 0.50) each. Overall the lowest accuracy results from the supervised classifiers. Thus, unsupervised, segment-based and rule-based approaches are recommended. The latter two allow the use of ancillary data what is becoming more and more important. On the other hand the implementation of the unsupervised classifier is solid, simple, and makes results reproducible easily.

In comparison to results of similar studies the obtained accuracy values have to be rated as moderate only. Koutsias and Karteris (2003) classified different forest types in Mediterranean areas of Greece based on Landsat TM imagery with an average accuracy of 85 %. Mertins and Lambin (2000) obtained accuracies of about 90 % classifying five land cover classes in the southern Cameroon. Although these and other studies (e.g. Roberts et al., 2003) are not fully comparable they indicate the

relation   of   the

tree canopies have be detected correctly using ADS40 data (19 % CIR and 17 % QuickBird respectively). The high values for the ADS40 data refer to the pronounced shadow appearance. Consequently, the proposed approach to detect tree canopies by identifying the adjacent shadow have to be rated as not suitable.

5.3 Possibilities for increasing the classification accuracy

Use of vegetation indices: The vegetation indices introduced in section 4.4 were calculated for the three input image data sets. Following, a comprehensive evaluation regarding the abilities to classify the five fire risk classes was carried out. It turned out that the SR is not useful due to its simple structure and reduced precision involved. The GNDVI which should enable a more detailed separation in areas covered by dense vegetation could not serve its purpose. The same was true for the SAVI which covered the largest range of values but lead only to a slightly lower accuracy than the NDVI. Thus, the NDVI was chosen as ancillary data within further classification tests.

When the image data was used in combination with the NDVI the resulting accuracy was almost unchanged (+/- 1-2 %). This was tested for the unsupervised, supervised und fuzzy classifiers. If the fire risk classes were classified using the NDVI only the accuracies resulted in 63 % for ADS40 data and 61 % for QuickBird data. Problems occurred while separating risk class 3 due to its inhomogeneous vegetation content (overlap with classes 2 and 4). Further, the phenological situation at the date of recording influences the results.

Using specially selected reference areas for validation: The reference map may contain errors e.g. due to generalization or seasonal vegetation deviations in comparison to the ADS40 base map. Thus, a second detailed high-precision reference map was created on-site in the Mission Trial area. Using this new reference the accuracy assessment was repeated and accuracy improvements up to 20 % were achieved (see table 4). Especially the results for the rule-based classifier and for the ADS40 input data have been optimized.
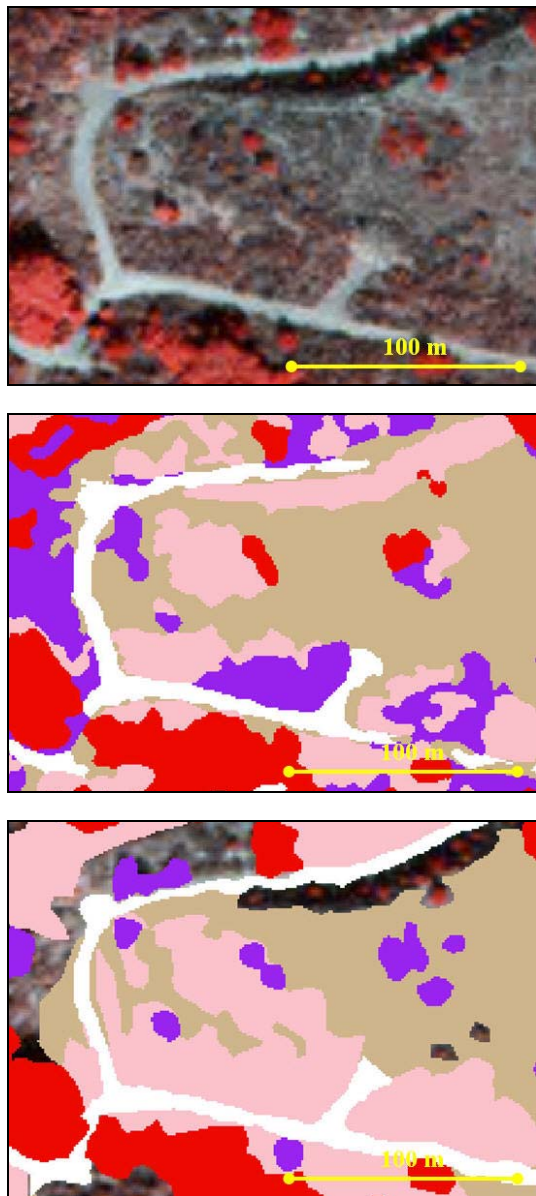

Figure 9.   Original image data (ADS40, above), segment-based classification result (middle), and reference map (below), see figure 7 for color code

resulting quality. In this context the possibilities to raise the accuracy described in section 5.3 become significant. Furthermore, it should be kept in mind that also the reference map is maybe subject to errors.

5.2 Accuracy of detected tree canopies

For evaluating the number of correctly detected trees a pixel- and an object-based accuracy assessment was carried out. A field inventory from the Mission Trail study site containing the tree canopies of 54 trees was used therefore. The pixel-based evaluated results have an accuracy of 35 % for ADS40, 17 % for CIR and 16 % for the QuickBird data. In case of the object-based accuracy assessment the correctly detected trees were counted if their area was delineated to a given extent. Even if a low proportion threshold of 40 % is applied only 43 % of the

	CIR	ADS40	QuickBird
ISODATA	72 % (+14)	76 % (+9)	65 % (+5)
Minimum distance	64 % (+13)	75 % (+20)	66 % (+9)
Parallelepiped	64 % (+12)	78 % (+18)	65 % (+6)
Maximum likelihood	64 % (+12)	78 % (+18)	65 % (+7)
Fuzzy-logic	65 % (+12)	81 % (+20)	66 % (+4)
Segment-based	65 % (+7)	71 % (+3)	70 % (+9)
Rule-based	72 % (+20)	78 % (+12)	73 % (+16)

Table 4.   Optimized classification accuracies using specially selected reference areas for validation (Mission Trial study site), values in brackets: improvements compared with the accuracy assessment in section 5.1/table 3

Combining fire risk classes: Due to spectral confusion between the five fire risk classes it was tested to use a combination of only three classes. Therefore, classes 2 and 3 as well as 4 and 5 became merged and the accuracy was re-evaluated.

In this case the accuracy was improved by 22 % in average for all classifiers and image data sets. The best results are obtained by the unsupervised, segment-based and rule-based classifiers

(85 % for ADS40 each). The result has to be discussed with the SDFRD, whether the higher accuracy or the thematic resolution is more important.

Classification of specific land cover: Ice plant as well as grass areas have a high relevance for the classification accuracy. For the Mission Trail study site the detection was tested and evaluated. A successful extraction was possible using only two of the classification approaches. The rule-based classifier yielded accuracies of 84 % based on QuickBird data (74 % CIR, 70 % ADS40) and the segment-based classifier 87 % (for QuickBird data only). All other combinations of classifiers and imagery failed.

Inclusion of LiDAR data: Coulter and Stow (2007) extended the study by deriving information on vegetation height, density, and structure from LiDAR data. The image classification derived using ADS40 multi-spectral imagery and LiDAR-derived products yielded an overall accuracy of 84 % for the five fire risk classes. The inclusion of the LIDAR-derived products in this classification substantially improved especially the discrimination of low stature, low risk vegetation (fire risk class 1).

6. CONCLUSION AND OUTLOOK

The primary goal of the study was to determine if very high resolution multi-spectral remote sensing imagery is suitable for classifying vegetation density and thus to support the fire risk management in the San Diego City canyons. This question can be answered yes. Irrespective of which image data set or which classification procedure was used a moderately successful classification of the vegetation was possible. Methods to increase the classification accuracy have been presented. A most successful result is possible by using specially selected reference areas for validation as well as the inclusion of the LIDAR-derived information (Coulter and Stow, 2007). A combination of the proposed improvements will yield optimal results. As imagery suitable for classifying the five fire risk classes the ADS40 data seems to be optimal. With regard to an operational and reproducible application the unsupervised classification can be recommended especially for this task. If additional data are available or if specific image objects have to be detected (e.g. Ice Plant or grass areas), a segmentation-based approach in combination with a rule-based classification should be used. The goal of detecting tree canopies was not possible within this study.

Further research will help to verify the presented results. The capabilities of the applied classification approaches and the image data sets should be expanded to analyze their potentials in detail. Investigations concerning the integration of additional data as well as the use of hyper-spectral data may be interesting. However, which research will be made in future in this field they will support the fire risk management actively and thus help to lower the fire risk for people living adjacent to the San Diego City canyons.

REFERENCES

Coulter, L., Kropp, S., Stow, D., Villavicencio, E., 2005. Mapping Vegetation Fire Fuels in San Diego City Canyons Using Remotely Sensed Imagery. NASA SSC Affiliated Research Center final report by San Diego State University.

Earth Science Applications Directorate, National Aeronautics and Space Administration, John C. Stennis Space Center, Mississippi.

Coulter, L., Stow, D., 2007. Classifying Vegetation Fire Fuels Using Multispectral Imagery and Lidar-derived Vegetation Height and Density. *Proceedings of the 21st Biennial Workshop on Aerial Photography, Videography, and High Resolution Digital Imagery for Resource Assessment*, Terra Haute, Indiana, May 2007. CD-ROM, 11 p.

Definiens, 2006. Definiens Professional 5.0 User Guide. Munich.

Erdas, 2003. ERDAS Field Guide. 7th ed., GIS & Mapping, LLC Atlanta, Georgia, USA (www.gis.leica-geosystems.com)

IPCC, 2007. IPCC Fourth Assessment Report: Climate Change 2007. http://www.ipcc.ch/ipccreports/assessments-reports.htm (accessed 02 May 2008)

Koutsias, N., Karteris, M., 2003. Classification analysis of vegetation for delineating forest fire fuel complexes in a Mediterranean test site using satellite remote sensing and GIS. *Int J Rem Sens*, 24 (15), pp. 3093-3104

Lillesand, T. M., Kiefer, R. W., 2004. *Remote Sensing and Image Interpretation*. 5th ed., Wiley, New York, 763 p.

Mertens, B., Lambin, E., 2000. Land-Cover-Change Trajectories in Southern Cameroon, Department of Geography, Universitè of Catholique de Louvain, Belgium

Navalur, K., 2007. *Mulispectral image analysis using the object-oriented paradigm.* CRC Press, Boca Raton, 163 p.

Roberts, D. A., Dennison, P. E., Gardner, M. E., Hetzel, Y., Ustin, S. L., Lee, C. T., 2003. Evaluation of the Potential of Hyperion for Fire Danger Assessment by Comparison to the Airborne Visible/Infrared Imaging Spectrometer. *IEEE Transactions on Geoscience and Remote Sensing*, 41 (6), pp. 1297-1310

Visual Learning Systems, 2006. Feature Analyst Version 4.0 for ERDAS Imagine. http://vls-inc.com/feature_analyst/publications.htm (accessed 18 April 2006)