MACHINE LEARNING FOR THE EXHAUSTIVE EVALUATION OF OBJECT-BASED FEATURE SPACES

N. Wolf [a, *], A. Hof [b], C. Jürgens [a]

[a] Department of Geography, Geomatics/Remote Sensing Group, Ruhr-Universität Bochum, 44780 Bochum, Germany – (nils.wolf, carsten.juergens)@rub.de
[b] Department of Geography, Landscape Ecology/Bio-Geography, Ruhr-Universität Bochum, 44780 Bochum, Germany - angela.hof@rub.de

KEY WORDS: Object-based Features, Machine Learning, Random Forests, Feature Scoring, Urban, WorldView-2, Turf Grass, Swimming Pools

ABSTRACT:
Segmentation provides means to extract spatial/object features which can be added at pixel level to the spectral signature vector. As shown in this paper, this framework allows effective combination of the pixel and the object domain for spectral-spatial classification. As an application, the mapping of Mediterranean urban leisure landscapes (San Roque and Santa Ponsa, both Spain) with WorldView-2 and airborne color imagery is presented. Turf grass, other vegetation and swimming pools are the surface features of interest as they have high relevance for urban ecological studies. The random forest machine learning technique is applied and compared to other well-known classifiers, such as a support vector machine. A recently published adaption of the random forest method is utilized to calculate so-called conditional variable importance in order to identify the relevant features. Especially for complex problems and high dimensionality, the relevance of individual features is far from being obvious to the human analyst and the actual pattern in the data remain ‘hidden’ when relying on standard methods, such as scatter plots. The findings and statements of this work are: random forests can deal with high-dimensional feature spaces which contain correlated and potentially unpredictive features. For machine learning applications, accessing object features at pixel level entails some advantages as the sampling/processing units are of uniform size and do not depend on the segmentation quality. Furthermore, it is shown that the random forest prediction accuracy is highest when complementing pixel (spectral signature) and object features.

1. INTRODUCTION

The increasing accessibility of spaceborne sub-meter-resolution imagery (e.g. WorldView-2, QuickBird or GeoEye-1) have led to new emerging application ranges for remote sensing of urban environments, including intra-urban structuring (Herold et al., 2005) and mapping of relevant urban surface materials (Brockhaus et al., 2010) and land covers (Benediktsson et al., 2003). Urban environments are among the most dynamic systems on Earth which therefore require constant monitoring and updating of geo databases. Against this background, automated routines are needed to convert the huge amounts of available remote sensing data into valuable information to accommodate planning and management activities.

For automated interpretation, the limiting factor in many urban studies is the inherent complexity of this environment. Complexity arises from the various artificial and natural surface materials encountered in urban environments such as asphalt, concrete, metals, tartan, bitumen, etc. (Heldens et al., 2008). Their spectral similarity but also their often unclear linkage to relevant urban land covers or uses impedes the decoding of spectral per-pixel signatures. Further complexity is introduced by the way different surface materials or land covers are spatially arranged to meaningful spatial entities.

Hence, alongside with the per-pixel spectral dimension of an image, incorporating a description of the spatial structure can be useful for image classification (Camps-Valls et al., 2010). Especially when the objects of interest are significantly larger than the sensor system’s ground resolution, there is wide consensus that spatial information holds valuable information which effectively complements the standard per-pixel spectral dimension (Blaschke, 2010). In order to generate a spatial description of an image, various techniques are known, such as window-based approaches based on the concepts of postclassification filtering, morphological (Benediktsson et al., 2003) and texture (Haralick et al., 1973) transformations, or Getis statistics (Ghimire et al., 2010). Window-independent approaches are for example based on graph theory (Sirmacek and Unsalan, 2009). All these techniques can be broadly categorized in preprocessing feature extraction and postprocessing filtering approaches (Camps-Valls et al., 2010).

Image segmentation provides another means for window-independent feature extraction in order to add a spatial description of the image to the predictor space. Pixels within homogeneous image regions are grouped together to objects and hence conceived as belonging together. As such, pixels can inherit the attributes from their corresponding object(s). However, the wealth of manifold object features (e.g. object’s spectral statistics, textures, geometries or their mutual relationships) is not always obvious to the analyst. Especially

* Corresponding author.

the features' interaction (e.g. correlation or dependency) and their direct dependence on the object creation process itself make it cumbersome for the analyst to find appropriate feature sets by using standard methods (e.g. visual inspection of feature layers, scatterplots, and histograms). This in particular applies to complex or difficult classification problems. Despite this fact, machine learning and feature selection is still underrepresented in object-based image analysis research (Novack et al., 2011).

The aim of this work is to empirically assess the value of various object features as spatial descriptors within a pixel-based framework for supervised classification. Incorporating object features into the pixel domain is assumed to be appropriate for training, tuning and testing of machine learning applications that require accurate and spatially independent data samples. These requirements are not necessarily met in an object-based framework where the processing/sample units are of non-uniform size and constitute a generalization of the pixel domain which falsely would be assumed to be hundred percent correct. Or in other words, according to (Chan et al., 2009): "Often, hard decisions are made in the early stages of the process, e.g., line extraction and segmentation. These decisions introduce errors which are then corrected in subsequent stages of the process. However, not all errors will be corrected."

As an application, the mapping of coastal urban leisure landscapes is presented which is aimed at extracting swimming pools, vegetation and – as a subgroup of vegetation – turf grass. These surface features are important determinants of water consumption and have important implications for urban studies related to water demand, irrigation and the role of green spaces in urban landscapes (Wentz and Gober, 2007; Hof and Schmitt, 2011; Salvador et al., 2011). For this purpose, random forests (decision tree-based ensemble methods) are used to classify two pansharpened WorldView-2 scenes and one aerial color image of coastal tourist areas in Mallorca and Andalusia, Spain. The prediction accuracy of random forests is compared to those of support vector machine, simple decision tree and nearest neighbor classifiers. Moreover, feature scoring based on random forests is used to quantify the importance of spectral bands and individual object features and, furthermore, to compare the performances of the pixel and object domain as well as to assess the synergy using both domains. It is further assessed to which extent classification results potentially suffer from the so-called *curse of dimensionality*. It can be assumed that random forests cope well with high dimensional features spaces (Caruana et al., 2008) which potentially consist of correlated and unpredictive features. If this is the case, the conclusion would be that, instead of pre-selecting features and searching appropriate segmentation scales, an unsurveyed feature set of multiple segmentation levels (quasi-continuous scale space) can be provided to the classifier and hence decrease laborious intervention by the analyst.

2. DATA

2.1 Remote Sensing Data and Study Sites

In late 2009, the Earth observation satellite WorldView-2 was launched. It collects spectral data in eight bands ranging from 400 to 1040 nm with a nominal ground resolution of 2 m, while the panchromatic mode covers a spectrum from 450 to 800 nm with nominal 50 cm ground resolution (DigitalGlobe, 2009). Two WorldView-2 images are available for this study: (1) A WorldView-2 scene (Catalog-ID: 1030050005F96700) of San Roque in the Cádiz province, Andalusia, Spain, which was acquired on 16th July 2010 with 11.9° off-nadir and 69.92° sun elevation angle. (2) A second WorldView-2 scene (Catalog-ID: 1030050005F96700) was acquired on 16th February 2011 with 19.61° off-nadir and 36.41° sun elevation angle. This scene covers Santa Ponsa on the Balearic Island of Mallorca, Spain. Both scenes have been pansharpened with the hyperspherical-color-space method (Padwick et al., 2010) which – according to our visual inspection – well combined spatial detail and spectral properties of both modes. The same study area of Santa Ponsa is furthermore covered by an airborne digital image with 40 cm ground resolution and three RGB color channels. The image was acquired during a flight campaign in March 2002 (SITIBSA (Serveis d'Informació Territorial de les Illes Balears), 2002).

For comparability, equally 125 ha subsets of the three images are considered for the experimental set up of this study. The WorldView-2 scene and the aerial image of Santa Ponsa share exactly the same geographical extent. Both investigation areas, Santa Ponsa and San Roque, show very similar urban landscapes. As high quality tourist destinations and residential areas, they are characterized by large properties with single family dwellings and spacious gardens with swimming pools (cp. ~6 ha clips in Figure 1).

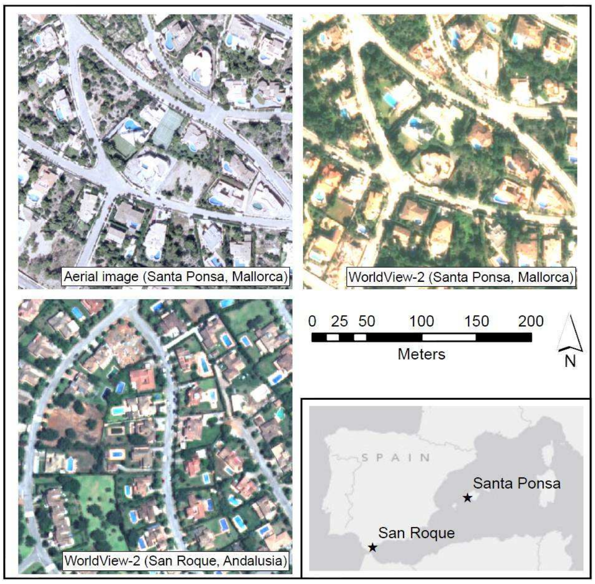

Figure 1. Clips of the study areas and image data

2.2 Reference Data Collection

A 4-class scheme is applied which rigidly decomposes a scene in (1) turf vegetation, (2) non-turf vegetation, (3) swimming pool (non-vegetation) and (4) non-swimming pool (non-vegetation). For each image, 2500 reference pixels are selected by simple random sampling and manually labeled according to the 4-class scheme by visually interpreting directly from the image. The idealized scheme neglects the various sources of uncertainty that accompany remote sensing and geospatial modeling (e.g. noisy and technically limited sensor measurement, degrading processing for signal storage and data transfer, and inherently vague concepts of classes; cp. Foody and Atkinson, 2002). Therefore, 'uncertain' pixels were discarded from the sample. The percentage of discarded pixels (Table 1) can be seen as a quality measure of the images and, furthermore, can be kept in mind for the interpretation of classification accuracy estimates which rely on the 'cleaned' sample. Consequently, accuracy measures only account for those parts of the images that can be visually interpreted.

Image	Total sample	Discarded	Left over
WorldView-2 (Santa Ponsa)	2500 px (100%)	959 px (38.4%)	1541 px (61.6%)
Aerial image (Santa Ponsa)	2500 px (100%)	476 px (19.0%)	1724 px (81.0%)
WorldView-2 (San Roque)	2500 px (100%)	486 px (19.4%)	2014 px (80.6%)

Table 1. Sample size and non-interpretable pixels

3. METHODS

3.1 Segmentation and Feature Extraction

Image segmentation provides means to represent the image content on multiple scales which is particularly suitable for complex scenes (Blaschke and Hay, 2001). In order to compute object-based features of various scales, a three-level segmentation hierarchy is generated by applying multiresolution segmentation (Baatz and Schäpe, 2000). The algorithm offers parameters to control the objects' size and form which enables the analyst to represent the image content on various scales. In a rather unsupervised manner, a sequence of scales (scale parameter: 10, 40 and 160; increased by the factor of 4) was applied to generate an object hierarchy which covers the whole span, from very fine to very broad image content representation.

Based on the segmentation levels, several object feature layers were extracted; comprising spectral, texture, geometry and context features (Table 1). An overview of various object features and their computation can be found in (Trimble Documentation, 2012). The combined feature stack of object and standard per-pixel spectral features consists of 82 layers for the 8-band datasets and 37 layers for the 3-band dataset.

Spectral statistics of multispectral bands	Mean Minimum Standard deviation
Texture of panchromatic band*	Grey Level Co-occurrence Matrix Homogeneity
Object geometry	Area Border length
Context of panchromatic band*	Mean difference to neighbor objects

** for the aerial image a panchromatic band is simulated by averaging RGB intensities*

Table 2. Object features

3.2 Random Forests

Random forests are tree-based ensemble methods which means that they use the results from many (usually hundreds or thousands) different decision tree models to calculate a response (e.g. by majority voting). In the standard implementation of (Breiman, 2001), the individual models (base learners) are simple, unpruned decision trees based on the Gini split criterion which determines an optimal feature (variable) and a threshold to partition the data at the trees' nodes. The decisive feature of random forests is the randomness which is injected at two stages of the tree construction processes. Firstly, trees are constructed on bootstrap samples of the training data and, secondly, the Gini splitting criterion only searches on a randomly drawn feature subset. For more in-depth information: A detailed introduction to tree-based models and ensemble methods is given by (Strobl et al., 2009) and a formal description of random forests can be obtained from (Breiman, 2001).

Recently, random forests became also popular in the remote sensing community (e.g. Pal, 2005; Ghimire et al., 2010; Wolf, 2011) because of their low computational costs and good prediction accuracy which is for many classification/regression problems comparable to the well-established support vector machines (Pal, 2005). Furthermore, a major benefit is that random forests hardly require any tuning.

3.3 Feature Importance

Feature importance scores are calculated using a further development of random forests, which implements so-called conditional feature importance. This adaption, which was recently introduced by (Strobl et al., 2008), provides a better estimate of feature importance as it removes the selection bias towards correlated features. For detailed information the reader is referred to the published literature of the originators (see also references provided in Table 3)

3.4 Evaluation Criteria

Random forests come with their internal test sample, the so-called out-of-bag observations, which can be used for a fair measure of prediction accuracy (Breiman, 1996). It is used in this study to calculate error matrices. In order to summarize a matrix to a single value measure, we combine the overall producer and user accuracies by taking the arithmetic mean (referred to as MPU from here on). In contrast to the standard measures such as overall accuracy and – to lesser extent – kappa, the MPU should better account for the extremely imbalanced class distributions with turf grass and especially pools being the minorities, the latter accounting for only about 1-2% of the total.

The random forest results are also compared to other well-known machine learning algorithms. For better comparability, the out-of-bag cases are not used for testing. Instead, all algorithms are trained and – if necessary – tuned on the same 75% subsample. The remaining 25% are used for calculating MPU values. Table 4 lists the used algorithms, their specifications and implementations as well as some key references.

Method	Specifications / Parameters	Implementation	References
Random forest	`ntree` = 5000 `mtry` = $\sqrt{\lfloor p \rfloor - 1}$	R package 'randomForest'	(Breiman, 2001)
Decision tree	Gini splits Fully grown No pruning	R package 'rpart'	(Breiman, 1984)
Support vector machine	RBF kernel `tune()`: `cost` = 32 `gamma` = 0.023	R package 'e1071'	(Chang and Lin, 2011)
k-nearest neighbor	k = 1	R package 'class'	(Ripley, 2007)
For calculation of feature importance			
Conditional random forests	`ntree` = 1000 `mtry` = $\sqrt{\lfloor p \rfloor - 1}$	R package 'party' `varimp()`	(Strobl et al., 2008)

Table 4. Machine learning algorithms

4. EXPERIMENTS AND RESULTS

4.1 Feature Sets

Three feature sets are defined in order to assess the general value of object features and to assess the synergy of integrating both per-pixel spectral and object features:

1. PX: standard *n* per-pixel spectral values of *n*-band imagery
2. OB: object features (extracted from segmentation levels)
3. CO: complete feature set which combines PX and OB

For each feature set, random forest MPU accuracy is recorded from 20 independent trials in order to account for the issues of data variance and algorithm stability. The overall tendency is the same for all three datasets: the OB set outperforms the PX set while the CO set brings – even if marginal – yet further improvement (Figure 2).

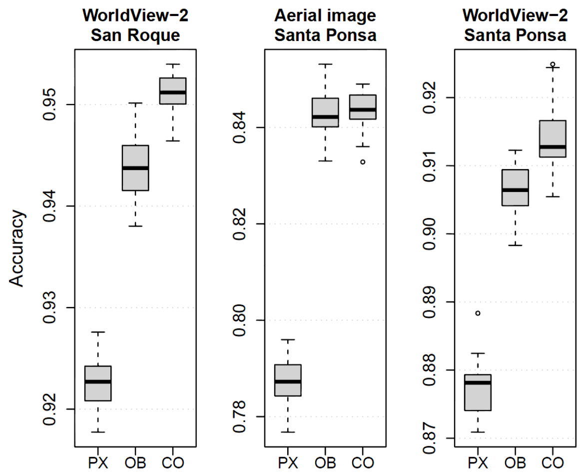

Figure 2. Comparison of feature sets: PX = per-pixel spectral values, OB = object features, CO = complete set that combines PX and OB

One of the twenty trials on the OB set is randomly chosen to present confusion rates in an error matrix (Table 1).

WorldView-2 / San Roque

cla/ref	*turf*	*non-turf*	*non-pool*	*pool*	user
turf	199	18	0	0	0.917
non-turf	15	753	3	0	0.977
non-pool	2	4	982	4	0.990
pool	0	0	2	36	0.947
producer	0.921	0.972	0.995	0.900	

Aerial image / Santa Ponsa

cla/ref	*turf*	*non-turf*	*non-pool*	*pool*	user
turf	43	15	8	0	0.652
non-turf	16	494	78	0	0.840
non-pool	8	44	1261	4	0.957
pool	0	1	4	46	0.902
producer	0.642	0.892	0.933	0.920	

WorldView-2 / Santa Ponsa

cla/ref	*turf*	*non-turf*	*non-pool*	*pool*	user
turf	56	18	0	0	0.757
non-turf	9	696	6	0	0.979
non-pool	2	15	694	1	0.975
pool	0	1	5	39	0.867
producer	0.836	0.953	0.984	0.975	

Table 5. Error matrices and producer and user accuracy of random forest classification using the complete feature set (CO)

4.2 Feature Importance

For more intuitive interpretability of feature importance scores, only two 2-class problems are considered: (1) separation of turf grass from other vegetation and (2) separation of swimming pools from other non-vegetated surfaces. Accordingly, the reference sample for training and testing is filtered.

Value of individual features: Figure 3 and Figure 4 show the best 15 features and their importance scores for both 2-class problems (only San Roque dataset). It can be observed that features from all segmentation scales (10, 40 and 160) as well as from the pixel domain are represented. Most contribution comes from the per-object spectral statistics (mean, minimum and standard deviation). Concerning the extraction of turf grass, the model also relies on texture and context features.

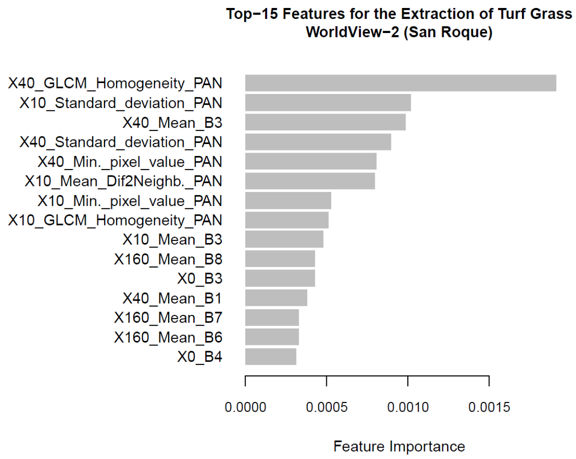

Figure 3. Feature importance scores (the prefix ‘X*number*_’ denotes the segmentation scale; i.e. ‘X10_’ for example refers to a ‘fine’ segmentation level with scale parameter of 10; ‘X0_’ indicates the pixel level)

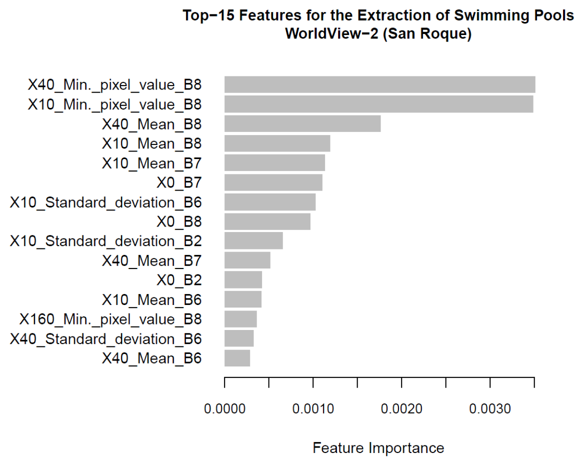

Figure 4. Feature importance scores

Value of individual WorldView-2 bands: In order to assess the value of individual WorldView-2 bands, feature importance scores are calculated based on models using only the PX feature set. Concerning the extraction of turf grass, the results obtained on the San Roque and the Santa Ponsa datasets are quite different. For San Roque the NIR2 (860-1040nm) and Green spectra (510-580nm) are most influential for the model. For Santa Ponsa, the Rededge spectrum is most decisive (Figure 5). The differences might be induced/intensified by seasonality (different phenological stages at times when the images were acquired, see Section 2.1).

For the extraction of swimming pools the results are better matching (Figure 6). For both datasets, the spectra between 705 and 1040 nm (Rededge, NIR1, and NIR2) as well as the Blue band provided most value to the model.

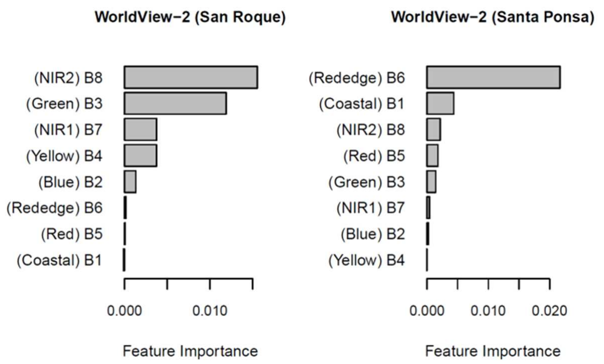

Figure 5. Importance of WorldView-2 bands for the extraction of turf grass

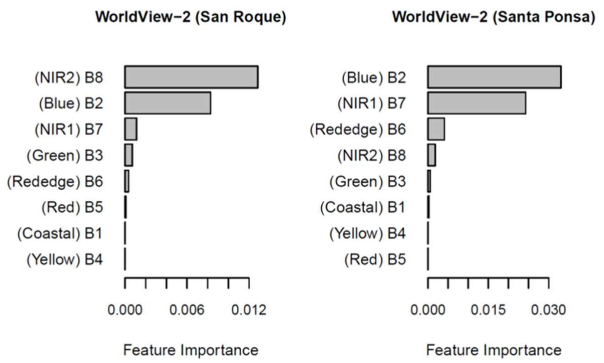

Figure 6. Importance of WorldView-2 bands for the extraction of swimming pools

4.3 Dimensionality

Figure 7 shows the effect of high dimensional feature spaces on classification accuracy (MPU values). As an initial step, features have been ranked according to their importance score. Then, MPU values are obtained from series of independent random forest trials, where the number of features used in the model is incremented step-wisely, starting with the strongest feature and proceeding with subsequent ranks until the last trial (using the whole set). According to Figure 7, dimensionality and potentially weak features appear to be no significant burden for the classifier.

4.4 Comparison of Machine Learning Algorithms

Simple decision tree and nearest neighbour classifiers as well as a state-of-the-art support vector machine were used as benchmark for the random forest approach (applied only for WorldView-2 / San Roque dataset). As it could be expected, nearest neighbour and simple decision tree provided worse accuracy values (MPU), while the random forest approach came close to the support vector machine model which performed best (Figure 8).

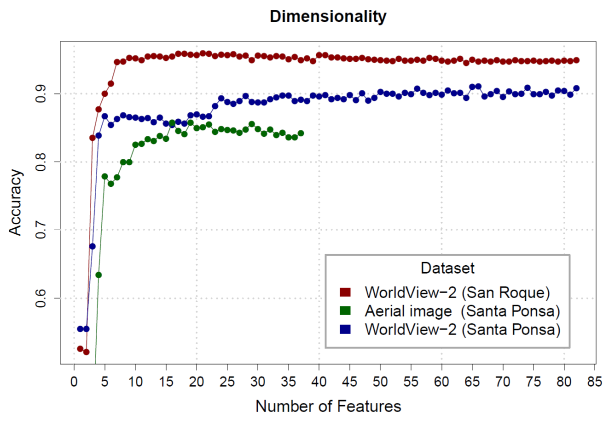

Figure 7. Dimensionality

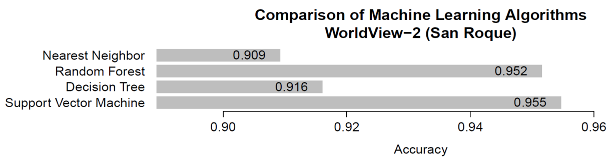

Figure 8. Comparative performances of classifiers

5. CONCLUSION

Urban landscapes are complex scenes and the automated generation of accurate mapping products requires exploiting the image content on the spectral and spatial/structural perspective as well as on various scales. Object-based image analysis provides means to extract manifolds of such features. However deciding which features are helpful is often difficult to decide for both the human analyst and the computer. Against this background, an integration of machine learning, pixel domain and object domain was presented. In our experimental setup, the synergetic use of both domains led to improved results and random forests showed a good response to high dimensionality with potentially correlated or weak features. Reasoning from that, the efforts for laborious manual feature selection (incl. definition of segmentation parameters) can be reduced, respectively handed over to the computer (as long as computational costs can be afforded).

REFERENCES

Baatz, M. and Schäpe, A., 2000. Multiresolution Segmentation: an optimization approach for high quality multi-scale image segmentation, in: Strobl, J., Blaschke, T., Griesebner, G. (Eds.), *Angewandte geographische Informationsverarbeitung XII. Beiträge zum AGIT-Symposium Salzburg 2000*. Wichmann Verlag, Heidelberg, pp. 12-23.

Benediktsson, J. A., Pesaresi, M. and Arnason, K., 2003. Classification and feature extraction for remote sensing images from urban areas based on morphological transformations. *IEEE Transactions on Geoscience and Remote Sensing*, 41 (9), pp. 1940-1949.

Blaschke, T., 2010. Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65 (1), pp. 2-16.

Blaschke, T. and Hay, G. J., 2001. Object-oriented Image Analysis and Scale-space: Theory and Methods for Modeling and Evaluating Multiscale Landscape Structure. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XXXIV-4/W5, pp. 22-29.

Breiman, L., 1984. Classification and regression trees. Wadsworth International Group, Belmont, California, USA.

Breiman, L., 1996. Out-of-bag estimation: Technical report, Department of Statistics, University of California at Berkeley, California, USA.

Breiman, L., 2001. Random Forests. *Machine Learning*, 45 (1), pp. 5-32.

Brockhaus, J., Wright, W., Hendricks, M. and Fleming, S., 2010. Delineation of roofing material within an urban environment: Integration of WorldView-2 Imagery and Lidar Data. Technical Report, United States Military Academy, New York, USA.

Camps-Valls, G., Shervashidze, N. and Borgwardt, K. M., 2010. Spatio-Spectral Remote Sensing Image Classification With Graph Kernels. *IEEE Geoscience and Remote Sensing Letters* 7 (4), pp. 741-745.

Caruana, R., Karampatziakis, N. and Yessenalina, A., 2008. An empirical evaluation of supervised learning in high dimensions. In: *International Conference on Machine Learning (ICML)*, pp. 96-103.

Chan, J., Bellens, R., Canters, F. and Gautama, S., 2009. An Assessment of Geometric Activity Features for Per-pixel Classification of Urban Man-made Objects using Very High Resolution Satellite Imagery. *Photogrammetric Engineering and Remote Sensing*, 75 (4), pp. 397-412.

Chang, C.-C. and Lin, C.-J., 2011. LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, 2, pp. 27:1-27:27.

DigitalGlobe, 2009. The Benefits of the 8 Spectral Bands of WorldView-2. White Paper.

Foody, G.M.and Atkinson, P.M., 2002. Uncertainty in remote sensing and GIS. J. Wiley, Hoboken, NJ.

Ghimire, B., Rogan, J. and Miller, J., 2010. Contextual land-cover classification: incorporating spatial dependence in land-cover classification models using random forests and the Getis statistic. *Remote Sensing Letters*, 1 (1), pp. 45-54.

Haralick, R. M., Shanmugam, K. and Dinstein, I., 1973. Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, 3 (6), pp. 610-621.

Heldens, W., Esch, T., Heiden, U. and Dech, S., 2008. Potential of hyperspectral remote sensing for characterisation of urban structure in Munich, in: Jürgens, C. (Ed.), *Remote sensing - New Challenges of High Resolution. Proceedings of the EARSeL Joint Workshop, March 5-7, 2008, Bochum, Germany*. Geographischen Instituts der Ruhr-Universität, Bochum, Germany.

Herold, M., Couclelis, H. and Clarke, K. C., 2005. The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, Environment and Urban Systems*, 29 (4), pp. 369-399.

Hof, A. and Schmitt, T., 2011. Urban and tourist land use patterns and water consumption: Evidence from Mallorca, Balearic Islands. *Land Use Policy*, 28 (4), pp. 792-804.

Novack, T., Esch, T., Kux, H. J. H. and Stilla, U., 2011. Machine Learning Comparison between WorldView-2 and QuickBird-2-Simulated Imagery Regarding Object-Based Urban Land Cover Classification. *Remote Sensing*, 3 (10), pp. 2263-2282.

Padwick, C., Deskevich, M., Pacifici, F. and Smallwood, S., 2010. WorldView-2 Pan-Sharpening. In: *Opportunities for emerging geospatial technologies*. American Society for Photogrammetry & Remote Sensing, Bethesda, Md.

Pal, M., 2005. Random forest classifier for remote sensing classification. *International Journal of Remote Sensing*, 26 (1), pp. 217-222.

Ripley, B.D., 2007. Pattern recognition and neural networks, 1st ed. Cambridge University Press, Cambridge.

Salvador, R., Bautista-Capetillo, C. and Playán, E., 2011. Irrigation performance in private urban landscapes: A study case in Zaragoza (Spain). *Landscape and Urban Planning*, 100 (3), pp. 302-311.

Sirmacek, B. and Unsalan, C., 2009. Urban-Area and Building Detection Using SIFT Keypoints and Graph Theory. *IEEE Transactions on Geoscience and Remote Sensing*, 47 (4), pp. 1156-1167.

SITIBSA (Serveis d'Informació Territorial de les Illes Balears), 2002. Ortofoto, 5.000, 2002 de las Islas Baleares, ETRS89.

Strobl, C., Boulesteix, A.-L., Kneib, T., Augustin, T. and Zeileis, A., 2008. Conditional Variable Importance for Random Forests. *BMC Bioinformatics*, 9 (1), p. 307.

Strobl, C., Malley, J. and Tutz, G., 2009. An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological Methods*, 14 (4), pp. 323-348.

Trimble Documentation, 2012. eCognition Developer 8.7.1: Reference Book, Trimble Germany GmbH, Munich, Germany.

Wentz, E. A. and Gober, P., 2007. Determinants of Small-Area Water Consumption for the City of Phoenix, Arizona. *Water Resources Management*, 21 (11), pp. 1849-1863.

Wolf, N., 2011. Feature Evaluation for a Transferable Approach of Object-based Land Cover Classification Based on Ikonos and QuickBird Satellite Data. *Photogrammetrie - Fernerkundung - Geoinformation* 2011, 3, pp. 135-144.