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Sub-Pixel Classification of Middle-Resolution Satellite Images – Evaluation of Regression Trees Applicability to Monitor Impervious Surfaces Coverage**

1. Introduction

The research on land cover and land use changes based on the remote sensed images is today one of the elementary methods which allow us to monitor the changes of the landscape structure [9, 10, 15]. Such research usually applies classification approach where all the land cover elements are categorised according to a priori defined classification scheme with a finite number of land cover classes. Because the minimal area of land cover polygon is usually restricted by adopted Minimal Mapping Unit, the definitions of applied classes are constructed in a way which allow areas with mixed types of land cover and land use to be incorporated in one category [23]. However, even if the classification is done for single pixels, we might encounter a mixture of various land cover types. Such situation is typical for low- and middle-resolution satellite images (Fig. 1), but appears also in case of high-resolution images.

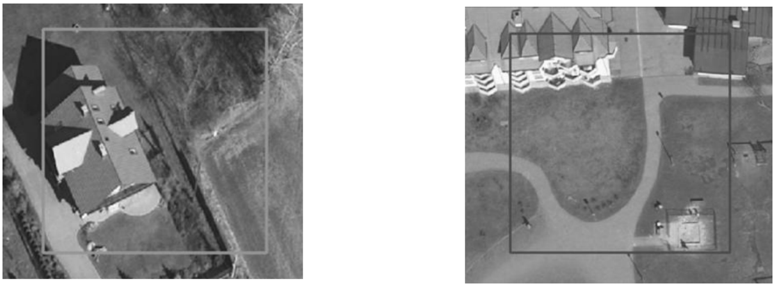

Fig. 1. The area of a Landsat TM pixel (30 m × 30 m) over an aerial orthophotomap. One can observe various land cover types within one pixel

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The above described classical approach to land cover and land use mapping does not suffice to assess all the landscape changes. These changes can have the forms of conversion or modification [22]. In the first case we observe a complete change of one land cover type into another (e.g. arable area – meadow, discontinuous built-up – continuous built-up). In case of modification the change is much more subtle. The category of the area does not change, but the proportions of the land cover within this area change even significantly. As an example we can mention the “discontinuous built-up” category with an increase of building developments due to urbanization processes (Fig. 2).

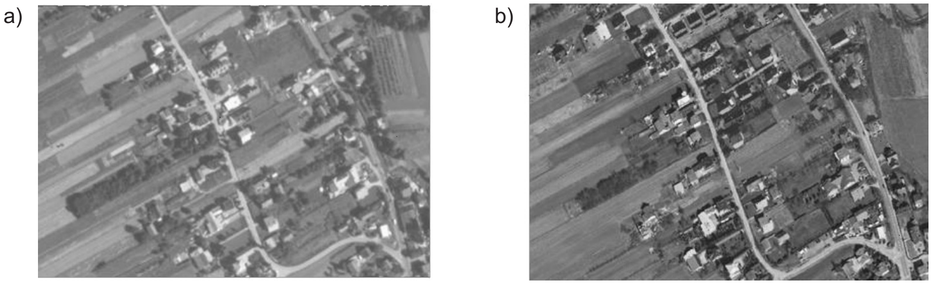

Fig. 2. Increased proportions of buildings within the “discontinuous built-up” category: a) year 1996; b) year 2009. The surroundings of Krakow

Changes with the form of a modification are not reflected on classical land cover and land use maps despite the fact that they influence the changes of landscape processes and functions [2, 15]. The increase in imagery resolution in the recent years does not always provide solution to this problem [13]. It seems that it should be sought for in a different approach to land cover mapping [23].

As a result of the development of remotely sensed images classification methods, there appeared the opportunity of sub-pixel classification. A final map presents the percentage of different land cover types within the classified pixel [13]. This solution was widely applied in National Land Cover Database (NLCD) which is the American equivalent of the European CORINE Land Cover database. Two additional thematic layers have been created within the NLCD beside the classical land cover and land use maps. They present the percentages of the impervious surfaces and the tree canopy within each pixel [17].

The impervious surfaces (areas where the rainfall does not infiltrate into the ground) exemplify such land cover type where obtaining the information on a sub-pixel level brings essential benefits in case of functional assessment of the landscape [8]. An increased percentage of such land cover type can bee treated as an indicator of ongoing urbanisation. It is also reflected in the changes of landscape functions. It might cause lower ground water recharge or an increase of the surface runoff. As a result of the higher percentage of impervious surfaces within the area of a catchment we may observe a decrease of the water quality in its principal stream and higher flood frequency [1, 6].

A vide selection of methods is applied to obtain information about the percentage of impervious surfaces within the area of a catchment. Ground measurements with the use of surveying techniques are time consuming and costly but the most accurate.

On the opposite pole we can place the methods where the imperviousness index is assessed on the basis of other, more easily accessed data, like the population density index, number of households per surface unit or the distance from the city centre [5].

On the accuracy scale between these two methods we can locate approaches which use aerial photographs and satellite images. Further distinction could be applied to those remote sensing approaches from the most accurate methods based on photo interpretation of detailed-scale aerial photographs to the traditional classification of the middle-resolution satellite images.

The classification of high-resolution satellite images and the sub-pixel classification of middle-resolution imagery (Landsat, ASTER, SPOT) provide relatively high accuracy among the remote sensing methods. The latter can be seen as an attractive method of obtaining information about the impervious surfaces for large areas [8]. Moreover, methods based on the middle-resolution images allow to assess the changes in the percentage of impervious surfaces during the period of over last thirty years [18, 21]. These advantages were vital while making decision about applying the sub-pixel classification of the middle-resolution satellite images to obtain the data for the ongoing research focused on the assessment of landscape function changes.

Many methods of sub-pixel classification have been used in the recent years in order to obtain information about the impervious surfaces from the middle-resolution satellite images. Among these methods there were: regression between the imperviousness index[1] and the vegetation index [3, 4, 31], spectral unmixing analysis [20, 24, 25], neural networks [8], regression trees [17, 26–28] and support vector machines [12].

The objective of the research described in the present paper was to test the regression trees approach. Its aim was also to assess the possibility of using the results of the method to monitor the changes of impervious surfaces coverage.

[1] The imperviousness index is defined as the ratio between the impervious surface area within the pixel and the whole pixel area.

2. Regression Trees

2.1. Theoretical Background

The regression trees belong to the machine-learning techniques and can be seen as a variant of classification decision trees. The later are designed for discrete target variable (like land cover classes), and the former are used when target variable is continuous (like land cover fractions) [29].

In classification decision trees a set of rules allowing the prediction of the target variable value (e.g. land cover type) is created on the basis of the training data (e.g. the sample of multispectral image pixels). The decision scheme has a form of a tree. The root node comprising of a complete set of classified data (all the pixels in case of a satellite image) provides the basis of such tree. At least two branches grow from the root node and split the dataset. New nodes are formed at the end of these branches. In these nodes new split of the dataset may be done and new branches created. This continues until leaves (terminal nodes) are reached and the whole dataset is divided into separate classes. Each split is accompanied by a test of one or more predictor variables (e.g. pixel values in image bands). Such test provides a decision rule which directs the classified pixels to the given branches. The pixels are directed down the tree to the leaves with ascribed decision classes. In case of regression trees, its leaves are ascribed different regression models instead of classes.

In this method some data attributes (predictor variables) may be left aside in the classification process. The classification is based only on the chosen predictor variables, selected automatically during the process of decision tree construction. Regression tree learning algorithms can differ in measures used in the process of selecting test attributes for given nodes. These measures are designed to guarantee the selection of attributes providing the maximum of information. The rules for creating nodes and leaves as well as the ways of dealing with inconsistencies in the training dataset also vary from one algorithm to another [19].

The tree constructed from training data may have too complex structure which might result in over-fitting. Such tree has lower generalisation capability and, in turn, lower classification accuracy when applied to data not represented in training dataset. In order to avoid excessive adjustment of the tree to the training data, different pruning methods are applied. To simplify a tree, its parts of little significance for the classification are removed and some nodes are turned into leaves. A simple tree gives worse results for the training dataset but it classifies better objects not represented in the learning examples [19].

The classification and regression trees have many advantages [7, 29]. Classification with this method allows the use of pixel values within each band of the classified image (or a set of images), results obtained from various transformations of the satellite images (e.g. vegetation indices or textural parameters) as well as other data (e.g. Digital Terrain Model). It is not necessary to make any assumption about statistical distribution of the data. The approach can be used either in case of linear and non linear relationships between input and target variables. The method has good computational efficiency and obtained tree can be presented as a set of easily interpretable rules.

2.2. Applications to Assessment of the Imperviousness Index from Middle-Resolution Satellite Images

The methodology of applying regression trees in assessing the imperviousness index is described in the paper by [30]. This approach has been used in the United States at various levels – from urban agglomerations (e.g. [27]) to the NLCD database for the whole of the country [17]. Xian and Crane [28] use the regression trees for assessing the imperviousness index for the Tampa Bay catchment (6600 km^2) in the West of Florida. They obtain the training and verification data about the percentage of impervious surfaces through the classification of aerial false-coloure orthophotomaps with 1m pixel size. Regression trees models for different time periods are based on single Landsat TM images taken in early spring. Spectral bands and NDVI image are used to create them.

The average absolute error for the obtained results of the assessment vary between 10% and 12% and the correlation coefficient between 0.7 and 0.8. The authors do not assess the accuracy of the impervious changes map. They stress, however, that in case of 5–8% of the pixels the index value decreased for no clear reason.

Xian [26] uses the regression trees to assess the impervious surfaces in the agglomerations of Seattle (6700 km^2) and Las Vegas (1320 km^2). In this case the training and verification data have been obtained through the classification of aerial orthophotomap with 0.3-meter pixel size. Spectral and thermal bands registered by Landsat ETM+ scanner, NDVI image and the terrain slope values have been used to create the model. In this case, the average absolute error based on the training data and the correlation coefficient reach the values of respectively 9.9% and 0.88 for Seattle and 11.2 and 0.85 for Las Vegas. The accuracy analysis of model-predicted imperviousness index based on the verification data allowed to assess the systematic error and root-mean-square error values as respectively 0.0 and 15.1% for Seattle and –6.0 and 16.1% for Las Vegas.

The method of sub-pixel classification with regression trees has been applied to create the NLCD database of land use and land cover for the whole area of the United States [17]. Classical map with land cover and land use categories according to a chosen classification scheme has been created beside two other maps. One of them shows the percentage of tree canopy and the second the percentage of impervious surface area within one pixel. In both cases the results were obtained with the use of regression trees model. Classification of aerial orthophotomaps with pixel size of 1m provided the training data. The model is based on three Landsat TM satellite images registered in spring, during the vegetation period and after leaves' fall. The images have undergone the Tasseled Cap transformation. The object shape parameters obtained through image segmentation have been used as well as the texture parameters assessed for them. Beside the image data, there have been used products based on the Digital Terrain Model (slope, aspect and positional index) and the soil database (soil available water capacity, soil organic carbon and soil quality) [16, 17].

3. Study Area and Image Data

3.1. Study Area

The catchments of Prądnik and Dłubnia cover rural, suburban and urban areas. Most of the area includes protected areas (Ojcowski National Park with its buffer area, Dłubniański Landscape Park, Landscape Park of Cracow's Valleys, Tenczyński Landscape Park). Over this area and in its surroundings there are also nature reserves and numerous features of natural importance. The loess soils of the area are among the most fertile soils in Poland.

On the other hand, densely urbanized parts of the city of Cracow lie within the both catchments. The expansion of urban areas and the migration of the town inhabitants to the surrounding villages, partly due to the attractiveness of the terrain, change the land cover. The changes partly have the form of modification. A suburban type of building developments (including impervious surfaces of paved drives and yards) appears in low-density rural areas with homesteads. Due to the high natural value and active urban sprawl process the catchments were chosen as the study area for evaluation of spatial changes of land-use and landscape functions based on multitemporal remotely sensed imagery.

3.2. Image Data

The imperviousness index has been assessed for current state and for the 1990s. Two types of image data have been used in the research. They were classified Landsat TM satellite images and colour aerial orthophotomaps. The latter ones provided calibration and verification data. The current calibration and verification data have been obtained from a 10-centimeter pixel size orthophotomap based on digital photogrammetric images taken on April 1st, 2009. The second orthophotomap has a 75-centimeter pixel size and is based on 1:26 000 scale images obtained in the PHARE programme in 1996–1997.

Landsat TM images (scene 188/25) have been obtained for both time periods. Cloudless multitemporal images taken during different seasons were aimed at. Unfortunately, it was impossible to gather data taken at the same time like the aerial photos.

Images taken at the closest time have been chosen as follows:

- current satellite data: 1.04.2007, 22.07.207, 7.08.2007,23.08.2007, 24.09.2007, 7.10.2007;
- satellite data for the mid-1990s: 12.03.1994, 2.07.1994, 22.10.1994, 24.08.1996, 4.03.1997,12.09.1997.

All the images have been orthorectified with the use of rigorous orbital model. The positional accuracy (*XY*) on the final orthophotomaps is up to 0.5 pixel (15 m). Atmospheric correction has not been done and the influence of topography has not been removed.

4. Impervious Index Estimations

4.1. Training and Testing Data

Fifteen testing fields (300 m × 300 m) have been selected for training and verification data. They include different kinds of urban, suburban, rural, industrial and commercial areas. Impervious surfaces have been derived in photo interpretation process from orthophotomaps for both time periods (Fig. 3).

Fig. 3. Sample result of impervious surfaces vectorisation on the aerial orthophotomap

The obtained vector files have been rasterised with 10 cm × 10 cm raster cell. The raster images provided the basis to assess the percentage of the impervious surfaces within pixels of the satellite orthophotomap which covered the testing fields. As a result, values of the imperviousness indices have been obtained for 1271 Landsat pixels. Values of these pixels in each spectral band of all images for both time periods form the input data along with the NDVI values assessed for them. The imperviousness indices form the target variable values. The obtained data has been randomly divided into learning set (1001 pixels) and testing set (270 pixels).

4.2. Regression Tree Models and Accuracy of Estimations

The data of learning set have been used to construct regression trees with Cubist 2.05 software. Data for both time periods have been modeled. For each time period following combinations of the input data have been tested:

- all spectral bands and NDVI values – all images (variant 1);
- all spectral bands – all images (NDVI values not included) (variant 2);
- only NDVI values – all images (variant 3);
- all spectral bands and NDVI value – selected image (each image has been modeled separately) (variant 4);
- all spectral bands and NDVI values – images obtained in spring, summer and autumn (4.03.1997, 24.08.1996, 12.09.1997 for the mid-1990s and 1.04.2007, 22.07.2007, 7.10.2007 for current state) (variant 5);
- only NDVI values – images obtained in spring, summer and autumn (variant 6).

In each case the result of the algorithm was a regression tree. The tree can also be presented as a set of rules which allow to assess the imperviousness index on the basis of the input data. An example of such rule for variant 6 (current state) has been presented below:

```
Rule 1: [854 cases, mean 0.507, range 0 to 1, est err 0.140]
    if
        ndvi_10 > -0.02
    then
        imp = 0.934 – 0.88 ndvi_10 – 0.75 ndvi_07 – 0.46 ndvi_04
Rule 2: [147 cases, mean 0.986, range 0.76 to 1, est err 0.017]
    if
        ndvi_10 <= -0.02
    then
        imp = 0.961 – 0.36 ndvi_07 – 0.25 ndvi_10 – 0.21 ndvi_04
```

where:

imp – imperviousness index,
ndvi_04 – NDVI value for image from 1.04.2007,
ndvi_07 – NDVI value for image from 22.07.2007,
ndvi_10 – NDVI value for image from 7.10.2007.

The obtained models have been applied to estimate the imperviousness index value for the set of verification data (270 pixels). The results have been compared with the index values obtained through the photo interpretation of aerial orthophotomaps. Tables 1–4 show the results of the comparison.

Table 1. Accuracies of imperviousness index estimation for mid-1990s (variants 1, 2, 3, 5, 6)

	Variant 1	Variant 2	Variant 3	Variant 5	Variant 6
Systematic error	0.022	0.021	0.012	0.013	0.014
Average absolut error	0.120	0.121	0.125	0.121	0.126
RMSE	0.158	0.158	0.166	0.164	0.168
Correlation coefficient	0.86	0.86	0.84	0.85	0.84

Table 2. Accuracies of imperviousness index estimation for mid-1990s (variant 4)

	12.03.1994	2.07.1994	22.10.1994	24.08.1996	4.03.1997	12.09.1997
Systematic error	0.019	0.032	0.055	0.014	0.028	0.025
Average absolut error	0.188	0.176	0.180	0.124	0.174	0.151
RMSE	0.241	0.232	0.232	0.169	0.220	0.204
Correlation coefficient	0.62	0.66	0.66	0.83	0.70	0.75

Table 3. Accuracies of imperviousness index estimation for year 2007 (variants 1, 2, 3, 5, 6)

	Variant 1	Variant 2	Variant 3	Variant 5	Variant 6
Systematic error	0.014	0.017	0.016	0.014	0.013
Average absolut error	0.113	0.112	0.129	0.114	0.134
RMSE	0.158	0.157	0.173	0.160	0.178
Correlation coefficient	0.86	0.86	0.83	0.86	0.82

Table 4. Accuracies of imperviousness index estimation for year 2007 (variant 4)

	1.04.2007	22.07.2007	7.08.2007	23.08.2007	24.09.2007	07.10.2007
Systematic error	0.019	0.012	0.006	0.003	0.013	0.016
Average absolut error	0.167	0.127	0.134	0.130	0.153	0.130
RMSE	0.218	0.167	0.182	0.175	0.197	0.180
Correlation coefficient	0.72	0.84	0.81	0.82	0.77	0.81

Variants 1 and 2 gave the best results for both time periods. The regression trees in these cases have been built on the basis of all accessible images. Variant 5 gave quite similar results. Here the data comes from only three images taken in spring, summer and autumn. The values of errors and correlation indices obtained in these three approaches are almost identical in case of the current state. Variant 5 gave slightly worse results than variants 1 and 2 for the 1990s. However, it is necessary to take into account the fact that in this case the images were registered in different years. In variants 3 and 6 the input data used to build the regression trees have been limited to the NDVI indices. Models in these attempts gave slightly higher imperviousness index assessment errors.

Worse result have been obtained for most attempts based on a single image (variant 4). For these models only three summer images (24.08.1996, 22.07.2007 and 23.08.2007) allowed to achieve the accuracy of imperviousness index estimation comparable with the ones from other variants.

To sum up, the best models provide the impervious index accuracy of ±16% for a single pixel. The average errors for the best models vary between 1.3% and 2.2%.

4.3. Applicability of the Model as a Monitoring Tool

One of the objectives of the research was to estimate the applicability of the tested method to monitor changes of impervious surfaces in land cover. For a set of verification data, difference of model-predicted imperviousness index values between both time periods have been compared with the difference of index values between both time periods obtained from the photo interpretation of aerial orthophotomaps (Tab. 5). The comparison has been done for all variants. In case of variant 4, the results were based on image data from August (24.08.1996 and 23.08.2007).

After the analysis, it can be stated that the change of imperviousness index values within one pixel has been modeled best in case of a triplet of images taken in spring, summer and autumn (variant 5). The assessment accuracy of change for this variant is ±14.5% and the correlation coefficient 0.46. The low value of mean average error (0.1%) should be stressed here.

Table 5. Accuracies of imperviousness index change estimation

	Variant 1	Variant 2	Variant 3	Variant 4	Variant 5	Variant 6
Systematic error	–0.007	–0.004	0.004	–0.012	0.001	–0.001
Average absolut error	0.109	0.108	0.112	0.125	0.109	0.114
RMSE	0.146	0.145	0.153	0.168	0.145	0.155
Correlation coefficient	0.424	0.448	0.413	0.340	0.465	0.402`

4. Conclusions

The aim of the presented research was to test the method of assessing the imperviousness index on the basis of middle-resolution satellite images with the use of regression trees. The task also included evaluation of the applicability of the method to monitor the changes of impervious surfaces coverage. The research has been done in the catchments of Prądnik and Dłubnia rivers. The imperviousness index has been assessed for two time periods – current state (2007) and the mid-1990s. The training and verification data for both time periods have been obtained from aerial orthophotomaps for urban, suburban, rural, industrial and commercial areas. Models built with the use of regression trees based on learning set of 1001 pixels have been verified by an independent testing set of 270 pixels.

In both time states the best assessment of imperviousness index have been achieved for the variants where the regression trees were built on the basis of all satellite data accessible for the time period. However, it is worth notifying that the variant with the input data limited to three images from spring, summer and autumn provided comparable accuracy of the results. These models have the systematic error between 1.3% and 2.2%, the mean error between 15.8% and 16.4% and correlation coefficient between 0.85–0.86 for the mid-1990s. For the year 2009 these values are respectively: 1.4–1.7%, 15.7–16.0% and correlation coefficient 0.86.

The accuracy of the imperviousness index obtained in the present research is comparable with the accuracy obtained with the use of regression trees in research reported in the literature [27, 28]. The imperviousness index accuracy for the same region (the southern part of Prądnik and Dłubnia catchment) was also assessed through photo interpretation of high-resolution satellite images by Hejmanowska *et al*. [14]. The results of the present research provide higher accuracy than the photo interpretation of panchromatic Ikonos images. Results of photo interpretation based on colour pan-sharpened images had lower mean error (12%) and higher average error (–4%).

Using a single satellite image to build a regression tree resulted in most cases in models which assessed the imperviousness index with lower accuracy.

However, for some images taken in summer, the obtained results have been similar to the ones based on multi-temporal images (see Table 1–4). For the mid-1990s the best single-image model was based on the image taken on 24.08.1996 (average error: 1.4%, mean error 16.9%, correlation coefficient: 0.83) and for the year 2009 on the images from 22.07.2009 (average error: 1.2%, mean error 16.7%, correlation coefficient: 0.84) and 23.08.2009 (average error: 0.3%, mean error 17.5%, correlation coefficient: 0.82).

Landsat TM satellite image from 24.08.1996 used in the present research was also used by Drzewiecki and Osak [11] to map the imperviousness index for the area of Cracow. In that study the method based on linear correlation between the imperviousness and vegetation indices was applied. The assessment accuracy was slightly lower than the one obtained in the presently tested regression trees method (average error: 2.0%, mean error: 19.5%).

The applicability of the tested method as a monitoring tool for changes of impervious surfaces coverage in land cover has been estimated in the present study. There have been compared results of imperviousness index value changes between the two time periods obtained for the tested pixels in the process of modeling and photo interpretation. The comparison showed that the variant that used a triplet of images from spring, summer and autumn to build regression trees provided the best assessment of the changes among all tested variants (see Tab. 5). Single-image models gave the worst results. The probable reason of such situation lies in the higher stability of models based on multi-temporal images. These models resulted in smaller average error and average absolute error values for both time periods. More images in the set of input data does not improve the results.

The comparison has shown high accuracy of imperviousness index change assessment for the whole population of pixels in verification dataset. The systematic error is 0.1%. However, the obtained assessment accuracy for a single pixel (±14.5%) can be too low for some applications. To sum up, it can be stated that the tested model can be applied to assess the changes of land cover on large areas (all the testing pixels cover the total area of 24.3 ha). In more detailed attempts the results should be verified on the basis of higher resolution images.

While assessing the applicability of the tested method to monitor the land cover changes it is necessary to stress that the present research does not explore all the possibilities that the regression trees method offers. The modeling was based only on spectral features of the satellite imagery. Supposedly, including textural parameters and non-image data in the model would improve the accuracy and stability of the assessment of imperviousness index for single time states, and, in result, also the accuracy of change assessment. Image stratification and separate models for different land cover types (e.g. models for urban, suburban or block estate areas) could improve the results as well.

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