Analysis of Land Cover Change in a Coastal Area using Remotely Sensed Data

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Abstract. Coastal area monitoring is a significant task in the national development and environmental protection. Study area of this work is the Baltic Sea Region, particularly focusing on the land cover changes in the coastal area from Cape Kolka to the Latvian-Lithuanian border. The aim of this research is to estimate and illustrate different examples of monitoring and mapping land cover changes in the coastal area using remotely sensed data – orthophoto, multispectral data and radar data. The results of the research include vector maps created from satellite images and comparison between different land cover value identification methods.

1. Introduction
Latvia’s sea coast is approximately 500 km long, the coastal zone during the last decades has been subjected to notable changes [1, 2].

The aim of this research is to estimate and illustrate different examples of monitoring and mapping land cover changes in the coastal area using remotely sensed data – orthophoto, multispectral data and high resolution infrared images. Research was done using vegetation indices and urban territories. It is new for the territory of Latvia to use high-resolution infrared images. Infrared images come together with traditional orthophoto. The quality of the Landsat images depends on cloud density. In the territory of Latvia, the cloud cover is observed for approximately 80\% days of the year.

Color infrared remote sensing and imagery are based on the fact that each type of land cover absorbs a particular portion of the electromagnetic spectrum and reflects the remaining portion, which can be recorded with a passive imaging system.
Determining how the object responds to the infrared light (absorbs, transmits, or reflects) one can explore such land cover conditions, which are undetectable on color imagery, as stressed vegetation, moist areas in the fields or plants.

Moderate resolution Landsat Thematic Mapper (TM) images have been used in various studies for land cover change in coastal area detection, such as automatic thresholding technique using vegetation indices [3, 4, 5]. Another method is satellite image classification to identify land cover classes like water and non-water, forest, man-made objects. Water identification is comparatively simple, because corresponding spectral class usually is well separated from other land cover classes.

Land cover classes, which we have detected, are bare soil, water, coastline, urban areas, cultivated land – agriculture, forests.

Landsat data are implemented in GIS and used for land use and land cover change detection in coastal areas, they can also be used in modeling of long term changes [8, 9, 10]. Nowadays Geographical Information Systems (GIS) can provide a suitable platform for data processing, analysis, update and retrieval.

2. Material and methods

2.1. Study area description

Research area of this work is the coastal area from Cape Kolka to the Latvian-Lithuanian border. The study area is situated next to the Baltic Sea and is subjected to the impact of west winds. The study particularly focused on the land cover change in the coastal area in 3 places (see figure 1):

![Figure 1. Study area and data.](image)

The areas are selected on the basis of the type of shore.

2.2. Data

The research was carried out using 4 Landsat 5 Thematic Mapper (TM) and one Landsat 8 Operational Land Imager (OLI) images corresponding to the 189-020 scene, it covered the period from July 1986 to July 2014. The TM and OLI images possess 30-meter spatial resolution with multispectral coverage ranging from visible lights to the middle infrared lights of the electromagnetic spectrum. We did not use the TM and TIRS (Thermal Infrared Sensor) thermal band data in this study.
All images used for the evaluation of the methodology were downloaded from the United States Geological Survey (USGS) Global Visualization Viewer (Glovis) website as Level 1T data with precision and terrain correction, and selected comparatively in cloud-free conditions. Images were orthorectified using second order polynomial and nearest neighbor method.

Preparing the processing algorithms and processing the data, the deference in satellite sensors was taken into account.

Bandpass wavelengths for Landsat 8 OLI and TIRS sensor, compared to Landsat 5 TM sensor:

**Table 1.** Bandpass wavelengths Landsat 5 and Landsat 8.

| Bands               | Landsat 5 Wavelength (micrometers) | Landsat 8 Wavelength (micrometers) |
|---------------------|------------------------------------|------------------------------------|
| Coastal aerosol     | -                                  | 0.43 - 0.45                        |
| Blue                | 0.45-0.52                          | 0.45 - 0.51                        |
| Green               | 0.52-0.60                          | 0.53 - 0.59                        |
| Red                 | 0.63-0.69                          | 0.64 - 0.67                        |
| Near Infrared (NIR)| 0.76-0.90                          | 0.85 - 0.88                        |
| SWIR 1/MIR          | 1.55-1.75                          | 1.57 - 1.65                        |
| SWIR 2              | 2.09-2.35                          | 2.11 - 2.29                        |
| Panchromatic        | 0.52-0.90                          | 0.50 - 0.68                        |
| Cirrus              | -                                  | 1.36 - 1.38                        |
| Thermal Infrared 1  | 10.40-12.50                        | 10.60 - 11.19                      |
| Thermal Infrared (TIRS) 2 | 11.50 - 12.51            |                                     |

**Figure 3.** Landsat 8 compared images.
Remote sensing image processing was performed using ERDAS Imagine, Integraph Geomedia and GRASS GIS.

The results compared with the reference data were obtained from the Latvian Geospatial Information Agency. As a reference, we used orthophotos and infrared images from research area.

2.3. Methodology

In order to determine land cover area changes in the coastal area, three remote sensing derived indices have been used: Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (MNDWI) and Normalized Difference Built-up Index (NDBI).

Using vegetation indices, we followed a four-step methodology to detect changes in the coastal area and create 6 land cover class vector maps. The first step was extracting the study area from a satellite image. Vegetation indices were calculated for the extracted area and then thresholded to binarize each image. A threshold binarization was used to separate the specific land cover classes. The threshold was determined on the basis of experiments for each vegetation index, and also on the knowledge of the common range of specific features. Finally, we classified individual changes.

The NDVI [6, 7] is the most commonly used spectral vegetation index, calculated by the formula:

$$NDVI = \frac{NIR - red}{NIR + red}$$

where NIR is a near infrared band, and red is a red band.

The value of this index ranges from -1 to 1. The common range for water is from 0.1 to -1. Soils generally exhibit a near-infrared spectral reflectance somewhat larger than the red, and thus tend to also generate rather small positive NDVI values (0.1 to 0.2). The common range for the forestry area is 0.6 – 0.8.

An urban and built-up area from data was detected using Normalized Difference Built-up Index (NDBI).

$$NDBI = \frac{MIR \cdot NIR}{MIR + NIR}$$

Figure 4. Ortophoto and infrared images.
where MIR is the middle infrared band.

Coastline and water objects (rivers, lakes etc.) are effectively mapped, detected through arithmetic manipulation of Modified Normalized Difference Water Index (MNDWI). The MNDWI is derived from the NDWI using the middle infrared instead of near-infrared [5, 11].

\[
MNDWI = \frac{\text{green} - \text{MIR}}{\text{green} + \text{MIR}}
\]

where green is the green band.

To correct the influence of soil brightness when vegetative cover is low Soil-Adjusted Vegetation Index (SAVI) was used:

\[
SAVI = \frac{\text{NIR} - \text{red}}{(\text{NIR} + \text{red} + L)*(1+L)}
\]

where \( L \) is soil brightness correction factor band. The value of \( L \) varies by the amount or cover of green vegetation.

3. Results

The method to combine different data proved to be relevant for the territory of Latvia. The combined images from Landsat images and Ortophoto images including the infrared images were used. To analyze different periods, we obtained the results of changes of the vegetation near the coastline. Using NDVI and supervised classifications for infrared images, we facilitate classification.

The coastline changes should be analyzed in the long term. A long period of observations allows detecting visible changes and geometric changes.

To ensure higher precision of the images in the shorter time period, infrared images that give precise information of the changes for geometry and visible information should be used. It is possible to get visible information from high precision orthophotos and geometrical information – from the combination of the image bands. The change of the vegetation for 10 years period was 5 %. Coastline changes depended on water level - 2 % amplitude.

4. Conclusion

Clouds can significantly reduce the quality of the results, especially using the green band for the processing. So more advanced methods should be used for eliminating cloud shadows before creating water masks to avoid false water area detection.

Geometric corrections are an important step before processing Landsat satellite images to ensure valid results.

At the same time, the limitation in spatial, spectral, and radiometric resolution in the remotely sensed data is an important figure affecting the estimation performance.

The technique produces vector files of land cover classes which can be analyzed using GIS to estimate rates of change over relatively long time periods or can be used for modeling long term changes.
5. References

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