Remote Sensing of Land-Cover/Land-Use in the Voghji River Basin, Syunik Region, Armenia

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1 Introduction

Detailed land-cover and land-use maps constitute an important basis for decision-making, as well as an important source of baseline information for environmental research. Changes in land-use/land-cover (LULC) in regions affected by mining activity are highly relevant for environmental degradation processes, such as deforestation, erosion and landslide occurrence. In Armenia, mining areas are predominantly located in the southern part of the country (Syunik province). LULC changes in this region often take place at small spatial scales, typically in the order of magnitude of a few hectares. Currently, no global or regional-scale LULC product (e.g. Bleyhl et al., 2017; Bontemps et al., 2015; Ran and Li, 2015) fulfills the requirements in terms of spatial resolution and thematic accuracy.

To better address the needs for improved base maps and academic staff skilled in image processing and analysis, the AUA GIS and Remote Sensing Lab proposed to carry out a LULC mapping exercise for the Voghji River basin based on freely available data from the novel Sentinel-1 and Sentinel-2 missions operated jointly by the European Space Agency (ESA) and the European Commission. The data from these missions are made available at no cost as part of the European Copernicus programme.

The main goals of this study were (a) to provide necessary base information on land use and land cover for further studies in the area on hazards related to tailings and reservoirs in the study area; (b) assess the usefulness of moderate-resolution Sentinels data for LULC mapping in the region in comparison to older products based on higher-resolution, but costly data; and (c) to build capacity at the AUA GIS and Remote Sensing Lab in optical and radar satellite data processing and image classification. In section 2, the study area, datasets and algorithms are described that were used and developed for the study. Results are reported and discussed in section 3. Section 4 concludes this report and an outlook on potential further work is given.

2 Methods and Material

2.1 Study area

Due to the aforementioned function of the study to provide base information for further studies on tailings, mines and reservoirs, the Voghji River basin was selected as study area as there are several tailing ponds (Artsvanik, Geghanush), mines (e.g. at Kajaran) and reservoirs (Geghi) present within the catchment. The entire catchment covers an area of 1244 km\textsuperscript{2} and is located in Syunik, the southernmost province of Armenia (Figure 1). Larger urban areas are Kapan and Kajaran. Elevation ranges between 628 m and 3800 m.
2.2 Datasets

2.2.1 Satellite data

Only freely available satellite datasets were used as input data for the land-cover/land-use classification. We chose data from the Sentinel-1 and Sentinel-2 missions as they currently offer the highest spatial resolutions. The available datasets are listed in Table 1. All scenes were acquired between July and beginning of October 2016 in order to minimise cloud cover, to have high reflectance in the Near Infrared (NIR) spectrum from green vegetation and to avoid confusion due to snow cover. For optical data, a virtually cloud-free scene acquired in August 2016 by the Multi-Spectral Imager (MSI) on board Sentinel-2A was chosen. The blue, green, red (bands 2-4) and one of the NIR bands (band 8) have a spatial resolution of 10 m, whereas the other bands have a resolution of 20 m (Drusch et al., 2012).

For the mapping of water bodies and urban areas, Sentinel-2 data were combined with Sentinel-1 SAR data. A series of 12 Sentinel-1 Interferometric Wide Swath (IWS) scenes for summer 2016 was downloaded from the Copernicus Data Hub. In order to take advantage of both backscatter intensity and interferometric parameters, single-look complex (SLC) products were used. The products have a spatial resolution of ca. 3 x 22 m (Torres et al., 2012). The data processing is described in the following section.

Figure 1: False-colour RGB composite (R: NIR, G: Red, B: Green channel) of Sentinel-2A image covering the study area. The inset shows the location of the study area within Armenia.
Table 1: Satellite datasets used as input data for the LULC classification.

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</tr>
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<tr>
<td>Sentinel-1B SAR</td>
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2.2.2 Field work

Field work took place on 3 and 4 October 2017. The locations where LULC was assessed are shown in Figure 1. Selection of the locations was motivated by the need to obtain a sample for every LULC class of interest. At the same time, the main limitation was accessibility due to the road network, steep terrain as well as access restrictions, mainly in the vicinity of the Artsvanik tailing pond and the Kajaran mine. In total, 31 sites were visited. The information was used to define areas for training the supervised classification applied to the Sentinel-2 scene. Examples of photos that were taken at the visited sites are shown in Figure 2.
Figure 2: Forest (top left), Open water and forested slope in the background (top right), shrubland (bottom left), agricultural field (bottom right).

2.2.3 Ancillary datasets
In addition to the aforementioned satellite datasets, a digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM) with a horizontal resolution of 1 arc-second, corresponding to ca. 30 m along the equator (Jarvis et al., 2008). The DEM was used for SAR data processing as well as for computing information such as local slope of the terrain to constrain the classification. Furthermore, a vector dataset on showing main roads in Armenia was available on the website of the AUA Acopian Center for the Environment¹, which was as well used in the post-processing of the classification results.

2.3 Data processing

Optical data processing
The Sentinel-2 scene was pre-processed to obtain surface reflectance values using the open software Sen2cor, which is provided by ESA. Sen2cor corrects top-of-atmosphere reflectance values for atmospheric effects with the help of the spectral information contained in the 12 MSI bands. The atmospheric correction was carried out for 10 m and 20 m spatial resolution. A false-colour composite of the corrected scene is shown in Figure 1.

SAR data processing
Built-up areas are typically characterised by a high backscatter coefficient due to the high density of corner scatterers in urban areas. At the same time, these permanent scatterers cause a high coherence of the phase information between overpasses of the same satellite (Pulvirenti et al., 2016). To exploit this behaviour, built-up areas were extracted based on the backscatter coefficient averaged over the summer season (July to beginning of October) and coherence between passes. To obtain these parameters, a processing chain based on Sentinel-1 Single-Look Complex (SLC) products was set up using the Sentinels Application Platform (SNAP, version 6.0). A flowchart of the processing chain is shown in Figure 3. For all the scenes, precise orbits were downloaded and used. Then, the SAR scenes were split to retain only the subswath and bursts covering the study area.

For computing coherence between subsequent passes of the satellite over the study area, two subsequent scenes were co-registered. Then, coherence between the co-registered scenes was computed over a moving window sized 15 x 3 (rg x az) pixels. After debursting the result, terrain effects were corrected using the Range-Doppler algorithm (Cumming and Wong, 2004). The obtained coherence images between subsequent image pairs were then averaged to obtain average coherence for summer 2016.

The backscatter coefficient, $\gamma^0$, was obtained from the split SLC products by first removing thermal noise induced by the radar antenna. Then the complex product was converted to detected intensity values and debursted. Speckle noise in the image was then reduced by first multilooking the image (averaging over neighbouring pixels) and then applying an adaptive GammaMAP filter over a moving window of 3 x 3 pixels. After filtering the image, terrain-flattening $\gamma^0$ (Small, 2011) was obtained using the DEM from the SRTM. The image was then geocoded using the Range-Doppler algorithm as in the case of coherence. $\gamma^0$ was then transformed to dB scale using the equation $\gamma_{\text{dB}}^0 = 10 \cdot \log_{10} \gamma_{\text{lin}}^0$.

¹ http://ace.aua.am/gis-and-remote-sensing/vector-data/
Figure 3: Processing chain applied to Sentinel-1 SLC datasets.

A false-colour composite in Figure 4 shows mean $\gamma^0$ in red, the standard deviation of $\gamma^0$ in green and average coherence in blue. Such RGB composites facilitate the distinction between different landcover classes based on multi-temporal SAR data (Amitrano et al., 2016; Schlaffer et al., 2016). The scenes used for Figure 4 were all acquired along an ascending pass. Forests produce high backscatter and low coherence and are, therefore, represented as red areas in the Eastern part of the study area. Built-up areas, on the other hand, additionally are characterised by high coherence between passes, and are hence displayed in violet tones. Examples are Kapan and Kajaran. However, under certain circumstances, vegetationless slopes which are illuminated by the side-facing radar beam also can display high backscatter and coherence, and can, therefore, be easily confused with urban areas. Such surfaces are mainly found in the western part of the study area. In order to account for this possible misclassification, additional filters based on terrain slope and terrain height were added to the workflow. Black areas show open water surfaces, where both backscatter and coherence are low, e.g. in the case of the Artsvanik and Geghi reservoirs visible in Figure 4.
Figure 4: RGB composite showing mean $\gamma_0$ (red), standard deviation of $\gamma_0$ (green) and average coherence (blue) for an ascending path of Sentinel-1 during summer 2016.

2.4 Image classification
2.4.1 Rural land use
The following LULC types were classified based on the 20 m multi-spectral Sentinel-2 image: agricultural areas, bare areas, forests, grasslands and pastures, shrubland, open water, mines, tailing ponds. A number of 372 training polygons were selected based on visual inspection of high-resolution imagery available in Google Earth. The training polygons were homogeneous in terms of their LULC class. Figure 5 shows the surface reflectance averaged over all the training areas. Classes are well separated in terms of their spectral profiles. As expected, classes with a high amount of green vegetation (forest, grassland, shrubland) have low reflectance in the visible spectrum and high values in the NIR range of wavelengths. Agricultural areas additionally show high reflectance in the Short-wave Infrared (SWIR) bands indicating low amounts of leaf and soil water content at this time of the year (August) (Fassnacht et al., 2016). Mines and bare areas have the highest reflectance values when averaged across all bands and have only small differences indicating some potential for confusion between the two classes. Tailings and open water are very well separated as water bodies absorb most of the incoming solar radiation at longer wavelengths, whereas tailings have rather high reflectances, especially in the visible spectrum.
5000 pixels were then randomly sampled from these training polygons, with the rest of the pixels contained within the training areas being available for validation. The sample was used for training a random forest classifier consisting of 500 trees. In many cases, random forest classification has been reported to display a higher performance for land-cover classification than parametric methods, e.g. maximum-likelihood classification (Bleyhl et al., 2017). Each pixel of the Sentinel-2 image was then assigned a class label based on the trained classifier. A majority filter with a moving window of 3 x 3 pixels was then applied to the classified image to regularise the result and remove isolated pixels. The classification and filtering were carried out using the R statistical language (R Core Team, 2017).

![Figure 5: Reflectance values for each class averaged over all training areas.](image)

2.4.2 Urban areas

Sentinel-1 $\gamma^0$ and coherence were used in combination with Sentinel-2 to derive built-up areas and to improve the classification of open water bodies and tailing ponds. Scenes acquired along both ascending and descending passes were used for this purpose (Table 1). A rule-based classification was used for deriving a preliminary classification of built-up areas based on $\gamma^0$, coherence, terrain slope and elevation (Table 2). The terrain-based rules were necessary as bare mountain slopes and ridges often produced high backscatter and coherence values similar to urban areas due to layover that was not corrected by the Range-Doppler terrain correction. After the rule-based classification, a minimum mapping unit (MMU) of 3 pixels was applied to the result to remove erroneous isolated built-up pixels.

<table>
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<th>Ascending</th>
<th>Descending</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma^0$</td>
<td>$&gt; -5.5$ dB</td>
<td>$&gt; -6$ dB</td>
</tr>
<tr>
<td>Coherence</td>
<td>$&gt; 0.7$</td>
<td>$&gt; 0.7$</td>
</tr>
<tr>
<td>Slope</td>
<td>$&lt; 10^\circ$</td>
<td>$&lt; 10^\circ$</td>
</tr>
<tr>
<td>Elevation</td>
<td>$&lt; 2000$ m</td>
<td>$&lt; 2000$ m</td>
</tr>
</tbody>
</table>
This first mask of built-up areas was then combined with Sentinel-2 data. For this purpose, the 10-m Sentinel-2 image containing four bands (R, G, B, NIR) was segmented into homogeneous objects using the Mean-Shift algorithm provided in Orfeo Toolbox. As input parameters, Mean-Shift uses a spatial radius $r_S$ (in pixels), a range radius $r_R$ giving the Euclidean distance in feature space and a minimum size for the derived regions (in pixels). The algorithms iteratively checks if the pixel values in a local neighbourhood of radius $r_S$ fall inside the Euclidean distance given by $r_R$. If they do, they are grouped in the same segment. Parameters were set to $r_S = 10$ pixels, $r_R = 15$ and minimum region size was set to 50 pixels based on trial and visual inspection of the segmentation result. The Sentinel-2 image was linearly scaled before applying the algorithm, so that the values of all bands range between 0 and 255. An example of the obtained segmentation for Kapan is shown in Figure 6.

All the segments containing at least 3 pixels of the preliminary built-up masks based on Sentinel-1 were then added to the urban class.

2.4.3 Open water and tailing ponds

In some instances, shadow pixels induced by steep terrain can be mistaken for water. Open water surfaces, on the other hand, typically return low SAR backscatter due to specular reflection. To counter this effect, water pixels on slopes steeper than 30° and having average $\gamma^0 > -16$ dB were reclassified to bare areas.

Tailing ponds are often mistaken with bare areas as they often show high reflectivity in the blue and green spectra, depending on the colour of the sludge suspended in the water. Hence, all mining and bare areas with $\gamma^0 < -18$ dB and on slopes < 30° were reassigned to the tailings class.

Figure 6: Segmentation of Sentinel-2 image in the urban area of Kapan.
2.4.4 Post-processing

The post-processing consisted mainly of applying MMUs to certain LULC classes and assembling the different classifications derived from optical and SAR data into a single LULC map. Firstly, urban areas derived as described in section 2.4.2 were superposed on the Sentinel-2-based LULC classification. Water bodies, mines and tailings were then superimposed on the result as some urban areas were falsely classified in mining areas, e.g. in the Kajaran mine. For tailings and mines, MMUs of 30 and 150 pixels, respectively, were applied.

2.5 Validation

The final LULC map was validated against a LULC map which was provided by the Water Resources Management project for the Southern regions of Armenia (funded by USAID). This reference map consists of a Level-2 Corine LULC classification (Büttner et al., 2010) and is based on RapidEye satellite imagery acquired in 2013. Due to the higher spatial resolution, it contains more LULC classes, such as “Industrial, commercial and transport units” and “Artificial, non-agricultural vegetated areas”. These classes, together with “urban fabric” were grouped into an “urban” class. As our LULC classification additionally contained the class “tailings”, which was not found in the reference map, we grouped together “mining” and “tailing” into a single class. The classification accuracy was based on a stratified random sample of 100 points per class. A confusion table was built based on this sample. Overall, producer’s and user’s accuracies are reported section 3. It should be noted that the classes “Urban fabric”, “Industrial, commercial and transport units” and “Mine, dump and construction sites” in the reference map seem to be based on manual image classification with a high level of generalisation, while our map is based on semi-automatic classification. So some substantial differences in class definition are to be expected and have to be taken into account when interpreting the derived accuracies. Furthermore, there is a time difference of three years between the reference map and the acquisition data of the imagery used in this study. Therefore, some moderate changes in land cover are to be expected. For example, our field visits showed that some shrubland areas had been cleared in the meantime and converted to agricultural areas. Once such site is shown in the bottom-right photo in Figure 2.

3 Results and Discussion

Error! Reference source not found. shows the result of the random forest classification. The overall landscape classes are well represented. Forested areas exist mainly in the eastern part of the catchment. The slopes of the valleys are covered by shrubland. Agricultural areas are mainly present east of Kapan along the Voghji River and the Artsvanik creek. The higher elevated areas are mainly covered by grasslands and, in the western part bare areas. The Kajaran mine, the Artsvanik and Geghanush tailings and the Geghi reservoir are also visible, with smaller classification errors. False water pixels occur in steep terrain, mainly due to terrain-induced shadows in the image. The valley floors were predominantly classified as bare areas. This is arguably due to the high amount of concrete and asphalt surfaces as well as due to the occurrence of mixed pixels in these areas as many features are below the image resolution of 20 m. In order to reassign these areas to a more realistic class, an additional class “Artificial Surfaces” was introduced. All bare area pixels shown in Error! Reference source not found. in a distance of < 100 m from main roads (as identified in the ACE main roads dataset), located on relatively flat ground (slope < 20 degrees) and having a classification probability < 80% were reclassified as Artificial Surfaces.

The obtained result after filtering, combination of Sentinel-1 and Sentinel-2, MMU application and reclassification is shown in Figure 3. In comparison to Error! Reference source not found., the final
result contains a class “Urban” and shows less isolated pixels due to the applied majority filter and MMUs. Also the false water areas caused by terrain-induced shadows are removed. Urban areas are mainly present around Kapan and Kajaran, as well as in the North-Eastern part of the catchment.

Figure 7: Result of the random forest classification of the 20-m Sentinel-2 image.

The obtained final map was validated against a high-resolution map based on the CORINE Level-2 LULC classification scheme. The confusion table and derived overall, Producer’s (PA) and User’s (UA) accuracies (in %) are shown in Table 3. An overall accuracy of 72% was obtained. The confusion table shows that the achieved accuracies varied strongly for the different classes. The highest PA and UA values were obtained for forest, mining (including tailing ponds as the reference map does not distinguish between the classes), open water and urban areas. The high accuracies for forest were expected due to the pronounced spectral profile of that class shown in Figure 5. In the other cases, additional information from Sentinel-1 SAR was applied to improve the classification. Agriculture has a very high PA but a very low UA of 43%, indicating that our map shows more agricultural areas than the reference map. These areas are mainly located in the south-eastern part of the catchment, close to the border with Azerbaijan. Confusion is predominantly with grassland and shrubland. Depending on the time of year, grassland and agricultural fields can have very similar spectral characteristics. Also, it is often hard to distinguish agricultural areas and grasslands in Google Earth imagery. Using additional imagery, acquired earlier during the vegetation period could help to make a clearer distinction as both
grassland and fields tend to be rather dry by mid-August. Different crop types also show typical seasonal behaviour when looking at vegetation index time series (e.g. Villa et al., 2015). It should also be noted that the reference map is based on imagery from 2013, three years before the data used here. Our ground assessment showed, for example, that some areas which were classified as shrubland in the reference map had in the meantime been converted to agricultural areas. Shrubland is in fact another problematic class for which PA and UA were 45% and 43%, respectively. Other than with agriculture, confusion was mainly with forest and grasslands. Correct classification of shrubland is typically difficult due to the large within-class variability of shrubland in terms of vegetation cover, percentage of woody vegetation, and terrain etc.

Other known limitations of the map include:

- Not all urban areas were correctly classified. Especially villages with a high proportion of green areas and low building density are often entirely misclassified as bare areas.

Table 3: Confusion table based on a stratified random sample of 800 points. User's and Producer's accuracies (last column and last row, respectively) are given in %.

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<thead>
<tr>
<th></th>
<th>Agriculture</th>
<th>Bare areas</th>
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<th>Grassland</th>
<th>Mining</th>
<th>Open water</th>
<th>Shrubland</th>
<th>Urban</th>
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Figure 8: Final LULC classification.
4 Conclusions and outlook

This preliminary study has shown the general applicability of using freely available optical and radar satellite data for deriving LULC patterns at the sub-national spatial scale (for areas $10^3$-$10^4$ km$^2$). Validation of the derived LULC map resulted in a high level of accuracy. Limitations of the approach are related to the occurrence of mixed pixels and surfaces whose spectral characteristics resemble those of bare areas, mainly in areas with a high amount of anthropogenic influence.

In future studies, some of these limitations may be overcome by using an object-based classification instead of the applied pixel-based approach. Such object-based methods have the advantage that similar pixels in a neighbourhood are first grouped into homogeneous objects. The classification can then not only use spectral reflectance values as input but also information about the statistical distribution within each local neighbourhood. Such approaches typically yield higher accuracies, especially when using high-resolution imagery (1 m – 5 m).

Moreover, data with higher resolution can be used for improving the LULC classification in areas where a high amount of mixed pixels occurs, e.g. in the valley floors. Many features there, such as roads, small gardens, etc., have dimensions below the spatial resolution of the imagery used in this study. Recently, AUA has gained access to PlanetScope data, which have a spatial resolution of 3 m and four spectral bands.

5 Acknowledgments

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6 References


