REGIONAL RETROSPECTIVE HIGH RESOLUTION LAND COVER FOR UKRAINE: METHODOLOGY AND RESULTS

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ABSTRACT

In this paper we propose a new methodology to automatically generate retrospective high resolution land cover maps on a regular basis for the whole territory of Ukraine. An ensemble of neural networks, in particular multilayer perceptrons (MLPs), is used for multi-temporal Landsat-4/5/7 satellites imagery classification with previously restored missing data due to clouds, shadows and non-regular coverage. This methodology was used to obtain land cover maps for the territory of Ukraine for three decades, namely 1990s, 2000s and 2010s, with overall accuracy more than 97%.

Index Terms — Land cover, classification, neural networks, retrospective, high resolution, remote sensing, Landsat, Ukraine.

1. INTRODUCTION

Land cover maps play an important role in studying and understanding processes in ecosystems and solving many applied problems of satellite monitoring. In particular, these maps are invaluable source of information to determine and quantify trends in land cover/use changes, improve the accuracy of classification and areas estimation, to analyze climate change and its impact on the biosphere. Land cover datasets based on satellite images have been used since the 1980s. They had low spatial resolution and not sufficiently accurate. A detailed review of the land cover maps and their characteristics are given in [1]. Low-resolution maps usually underestimate or overestimate certain land cover types. Therefore, creation of global and regional land cover maps based on high resolution satellite images (such as Landsat series at 30 m) is an extremely important task. In 2013-2014, several global maps have been made available [2]–[3], but they are not accurate enough at regional level.

In this study, we produced land cover maps for the whole territory of Ukraine based on the Landsat-4/5/7 images for three decades, namely 1990s, 2000s and 2010s. These maps allow estimation of the general trends of land cover/land use in Ukraine. This paper discusses methodological aspects to obtain retrospective maps of land cover based on Landsat images at regional scale, including all preprocessing steps for satellite imagery, formation of training and test sets, classification method and analysis of obtained results.

2. SATELLITE DATA DESCRIPTION

Visible (blue, green, red), near-infrared (NIR) and mid-infrared (MIR) bands of Landsat-4/5/7 at 30 m spatial resolution were used for classification. We used atmospherically corrected products for Landsat-4/5/7 provided by the US Geological Survey (USGS) EarthExplorer system. Each Landsat scene was reprojected to the Albers Equal Area (AEA) projection to enable equal areas at different latitudes. In order to handle areas in the images that were contaminated with clouds, we restored clouded and shadowed pixels using the approach proposed in [4]–[8]. In total, we used 117, 161 and 185 Landsat-4/5/7 scenes for producing maps for 1990, 2000 and 2010, respectively. For the 1990s time period, parts of Ukraine were covered by a single image only (Fig. 1). Therefore, we used Landsat images acquired in 1989 and 1991 to fill the gaps from 1990-year images due to clouds contamination.

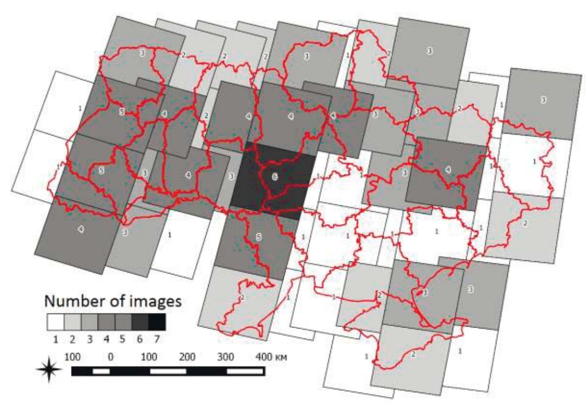

Fig. 1. Number of Landsat-4/5/7 images that cover whole territory of Ukraine in 1990.

3. TRAINING AND VALIDATION SETS CREATION

Classification was performed for six main land cover classes of the European Land Use and Cover Area frame Survey (LUCAS) nomenclature: artificial surface, cropland, grassland, forest, bare land and water. We formed training and test sets using a photointerpretation method with uniform spatial sampling over the territory of interest and proportional representation of all classes [8]–[10]. As a result, we gathered 14,261, 13,492 and 13,575 polygons for 1990, 2000 and 2010, respectively that cover whole territory of Ukraine evenly (Fig. 2). These polygons were randomly divided into training (50%) and test (50%) sets. We used a vector mask of inhabited localities for the whole territory of Ukraine in order to exclude from the consideration the territory of cities and villages.

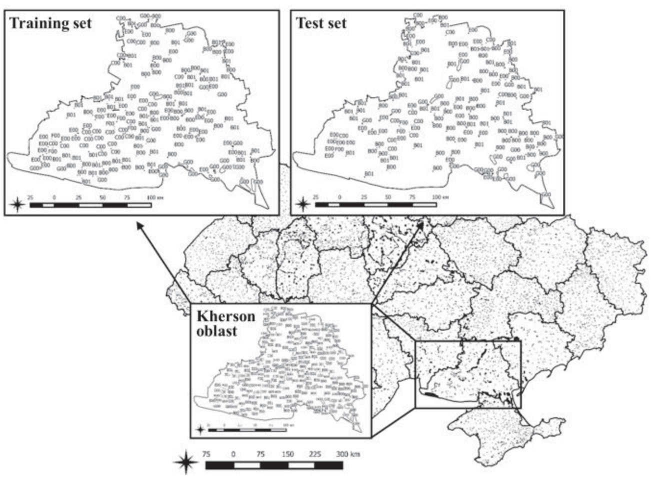

Fig. 2. Samples uniformly distributed over the whole territory of Ukraine. Example of random division of samples into training (50%) and test (50%) sets in Kherson oblast is shown.

4. DATA PREPROCESSING AND CLASSIFICATION METHOD

During preprocessing stage, Landsat-4/5/7 scenes were merged to multi-channel images for each path, row and date. The resulting images contained six spectral bands and three bands with shadow, cloud and cloud contours masks. For classification, we selected images with less than 50% of cloud cover. First, we restored cloudy pixels from time-series of images using self-organising Kohonen maps (SOM) [4]–[8]. After that, we provided classification based on the time-series of restored images available for the certain year [9]–[17]. Classification was done using an ensemble of neural networks, namely multilayer perceptrons (MLPs). During the neural network training cross-entropy error function was minimized

$$E(\mathbf{w}) = -\ln p(\mathbf{T} \mid \mathbf{w}) = -\sum_{n=1}^{N}\sum_{k=1}^{K} t_{nk} \ln y_{nk} ,$$

where $\mathbf{w}$ is the vector of weight coefficients, $\mathbf{T}$ is the set of vectors of target outputs in the training set; N is number of samples; K is the number of classes; t_{nk} is the target outputs; y_{nk} is the MLP outputs. Experiments showed neural network ensemble to improve classification accuracy compared to a single neural network [18]–[23]. After classification, each neural network gave a posteriori probability of the input pixel belonging to each class. In an ensemble, we estimated the average a posteriori probability from all networks and assign to the pixel class with the highest probability: $p_i^e = \frac{1}{L}\sum_{l=1}^{L} p_i^l$, $k^* = \arg\max_{k=1,K} p_k^e$, where k^* is the class assigned to the pixel by the ensemble of classifiers, p_i^e is a posteriori probability of the class, provided by the ensemble, p_i^l is a posteriori probability for each MLP, L is the number of classifiers in the ensemble.

We conducted two different experiments with Landsat time-series images fusion. Within the first approach, time-series of satellite imagery were fused in a single feature vector that was used for classification and generation of classification map. The second approach was to classify each image separately and then fuse multiple classification maps into a single map. Fusion of classification maps was done by maximizing average a posteriori probability of classes taking into account the number of cloud-free pixels. This was to ensure that only pixels of high quality are used for final decision on a land cover class.

As a result, first approach with fusion of all images during classification phase using neural networks ensemble provided the most accurate final classification maps and the the highest OA.

5. CRITERION FOR QUALITY ESTIMATION AND ACCURACY ANALYSIS

The developed methodology was used to generate land cover maps for the whole territory of Ukraine based on the Landsat-4/5/7 images for three decades: 1990s, 2000s and 2010s (Fig. 3). These maps make possible to estimate general trends of different land cover/land use in Ukraine in these time periods. For example, comparison of cropland areas for 1990, 2000 and 2010 revealed the increase of grassland instead of cropland, in particular, in the northern part of Ukraine. The main reason is that many lands were abandoned due to their low fertility, and cultivation of that land was not profitable and feasible for farmers.

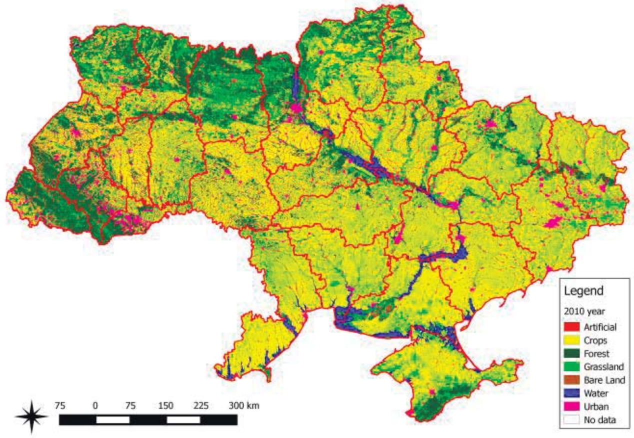

Fig. 3. Final crop classification map for the whole Ukraine using Landsat 5/7 satellite imagery in 2010.

To assess the accuracy of classification we used two approaches: accuracy assessment on independent test set and comparison of the class areas in land cover with official statistics. Test sets had 5353, 6111 and 6426 polygons for 1990, 2000 and 2010, respectively. Percentage of each class in the test set roughly corresponded to the class percentage at land cover for each oblast according to the statistics.

Table 1. The overall accuracy (OA), producer's accuracy (PA) and user's accuracy (UA) for the classification whole territory of Ukraine in 1990, 2000 and 2010 years

Year	2010		2000		1990	
Class	PA, %	UA, %	PA, %	UA, %	PA, %	UA, %
Artificial	100	79.9	73.3	83.9	97.8	92.7
Cropland	97.5	98.5	97.1	98.6	97.5	98.2
Forest	97.2	97.4	98.8	98.4	96.7	98.5
Grassland	90.7	85.4	90.5	84.6	90	82.5
Bare land	93.6	96.9	96.2	89.7	94.5	93.4
Water	99.5	99.8	99.5	99.9	99.5	99.7
OA, %	**97.5**		**97.7**		**97.3**	

The overall classification accuracy achieved in the study was more than 97% (Table 1). Accuracies for each individual class were more than 70%. The lowest accuracy was for artificial since this class had small representation in the sets and small area polygons, and for grassland since it is difficult to separate grassland from cropland. Another validation approach is the comparison of the areas of each class with official statistics. This comparison of the obtained areas and official statistics was provided for each oblast and for the whole territory of Ukraine for each time period (1990, 2000, and 2010). Though statistical data are not quite consistent and reliable, it is the only way to evaluate the classification accuracy not only in a limited area, but for the whole territory of Ukraine. As a result, overall accuracy for each oblast is higher than 88% and the average overall accuracy by oblast was equal approximately 97%. For most oblasts in Ukraine the ratio between difference in official statistics and classification results and oblast area was in the range of 5% to 15% for grassland and cropland and was within 5% for the forest class.

We also compared (Table 2) the accuracy of our classification for Ukraine with global land cover map GlobeLand30-2010 at 30 m resolution [24]. The overall accuracy of our classification for Ukraine was approximately 8% higher than GlobeLand30-2010. Also accuracy of grassland from our maps was +25% (producer's accuracy) and +55% (user's accuracy) better than GlobeLand30-2010. The main problem of the GlobeLand30-2010 map is that it does not take into account regional specifics.

Table 2. Overall accuracy, producer's accuracy (PA) and user's accuracy (UA) comparison of Land Cover30-2010 and GlobeLand30-2010.

Product	Land Cover30-2010		GlobeLand30-2010	
Class	UA, %	PA, %	UA, %	PA, %
Artificial	100	79.9	79.5	3.4
Cropland	97.5	98.5	99.4	85.3
Forest	97.2	97.4	89.9	95.9
Grassland	90.7	85.4	34.4	60.5
Bare Land	93.6	96.9	0.4	57.1
Water	99.5	99.8	96.6	99.9
Overall accuracy, %	**97.5**		**89.7**	

6. CONCLUSIONS

This paper presented a retrospective land cover mapping methodology for the territory of Ukraine based on Landsat data at 30 m resolution. The proposed methodology involved restoration of no-data pixels due to presence of clouds and shadows in Landsat optical images and classification of multi-temporal satellite images based on the fusion of all images in classification phase using neural networks ensemble. The maps were produced for the whole territory of Ukraine at 30 m spatial resolution. The overall accuracy was more than 97% for three different time periods (1990, 2000 and 2010), and considerable improved the quality of maps comparing to other land cover maps available for Ukraine at 30 m spatial resolution, namely GlobeLand30-2010 by approximately 8%. The proposed methodology allows one to automatically obtain land cover maps for the territory of Ukraine on a regular basis that is extremely important for many applications.

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