Two-level Model for Land Degradation Mapping on Multispectral Satellite Imagery

Sergey Stankevich¹, Anna Vasko¹, Victoria Gubkina²
Scientific Centre for Aerospace Research of the Earth
Kiev, Ukraine

st@casre.kiev.ua

National Mining University
Dnepropetrovsk, Ukraine
gubkinav@list.ru

Abstract — Two-level model for land degradation mapping on multispectral satellite imagery of low and medium spatial resolution is shown. First level model applies several different thematic classifications of source multispectral images, e.g. vegetation change, soil erosion etc. Second level gives data fusion of specific thematic classifications of the first level into final thematic map to improve accuracy and reliability owing to joint interpretation. Proposed model will be useful for information support systems to provide land management.

Keywords — remote sensing thematic mapping, twolevel probabilistic model, change detection, geospatial data fusion, multispectral satellite imagery, land degradation.

1 INTRODUCTION

Land is one of the most valuable and universal natural resources which mainly determine possibilities and perspectives of socio- economic development of the given area. Changing environment conditions may result in worsening and land degradation. The danger of land degradation is in exhausting food and natural resources, food chain pollution and negative influence on population health.

The term "land degradation" means decreasing or losing biological and economic productivity, a structure of natural and irrigable farm areas, forests and timberland in arid, semi-arid and sub-humid dry lands due to land use or activity of such processes as wind or water soil erosion, worsening physical, chemical, biological or economic features, long-term deprivation of natural vegetation cover.

Soil erosion is a natural geological process of upper soil layer destruction and bedrock dissociation under the influence of precipitation, wind, temperature fluctuations, landslides, crustal movements and earthquakes [1].

Biophysical, biochemical and socio-economic changes resulting in land degradation and desertification can be detected by multispectral satellite imaging.

2 INDICATORS

General indicators of land degradation are mechanical disturbances, water and wind erosion, salinization and bogginess. Either satellite imagery or indirect methods applied can help to detect the indicators majority.

Land littering is the process of accumulating production and utility wastes, stock-keeping inventory, building materials and the same ones in the places which are not appropriated for these goals.

Design, disposal, construction and implementation of objects which have negative influence on land condition, that is technical, reclamative and sewage treatment works, open pits, tailing dumps etc.

It is possible to detect water erosion occurring on lea lands using indirect indicator of vegetation condition. The areas of active water erosion are characterized by low vegetation index values [2]. Degradated and mineralized soils have higher spectral radiance in visual spectral bands. Decreasing vegetation cover density is a very important indicator of land degradation. The places of land polluted by oil and oil products in the sites of oil extraction, accidents at oil and product pipelines, technological emissions from industrial enterprises etc. are sure to be detected on satellite images. There can be shown burnt places caused by great and middle forest and steppe fires and the places of mass burning out of previous year dry grass.

The digital terrain elevation maps and multispectral imagery are master data. The results of their preliminary classification can be applied for developing the scheme of surface data collection and for choosing regions of interest (ROI) to complete final classification.

3 MODEL

The main task of multispectral satellite imagery processing is to extract the features being the most reliable to represent the land degradation phenomena. Vegetation cover change [3] and soil erosion dynamics [4] are the most adequate indicators of land degradation in Ukraine. To detect above mentioned indicators we

need multispectral imagery of Earth observation satellite systems of low and medium spatial resolution and auxiliary geospatial data – digital terrain elevations, soil maps, climatic characteristics of study area and so

on. Table 1 shows the main specifications of remote sensing satellite systems to be applied for land degradation mapping.

Satellite/Sensor	Orbit alti-	Spectral bands	Spatial resolu-	Swath width,	Revisit time,
	tude, km	Spectral ballas	tion, m	km	days
NOAA/AVHRR	863	5 (VNIR, SWIR,	1100	2700	0.5
		TIR)*			
NPOESS/VIIRS	833	22 (VNIR,	400, 800, 1600	3000	0.5
		SWIR, TIR)			
EOS/MODIS	697	36 (VNIR,	250, 500, 1000	2330	1
		SWIR, TIR)			
EOS/ASTER		14 (VNIR,	15, 30, 90	60	16
		SWIR, TIR)			
Landsat-5/TM	705	7 (VNIR, SWIR,	30, 60	183	8
		TIR)			
EO-1/ALI	705	9 (VNIR, SWIR)	30	37	16
EO-1/Hyperion		220 (VNIR,	30	7.7	
		SWIR)			
Envisat/MERIS	782	15 (VNIR)	275	1150	4
SPOT-5/HRG	822	4 (VNIR, SWIR)	10, 20	60	26
RapidEye/JSS-56	630	5 (VNIR)	6.5	77	1
ALOS/AVNIR-2	692	4 (VNIR)	10	70	4
Resourcesat-2/LISS-3	817	4 (VNIR, SWIR)	23.5, 70.5	140	11
Sich-2/MSU-8	668	4 (VNIR, SWIR)	7.8, 39.5	46.6	16

Table 1: Specifications of remote sensing satellite systems.

Vegetation cover changes are mapped using standard methods of change detection on multispectral satellite imagery [5]. But taking into consideration the conditions of soil erosion taking place on agricultural landscapes of Ukraine it should be noted that it is more advisable to use modified soil-adjusted vegetation index (MSAVI) instead of normalized difference vegetation index (NDVI), besides MSAVI can be calculated by this expression:

MSAVI =
$$\frac{2E_N + 1 - \sqrt{(2E_N + 1)^2 - 8 \cdot (E_N - E_R)}}{2}, (1)$$

where E_N and E_R are optical signals of multispectral image in near-infrared spectral band and in red one correspondingly [6].

The main factors of soil degradation occurring within Ukraine are water induced erosion (about 78%) and wind induced erosion (about 20%) [7].

Water induced erosion depends on the type and mineral structure of the soil, precipitation level, geometrical slope of hills and vegetation cover density. The value of erosion (mm per month) can be calculated by regression dependence [8]

$$Z_S = k_S Q^2 (\text{tg } \eta)^{1.67} \exp(-0.07 \text{ VC}),$$
 (2)

where k_S is soil erodibility coefficient, $k_S \cong 0.21$ is for Ukrainian black soils, Q is overland water flow (mm per month), tg η is terrain slope (%), VC is vegetation cover (%). Overland water flow is determined by ratio of rainfall precipitation P (mm per month) to water retention R (mm per month):

$$Q = \frac{(P - 0.2R)^2}{P + 0.8R},\tag{3}$$

where R depends on tabulated hydrologic soil-cover complex number CN shown as [9]

$$R = 25.4 \left(\frac{1000}{\text{CN}} - 10 \right). \tag{4}$$

As a rule vegetation cover is considered to be proportional to NVDI within the range of the study area [10]:

$$VC = \frac{NDVI - NDVI_0}{NDVI_1 - NDVI_0},$$
 (5)

where NDVI₁ is NDVI value for 100 per cent of vegetation cover and NDVI₀ is NDVI value for barren land.

Wind induced erosion is determined by interaction of structural soil particles with near-ground wind stream. Simplified model has the form of [11]:

^{*} VNIR – visible and near-infrared spectral bands, SWIR – short-wave infrared spectral bands, TIR – thermal infrared spectral bands.

$$Z_W \approx 0.059 (w - u) d^{-3.67}$$
, (6)

where Z_W is the value of wind induced erosion (mm per month), w is near-ground wind velocity (m per second), u is critical wind velocity (m per second),

$$u = 3.202 + 0.025d, \tag{7}$$

d is an equivalent diameter of soil structures (mm). Mainly, velocity of near-ground wind under fixed dynamic velocity of wind w_0 is determined by vegetation cover resistance [12]:

$$w = w_0 \exp(-0.0139 \text{ VC})$$
. (8)

4 DATA FUSION

Complexity and ambiguity of the problem of land degradation remote mapping leads to necessity of considering several different indicators i.g. vegetation change, terrain slope, precipitation regime etc. Special models for geospatial data fusion are needed to provide mutual account of this heterogeneous information [13].

Spatial classifications are applied to provide eventual results of various thematic processing of remote sensing data [14]. Spatial classification can be hard class pixel map or soft one, for example, probabilistic, fuzzy, subpixel fraction etc.

Thematic spatial classifications are built at the first stage of data processing of remote sensing. At the second stage the first stage data (partial classifications) are fused into final resulting classification to increase accuracy or reliability owing to joint interpretation. Second stage fusion models are built on classical statistical methods, for example, on Bayesian inference or are based on alternative methods, for example, on Dempster-Shafer theory.

Thus, a two-level model for thematic mapping in remote sensing is outlined (Fig. 1). A few partial classifications of source multispectral imagery (MSI) are carried out based on several independent models and then data of partial classifications are fused into final thematic map.

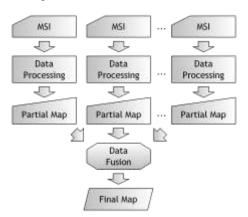


Figure 1: Dataflow chart of two-level thematic mapping.

5 RESULTS

To demonstrate the possibilities of described two-level model the land degradation mapping of Bobritsa village (situated 20 km south-western of Kiev) was carried out using EO-1/ALI multispectral satellite imagery from April, 2010 till April, 2011. Processing dataflow is shown on Fig. 2. Using source multispectral imagery (Fig. 2a) the MSAVI (1) was calculated and its changes were mapped. At the same time water (2) and wind (6) erosion were being evaluated and their changes were mapped as well (Fig. 2d).

Necessary auxiliary parameters were taken out directly from multispectral imagery (vegetation cover), ASTER GDEM digital terrain elevation data [http://asterweb.jpl.nasa.gov/gdem.asp] (Fig. 2c, terrain slope), soil [http://eusoils.jrc.ec.eu/ukraine/] and climate [http://www.climatetemp.info/ukraine/] data warehouses (soil erodibility, soil hydrologic complex number, rainfall precipitation and wind velocity).

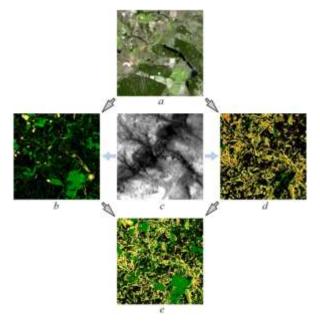


Figure 2: Processing dataflow for land degradation mapping.

a – source EO-1/ALI multispectral satellite image, b – MSAVI vegetation index change of the study area, c – ASTER GDEM digital terrain elevation data of study area, d – soil erosion changes of study area, e – final map of land degradation of study area.

At the end of processing partial thematic maps Fig. 2b and Fig. 2d were fused into final map of land degradation Fig. 2e in accordance with the Fig. 1 model.

6 CONCLUSIONS

Described two-level model for land degradation mapping on multispectral satellite imagery will be useful to automate the monitoring of natural and agricultural areas in the zones which are subject to technogenic and environmental hazards. Among the model advantages are improved reliability (due to integration of essentially different geo-ecological indicators) and flexibility (due to architecture openness and simplicity of assimilation of new processing dataflows).

Proposed model will be helpful when implemented into the information support system for land management

Further research should be aimed at: i) improvement of available specific models for assessment individual indicators of land degradation; ii) development of new and more effective data fusion engine of heterogeneous data; iii) validation of data obtained at ground test sites with carrying out field geo-ecological research.

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