LAND USE MAPPING USING VISUAL AND DIGITAL INTERPRETATION OF TM AND GOOGLE EARTH IMAGES IN SHIRVANDARASI WATERSHED (NORTH-WEST OF IRAN)

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ABSTRACT: This study was conducted to use Landsat and Google earth (digital globe) imagery for land use mapping in ShirvanDarasi watershed in north of Ardabil province. A TM image by considering seasonality and phenological pattern was selected. Pre image processing stages such as atmospheric and geometric correction, and topographic normalization were conducted before image utilization. Moreover, image of the study area extracted from Google earth and imported to ArcGIS environment. Ancillary data such as DEM and slope were derived and added to the datasets of this study for controlling different land uses. Field visit and appropriate ground control points were collected for visual and training area selection, and finally land uses such as rangeland, orchards, irrigated and dry farming, residential and industrial areas, roads and out crops were considered and land use of the selected images were derived. Finally accuracy of the produced maps were computed and compared. Results show that, the produced map of the image of Google earth using visual interpretation showed high overall accuracy (90%) and Kappa (0.94). On the other hand, results of the digital interpretation of TM image (unsupervised) showed very low overall accuracy (24%) and Kappa (0.24) statistics.

1. INTRODUCTION

Information on land use is required in many aspects of sustainable management of land resources and policy development, as a prerequisite for monitoring and modeling land use and environmental change, and as a basis for land use statistics at all levels. An in-depth knowledge of the capabilities and limitations of the resource base will enhance optimization of sound land uses in an environment where policies will support such choices. In many countries, land-use information is lacking despite many efforts being undertaken to generate information through field surveys, projects and local efforts (Jansen & Di Gregorio, 2004).

Land use classification and evaluation surveys using remote sensing have been conducted successfully for many studies (i.e. Wu et al. 1985; Ratanasermpong et al. 1995; Baban, 2001). In Iran, Landsat Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM^{+}) data have been used for land use surveys and the results have showed that it is possible to map different land uses. Landsat imagery and GISs have also been used to detect land use changes for different purposes. Moreover, there is increasing evidence that Google earth images extracted and imported to GIS and visually interpreted for land use mapping. However, there is little knowledge about the capability of Landsat and Google earth data for the north west of Iran. This study aimed to examine and compare the capability of Landsat TM and derived imagery from Google earth for the purpose of land use mapping using visual and digital interpretation based on the ShrivanDarasi Watershed.

2. MATERIALS AND METHODS

2-1. STUDY AREA

ShirvanDaraci with 14666 ha is located in North West of Iran (north of Ardabil province / 47 43' 15" to 47 52' 49"E and 38 35' 30" to 38 35' 34" N / Figure 1). Altitude varies from 938 to 4781m. Annual precipitation varies from 217 to 524mm, mean annual temperature is 8.6 to 17.15ºC (by considering high elevation variation), and generally with cold semi-arid climate. More than 50% of this watershed is mountainous area, the major land uses are rangeland (more than 80%) and rest of the land uses are dry farming, irrigated farming, gardens (horticulture) and residential lands, respectively.

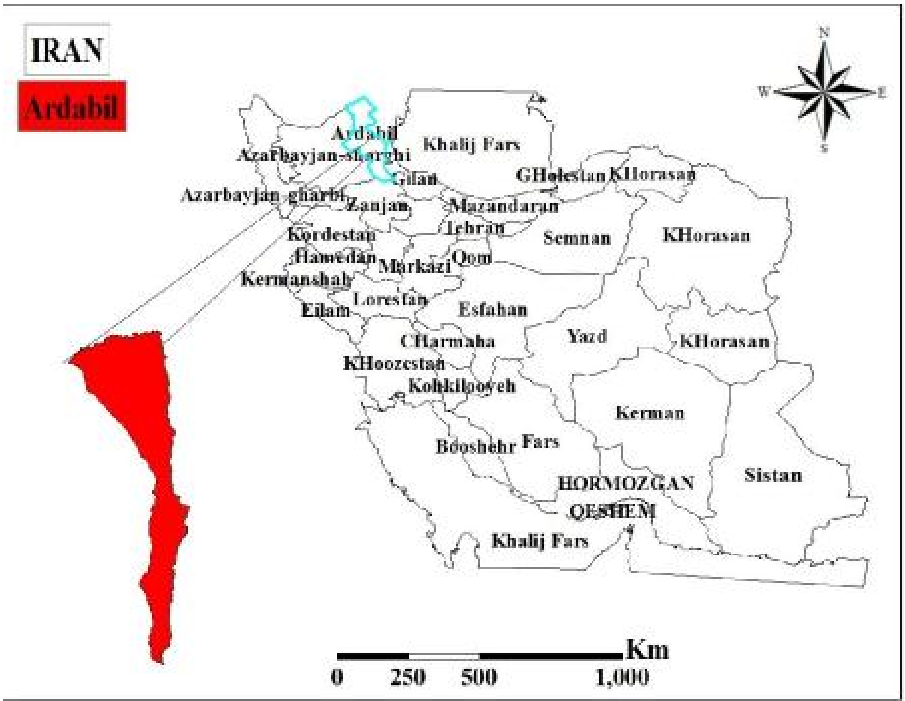

Figure 1: Study location in Iran and Ardabil province

2-2. IMAGE SELECTION AND PREPROCESSING

By considering seasonality and phenological patterns of the study area, according to the 3843m altitude differences, there is no considerable seasonality variation, but phenological stages are different (there are 4 discernible seasons, but with different temperature and type of precipitation in different elevation, phenological stages are different). However, by considering these issues the best time of the image selection to cover both low and high altitude areas was to select an image in late July of each year. Because of the moisture effects on the image acquired data (Bastin *et al.*, 1993), 15 days before image selection were

considered, however there was no considerable rainfall in this period. Therefore, an image by considering seasonality and phenological patterns and moisture content was selected.
The c Landsat ETM+ copyright 2012 (166-34/ the available image/ TM 27/07/2010_c) was selected based on average of the full growth of annuals and perennials for this study (average of the watershed). Obtained image has been registered to the UTM map projection with a d*a*tum of the WGS84. However, according to the collected Ground Control Points (GCP) and other GIS layers such as registered topographic maps, acquired images were still required to be rectified by affine transformation model to the WGS84 to align accurately with the GIS layers and collected GPS points. In image rectification Root Mean Squire (RMS) errors of 41 points selected from 150 GCP were less than 2 pixels and total RMS was 0.25 pixels. Image preprocessing stages, including atmospheric, geometric and radiometric corrections, topographic normalization and image enhancements, were conducted before image utilization (Chavez 1996; Lillesand & Kiefer, 2000).

2-3. VISUAL INTERPRETATION

Google earth and TM images visually interpreted using 7 classes including: rangeland (R), dry farming (IF), **g**arden (horticulture) and wild tree complexes (GT), residential areas (Ria), irrigated farming (IR), out crops (OC), water ways (Ww).

2-4. DIGITAL INTERPRETATION (TM IMAGE)

Selected TM image was classified using unsupervised (7 classes) and supervised methods (7 classes based on training areas for those defined classes). Maximum likelihood algorithm was considered in supervised classification.

2-5. FIELD DATA COLLECTION

For accuracy assessment 148 samples on an area of 100×100m of different land uses were recorded. Center of each plot was recorded using GPS. Land use and land cover data were recorded. The data from the GPS to the computer were transferred using OziExplorer3.95.4q software.

2-6. ACURACCY ASSESSMENT

Equations 1 and 2 were used for overall accuracy and Kappa coefficient calculations.

$$OA = \frac{1}{N\left(\sum P_{ii}\right)}$$ Equation 1

Where: OA, overall accuracy; N. The total number of pixels, the experimental; Pii. Class correctly classified pixels in total.

$$K = \frac{\left(OA - \frac{1}{q}\right)}{\left(1 - \frac{1}{q}\right)}$$ Equation 2

Where: K-factor kappa; q-number of land cover classes.
Because of road accessibility problem out crop classes were not assessed and included in accuracy assessment processes.

3. RESULTS

The classified maps from visual interpretation of TM and Google earth images are presented in Figure 2A&B. The classified maps from digital interpretation of TM image are presented in Figure 3A&B. Seven land uses from two images including TM 2010 and Google earth are extracted and mapped. Area of each land uses were calculated in hectare and percent (Table1). The thematic content of the classified image was quantitatively assessed for accuracy by evaluating the correspondence between the class label assigned to a pixel in the image and the 'true' class as measured on the ground. Accuracy assessment results of the produced maps are presented in Table 2. By considering the accuracy assessment results of the produced maps the Google earth derived image has the best result and unsupervised map has the worst result. According to Google earth derived map the main land use is rangeland with about 10292 ha (70%) of the study area. Out crops with about 361 ha (2%) is the smallest land use in this watershed.

4. DISCUSSION

During field work it was evident that topography was the main influence factor on the distribution of land use on the watershed. Examining the classified image reinforces this observation. Low-lying areas of alluvium with area covered by irrigated farming, dry farming, garden and wild trees (mixed horticulture) and water way. On the other hand, mountainous area covered by rangeland mainly and in summit of the Sablan is covered by out crop. There were some difficulties in distinguishing between different land uses, particularly between residential areas, waterway with rangeland using digital interpretation. First, their existence in small spatial units produces mixed class with each other, which exist nearby. These results clearly suggest that the spectral and spatial characteristics of Landsat TM data could not serve to identify and map land use types in ShrivanDarasi watershed.

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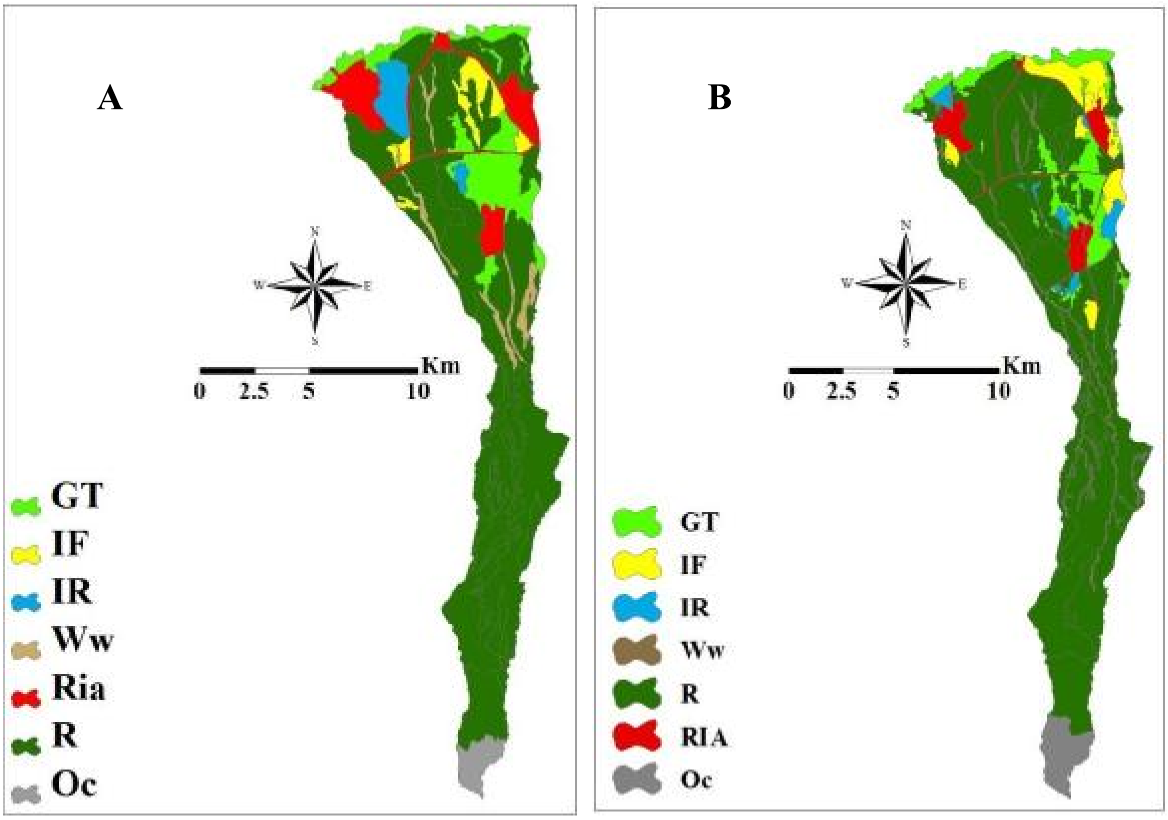

Figure 2: Derived land use maps from visual interpretation: A) Landsat TM 2010 image, B) Google earth /digital globe 2009

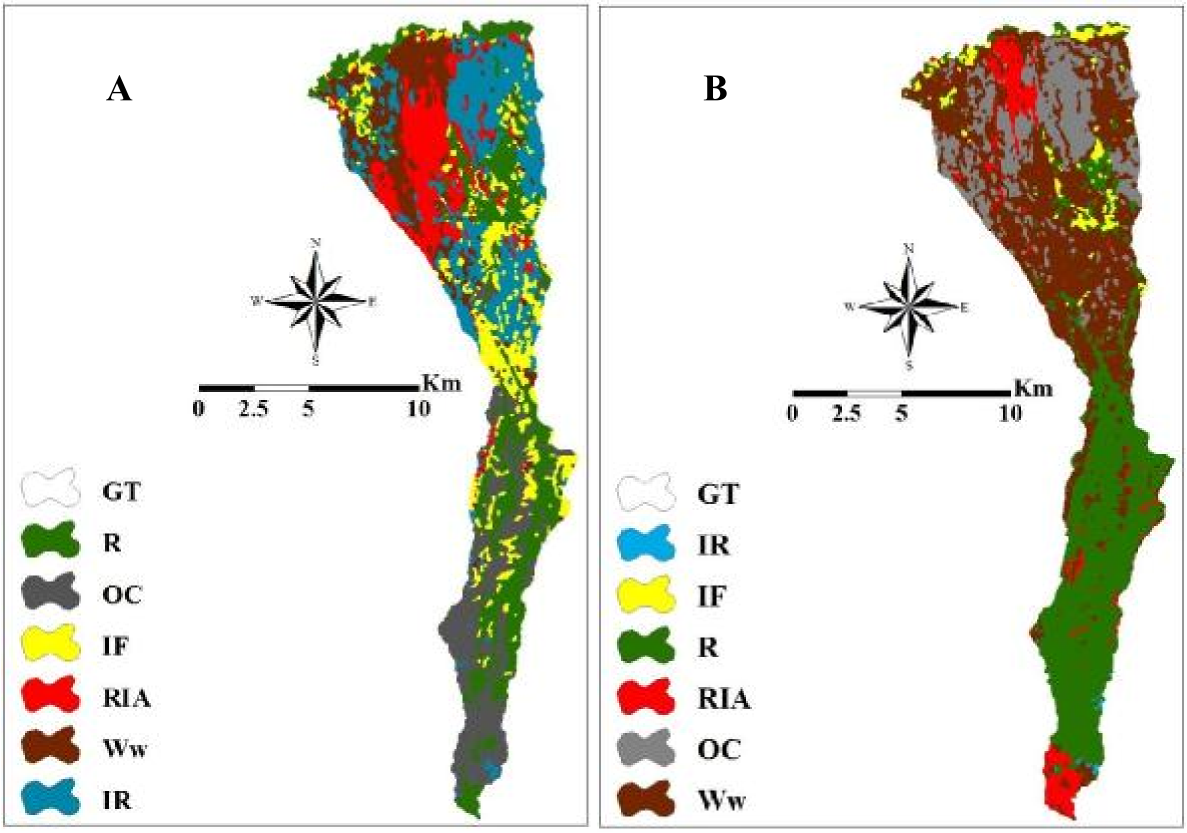

Figure 3: Derived land use maps from digital interpretation: A) unsupervised classification (TM image), B) supervised classification (TM image)

Table 1: Area information derived from 4 produced maps

	Visual interpretation				Digital interpretation (TM image)			
	TM 2010		Google earth 2009 (Digital globe)		Unsupervised classification		Supervised classification	
	Area (ha)	Area %	Area (ha)	Area %	Area (ha)	Area %	Area (ha)	Area %
Rangeland	9826.40	67.00	10292.20	70.18	5954.13	40.59	4417.16	30.11
Irrigated farming	530.89	3.44	319.21	2.18	60.10	0.40	1032.24	7.03
Dry farming	512.24	3.49	319.21	2.18	1477.33	10.07	1575.13	10.74
Garden & Wild tree	1719.23	11.72	1381.34	9.42	429.30	2.92	848.05	5.78
Out crop	361.38	2.46	566.58	3.86	51.79	0.30	2365.48	16.12
Water way	470.38	3.21	427.41	2.91	932.30	6.32	1775.96	12.10
Residential area	1272.48	8.68	787.94	5.37	5761.02	39.28	2651.96	18.08

Table 2: Summary table of error matrix and accuracy of visual and digital interpretation for map classes

	No. of GCP	Visual interpretation				Digital interpretation (TM image)			
		TM 2010		Google earth 2009 (Digital globe)		Unsupervised classification		Supervised classification	
		Pro. A.	User A.	Pro. A.	User A.	Pro. A.	User A.	Pro. A.	User A.
Rangeland	81	0.71	0.87	0.77	0.93	0.19	0.55	0.26	0.54
Irrigated farming	5	0.20	0.20	0.71	0.71	0.33	0.08	0.20	0.50
Dry farming	13	0.62	0.57	0.69	0.5	0.50	0.22	0.46	0.33
Garden & Wild tree	34	0.85	0.73	0.90	0.93	0.12	1	0.15	0.63
Out crop	0	-	-	-	-	-	-	-	-
Water way	1	1	0.25	0.00	0.00	1	0.6	0	0
Residential area	14	0.79	0.52	1	0.66	0.38	0.08	0.71	0.13
Overall accuracy		72		90		24		43	
Kappa coefficient		0.74		0.94		0.24		0.43	