RADIOMETRIC CALIBRATION METHODS FOR CHANGE DETECTION ANALYSIS OF SATELLITE DATA AIMED AT ENVIRONMENTAL RISK MONITORING.

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ABSTRACT:

The research proposes the investigation of automatic methods, in order to prepare next Change detection techniques for environmental risk monitoring, executable on satellite data that are heterogeneous for spatial and spectral resolution. Homogenization and registration in an unique digital information environment, with the identification and quantification of variation occurred in a chosen test area, will permit the rapid evaluation of risk level and the consequent planning of prevention and intervention works. To that end, the most suitable radiometric correction techniques and the development of innovative algorithms and automatic methodology were executed, in order to improve the accuracy level of results. With this aim, the relative radiometric normalization *scene-to-scene* with ELC (*Empirical Line Calibration*) and MAD (*Multivariate Alteration Detection)* techniques on Landsat ETM+ and ASTER data were investigated. In the ELC technique Pseudo-Invariant Features (PIFs) were manually selected, whereas the Features to derive the normalization coefficients were automatically identified with the aid of an algorithm based on MAD transformation. The exactness of both the procedures was evaluated by executing a quantitative and qualitative comparison of gains and offset values resulted in the analysis.

1. INTRODUCTION

In the last years the field of Environmental Risk monitoring has raised a particular importance, also according to minor short-term stability and predictability of climatic events.

The mitigation of the effects of disasters requires relevant information in real time. Since disasters that cause huge social and economic disruptions normally affect large areas or territories and are linked to global change, it is not possible to effectively collect continuous data on them using conventional methods. Remote sensing technology, with its capability of collecting digital data at global and regional scales rapidly and repetitively, can be used to monitor the current situation before, during or after disaster. Moreover, such technology is a considerable communication medium (Ottichilo, 2003) and the processed data can be integrated in GIS for further analysis.

The prerequisite in using remote sensing data for digital Change detection is that the process can identify change between two (or more) dates that is uncharacteristic of normal variation.

According to Jungho and Jensen (2005) the goal of remote sensing Change detection is to (a) detect the geographic location of change found when comparing two (or more) dates of imagery, (b) identify the type of change if possible, and (c) quantify the amount of change.
To be effective, change detection approaches must maximize inter-date variance in both spectral and spatial domains (i.e. using vegetation indices and texture variables) (Rogan et al., 2004). As past experiences pointed out, digital change detection is a difficult task to perform. An interpreter analysing aerial photography will almost always produce more accurate results with a higher degree of precision (Edwards, 1990), even if different interpreters could produce different results with substantial data acquisition costs. Apart from offering consistent and repeatable procedures, digital methods can also more efficiently incorporate features from the non-optical parts of the electromagnetic spectrum (Coppin et al., 2004).

Numerous methods have been developed for change detection: e.g. change detection using write function memory insertion; multi-date composite image change detection; image algebra change detection using univariate image differencing, image regression, image rationing, vegetation index differencing; manual on-screen digitization of change; postclassification comparison change detection; knowledge-based vision systems for detecting change (Ġuler et al., 2007).

The limits of these techniques are connected to the difficulty to achieve absolute accuracy (Meyer et al., 1993), to the temporal stability of sensor calibration, to the level of correlation of bands, and to the geometry of sun-earth-sensor.
Such elements do not enable an effective comparison among images, because such data have not a common radiometric reference.

The radiometric calibration makes this technique particularly advantageous and can be absolute or relative. Such pre-processing method is important in land cover classifications and for many other applications, such as image mosaicing or tracking vegetation indices over time etc. (Yang and Lo, 2000). Furthermore, if change detection procedures, such as image differencing or change vector analysis, is preferred it must generally be preceded by radiometric calibration (either absolute or relative), in order to quantify temporal phenomena from multi-date imagery.

Absolute radiometric correction of multi-temporal satellite imagery requires atmospheric corrections associated with the atmospheric properties at the time of the image acquisition. The digital number of a pixel is converted to a percent reflectance value using established transformation equations or atmospheric models (Song et al., 2001).

Data for the characterisation of the relevant atmospheric processes modulating the incoming radiation at the satellite sensor require auxiliary data of parameters, such as the content of aerosols, ozone or water vapour in different atmospheric layers (Mitchell et al., 1993;Vermote et al., 1995).

Whenever atmospheric parameters for historical dates of imagery are not available or absolute surface radiances are not necessary, a relative calibration (named by many authors as normalisation) of the satellite images to a master scene, based on the radiometric information intrinsic to the images, is an alternative (Hall et al.,1991; Furby et al., 2001; Du et al., 2002;).

One advantage of this procedure is that the original radiometric condition of the reference image is retained, obviating the computational effort required to convert each image to units of radiance or reflectance (Yuan and Elvidge, 1996). With this aim Jensen (1996) suggested the Multiple-date Empirical Radiometric Normalization. This method involves the selection of ground targets whose reflectance values are considered constant over time, otherwise named by Schott et al. (1988) as Pseudo-Invariant Features (PIFs). Selection of such ground targets results in radiometric normalization that is entirely dependent on the abilities and local knowledge of the analyst (Janzen et al., 2006) and, consequently, it is subjected to unavoidable errors in the procedure accuracy. A further limit is the case in which satellite data are afflicted by intrinsic radiometric problems with different climatic conditions related to acquisition phase, as cloud or snow covers (Moran et al., 1992; Caprioli at al., 2006).

Although the principle is similar (invariant pixels are used in an regression approach), MAD transformation (Canty, 2005) is fully automatic, overcoming the above-mentioned problems with the concentration of information on the global change rate. Moreover, it is invariant compared with linear effects caused by atmospheric conditions and sensor calibration (Nielsen et al., 1998). The main progress is the automatic identification of ”no change pixels”, that are homogeneously distributed over the entire image and different surface types.
In this study the radiometric normalization scene-to-scene with ELC (Empirical Line Calibration) and MAD (Multivariate Alteration Detection) techniques on Landsat ETM+ and ASTER data were analysed, by executing a quantitative and qualitative comparison. With the ELC technique Pseudo-Invariant Features (PIFs) were manually selected, whereas the Features to derive the normalization coefficients were automatically identified with the aid of an algorithm based on MAD transformation (Canty et al., 2004).

2. DATA AND METHODS

The three Landsat ETM+ data used in this study were acquired over Aurunci chain, in southern Apennine of Lazio (Italy), on September 24, 1999 (Fig. 1A), April 6, 2001 (Fig. 1B) and February 2, 2002 (Fig.1C).

Every image was a subset of the whole scene with the dimensions of 650 × 650 pixels. This territory was chosen because it presents a diversified morphology with active anthropic dynamics and permits to test the effectiveness of normalization algorithms, both the consolidated (ELC) and the innovative (MAD) ones, even in unfavourable climatic and territorial situations. With this aim, Landsat ETM+ satellite data, acquired in different period of the year, were analysed, with various atmospheric and illuminated conditions.

In order to validate both the procedures further investigations were executed on ASTER data with different intrinsic image characteristics and a subset area test of dimensions 700 × 700 pixels (Fig. 2A and Fig. 2B). The acquisitions were made on June 24, 2003 and September 14, 2004, that is with similar atmospheric conditions, on a flat coastal territory of Apulia (Italy).

The above-mentioned intrinsic characteristics of data had permitted the better evaluation of results, by executing a quantitative and qualitative comparison of gains and offset values obtained on diversified territorial and atmospheric contexts.

Before the execution of radiometric correction procedures, the images were co-registered by means of *Image-to-Image* technique provided by ENVI image processing software. 30 GCPs (*Ground Control Points*) on Landsat ETM+ 1999 data and 28 GCPs on ASTER 2003 data, as reference images, were identified.
With this aim, a not parametric model, based on the 3° order polynomial function, was used and a value lower than 0.5 pixel for RMS was obtained. Next, the whole set of images were resampled with *Nearest Neighbour* method (30 m for the Landsat ETM+ data and 15m for ASTER data), in order to not alter heavily the radiometric content of images.

In the first phase of this study, related to ELC processing (Envi User’s Guide, 2003), the pixel indispensable to calculate the calibration parameters (*gain* and *offset*) were manually selected from the ground truth data. ENVI refers to the slope curve as Solar Irradiance and the intercept curve as Path Radiance what we had intended respectively as *gain* and *offset*.

With this aim some targets or pseudo-invariant regions (Sand, Buildings, Water, Bare soil, Rock) from the positional point of view and with similar radiometric characteristics were selected.

Figure. 1A –1B – 1C. Landsat ETM+ data over Lazio (Italy): September 1999, April 2001, February 2002

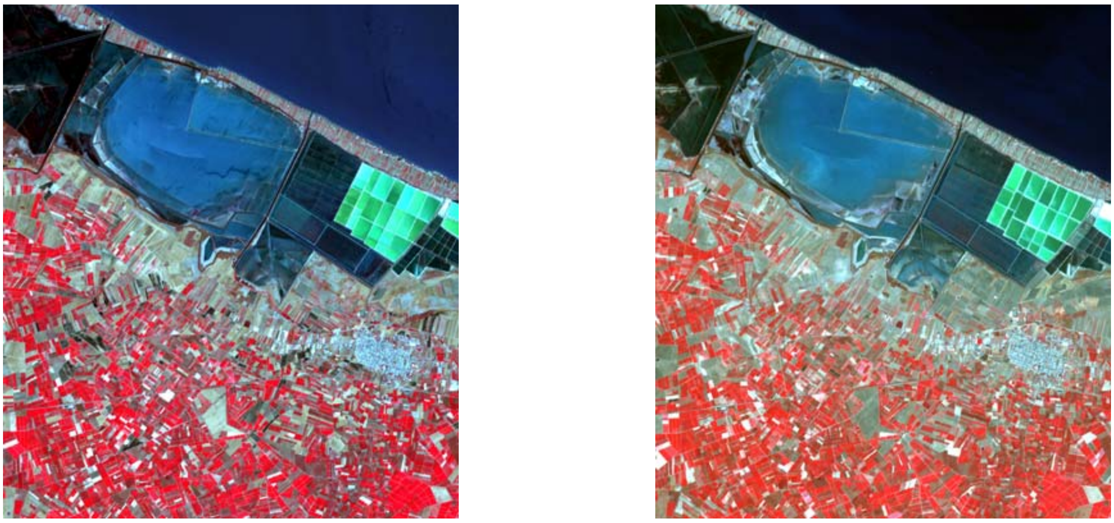

Figure. 2A - 2B. ASTER data over Apulia (Italy): June 2003, September 2004

The dimension of every target was approximately of 5 x 5 pixels, making the selection with the help of band ratio and principal component analysis.

In a comparative way MAD technique was next implemented by using CDSAT - ENVI plug-in. Such procedure permitted the automatic identification of invariant pixels, while the calibration parameters were determined with orthogonal regression. As Canty et al. (2004) pointed out, while in the model for least squares regression the x is considered as an independent predictor and is assumed to be error-free, the orthogonal regression allows for error in both x and y spaces, because in the calibration case both the reference and the target variable are considered arbitrary.

The exactness of both the procedures was evaluated by means of the comparison of gains and offset values (Table 1 and Table 2) obtained on both the two different sensors data. Such values must be near respectively to one and zero (Du et al., 2002), in order to not loose the radiometric resolution in comparison to the initial data.

A further analysis was conducted in order to verify the possibility to use MAD procedure to choose bands with optimal behaviour as regards gain and offset results. In the column named *Test* of the Table 1 and Table 2 the values considered positive of *Gain* (g_k < 0.75) and *Offset* ($o_k < \sigma_{offset}$) in absolute terms were pointed out, in order to allow an easy selection of best bands for next multitemporal analysis. For the entire image of every band we imposed that:

Test = 1

if both the conditions $\left|1-(g_k)\right| < 0.75$

and

$\left|o_k\right| < \sigma_{offset}$ are verified

The decision thresholds (0.75 and σ_{offset}) were chosen on the base of experiences conducted with empirical procedures made in precedent works (Caprioli et al., 2006; Hong and Zang, 2005).

	ELC -Empirical Line Calibration						**Radiometrical Normalization with MAD**					
	A → C			**B → C**			**A → C**			**B → C**		
	Gain	**Offset**	**Test**	**Gain**	**Offset**	**Test**	**Gain**	**Offset**	**Test**	**Gain**	**Offset**	**Test**
Band 1	1,65	-21,41	1	1,14	-23,47	0	0,85	1,79	1	1,37	-4,47	1
Band 2	1,50	-6,54	1	1,14	-19,85	0	0,94	-7,01	1	1,31	1,45	1
Band 3	1,43	-4,46	1	1,16	-21,24	0	1,01	-8,84	0	1,35	-1,16	1
Band 4	1,41	6,28	1	1,77	-26,00	0	1,17	-0,46	1	1,59	1,84	1
Band 5	1,12	15,15	1	1,16	-16,01	1	1,03	-5,22	1	1,25	9,07	0
Band 6	2,76	-166,37	0	1,10	21,83	0	1,49	-20,13	0	1,36	-14,70	0
Band 7	1,21	3,99	1	1,24	-18,39	0	1,04	-4,44	1	1,21	4,03	1
Mean	1,58	-24,77		1,24	-14,73		1,07	-6,33		1,35	-0,56	
St. dev. σ	0,51	58,79		0,22	15,23		0,19	6,57		0,11	6,96	

Table 1. Results of gains and offsets obtained with ELC and MAD methods on Landsat ETM+ data

	ELC -Empirical Line Calibration			**Radiometrical Normalization with MAD**		
	A → B			**A → B**		
	Gain	**Offset**	**Test**	**Gain**	**Offset**	**Test**
Band 1	1,13	15,87	0	1,39	1,66	1
Band 2	1,08	19,44	0	0,78	27,83	0
Band 3	0,99	21,77	0	1,00	21,42	0
Band 4	1,05	4,36	1	0,99	4,69	1
Band 5	1,11	1,23	1	1,02	1,37	1
Band 6	1,10	1,16	1	1,02	1,27	1
Band 7	1,06	1,21	1	0,96	1,31	1
Band 8	1,03	0,81	1	0,99	0,86	1
Band 9	1,31	0,39	1	1,11	0,47	1
Band 10	2,41	-9,87	0	2,06	-7,21	0
Band 11	2,11	-8,21	0	2,00	-7,35	0
Band 12	2,22	-9,66	0	1,98	-7,67	0
Band 13	2,46	-12,22	0	2,04	-8,51	0
Band 14	2,41	-11,47	0	2,09	-8,77	0
Mean	1,53	1,06		1,39	1,53	
St. dev. σ	0,62	11,27		0,52	10,90	

Table 2. Results of gains and offsets obtained with ELC and MAD methods on ASTER data

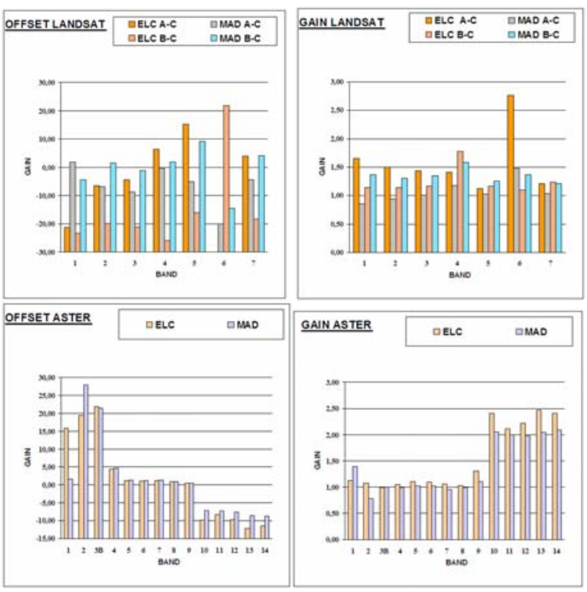

Figure3A-Figure.3B-Figure.3C-Figure.3D.
Comparison between the results of Gain and Offset calculated for every single sensor band

For both the procedures (ELC and MAD) the gains and offsets values of thermal bands of Landsat ETM+ and ASTER sensors were widely higher than values of remaining bands. This is due to the alterations inducted by the resampling of the lower geometric resolution data (from 60 m for Landsat ETM+ to 30 m and from 90 m for ASTER to 15 m) and by the intrinsic characteristics of bands that works in thermal range and with electromagnetic radiation emitted rather than reflected.

On the whole the results obtained from ASTER data are better than Landsat ETM+ data (Fig. 3A - Fig. 3B - Fig. 3C - Fig.3D). Besides the augmented spatial resolution, ASTER data present the absence of clouds, the different sun angle and the temporal range with acquisition date of similar climatic conditions. All these aspects had carried out positive results, in order to permit coherent multitemporal analysis with comparable data homogenised with normalization.

3. CONCLUSION

The analysis of the results demonstrated the advantages in using of the automatic MAD technique for radiometric normalization of multitemporal satellite data in terms of saving processing time. Moreover, MAD technique identifies several PIFs in comparison with the ELC method, with a consequent better accurate analysis. The procedure requires only a subjective parameter such as chi square percentile, without any others adjustable criteria for defining PIF features.

On the whole, the MAD and the ELC based normalisation techniques generally produce comparable results, especially for images with lower level of noise.

A certain amount of problems were proved on image with intrinsic radiometric problems, such as haze phenomenon and cloud covers.

Generally, the mean values after the image normalisation in both approaches are well represented. The variances of the no change pixels in both normalisation approaches are slightly underestimated. The regression parameters on the no change pixels are slightly better represented in the MAD based approach.

Due to its completely automatic operation, and as parameters are free and fast, the MAD based normalisation technique was favoured in comparison with the definition of decision thresholds or individuation of PIF (*Pseudo Invariant Features*) with subjective criterions by using ELC techniques. In fact, with MAD transformation the basic data come completely from the same image, without interference of unfavourable climatic conditions or every type of noise/variation in terms of reflectance.

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