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ESTIMATION AND MAPPING OF NDVI UNCERTAINTY FROM LANDSAT 8 OLI DATASETS: AN OPERATIONAL APPROACH

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ABSTRACT

Within remote sensing applications aimed at monitoring vegetation, spectral indices represent an effective and widely used tool. Unfortunately, in the most of cases users do not take into account any estimation of index uncertainty. This information can be useful and desirable especially in multi-temporal analysis to define index sensitivity with the aim of identifying significant differences between pixels of the same scene or of the same pixel in time. The goal of this work is to investigate potential uncertainty affecting spectral indices, with particular focus on NDVI (*Normalized Vegetation Index*). An "open" (entirely controllable) self-developed radiative transfer model is considered for this study. Uncertainty concerning factors involved in the model was considered to estimate its effects on NDVI final accuracy. For this task the statistical model of the variance propagation law was adopted. Two Landsat 8 OLI images acquired over a sample study area sited in Piemonte (NW Italy) were used to compute NDVI images at two different dates, estimate its uncertainty and investigate the way this information can be exploited during a change detection analysis.

***Index Terms*—** Landsat 8 OLI, NDVI accuracy, change detection, Variance Propagation Law

1. INTRODUCTION

In optical satellite remote sensing applications aimed at investigating vegetation, spectral indices derived from optical multi/hyper-spectral imagery are widely and successfully used. In this context it is very important to proceed in the evaluation of spectral index reliability by considering and quantifying the role of those physical factors involved in the adopted radiative transfer model that introduce elements of uncertainty. This issue should be a mandatory one but, unfortunately, is often neglected in many scientific works. The potential uncertainty (or precision) affecting spectral measurement is, in fact, a basic requirement for a correct interpretation of results, especially while approaching change detection applications [1] [2]. This information is strongly needed: a) to map significant index differences between pixels of the same scene (at the same time); b) which pixels are really (significantly) changed over time.

In this paper authors present an operational approach that, starting from a simplified imagery calibration model, is able to generate estimates of NDVI (*Normalized Differencing Vegetation Index*) uncertainty at each scene location and, consequently to propagate it over differences in time. The approach is tested by processing two Landsat 8 OLI image subsets representing an agricultural context in the south western Piemonte region (NW Italy). Some discussions are finally given concerning the relationship between NDVI values, NDVI differences and the correspondent estimated uncertainty.

2. MATERIALS AND METHODS

This work presents an operational approach to generate, at each position of a multispectral image, an estimate of NDVI accuracy. The statistical model of the Variance Propagation Law (VPL) [3] is suitable to estimate uncertainty affecting "indirect" measurements, deducing it from the ones supposed for the "direct" measures they depend on [4] [5]. Direct measures in NDVI calculation are represented by those physical factors, participating to reflectance recovering [6], within the adopted radiative transfer model: at-sensor radiance, sun irradiance, area topography [7] and atmosphere [8] [9].

A simplified "open" radiative transfer model for at-the-ground reflectance computation was adopted for this work and VPL was applied to generate for each L8 OLI band the correspondent reflectance uncertainty. The formulation of the used simplified radiative transfer model is the following:

$$\rho_\lambda(x,y) = \frac{\pi \cdot \left[L_\lambda(x,y) - \hat{L}_\lambda{}^{atm}(x,y)\right]}{\tau_\lambda(x,y) \cdot \left[\tau_\lambda(x,y) \cdot k \cdot \sin[\beta(x,y)] \cdot I_\lambda + \pi \cdot \hat{L}_\lambda{}^{atm}(x,y)\right]}$$

Where ρ_λ is the at-the-ground reflectance value, L_λ is the at-sensor-radiance [$W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$] obtained applying the GAIN and OFFSET values supplied with L8 OLI images, L_λ^{atm} the atmosphere scattered radiance [$W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$], τ_λ the atmospheric transmittance, k the astronomical coefficient ($k=1/d^2$) related to the Earth-Sun distance (d), I_λ the sun irradiance [$W \cdot m^{-2} \cdot \mu m^{-1}$] and β is the sun incidence angle (rad)

Factor		Definition	Description
At-sensor-Radiance *[W·sr^{-1}·m^{-2}·µm^{-1}]*	$L_\lambda(x,y)$	$\sigma_{L_\lambda} = \dfrac{\mathrm{GAIN}_\lambda \cdot (2^{16}-1)}{(2^{12}-1)}$	Constant over the scene, different for each band. It is assumed to be equal to the <u>original</u> (12 bits) radiometric resolution of L8 OLI imagery.
Atmospheric scattering [W·sr^{-1}·m^{-2}·µm^{-1}]	$\hat{L}_\lambda^{\;atm}(x,y)$	$\sigma_{\hat{L}_\lambda}^{atm} = f[dark\ pixels, air\ mass\ coeff., DEM]$	Standard deviation of radiances of dark pixels (different for each band, constant over the scene).
Atmospheric transmittance	$\tau_\lambda(x,y)$	$\sigma_{\tau_\lambda}(x,y) = f\left[(\sigma_{\hat{L}_\lambda}{}^{atm}(x,y), DEM\right]$	Different for each band, varying over the scene.
Sun Irradiance [W·m^{-2}·µm^{-1}]	I_λ	σ_{I_λ}	Equal for all bands and constant over the scene (0.05)
Sun incidence angle *[rad]*	$\beta(x,y)$	$\sigma_\beta = \dfrac{\sqrt{2}\cdot\sigma_{DEM}}{2GSD\cdot\left[1+\left(\frac{\Delta h(x,y)}{GSD}\right)^2\right]}$	Equal for all bands, varying over the scene. Δh is the maximum local height difference around the pixel calculated from DEM (σ_{DEM} = 8 m).

Table 1. Uncertainty of factors involved in the radiative transfer model

calculated at each position using SRTM (Shuttle Radar Topography Mission) Digital Elevation Model (DEM).
Uncertainty of factors involved in the radiative transfer model were set according to table 1.
Reflectance uncertainty affecting bands used for NDVI computation was further propagated along its formula to obtain correspondent NDVI uncertainty estimate. Since estimation is local, both reflectance and NDVI uncertainty vary over the scene according to local lighting conditions. Therefore an NDVI uncertainty map, $\sigma NDVI$(x,y), can be generated for each processed image. When NDVI difference in time, $\Delta NDVI(x,y)$, is required to investigate vegetation changes, NDVI uncertainty has to be further propagated along the difference for accuracy estimation of measured NDVI differences, $\sigma\Delta NDVI(x,y)$. Resulting $\sigma\Delta NDVI(x,y)$ map can be finally used to separate, over the scene, significant, *SD(x,y)*, from not-significant differences.

$$SD(x,y) = |\Delta NDVI(x,y)| > \sigma_{\Delta NDVI}(x,y)$$

3. RESULTS

Two sample image subsets were considered showing the study area on April 14th 2014 and August 11th 2014.
A preliminary investigation was made exploring the behavior of reflectance uncertainty respect to spectral signature of surfaces. In Fig. 1 the average spectral signatures of two reference classes (vegetation and urban) represented by 50 pixels each, extracted by image interpretation from the August 11th L8 OLI image, are compared with the correspondent band reflectance uncertainty. It is easy to notice a high correlation, demonstrating that local variance is strictly dependent on surface type. Aside this first consideration, and obviously strictly related to it, it can be easily deduced that reflectance uncertainty is band dependent. NDVI images were then computed for the two dates using calibrated reflectances.

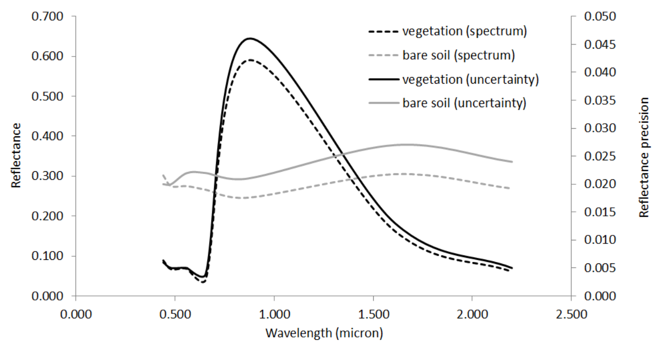

Fig. 1. Average spectral signature and "uncertainty signature" of two groups of pixels (50) representing vegetation and urban, extracted from the August 11th L8 OLI image.

Contemporarily, reflectance uncertainty estimation given by model at the previous step for RED and NIR bands, was propagated along NDVI formula in order to generate NDVI uncertainty estimate for the two periods. Looking at results given in Fig. 2 (c-d), a strong dependence of NDVI uncertainty from season and position is evident. Comparing Fig. 2 (c-d) with Fig. 2 (a-b) it can be noted that NDVI uncertainty behaves oppositely respect to the one of the NDVI it refers to. A further demonstration of this strict dependence comes from scatterplots of Fig.2 (e-f), suggesting that the higher is NDVI value, the lower is its uncertainty. NDVI difference image (August minus April), hereinafter called $\Delta NDVI(x,y)$, was then computed to map NDVI changes in the reference period. The correspondent $\sigma_{\Delta NDVI}(x,y)$ uncertainty map was generated too (Fig. 2 – g). Finally, authors proceeded to exemplify the way this information can be exploited to separate significant from not-significant NDVI differences (Fig. 2 - h).

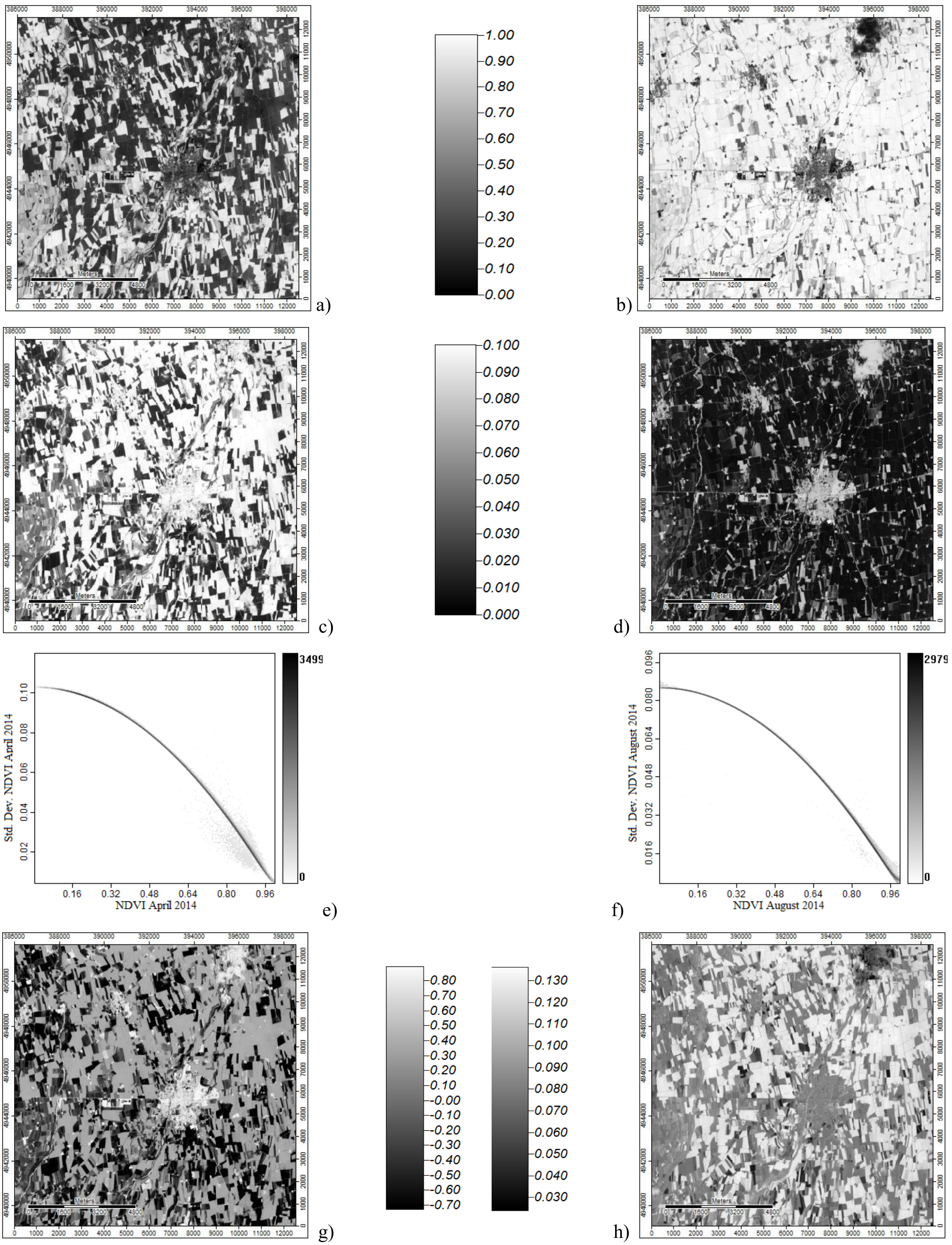
a)
b)
c)
d)
e)
f)
g)
h)
Meters
Std. Dev. NDVI April 2014
NDVI April 2014
3499
Std. Dev. NDVI August 2014
NDVI August 2014
2979

Fig. 2. (a-b) April and August NDVI and (c-d) NDVI uncertainty image subsets. The higher is signal (NDVI) the lower is its uncertainty (NDVI precision). (e-f) Scatterplots relating NDVI and its uncertainty for April 14th 2014 and August 11th 2014. The right sided bar reports observations' frequency (number of pixels). (g) NDVI difference image subset and (h) its uncertainty map.

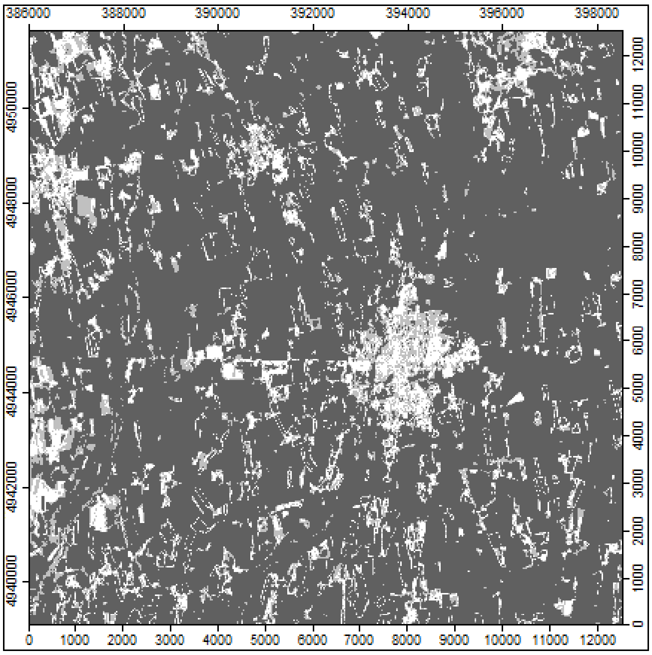

Fig. 3. Significant NDVI differences map: white = "Not significant", light gray = "significant > 1 σ", dark gray = "significant > 2 σ"

The adopted criterion states that NDVI difference values lower than thresholds corresponding to 1 or 2 times the local value of $\sigma\Delta NDVI$ are not-significant, i.e. no real change at that position occurred in the reference period.

4. CONCLUSIONS

Spectral indices are widely used in many environmental applications. Many of them are mapped to describe changes in time. In this work we focused on the importance of estimating uncertainty related to spectral indices derived from L8 OLI images. Proposed method relies on the Variance Propagation Law and requires the adoption of an "open" radiative transfer model during image calibration.

As far as NDVI and NDVI difference is concerned, we found that $\sigma NDVI$(x,y) strongly and inversely correlates with NDVI values (Fig.2, c-d.) This latter suggests that the higher is NDVI value, the lower is its uncertainty. Estimated values for $\sigma NDVI$ through the proposed method, are consistent with the ones reported for other sensors [10].

We also showed that $\sigma NDVI$(x,y) and $\sigma\Delta NDVI(x,y)$ can be effectively used to better interpret data. Specifically NDVI significant differences can be recognized and separated from the ones due to intrinsic uncertainty of recording instrument or RTM. Authors retain that this approach can be effectively applied to all spectral indexes and sensors, helping to improve reliability of many results concerning change detection and spectral index mapping.

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