Accuracy of narrow-band spectral indices estimation by wide-band remote sensing data

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The spectral resolution of remote sensing data plays an important role in resource and environmental applications. The high spectral resolution allows to analyze the fine structure of spectra of terrestrial formations. Such analysis provides a more accurate and reliable determination of ones’ type and condition (Agapiou, Hadjimitsis & Alexakis, 2012).

One of important tools for spectra analysis in remote sensing are various spectral indices – i. e. non-linear ratios of the spectral reflectance $\rho_{\lambda}$ in different spectral bands, where $\lambda$ denotes the radiation wavelength (Xue & Su, 2017). The best-known example of a spectral index is the normalized difference vegetation index (NDVI) (Huete & Jackson, 1987). In the case of high spectral resolution it is possible to use not wide-band, but more accurate narrow-band spectral indices, for example, a structure insensitive pigment index (SIPI) (Penuelas & Gamon, 1995).

The remaining part of paper is organized as follows. The next section formulates the problem statement, then the methods used to convert wide-band indices into narrow-band ones are described, after it the accuracy of obtained results is evaluated, and finally the research conclusion is made.

**Problem**

The ground-based precision spectrometric measurements, as well as hyperspectral aerial and satellite imagery, are used to obtain the narrow-band spectral indices (Thorpe, Tian, Yao & Tang, 2004). However, the most of airborne and satellite imaging systems are multispectral now, that means ones are not intended for registration of narrow-band spectral indices. On the other hand, the narrow-band indices are more preferable for characterization of agricultural crops and other plants (Thenkabail, Smith & De Pauw, 2002). For instance, the narrow-band indices produce more reliable regressions with the biophysical parameters studied (Siegmann, Jarmer, Lilienthal, Richter, Selige & Höfle, 2013). Thus, there is an topical and important challenge of restoring the values of narrow-band spectral indices by wide-band remote sensing data.

**Methods**

The direct simulation of biophysical processes resulting in certain spectral reflectance of vegetation and other land covers is most preferable. A similar approach...
is described in (Cundill, Van der Werff & Van der Meijde, 2015). However, in real world condition, as a rule, there is insufficient data for satisfactory accuracy of one’s application. At the same time, a certain similarity of spectral responses of the narrow-band hyperspectral and broadband multispectral imaging systems makes it possible to expect the statistical cross-coupling of their signals. Three sequentially more complicated methods for relying on such dependencies are discussed below.

**Spectral bands interrelations**

The simplest and native way is to determine relationships between wide-band and narrow-band spectral signals. The desired relationship is expected to be stochastic because the composition of the reflective covers or their mixes within each pixel is random. Regressional dependence of the narrow-band reflectance on single or more wide-band ones is constructed (Theiler & Wohlberg, 2013). A simple linear regression is well adequate if similar spectral bands are selected (Heo & Fitzhugh, 2000).

**Spectral indices interrelations**

A more complex model assumes the restoration of regressional dependence between spectral indices. Analogues of narrow-band spectral indices are built on the basis of similar wide bands, which are selected in the same way as in the previous case. When several wide bands are involved to emulate a single narrow-band signal, they are weighed inversely to distance inside spectrum.

**Spectral reflectance interrelations**

The most accurate is the method of spectra translation (Popov, Stankevich & Kozlova, 2007). The reference spectra are extracted from the spectral library by results of wide-band spectral signatures classification. Any necessary narrow-band signal can be calculated on the basis of reference spectra. If the soft-type classification is applied, then the assigned reference spectra are weighed proportionally to their fractions or confidences. Narrow-band spectral indices are calculated by the corresponding designated narrow-band signals.

**Materials**

Testing of methods for determining narrow-band spectral indices by wide-band remote sensing data was performed using actual both hyperspectral and multispectral satellite imagery. Hyperspectral Hyperion and multispectral ALI simultaneous images from the EO-1 satellite system (Ungar, Pearlman, Mendenhall & Reuter, 2003) were acquired over the same territory (Fastov district, Kiev region, Ukraine). Calibrated and georeferenced level 1T images were preprocessed, atmospherically corrected (Cetin, Musaoglu & Kocal, 2017), converted into surface reflectance and geometrically stacked one with another (Fig. 1).

Inside stacked ALI and Hyperion images coincided test plots of different types were assigned – agricultural crops, arable land, natural vegetation, open soil, artificial surfaces – 8 spectral classes total. All further measurements and estimations were made within these test plots.

![Fig. 1. Natural color synthesized simultaneous EO-1/ALI (a) and EO-1/Hyperion (b) stacked satellite images, July 30, 2014, 30 m ground resolution](image)

**Results and discussion**

Three well-known narrow-band spectral indices, widely used for the vegetation state assessment and which covering a wide range of spectrum – from 550 nm (visible) to 1680 nm (SWIR) (Haboudane, Miller, Tremblay, Zaro-Tejeda & Dextraze, 2002; Herrmann, Karnieli, Bonfil, Cohen & Alchanatis, 2010; Wang & Wei, 2016) were selected for testing. These ones are the transformed chlorophyll absorption in reflectance index (TCARI)

$$TCARI = \left( \frac{\rho_{700} - \rho_{670}}{\rho_{550}} - 0.2 \right) \frac{\rho_{700}}{\rho_{670}},$$

(1)

optimized soil-adjusted vegetation index (OSAVI)

$$OSAVI = \frac{1.16 (\rho_{700} - \rho_{670})}{\rho_{700} + \rho_{670} + 0.16},$$

(2)

and the normalized difference nitrogen index (NDNI)

$$NDNI = \frac{\ln \rho_{1680} - \ln \rho_{1510}}{\ln \rho_{1680} + \ln \rho_{1510}}.$$  

(3)

Here $\rho_{\lambda}$ denotes the spectral reflectance at $\lambda$ wavelength.

First of all the significance of regressional dependencies between narrow-bands reflectance and wide-bands one was estimated. The following spectral bands involved for TCARI, OSAVI and NDNI spectral indices calculating (1)-(3) were selected:

| Reference ($\lambda$, nm) | ALI spectral band ($\lambda$, nm) | Hyperion spectral band ($\lambda$, nm) |
|--------------------------|----------------------------------|-------------------------------------|
| 550                      | 4 (567)                          | 20 (549)                            |
| 670                      | 4 (660)                          | 32 (671)                            |
| 700                      | 6 (790)                          | 35 (701)                            |
| 800                      | 7 (866)                          | 45 (803)                            |
| 1510                     | 9 (1640)                         | 137 (1518)                          |
| 1680                     | 10 (2226)                        | 153 (1679)                          |

The significance of linear regressions between ALI and Hyperion spectral bands from Table 1 was expressed by the corresponding coefficients of determination:
Table 2. The ALI and Hyperion spectral bands linear regression’s determination

| ALI → Hyperion bands’ regression | 4→20 | 5→32 | 6→35 | 7→45 | 9→137 | 10→153 |
|----------------------------------|------|------|------|------|-------|--------|
| Coefficient of determination     | 0.97 | 0.99 | 0.09 | 0.99 | 0.98  | 0.82   |

As follows from the Table 2, there is a quite good significance of regressional dependencies between ALI and Hyperion spectral bands except the 700 nm reference one, which affects the accuracy of the TCARI index simulation.

The coefficients of determination for regressions between the ALI and Hyperion spectral indices immediately (this is the second method) are slightly lower, especially for NDNI:

Table 3. The ALI and Hyperion spectral indices linear regression’s determination

| ALI → Hyperion indices’ regression | TCARI | OSAVI | NDNI |
|-----------------------------------|-------|-------|------|
| Coefficient of determination      | 0.75  | 0.96  | 0.44 |

However, the overall accuracy of calculating the vegetation indices by ALI regression-restored Hyperion’s spectral bands is worse than by the regression between the indices directly:

Table 4. The ALI-based Hyperion spectral indices restoration accuracy

| ALI-based restored Hyperion index | TCARI | OSAVI | NDNI |
|-----------------------------------|-------|-------|------|
| Restoration method                |       |       |      |
| MAE                               | 1.32  | 0.27  | 0.26 |
| RMSE                              | 2.47  | 0.32  | 0.28 |

The restoration accuracy was estimated by test plots of various classes in ALI and Hyperion images. The mean absolute error (MAE) and the root mean square error (RMSE) of spectral indices were used to characterize the accuracy of ones restoration. Significant errors in the TCARI vegetation index restoration as it seems caused by insufficient regression’s determination for the 700 nm reference band.

In Fig. 2 the vegetation indices distributions are displayed of Fig. 1 multispectral images, obtained by the methods described above.

Fig. 2. The TCARI, OSAVI, and NDNI vegetation indices distributions by Hyperion hyperspectral image (a), by ALI-based regression-restored bands (b), and by ALI → Hyperion indices’ regression (c)

Lastly, the restoration of narrow-band vegetation indices based on the wide-band spectra classification and translation demonstrates the best accuracy for the same ALI image:

Table 5. The ALI-based Hyperion vegetation indices restoration accuracy by spectra translation method

| ALI-based restored Hyperion index | TCARI | OSAVI | NDNI |
|-----------------------------------|-------|-------|------|
| MAE                               | 0.006 | 0.045 | 0.011|
| RMSE                              | 0.008 | 0.067 | 0.014|

In this case the major errors provide rather considerable spacing between ALI and Hyperion SWIR spectral band which affect the NDNI index only.

Conclusions

Thus, the experimental study on the restoration accuracy of narrow-band spectral indices by wide-band multispectral image was carried out. The best results are provided by the previously patented method of spectra translation, which is recommended for further practical application. But this method implementation requires the external spectral library engagement with land cover
typical spectra over the study area. It is very desirable to include high resolution (not worse than 1–2 nm) both VNIR and SWIR precision spectra into such library to provide the possibility of signals reconstruction in all spectral bands of any imaging system.

Development and practicing of similar spectral library should be the key focus of future research.

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