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

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Narrow-band spectral indices are quite informative and important in various applications of remote sensing – to assess the condition of vegetation, soils, water bodies and other land surface formations. However, direct measurement of narrow-band spectral indices requires hyperspectral imaging. But most of modern multispectral aerospace imaging systems are wide-band. Accordingly, it is not possible to calculate the narrow-band index directly from wide-band remote sensing data. This paper discusses approaches to the narrow-band spectral indices restoration by wide-band remote sensing data using statistical models of interrelations of narrow- and wide-band indices itself, of source wide-band and narrow-band signals in close spectral bands, as well as of land surface reflectance quasi-continuous spectra translation from wide bands to narrow ones.
The experimental accuracy estimation of narrow-band spectral indices restoration by wide-band multispectral satellite image is performed. Three most complicated narrow-band spectral indices, which covering a range of spectrum from visible to short-wave infrared, were considered, namely – the transformed chlorophyll absorption in reflectance index (TCARI), the optimized soil-adjusted vegetation index (OSAVI) and the normalized difference nitrogen index (NDNI). All three mentioned methods for narrow-band spectral indices restoration are analyzed. The worst result is demonstrated for regression-restored signals in spectral bands, and the best result is for the spectra translation method. Therefore, the method on the basis of spectra translation is recommended for practical implementation.
Keywords: narrow-band spectral index, multispectral imagery, spectral band, regressional dependence, accuracy estimation, spectral library

Introduction

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 ρ_λ in different spectral bands, where λ 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 (Thorp, 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

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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.

a *b*

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

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, Zarco-Tejada & 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)

$$\text{TCARI} = \left(\rho_{700} - \rho_{670} - 0,2\,(\rho_{700} - \rho_{550})\,\frac{\rho_{700}}{\rho_{670}}\right), \quad (1)$$

optimized soil-adjusted vegetation index (OSAVI)

$$\text{OSAVI} = \frac{1{,}16\,(\rho_{800} - \rho_{670})}{\rho_{800} + \rho_{670} + 0{,}16}, \quad (2)$$

and the normalized difference nitrogen index (NDNI)

$$\text{NDNI} = -\frac{\ln\rho_{1680} - \ln\rho_{1510}}{\ln\rho_{1680} + \ln\rho_{1510}}. \quad (3)$$

Here ρ_λ denotes the spectral reflectance at λ 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:

Table 1. The ALI and Hyperion spectral bands, involved for spectral indices calculation

Reference (λ, nm)	ALI spectral band (λ, nm)	Hyperion spectral band (λ, nm)
550	4 (567)	20 (549)
670	5 (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**

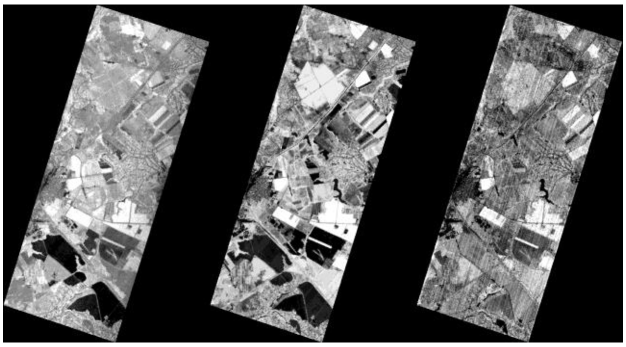
However, the overall accuracy of calculating the vegetation indices by ALI regression-restored Hyperion's spectral bands is worse than by the regression between the indices directly:

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

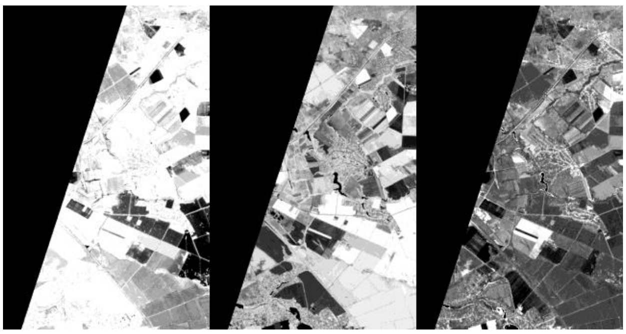
ALI-based restored Hyperion index	TCARI	OSAVI	NDNI	TCARI	OSAVI	NDNI
Restoration method	by regression-restored bands			by regression-based indices		
MAE	**1.32**	0.27	0.26	0.11	0.03	0.05
RMSE	**2.47**	0.32	0.28	0.22	0.05	0.08

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.

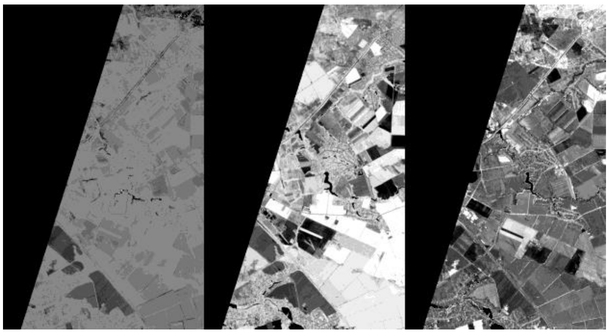
In Fig. 2 the vegetation indices distributions are displayed of Fig. 1 multispectral images, obtained by the methods described above.



a



b



c

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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ТОЧНІСТЬ ОЦІНЮВАННЯ ВУЗЬКОСМУГОВИХ СПЕКТРАЛЬНИХ ІНДЕКСІВ ЗА ШИРОКОСМУГОВИМИ ДАНИМИ ДИСТАНЦІЙНОГО ЗОНДУВАННЯ

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Вузькосмугові спектральні індекси досить інформативні та важливі в різних застосуваннях дистанційного зондування – для оцінювання стану рослинності, ґрунтів, водойм та інших утворень земної поверхні. Проте для прямого вимірювання вузькосмугових спектральних індексів потрібне гіперспектральне знімання. Більшість же сучасних багатоспектральних аерокосмічних знімальних систем є широкосмуговими. Відповідно, неможливо розрахувати вузькосмуговий індекс безпосередньо за широкосмуговими даними дистанційного зондування. У статті розглядаються підходи до відновлення вузькосмугових спектральних індексів за широкосмуговими даними дистанційного зондування з використанням статистичних моделей взаємозв'язків власне вузько- і широкосмугових індексів, вхідних широко- і вузькосмугових сигналів у близьких спектральних діапазонах, а також трансляції квазібезперервних спектрів відбиття земної поверхні з широких діапазонів у вузькі.

Виконано експериментальне оцінювання точності відновлення вузькосмугових спектральних індексів за широкосмуговими багатоспектральними супутниковими зображеннями. Розглядалися три найбільш складні вузькосмугові спектральні індекси, які охоплюють спектральний діапазон від видимого до короткохвильового інфрачервоного, а саме – TCARI (transformed chlorophyll absorption in reflectance index), OSAVI (optimized soil-adjusted vegetation index) та NDNI (normalized difference nitrogen index). Проаналізовано усі три згадані методи відновлення вузькосмугових спектральних індексів. Найгірший результат продемонстровано для регресійно відновлених сигналів в спектральних діапазонах, а найкращий результат – для методу трансляції спектрів. Тому метод на основі трансляції спектрів рекомендовано для практичного застосування.

Ключові слова: вузькосмуговий спектральний індекс, багатоспектральне зображення, спектральний діапазон, регресійна залежність, оцінювання точності, бібліотека спектрів

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