UDC 528.88:556.551:574.583::547.979.8

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A REMOTE SENSING APPROACH TO ASSESS ALGAL ß-CAROTENE CONTENT IN SOLAR SALT EVAPORATION PONDS

Dunaliella salina, ß-carotene, Landsat 5TM, Landsat 7ETM+, reflectance, near infra-red (NIR), short wave infra-red (SWIR).

Red "bloom" induced by planktonic microalga Dunaliella salina Teod. is typical of solar salt evaporation ponds. The alga is able to accumulate ß-carotene, coloring its cells orange-red and, due to its massive development, shading the pond brine. The algal biomass enriched with ß-carotene could be the additional high value by-product of solar salt manufacture. The annual world market of algal ß-carotene as a food color and a potent antioxidant in food supplements totals about US$200 million, the demand constantly growing. The market is dominated by Australia based division of Henkel/Cognis (currently owned by BASF), where the alga is grown in specialized open ponds [1]. Despite the facts that Ukraine possesses quite large suitable solar salt works area, and the original idea is authored by Ukrainian researchers [2], algal ß-carotene still is not manufactured in Ukraine industrially. As ß-carotene accumulation in pond brine can be visually detected by brightness of orange-red hue, we suppose that the satellite imagery could be used to assess the natural resources of algal ß-carotene in Ukraine and compare to other production sites of the world.

Satellite remote sensing is a standard instrument to monitor and assess algal blooms, mostly applied to harmful blooms in the open ocean [3]. Little work was published on satellite remote sensing of D. salina "bloom" [4–6], revealing a specific problem: algal "bloom" is often masked by pink halobacterial "bloom", though, it is possible to differentiate them by spectral signatures [5]. Techniques to quantitatively assess D. salina ß-carotene concentrations in open ponds by satellite imagery were not proposed in the literature.

In 2006–2008 we monitored D. salina "bloom" in the ponds of Heroyske salt works (46°29'19.84»N, 31°54'15.96»E), Kherson region [7]. The present research attempts to calibrate satellite images against field data on D. salina ß-carotene concentration expressed per 1 L of brine.

Field sampling and sample analysis were described in [7]. Spectral images, dated ± 6 days around sampling, taken by satellite instruments of moderate resolution (15 and 30 m), were retrieved from USGS web site via EarthExplorer interface (data available from the U. S. Geological Survey). Scenes with cloud cover over the area of interest were discarded, resulting in 8 Landsat 5TM and 13 Landsat 7ETM+ images (courtesy of the U. S. Geological Survey). Quantum GIS 2.18.15 [8] and Semi-Automatic Classification Plugin (SCP) 5.3.11 [9] were used. DN values were automatically converted into reflectance, Landsat 7ETM+ images pansharpened, DOS1 atmospheric correction applied to all the images. Google Satellite image (© 2018, DigitalGlobe) was used to delineate salt work ponds by vector polygons. Several types of spectral indices (single band reflectance, band ratios, band differences, and normalized band differences) were calculated pixel-wise and their mean values for each pond of interest extracted with QGIS Zonal Statistic Tool. Pearson correlations between mean indices and field measured variables were analyzed using R [10] and RStudio [11].

The strongest statistically significant positive linear correlation was found between algal ß-carotene concentration in the brine and the normalized difference of NIR and SWIR (1.55–1.75 nm) reflectance, especially for ponds 8 and 11 (fig. 1), which were excluded from salt work operation during the study and managed to stimulate the algal "bloom" [7].

Notably, the correlation coefficient increased as sampling and snapshot

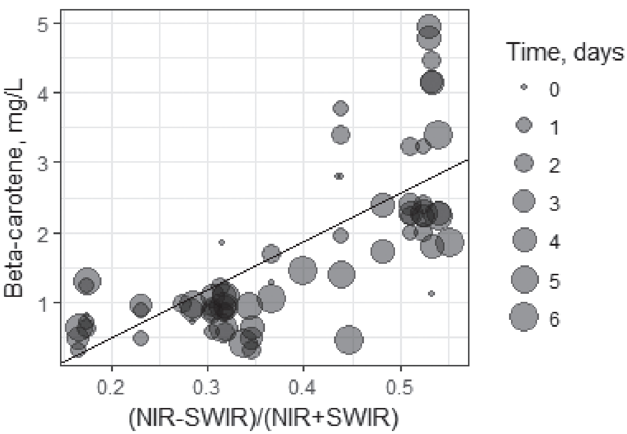

Fig. 1. Pearson correlation between brine concentration of ß-carotene (mg/L) and normalized difference NIR-SWIR index in ponds 8 and 11, depended on time passed between sampling and snapshot (linear fit drawn for 3 days interval)

dates converge up to 3 days (Table 1). Further decrease of correlation coefficient and p-value increase at 0–2 days interval were probably due to insufficient amount of data remained.

Table 1.

Pearson correlation between brine concentration of ß-carotene mg/L and normalized difference NIR-SWIR index depended on time passed between sampling and snapshot

Time, days	Pearson correlation coefficient	p-value
0	0.4870026	0.2677
1	0.7106082	0.000949
2	0.7447124	6.705e-07
3	0.7660896	3.374e-09
4	0.7594349	4.347e-11
5	0.7503144	5.157e-12
6	0.7276533	1.417e-12

We found the empirical relation between ß-carotene quantity and the index based on two infrared reflectance bands (NIR and SWIR). Theoretical grounds of that remain unclear, although near infra-red reflectance spectroscopy is already in use to evaluate in vivo carotenoid content in plant fruits [12]. Some more algorithms (e.g. three-band indices, spectral angle etc.) could be tested to find better fit between field data and satellite imagery of D. salina ponds.

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