METHODS AND PROCESSING TOOLS
AND INTERPRETATION OF SPACE INFORMATION

Information Content of Spectral Vegetation Indices for Assessing the Weed Infestation of Crops Using Ground-Based and Satellite Data

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Abstract—This paper presents the results of a study assessing the degree of weed infestation of wheat crops. They are obtained using optical ground-based and satellite spectral data with a 3-m spatial resolution from PlanetScope Dove satellites for 2019. The vegetation indices, including the normalized difference vegetation index (NDVI), the relative chlorophyll index (Chlorophyll Index Green—ClGreen or GCI), the modified soil-adjusted vegetation index (MSAVI2), and the visible atmospherically resistant index (VARI) are used in the interpretation of ground-based spectrometric and space images. This paper indicates the possibility of assessing the degree of weed infestation of agricultural fields. The higher the weed infestation, the lower the index values. The dynamics of VARI is found to be different from the dynamics of NDVI, ClGreen, and MSAVI2 during the growing season. The strong correlation between NDVI, ClGreen, and MSAVI2 and the weak correlation between VARI and other indices are observed. The possibility of identifying weedy sites in the agricultural fields is shown using the spatial distribution map of ClGreen dated August 2, 2019.

INTRODUCTION

According to the data of Earth remote sensing (ERS), assessing the sanitary condition of crops, i.e., detecting infection centers and pests and identifying weed infestation, takes a special partition among crop condition monitoring tasks (Mikhailenko and Voronkov, 2016). Poorly studied factors influencing the spectral reflectance of crops and, consequently, the success in detecting their condition according to remote-sensing data include the weed infestation of crops (Thorp and Tian, 2004).

Weeds are a regular component of agroecosystems. With their high number, they reduce yield and quality of agricultural products and make many types of field operations, including tilling and harvesting, harder. The weed infestation of crops may be the most relevant when there is a low level of agriculture and farmers lack the funds to purchase agrochemicals for weed control.

The nature and degree of weed infestation, weed phenology, in contrast to the crop phenological development, varies considerably from season to season. This is due to the characteristics of meteorological conditions in the year, the type of crop rotation, soil conditions, and agricultural practices (Petit et al., 2011; He Y. et al., 2020).

The effect of weed infestation on the spectral appearance of crops are still poorly understood. These studies are conducted mainly because of the development of precision farming and local application of weed-control agents (Lamba and Brown, 2001; Martin et al., 2011; Pflanz et al., 2018). However, these studies do not refer to remote sensing for recognizing weed species, since the accuracy of determining weed distribution areas is of greater consequence and weed species are determined directly in the field. There are still very few studies on the spectral reflectance of different weed species and its dynamics during the growing season (Vrindts et al., 2002; Che'Ya et al., 2013).

In comparison with traditional ground-based methods, ERS methods have significant advantages in terms of the ability to view large territories instantaneously, including remote and inaccessible sites, as well as of the regularity of photographic reproduction of the studied
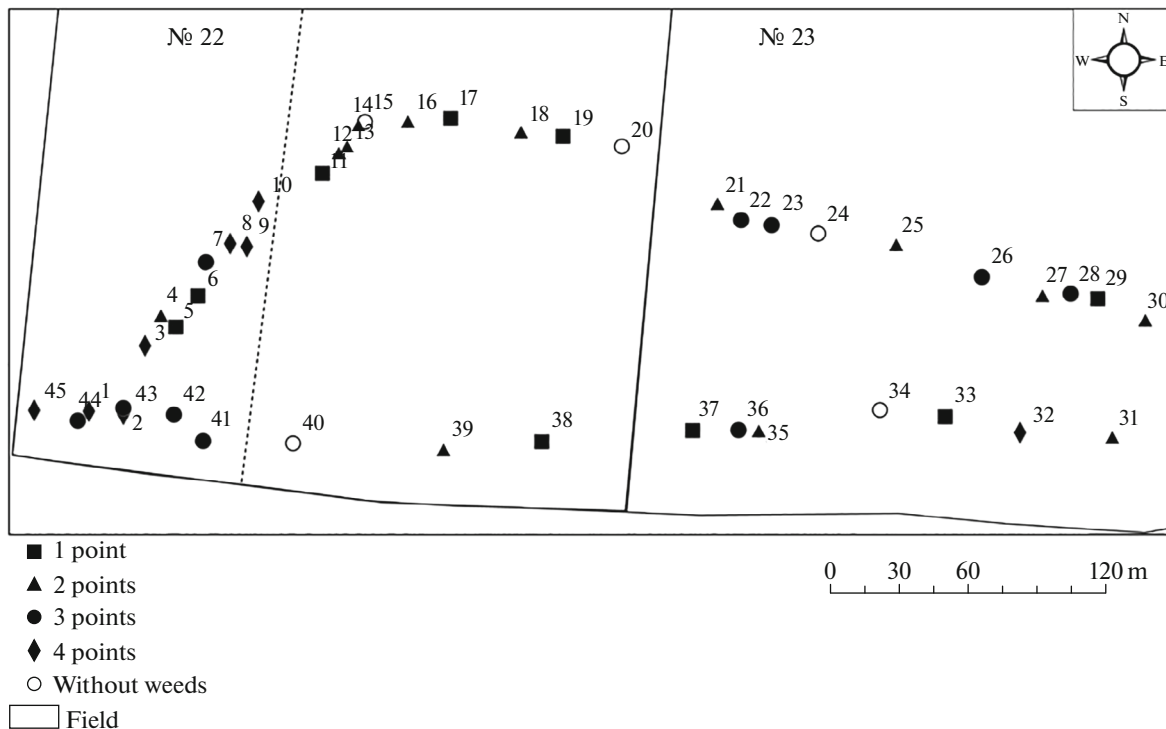
Fig. 1. Map of test locations with different degrees of infestation of the fields sown (nos. 11−40) and unsown (nos. 1−10 and 41−45) with wheat.

objects and territories (Bondur and Vorobev, 2015). The unique potentials of space surveys in the different ranges of the electromagnetic spectrum provide digital multispectral survey. There is great potential in using satellite data to solve agricultural problems.

However, the task of using ERS for identifying weed distribution centers is more difficult than the traditional task for the determining crop species and yield. Cultivated crops occupy rather large and homogeneous areas and have salient spectral characteristics within the same species. Unlike them, weeds grow heterogeneously within the same field, and their spectral characteristics are strongly dependent on both the main crop type and the infestation degree of the studied plot (Arkhipova et al., 2014).

Extensive information on the surface state carries the reflection of light from it in the different spectral ranges. Thus, the vegetation indices obtained from remote-sensing data take the leading role in assessing the vegetation condition (Bondur, 2014; Bondur and Vorobev, 2015).

The purpose of this paper is to assess the degree of weed infestation of crops using different spectral vegetation indices (NDVI, VARI, ClGreen, and MSAVI2) that are calculated from ground-based spectrometric and satellite data of PlanetScope during the 2019 growing season.

OBJECT AND METHODS

Study Object

The study object is crops planted in the territory of the Krasnoyarsk Scientific Research Institute of Agriculture (Federal Research Center Krasnoyarsk Scientific Center, Siberian Branch, Russian Academy of Sciences) near the village of Minino (Central Siberia, Krasnoyarsk krai).

Spring wheat crops of Svirel' (*Triticum vulgare*) with different degrees of weed infestation were studied during the 2019 growing season. Plots 22 and 23 were used (Fig. 1). The part of the field in plot 22 remained idle (to the left of the dotted line).

The fields are located in the southern part of the Krasnoyarsk forest steppe 5−7 km from Krasnoyarsk. The geographic coordinates are as follows: 56°4′35″ latitude and 92°4′49″ longitude. The territory is flat, southern, and open. This part of the forest steppe is rather warm and has particularly steppified areas suitable for the tilled field.

The geobotanical, ground-based spectrometric, and satellite data of PlanetScope were used to assess the weed infestation degree of wheat crops.

Geobotanical Methods

The visual method for assessing weeds is used to biologically assess the weed infestation degree of grain crops. It consists of the following: the experimental

Table 1. Weed species found in fields with different degrees of infestation

Weed species	Number of locations where the weeds are found
Witchgrass (*Panicum capillare* L.)	15
Creeping Thistle (*Cirsium arvense* L.)	16
White Goosefoot (*Chenopodium album* L.)	5
Perennial Sowthistle (*Sonchus arvensis*)	9
Bluebur (*Lappula myosotis* Moench.)	4
Ruderal Hemp (*Cannabis ruderalis* Janisch.)	7
Redroot Pigweed (*Amaranthus retroflexus* L.)	4
Wild Oat (*Avena fatua* L.)	4

field is crossed diagonally and the weeds of all species are recorded at regular intervals. The observational data are scored on a four-point scale: (1) a weak degree of weed infestation, weeds are rare (up to 5% of the number of cultivated crops); (2) a medium degree of weed infestation, weeds are visible among cultivated crops (up to 25%); (3) a strong degree of weed infestation, the number of weeds is close to the number of cultivated crops (up to 50%); and (4) a very strong degree of weed infestation, the number of weeds is equal to or greater than cultivated crops and the growth of the latter ones is strongly depressed.

The number of weeds were calculated per 0.1 m². The repetition included 45 test locations. Each location was linked with a geographic coordinate system. Along with the degree of weed infestation of crops, weed species were determined (Table 1) and a ground-based spectrophotometric survey of the condition of the wheat crop and uncultivated fallow was conducted.

Ground-Based Spectrophotometric Methods

It is the practice to express the reflective spectral properties of natural objects by the spectral brightness coefficient (SBC). The ground-based measurements of spectral brightness coefficients were conducted simultaneously with geobotanical studies dated July 9, 2019, in the agricultural fields at "locations" with different degrees of weed infestation. The area of the "test location" is a circle with a diameter of 50 cm.

The field spectrometer system was used to conduct ground-based spectrometry. It included a Spectral Evolution PSR-1100F field portable spectroradiometer, a GETAC handheld computer (PDA), a Spectral Evolution calibration reflection standard, a digital camera, and the relevant software (Shevyrnogov et al., 2018; Pisman et al., 2019). This system was used to measure the spectral brightness coefficient of the object in the range from 320 to 1100 nm. The spectra are bound to the location coordinates via GPS, altitude. They are provided with appropriate photography and voice notes. The SBC measurements of wheat crops were conducted from 11 am to 3 pm local time, which provided sufficient light conditions for objects at the latitude of these operations (Sid'ko et al., 2014).

PlanetScope Satellite Data

PlanetScope satellite data were used to interpret the agricultural crops with different degrees of weed infestation. The largest PlanetScope satellite constellation provides high spatial resolution (3 m) data on a daily basis from Dove satellites (Planet Team, 2019). The spectral channels include four ranges (or bands): 455−515, 500−590, 590−670, and 780−860 nm. The data is commercially and non-commercially available with the aim of enabling researchers to download up to 5000 km² of data per month.

The vegetation indices are calculated from ground-based spectrometric and satellite data given in Table 2.

The normalized difference vegetation index (NDVI) is an indicator that detects the presence of vegetation and its condition (relative biomass). This index takes advantage of the contrast of characteristics between two channels from a multispectral raster dataset—the chlorophyll pigment absorption in the red channel and the high vegetation reflectance in the near-infrared (NIR) channel (Solpieva and Urmambetova, 2018; Bondur and Vorobev, 2015).

The Chlorophyll Index Green (ClGreen or GCI) is a relative chlorophyll index indicating the photosynthetic activity of vegetation cover and used to assess the chlorophyll a and b content in crop leaves (Moran et al., 2000). Its maximum values are associated with the highest chlorophyll content in crop leaves (Tovstik et al., 2019). Healthy vegetation having a high chlorophyll content in the leaves falls between 1 and higher.

The modified soil-adjusted vegetation index (MSAVI2) is resistant to the soil influence. Its values range between −1 and 1 (Qi et al., 1994).

The visible atmospherically resistant index (VARI) is designed to emphasize vegetation in the visible portion of the spectrum, while mitigating illumination differences and atmospheric effects (Gitelson et al., 2002). It is ideal for RGB or color images and uses all three color channels (Solpieva and Urmambetova, 2018).

RESULTS AND DISCUSSION

Weeds are wild plants that grow on land used for the cultivation of crops. The harm caused by weeds is associated with both reduction in yields and deterio-

Table 2. Formulas for the spectral indices according to ground-based spectrometric (Spectral Evolution PSR−1100F) and PlanetScope satellite data

Vegetation indices	Calculation formula
NDVI (Normalized Difference Vegetation Index)	$\dfrac{b4 - b3}{b4 + b3}$
ClGreen (Green Chlorophyll Index)	$\dfrac{b4}{b2} - 1$
MSAVI2 (Modified Soil Adjusted Vegetation Index 2)	$\dfrac{2b4 + 1 - \sqrt{(2b4 + 1)^2 - 8(b4 - b3)}}{2}$
VARI (Visible Atmospheric Resistant Index)	$\dfrac{b2 - b3}{b2 + b3 - b1}$

$b1-b4$ for satellite data are the spectral reflectance coefficients (SRCs) of the PlanetScope appropriate channels (1−4); average values of spectral brightness coefficient (SBC) for ground-based measurements are as follows: $b1$ in the range of wavelengths from 455 to 515 nm, $b2$ in the range of wavelengths from 500 to 590 nm, $b3$ in the range of wavelengths from 590 to 670 nm, and $b4$ in the range of wavelengths from 780 to 860 nm.

ration of agricultural products. Crop plants and weeds compete with each other for water, light, nutrients, etc.

Geobotanical studies helped define the degree of weed infestation of crops (Fig. 1) and the major weed species (Table 1). As a result, we studied plots with the following degree of weed infestation: (1) at 9 locations, (2) at 13 locations, (3) at 10 locations, and (4) at 8 locations.

The application of the results of ground-based spectrometric studies is essential for a more accurate interpretation of satellite images (Hutto et al., 2006; Hese and Schmullius, 2009; Pflugmacher, 2011). The processing of big data and identification of optimal vegetation index are necessary to assess the vegetation condition in the fields. In this regard, a comparative analysis of different vegetation indices, including NDVI, ClGreen, MSAVI2, and VARI, was conducted here to assess the weed infestation of crops.

NDVI is the most common and widely used vegetation index. It is an indicator of crop health, which is based on how a crop reflects and absorbs different light waves. One disadvantage of NDVI is that, when a certain threshold of crop development is reached, the index loses its sensitivity. In other words, if the crop is actively growing, an abnormally green crop cannot be distinguished from a "normal" green crop according to NDVI. Regarding all the other indices, their accuracy depends on the weather: if clouds hang over some field for a long time, the satellite image will not be accurate (Ikenov, 2019).

Figure 2 presents the average NDVI values of wheat crops with different degrees of weed infestation calculated from satellite data (A) and ground-based spectrometric data (B). Since several repetitions for ground-based spectra were made, the average NDVI values of wheat crops with different degrees of weed infestation can improve interpretation accuracy.

The data obtained from the PlanetScope images (Fig. 2a) and using the ground-based spectrometer (Fig. 2b) demonstrate the remarkable qualitative reproducibility. The average NDVI of wheat crops with a high infestation degree is below that with a low infestation degree. However, the NDVI values according to the spectrometer data are on average nearly two times higher than the NDVI values according to the PlanetScope image. In our view, this is due to the divergence of the spacetime scales. The spatial resolution is equal to a circle 50 cm in diameter for ground-based spectrometry and 3 m in diameter for satellite spectrometry. The ground-based measurements are based on the limited number of crops in a small plot, but satellite data cover a large plot of land with a large number of crops (Herrmann et al., 2013).

Decreasing the NDVI values during the active growing season (before the milk stage) indicates the stress condition of crops. This may be the damage caused by natural hazards on crops (hail, showers, drought, and fires) as well as pest infestations. One example of the factor influencing the reduction in NDVI may be soil moisture deficit and weed infestation of crops. The NDVI value allows identifying the problem areas of suppressed vegetation, while providing decision-making support for yield enhancement (Shukilovich et al., 2016).

The vegetation indices, including ClGreen, MSAVI2, and VARI, calculated from satellite data dated July 9, 2019, are studied for further analysis of the possibility to assess the degree of weed infestation of crops (Fig. 3).

In addition to NDVI, the relative chlorophyll index (ClGreen) is also an indicator of photosynthetic activity of the vegetation cover (Moran et al., 2000; Sims and Gamon, 2002). The satellite-derived data show that wheat crops with a low infestation degree and without infestation have a chlorophyll index in the range above 1, but wheat crops with a high infestation degree have a chlorophyll index in the range below 1 (Fig. 3b). The
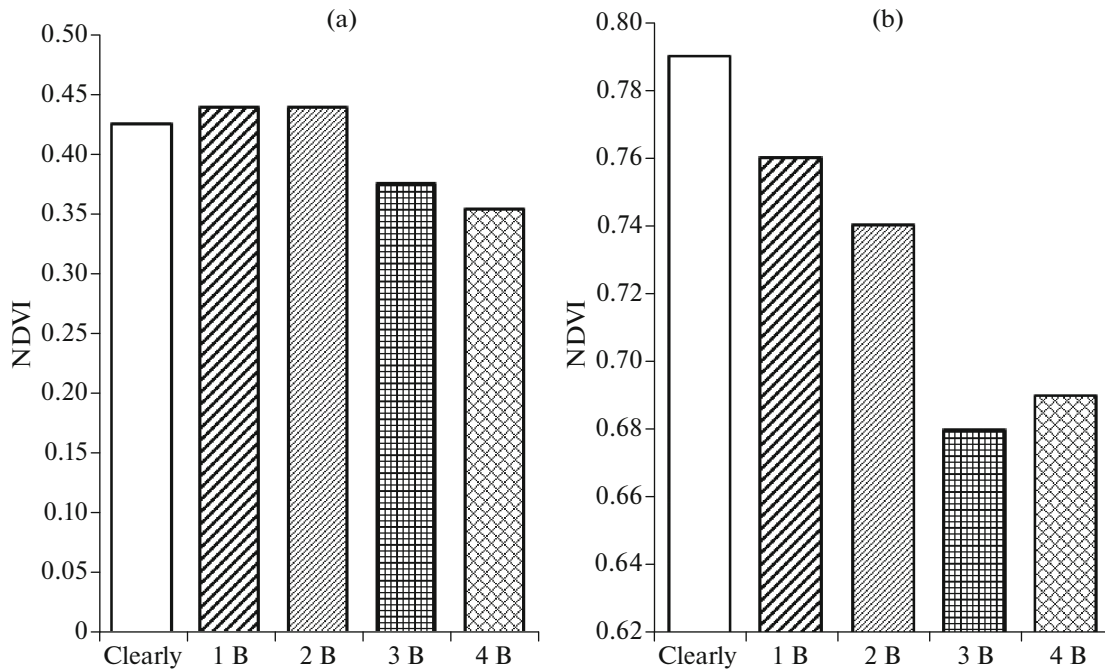
Fig. 2. Average NDVI value of wheat crops with different degrees of weed infestation according to PlanetScope satellite data (a) and the results of ground-based spectrometry (b) calculated from the data on July 9, 2019.

highest ClGreen values correlate with the highest chlorophyll content in the crop leaves, which indicates the "health" of crops (Tovstik et al., 2019).

The modified soil-adjusted vegetation index (MSAVI2) and its transformations are very useful drought-monitoring tools (Voronina, 2014; Gopp, 2019; Gaznayee and Al-Quraishi, 2019). The results showed that the highest MSAVI2 value was 0.6 for wheat crops with a low infestation degree and without infestation (Fig. 3c). The high values indicate perfect and healthy vegetation. The lowest MSAVI2 value was about 0.5 for wheat crops with a high infestation degree. The reduction in the MSAVI2 values typically corresponds to the reduction in annual precipitation, which is considered a vitally important factor influencing the vegetation cover growth in the study area. In our case, the weather conditions are similar for the studied crops with different degrees of weed infestation. For this reason, it can be said that the degree of weed infestation has an influence on MSAVI2.

VARI identifies the irregularities in the field, because this index is very sensitive to light conditions. The average VARI of wheat crops with a high infestation degree is also below that with a low infestation degree, like NDVI, ClGreen, and MSAVI2 (Fig. 3d).

Thus, a comparative analysis on how the degree of weed infestation in the agricultural fields may influence the value of the studied indices, including NDVI, ClGreen, MSAVI2, and VARI, derived from satellite data dated July 9, 2019, showed identical results. The assessment of the infestation degree of wheat crops

was found to coincide qualitatively in NDVI, ClGreen, MSAVI2, and VARI. The values of the studied vegetation indices for wheat crops with a low infestation degree and without infestation are above the values of the indices for wheat crops with a high infestation degree.

All plants, both crops and weeds, have certain phenological stages of development during the growing season. The changes taking place have an effect on the seasonal dynamics of their vegetation indices (Tovstik et al., 2019).

The graphs given in Fig. 4 show how the satellite-derived NDVI, ClGreen, MSAVI2, and VARI values of wheat crops with different degrees of weed infestation changed during the 2019 growing season. An analysis of these graphs allows for the conclusion that the regularities of changes in the studied indices are common to all fields. The values of the indices for the sown fields show a steady increase from June 15. This corresponds to the processes of seedling emergence and growth and an increase in the projective cover of vegetation. The chlorophyll content decreases starting from ripening stage after August 20 and, consequently, the value of the indices reduces.

Generally, we found a qualitative similarity of the dependence of all indices on the infestation degree of wheat crops during the growing season (Fig. 4). The values of the studied vegetation indices for wheat crops with a low infestation degree (1−2) are higher than those with a high infestation degree (3−4) during the active vegetation season (in July and August). How-
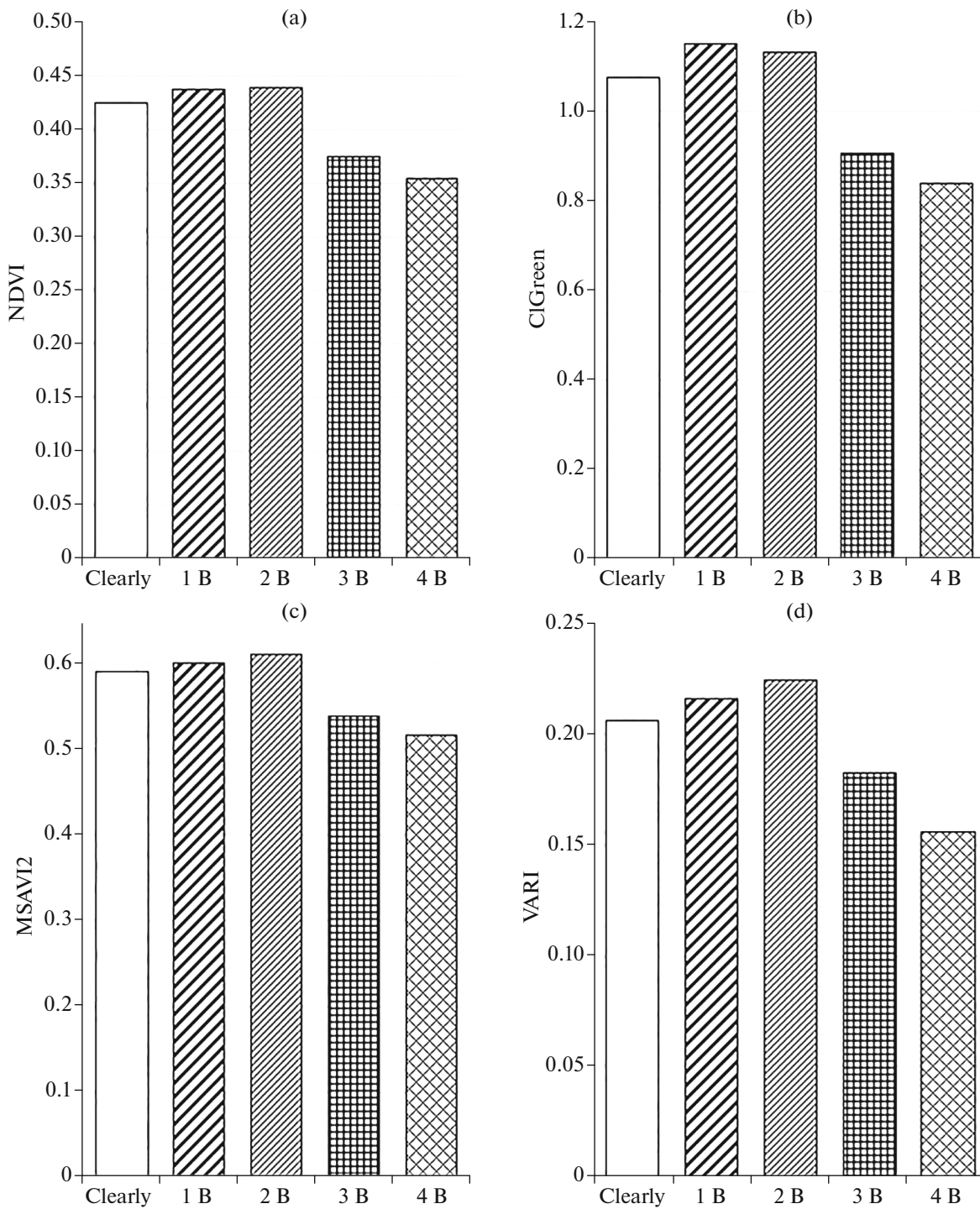
Fig. 3. Values of vegetation indices, including NDVI (a), ClGreen (b), MSAVI2 (c), and VARI (d), for wheat crops with different degrees of weed infestation according to PlanetScope satellite data on July 9, 2019.

ever, the VARI dynamics differs from the NDVI, ClGreen, and MSAVI2 dynamics (Fig. 4d). The VARI value is out of phase with the values of other indices on some dates.

The link analysis identified a high positive correlation ($r^2 = 0.95$) among vegetation indices, including NDVI, ClGreen, and MSAVI2, and a low positive correlation between VARI and other indices, including NDVI, ClGreen, and MSAVI2 ($r^2 = 0.3$) (Table 3). This demonstrates the difference between the VARI dynamics and the dynamics of other indices during the growing season (Fig. 4).
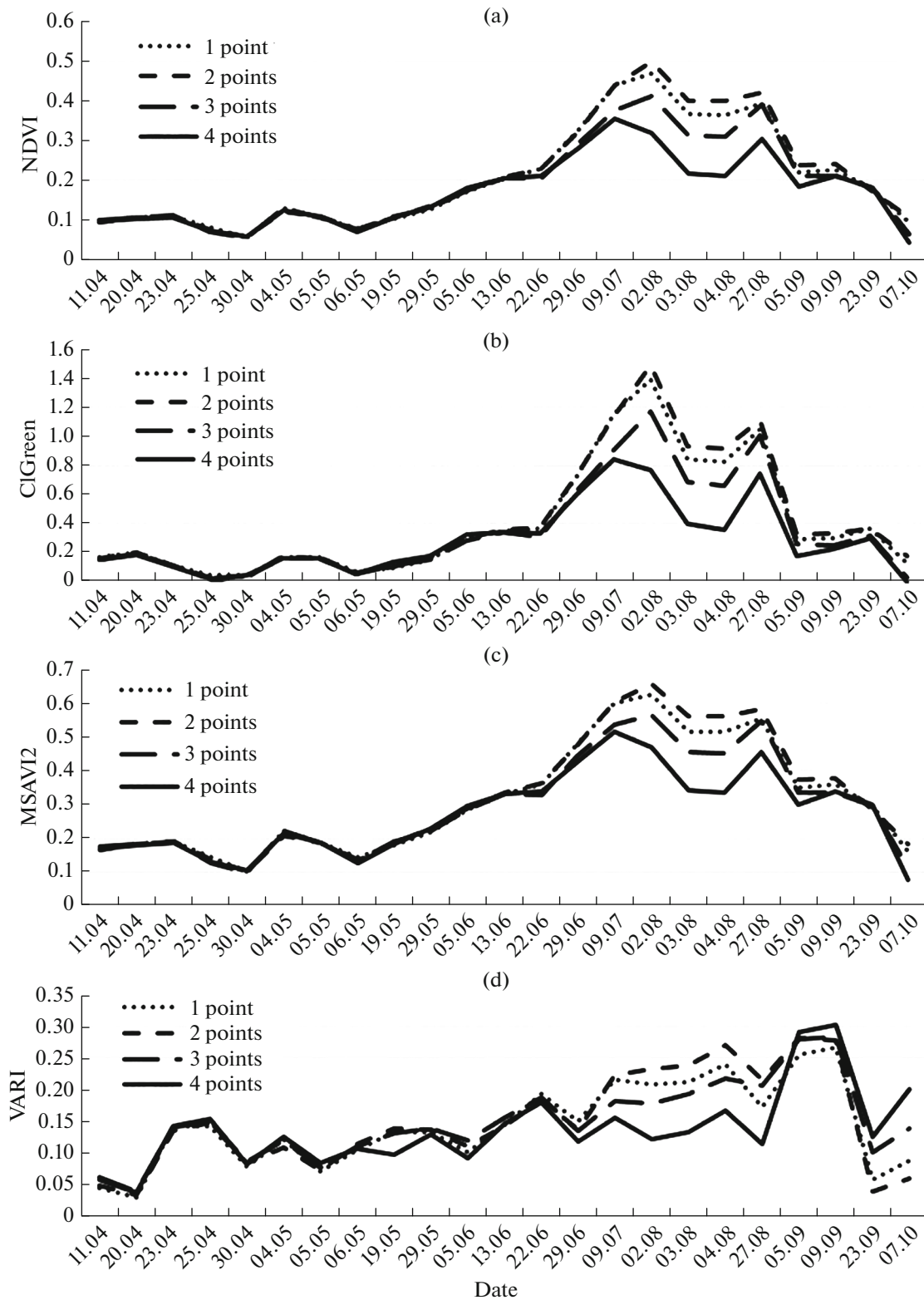
Fig. 4. Dynamics of the vegetation indices, including NDVI, ClGreen, MSAVI2, and VARI, for wheat crops in relation to the degree of weed infestation during the 2019 growing season according to PlanetScope satellite data.
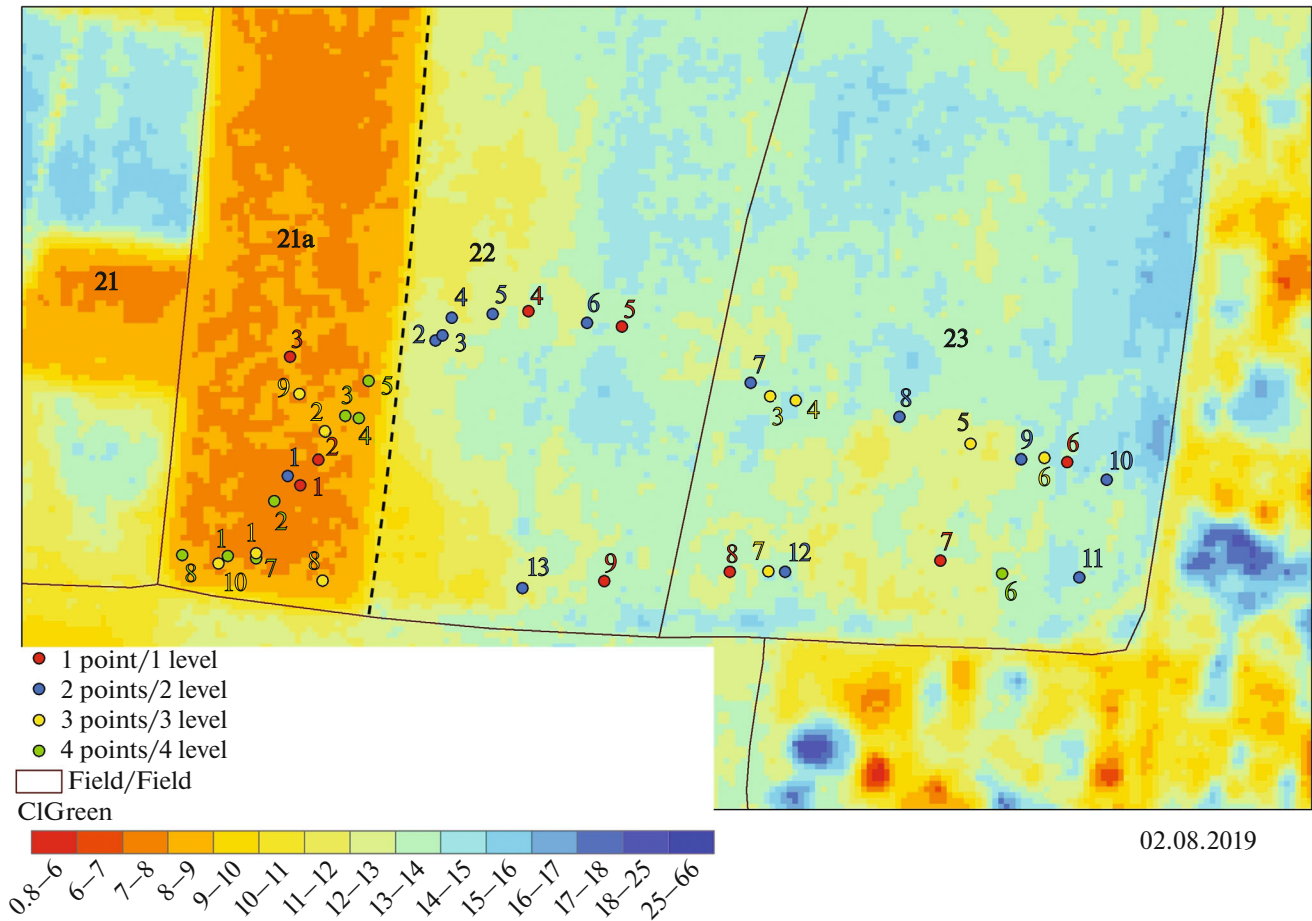
Fig. 5. Spatial distribution map of ClGreen for wheat crops on April 27, 2019 (according to PlanetScope satellite data). The locations at which the ground-based geobotanical and spectrometric measurements were conducted are marked with circles.

Atmospherically resistant indices, like VARI, achieve a decrease in the sensitivity to the atmospheric effect at the cost of a reduction in the dynamic range. These indices are used to assess the proportion of vegetation or vegetation fraction. Generally, they are less sensitive to vegetation cover change than NDVI.

If the vegetation is not high, they are strongly influenced by the soil layer (Qi et al., 1994; Gitelson et al., 2003). This is probably explained by the difference in the VARI dynamics from the dynamics of other indices, including NDVI, MSAVI2, and ClGreen, especially in spring and autumn months.

Figure 5 shows the spatial distribution map of ClGreen for agricultural fields with different degrees of weed infestation. ClGreen best demonstrates the dependence of its value on the weed infestation degree of the fields in August (dated August 2, 2019). The darker rectangle on the left represents an idle weed-grown field. The weed plants are in the flowering stage at that time during the growing season and thus contain almost no chlorophyll. This implies the low value of the chlorophyll index in the idle field. Wheat is at the end of flowering stage in the sown fields in early August (dated August 2, 2019). It currently contains a

Table 3. Correlation among the vegetation indices calculated from PlanetScope satellite data (the determination coefficient, r^2)

Vegetation indices	NDVI	ClGreen	MSAVI2	VARI
NDVI	1	0.947	0.994	0.306
ClGreen	0.947	1	0.918	0.19
MSAVI2	0.994	0.918	1	0.355
VARI	0.306	0.19	0.355	1

large amount of chlorophyll, so a high value of ClGreen for crops is found. Therefore, the possibility of interpreting agricultural fields with different degrees of weed infestation is revealed using PlanetScope satellite data.

CONCLUSIONS

As assessment of the weed infestation degree of crops based on different spectral vegetation indices, including NDVI, ClGreen, MSAVI2, and VARI, which were calculated from ground-based spectrometric and satellite data of PlanetScope during the 2019 growing season, led to the following conclusions.

The possibility of identifying weedy sites in the agricultural fields is shown.

The ground-based spectra and satellite data collected September 7, 2019, demonstrate that the NDVI values derived from satellite data for clear plots (without infestation) and for plots with a low infestation degree (1−2) range from 0.425 to 0.44. The NDVI values for plots with a high infestation degree (3−4) range from 0.35 to 0.375 (Fig. 2a). The NDVI values derived from ground-based spectrometric data for both clear plots and plots with a low infestation degree range from 0.74 to 0.79. The NDVI values for plots with a high infestation degree range from 0.68 to 0.69 (Fig. 2b).

The values of the vegetation indices, including NDVI, ClGreen, MSAVI2, and VARI, derived from satellite data for both clear plots and plots with a low infestation degree, are significantly higher than the values of these indices for plots with a high infestation degree (Fig. 3).

A qualitative similarity of the dependence of all indices on the infestation degree of wheat crops during the growing season is found. The value of the indices is reduced with increasing infestation of crops. However, the VARI dynamics differs from the NDVI, ClGreen, and MSAVI2 dynamics. The VARI value is out of phase with the values of other indices on some dates.

The correlation link analysis identified a high positive correlation among the vegetation indices, including NDVI, ClGreen, and MSAVI2, and a low positive correlation between VARI and other indices.

The spatial distribution map of ClGreen for the agricultural fields with different infestation degree is derived from PlanetScope satellite data with a 3-m spatial resolution on August 2, 2019. This map helps assess the degree of weed infestation of agricultural fields in the large territories.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

Arkhipova, O.E., Kachalina, N.A., Tyutyunov, Yu.V., and Kovalev, O.V., Assessment of infestation of anthropogenic phytocenoses based on remote sensing data (on the example of common ragweed), *Issled. Zemli Kosmosa*, 2014, no. 6, pp. 15−26.

Bondur, V.G., Modern approaches to processing large hyperspectral and multispectral aerospace data flows, *Izv., Atmos. Ocean. Phys.*, 2014, vol. 50, no. 9, 840−852.

Bondur, V.G. and Vorobev, V.E., Satellite monitoring of impact Arctic regions, *Izv., Atmos. Ocean. Phys.*, 2015, vol. 51, no. 9, pp. 949−968.

Che'Ya, N., Gupta, M., Doug, G., Lisle, A., Basnet, B., and Campbell, G., Spectral discrimination of weeds using hyperspectral radiometry, in *Proc. 5th Asian Conf. on Precision Agriculture (ACPA)*, Jeju, Korea, 2013, p. 325.

Gaznayee, H.A. and Al-Quraishi, A.M.F., Analysis of agricultural drought, rainfall, and crop yield relationships in Erbil province, the Kurdistan region of Iraq based on Landsat time-series MSAVI2, *J. Adv. Res. Dyn. Control Syst.*, 2019, vol. 11, pp. 536−545.
https://doi.org/10.5373/JARDCS/V11SP12/20193249

Gitelson, A., Stark, R., Grits, U., and Rundquist, D.C., Vegetation and soil lines in visible spectral space: A concept and technique for remote estimation of vegetation fraction, *Int. J. Remote Sens.*, 2002, vol. 23, pp. 2537−2562.

Gitelson, A.A., Viña, A., Arkebauer, T.J., Rundquist, D.C., Keydan, G., and Leavitt, B., Remote estimation of leaf area index and green leaf biomass in maize canopies, *Geophys. Res. Lett.*, 2003, vol. 30, no. 5, 1248.
https://doi.org/10.1029/2002GL016450

Gopp, N.V., Savenkov, O.A., and Smirnov, A.V., Digital mapping of spring wheat yield based on vegetation indices and assessment of its changes depending on the properties of anthropogenically transformed soils, *Sovrem. Probl. Distantsionnogo Zondirovaniya Zemli Kosmosa*, 2019, vol. 16, no. 3, pp. 125−139.

He, Y., Chen, F., Jia, H., Wang, L., and Bondur, V.G., Different drought legacies of rain-fed and irrigated croplands in a typical Russian agricultural region, *Remote Sens.*, 2020, vol. 12, no. 11, id 1700.

Herrmann, I., Shapira, U., Kinast, S., Karnieli, A., and Bonfil, D.J., Ground-level hyperspectral imagery for detecting weeds in wheat fields, *Precis. Agric.*, 2013, vol. 14, pp. 637−659.
https://doi.org/10.1007/s11119-013-9321-x

Hese, S. and Schmullius, C., High spatial resolution image object classification for terrestrial oil spill contamination mapping in West Siberia, *Int. J. Appl. Earth Obs. Geoinf.*, 2009, vol. 11, no. 2, pp. 130−141.
https://doi.org/10.1016/j.jag.2008.12.002

Hutto, K.C., Shaw, D.R., Byrd, J.D., and King, R.L., Differentiation of turfgrass and common weed species using hyperspectral radiometry, *Weed Res.*, 2006, vol. 54, no. 2, pp. 335−339.
https://doi.org/10.1614/WS-05-116R.1

Ikenov, I.A., Information system for assessing the state of vegetation on agricultural fields, *Vestn. Nauki*, 2019, vol. 4, no. 5, pp. 485−491.

Lamba, D.W. and Brown, R.B., PA—precision agriculture: Remote-sensing and mapping of weeds in crops, *J. Agric. Eng. Res.*, 2001, vol. 78, no. 2, pp. 117−125. https://doi.org/10.1006/jaer.2000.0630

Martin, M.P., Barreto, L., Riaso, D., Fernandez-Quintanilla, C., and Vaughan, P., Assessing the potential of hyperspectral remote sensing for the discrimination of grassweeds in winter cereal crops, *Int. J. Remote Sens.*, 2011, vol. 32, no. 1, pp. 49−67. https://doi.org/10.1080/01431160903439874

Mikhailenko, I.M. and Voronkov, I.V., Methods for detection of weeds, pests and diseases of plants from remote sensing data, *Sovrem. Probl. Distantsionnogo Zondirovaniya Zemli Kosmosa*, 2016, vol. 13, no. 3, pp. 72−83.

Moran, J.A., Mitchell, A.K., Goodmanson, G., and Stockburger, K.A., Differentiation among effects of nitrogen fertilization treatments on conifer seedlings by foliar reflectance: A comparison of methods, *Tree Physiol.*, 2000, vol. 20, pp. 1113−1120. https://doi.org/10.1093/treephys/20.16.1113

Petit, S., Boursault, A., Guilloux, M., Munier-Jolain, N., and Reboud, X., Weeds in agricultural landscapes. A review, *Agron. Sustain. Dev.*, 2011, vol. 31, no. 2, pp. 309−317. https://doi.org/10.1051/agro/2010020

Pflanz, M., Nordmeyer, H., and Schirrmann, M., Weed mapping with UAS imagery and a bag of visual words based image classifier, *Remote Sens.*, 2018, vol. 10, no. 10, id 1530. https://doi.org/10.3390/rs10101530

Pflugmacher, D., Krankina, O., Cohen, W.B., and Friedl, M.A., Sulla Menashe, D., Kennedy, R.E., Nelson, P., Loboda, T.V., Kuemmerle, T., Dyukarev, E., Elsakov, V., and Kharuk, V.I., Comparison and assessment of coarse resolution land cover maps for Northern Eurasia, *Remote Sens. Environ.*, 2011, vol. 115, pp. 3539−3553.

Pisman, T.I., Shevyrnogov, A.P., Larko, A.A., Botvich, I.Y., Emelyanov, D.V., Shpedt, A.A., and Trubnikov, Y.N., The information content of spectral vegetation indices in the interpretation of satellite images of cultivated fields, *Biophysics*, 2019, vol. 64, no. 4, pp. 588−592.

Planet Team, Planet Application Program Interface: In Space for Life on Earth; Planet Company: San Francisco, Calif., 2018. https://api.planet.com. Accessed January 10, 2019.

Qi, I., Chehbouni, A., Huete, A.R., Kerr, Y.H., and Sorooshian, S., A modified soil adjusted vegetation index, *Remote Sens. Environ.*, 1994, pp. 119−126.

Shevyrnogov, A.P., Pisman, T.I., Kononova, N.A., Botvich, I.Yu., Larko, A.A., and Vysotskaya, G.S., Seasonal dynamics of vegetation on fallow lands in Krasnoyarsk forest steppe according to terrain and satellite data, *Izv., Atmos. Ocean. Phys.*, 2019, vol. 66, no. 9, 1353−1361.

Shukilovich, A.Yu., Fedotova, E.V., and Maglinets, Yu.A., The use of the MODIS sensor for operational monitoring of agricultural lands, *Zh. Sib. Fed. Univ. Tekh. Tekhnol.*, 2016, vol. 9, no. 7, pp. 1035−1044. https://doi.org/10.17516/1999-494X-2016-9-7-1035-1044

Sid'ko, A.F., Botvich, I.Yu., Pisman, T.I., and Shevyrnogov, A.P., Angular distribution of reflective characteristics of agrocenoses according to ground-based remote measurements, *Zh. Sib. Fed. Univ. Tekh. Tekhnol.*, 2014, no. 6, pp. 665−673.

Sims, D.A. and Gamon, J.A., Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages, *Remote Sens. Environ.*, 2002, pp. 337−354. https://doi.org/10.1016/S0034-4257(02)00010-X

Solpieva, Zh.A. and Urmambetova, T.K., Assessment of the state of spruce forests according to Landsat-8 satellite data on the example of the Chon-Kemin national park, *Vestn. Kyrgyz. Gos. Univ. Stroit. Transp. Arkhit. im. N. Isanova*, 2018, no. 1, pp. 36−40.

Thorp, K. and Tian, L.F., A review on remote sensing of weeds in agriculture, *Precis. Agric.*, 2004, vol. 5, no. 5, pp. 477−508. https://doi.org/10.1007/s11119-004-5321-1

Tovstik E.V., Adamovich T.A., and Ashikhmina, T.Ya., Identification of sites of mass growth of *Heracleum sosnowskyi* using spectral indices according to Sentinel-2 data, *Teor. Prikl. Ekol.*, 2019, no. 3, pp. 34−40.

Voronina, P.V. and Mamash, E.A., Classification of thematic tasks of agricultural monitoring using MODIS remote sensing data, *Vychisl. Tekhnol.*, 2014, vol. 19, no. 3, pp. 76−102.

Vrindts, E.J., De Baerdemaeker, J., and Ramon H., Weed detection using canopy reflection, *Precis. Agric.*, 2002, vol. 3, no. 1, pp. 63−80. https://doi.org/10.1023/A:1013326304427

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