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Modeling and Forecasting the Phytocenosis Transformation Using the Tangential Photodocumentation

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***Abstract* — The work set its task to develop and verify a possibility to use in practice the method of remote analysis of phytocenoses based on tangential shooting in usual color format and as simple as possible transformation of the obtained digital information. We implemented this idea by developing a technique of shooting with the calculation of the index of phytocenosis diversity. The first step of algorithm consisted of obtaining tangential images of plant communities and its transformation into two original indexes. Then we compared these indexes with the results of real field observations and analysis of native and transformed hyperspectral space images on the same territories, including technogenic intrusions on the border with agro-ecosystem. As it turned out, although the method is somewhat inferior to NDVI mapping in its sensitivity, the use of simple equipment and ground-based nature of the photo shooting makes it prospective for express analysis of territories. This is useful for identifying 'area of interest' and 'risk territories' in the analysis of various phytocenoses both in ecology and agriculture.**

Keywords: phytocenoses, agro-ecosystems, anthropogenic transformation, ecological monitoring, forecast model, remote sensing

I. Introduction

Intensive human economic activity is a serious challenge to nature; it is almost inevitably accompanied by a violation of the natural topography, vegetation and soil quality. This leads to partial deflation of soil coverage, flushing of vegetation-free soil areas, landscape degradation, pollution of adjacent soil areas and water bodies [1, 2]. Such anthropogenic transformation of territories is particularly dangerous in the arid zone, where the restorative forces of nature were not so great, and there are additional natural factors contributing to deflation [3, 4].

As a result, currently the vegetation in the arid agriculture zone looks like a steady alternation of agro-ecosystems and natural phytocenoses with a significant level of anthropogenic transformation and the level of desertification up to 25-35% by area [5, 6].

From ecological point of view the events when sets of significantly transformed plant cover unrecoverable penetrated on the territory of controlled agro-ecosystems are of interest. They can be defined as technogenic intrusions. It is shown for species composition of intrusions usually to be reduced and have a direct and indirect negative impact on the adjacent agro-ecosystem contributing to the violation of consort bonds in it [7, 8].

This situation requires scientifically proved rehabilitation programs and management decisions in agriculture, which creates a need for dynamic monitoring of landscapes and phytocenoses in the vast territories of the arid zone. This problem cannot be solved with the help of classical methods of field observations, including the assessment of soil and vegetation *in situ* in combination with subsequent laboratory research, due to the enormous complexity and economic costs of such technologies. Therefore, only automated remote sensing techniques are currently acceptable for obtaining comprehensive information about the state of arid phytocenoses.

A comprehensive geoinformation assessment of the Earth's surface state based on data from multispectral space images became the main integrated approach to solving such problems. Successfully used to assess forest areas [9, 10], these methods were applied to assess the state and biomass of pastures and crops [11 – 13]. The normalized difference vegetation index (NDVI) became the most popular in the analysis of space images, although its informative limitations are well known due to problems with the transparency of the atmosphere, observation time, and resolution of the digitized image [14 – 16].

The use of low altitude unmanned aerial vehicles (UAVs) reduces most of the disadvantages of space sensing, although it is limited in research area and has several limitations related to weather and prohibitions of flight over certain territories. Nevertheless, the main progress in obtaining primary information for modeling and forecasting the behavior of phytocenoses is currently associated with the use of UAVs [17]. In particular, the level of resolution of images and dynamic video surveillance obtained using UAVs at various agro-ecosystems allows to calculate such an important indicator as the average height of plants [18-21], and this becomes the key to the most accurate calculation and

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prediction of biomass. Several studies confirm that combining spectral information and averaged plant height information could significantly improve biomass estimates [22, 23]. These results have recently been supplemented by machine learning technologies [24-26].

The aim of the work was to test the possibility of assessing the actual state of agro-ecosystems and technogenic intrusions using tangential photo documentation to obtain informative characteristics enough to build a prognostic model of consort bonds in these systems.

This model can be useful in making decisions on the introduction of certain agricultural and / or environmental technologies for the development of agricultural areas or individual farms.

II. Materials and Methods (Model)

The total number of monitored intrusions is eighteen at six sites located in the Volgograd and Astrakhan regions of Russia. For each intrusion, the following key characteristics were determined by direct in situ survey: topography (1) and micro-relief of the surface (2), soil type (3) and depth of the humified layer (3), features of anthropogenic impact (4) and features of the adjacent territory in azimuth (5).

Within the framework of the geobotanical description we separately noted the tiers, projective coverage (PP), the total number of species and their phenophases, the presence of dominants and subdominants, as well as the degree of negative impact of this intrusion on the adjacent agro-ecosystem (high, moderate or low) [7]. The control (expert) assessment of the impact of intrusions on the agro-ecosystem was to determine the average height and phenological parameters of the cultivated crop, as well as the abundance of weeds in the field. We identified these features directly at the boundary with the intrusion and at a distance of 50 m deep into the field. Differences were expressed in score scale of 1 to 10.

All intrusions were subjected to serial tangential photography at an angle of 30-45 degrees to the horizon for at least 50 m, that is, with the capture of adjacent areas of agro-ecosystem. For further analysis, we used ImageJ (Wayne Rasband, USA) and Excel (Microsoft, USA). On tangential digital images, the ‘area of interest’ was expertly identified and formalized as a rectangular collection of pixels completely lying within the area expertly identified as ‘plants’. Next, we converted the RGB (Red, Green, Blue) scale in the selected area of values into the HSL (Hue, Saturation, Lightness) scale. Only H and S indicators were used for further analysis, since the L values depended primarily on the lighting conditions at the time of shooting. These values were averaged in squares with a side length equal to 10% of the long side of the ‘zone of interest’ rectangle to smooth out small artifacts.

Further, we subdivided all values taken separately for H and S into five corridors in ascending order of the value of the indicator from Min to Max. They corresponded to extremely low, low, medium, high and extremely high value of the indicators. Then the number of hits in each of the 25 possible combinations of h and S values was calculated (Fig. 1).

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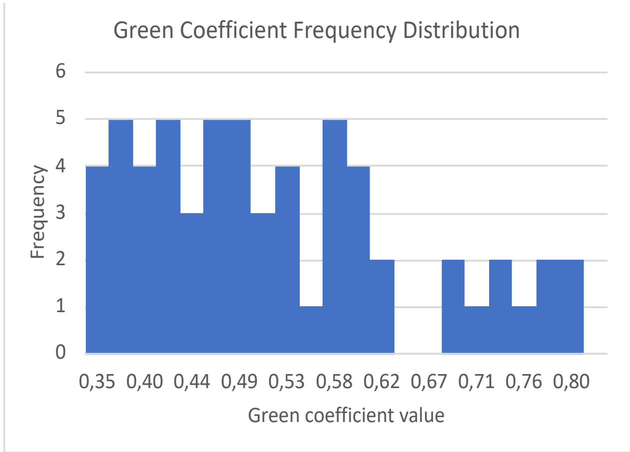
The next step was to calculate two integral indicators according to the given data. The first of them is a weighted product of the values H and S, which we called the ‘green coefficient’ (GC) and use it as a potential analogue of the previously described NDVI index. GC was calculated by the following formula:

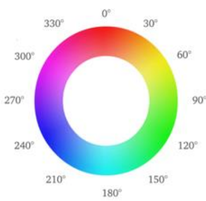
A B



C

			Saturation				
		from	0	0,1568	0,1707	0,1846	0,1985
Hue	from	to	0,1568	0,1707	0,1846	0,1985	1
	0	57	2	7	18	1	0
	57	66	2	14	2	0	0
	66	75	4	7	6	1	0
	75	84	1	6	7	6	1
	84	120	0	1	3	5	3

D



E

Fig. 1. Distribution of the main spectral characteristics of color reproduction in the isolation of plants in technogenic intrusion. A. The selected portion of the digital image. B. Averaged values of the color. C. Frequency distribution of the green ratio. D. Number of hits in combination H and S. E. Radial color palette H.

$$GC = \begin{cases} 0 : H \in [0, 60] \cup [180, 360) \\ \frac{120S}{|H - 120|} \end{cases} \quad (1)$$

The second index, defined as the number of combinations of H and S with the number of hits greater than one, we call the ‘diversity index’ (DI). It is easy to see that when analyzing an image with a perfectly uniform fill, the DI will be equal to one. The maximum possible value is 25, and it corresponds to the case when the photo in question presents all combinations of green shades of and saturation in an amount greater than 1. Single hits can be caused by artifacts in the image (buildings, agricultural machinery) and therefore must be discarded.

In our opinion, these indicators allow us to dynamically assess the spread of shades of green in the selected area and, collectively, they reflect the diversity of plant species and phenophases in surveyed phytocenosis.

Since the values of the indicators are calculated on each digitized image separately, an internal standard is set to avoid errors associated with variations in the lighting the object and the characteristics of plant communities in this area. The value of the indicator 17 or more reflected high diversity and, indirectly, the strength and stability of phytocenosis, and, respectively, a value of less than 8 was the sigh of impoverishment of phytocenosis and deflation,

Multispectral high-resolution Landsat space images available on the USGS Earth Resources Observation and Science platform and processed using the ArcGISPro software package were used as comparison images to determine the capabilities of this method. We used normalized difference vegetation index NDVI and normalized difference moisture index NDMI as reference integral indicators. These indicators reflect the total amount of biomass and humidity of vegetation cover in the studied areas [14, 16].

III. Results and Discussion

A. Results of field observations

All surveyed areas had similar landscape, geomorphological and soil characteristics. The terrain was flat, usually it had a slight slope towards natural depressions. The soils are light brown, the humus layer was scarce, it thickness was about 2-10 cm. Climatic and hydrological characteristics corresponded to regional ones. Table 1 presents the main geobotanical characteristics and results of remote measurements depending on the degree of negative impact on the adjacent agro-ecosystem.

The results of field observations well show for technogenic intrusion with significant impact on adjacent agricultural fields to have more relatively more variable tiers, greater PC value, and diversity of species. Their negative impact on the field is noticeable at a depth of at least 40-50 m from the intrusion boundary. Technogenic intrusions with a weak impact on the adjacent agro-ecosystems demonstrate the opposite of generalized characteristics.

TABLE I. Main Geobotanical Characteristics of Intrusions

Indicator	Impact on the agro-ecosystem		
	Low (n = 5)	***Moderate (n = 7)***	***High (n = 6)***
Tiers, m	0.2 – 0.8	0.2 – 1.2	0.2 – 1.6
Projective coverage, %	20 – 45	35 – 70	60 – 80
Total number of species	5 – 8	6 – 12	8 – 15
The number of dominants	0 – 1	1 – 2	1 – 2
The number of ubdominants	0 – 1	0 – 2	1 – 3

B. Results of remote sensing

Preliminary analysis showed that the used color transformations quite objectively reflected the nature of PC in the territory of agro-ecosystems and technogenic intrusions. They are quite consistent with the NDVI analysis. The loss in quality, which is observed in analogical analysis of conventional space and aerial images, is fully compensated by the absence of the need to use expensive hyperspectral remote sensing equipment (Fig. 2).

The results of remote sensing, presented in table 2, show that technogenic intrusions with a significant impact on the agro-ecosystem, had, other things being equal, relatively large values of NDVI, GC and DI by our original method.

The obtained correspondences convince us that the developed and used technique correctly reflected the properties of technogenic intrusions with respect to the strength of their consort bonds and the ability to actively exist and develop in a competitive environment.

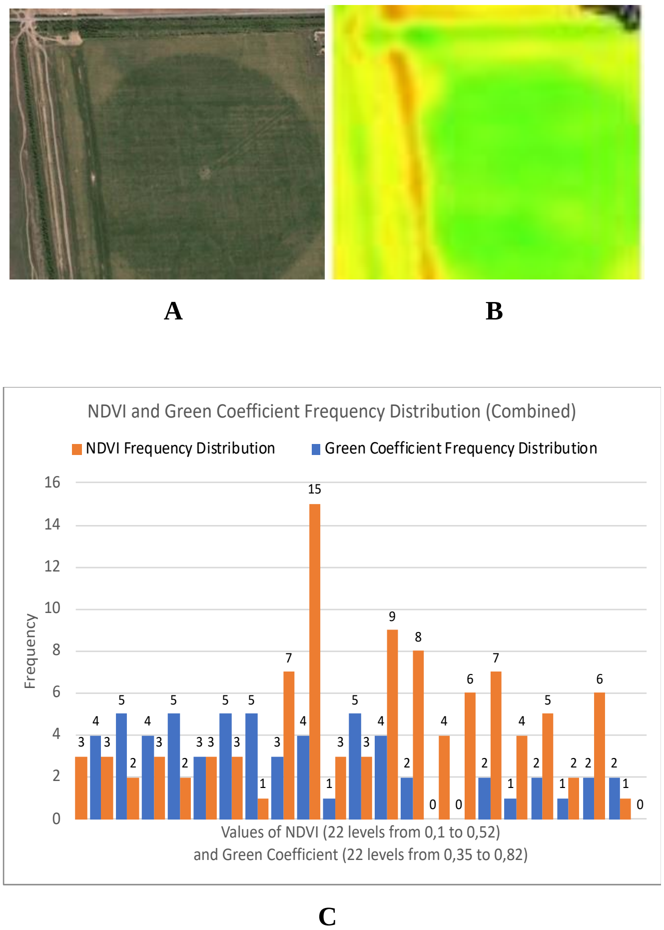


Fig. 2. A. The zone of interest, including intrusions, on the space image demonstrates the heterogeneity of the plant cover both on the field and on the location of intrusions. B. The same area, visualized in DVI format, shows clearer differences in the magnitude of the projective coverage of the agro-ecosystem and adjacent areas. C. Comparison of the frequency distribution of the green coefficient and NDVI shows a similar but not identical variation in the amplitudes of the values.

TABLE II. MAIN CHARACTERISTICS OF INTRUSIONS BASED ON THE RESULTS OF REMOTE SENSING

Indicator	**Impact on the agro-ecosystem**		
	Low (n = 5)	***Moderate (n = 7)***	***High (n = 6)***
NDVI	0.12 – 0.24	0.18 – 0.52	0.30 – 0.62
Green coefficient (median value)	0.28 – 0.34	0.32 – 0.4	0.36 – 0.44
Diversity index	6 – 10	8 – 20	15 – 22

Figure 3 further demonstrates how NDVI and Green coefficient as indicators reflected in a similar but not identical manner the spatial biomass distribution in the certain agro-ecosystem. In some cases we may consider, that our method allowed getting clearer results.

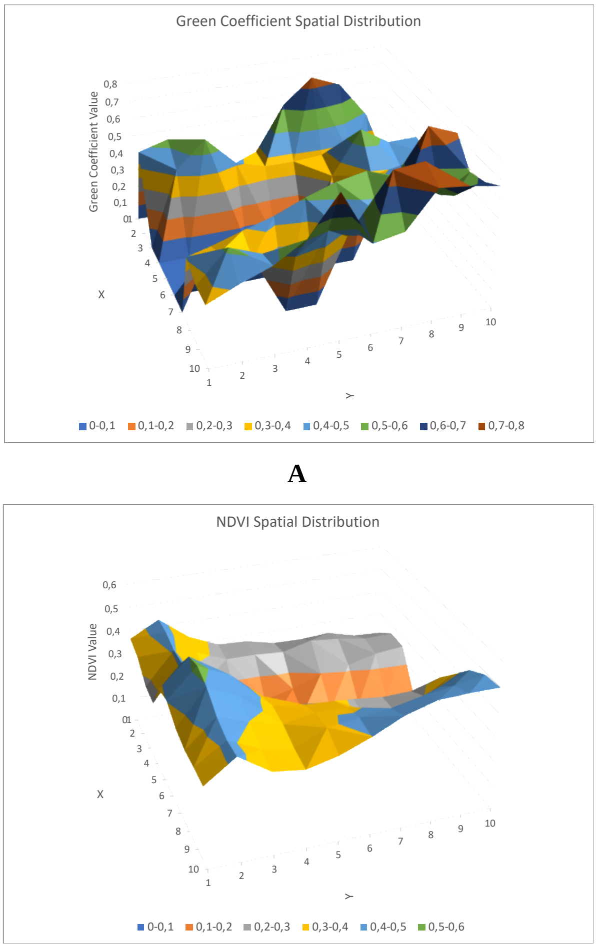


Fig. 3. The spatial value of the Green coefficient and NDVI on the space image shows a similar, but not identical sensitivity of the indicators.

Our observations testify that NDVI, median of green coefficient and diversity index are increasing simultaneously with the intrusion influence rate.

However, the spatial distribution of NDVI and GC are significantly different. This fact makes us believe that the GC is not just substitute of NDVI but probably has its own value, making a researcher able to extract additional information from space or drone images. The additional advantage of the proposing method over NDVI is it uses conventional images instead of hyperspectral ones. So, one could use it with current monitoring infrastructure and observe changes in real time.

According the results of comparative analysis the used remote methods in general adequately reflected the situation on the agricultural fields and technogenic intrusions. Both NDVI and GC or DI proposed by us allow to accurately identify spatial differences in the volume of plant biomass, as well as to be used for the integrated assessment of these plant communities. At the same time, an additional possibility arises in the case of the use GC and DI, when on the basis of spatial analysis we can establish the plant diversity, further forecasting its stability and potential invasiveness of intrusions in relation to the adjacent agro-ecosystem.

We have already shown that the zone of contact between the intrusion and the agro-ecosystem could be characterized by a finite number of formalized indicators, so that on this basis it is possible to build a predictive model sufficient to test the potential effectiveness of management decisions [27]. A number of studies have demonstrated the effectiveness of such approaches in combination with machine learning algorithms to solve the problem of plant invasion on the territory of agricultural fields [28 – 30].

We hope that furthermore detailed and long-term studies will allow us to develop this express method of remote sensing into a technology ensuring the management of agricultural ecosystems.

IV. CONCLUSION

The method of ground remote photography of plant communities on the example of agricultural fields and technogenic intrusions in the arid zone allows for express analysis of their condition. The original indicators (Green Coefficient and Diversity Index'), which we proposed for the analysis of the obtained images, sufficiently reflect such important indicators of agro-ecosystem state as the biomass volume and resistance to surrounding actions. For technogenic intrusions, they can also be used as indicators of invasiveness against the adjacent agro-ecosystem, which is confirmed by parallel field studies.

In terms of information content, the proposed indicators are not inferior to the classical estimates using NDVI, and do not require equipment to obtain spectral images. This method can be useful for identifying 'area of interest' and 'risk territories' in the analysis of various phytocenoses both in ecology and agriculture.

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