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Soil patterns as a factor of crop heterogeneity

I Savin[1,2,6*], A M Ali[2,3], I Gitas[4], D E Kucher[2], P A Dokukin[2] and A K Radzhabov[5]

[1] Dokuchaev Soil Science Institute, 7, Pyzhevsky per., Moscow 119017, Russian Federation
[2] Peoples' Friendship University of Russia (RUDN University), 6, Miklukho-Maklaya st., Moscow 117198, Russian Federation
[3] National Authority for Remote Sensing and Space Sciences (NARSS), 23, Joseph Tito st., Cairo 1564, Egypt
[4] Aristotle University of Thessaloniki, University Campus, Thessaloniki, 54124 Hellas
[5] Russian State Agrarian University – Moscow Timiryazev Agricultural Academy, 49, Timiryazev st., Moscow 127550, Russian Federation
[6] Belgorod State University, 85, Pobedy st., Belgorod 308015, Russian Federation

[*]Email: savin_iyu@esoil.ru

Abstract. Crop heterogeneity constitutes the basis for taking managerial decisions in precision farming systems. Although the general perception is that heterogeneity within a plot is related to heterogeneity of soil cover, this needs further study and remains an active subject of research. This paper examines the relationship between the heterogeneity of different crops in the Tula region of the Russian Federation based on vegetation observations during the period 2015–2020 with the mapping units of a large (scale 1:10,000) soil map. NDVI values calculated from Sentinel-2 satellite data were used as a measure of crop heterogeneity. The comparison of NDVI values and the soil mapping units showed that there is a degree of correlation which, however, was not particularly high. Results indicate that correlation depends on the crop type, the phenological phase of vegetation, as well as on the meteorological conditions during the vegetation season, the soil moisture and the presence of weeds. It could be concluded that the soil map alone cannot be used as a reliable source for explaining crop heterogeneity in the Tula region and that other factors should be considered.

1. Introduction

As few biodiversity studies have explicitly considered this important ecosystem feature, the role of soil heterogeneity as a modulator of ecosystem responses to biodiversity changes remains poorly understood [1]. Ecosystem functioning studies have explicitly considered the spatial heterogeneity in the availability of soil resources (hereafter soil heterogeneity [2–4]. Therefore, little is known on the potential effects of soil heterogeneity as a modulator of ecosystem responses to changes in biodiversity, particularly when these relate to modifications in the diversity of functional groups. Soil heterogeneity has also been found to increase the slope of the diversity–ecosystem function relationship, suggesting that biodiversity may have its greatest impact on the functioning of diverse, naturally heterogeneous ecosystems [5].

Soil is the basis for cultivating crops and is one of the factors that predetermine their yield. Information on soil condition is taken into account when planning the use of fertilizers, crop protection products, and when determining irrigation rates [6].

In most cases, the soil cover of individual fields is not uniform [7]. But the heterogeneity of the soil cover within individual fields within traditional farming systems is rarely taken into account. Usually this is done when using precision farming systems [8]. But their implementation and use are in many cases very costly.

In traditional farming systems, the source of information on soil inhomogeneity within a field is a soil map, which is a model of soil inhomogeneity [9]. At compiling up of the soil map authors use classification of soils which often does not consider all agronomically important properties of soils. Therefore, using a soil map to account for soil inhomogeneities within individual fields may be inefficient [10]. Despite the great importance of the problem of taking into account the influence of soils on the heterogeneity of crops, there are still few studies in this direction.

Vegetation indices are classified as dimensional, radiometric measurements that act as indicators of relative abundance and green vegetation activity, often including leaf area index, plant cover percentage, chlorophyll content, plant biomass, and photo synthetically active radiation absorbed [11]. NDVI is characterized as a reduction in soil biological productivity [12, 13]. Indices such as the Normalized Vegetation Difference Index (NDVI) reflect the overall impact of rainfall and soil characteristics, crop phenology [14, 15], and crop yield estimation [16, 17]. NDVI has become the most important tool for monitoring and detecting the relationship between soil characteristics and crop heterogeneity [18].

Information on crop heterogeneity is often used to correct applied agricultural technologies, to assess expected crop yields, in crop insurance [19]. Therefore, obtaining accurate and reliable information, as well as information on the factors that predetermine the appearance of heterogeneity is an important task.

In the proposed article by the example of one of the test fields is given an analysis of the relationship between soil mapping units and crop irregularities in different years.

2. Material and methods

The study was conducted on the example of one of the fields of Tula region of Russia (figure 1).

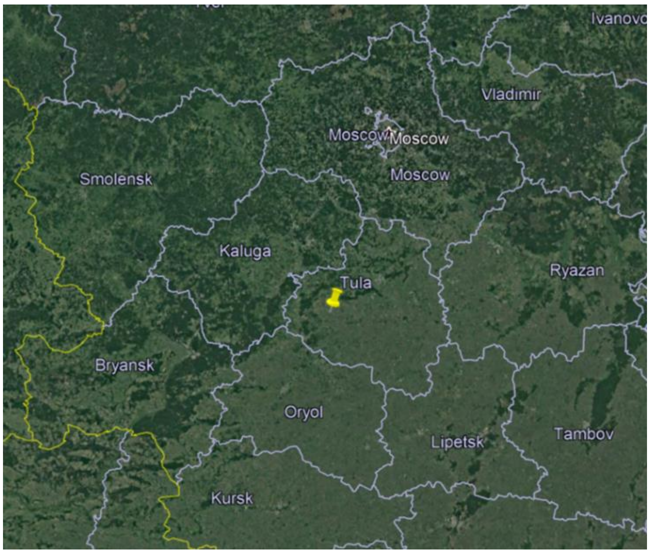

Figure 1. Test plot allocation.

The territory is slightly undulated plane, dissected by small rivers' valleys.

The climate is temperate with moderately cold winter (air temperature is near 10 ºC) and warm summer (air temperature is near +25 ºC). Amount of precipitation is near 450 mm per year.

The field has a contrasting soil cover. The soil map of the field is shown in figure 2. The map was created based on traditional soil field surveying approach [20]. Soil mapping units were delineated based on field soil profiles description, and using aero photo images. Original scale of the paper map is 1:10,000. It was digitized, and georeferenced using high resolution space images (WorldView-2).

Ranking of the field soil by potential productivity is shown in table 1. The potential productivity ranking is based on the approach of soil bonitet, which is a main method for land evaluation in Russia [21].

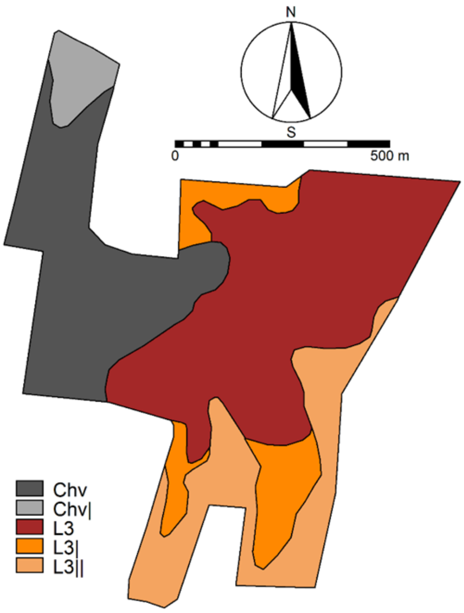

Figure 2. Soil map of the test plot (Chv – chernozems, Chv| chernozems slightly eroded, L3 – grey forest soil, L3| grey forest slightly eroded soil, L3|| grey forest moderately eroded soil).

Table 1. Soils of test plot.

Soil	Texture	Humus content, %	Potential productivity range
Chv – chernozems	heavy loam	4.7	1
Chv| – chernozems slightly eroded	heavy loam	3.2	2
L3 – grey forest soil	heavy loam	2.8	3
L3| – grey forest slightly eroded soil	heavy loam	2.3	4
L3|| – grey forest moderately eroded soil	heavy loam	1.8	5

The amount of precipitation in this area is sufficient for the growth of all cultivated crops, so irrigation is not used. The crops in this field are cultivated in a special crop rotation. As a result, spring barley was cultivated in the field in 2015, corn for grain in 2016, spring wheat in 2017, fallow lands were in 2018, winter wheat in 2019, and winter barley in 2020. Phenological development of crops is shown at figure 3. Crop phenological dates were received from the owner of the land of test filed.

Crop heterogeneity was assessed using the NDVI vegetation index, calculated using satellite data from Sentinel-2. This index has been most frequently used to assess the crop status for several decades already [22]. Most precision farming systems also function using this index [23]. We use NDVI values spatial variability within soil mapping units as an indicator of crop heterogeneity.

Between 2015 and 2020, all cloudless scenes were selected, atmospheric corrections were made and NDVI values were calculated. In total, 20 images of the NDVI test field were selected and analyzed (figure 3).

The soil map plots were combined in the GIS (we use ILWIS v.3.3) with the NDVI maps calculated based on Sentinel-2 data. Average NDVI value and its standard deviation were determined for each soil mapping unit. In addition, the correlation between NDVI maps of different dates of images acquisition was analyzed. The results of the analysis were used as an indicator of stability of detected NDVI irregularities in the field in time.

In addition, visual analysis and comparison of NDVI maps was performed.

year	month											
	1	2	3	4	5	6	7	8	9	10	11	12
2015				SBs				SBh	★			
2016					Cs				★ Ch			
2017				SWs			★	★ SWh	★			
2018			F	F	F	F	F	F	★★ WWs	★★	★★	
2019				★★		★★★		★★ WWh		WBs		
2020						★★	WBh					

Figure 3. Crop phenology (SBs – spring barley sowing; SBh – spring barley harvesting: Cs – corn sowing; Ch – corn harvesting; WWs – winter wheat sowing; WWh – winter wheat harvesting; WBs – winter barley sowing; WBh – winter barley harvesting; F – fallow lands), and Sentinel images acquisition months (red stars).

3. Results and discussion

Figure 4 shows the NDVI maps on the test field for all selected Sentinel-2 scenes.

Visual analysis of the maps allows us to conclude that NDVI irregularities often quite well coincide with the soil mapping units (black lines on the figures). But this is not the case for all dates and not for all crops.

Table 2 shows the results of statistical analysis of NDVI distribution within the soil mapping units of one type (NDVI mean value and its standard deviation). Although the mean values for different soil mapping units are close to each other, in many cases they differ statistically significantly.

The results of correlation analysis between NDVI maps obtained for different dates are shown in table 3. Green color in the table highlights cases of significant correlation coefficients exceeding 0.6.

NDVI maps obtained for different dates and for different crops showed that there is no clear confinement of observed inhomogeneities to soil cover. Analysis of the soil map of the field shows that there are more fertile chernozem soils and less fertile grey forest soils, as well as their eroded variants, the potential fertility of which is lower than the fertility of uneroded dominant soils. But this general idea of the potential fertility of soils, based on generally accepted in Russia approaches of soil bonitet [21], is not shown in all cases. Thus, in the area with uneroded chernozems NDVI values (as an indicator of above-ground phytomass) in some periods were lower than in the mapping units of grey forest soils. This is most clearly seen on NDVI maps for April 2019 and November 2018. Moreover, from figure 4 it follows that the crop status in areas with medium eroded soils (southeast part of the field) was in many cases higher than in the background watershed soils. This is probably due to the quality of the soil map, which does not show the areas of overwatered soils of the concave parts of lower parts of the slopes, on which under conditions of additional water content, crops may have more phytomass than on eroded soils and soils of watersheds. This may also be due to the fact that these areas are usually has more weeds, which could also cause an increase in NDVI.

Both high and low NDVI values may occur simultaneously in the same soil mapping unit. Of all the analyzed images, the most contrasting is the unit of the chernozems at November 23, 2018 (figure 5).

Such distribution of NDVI is due to specific weather conditions. The higher amount of precipitation led to overlodging of soils and, consequently, to soaking of crops.

This had the greatest impact on more humusized chernozems and on the part of the field adjacent to the forest area, the proximity to which was expressed in even greater moisturizing and soaking of winter crops in autumn.

In the post-winter period, soaked crops were fed with nitrogen fertilizers, which led to the fact that at the peak of the vegetation season they were already superior to crops (according to NDVI) that were not subject to autumn overwetting.

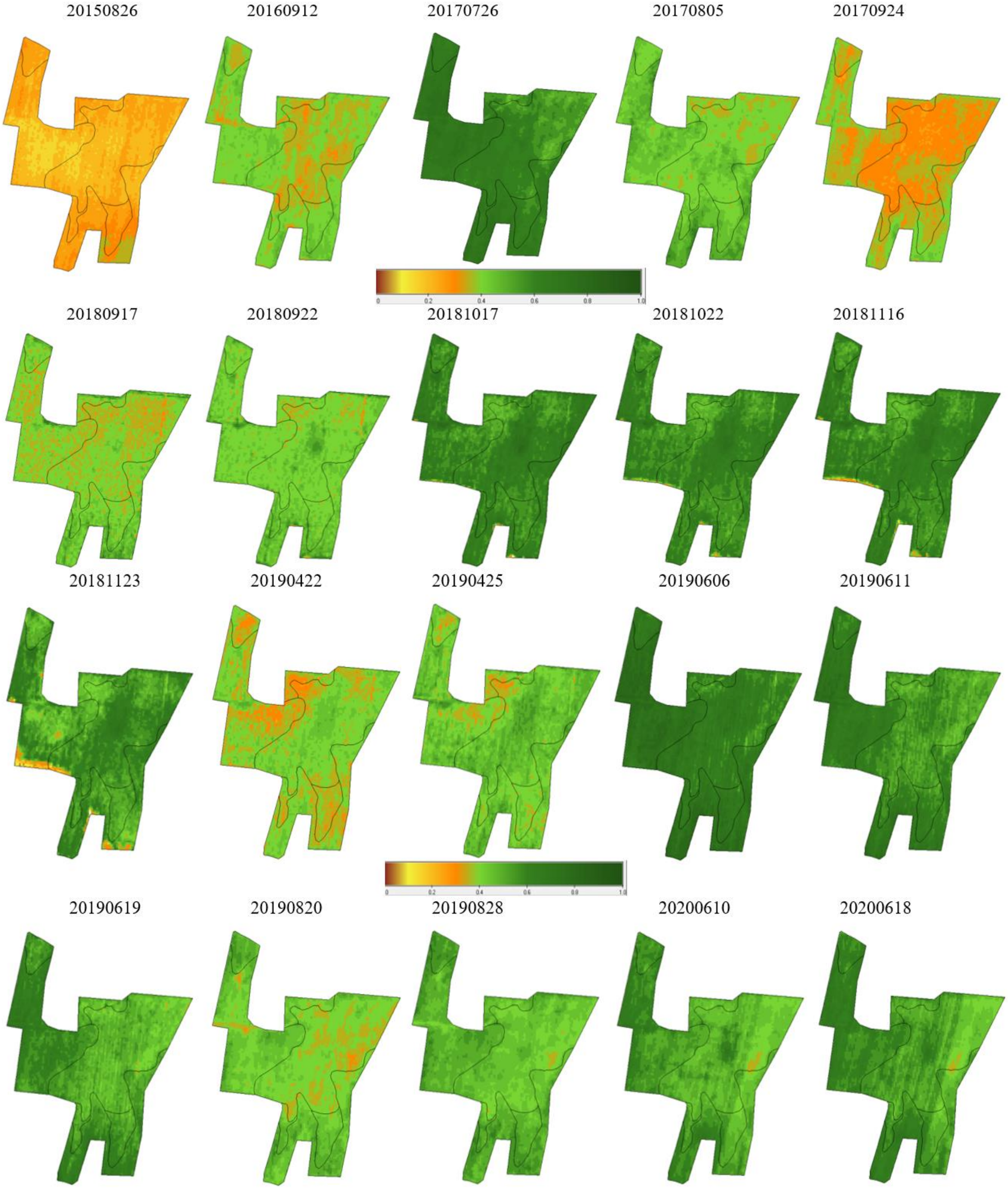

Figure 4. NDVI maps for test plot for different dates.

From the data in figure 4 it is also clearly seen that the peculiarities of heterogeneity in NDVI are different for different crops. And in most cases, they are preserved for the whole period of vegetation of the crop, sometimes intensifying, sometimes smoothing. This is explained by the fact that different crops have different ecological requirements and react differently both to soil conditions and to weather conditions of a particular vegetation season.

When averaging NDVI data for individual soil units, visually visible heterogeneities on the maps (figure 4) are smoothed rather strongly. As a result, average NDVI values for different soil mapping units and for different dates are quite close to each other. Big differences are observed only for different crops. This can be clearly seen from the data in table 2.

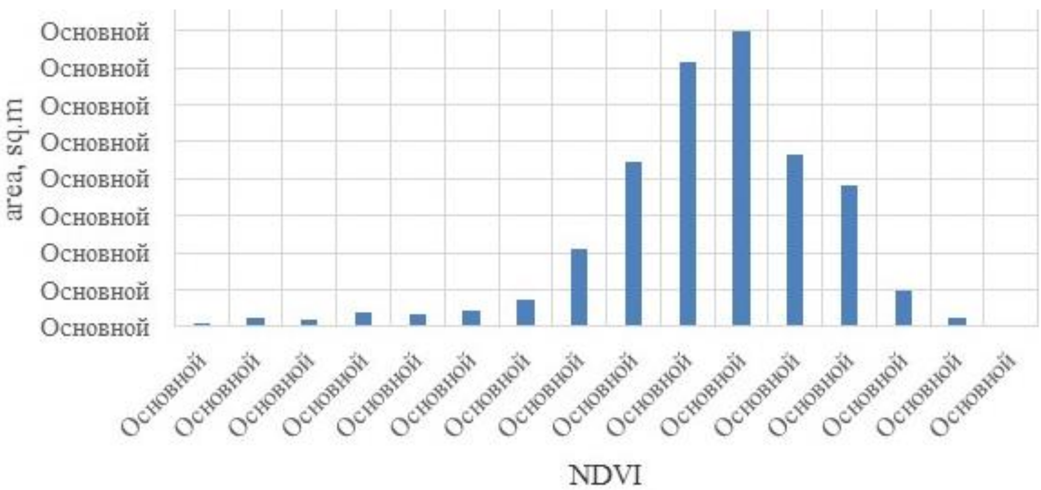

Figure 5. Histogram of NDVI for chernozems for November 23, 2018.

Table 2. Results of statistical analysis of NDVI distribution within the soil mapping units (NDVI mean value and its standard deviation).

Soil code	Date																			
	20150826		**20160912**		**20170726**		**20170805**		**20170924**		**20180917**		**20180922**		**20181017**		**20181022**		**20181116**	
	ndvi_av	ndvi_std	ndvi_av	ndvi_std	ndvi_av	ndvi_std	ndvi_av	ndvi_std	ndvi_av	ndvi_std	ndvi_av	ndvi_std	ndvi_av	ndvi_std	ndvi_av	ndvi_std	ndvi_av	ndvi_std	ndvi_av	ndvi_std
Chv	0.2	0.04	0.4	0.03	0.7	0.04	0.45	0.04	0.35	0.04	0.39	0.04	0.42	0.04	0.6	0.06	0.59	0.06	0.6	0.08
Chv|	0.25	0.02	0.39	0.04	0.65	0.03	0.42	0.03	0.35	0.03	0.42	0.04	0.42	0.04	0.59	0.06	0.56	0.04	0.57	0.06
L3	0.22	0.03	0.37	0.03	0.58	0.05	0.4	0.03	0.31	0.03	0.38	0.04	0.42	0.04	0.61	0.06	0.6	0.06	0.61	0.06
L3|	0.26	0.03	0.39	0.04	0.61	0.05	0.42	0.04	0.34	0.03	0.42	0.05	0.42	0.04	0.56	0.05	0.55	0.04	0.56	0.05
L3||	0.27	0.05	0.4	0.04	0.66	0.05	0.48	0.05	0.37	0.04	0.44	0.05	0.45	0.05	0.61	0.06	0.59	0.05	0.6	0.07
	20181123		**20190422**		**20190425**		**20190606**		**20190611**		**20190619**		**20190820**		**20190828**		**20200610**		**20200618**	
Chv	0.52	0.11	0.38	0.04	0.43	0.05	0.75	0.05	0.68	0.05	0.6	0.05	0.44	0.04	0.5	0.04	0.57	0.05	0.61	0.05
Chv|	0.5	0.06	0.36	0.04	0.4	0.04	0.68	0.05	0.62	0.04	0.56	0.04	0.5	0.04	0.54	0.03	0.56	0.03	0.6	0.04
L3	0.57	0.07	0.4	0.04	0.45	0.05	0.63	0.06	0.54	0.05	0.48	0.04	0.39	0.03	0.44	0.04	0.47	0.05	0.51	0.06
L3|	0.52	0.05	0.36	0.04	0.41	0.04	0.66	0.06	0.58	0.05	0.52	0.05	0.44	0.04	0.48	0.04	0.5	0.05	0.53	0.05
L3||	0.55	0.09	0.39	0.04	0.44	0.04	0.72	0.06	0.64	0.07	0.58	0.06	0.45	0.05	0.5	0.05	0.54	0.07	0.57	0.08

This is also confirmed by the data in table 3. NDVI maps constructed for different dates but for the same crop are much better correlated with each other than NDVI maps constructed for other crops. In addition, table 3 shows that the correlation between the NDVI maps increases during periods of maximum crop development. This is because at the time of maximum above-ground phytomass, the crops become the most homogeneous in terms of NDVI, which results in the greatest similarities among them. The biggest differences (and, accordingly, the lowest values of correlation coefficients) are observed at the beginning of the growing season, when the vegetation in the fields is green, but its projective coverage is still low. During the period of crop ripening the color of crops becomes homogeneous yellow and more similar to soil color, which leads to greater homogenization of the image of crops. This pattern can be disturbed only with high crop weedness, when a large number of green weeds can lead to increased spatial heterogeneity in crop NDVI [24, 25]. This is most probably the reason for the crop heterogeneity detected in September 2017 and August 2019.

It should be noted that such factors as the quality of the soil map and the use of NDVI as an indicator of crop heterogeneity could have influenced the results of the analysis.

Table 3. Correlation between NDVI maps for different dates.

	ndvi_20150826	ndvi_20160912	ndvi_20170726	ndvi_20170805	ndvi_20170924	ndvi_20180917	ndvi_20180922	ndvi_20181017	ndvi_20181022	ndvi_20181116	ndvi_20181123	ndvi_20190422	ndvi_20190425	ndvi_20190606	ndvi_20190611	ndvi_20190619	ndvi_20190820	ndvi_20190828	ndvi_20190902	ndvi_20190909	ndvi_20200610	ndvi_20200618
ndvi_20150826	1	0.16	-0.06	0.27	0.38	0.37	0.21	-0.11	-0.2	-0.2	-0.13	-0.12	-0.11	0.02	0.07	0.14	0.37	0.27	0.23	0.19	0.08	0.04
ndvi_20160912	0.16	1	0.32	0.36	0.36	0.2	0.17	0.05	0.01	0.01	-0.09	-0.03	0	0.42	0.43	0.41	0.42	0.47	0.48	0.45	0.28	0.28
ndvi_20170726	-0.06	0.32	1	0.68	0.42	0.12	0.17	0.04	0.07	0.05	-0.06	-0.05	-0.04	0.77	0.77	0.77	0.44	0.56	0.59	0.61	0.73	0.78
ndvi_20170805	0.27	0.36	0.68	1	0.61	0.31	0.32	0.1	0.09	0.05	-0.01	0.01	0.04	0.59	0.6	0.65	0.47	0.52	0.55	0.54	0.53	0.54
ndvi_20170924	0.38	0.36	0.42	0.61	1	0.39	0.29	0.08	0.04	-0.03	-0.1	-0.05	-0.02	0.46	0.53	0.58	0.51	0.53	0.56	0.56	0.46	0.44
ndvi_20180917	0.37	0.2	0.12	0.31	0.39	1	0.5	0.2	0.1	0.09	0.01	0.07	0.11	0.19	0.23	0.26	0.38	0.35	0.38	0.38	0.25	0.23
ndvi_20180922	0.21	0.17	0.17	0.32	0.29	0.5	1	0.5	0.45	0.31	0.21	0.36	0.35	0.25	0.26	0.27	0.19	0.26	0.28	0.31	0.35	0.27
ndvi_20181017	-0.11	0.05	0.04	0.1	0.08	0.2	0.5	1	0.72	0.76	0.53	0.6	0.61	0.13	0.1	0.06	-0.15	-0.04	0.04	0.09	0.2	0.11
ndvi_20181022	-0.2	0.01	0.07	0.09	0.04	0.1	0.45	0.72	1	0.7	0.6	0.62	0.63	0.18	0.12	0.08	-0.21	-0.08	-0.01	0.06	0.23	0.13
ndvi_20181116	-0.2	0.01	0.05	0.05	-0.03	0.09	0.31	0.76	0.7	1	0.68	0.57	0.59	0.13	0.09	0.03	-0.22	-0.11	-0.03	0.02	0.15	0.1
ndvi_20181123	-0.13	-0.09	-0.06	-0.01	-0.1	0.01	0.21	0.53	0.6	0.68	1	0.49	0.51	0.03	-0.04	-0.08	-0.25	-0.17	-0.11	-0.08	0.04	0
ndvi_20190422	-0.12	-0.03	-0.05	0.01	-0.05	0.07	0.36	0.6	0.62	0.57	0.49	1	0.77	0.11	0.05	-0.02	-0.33	-0.2	-0.12	-0.05	0.1	0.04
ndvi_20190425	-0.11	0	-0.04	0.04	-0.02	0.11	0.35	0.61	0.63	0.59	0.51	0.77	1	0.16	0.08	0.02	-0.3	-0.17	-0.08	-0.01	0.14	0.06
ndvi_20190606	0.02	0.42	0.77	0.59	0.46	0.19	0.25	0.13	0.18	0.13	0.03	0.11	0.16	1	0.89	0.9	0.39	0.54	0.61	0.66	0.71	0.74
ndvi_20190611	0.07	0.43	0.77	0.6	0.53	0.23	0.26	0.1	0.12	0.09	-0.04	0.05	0.08	0.89	1	0.89	0.45	0.59	0.66	0.72	0.75	0.77
ndvi_20190619	0.14	0.41	0.77	0.65	0.58	0.26	0.27	0.06	0.08	0.03	-0.08	-0.02	0.02	0.9	0.89	1	0.49	0.61	0.67	0.7	0.75	0.75
ndvi_20190820	0.37	0.42	0.44	0.47	0.51	0.38	0.19	-0.15	-0.21	-0.22	-0.25	-0.33	-0.3	0.39	0.45	0.49	1	0.87	0.81	0.75	0.47	0.5
ndvi_20190828	0.27	0.47	0.56	0.52	0.53	0.35	0.26	-0.04	-0.08	-0.11	-0.17	-0.2	-0.17	0.54	0.59	0.61	0.87	1	0.85	0.82	0.59	0.61
ndvi_20190902	0.23	0.48	0.59	0.55	0.56	0.38	0.28	0.04	-0.01	-0.03	-0.11	-0.12	-0.08	0.61	0.66	0.67	0.81	0.85	1	0.89	0.64	0.67
ndvi_20190909	0.19	0.45	0.61	0.54	0.56	0.38	0.31	0.09	0.06	0.02	-0.08	-0.05	-0.01	0.66	0.72	0.7	0.75	0.82	0.89	1	0.68	0.71
ndvi_20200610	0.08	0.28	0.73	0.53	0.46	0.25	0.35	0.2	0.23	0.15	0.04	0.1	0.14	0.71	0.75	0.75	0.47	0.59	0.64	0.68	1	0.89
ndvi_20200618	0.04	0.28	0.78	0.54	0.44	0.23	0.27	0.11	0.13	0.1	0	0.04	0.06	0.74	0.77	0.75	0.5	0.61	0.67	0.71	0.89	1

Soil map is a standard product created by the developed method. But it doesn't reflect the heterogeneity of the soil cover of small sizes, which can affect the Sentinel-2 survey data and, consequently, the NDVI values.

Reflection of such inhomogeneities on the map is most important for small fields. The field that we used as a test field is large, but the presence of micronutrient heterogeneity in the field may also have affected the analysis results. In addition, not all soil properties that may influence the state of crops are reflected on soil maps [10].

NDVI is not an ideal indicator of crop status. It is known that at high density of crops NDVI can be saturated [26–28]. In addition, it is influenced by the weedness of crops, which is different for different crops and can have a great influence on the values of this index in different periods of the vegetation season [29]. Also, the NDVI values can be influenced by spectral heterogeneity of soil surface on the field, which can be expressed in overestimation of real correlation between the state of crops and soils [30].

4. Conclusion

As a result of the conducted researches, it was found that the state of crops on the test field demonstrates the correlation with the soil map, but the influence of soils is not decisive.

The state of crops was influenced by such factors as soil humidity, meteorological conditions of the vegetation season, type of cultivated crop, phase of crop development, crop weedness. Crop status was the most contrasting at the beginning of the vegetation season. In the middle of the season heterogeneity of crops was smoothed out. And when a crop matures, heterogeneity may be more related to weeds infestation than to the state of the crop itself. Therefore, a soil map cannot be a reliable source of information for predicting crop heterogeneity, which should be taken into account when planning agricultural operations, as well as when using soil maps in precision farming systems. The results are likely to be somewhat different in other regions and for other crops.

Acknowledgments

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References

[1] García-Palacios P, Maestre F T and Gallardo A 2011 Soil nutrient heterogeneity modulates ecosystem responses to changes in the identity and richness of plant functional groups *J. Ecol.* **99(2)** 551–62

[2] Maestre F T and Reynolds J F 2006 Spatial heterogeneity in soil nutrientsupply modulates nutrient and biomass responses to multiple global changedrivers in model grassland communities *Glob Chang Biol* **12** 2431–41

[3] Maestre F T and Reynolds J F 2007 Biomass responses to elevated CO_2, soil heterogeneity and diversity: an experimental assessment with grasslandassemblages *Oecologia* **151** 512–20

[4] Wacker L, Baudois O, Eichenberger-Glinz S and Schmid B 2008 Environmental heterogeneity increases complementarity in experimental grasslandcommunities *Basic Appl Ecol.* **9** 467–74

[5] Tylianakis T, Rand T A, Kahmen A, Klein A M, Buchmann N, Perner J and Tscharntke T 2008 Resource heterogeneity moderates thebiodiversity–function relationship in real world ecosystems *PLOS Biology* **6** e47

[6] Kiryushin V I 2018 *Ecological bases of agricultural landscape design* (St. Petersburg: Quadro) p 567 (in Russian)

[7] Friedland V M 1984 *Structure of the world soil cover* (Moscow: Mysl) p 235 (in Russian)

[8] Pantazi X E, Moshou D and Bochtis D 2020 *Intelligent data mining and fusion systems in agriculture* (Academic Press) p 330

[9] Savin I Yu, Stolbovoy V S, Ivanov A L, Prudnikova E Yu, Zholev A V and Voronin A Ya 2019

Technologies of compilation and updating of soil maps (Moscow: Pero) p 328 (in Russian)
[10] Savin I Yu 2016 Classification of soils and agriculture *Dokuchaev Soil Bull.* **84** 3–9
[11] Jensen J R 2000 *Remote sensing of the environment: an earth resource perspective* (New Jersey)
[12] Stafford-Smith M and Reynolds J F 2002 *Global desertification: do humans create deserts?* (Berlin: Dahlem University)
[13] Wessels K J, Prince S D, Frost P E and Van Z Y 2004 Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series *Remote Sens Environ* **5(9)** 47–67
[14] Ali A M, Aboelghar M A, El-shirbeny M A and Salem N H 2018 Comparative analysis of some winter crops area estimation using landsat-8 and sentinel-2 satellite imagery *Futur. Food J. Food Agric. Soc.* **6(2)**
[15] Ali A M, El-Shirbeny M A and Saleh N H S 2018 Comparative analysis of some winter crops area estimation using landsat-8 and sentinal-2 satellite imagery *Asian J. Agric. Biol.* **6** 189–97
[16] Aboelghar M, Ali A S 2014 ArafatSpectral wheat yield prediction modeling using SPOT satellite imagery and leaf area index *Arab. J. Geosci.* **7(2)** 465–74
[17] Ali A M, Savin I, Poddubskiy A, Abouelghar M, Saleh N, Abutaleb K, El-Shirbeny M and Dokukin P 2020 Integrated method for rice cultivation monitoring using Sentinel-2 data and Leaf Area Index *Egypt. J. Remote. Sens. Space Sci.* In Press
[18] Ati A S, Ibrahim A and Jubair A R 2014 Relationship between the normalized difference vegetation index (NDVI) and some soil characteristics in the North of Iraq *IOSR J. of Agric. and Veter. Sci.* **7(10)** 39–45
[19] Villalobos F J and Fereres E 2017 *Principles of agronomy for sustainable agriculture* (Springer) p 555
[20] *All-union instruction on soil surveys and drawing up large-scale soil maps* 1972 (Moscow: Ministry of Agriculture) p 28 (in Russian)
[21] Savich V I, Bulgakov D S, Vukolov N G, Raskatov V A, Vasiliev A A, Syunyaeva O I and Chanyshev I O 2010 *Integral assessment of soil fertility* (Moscow: RGAU-MSHA) p 347 (in Russian)
[22] Pettorelli N 2013 *Potentials and limits of vegetation indices for LAI and APAR Assessment. Remote sensing of environment. The normalized difference vegetation index* (OUP Oxford) p 194
[23] Bradley G P 2019 *Integrated remote sensing and crop system modeling for precision agriculture across spatial and temporal scales* (Michigan: Michigan State University) p 142
[24] Savin I Yu, Dokukin P A, Vernuk Yu I and Zholev A V 2017 About the influence of contamination on NDVI of spring barley sowing, determined from MODIS satellite data *Sovr. Probl. DZZ Kosm.* **14(3)** 185–95
[25] Savin I Yu, Shishkonakova E A, Prudnikova E Yu, Vindeker G V, Grubina P G, Sharychev D V, Shchepot'ev V N, Vernuk Yu I and Zhogolev A V 2020 About influence of the winter wheat sowing clogging on their spectral reflectivity *Agr. Biol.* **55(1)** 53–65
[26] Elvidge C D and Lyon R J P 1985 Influence of rock-soil spectral variation on assessment of green biomass *Remote Sens. Environ.* **17** 265–79
[27] Huete A R, Jackson R D and Post D F 1985 Spectral response of a plant canopy with different soil backgrounds *Remote Sens. Environ.* **17** 37–53
[28] Baret F and Guyot G 1991 Potentials and limits of vegetation indices for LAI and APAR assessment *Remote Sens. Environ.* **35** 161–73
[29] Thorp K and Tian L F 2004 A review on remote sensing of weeds in agriculture *Precis. Agric.* **5(5)** 477–508
[30] Prudnikova E, Savin I, Vindeker G, Grubina P, Shishkonakova E and Sharychev D 2019 Influence of soil background on spectral reflectance of winter wheat crop canopy *Remote Sens.* **11** 1932