

# The normalized difference vegetation index (NDVI) as a proxy of soil fertility under no-tillage: Features for different Chernozems and applied treatments in Russian forest-steppe region

Sofia Sushko<sup>1</sup>, Kristina Ivashchenko<sup>1</sup>, Aleksei Dobrokhoto<sup>2</sup>, Ludmila Orlova<sup>3,4</sup>, Elena Zakharova<sup>5</sup>, Eugeny Gerasimov<sup>4</sup>, and Svetlana Neprimerova<sup>2</sup>

<sup>1</sup>Laboratory of Carbon Monitoring in Terrestrial Ecosystems, Institute of Physicochemical and Biological Problems in Soil Science, Russian Academy of Sciences, ul. Institutskaya, 2, Pushchino, Moscow Region, 142290, Russian Federation

<sup>2</sup>Agrophysical Research Institute, Grazhdansky pr., 14, Saint Petersburg, 195220, Russian Federation

<sup>3</sup>National Conservation Agriculture Movement, ul. Kuibysheva, 88, Samara, 443099, Russian Federation

<sup>4</sup>Agro-Innovation Center "Orlovka", ul. Tsentral'naya, 42, Stary Amanak, 446472, Russian Federation

<sup>5</sup>Samara State Medical University, ul. Chapaevskaya, 89, Samara, 443099, Russian Federation

Address correspondence and requests for materials to Sofia Sushko, rogovaja7@mail.ru

**Citation:** Sushko, S., Ivashchenko, K., Dobrokhoto, A., Orlova, L., Zakharova, E., Gerasimov, E., and Neprimerova, S. 2024. The normalized difference vegetation index (NDVI) as a proxy of soil fertility under no-tillage: Features for different Chernozems and applied treatments in Russian forest-steppe region. *Bio. Comm.* 69(4): 249–256. <https://doi.org/10.21638/spbu03.2024.405>

**Authors' information:** Sofia Sushko, PhD in Biology, Researcher, [orcid.org/0000-0003-0664-7641](https://orcid.org/0000-0003-0664-7641); Kristina Ivashchenko, PhD in Biology, Senior Researcher, [orcid.org/0000-0001-8397-158X](https://orcid.org/0000-0001-8397-158X); Aleksei Dobrokhoto, PhD in Biology, Researcher, [orcid.org/0000-0002-9368-6229](https://orcid.org/0000-0002-9368-6229); Ludmila Orlova, PhD in Economics, [orcid.org/0000-0002-6941-8523](https://orcid.org/0000-0002-6941-8523); Elena Zakharova, Researcher, [orcid.org/0000-0002-7287-5960](https://orcid.org/0000-0002-7287-5960); Evgeny Gerasimov, Senior Agronomist; Svetlana Neprimerova, Researcher, [orcid.org/0000-0001-7018-9994](https://orcid.org/0000-0001-7018-9994)

**Manuscript Editor:** Evgeny Abakumov, Department of Applied Ecology, Faculty of Biology, Saint Petersburg State University, Saint Petersburg, Russia

**Received:** January 1, 2024;

**Revised:** May 28, 2024;

**Accepted:** July 8, 2024.

**Copyright:** © 2024 Sushko et al. This is an open-access article distributed under the terms of the License Agreement with Saint Petersburg State University, which permits to the authors unrestricted distribution, and self-archiving free of charge.

**Funding:** Field data survey and lab soil analysis were supported by the state assignment of the Ministry of Science and Higher Education of the Russian Federation (no. 122111000095–8). Processing of remote sensing data was carried out within the state assignment of the Ministry of Science and Higher Education of the Russian Federation (no. FGEG-2022-0007).

**Ethics statement:** This paper does not contain any studies involving human participants or animals performed by any of the authors.

**Competing interests:** The authors have declared that no competing interests exist.

**Data availability statement:** Detailed data supporting the outcomes of this study are available by contacting the corresponding author.

## Abstract

Using the normalized difference vegetation index (NDVI) as a proxy for soil fertility would be highly useful for adapting no-tillage to specific environmental conditions and for monitoring soil quality. Therefore, our study aimed to evaluate the relationship between satellite-based NDVI (May–August 2022) and soil fertility under no-tillage in the forest-steppe of Russia, considering different Chernozems (Haplic and Luvic) and treatments (none / with microbial inoculation and irrigation). Among the soil fertility indices (0–10 cm), content of organic and inorganic C (SOC and  $C_{inorg}$ ), total N, available P and K, SOC : N, pH, microbial biomass (MBC) and respiration were assessed. Overall, soil nutrient dependence of NDVI was found for Luvic Chernozem in both microbe-inoculated (SOC, N, K with  $R^2 = 0.72 - 0.95$ ) and untreated sites (SOC, SOC:N with  $R^2 = 0.58 - 0.66$ ). For Haplic Chernozem, only a negative relationship between NDVI and  $C_{inorg}$  was found ( $R^2 = 0.47$ ) at an untreated site, which was eliminated by using irrigation with microbial inoculation. Thus, NDVI can be a robust tool for predicting soil nutrient levels for no-tilled Luvic Chernozem, but not for Haplic Chernozem. At the same time, applied treatments can significantly change the specifics of this relationship, which is important to consider in remote sensing of soil fertility.

**Keywords:** microbial inoculants, irrigation, Haplic / Luvic Chernozems, soil nutrient levels, microbial biomass, inorganic carbon.

## Introduction

The normalized difference vegetation index (NDVI) is a widely used remote sensing spectral approach representing the difference between red (chlorophyll absorbed) and near-infrared (photosynthetically useless) image bands (Rouse, Haas, Schell, and Deering, 1974). Essentially, the index rising shows an increase in photosynthetically active biomass (Tucker, 1979; Goswami, Gamon, Vargas, and Tweedie, 2015; Barboza et al., 2023). Therefore, NDVI has been successfully applied to study the spatio-temporal variability of vegetation productivity and plant species distribution depending on various natural and anthropogenic factors (Pettoirelli et al., 2005). Specifically, this indicator is actively used in agricultural practice to monitor crop growth, phenology and health (Rahman, Islam, and Rahman, 2004; Funk

and Budde, 2009; Shafi et al., 2020), and to timely identify water and nutrient requirements (Cabrera-Bosquet et al., 2011; Prakasha, Somashekar, and Shivanand, 2020; Kimaro et al., 2023). In precision agriculture, NDVI remains the most frequently used vegetation index (Radočaj, Šiljeg, Marinović, and Jurišić, 2023). This has resulted in a well-developed commercial market for NDVI estimation for farmers based on satellite or drone imagery and handheld sensors (e.g., “GreenSeeker” and “Crop Circle”). Thus, NDVI is a widely recognized and readily available tool for rapidly assessing the spatial heterogeneity of vegetation productivity characteristics.

As plant productivity is largely related to soil fertility, NDVI is also a good predictor of the spatial distribution of nutrient availability and stocks (such as total/organic carbon, nitrogen, phosphorus and potassium) for different agricultural soils (Sumfleth and Duttman, 2008; Whetton, Zhao, Shaddad, and Mouazen, 2017; Liu et al., 2018; Zhang et al., 2019) including arable Chernozems in some Russian regions (Gopp et al., 2017; Gopp and Savenkov, 2019; Suleymanov et al., 2021). This relationship could be useful in understanding the effectiveness of different agricultural practices in improving soil quality, including carbon stocks. The latter is particularly relevant for the implementation of the “4 per 1000” initiative ([www.4p1000.org](http://www.4p1000.org)), which aims to develop carbon sequestration farming to mitigate climate change and improve food security (Chabbi et al., 2017). In this context, a no-till system that follows natural principles (i.e., no/minimal soil mechanical disturbance; continuous crop residue coverage; diverse crop rotation) can be promising (Ogle et al., 2019; Kan et al., 2022). According to a recent review by Kassam, Friedrich, and Derpsch (2019), no-till land accounts for about 180 million hectares worldwide (12.5% of the total global cropland), with an annual expansion of 10.5 million hectares. Despite this, Russian farmers remain extremely skeptical about this agricultural practice due to its complex and costly adaptation to different soil and climate conditions, as well as potential yield losses. Therefore, the no-till land in Russia is only 1.5–2 million hectares, located mainly in the forest-steppe and steppe regions with Chernozems (Cherkasov, Pykhtin, and Gostev, 2017; Turin, 2020). Thus, the applicability of remote sensing for predicting spatial changes in soil fertility indices under no-tillage can greatly facilitate (i) its adaptation to specific environmental conditions, (ii) monitoring soil quality, especially carbon stock dynamics, and (iii) the further expansion of this practice across Russia.

There is a well-known problem of achieving effective weed control under no-tillage, which can be exacerbated by environmental policies aimed at reducing pesticide usage (Soane et al., 2012). Therefore, some farmers use various microbial inoculants to reduce dependence on pesticides as well as chemical fertilizers. At the same

time, such biological treatments can alter the functioning of soil microbial communities and the resulting soil-plant-microbe interactions in unpredictable ways (Vázquez, César, Azcón, and Barea, 2000; Trabelsi and Mhamdi, 2013; Cassan and Diaz-Zorita, 2016). This, in turn, may be reflected in the relationship between crop productivity (NDVI) and soil nutrient variability. In this regard, our study aimed to investigate the predictive power of NDVI on the spatial variability of soil fertility indices (including nutrient levels and microbial activity) in no-till farming, considering the effects of different applied treatments on Haplic and Luvic Chernozems.

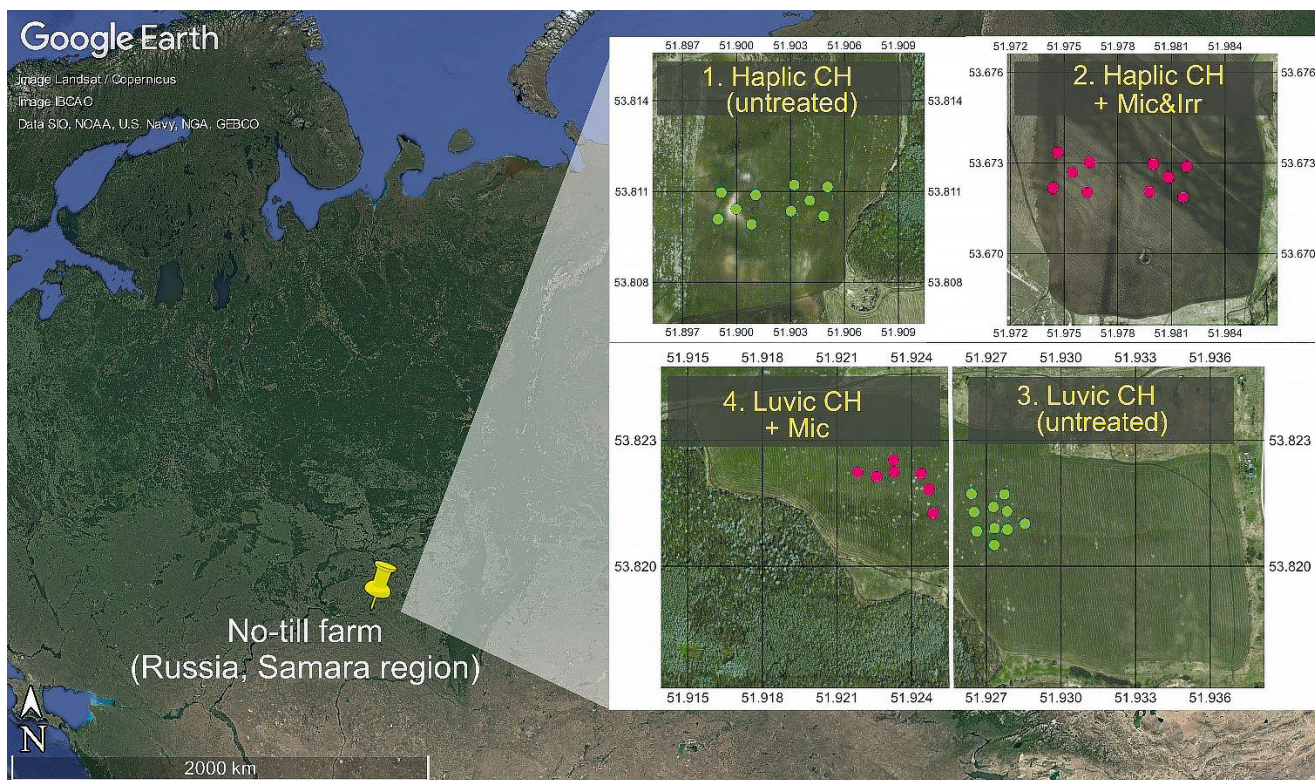
## Materials and methods

### Study sites and sampling design

The study was carried out at a private no-till farm of “Orlovka — Agro-Innovation Center” LLC located in the Samara region of Russia (53°49'N / 51°55'E). This area belongs to the forest-steppe with a warm-summer humid continental climate (Dfb according to the Köppen climate classification). The mean annual temperature is 4.7°C, and the mean annual precipitation is 459 mm, of which 130 mm falls in the summer (1991–2020; data from the closest WMO weather station “28806 Buguruslan”). The history of agricultural use of the area goes back about a century (recorded since 1929). The current farm was preceded by another crop farm, JSC “Soviet Russia”. Prior to no-till farming, conventional tillage (plowing to 23–25 cm) was used in this area. The dominant soil subtypes are Haplic and Luvic Chernozems, formed on brown clays and clay marls. The farm area (approx. 4,000 ha) is slightly undulating, with elevation ranging from 55 to 217 m a.s.l. (average 120 m a.s.l. according to Copernicus GLO-30 DEM). Currently, the farm crop rotation includes spring wheat, sunflower, soybean and flax.

In 2022, Haplic Chernozem (5-year no-till) and Luvic Chernozem (8-year no-till) sites were surveyed on the farm. Within each site, different treatments were considered: none / with microbial inoculation and irrigation for Haplic Chernozem; none / with microbial inoculation for Luvic Chernozem (Table 1). Non-irrigated and non-microbe-inoculated soils were hereafter referred to as “untreated” soils. In the study year, spring wheat and flax were cultivated on Haplic and Luvic Chernozem sites, respectively.

Microbial inoculants used for Haplic Chernozem were a fungal control agent (*Trichoderma harzianum* with  $1 \times 10^{10}$  UFC g<sup>-1</sup> and 0.08 L ha<sup>-1</sup>; Russian “Agro-BioTechnology” LLC) and a straw-decomposing accelerator (combination of *Trichoderma*, *Bacillus*, *Actinomyces*, nitrogen-fixing and lactic acid bacteria with  $1 \times 10^9$  UFC g<sup>-1</sup> and 2.5 L ha<sup>-1</sup>; Russian “Scientific Research Institute Biopreparaty” LLC). Microbial treat-



**Fig. 1.** Scheme of soil sampling for no-tilled Haplic and Luvic Chernozems (CH) on the untreated, microbe-inoculated (Mic) and irrigated (Irr) sites. Only 7 points are shown for “Luvic CH + Mic” site as the remaining coordinates are not available.

**Table 1. Applied treatments and cultivated crops (2022) at Haplic and Luvic Chernozem (CH) sites under no-tillage**

Site	Mic	Irr	HS (L ha <sup>-1</sup> )	NF (kg N ha <sup>-1</sup> )	Crop	S/H (dd.mm)
Haplic CH (untreated)	No	No	4	34	Wheat	09.05/30.08
Haplic CH + Mic&Irr	Yes	Yes	4	86	Wheat	08.05/22.08
Luvic CH (untreated)	No	No	No	34	Flax	03.06/11.09
Luvic CH + Mic	Yes	No	No	34	Flax	03.06/11.09

Notes: Mic, microbial inoculation; Irr, irrigation; HS, humic substances; NF, nitrogen fertilizers; S/H, sowing and harvesting dates.

ments were applied annually before sowing and after harvesting for five years (2018–2022). Irrigation was carried out using a center pivot system. In addition, nitrogen fertilizers (34–86 kg N ha<sup>-1</sup> at sowing) and humic fertilizers (4 L ha<sup>-1</sup> at heading stage) were applied to both Haplic Chernozem sites (the microbial / irrigation treated and the untreated). Pesticide treatments for wheat included herbicides (2,4-D 2-ethylhexyl ester + florasulam; tribenuron-methyl), fungicides (pyraclostrobin + epoxiconazole; propiconazole + tebuconazole) and insecticides (alpha-cypermethrin; thiamethoxam).

The microbial inoculant for Luvic Chernozem was *Azospirillum* sp. (2 × 10<sup>9</sup> UFC g<sup>-1</sup> and 0.5 L ha<sup>-1</sup>; Russian “Ecos” LLC), which was used once (in 2022) during the budding phase to promote flax growth. Nitrogen fertilizers (34 kg N ha<sup>-1</sup> at sowing) were applied to both Luvic Chernozem sites (the microbial treated and the untreated). Pesticide treatments for flax included only herbicides (dimethylamino + sodium + potassium salt mixture; clopyralid-olamine; clethodim).

In October 2022, soil samples were taken from the upper 0–10 cm layer at 10 spatially distributed points per site. Within the individual Haplic Chernozem site, the point locations were evenly distributed across two one-hectare squares (in the corners and in the center), somewhat approximating a grid sampling design (Fig. 1). Within the Luvic Chernozem site, the points were randomly distributed across ~2 ha sampling area with a minimum spacing of 30 m to match the spatial resolution of the Landsat 8–9 imagery. Totally, 40 freshly collected samples (4 fields × 10 sampling points) were transported to the laboratory for the immediate microbial and chemical testing.

### Soil analysis

The soil samples were sieved through a 2 mm mesh to exclude stones and roots. Then, one portion of the samples was air-dried and used for chemical analysis. The

remaining portion of fresh soil samples was moistened up to 55–65 % water-holding capacity, pre-incubated at 25 °C for 72 hours (Jones, Verheijen, Reuter, and Jones, 2008), and then used for microbial analysis. Soil pH was measured in 1 N potassium chloride solution (soil : KCl solution = 1:2.5) using a pH-meter (“Ionometric converter I-500”, Russia). Soil organic carbon (SOC) content was determined by the dichromate oxidation technique followed by colorimetry (FAO, 2019). Soil total carbon ( $C_{\text{tot}}$ ) and nitrogen (N) were analyzed by the dry combustion method using a CHNS analyzer (“Vario EL III”, Germany). Inorganic carbon ( $C_{\text{inorg}}$ ) was calculated from the difference between  $C_{\text{tot}}$  and SOC. Available phosphorus (P) and potassium (K) contents were determined by soil extraction with dilute hydrochloric acid (0.2 M HCl) and then quantified with a photoelectric colorimeter/flame photometer. Microbial biomass carbon (MBC) was measured by the substrate-induced respiration method (Anderson and Domsch, 1978; ISO 1997). Basal respiration (BR) was measured as the rate of soil  $\text{CO}_2$  release using gas chromatography (“KrystaLLyuks-4000 M”, Russia) (ISO 2002). The MBC and BR values were determined under optimum hydrothermal conditions for the microorganisms: 22 °C and 55–65 % water holding capacity.

### NDVI calculation

Landsat 8–9 satellite imagery of the study area with a spatial resolution of 30 m were derived from USGS EarthExplorer (<https://earthexplorer.usgs.gov/>). Only cloud-free remote imagery from May to October 2022 were selected, including 14 dates (dd.mm): 07.05; 08.05; 24.05; 25.06; 02.07; 10.07; 11.07; 18.07; 11.08; 12.08; 19.08; 20.08; 28.08, 13.09. Pre-processing of the image dataset included radiometric calibration and atmospheric correction (Vermote, Roger, Franch, and Skakun, 2018). NDVI was calculated by the equation (Rouse, Haas, Schell, and Deering, 1974):

$$NDVI = \frac{(NIR - R)}{(NIR + R)},$$

where NIR is near-infrared reflection; R is visible red reflection. The NIR band for Landsat 8–9 imagery is 851–879 nm, and the R band is 636–673 nm.

### Statistical analysis

The spatial variability of the soil fertility indices was quantified by the coefficient of variation (CV, %), which is the ratio of the standard deviation to the mean. The significance of differences between two independent groups (untreated and treated sites) was tested using

the Welch’s t-test. Simple linear regression was used to test the significance of NDVI in predicting the spatial variability of soil fertility indices for each Chernozem site individually. Prior to the statistical analysis, the variable distribution was checked with the Shapiro-Wilk normality test. Box-Cox transformation was performed for variables with non-normal distribution. Statistical analysis and results visualization were carried out in the R software system (version 4.1.2) (RStudio Team, 2023).

## Results

### Spatial variability of soil fertility indices

The main difference between the studied Chernozems (CH) was pH value, which was higher for Haplic CH (slightly alkaline) than for Luvic CH (neutral) (Table 2). Within each soil subtype, the elevation and some soil properties varied significantly between the untreated and the treated sites. For Haplic CH, the microbe-inoculated and irrigated site was located about 130 m lower than the untreated site and had higher SOC, P and, conversely, lower  $C_{\text{inorg}}$ . Moreover, the spatial variability of most soil properties (except P and K contents) in the treated site was 1.5–3.0 times lower than at the untreated one. In the case of Luvic CH, the microbe-inoculated site was located 5 m higher than the untreated site and had lower pH, P, K and MBC and BR. At the same time, the spatial variability of soil properties was mainly the same at both Luvic CH sites.

**Table 2. Elevation and soil properties (0–10 cm) for no-till Haplic and Luvic Chernozems (CH) on untreated, microbe-inoculated (Mic) and irrigated (Irr) sites**

Property	Haplic CH (untreated)	Haplic CH + Mic&Irr	Luvic CH (untreated)	Luvic CH + Mic
Elevation (m a. s. l.)	198 (1)	64 (4)***	151 (1)	156 (1)***
pH <sub>KCl</sub>	6.8 (6)	6.9 (3)	5.6 (4)	5.3 (3)**
$C_{\text{inorg}}$ (%)	1.06 (84)	0.42 (57)*	0.39 (36)	0.37 (41)
SOC (%)	3.75 (24)	4.42 (8)*	4.52 (6)	4.52 (5)
N (%)	0.34 (27)	0.39 (9)	0.37 (5)	0.38 (5)
SOC:N	11.3 (9)	11.5 (6)	12.2 (4)	12.1 (3)
P (mg kg <sup>-1</sup> )	95 (30)	151 (28)***	104 (26)	69 (23)**
K (mg kg <sup>-1</sup> )	218 (27)	183 (24)	235 (12)	163 (23)**
MBC (μg g <sup>-1</sup> )	708 (53)	833 (23)	916 (34)	560 (26)**
BR (μg C g <sup>-1</sup> h <sup>-1</sup> )	0.39 (55)	0.45 (23)	0.62 (45)	0.42 (40)*

Notes: SOC, soil organic carbon;  $C_{\text{inorg}}$ , inorganic carbon; N, total nitrogen; P, available phosphorus; K, available potassium; MBC, microbial biomass carbon; BR, basal respiration.

Data are mean values with coefficient of variation (%) in parentheses ( $n = 10$ ; \* $p \leq 0.05$ , \*\*0.01, \*\*\*0.001 for Welch’s t-test).

### Changes in NDVI values

Regardless of the soil subtypes and applied treatments, the NDVI values changed similarly throughout the observed growing season (Fig. 2). The index was low at the beginning and the end of the season, with a peak in the middle (0.60–0.87 in June–July). As expected, using additional ameliorative treatments significantly increased crop productivity and consequently NDVI. In the case of Haplic CH with wheat, the NDVI means for the growing season were 0.49 and 0.58 for the untreated and the microbe-inoculated + irrigated sites, respectively ( $p < 0.001$  for Welch’s t-test). For Luvic CH with flax, the means were 0.48 and 0.52 for the untreated and the microbe-inoculated sites, respectively ( $p < 0.001$  for Welch’s t-test).

### Relationship between NDVI and soil fertility indices

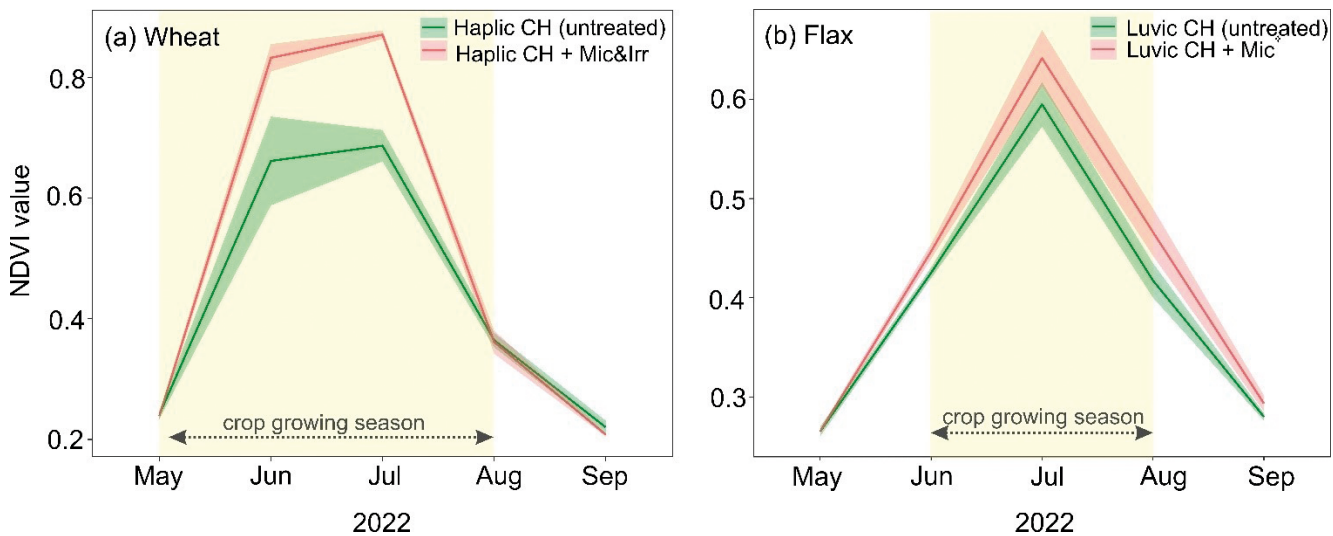
Simple linear regression has shown different drivers of NDVI variability depending on the soil subtypes and the applied treatments (Fig. 3). For the untreated Haplic

CH, the spatial variability of NDVI averaged over the growing season (May–August) was determined by  $C_{inorg}$  content (negative relationship;  $R^2 = 0.47$ ). However, for the microbe-inoculated and irrigated Haplic CH, NDVI was positively associated with elevation ( $R^2 = 0.78$ ) and negatively associated with MBC ( $R^2 = 0.80$ ). In the case of Luvic CH, the mean NDVI variability (June–August) at the untreated site was determined by SOC and SOC:N values (positive relationships;  $R^2 = 0.66$  and  $0.58$ , respectively). Applying microbial inoculation for Luvic CH only increased the dependence of NDVI on SOC ( $R^2 = 0.73$ ), as well as other nutrients — N and K (positive relationships;  $R^2 = 0.95$  and  $0.72$ , respectively).

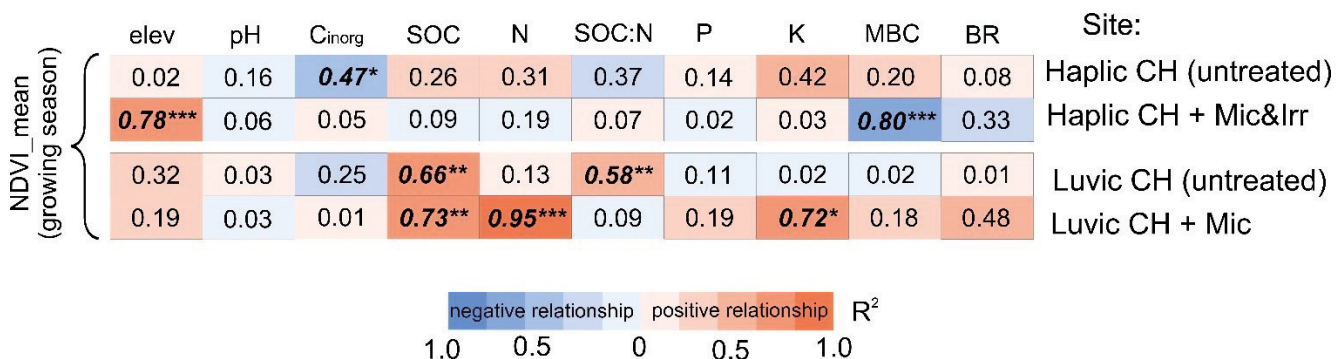
### Discussion

#### NDVI-nutrient relationship: different soil subtypes and agricultural treatments

This study did not show a general trend between spatial changes in NDVI and soil fertility indices for different soil subtypes and applied treatments. In particular, SOC



**Fig. 2.** Temporal dynamics of monthly average normalized difference vegetation index (NDVI) for wheat at Haplic Chernozem (a) and flax at Luvic Chernozem (b) under no-tillage of untreated, microbe-inoculated (Mic) and irrigated (Irr) sites. Line shows the mean with 95 % confidence interval ( $n = 10$  and  $n = 7$ ).



**Fig. 3.** Heatmap showing coefficient of determination ( $R^2$ ) of linear regression between normalized difference vegetation index (NDVI) averaged over the growing season, elevation (elev) and Chernozem properties (CH; 0–10 cm) under no-tillage of untreated, microbe-inoculated (Mic) and irrigated (Irr) sites ( $*p \leq 0.05$ ,  $**0.01$ ,  $***0.001$ ;  $n = 10$  and  $n = 7$ ).

content played a more important role in determining NDVI variability for Luvic CH than for Haplic CH. This can be related to the fact that SOC provides a slow and continuous supply of essential nutrients to plants, reducing their leaching along both the soil profile and slope (Wander, 2004). The latter could be particularly relevant for Luvic CH, as evidenced by higher levels of labile P and K at the lower site than at the upper site (Table 2). Moreover, inoculation with *Azospirillum*, well-known as a plant growth promoter, only increased the nutrient dependence of NDVI (Fig. 3). *Azospirillum*'s ability to biologically fix N and produce phytohormones can improve nutrient use efficiency in crops (Cassan and Diaz-Zorita, 2016; Zeffa et al., 2019).

At the same time, for the slightly alkaline and non-irrigated Haplic CH, NDVI was negatively associated with  $C_{inorg}$  content, which largely determines the availability of some macro- and micronutrients to plants (such as P, K, Fe and Zn) (Wahba, Labib, and Zaghoul, 2019). As a result, crops grown on calcareous soils (rich in  $C_{inorg}$ ) have reduced levels of chlorophyll, endogenous growth promoters (auxins, gibberellins and cytokinins) and subsequent crop productivity (Shukry, Khattab, and EL-Bassiouny, 2007). However, irrigation can mitigate the inhibitory effect of excess  $C_{inorg}$  on plant growth and development (Shukry, Khattab, and EL-Bassiouny, 2007; Wahba, Labib, and Zaghoul, 2019) due to its leaching from the upper soil horizon (Khokhlova, Arlashina, and Kovalevskaya, 1997; de Soto et al., 2017). This effect was also consistent with our results: the  $C_{inorg}$  in the irrigated Haplic CH was half that of the non-irrigated one (Table 2). Interestingly, there was a strong negative relationship between NDVI and MBC in the microbe-inoculated and irrigated Haplic CH, which could be explained by plant-microbe competition for the nutrients under developing abundant monocrop biomass (Kuzyakov, 2002). In addition, a strong positive relationship between NDVI and elevation variability for irrigated Haplic CH was found (Fig. 3). A possible explanation for the sensitivity of NDVI to topography under irrigation could be related to the uneven spatial redistribution of water across the field, leading to unfavorable excess moisture in lower areas. This indicative ability of NDVI in assessing irrigation efficiency has been often used to develop irrigation management strategies (Hunsaker et al., 2007; Poudel, Stephen, and Ahmad, 2021; Yousaf et al., 2021).

### Prospects of using NDVI as a proxy of Chernozem's fertility

NDVI, along with the soil type and some climatic and topographic variables, is one of the most informative and widely used predictors in the digital mapping of SOC content and stocks (Gopp et al., 2023). Regarding

the Chernozem zone in Russia, a significant positive relationship between NDVI and SOC content in the plow layers (0–10/0–30 cm layers) was shown for the Novosibirsk region ( $R^2=0.52$ ; Gopp et al., 2017) and for the Republic of Bashkortostan ( $R^2=0.46$ ; Suleymanov et al., 2021). However, other studies conducted in the Novosibirsk region found no such relationship (Gopp et al., 2019a; 2019b). Similarly ambiguous results have been observed in relation to predicting other Chernozems fertility indices (e.g., N and P levels) (Gopp et al., 2017; Gopp and Savenkov, 2019), which is generally consistent with our results (Fig. 3). Such differences in the predictive ability of NDVI for understanding the spatial distribution of soil properties can be explained by the interaction of different factors: relief characteristics and the development of erosion processes (Gopp et al., 2017; Gopp and Savenkov, 2019), meteorological conditions in a particular year (Whetton, Zhao, Shaddad, and Mouazen, 2017), variability range of soil property and individual limiting factors (Verhulst et al., 2009), time series of used satellite imagery (Zhang et al., 2019), applied agricultural treatments and so on. Identifying clear patterns of relationships between remote sensing data and soil properties for the Chernozem zone under different agro-ecological conditions requires further investigation. Moreover, the collection of additional data is necessary for the development of more accurate soil modelling and digital mapping, which is particularly relevant for the vast territory of Russia (Suleymanov, Arrouays, and Savin, 2024).

### Conclusion

This study examined the predictive power of NDVI in understanding the spatial variability of soil fertility under no-tillage with different soil subtypes (Haplic and Luvic Chernozems) and treatments (microbial inoculation, irrigation). In general, SOC was a more important factor in NDVI variability for Luvic Chernozem (CH) than for Haplic CH, regardless of applied treatments. The application of microbial inoculation (*Azospirillum* sp.) in Luvic CH only increased nutrient dependence of NDVI, especially for N and K. For Haplic CH, NDVI was negatively associated with  $C_{inorg}$ , which was eliminated by using irrigation. Additionally, irrigation and microbial inoculation (*Trichoderma*, *Bacillus*, *Actinomyces*, etc.) in Haplic CH induced the highest NDVI among all studied sites, which was negatively correlated with MBC due to possible microbial-plant competition. Thus, our results demonstrate the ambiguity of using easily accessible NDVI as a proxy for spatial variability in soil fertility under no-tillage with different soils and treatments. Generally, this index can be a more reliable tool for understanding the spatial variability of soil fertility in the case of no-tilled Luvic CH than in the case of Hap-

lic CH. At the same time, applied treatments can significantly change the specifics of this relationship, which is important to consider in remote sensing of soil fertility.

## References

- Anderson, J.P.E. and Domsch, K.H. 1978. A physiological method for the quantitative measurement of microbial biomass in soils. *Soil Biology and Biochemistry* 10:215–221. [https://doi.org/10.1016/0038-0717\(78\)90099-8](https://doi.org/10.1016/0038-0717(78)90099-8)
- Barboza, T. O. C., Ardigueri, M., Souza, G. F. C., Ferraz, M. A. J., Gaudencio, J. R. F., and Santos, A. F. 2023. Performance of vegetation indices to estimate green biomass accumulation in common bean. *AgriEngineering* 5:840–854. <https://doi.org/10.3390/agriengineering5020052>
- Cabrera-Bosquet, L., Molero, G., Stellacci, A. M., Bort, J., Nogués, S., and Araus, J. L. 2011. NDVI as a potential tool for predicting biomass, plant nitrogen content and growth in wheat genotypes subjected to different water and nitrogen conditions. *Cereal Research Communications* 39:147–159. <https://doi.org/10.1556/CRC.39.2011.1.15>
- Cassan, F. and Diaz-Zorita, M. 2016. *Azospirillum* sp. in current agriculture: From the laboratory to the field. *Soil Biology and Biochemistry* 103:117e130. <https://doi.org/10.1016/j.soilbio.2016.08.020>
- Chabbi, A., Lehmann, J., Ciais, P., Loescher, H.W., Cotrufo, M. F., Don, A., SanClements, M., Schipper, L., Six, J., Smith, P., and Rumpel, C. 2017. Aligning agriculture and climate policy. *Nature Climate Change* 7:307–309. <https://doi.org/10.1038/nclimate3286>
- Cherkasov, G. N., Pykhtin, I. G., and Gostev, A. V. 2017. Areal of application of zero and surface tillage in the cultivation of cereal crops in the European part of the Russian Federation. *Zemledelie* 2:10–14. (In Russian)
- de Soto, I. S., Virto, I., Barré, P., Fernández-Ugalde, O., Antón, R., Martínez, I., Chaduteau, C., and Enrique, A. 2017. A model for field-based evidences of the impact of irrigation on carbonates in the tilled layer of semi-arid Mediterranean soils. *Geoderma* 297:48–60. <https://doi.org/10.1016/j.geoderma.2017.03.005>
- FAO. 2019. Soil organic carbon Walkley-black method: Titration and Colorimetric Method. Global Soil Laboratory Network GLOSOLAN. Available at: <https://www.fao.org/3/ca7471en/ca7471en.pdf>.
- Funk, C. and Budde, M. E. 2009. Phenologically-tuned MODIS NDVI-based production anomaly estimates for Zimbabwe. *Remote Sensing of Environment* 113:115–125. <https://doi.org/10.1016/j.rse.2008.08.015>
- Gopp, N. V. and Savenkov, O. A. 2019. Relationships between the NDVI, yield of spring wheat, and properties of the plow horizon of eluviated Clay-Illuvial Chernozems and Dark Gray Soils. *Eurasian Soil Science* 52:339–347. <https://doi.org/10.1134/S1064229319030050>
- Gopp, N. V., Meshalkina J. L., Narykova, A. N., Plotnikova, A. S., and Chernova, O. V. 2023. Mapping of soil organic carbon content and stock at the regional and local levels: the analysis of modern methodological approaches. *Voprosy lesnoi nauki* 6 (1):1–59. <https://doi.org/10.31509/2658-607x-202361-120> (In Russian)
- Gopp, N. V., Nechaeva, T. V., Savenkov, O. A., Smirnova, N. V., and Smirnov, V. V. 2017. Indicative capacity of NDVI in predictive mapping of the properties of plow horizons of soils on slopes in the south of Western Siberia. *Eurasian Soil Science* 50:1332–1343. <https://doi.org/10.1134/S1064229317110060>
- Gopp, N. V., Nechaeva, T. V., Savenkov, O. A., Smirnova, N. V., and Smirnov, V. V. 2019a. Effect of slope mesorelief on the spatial variability of soil properties and vegetation index based on remote sensing data. *Izvestiya, Atmospheric and Oceanic Physics*. 55:1329–1337. <https://doi.org/10.1134/S0001433819090202>
- Gopp, N. V., Savenkov, O. A., Nechaeva, T. V., Smirnova, N. V., and Smirnov, V. V. 2019b. Application of NDVI in digital mapping of phosphorus content in soils and phosphorus supply assessment in plants. *Izvestiya, Atmospheric and Oceanic Physics* 55:1322–1328. <https://doi.org/10.1134/S0001433819090196>
- Goswami, S., Gamon, J., Vargas, S., and Tweedie, C. 2015. Relationships of NDVI, Biomass, and Leaf Area Index (LAI) for six key plant species in Barrow, Alaska. *PeerJ Preprints* 3:e913v1. <https://doi.org/10.7287/peerj.preprints.913v1>
- Hunsaker, D.J., Fitzgerald, G.J., French, A. N., Clarke, T. R., Ottman, M.J., and Pinter, P.J. 2007. Wheat irrigation management using multispectral crop coefficients: II. Irrigation scheduling performance, grain yield, and water use efficiency. *Transactions of the ASABE* 50:2035–2050. <https://doi.org/10.13031/2013.24106>
- ISO. 1997. Soil quality — Determination of soil microbial biomass — Part 1: substrate-induced respiration method (ISO standard no. 14240–1:1997). Geneva: International Organization for Standardization.
- ISO. 2002. Soil quality — Laboratory methods for determination of microbial soil respiration (ISO standard no. 16072:2002). Geneva: International Organization for Standardization.
- Jones, R.J.A, Verheijen F.G.A, Reuter H.I., and Jones A.R. 2008. Environmental assessment of soil for monitoring. Procedures and Protocols (EUR 23490 EN/5). Luxembourg: Office for the Official Publications of the European Communities.
- Kan, Z. R., Liu, W. X., Liu, W. S., Lal, R., Dang, Y. P., Zhao, X., and Zhang, H.-L. 2022. Mechanisms of soil organic carbon stability and its response to no-till: A global synthesis and perspective. *Global Change Biology* 28(3):693–710. <https://doi.org/10.1111/gcb.15968>
- Kassam, A., Friedrich, T., and Derpsch, R. 2019. Global spread of conservation agriculture. *International Journal of Environmental Studies* 76(1):29–51. <https://doi.org/10.1080/0207233.2018.1494927>
- Khokhlova, O. S., Arlashina, E. A., and Kovalevskaya I. S. 1997. The effect of irrigation on the carbonate status of Chernozems of Central Precaucasus (Russia). *Soil Technology* 11:171–184. [https://doi.org/10.1016/S0933-3630\(96\)00134-1](https://doi.org/10.1016/S0933-3630(96)00134-1)
- Kimaro, O. D., Gebre, S. L., Hieronimo, P., Kihupi, N., Feger, K. H., and Kimaro, D. N. 2023. Handheld NDVI sensor-based rice productivity assessment under combinations of fertilizer soil amendment and irrigation water management in lower Moshi irrigation scheme, North Tanzania. *Environmental Earth Sciences* 82:78. <https://doi.org/10.1007/s12665-022-10730-0>
- Kuzyakov, Y. 2002. Review: Factors affecting rhizosphere priming effects. *Journal of Plant Nutrition and Soil Science* 165:382–396. [https://doi.org/10.1002/1522-2624\(200208\)165:4<382::AID-JPLN382>3.0.CO;2-%23](https://doi.org/10.1002/1522-2624(200208)165:4<382::AID-JPLN382>3.0.CO;2-%23)
- Liu, X., Yu, M., Ma, J., Luo, Z., Chen, F., and Yang, Y. 2018. Identifying the relationship between soil properties and rice growth for improving consolidated land in the Yangtze River Delta, China. *Sustainability* 10:3072. <https://doi.org/10.3390/su10093072>
- Ogle, S. M., Alsaker, C., Baldock, J., Bernoux, M., Breidt, F.J., McConkey, B., Regina, K., and Vazquez-Amabile, G. G. 2019. Climate and soil characteristics determine where

- no-till management can store carbon in soils and mitigate greenhouse gas emissions. *Scientific Reports* 9:11665. <https://doi.org/10.1038/s41598-019-47861-7>
- Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J. M., Tucker, C. J., and Stenseth, N. C. 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology and Evolution* 20:503–510. <https://doi.org/10.1016/j.tree.2005.05.011>
- Poudel, U., Stephen, H., and Ahmad, S. 2021. Evaluating irrigation performance and water productivity using EEFlux ET and NDVI. *Sustainability* 13:7967. <https://doi.org/10.3390/su13147967>
- Prakasha, G. M., Somashekar, K. S., and Shivanand, G. 2020. A novel approach for increasing productivity under precision nitrogen management in maize (*Zea mays* L.) through crop sensors. *Journal of Pharmacognosy and Phytochemistry* 9(5):97–103.
- Radočaj, D., Šiljeg, A., Marinović, R., and Jurišić, M. 2023. State of major vegetation indices in precision agriculture studies indexed in Web of Science: A Review. *Agriculture* 13: 707. <https://doi.org/10.3390/agriculture13030707>
- Rahman, M. R., Islam A. H. M. H., and Rahman, M. A. 2004. NDVI derived sugarcane area identification and crop condition assessment. *Plan Plus* 1:1–9.
- Rouse, J. W., Haas, R. H., Schell, J. A., and Deering, D. W. 1974. Monitoring vegetation systems in the Great Plains with ERTS. Proceedings of ERTS-1 Symposium NASA. *Washington DC*. p. 309-317.
- RStudio Team. 2023. RStudio: integrated development for R. Boston: Posit PBC. Available at: <http://www.rstudio.com>.
- Shafi, U., Mumtaz, R., Iqbal, N., Hassan Zaidi, S. M., Raza Zaidi, S. A., and Hussain, I. 2020. A multi-modal approach for crop health mapping using low altitude remote sensing, internet of things (IoT) and machine learning. *IEEE Access* 8:112708–112724. <https://doi.org/10.1109/ACCESS.2020.3002948>
- Shukry, W. M., Khattab, H. K. I., and EL-Bassiouny, H. M. S. 2007. Physiological and biochemical studies on flax plant grew in calcareous soil amended with water hyacinth dry manure. *Journal of Applied Sciences Research* 3:64–72.
- Soane, B. D., Ball, B. C., Arvidsson, J., Basch, G., Moreno, F., and Roger-Estrade, J. 2012. No-till in northern, western and south-western Europe: A review of problems and opportunities for crop production and the environment. *Soil and Tillage Research* 118:66–87. <https://doi.org/10.1016/j.still.2011.10.015>
- Suleymanov, A., Arrouays, D., and Savin, I. 2024. Digital soil mapping in the Russian Federation: A review. *Geoderma Regional* 36:e00763. <https://doi.org/10.1016/j.geoderma.2024.e00763>
- Suleymanov, A., Gabbasova, I., Suleymanov, R., Abakumov, E., Polyakov, V., and Liebelt, P. 2021. Mapping soil organic carbon under erosion processes using remote sensing. *Hungarian Geographical Bulletin Hungarian Geographical Bulletin* 70:49–64. <https://doi.org/10.15201/hun-geobull.70.1.4>
- Sumfleth, K. and Duttman, R. 2008. Prediction of soil property distribution in paddy soil landscapes using terrain data and satellite information as indicators. *Ecological Indicators* 8:485–501. <https://doi.org/10.1016/j.ecolind.2007.05.005>
- Trabelsi, D. and Mhamdi, R. 2013. Microbial inoculants and their impact on soil microbial communities: A review. *BioMed Research International* 2013:863240. <https://doi.org/10.1155/2013/863240>
- Tucker, C. J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment* 8:127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0)
- Turin, E. N. 2020. Advantages and disadvantages of no-till farming around the world (review). *Tauride Bulletin of Agrarian Science* 2(22):150–168. <https://doi.org/10.33952/2542-0720-2020-2-22-150-168>. (In Russian)
- Vázquez, M. M., César, S., Azcón, R., and Barea, J. M. 2000. Interactions between arbuscular mycorrhizal fungi and other microbial inoculants (*Azospirillum*, *Pseudomonas*, *Trichoderma*) and their effects on microbial population and enzyme activities in the rhizosphere of maize plants. *Applied Soil Ecology* 15:261–272. [https://doi.org/10.1016/S0929-1393\(00\)00075-5](https://doi.org/10.1016/S0929-1393(00)00075-5)
- Verhulst, N., Govaerts, B., Sayre, K. D., Deckers, J., François, I. M., and Dendooven, L. 2009. Using NDVI and soil quality analysis to assess influence of agronomic management on within-plot spatial variability and factors limiting production. *Plant Soil* 317:41–59. <https://doi.org/10.1007/s11104-008-9787-x>
- Vermote, E., Roger, J. C., Franch, B., and Skakun, S. 2018. LaSRC (Land Surface Reflectance Code): Overview, application and validation using MODIS, VIIRS, LANDSAT and Sentinel 2 data's. Proceedings of IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2018). Spain. P. 8173–8176.
- Wahba, M. M., Labib, F., and Zaghoul, A. 2019. Management of calcareous soils in arid region. *International Journal of Environmental Pollution and Environmental Modelling* 2(5):248–258.
- Wander, M. 2004. Soil organic matter fractions and their relevance to soil function; pp. 67–102 in: Magdoff, F. and Weil, R. R. (eds), *Soil organic matter in sustainable agriculture*. 1<sup>st</sup> ed. CRC Press, Boca Raton.
- Whetton, R., Zhao, Y., Shaddad, S., and Mouazen, A. M. 2017. Nonlinear parametric modelling to study how soil properties affect crop yields and NDVI. *Computers and Electronics in Agriculture* 138:127–136. <https://doi.org/10.1016/j.compag.2017.04.016>
- Yousaf, W., Awan, W. K., Kamran, M., Ahmad, S. R., Bodla, H. U., Riaz, M., Umar, M., and Chohan, K. 2021. A paradigm of GIS and remote sensing for crop water deficit assessment in near real time to improve irrigation distribution plan. *Agricultural Water Management* 243:106443. <https://doi.org/10.1016/j.agwat.2020.106443>
- Zeffa, D. M., Perini, L. J., Silva, M. B., de Sousa, N. V., Scapim, C. A., de Oliveira, A. L. M., de Amaral Júnior, A. T., and Gonçalves, L. S. A. 2019. *Azospirillum brasilense* promotes increases in growth and nitrogen use efficiency of maize genotypes. *PLoS ONE* 14:e0215332. <https://doi.org/10.1371/journal.pone.0215332>
- Zhang, Y., Guo, L., Chen, Y., Shi, T., Luo, M., Ju, Q. L., Zhang, H., and Wang, S. 2019. Prediction of soil organic carbon based on Landsat 8 monthly NDVI data for the Jiangnan Plain in Hubei Province, China. *Remote Sensing* 11:1683. <https://doi.org/10.3390/rs11141683>