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Normalized Difference Vegetation Index (NDVI) for soybean biomass and nutrient uptake estimation in response to production systems and fertilization strategies

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The system fertilization approach emerged to improve nutrient use efficiency in croplands. This new fertilization concept aims at taking advantage of nutrient cycling within an agroecosystem to obtain maximum production from each nutrient unit. To monitor this effect, methodologies such as the Normalized Difference Vegetation Index (NDVI) are promising to evaluate plant biomass and nutrient content. We evaluated the use of NDVI as a predictor of shoot biomass, P and K uptake, and yield in soybean. Treatments consisted of two production systems [integrated crop-livestock system (ICLS) and cropping system (CS)] and two periods of phosphorus (P) and potassium (K) fertilization (crop fertilization—P and K applied at soybean sowing—and system fertilization—P and K applied in the pasture establishment). NDVI was evaluated weekly from the growth stage V2 up to growth stage R8, using the Greenseeker[®] canopy sensor. At the growth stages V4, V6, R2, and R4, plants were sampled after NDVI evaluation for chemical analysis. Soybean yield and K uptake were similar between production systems and fertilization strategies ($P > 0.05$). Soybean shoot biomass and P uptake were, respectively, 25.3% and 29.7% higher in ICLS compared to CS ($P < 0.05$). For NDVI, an interaction between the production system and days after sowing ($P < 0.05$) was observed. NDVI increased to 0.95 at 96 days after sowing in CS and to 0.92 at 92 days after sowing in ICLS. A significant relationship between NDVI

and shoot biomass, and P and K uptake was observed ($P < 0.05$). Our results show that the vegetation index NDVI can be used for estimating shoot biomass and P and K uptake in the early growth stages of soybean crops, providing farmers with a new tool for evaluating the spatial variability of soybean growth and nutrition.

KEYWORDS

system fertilization, nutrient cycling, mixed system, fertilization approach, phosphorus uptake, potassium uptake, integrated crop-livestock system

1. Introduction

Soybean is one of the worldwide essential agricultural commodities for feeding the growing population, and their production requires a large amount of nutrients, mainly phosphorus (P) and potassium (K) (Divito and Sadras, 2014; FAO, 2017). Studies have shown that growing soybean production over time is accompanied by, in part, an increasing use of fertilizers (Tilman et al., 2001; FAO, 2018). In this sense, FAO (2019) estimates an average annual increase of 1.3% in world synthetic fertilizer demand for nitrogen (N), P, and K, and studies have shown that increases in fertilizer use can result in increased amounts of nutrients and toxins levels in ground and surface waters, incurring health and water purification costs and decreasing fishery and recreational values (Tilman et al., 2002; Kondraju and Rajan, 2019).

Food production requires large amounts of nutrients; N, P, and K are the most frequently deficient in soils. Considering that soybean has the capability to fix N from the atmosphere through a symbiotic relationship with rhizobium bacteria, P and K fertilizers are the main nutrients used on soybean crops with a direct influence on their development and productivity (Gonçalves et al., 2010). The deficiency of these nutrients can affect plant physiology due to its central role in many metabolic pathways, resulting in growth reduction, nutrient remobilization, and changes in carbon metabolism (Richardson et al., 2009), as well as decreased chlorophyll concentration in the leaves (Ayala-silva and Beyl, 2005).

Specialized agriculture decreased the diversity of agricultural commodities (Reinsch et al., 2021) and has changed the entire energy system and nutrient flow when compared to nature-mimicking ecosystems (Gates, 2003). Specialized agriculture of high input use disagrees with the principles and natural flow that exist in nature, bringing severe consequences such as loss of heterogeneity (Lemaire et al., 2014) as well as the biodiversity of soil, plants, insects, and birds (Kleijn et al., 2009). Thus, with population growth and greater demand for food sources, conservative attitudes are necessary to reconnect production with nature (Sollenberger et al., 2019).

Recently, sustainable intensification alternatives to specialized systems [i.e., integrated crop-livestock systems (ICLS), Carvalho et al., 2018] associated with the system fertilization approach (Farias et al., 2020) emerged as a modern tool based on the sustainable integration of food production and maintenance of environmental services (Bernardon et al., 2021). System fertilization consists of anticipating fertilizer application usually applied in the establishment of cash crops, to the winter/cover crop phase, to connect the different phases of a rotation system with the optimization of natural resources and minimal losses. In addition, it also facilitates the sowing operation of the cash crop, since this fertilizer is available in the system even before the process of implantation of the grain crop (Bernardon et al., 2021). Using this fertilization approach, the levels of synergy between the elements increase the nutrient use efficiency and influence the characteristics of the system (Martins et al., 2017), making it more robust, biodiverse, and resilient (Franzluëbbers, 2007). This management strategy, in addition to generating economic benefits, contributes to raising the level of soil aggregates and to a better structural development of this complex and interconnected environment (Bronick and Lal, 2005).

To monitor food production systems, the use of remote and proximal sensing techniques has attracted attention recently owing to their many advantages, such as speed of measurement, precision, simple application, and the possibility to estimate several parameters related to crops. Spectral vegetation indices (e.g., Normalized Difference Vegetation Index—NDVI) have been widely used to evaluate the vegetation cover (Reinermann et al., 2020) and to monitor crop growth (Atzberger, 2013). NDVI can be used to estimate leaf area index (LAI) in wheat (Tan et al., 2020), and N fertilization and heat stress effect in maize (Elazab et al., 2016) and to monitor disease incidence level in soybean by spectral differences between infected plants when compared to healthy ones (Gazala et al., 2013). In this sense, nondestructive methodologies can be a valuable tool for determining the nutritional status of crops under field conditions, with low costs and labor requirements (Baresel et al., 2017). Therefore, NDVI can present a sensitive response to low LAI and soybean biomass within a specific phenological stage

of the crop, providing important information in the detection of the potential yield in soybean crops (Kross, 2015). In fact, NDVI values are related to increases in shoot biomass, LAI, and soil cover fraction (Andrade et al., 2022) and can be used to monitor phenological stages and biomass production of soybean (Sarmiento et al., 2020).

We hypothesized that measurements of the NDVI can be used as a predictor of shoot biomass, P and K uptake, and yield in soybean crops. For this, we investigated these factors in an ICLS comparing the effects of system and conventional (crop) fertilization.

2. Materials and methods

2.1. Field experimental description

The experiment started in 2017 at the Agronomic Experimental Station of the Federal University of Rio Grande do Sul (EEA-UFRGS), located in Eldorado do Sul, southern Brazil (latitude 30°05'22"S and longitude 51°39'08"W and altitude 46 m). The region is characterized as subtropical humid "Cfa" according to the Köppen classification (Alvares et al., 2013). Annual average air temperatures were 19.8 and 19.2°C, and annual rainfall was 1,510 and 1,214 mm in 2017 and 2018, respectively. The monthly precipitation and the mean daily air temperature during the soybean growing seasons of 2017/2018 and 2018/2019 are shown in Figure 1. Mean air temperature in both seasons was similar to the historical mean air temperature at EEA-UFRGS (climate normal for the period 1970–2009). Furthermore, monthly precipitation in the growing season of 2017/2018 was close to the climate normal (1970–2009), while in the season of 2018/2019, the monthly precipitation between December 2018 and April 2019 was lower when compared to the climate normal, indicating a drier growing season (Figure 1). Soil is classified as an Acrisol, according to FAO (2015). Soil samples were taken at plot level in June 2017, from layer 0 to 10 cm depth, and presented 134, 239, and 627 g kg⁻¹ of clay, silt, and sand, respectively. Besides, it presented organic carbon of 17 g kg⁻¹, pH (H₂O) of 3.9, and 94 and 97 mg dm⁻³ of available P and K by Melich-1, respectively. It also presented 1.1 cmol dm⁻³ of Ca and 0.5 cmol dm⁻³ of Mg and 14.9% of base saturation (V%) and 48.5% of Al saturation. Based on these analyses, 7.5 Mg ha⁻¹ of dolomitic limestone [CaMg (CO₃)₂] with a total neutralization power of 72% was applied to the soil surface in August 2017 to raise soil pH to 6.0 (CQFS-RS/SC., 2016).

In 2017, the experimental area (4.8 ha) was arranged in a factorial model (2 × 2) in a randomized complete block design with four replicates (16 experimental units). The aim was to test the effect of the grazing animal (non-grazed system named "cropping system" (CS) or grazed system characterizing an integrated crop-livestock system named

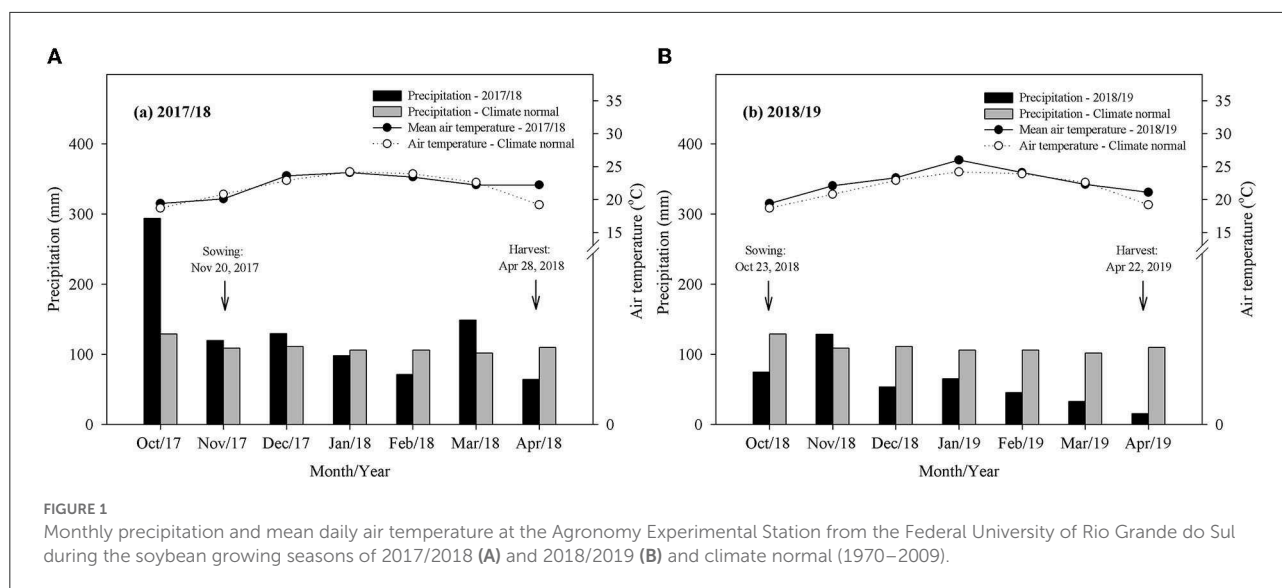
"ICLS") and fertilization strategies ("crop fertilization"—P and K applied at soybean establishment—or "system fertilization"—P and K applied at the winter/cover crop phase). Thus, treatments were (i) ICLS with system fertilization—ICLS + SysF, (ii) ICLS with crop fertilization—ICLS + CF, (iii) cropping system with system fertilization—CF + SysF, and (iv) cropping system with crop fertilization—CS + CF (for more details, refer to Farias et al., 2020).

In both evaluated years (growing seasons of 2017/2018 and 2018/2019), Italian ryegrass (*Lolium multiflorum*) was cultivated in the autumn-winter period (pasture phase) and soybean (*Glycine max.*) was cultivated in the spring-summer period (crop phase). In the ICLS treatment, Italian ryegrass was grazed by sheep at ~10 months of age and an initial body weight of 24.5 ± 0.44 and 29.9 ± 2.9 in 2017 and 2018, respectively. The pasture was managed to keep the average sward height at 15 cm in a continuous stocking with a variable stocking rate according to the "Rotatinuous" grazing management concept (Carvalho, 2013). In the CS, Italian ryegrass was used as a non-grazed cover crop. N fertilization was applied in the pasture phase, regardless of the treatment, in the amount of 150 kg of N ha⁻¹ performed in the form of urea when the plants presented three fully expanded leaves. At the end of the stocking period, glyphosate (3 L ha⁻¹) and saflufenacil (100 g ha⁻¹) were applied. Soybean seeds were treated with insecticide and fungicide, inoculated, and sown on 20 November 2017 and 23 October 2018, in rows spaced 0.45 m apart at a density of 36 seeds m⁻², under no-tillage system. Soybean harvest occurred in every season at the end of April. Genotypes used were DM 5958 RSF IPRO (2017/2018) and NA 5909 RG (2018/2019). Fertilization rates for P₂O₅ and K₂O were calculated for a soybean grain production of 4.0 Mg ha⁻¹ and applied in the pasture or crop phase, according to the fertilization strategy.

2.2. Soybean evaluations

The soybean phenological growth stage was evaluated weekly according to Fehr and Caviness (1977) over the growing seasons of 2017/2018 and 2018/2019. The soybean growth stage was determined when more than 50% of the plants are in this stage.

The NDVI was evaluated weekly from the phenological stage V2 (second trifoliolate—two sets of unfolded trifoliolate leaves) up to R8 (full maturity—95% of the pods have reached their full mature color) using the handheld canopy sensor GreenSeeker[®] (Trimble Navigation Limited, Sunnyvale, CA, USA). This sensor is made up of electroluminescent diodes (LEDs) emitting radiation in the red and near-infrared (NIR) regions of the electromagnetic spectrum and the reflected radiation by the canopy in both regions is then measured by a silicon photodiode positioned in front of the device. The NDVI is determined by the relation: $(\rho_{\text{NIR}} - \rho_{\text{R}}) / (\rho_{\text{NIR}} + \rho_{\text{R}})$, where ρ_{NIR} and ρ_{R} denote



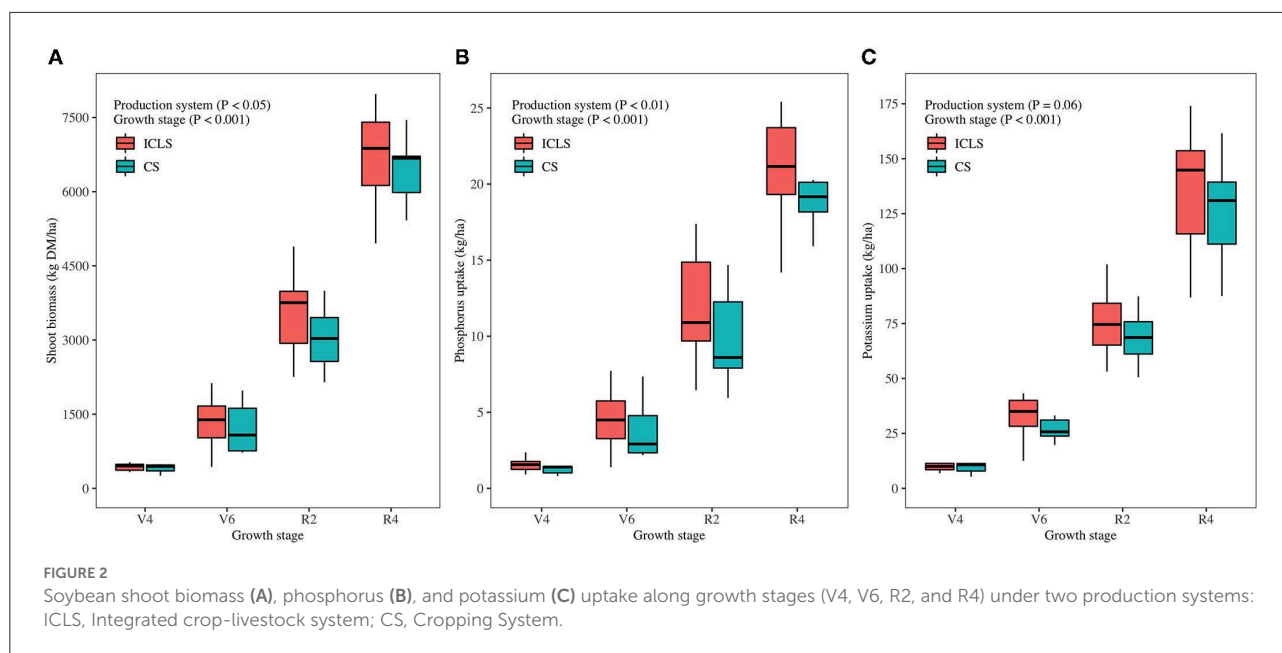
the NIR (770 ± 15 nm) and red (660 ± 15 nm) reflectance, respectively. NDVI values can vary numerically from -1 to $+1$, with positive values indicating the vegetative vigor of the crop, while negative values indicate the presence of bare soil or the absence of vegetation (Liu et al., 2006). The equipment was positioned at ~ 1.0 m above the canopy, and readings were obtained for ten randomly distributed points (0.45 m² for each point) in the paddock.

Soybean shoot biomass was determined at the phenological stages V4 (fourth trifoliolate—four unfolded trifoliolate leaves), V6 (sixth trifoliolate—six unfolded trifoliolate leaves), R2 (full flowering—open flower at one of the two uppermost nodes), and R4 (full pod—pods are 2 cm at one of the four uppermost nodes), by sampling plants in an area of 0.45 m² in four randomly chosen points in each paddock. Shoot dry biomass was determined after drying the samples at 65°C until a constant mass was reached. The amount of accumulated P and K in shoots (P and K uptake) was determined by multiplying shoot dry biomass by the plant P and K concentrations. These analyses were performed according to the methodology proposed by Tedesco et al. (1995). P and K concentrations were determined spectrophotometrically by the addition of ammonium and aminonaphthalenesulfonic acid and by flame photometry, respectively, after acid digestion of the plant tissue (Tedesco et al., 1995).

Soybean grain yield at maturity (phenological stage R8) was evaluated by harvesting six randomly selected areas (0.9 m² each) in each paddock and weighing the grains. Grain yield was extrapolated to “kg ha⁻¹” and expressed at 130 g kg⁻¹ of moisture.

2.3. Statistical analysis

Data were analyzed by analysis of variance (ANOVA) using a mixed model by the LMER function of package lme4 using the R software (version 4.1.1). The assumptions of normality, variance homogeneity, and independence of residuals were checked by the Shapiro test ($P > 0.05$), Bartlett test ($P > 0.05$), and visual residual analysis, respectively. The production system (ICLS vs. CS), fertilization strategy (crop fertilization vs. system fertilization), growth stage (V4, V6, R2, and R4), and their interactions were considered fixed effects in the statistical model. For soybean yield, only the production system, fertilization strategy, and its interaction were considered fixed effects. Random effects included paddock or block and year. Models with the inclusion of different random effects were tested and the best fit model was selected by the AIC criterion (Akaike, 1973). For NDVI, the fixed effects of the production system, fertilization strategy, days after sowing, and their interactions were considered fixed effects. For testing NDVI as a predictor, the model included the fixed effects of the production system, fertilization strategy, NDVI, year, and their interactions. As there was no significant effect of year and its interactions ($P > 0.05$), the model was simplified. Therefore, block and year were considered random effects. When the NDVI effect or its interaction was significant ($P < 0.05$), regression analyses (linear, non-linear, and polynomial) were tested, considering NDVI as an explanatory variable. As no relationship was established with NDVI in the R4 stage, the models were generated including only the stages V2, V4, and R2. When significant at 5% ($P < 0.05$), models were compared by the AIC criterion; the regression model with the smallest AIC value was selected.



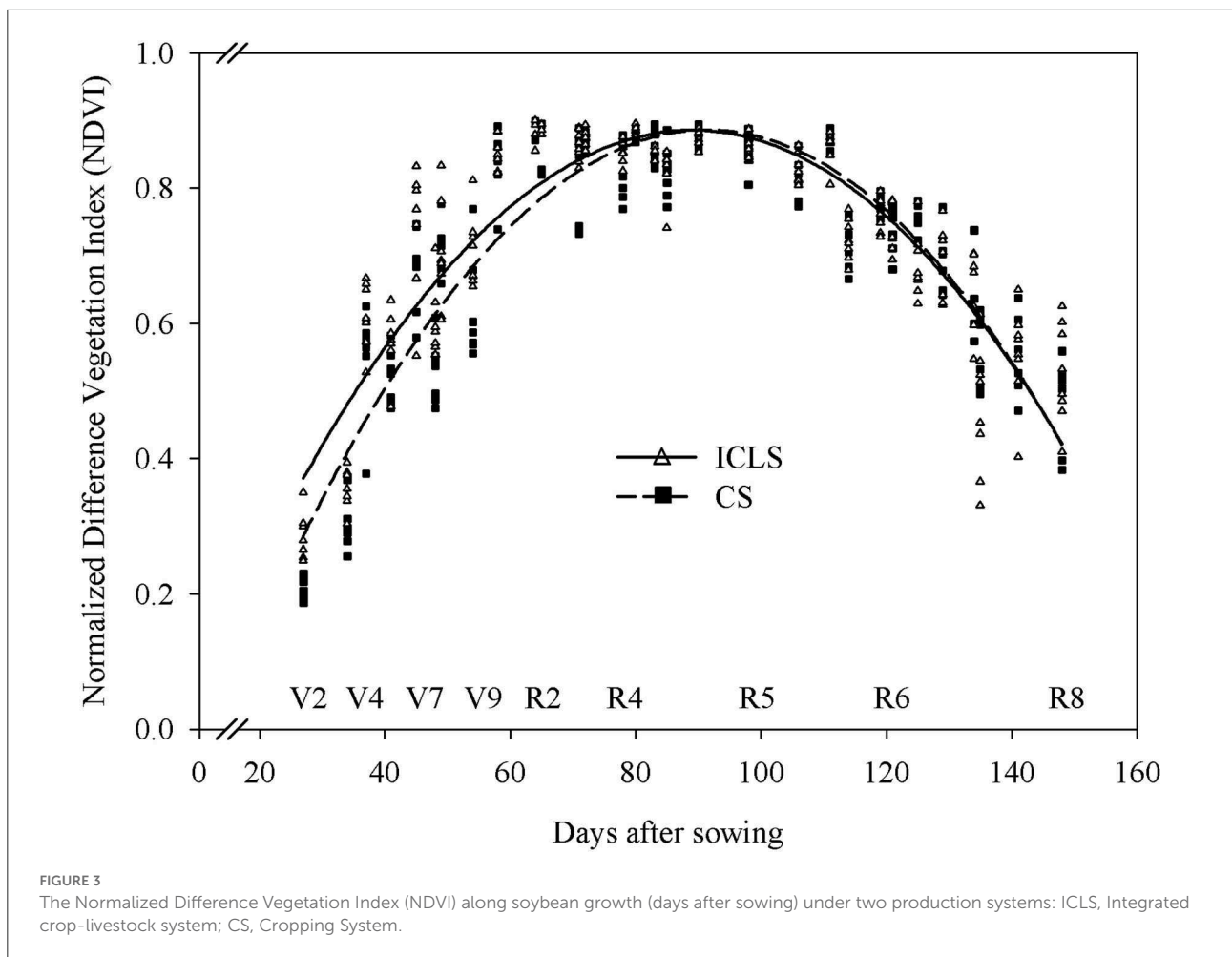
3. Results

Soybean yield was similar (2.886 ± 477 kg DM ha⁻¹) between production systems and fertilization strategies ($P > 0.05$). Soybean biomass and P and K uptake presented no interaction ($P > 0.05$) between the production system and fertilization strategy, nor did their interactions with the growth stage ($P > 0.05$). A significant effect of the production system and soybean growth stage was observed for shoot biomass ($P < 0.05$, Figure 2A) and P uptake ($P < 0.001$, Figure 2B). In this sense, ICLS presented 25.3 and 29.7% higher soybean biomass and P uptake compared to CS across growth stages, respectively. K uptake increased significantly over the soybean growth stage ($P < 0.001$) and ICLS presented an 18.8% higher K uptake compared to CS ($P = 0.06$, Figure 2C). In contrast, the fertilization strategy presented no effect on soybean shoot biomass and P and K uptake. NDVI values increased during the growing cycle between the phenological stages V2 (second trifoliolate) up to R4 (full pod development) and decreased afterward (Figure 3). No interaction between the production system and the fertilization strategy ($P > 0.05$) was observed for NDVI, and neither was the effect of the fertilization strategy ($P > 0.05$). We observed an interaction between the production system and days after sowing ($P < 0.05$); thus, we tested different regression models for CS and ICLS. NDVI was adjusted to a quadratic regression model (Figure 3) as a function of days after sowing for both production systems (CS and ICLS): CS: $y = -0.35 + 0.027x - 0.00014x^2$; $R^2_{adj} = 0.7679$; SE = 0.09; $P < 0.001$; ICLS: $y = -0.19 + 0.024x - 0.00013x^2$; $R^2_{adj} = 0.7160$; SE = 0.09; $P < 0.001$. The quadratic regression models show an

increase of NDVI until ~ 0.90 at 96 days after sowing in CS and until 0.92 at 92 days after sowing in ICLS (Figure 3).

The NDVI was closely related to shoot biomass of soybean for values of this index between 0.4 and 0.85, and the increase in biomass production within this range was reflected in linear increments in the NDVI values (Figure 4). Furthermore, no interaction was observed between NDVI, production system, and fertilization strategy ($P > 0.05$). A significant effect of NDVI was observed ($P < 0.05$), with shoot biomass adjusted to an exponential model (Figure 4), independent of treatment: $y = -6194 + 3925.7^x$; $R^2_{adj} = 0.8228$; SE = 542.8; $P < 0.001$. Considering the regression model between the NDVI and shoot biomass, no significant interaction between the NDVI and the growing season was observed ($P = 0.3735$), indicating that the relationship between both variables was similar to the growing seasons of 2017/2018 and 2018/2019 and, therefore, a single model can be used to describe the association between the NDVI and soybean shoot biomass (Figure 4), regardless of growing season and treatments (production system—CS and ICLS, and fertilization strategy—CF and SysF).

Similarly, the P and K uptake were related to the NDVI values in the early stages (V2, V4, and R2) (Figures 5, 6). An exponential model was adjusted for P uptake ($P < 0.05$), independent of treatment (Figure 5): $y = -20.1 + 12.7^x$; $R^2_{adj} = 0.7448$; SE = 2.2; $P < 0.001$. No significant interaction between the NDVI and the growing season for P uptake was detected ($P = 0.2512$), indicating that a single regression model depending on the production system (CS and ICLS) can be used to describe the relationship between both variables (Figure 5), regardless of the growing season and the fertilization strategy.



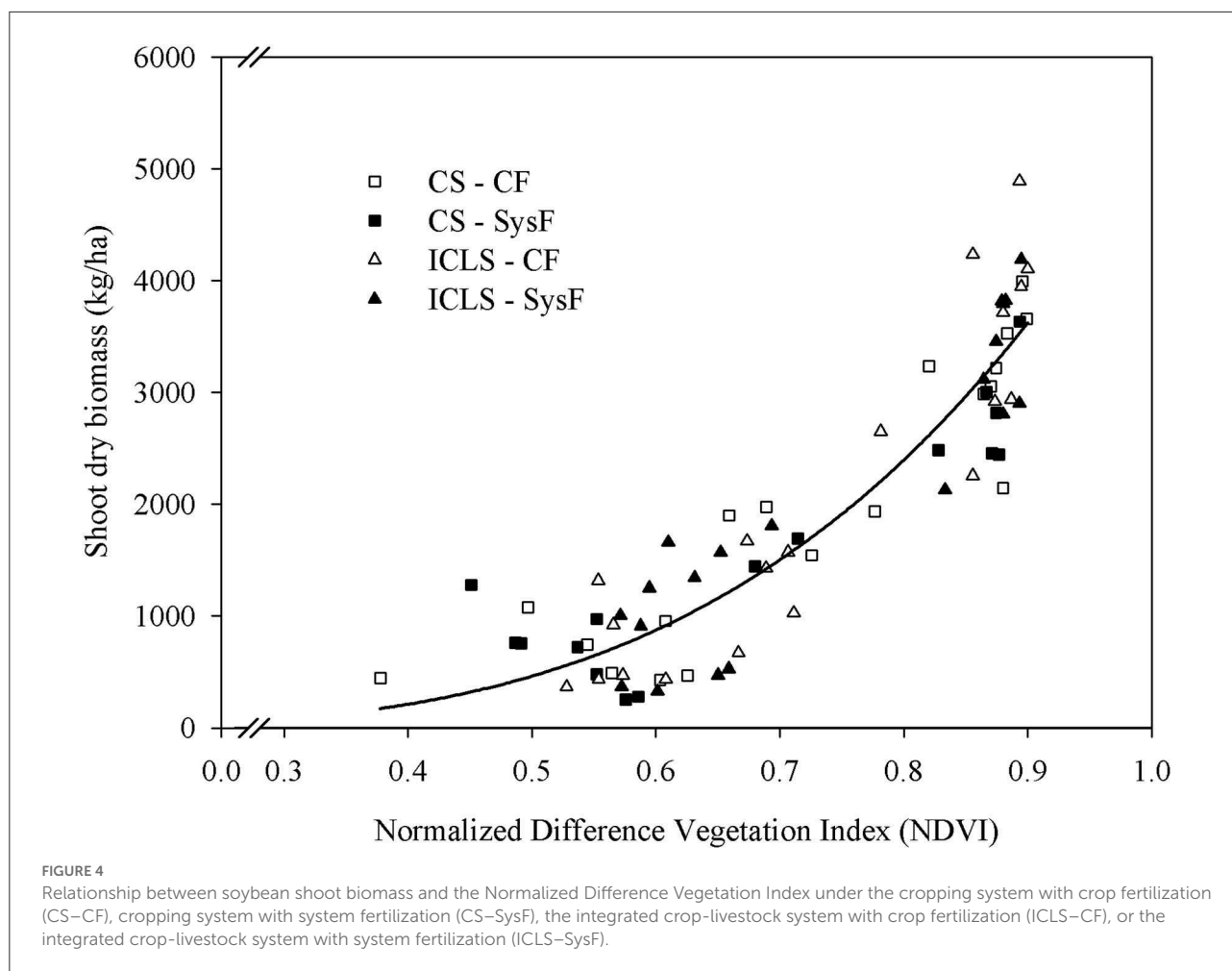
Considering the K uptake, no interaction was observed between NDVI, production system, and fertilization strategy ($P > 0.05$, Figure 6). An effect of NDVI was observed ($P < 0.05$), with K uptake adjusted to an exponential model (Figure 6), independent of treatment: $y = -115.3 + 76.7^x$; $R^2_{\text{adj}} = 0.7468$; $SE = 13.4$; $P < 0.001$. Furthermore, no significant interaction between the NDVI and the growing season was observed for K uptake ($P = 0.6781$), so a single model can be used to describe the association between both variables, regardless of production system and fertilization strategy (Figure 6).

4. Discussion

The NDVI values were affected by the progress of the growing cycle of the soybean. In general, the quadratic behavior of NDVI values shown in Figure 3 could be related to the fact that NDVI increased until ~ 90 days after sowing (phenological stage R4–R5), decreasing afterward up to the harvest maturity (phenological stage R8). NDVI dynamics between growth stages V2 (25 days after sowing) and R4 (full pod) was affected by

grazing, being higher for the ICLS. This effect may be related to a higher plant biomass of soybean promoted by the ICLS (Figure 2A), since an interaction effect of the production system and days after sowing ($P < 0.05$) was observed (Figure 3). Grazing can affect the subsequent crop, and grazing intensity is a key factor. Kunrath et al. (2015) evaluated grazing intensities in a long-term ICLS and found that under moderate or light grazing intensity (20, 30, or 40 cm of sward height), soybean presented a similar growth pattern and yield compared to the non-grazed treatment.

Throughout its growing cycle, soybean tends to accumulate photoassimilates in the vegetative growth stages and has the highest NDVI values in the reproductive stages. The increase in NDVI values from V2 up to R4 is related to an increase in shoot biomass and LAI. The more leaf layers in the canopy, the higher the LAI and, consequently, the lower the visible and the higher the near-infrared reflectance, resulting in higher NDVI values (Figure 3). In the subsequent growth stages, as shown in Figure 3, the values tend to stabilize and then decrease, as the plant begins to mobilize its reserves for the reproductive organs, in addition to the starting of leaf senescence and, consequently,

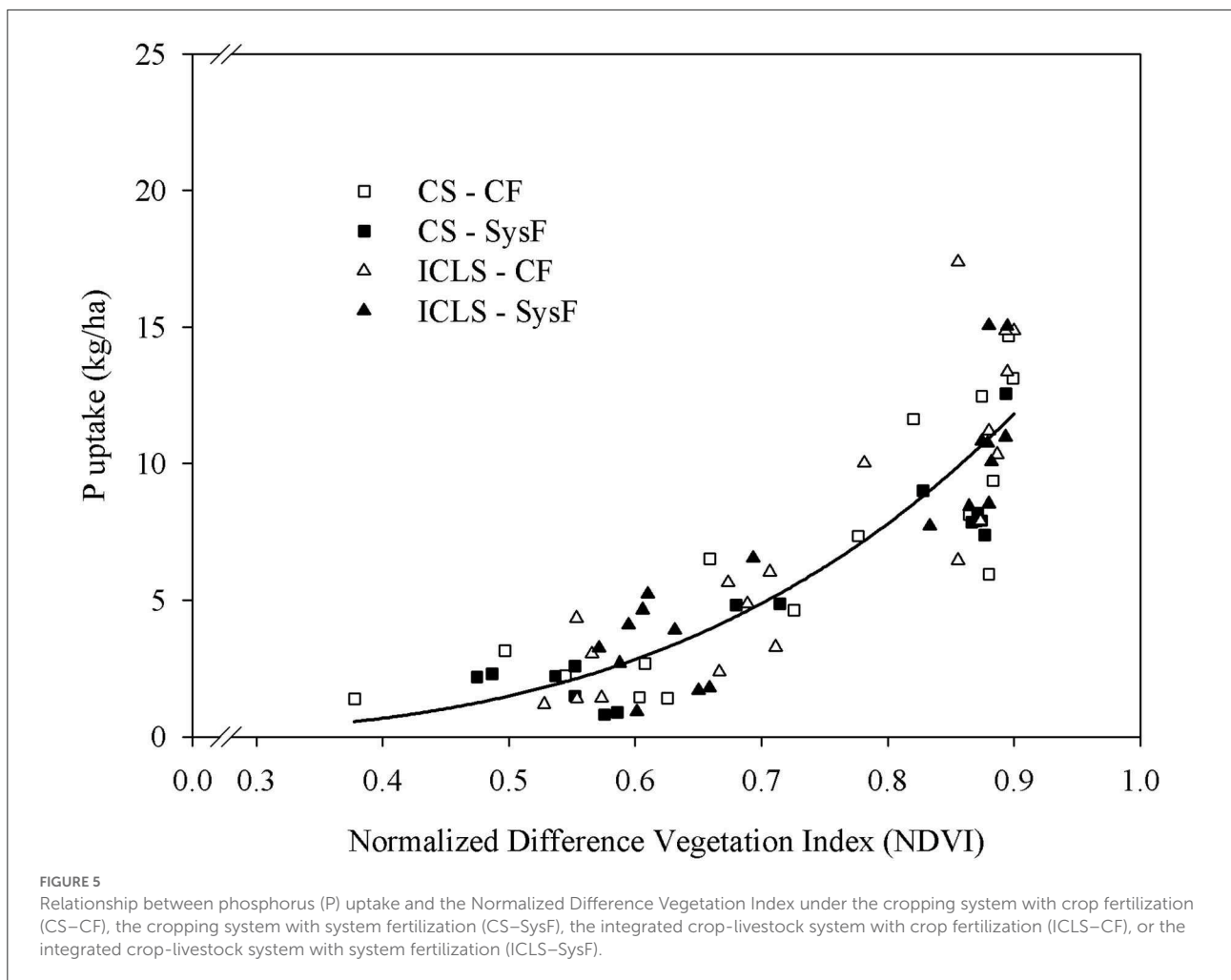


chlorophyll degradation (Duan et al., 2017; Kuiawski et al., 2017).

The NDVI was positively correlated to soybean shoot biomass up to $5,000 \text{ kg ha}^{-1}$ of biomass, corresponding to an NDVI value of approximately 0.90 (Figure 4). This relationship was not affected by the production system and the fertilization approach. Afterward, the absence of a significant relationship from this point on can be explained by the saturation that occurs with the NDVI when the plant reaches its maximum accumulation of biomass. There is an exponential relationship between NDVI and shoot biomass until $5,000 \text{ kg ha}^{-1}$ of dry biomass. After that, no relationship can be found between both variables. According to Werner et al. (2018), in the early growth stages, the reduced shoot biomass results in lower canopy closure, while, in the reproductive growth stages, the interrow spaces close, resulting in the NDVI saturation effect, i.e., even with increasing soybean shoot biomass, the NDVI value remains stable, as shown for shoot biomass and P and K uptake (Figures 4–6).

The saturation effect is especially important when considering the NDVI, which considers for its calculation the crop reflectance in the red and NR regions of the electromagnetic spectrum. The reflectance in the red region is the one that presents the greatest variation throughout the crop development cycle, since the red radiation is mainly absorbed by chlorophylls for the photosynthetic process, resulting in high absorption and low reflectance throughout the development of the crop. Thus, with the increase in LAI, there is an increase in the absorption in the red band by chlorophylls, reducing the reflectance until the moment when, even with a high LAI, the reflectance is not reduced, remaining constant (about 3–4%) and resulting in the saturation effect. This effect occurs in situations of high biomass production, high LAI, and/or high degree of soil cover by the crop. In this condition, even if there is an increase in these parameters, the values of NDVI do not change.

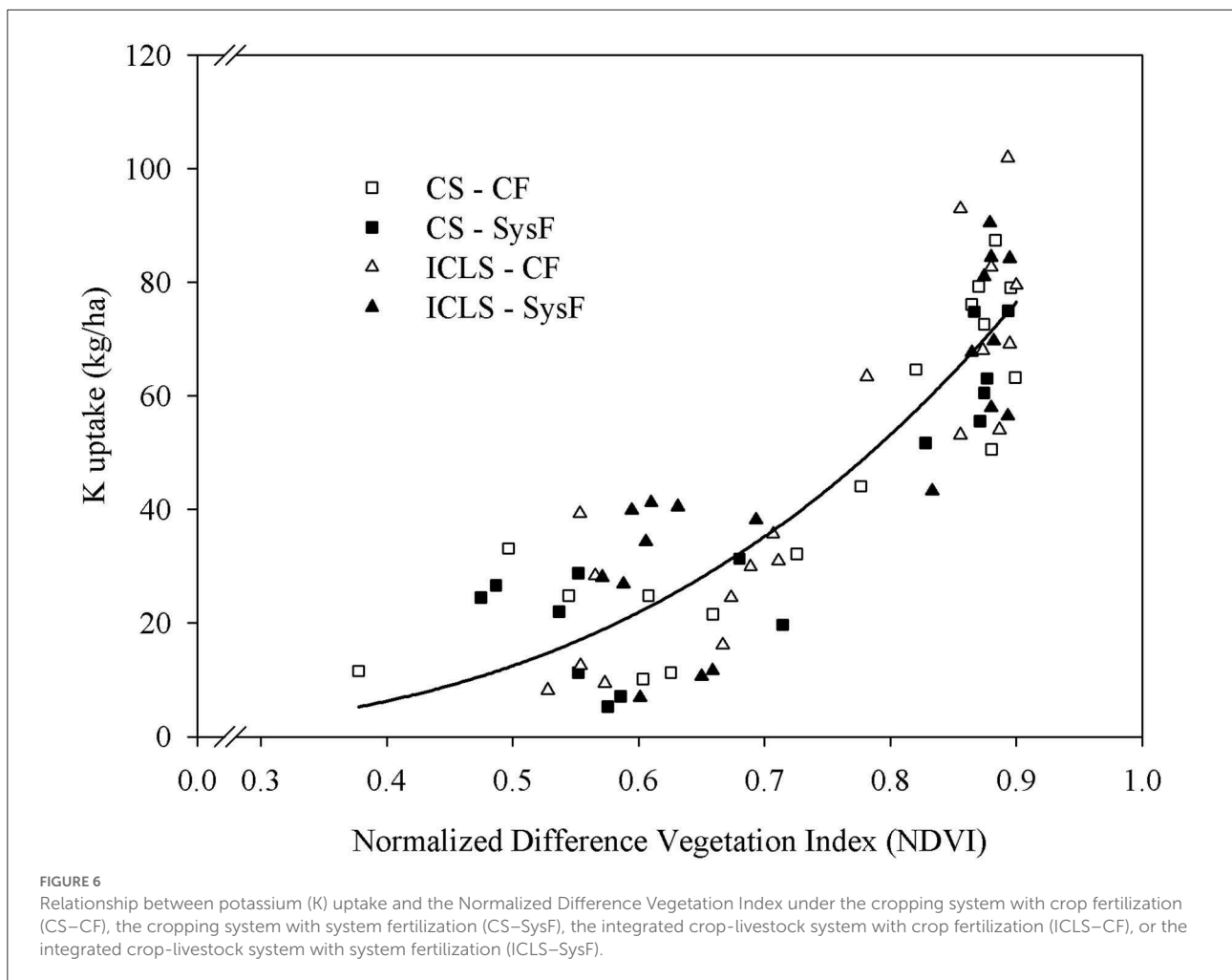
Several studies involving the NDVI have been conducted to identify variability in biomass production, amount of nutrients absorbed, and productivity estimation in wheat (Raun et al.,



2005; Vian et al., 2018; Trentin et al., 2021), soybean (Miller et al., 2018; Araújo et al., 2020), and irrigated rice (Ali et al., 2014; Zhang et al., 2019). In our study, soybean yield was not associated with NDVI evaluated in the growth stages V4, V6, R2, and R4. In contrast, Ma et al. (2001) obtained $R^2 = 0.80$ between the spectroradiometer NDVI at R5 and soybean yield, while Araújo et al. (2020) reported an $R^2 = 0.53$ at the R1 growth stage (beginning of flowering) between both variables. This behavior may be related to the lower variability of the NDVI and the saturation of this index with the advance of the soybean growing cycle and to the phenotypic plasticity of the plant. Differences in soybean biomass production can be distinguished in the early growth stages. However, with the advance in crop development, the variability decreases, and the biomass no longer shows a significant difference promoted by different plant populations or nutrient availability. The phenotypic plasticity is promoted by changes in plant height and number of nodes and branches, resulting in wide adaptability of the crop to different management conditions, e.g., changes in plant density or nutrient availability (Rambo et al., 2003).

Soybean yield was not affected by the production systems and fertilization strategies, which demonstrates that P and K nutrients were not limiting in the four evaluated systems. This result shows that ICLS with system fertilization is promising in releasing the fertilizers applied in the pasture phase. Moreover, grazing imposes a continuous recycling of nutrients through animal excreta and low nutrient export in animal liveweight, compared to grain harvesting (Williams, 2007; Alves et al., 2019; Arnuti et al., 2020). In a recent study, Farias et al. (2020) showed a positive impact of system fertilization on the productivity of agroecosystems. They found higher forage production compared to crop fertilization and similar soybean grain production between both approaches, promoting the optimization of land use.

The NDVI is obtained by the following relationship: $(NIR - R)/(NIR + R)$, where NIR and R refer to the near-infrared and red reflectance, respectively. This index presents a numerical variation from -1 to $+1$, with positive values indicating the vegetative vigor of the crop, while negative values indicate the absence of vegetation or soil exposure (Rouse et al., 1973; Liu



et al., 2006). By means of reflectance evaluations, vegetation sensors, such as the Greenseeker[®], are able to capture the spectral properties of the canopy, which are related to the nutritional status of the plant (Mulla, 2013). The sensors perform readings in the radiation absorption bands in the visible range (480–680 nm), which are related to the absorption of incident radiation by chlorophyll molecules, and in the NIR range (700–1,300 nm), where there is high reflectance by vegetation.

The increase in NDVI due to greater shoot biomass accumulation (Figure 4) may be explained by the spectral signature of the soybean in the red and NIR regions of the electromagnetic spectrum. The greater the accumulation of photosynthetically active biomass, the higher the reflectance of NIR radiation, and the lower the reflectance of red radiation, resulting in an increase in NDVI value (Smith et al., 2017), which indicates a greater amount of chlorophyll and biomass of the crop. The wavelength in the red spectral range is absorbed by the chlorophylls, making the reflectance values decrease as the chlorophyll contents increase. On the other hand, the reflectance

values in the NIR region are an indirect measure of the amount of biomass (Peñuelas and Filella, 1998).

Therefore, NDVI measured by a canopy sensor was suitable to differentiate soybean growing conditions between the V2 and R4 growth stages provided by different production systems (Figure 2) and between shoot biomass variations up to the value of 5,000 kg ha⁻¹ (Figure 4). Remote sensing tools, such as vegetation sensors, can help to estimate the nutritional status of the crop, in real time, throughout the development of the plants. The principle of the functionality of these sensors is, basically, to capture the different lengths of electromagnetic radiation reflected by the plants, generating vegetation indices that can be quantified and, later, used to generate information on the nutritional conditions of the plants in the area under study, such as biomass and chlorophyll content (Khanal et al., 2017). Vegetation indices, such as the NDVI, can be used to detect invasive plants in crop areas (Merotto et al., 2012) and to estimate biomass and grain productivity (Schaefer and Lamb, 2016; Sanodiya et al., 2017).

In this sense, the use of NDVI as an indicator of the nutritional status of the plant in relation to P and K must be preceded by the analysis of its relationship with the traditional variables used to quantify the nutritional status of the plants (Raun et al., 2005), as P and K uptake (Figures 5, 6). According to our results, the estimation of P and K uptake in the early growth stages to identify its deficiency in soybean crops based on the NDVI is feasible, which ensures agility to these evaluations in a nondestructive way, improving the efficiency of P and K fertilization and providing farmers with a new tool for evaluating the spatial variability of soybean growth and nutrition.

5. Conclusion

Our findings highlight that ICLS presents higher soybean shoot biomass and P uptake compared to CS, without a difference in K uptake. The crop and system fertilization strategies are similar in terms of soybean shoot biomass and P and K uptake. The use of vegetation index NDVI is promising in differentiating an ICLS from CS in terms of soybean growth. Furthermore, NDVI can be used for estimating shoot biomass and P and K uptake in the early growth stages of soybean crops (until stage R2). In contrast, soybean yield cannot be estimated by the NDVI evaluated in the growth stages V4, V6, R2, and R4.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

Conceptualization: PF, CaB, GF, TT, and AM. Statistical analysis, data curation, and visualization: GF, CBrem, and CBred. Investigation and project administration: GF and LA. Writing: GF, CBrem, JL, CBred, LA, TT, GF, GS, AM, and PF.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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