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Assessing Drone-Based Remote Sensing Indices for Monitoring Rice Nitrogen Plant Status Under Different Irrigation Techniques

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Abstract: The rice sector is facing the challenge of increasing rice yields while maintaining or improving input use efficiency. The purpose of this study was to determine the most effective vegetation indices for monitoring nitrogen uptake (N uptake) under different irrigation techniques. The study was conducted in Uruguay over two rice-growing seasons. A split plot experimental design featured two irrigation treatments (main plots): continuous flooding (C) and alternate wetting and drying (AWD). The nitrogen-rate (N-rate) treatments (split plots) included no nitrogen, the recommended N-rate based on soil analyses, and two additional doses ($\pm 50\%$ of the recommendation). The plant N uptake relationships with selected drone-based vegetation indices (VIs) were assessed at panicle initiation. The presence or absence of standing water during image collection affected the VIs and their relationships with N uptake. The relationships estimated for traditional irrigation may not be applicable for AWD. The SCCCI was the top index with a significantly stronger relationship with N uptake under the C ($R^2 = 0.84$) and AWD ($R^2 = 0.71$) irrigation techniques in relation to all evaluated vegetation indices. The Clre, NDRE², NDRE, and CLg also had a significant relationship with N uptake under both irrigation treatments in both seasons, though their average R^2 values of 0.75, 0.74, 0.73, and 0.71, respectively, were lower than the SCCCI (average $R^2 = 0.78$). The findings would assist rice growers for selecting effective VIs for remote crop monitoring.

Keywords: vegetation indices; VI; drones; N; nitrogen uptake; rice; irrigation; AWD; fertilization



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1. Introduction

Rice stands as the primary staple food crop worldwide. Given the projection of a global population of 9.7 billion by 2050 [1], the rising demand for food implies a continual enhancement in rice yields and input efficiency [2].

With an area of ca. 150,000 hectares planted annually and a production of 1.4 million tons, rice is the major irrigated crop in Uruguay. The country has a subtropical to temperate climate, with abundant water resources and rainfall during the rice-growing season (late September to March), which averages 624 mm [3]. All rice cultivated in Uruguay is irrigated, with fields flooded from 15–35 days post-emergence until ca. 10 days before harvest, when water is drained from fields to let the soil dry. Rice production in Uruguay is highly mechanized, with 90% of the rice fields using direct drilling and planting during October [4,5]. Traditional nitrogen (N) fertilization management in Uruguay consists in applying 80–90 kg N ha^{−1} year^{−1} at tillering and panicle initiation [4]. Current rice yields in Uruguay are about 9.5 Mg ha^{−1} [4], representing 68% of the estimated yield potential that has been determined at 14 Mg ha^{−1} [6]. Therefore, there is room for increasing rice grain yields. However, as yields approach 80% of the yield potential level, it becomes challenging to keep increasing production [7,8] while maintaining the already high input use efficiency achieved in Uruguay [9].

Nitrogen and water are the main limiting factors for closing the gap between actual and potential grain yield [10]. The evaluation of technologies that could assist in optimizing fertilization and irrigation management techniques in rice production is, thus, beneficial for the rice sector. Optimal nitrogen-rate (N-rate) fertilization is crucial for rice production, not only to maximize grain yield and quality, but also to reduce production costs and prevent the risk of lodging [11], reducing the potential negative impacts of excessive nitrogen fertilization on the environment [12] and greenhouse gas emissions [13].

Remote sensing has become an important tool for agricultural management decision-making [14], allowing to monitor changes in the leaves reflectance of crops that can be indicative of biotic or abiotic stress. In recent years, research has focused on the use of canopy reflectance measurements from drones and satellite platforms for crop monitoring because of the advantages they offer in terms of the area covered in comparison to proximal measurements [15,16]. Satellites platforms offer a broader area coverage with a higher temporal resolution [17,18]. Compared to satellite platforms, drones offer a higher pixel resolution and flexibility in terms of the time of image acquisition [19], making this technology more accessible to farmers for real-time crop monitoring. Drone prices have decreased significantly over the last years [20]. Having access to drone-based multispectral vegetation indices (VIs) for rice crop monitoring is a recent practice in Uruguay that is gaining the attention of rice producers, due to its potential for decision-making processes such as N-rates application management.

Some of the VIs described as effective in detecting plant N content include the traditional Normalized Difference Vegetation Index (NDVI), the Normalized Difference Red Edge (NDRE) [21–26], the chlorophyll indices estimated from the green, red, or red-edge bands, Clg, Clr, and Clre, respectively [15,22,27–29], the square of the NDRE [24,30], and ratio indices like the Simplified Canopy Chlorophyll Content Index, SCCCI [31,32], and Red Edge Ratio Index RE/R [33]. These VIs include information from some of the near-infrared (NIR), red-edge (RE), red (R), and green (G) regions of the electromagnetic spectrum that have been identified to change in response to biomass, chlorophyll, and plant nitrogen content among other factors [34,35].

Most VIs proposed for monitoring rice nitrogen content have been tested in ponded rice, as that is the traditional water management practice worldwide. In the last decade, however, there has been growing interest within the rice sector in the use of alternative water management practices that could lead to increased water productivity. The “safe” alternate wetting and drying (AWD) management, in which the crop is not permanently ponded, and water depths never dropped below the root zone, is one of the irrigation techniques that has been found not to compromise grain yield and quality, while reducing total water used and increasing water productivity [36–38]. Potential water savings achieved as a result of reducing the period during which the rice crop is ponded can be very beneficial for the rice industry and contribute to the optimization of the water resources in the agriculture sector.

Standing water in the background of ponded rice influences light reflectance particularly at stages of the crop when canopy closure has not been achieved. Therefore, differences in background between ponded and non-ponded rice, as is the case for rice traditionally managed and under the AWD technique, could impact the performance of VIs for rice N monitoring [39,40].

Most VIs for monitoring rice nitrogen plant status have been tested with traditional irrigation techniques. However, the rice sector faces the challenge of increasing yields and enhancing input use efficiency, while the shift to alternative irrigation practices may impact the performance of these VIs. In this study, the relationships between N uptake (N uptake) and the normalized (NDVI, NDRE, and NDRE²), chlorophyll (Clg, Clr, and Clre), and ratio indices (SCCCI, RE-Ratio, and Simple-Ratio), identified as sensitive to N and chlorophyll content, were explored in a rice crop under traditional and AWD management. The objective of this study was to identify the best-performing VI in tracking crop variability in N-uptake and assess possible differences between irrigation management strategies. For

this purpose, N trials were conducted over two rice-growing seasons in ponded and non-ponded irrigation techniques, with N-rates ranging from zero to 1.5 times the recommended rate, which was estimated based on soil fertility determinations.

2. Materials and Methods

2.1. Study Site Description and Field Management

The study was conducted at the National Institute of Agricultural Research (INIA) experimental site, in Paso Farias in the North region of Uruguay (Lat: -30.50 S, Long: -57.12 W) during the: 2021–2022 (S1) and 2022–2023 (S2) rice-growing seasons (Figure 1). The soil properties at the experimental site were representative of the soil types of the North rice region, as detailed in Table 1.

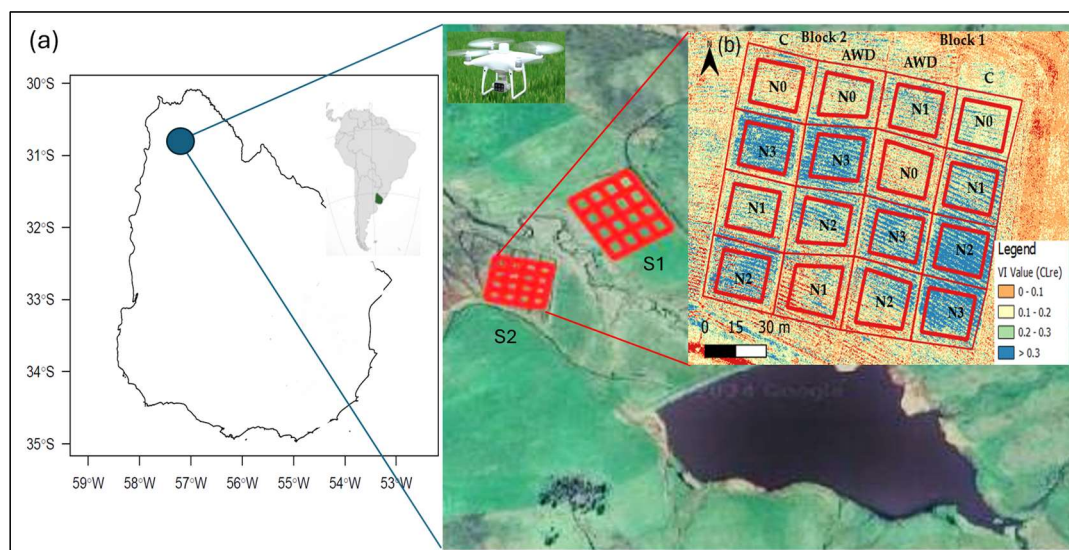


Figure 1. (a) Location of the experimental sites during the rice-growing seasons S1: 2021–2022 and S2: 2022–2023 at the National Institute of Agricultural Research (INIA), Paso Farias North region of Uruguay. (b) Experimental design, treatments, and chlorophyll red-edge (CLre) map for panicle initiation on 13 December 2022, showing the mask used to extract the spectral information within each plot.

Table 1. Selected soil chemical properties for both experimental sites determined at the Agro-Industry Analytical Laboratory (www.laai.com.uy, accessed on 1 October 2024). PMN: potential of nitrogen mineralization.

Soil Parameters	Seasons	
	S1: 2021–2022	S2: 2022–2023
pH (water)	7.1	6.4
Tit. Acidity (meq/100 g)	1.7	2.8
Organic Matter %	4.0	–
P Citric Acid (ppm)	3.0	8.0
Ca (meq/100 g)	35.2	30.7
Mg (meq/100 g)	18.6	14.2
K int. (meq/100 g)	0.4	0.4
Na (meq/100 g)	0.3	0.5
PMN (mg/kg)	11.0	25.0
CIC	56.2	48.6
Total Bases	54.5	15.8
Bases Saturation (%)	97	94
Soil classification [41]	Vertisols (VR)	

Previous land use was fallow without pasture or crop for summer tillage. This minimum tillage soil preparation technique involved disc plowings to control weeds and incorporate any crop plant stubble into the soil, followed by a landplane leveler to enhance the soil bed. The field layout consisted of contour levees, 20–30 cm in height, constructed within a vertical interval of 6 cm. All tillage operations, as well as pre- and post-emergence herbicide applications for weed control and urea application at early tillering, were conducted before permanent flooding on dry soils.

The *Indica* type cultivar INIA Merin was directly drilled at a depth of 2.5–3.0 cm and a seeding rate of ca. 150 kg ha⁻¹ using a 13-line commercial machine (Semeato), in both rice-growing seasons.

The fertilization management included a basal application of nitrogen at 10 kg N ha⁻¹ along with phosphorus at 50 kg P₂O₅ ha⁻¹ and potassium at 50 kg K₂O ha⁻¹ for 2021/22. During the second season, 2022/2023, the basal application was 4 kg N ha⁻¹, 19 kg P₂O₅ ha⁻¹, and 94 kg K₂O ha⁻¹. Two broadcasted urea were applied at tillering on the 21st and 7th of November for the rice-growing seasons 2021/2022 and 2022/2023, respectively (prior to permanent water flooding), and at panicle initiation on the 9 and 21 December in the first and second rice season, respectively. The recommended rate (N2) at PI was determined based on the results from the soil fertility analyses using the Fertilizarr application [42]. This app is available online and uses information from soil analysis, soil texture, field history, rice variety, and previous yield to determine the N-rates fertilization.

2.2. Treatments and Experimental Design

The experimental sites consisted of two irrigation and four N-rate treatments distributed in a split-plot design with irrigation as the main-plot factor and N rates as subplots. The split-plot and main-plot area was 1917 m² (48 m × 40 m) and 7680 m² (48 m × 160 m), respectively, in 2021/2022. In the second rice season (2022/2023), the split-plot area was 1024 m² (34 × 30 m) and the main-plot area was 4080 m² (34 m × 120 m).

The two irrigation treatments were traditional continuous flooding (C) and safe alternate wetting and drying (AWD). The irrigation treatments were separated by a double bank, with a 3 m gap between them. In treatment C, a permanent water layer of 10 cm above ground level was maintained from 20 days after emergence (V3–V4). In the AWD treatment, irrigation frequency was set at 5–7 days. Irrigation events in this treatment (AWD) re-established the water layer at ca. 5–10 cm above ground level and then, the topsoil (0–15 cm) was allowed to dry until the next irrigation event took place. Water management within each irrigation treatment was the same until the start of flowering in both rice-growing seasons (Figure 2I). However, extreme drought conditions experienced in the first year of study (2021/2022) prevented the field from being ponded. This resulted in the crop being flushed irrigated from flowering until harvest in both the traditional and AWD treatments. Images had been already collected to assess the performance of the VIs at PI before the differences in the irrigation treatments due to the drought conditions that occurred in the second half of the first rice-growing season.

The N-rate treatments included a control with no nitrogen application (N0), a treatment with the recommended rate (N2), which was estimated based on the soil analysis parameter potential of nitrogen mineralization (PMN), and two additional doses, 50% below (N1) and 50% above (N3) the recommended rate (Figure 2).

2.3. Crop Parameters Measured

2.3.1. Biomass, Nitrogen Percentage (N%), and Plant Nitrogen Uptake (N Uptake)

Biomass was determined at panicle initiation (PI). Five samples of 0.17 m² each (0.85 m² in total) were collected per plot by cutting the plants at ground level and oven drying the plant material at 60 °C until constant weight. All samples were collected from the center of each subplot, avoiding the edges by at least 4 m.

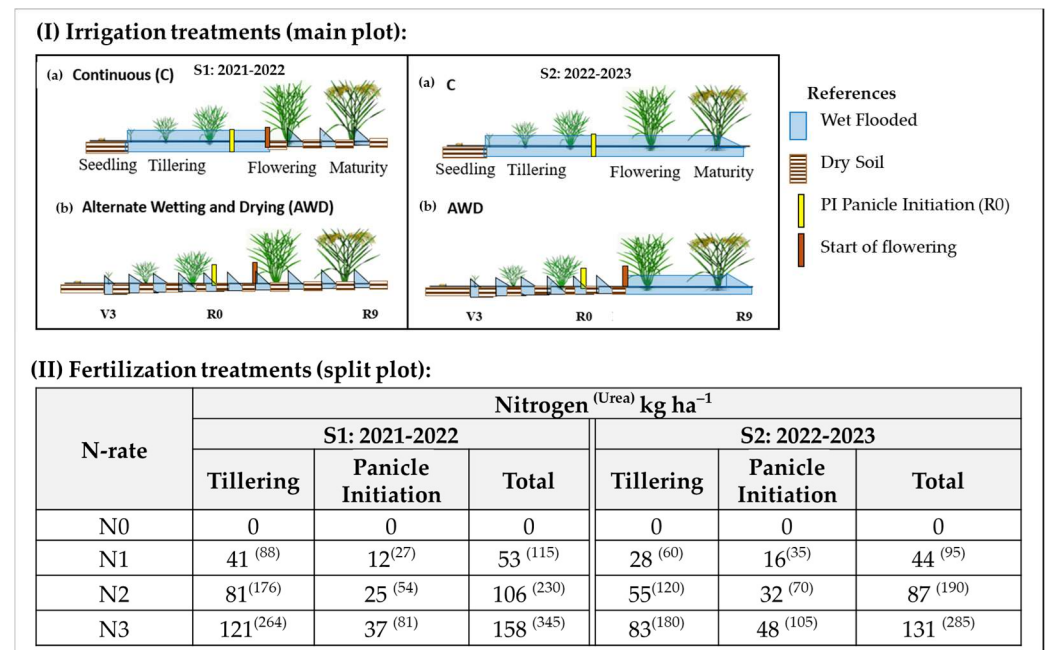


Figure 2. Representation of (I) irrigation treatments: (a) continuous flooded irrigation (C) and (b) alternate wetting and drying (AWD) (II) Nitrogen-rate (N-rate) treatments evaluated in the study during the S1: 2021–2022 and S2: 2022–2023 rice-growing seasons. Numbers in superscript inside parentheses are Urea kg ha⁻¹.

Plant leaves tillers samples were grinded at panicle initiation and analyzed for total N (%) using a spectrometer. The ground and sieved samples (1 mm sieve) were analyzed by the Dumas method using a LECO CHN 628 elemental analyzer (LECO corporation, St. Joseph, MI, USA: www.leco.com, accessed on 1 October 2024). Nitrogen uptake (kg N ha⁻¹) was determined as the product of total aboveground biomass and N concentration percentage (N%).

2.3.2. Grain Yield and Quality

Rice grain yield (normalized to 14% moisture) was determined by harvesting an area of 80 m² per plot with an experimental header (Foton Lovol AF88T). Two cuts of 20 m length by 2 m wide were harvested in each plot when grain moisture was below 21% and average green percentage was lower than 8% following local rice industry guidelines. Grain moisture percentage was determined using an electronic moisture tester (Steinlite, Atchinson, KS, USA).

Grain quality parameters were determined in the laboratories of the Rice Growers Association (ACA). The main parameters determined were the whole grain and total white. The whole grain percentage is defined as the unbroken intact grains plus large broken grains measuring $\frac{3}{4}$ or more of the average whole grain length. This parameter was gauged using specialized “Trieur” cylinders. The total white percentage that indicates the extent of whiteness achieved through milling cargo rice (ranging from 37° to 40°) was assessed using a grinder and a white grade meter.

2.4. Drone-Based Multispectral Imagery

A drone equipped with a multispectral imaging system (P4 Multispectral, DJI, Montevideo, Uruguay) was used to monitor the crop at PI, which, for the 2021–2022 and 2022–2023 rice-growing seasons, occurred on 13 and 21 December, respectively. The mask used to extract spectral information within each plot ensured a minimum separation of 4 m between N-rate treatments.

The imaging system consisted of six sensors (1/2.9" CMOS), including one RGB sensor for visible light imaging and five monochrome sensors for multispectral imaging covering

the blue (B; 450 nm $\pm$ 16 nm), green (G; 560 nm $\pm$ 16 nm), red (R; 650 nm $\pm$ 16 nm), red-edge (RE; 730 nm $\pm$ 16 nm), and near-infrared (NIR; 840 nm $\pm$ 26 nm) bands. The drone was equipped with a sunlight sensor that enabled it to capture solar irradiance.

The flight mission was uploaded onto the drone using the Pix4D capture mobile application. Images were then captured at an altitude of 76 m above ground level, which provided a ground resolution of 4.0 cm per pixel. The Pix4DMapper software (version 4.2.27) was utilized to process the images. The output was a georeferenced orthomosaic for each day with images at PI.

The orthomosaic generated was post-processed in QGIS (version 3.26). Vector grids were created for the subplots and the average reflectance and standard deviation data for each band were obtained for each subplot using the zonal statistics tool available in QGIS. This information was used to compute in excel the VIs described in Table 2.

Table 2. Vegetation indices used in the study with their respective formulation.

Vegetation Index	Formulation	Reference
NDVI	$(\text{NIR} - \text{R})/(\text{NIR} + \text{R})$	[43]
NDRE	$(\text{NIR} - \text{RE})/(\text{NIR} + \text{RE})$	[21,44]
NDRE ²	$((\text{NIR} - \text{RE})/(\text{NIR} + \text{RE}))^2$	[24]
CLg	$\text{NIR}/\text{G} - 1$	[22,28,45]
CLr	$\text{NIR}/\text{R} - 1$	[22,28]
CLre	$\text{NIR}/\text{RE} - 1$	[22,28]
SCCCI	NDRE/NDVI	[31]
RE-Ratio	RE/R	[33,46]
Simple-Ratio	NIR/R	[22]

For comparison purposes, the VIs were normalized using the Sufficiency Index (SI), which was originally devised by Holland and Schepers [47], for corn crops, and it was recently applied to rice crops by Rehman et al. [26,48]. The SI was calculated by dividing the VI from the target plot by the VI of a neighboring N-enriched plot (N3 treatment in this study), where nitrogen was not a limiting factor, therefore ranging from 0 to 1. The SI was used to compare VIs within the same block, under identical irrigation techniques and at the same phenological stage.

2.5. Data Analysis

Statistical analyses were performed in R software (R version 4.2.2) [49], using the emmeans and nlme packages. A linear mixed effect model was used to fit each of the response variables. Analyses of variance were followed by means separation using the Tukey test when statistically significant differences (at $p < 0.05$) were obtained. Pearson correlation analysis was performed using the cor.test function [49]. Linear regression models were fitted using the lm function from the stats package in R [50], to quantify the relationships between the VIs and N uptake.

3. Results

3.1. Biomass, N%, and N Uptake

Statistically significant differences in biomass and N uptake were observed among N-rate treatments at PI in both rice-growing seasons. The highest N-rate treatment (N3) produced more biomass and had the highest N uptake, although no statistically significant differences were found compared to the recommended N-rate (N2) (Table 3). In the first rice season, N uptake was mainly driven by biomass accumulation, while in the second season, both parameters, biomass and nitrogen concentration (N%), influenced N uptake (Table 3). In both rice-growing seasons, treatments N2 and N3 produced more plant biomass than the control treatment (N0).

Table 3. Above-ground plant biomass, nitrogen percentage, and nitrogen uptake (N uptake) by irrigation (alternate wetting and drying (AWD) and continuous flooded irrigation (C)) and nitrogen-rate (N-rate) treatments at panicle initiation by rice-growing season (S1: 2021/2022 and S2: 2022/2023).

Treatments	S1: 2021/2022			S2: 2022/2023		
	Biomass DM kg ha ⁻¹	Nitrogen (N%)	N Uptake Kg N ha ⁻¹	Biomass DM kg ha ⁻¹	Nitrogen (N %)	N Uptake Kg N ha ⁻¹
Irrigation						
AWD	1799	1.9	34.4	1526	2.4	37.1
C	2150	1.9	39.4	1585	2.4	38.9
Irrigation effect	ns	ns	ns	ns	ns	ns
N rate						
N0	1450 ^c	1.8	26.2 ^c	1206 ^b	2.0 ^b	24.4 ^b
N1	1874 ^{bc}	1.8	34.8 ^{bc}	1473 ^{ab}	2.1 ^b	30.6 ^b
N2	2127 ^{ab}	1.9	38.6 ^{ab}	1718 ^a	2.8 ^a	47.0 ^a
N3	2448 ^a	2.0	48.0 ^a	1826 ^a	2.8 ^a	50.0 ^a
N-rate effect	***	ns	***	**	**	**
Irrigation × N-rate effect	ns	ns	ns	ns	ns	ns
Mean	1975	1.9	36.9	1556	2.4	38.0

Means followed by different letters within each column are statistically different. Asterisks indicate statistical significance at $p < 0.001$ '***' and $p < 0.01$ '**'. 'ns': non-significant differences.

3.2. Rice Grain Yield and Quality

The irrigation treatments did not result in significant differences in grain yield and milling quality. The average grain yield was 6.7 Mg ha⁻¹ and 10.4 Mg ha⁻¹ in the first and second rice-growing seasons, respectively. The yield obtained in the treatment with the highest N-rate (N3) was 10% higher than in the N1 and N0 treatments in the second rice season. However, there were no significant differences between N3 and the recommended N2 rate (Table 4). The lower yield recorded in the first rice-growing season was due to the extreme weather conditions (drought and water scarcity) experienced early in 2022 and the need to implement a water-saving irrigation technique from 5 January (the start of flowering) to maturity in both irrigation treatments. In both seasons, there were no significant differences in quality parameters within irrigation and N-rate treatments (Table 4).

Table 4. Rice grain yields 14% (Mg ha⁻¹) and quality parameters for each irrigation (alternate wetting and drying (AWD) and continuous flooded irrigation (C)) and nitrogen rate (N-rate) treatments at panicle initiation by rice-growing season (S1: 2021–2022 and S2: 2022–2023).

Treatments	S1: 2021–2022			S2: 2022–2023		
	Rice Yield (Mg ha ⁻¹)	Whole Grain %	Total White %	Rice Yield (Mg ha ⁻¹)	Whole Grain %	Total White %
Irrigation						
AWD	7.2	64.9	70.9	10.1	50.9	70.2
C	6.2	65.0	70.3	10.8	45.7	70.0
Irrigation effect	ns	ns	ns	ns	ns	ns
Nitrogen rate						
N0	5.8	64.8	69.8	9.9 ^b	46.3	69.8
N1	6.4	66.1	70.2	10.0 ^b	47.8	70.2
N2	7.2	63.5	71.1	10.8 ^{ab}	48.2	70.2
N3	7.2	65.4	71.4	11.1 ^a	51.0	70.3
N-rate effect	ns	ns	ns	***	ns	ns
Irrigation × N-rate effect	ns	ns	***	ns	ns	ns
Mean	6.7	65.0	70.6	10.4	48.3	70.1

Means followed by different letters are significantly different. Asterisks indicates statistical significance at $p < 0.001$ '***', 'ns': non-significant differences.

3.3. Spectral Measurements

Vegetation indices were all significantly influenced by the N-rate applied at panicle initiation. All VIs distinguished the treatment with the highest N-rate (N3) from those fertilized below the recommended rate (N0 and N1) in both rice-growing seasons (Table 5). However, no statistically significant differences in the VIs were observed between the treatment with the recommended N rate (N2) and the treatment that received the highest N-rate (N3). Most of the VIs distinguished the N2 treatment from the N1 treatment (Table 5).

Table 5. Comparison of the vegetation indices across irrigation (alternate wetting and drying (AWD) and continuous flooded irrigation (C)) and nitrogen-rate (N-rate) treatments at panicle initiation by rice-growing season (S1: 2021–2022 and S2: 2022–2023).

Season-S1: 2021–2022									
Treatments	NDVI	NDRE	NDRE ²	Clg	CLr	Clre	SCCCI	RE-Ratio	Simple-Ratio
Irrigation									
AWD	0.73	0.12	0.018	3.01	6.04	0.28	0.16	5.39	4.39
C	0.77	0.13	0.019	3.29	7.31	0.31	0.17	6.24	5.14
Irrigation effect	ns	ns	ns	ns	ns	ns	ns	ns	ns
Nitrogen rate									
N0	0.69 ^b	0.09 ^b	0.010 ^b	2.28 ^b	4.41 ^b	0.18 ^b	0.12 ^b	4.57 ^b	5.41 ^b
N1	0.69 ^b	0.10 ^b	0.010 ^b	2.45 ^b	4.79 ^b	0.22 ^b	0.14 ^b	4.75 ^b	5.79 ^b
N2	0.80 ^a	0.15 ^a	0.023 ^{ab}	3.68 ^a	8.16 ^a	0.35 ^a	0.19 ^a	6.75 ^a	9.16 ^a
N3	0.82 ^a	0.18 ^a	0.030 ^a	4.20 ^a	9.35 ^a	0.43 ^a	0.22 ^a	7.20 ^a	10.35 ^a
N-rate effect	***	***	**	***	***	**	***	***	***
Irrigation × N-rate effect	***	ns	ns	ns	ns	***	ns	**	**
Mean	0.75	0.13	0.018	3.15	6.68	0.29	0.17	5.82	7.67
Season-S2: 2022–2023									
Treatments	NDVI	NDRE	NDRE ²	Clg	CLr	Clre	SCCCI	RE-ratio	Simple-ratio
Irrigation									
AWD	0.62	0.1	0.011	1.99	3.39	0.22	0.16	3.56	4.39
C	0.66	0.12	0.015	2.32	4.14	0.27	0.18	3.98	5.14
Irrigation effect	ns	ns	ns	ns	ns	ns	ns	ns	ns
Nitrogen rate									
N0	0.55 ^c	0.07 ^b	0.006 ^b	1.55 ^b	2.48 ^c	0.16 ^b	0.13 ^b	3.00 ^c	3.48 ^c
N1	0.61 ^b	0.09 ^b	0.009 ^b	1.91 ^b	3.22 ^{bc}	0.21 ^b	0.15 ^b	3.48 ^{bc}	4.22 ^{bc}
N2	0.68 ^a	0.13 ^a	0.017 ^a	2.46 ^a	4.32 ^{ab}	0.29 ^a	0.19 ^a	4.08 ^{ab}	5.32 ^{ab}
N3	0.72 ^a	0.14 ^a	0.021 ^a	2.71 ^a	5.03 ^a	0.33 ^a	0.20 ^a	4.53 ^a	6.03 ^a
N-rate effect	***	***	***	***	***	**	***	***	***
Irrigation × N-rate effect	***	**	*	***	***	***	*	**	**
Mean	0.64	0.11	0.013	2.16	3.76	0.25	0.17	3.77	4.76

Means followed by different letters are significantly different. Asterisks indicates statistical significance at $p < 0.001$ '***', $p < 0.01$ '**', and $p < 0.05$ '*'. 'ns': non-significant differences.

Despite that the irrigation treatments (C and AWD) did not have a significant effect on the VIs, a significant interaction was observed between the irrigation and N-rate treatments for some of the VIs in 2021–2022 (NDVI, CLre, RE-Ratio, and Simple-ratio) and for all the VIs in the 2022–2023 rice-growing season (Figure 3). This interaction indicated that the VIs responded differently to the N-rate treatments depending on the irrigation technique. Significantly higher values of SCCCI, NDRE, NDRE², CLg, and Clre were observed in the N2 treatment compared to the N1 treatment, only under the continuous irrigation treatment in 2022/23. Most of the VIs (except Clg under AWD in 2022/2023) were not statistically different in any of the irrigation techniques when comparing the N2 and N3 treatments. The CLr and RE-Ratio, and NDVI (except for AWD in 2021/2022), failed to detect significant differences between the N2 and N1 treatments under both irrigation techniques in 2022/2023 (Figure 3).

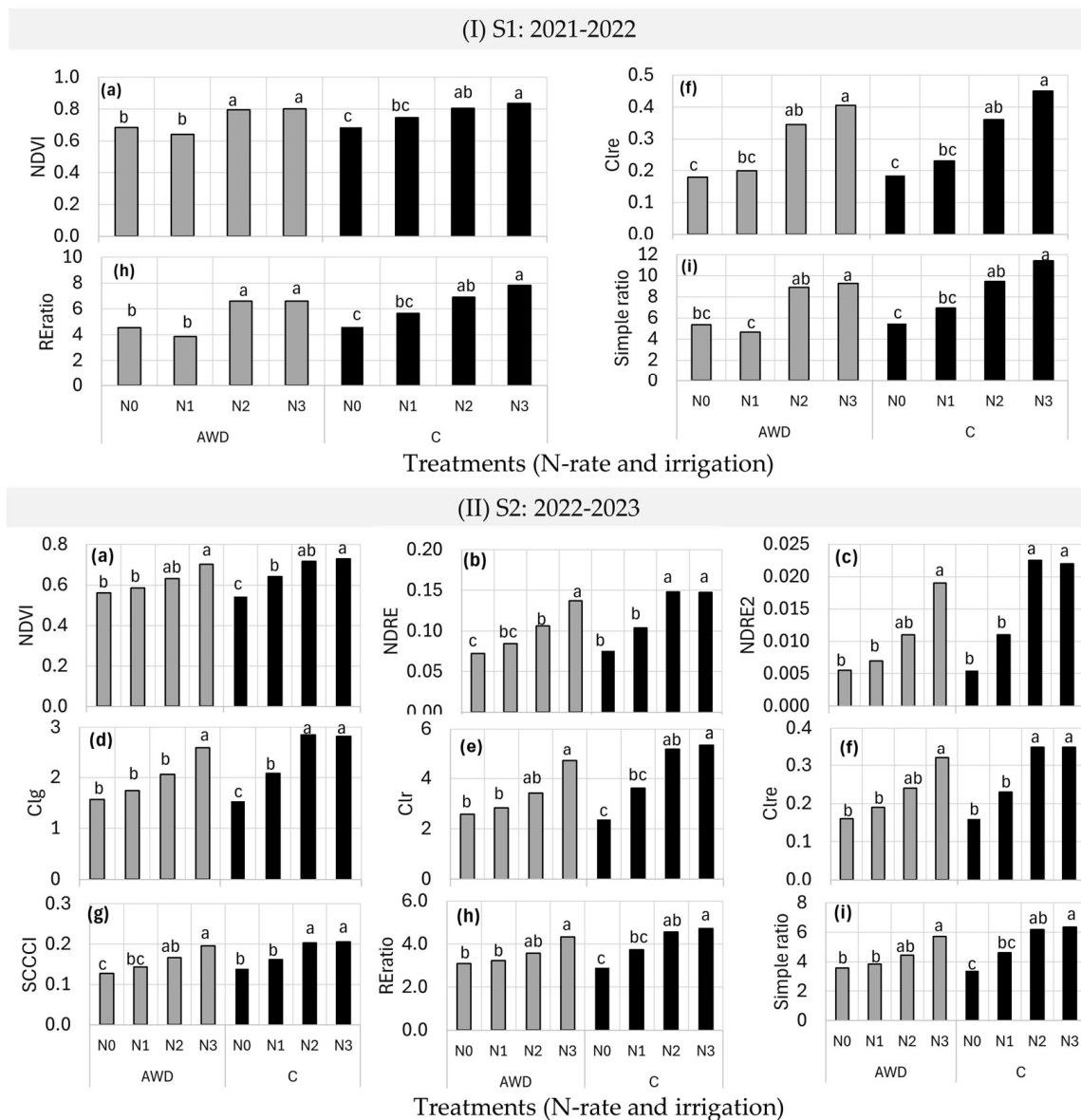


Figure 3. Normalized difference vegetation indices (a) NDVI, (b) NDRE, and (c) NDRE^2 ; chlorophyll indices (d) CLg, (e) CLr, and (f) CLre; and ratio indices (g) SCCC, (h) RE-Ratio, and (i) Simple-Ratio at panicle initiation (S1 = 21 December 2021; S2 = 13 December 2022) by irrigation (alternate wetting and drying (AWD) and continuous flooded irrigation (C)), N-rate treatments (N0, N1, N2, and N3), and rice-growing season (I) S1: 2021–2022 and (II) S2: 2022–2023 at panicle initiation. Different letters within each irrigation treatment indicate statistically significant differences in VIs between N-rate treatments with a probability less than 5%.

The sufficiency index allowed us to compare the sensitivity of the VIs to a range of N-rate treatments by irrigation and rice-growing season (Figure 4). The NDRE^2 was the index with the highest range of variation (0.21 to 1.0) with respect to the N3 rate treatment in both irrigation strategies. The NDRE, the chlorophyll indices (CLg, CLr, and CLre) and ratio indices (SCCCI, RE-Ratio, and Simple-Ratio) all showed a similar range of variation among them, except for the NDVI, for which the sufficiency index ranged from ca. 0.8 to 1 for the N0 and N3 treatments, respectively.

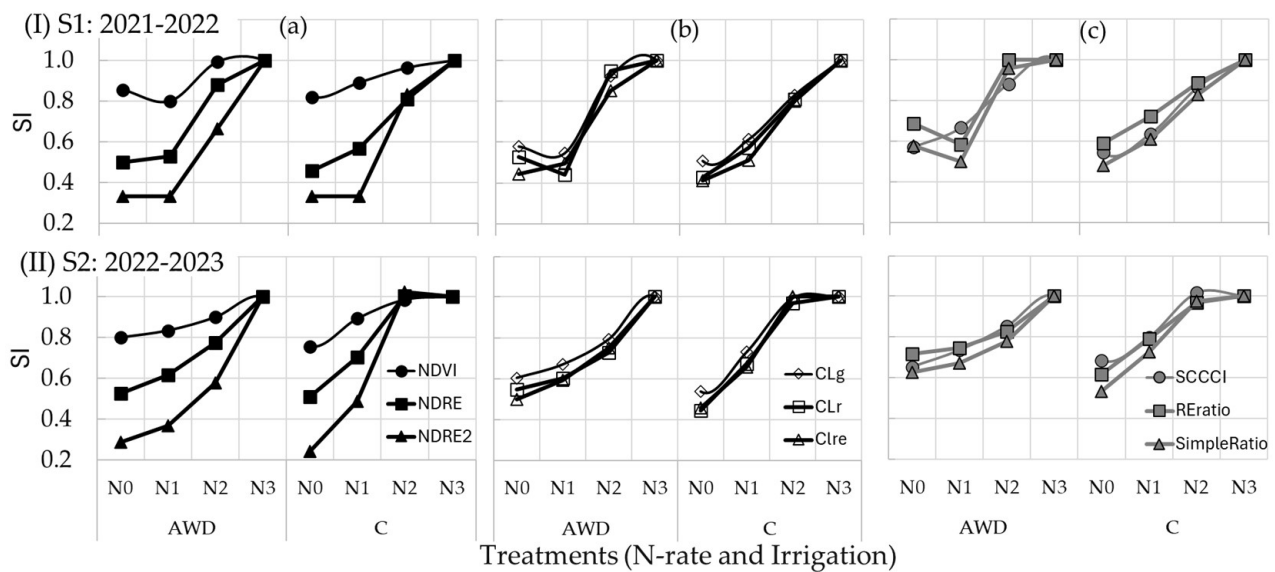


Figure 4. Sufficiency Index (SI) for the VIs assessed separated by irrigation (alternate wetting and drying (AWD) and continuous flooded irrigation (C)), N-rate treatments (N0, N1, N2, and N3), and rice-growing season (I) S1: 2021–2022 and (II) S2: 2022–2023 at panicle initiation. (a) Normalized indices (NDVI, NDRE, and NDRE²), (b) chlorophyll indices (CLg, CLr, and CLre), and (c) ratio indices (SCCCI, RE-Ratio, and Simple-Ratio).

3.4. Relationship Between N Uptake and the Vegetation Indices at Panicle Initiation (PI)

All the VIs had a significant relationship with N-uptake under the traditional continuous irrigation treatment, with coefficients of determination (R^2) ranging from 0.71 to 0.84. However, under the AWD treatment, the VIs relationships with N uptake were either weak or not significant in the first rice-growing season, with R^2 values ranging from 0.54 to 0.67, while in the second season, R^2 values were higher, ranging from 0.65 to 0.82 (Figure 5). To better compare visually the relationship between N uptake and each VI, the R^2 values sorted from highest to lowest, as well as the level of significance, are illustrated in Figure 6. The SCCCI was the highest linked index with N uptake during both seasons under the traditional irrigation management ($R^2 = 0.84$). Under the AWD treatment, the SCCCI index also reported the highest value ($R^2 = 0.82$) in the second rice season and was among the three top indices with an R^2 value of 0.60 in the first rice-growing season. The NDRE, NDRE², CLre, CLg, and SCCCI were the only indices that significantly correlated with N uptake in the AWD treatment in both seasons. The CLr, RE-Ratio, and Simple-Ratio were not correlated with N uptake in the 2021/2022 season and had the lowest significance and R^2 values among the VIs assessed in 2022/2023.

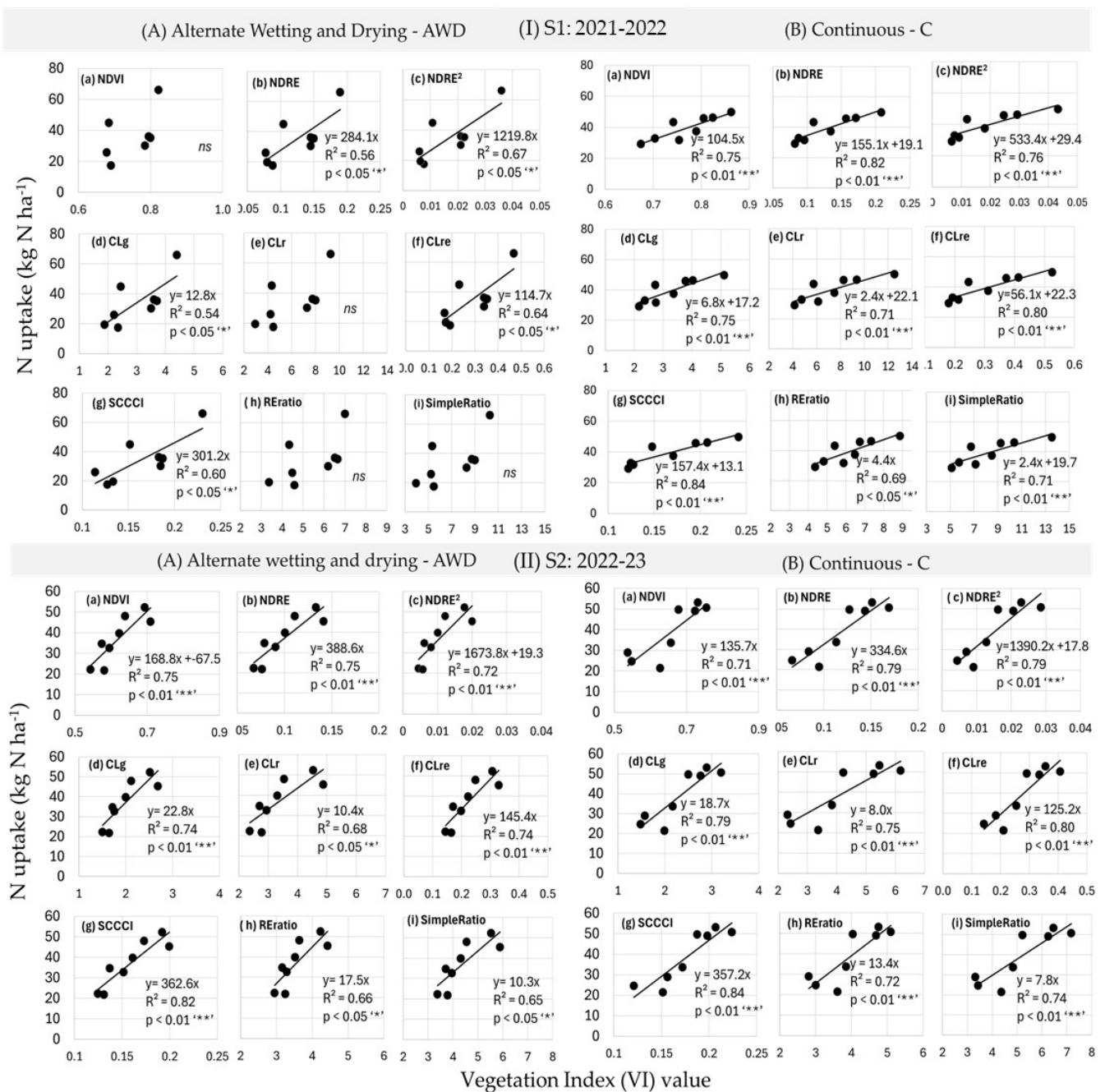


Figure 5. Relationship between the indices value and nitrogen uptake (N uptake) at panicle initiation by season and irrigation techniques (A) alternate wetting and drying (AWD) and (B) continuous flooded (C) for the normalized indices (a) NDVI, (b) NDRE, and (c) NDRE², chlorophyll indices (d) CLg, (e) CLr, and (f) CLre, and ratio indices (g) SCCCI, (h) RE-Ratio, and (i) Simple-Ratio. Linear regression model parameters are shown only when statistically significant different. Asterisks indicates statistical significance at $p < 0.01$ '***' and $p < 0.05$ '**'. 'ns': non-significant.

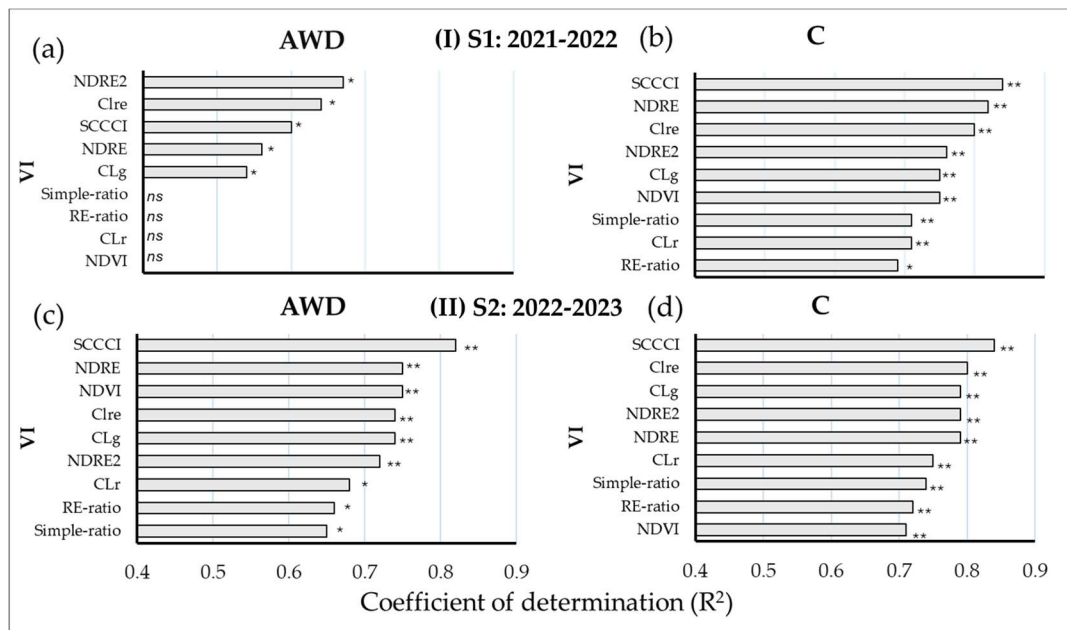


Figure 6. Coefficient of determination (R^2) for the relationship between nitrogen uptake and the vegetation indices at panicle initiation by seasons (I) S1: 2021–2022 and (II) S2: 2022–2023 and by irrigation techniques (a,c) alternate wetting and drying (AWD) and (b,d) continuous flooded irrigation (C). Vegetation indices (VIs) are sorted from highest to lowest R^2 . Asterisks indicates statistical significance at $p < 0.01$ '**' and $p < 0.05$ '*'. 'ns': non-significant.

4. Discussion

In this study, two irrigation techniques and four nitrogen rates were implemented in a rice field with the aim to evaluate remote sensing indices for the precise monitoring of rice nitrogen status. Selected vegetation indices described in the literature as sensitive to plant N content were compared to identify the best-performing vegetation indices that can be used by farmers and rural professionals to monitor rice nitrogen status at panicle initiation under ponded and non-ponded conditions.

4.1. VIs Comparison for Monitoring Rice N Plant Status at Panicle Initiation

All evaluated indices, including the NDRE² and NDRE, the chlorophyll indices (Clre, CLg, and CLr), and the ratio indices like the SCCCI, were more effective in detecting the variability due to N-rate effects, showing a higher range of variation in the sufficiency index value among N-rate treatments in relation to the traditional NDVI (Figure 4).

Among the VIs, the SCCCI, which normalizes NDRE by NDVI, had the highest coefficient of determination with N uptake in both seasons, except for the first growing season in the AWD treatment. This could be attributed to the absence of standing water during image acquisition in the first rice season and its presence in the second. Raper and Varco [31], and Ballester et al. [46], also found the SCCCI as a strong index to detect the variability in plant N content in cotton crops. To the best of our knowledge, this is the first study that evaluated the SCCCI index to predict N uptake in rice crops under different irrigation treatments.

All vegetation indices containing information from the red-edge band proved to be better indices for detecting differences within nitrogen rates and N uptake at panicle initiation than the traditional NDVI. This result is consistent with what has been found in previous studies on rice crops [15,23,24,26,30] and can be explained because the red-edge region is a good indicator of chlorophyll content, and therefore, it indirectly reflects the nitrogen status of plants [30,51,52].

The chlorophyll index using the green band, in our study, showed a similar range of variation of the sufficiency index among N-rate treatments in relation to Clre (Figure 4).

The CLg index had a significant linear response to predict N uptake at PI in both rice seasons, with an average coefficient of determination of 0.84 under the continuous irrigation treatment. These results are in accordance with those of Brinkhoff et al. [30], who found a highly correlated lineal response between Clg and N uptake at PI ($R^2 = 0.9$), highlighting that this index can be useful when the red-edge band data are not available. Xue et al. [53] published that the ratio of NIR/green was the best index related to leaf nitrogen content at panicle initiation and the green band (560 nm) was the best wavelength to identify differences between nitrogen treatments in rice.

The accuracy for predicting N uptake has been described in previous studies using drones for different VIs like the Clre, CLg, NDRE, and NDVI. Zheng et al. [15] reported R^2 values of 0.70 for the CLre and CLg indices and an R^2 value of 0.52 for the NDVI. Li et al. [54], in another study using drone-based imagery, reported R^2 values of 0.67 and 0.64 for the NDVI and NDRE, respectively. A stronger coefficient of determination with N uptake was recorded in the current study, with an average R^2 of 0.81, 0.80, 0.77, and 0.73 for NDRE, CLre, Clg, and NDVI, respectively, under the same continuous irrigation management. The SCCCI index had the highest coefficient of determination with N uptake in our study at PI in both seasons under the traditional irrigation ($R^2 = 0.84$) and AWD treatments ($R^2 = 0.71$).

4.2. Effects of Water Management on the Vegetation Indices and N Uptake at PI

Relationships to predict N uptake at panicle initiation were found to vary according to the irrigation technique in the current study. During panicle initiation, it was highlighted that differences for all VIs within fertilization treatments were influenced by the irrigation technique, with the interaction within irrigation and fertilization being significant for all evaluated VIs in the 2022/2023 rice-growing season (Table 5, Figure 3).

All evaluated VIs (except NDVI in 2022/2023), had a stronger association and higher R^2 with N uptake under the continuous irrigation technique, compared to the AWD. Under this alternative technique, all vegetation indices showed a stronger association with N uptake during the second rice-growing season compared to the previous one. The absence and presence of standing water during image acquisition in the first and second rice season, respectively, could explain the observed differences (Figure 6). Standing water has the potential to affect the VIs and their relationship with the plant N status, especially before canopy closure [55]. Alternative irrigation techniques would likely have a higher reflectance of near-infrared bands during the drying events. Several studies have also found that standing water can affect band reflectance and the values of VIs commonly used to monitor rice and its sensitivity to estimate biophysical parameters [39,40]. A lower water depth has also been identified to increase the spectral reflectance due to a lower radiant absorption in water [56].

The SCCCI index showed similar relationships and the highest coefficient of determination with N uptake for both irrigation techniques in the second rice-growing season (Figure 6). It was one of the few indices, along with Clre, NDRE, $NDRE^2$, and Clg, significantly correlated with N uptake in the first rice season under the AWD irrigation. The lack of a significant N-uptake response and lower R^2 values observed for some of the evaluated VIs under AWD could be linked to different band reflectance from stressed plants during soil-drying events. Stressed crops can exhibit a smaller difference in band reflectance values between the red and near-infrared regions, in comparison with healthy crops, affecting the calculated vegetation index value [57]. Additionally, the reflectance in the NIR wavebands region can be affected by the exposed surface water before canopy closure [55].

The models and relationships of VIs to predict N uptake at PI may need to be determined for each irrigation method. Models published in the literature for most VIs were obtained under continuous traditional irrigation, where water is ponded, and this study highlights that they may not apply for the alternate wetting and drying technique (AWD). Models to predict N uptake would need to be determined specifically for alternative irrigation methods as these strategies involve periods of no standing water, lower water depth,

and dry soil surface. Global water scarcity [58–60] is driving a growing interest in these irrigation techniques such as aerobic [61] and alternate wetting and drying to enhance water productivity [3,38].

4.3. Considerations and Future Studies

The maximum attainable yield of ca. 11 Mg ha^{−1} in the current study was obtained with the recommended N-rate based on soil analyses (N2), with no significant differences with the highest N-rate doses (N3) in the second rice-growing season. This yield was achieved with an average N uptake at PI of ca. 47–50 kg N ha^{−1} for the N2 and N3 treatments, respectively (Table 3). These values are in accordance with the reported critical level of N uptake of 51 kg N ha^{−1} at PI obtained from 43 trials conducted in commercial farms during three rice seasons in Uruguay [62]. The relationships between N uptake and VIs (Figure 5) would potentially allow to determine the increase in the VI value required to achieve the target N uptake at panicle initiation, to obtain the maximum attainable yield. Future studies to identify not only effective VIs that accurately indicate the required N-rate application, but also the VI value at which no additional nitrogen is required, would positively contribute to the sustainability of the rice sector.

Further studies including more sites, seasons, and varieties are required to develop more robust models that can be used and validated in commercial farms to enhance remote sensing for midseason nitrogen applications under varying irrigation methods. Machine learning models offering the advantages for processing multi-source data could be an area for future research.

Future research should also examine the impact of standing water commonly found in traditionally irrigated rice on spectral reflectance and vegetation indices calculations. The evaluation of different irrigation techniques (continuous, AWD, and aerobic), and their effects on the developed relationships and models to optimize water and nitrogen use efficiencies, would be a useful future endeavor.

5. Conclusions

This study identified vegetation indices for remote monitoring of rice crops that could support nitrogen management strategies in Uruguay. The SCCCI was identified as a promising index for crop monitoring and management optimization, under the Uruguayan rice-growing environment. This index showed a strong relationship with N uptake at panicle initiation, across both seasons and irrigation techniques. Other vegetation indices utilizing the red-edge band, like Clre, NDRE², and NDRE, and the chlorophyll index Clg, also had a significant relationship with N uptake, though with a lower coefficient of determination (R²) than SCCCI.

The existence or absence of a water layer at the moment of the image acquisition was found to affect the VIs and their relationship with N uptake. This result suggests that relationships and models developed to predict N uptake at panicle initiation for continuous flooded irrigation may not be applicable for alternative irrigation techniques with alternating wet and dry soil conditions. The findings of this study are important to assist rice farmers in selecting effective VIs for monitoring rice crops.

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