Research Article

Density and Yield of Rice (*Oryza Sativa* L.) Crop Comparing Two Sowing Methods With Satellite Monitoring

Juan Gonzalo Ardila Marín[1], Diana Carolina Polania Montiel[2], Luis Manuel Navas Gracia[3], Jordan Alexis Castillo Coronado[4] and Jean Carlos Acosta Vargas[5*]

[1]Programa Ingeniería agrícola, Facultad de Ingeniería, Universidad Surcolombiana, Neiva, Colombia; [2]Programa Ingeniería agrícola, Facultad de Ingeniería, Universidad Surcolombiana, Neiva, Colombia; [3]Doctorado en Ciencia e Ingeniería Agroalimentaria y de Biosistemas Universidad de Valladolid, Palencia, España; Programa; [4]Ingeniería agrícola, Facultad de Ingeniería, Universidad Surcolombiana, Neiva, Colombia; [5]Programa Ingeniería agrícola, Facultad de Ingeniería, Universidad Surcolombiana, Neiva, Colombia.

Abstract | The sustainability of rice cultivation (*Oryza sativa* L.) is adversly affected by current production practices and technologies, resulting in high costs and inefficient use of resources. This reality has driven the implementation of cultivation techniques such as mechanised and direct seeding. Accordingly, this project conducted manual phenological monitoring and satellite imagery tracking of two experimental plots at the USCO Farm in Palermo (Huila), where 150 kg ha^{-1} paddy was sown using two different techniques: direct seeding on wet soil by broadcasting and mechanised direct seeding on dry soil. For comparison, monitoring was carried out at nine random points in each plot, where phenological sampling was performed through counts, height measurements, and threshing at maturity. In parallel with this monitoring, satellite images and the normalised difference vegetation index (NDVI) and green NDVI (GNDVI) spectral vegetation indices were used to corroborate differences in the plots. The results showed that 156 plants m^{-2} germinated in the broadcast plot, while 218 plants m^{-2} germinated in the mechanised plot. Phenological monitoring indicated greater vigour and better development in the mechanised plot, but the lower sowing density in the broadcast plot allowed for better panicle formation and grain filling, leading to similar production. Mechanised seeding with a lower seed rate is recommended so that plants can better utilise aerial space and available soil resources.

Received | August 18, 2024; **Accepted** | January 8, 2026; **Published** | April 20, 2026
***Correspondence** | Jean Carlos Acosta Vargas, Programa Ingeniería agrícola, Facultad de Ingeniería, Universidad Surcolombiana, Neiva, Colombia; **Email:** acostajeancarlos74@gmail.com
Citation | Ardila-Marín, J.G., D.C. Polania-Montiel, L.M. Navas-Gracia, J.A. Castillo-Coronado and J.C. Acosta-Vargas. 2026. Density and yield of rice (*oryza sativa* L.) crop comparing two sowing methods with satellite monitoring. *Sarhad Journal of Agriculture,* 42(2): 643-656.
DOI | https://dx.doi.org/10.17582/journal.sja/2026/42.2.643.656
Keywords | Precision agriculture, Agricultural sciences, Phenology, Mechanisation, Remote sensing

Introduction

A sustainable supply of rice (*Oryza sativa* L.) must be ensured because it is a staple food crop that provides nutrition to more than 50% of the world's population, and there has been a significant decline in its productivity due to climate change (Jat *et al.*, 2022; Yawata *et al.*, 2019). Economic factors and technological opportunities have led to a shift from transplanting methods to direct seeding methods, including the cost of labour, the availability of short-duration rice varieties, and chemical methods for weed control (Negi *et al.*, 2024). Direct seeding methods have played a crucial role in the intensification of rice systems and are considered a sustainable strategy for resilience under adverse climatic conditions. Additionally, dry seeding methods can help achieve greater water use efficiency (Jat *et al*., 2022; Singh *et al*., 2023). The traditional method for dry direct seeding is manual broadcasting on tilled soil, which often requires a lot of labour and can create a potential bottleneck for timely crop establishment. Mechanical row seeding (i.e., using some type of mechanical implement to place the seed below the soil surface) can reduce labour requirements and improve emergence by placing seeds at a more uniform depth (Ahmed *et al*., 2025; Andriatsiorimanana *et al*., 2024). However, Fukai *et al.* (2019) explain that the labour-saving advantage of mechanised seeding is over manual transplanting, being more costly than broadcasting, but it requires less seed (40 to 50 kg ha^{-1}) compared to 120 kg ha^{-1} with broadcasting. Additionally, since the plants are established in rows, it facilitates weeding and reduces weed problems compared to broadcasting. Mechanisation is necessary for rice production to reduce production costs and promote efficiency (He *et al*., 2022; Shi *et al*., 2021). Thus, an imminent water crisis, rising labour costs, and the development of seeders have driven the gradual expansion of the area under mechanised dry direct seeding (Abanco and Valle, 2020; Tian *et al*., 2011).

For rice, planting density is a key factor in plant growth. A low density reduces above-ground and below-ground competition among plants, providing the opportunity to increase their supply of solar energy and nutrients, enhancing their growth – not per unit area of land as there are still fewer plants, but with larger individual size (Das *et al*., 2020; Shimono, 2011). According to (Hayashi *et al*., 2006), rice at a lower density is less sensitive to water deficit due to its deeper and thicker roots that can extract more water from a deeper soil layer. Therefore, in non-flooded rice fields, a lower planting density could be suitable to increase grain yield (Gai *et al*., 2025). Rice yield is positively related to the number of panicles, which is determined by the number of tillers that develop during the vegetative stage (Zhang *et al*., 2025). Planting density is a factor that influences tiller production in rice (Gai *et al*., 2025; Zhu, 2025). Generally, increasing density leads to a higher number of plants per unit area of land, while the Leaf Area Index (LAI) has a negative effect on tillering. A high LAI associated with high planting density can cause a low number of tillers (Zhang *et al*., 2025; Zhong *et al*., 2002).

It is important to provide rice producers with a tool that allows for the comparison between actual and estimated yields, enabling precise, rapid, and economical estimations, knowing that manual surveys require a significant amount of effort and time (Yawata *et al*., 2019). Over the years, many methodologies for estimating rice yield using images and spectral vegetation indices have been studied. Wang *et al.* (2017) analysed the ability to estimate the Leaf Area Index (LAI) of various Normalized Difference Vegetation Index (NDVI) established by substituting the Red Band of the General NDVI with all possible combinations of red, green, and blue bands. They used data from rice (*Oryza sativa* L.) under different conditions. The comparison showed that Green NDVI (GNDVI) and Green-Blue NDVI (GBNDVI) had the best relationships with LAI. (Kimura *et al.* 2004) tested these indices with the Vegetation Index for Chlorophyll Concentration (VICC) in addition to LAI. The study by Tian *et al.* (2011) did the same but in estimating Leaf Nitrogen Concentration (Leaf Nitrogen Concentration – LNC) with multiple field experiments on rice with different nitrogen rates, using non-destructive and rapid evaluation enabled by various hyperspectral vegetation indices. Phadikar and Goswami (2016) compared the effectiveness of NDVI and GNDVI in the automatic identification of rice diseases caused by the pathogens Magnaporthe grisea and Bipolaris oryzae. Cárdenas *et al.* (2019) used these indices to identify, during the reproductive phase, which areas of rice crops were stressed or healthy, and even the planting density, employing images obtained with cameras installed on drones, as did Candiago *et al.* (2015), while Yawata *et al.* (2019) used the same indices to evaluate yield but from satellite images.

Considering the widespread acceptance of using NDVI and GNDVI in planting density and monitoring the phenological dynamics of rice cultivation, the present research conducted phenological monitoring via Sentinel-2 satellite images at three key dates of crop development and with conventional invasive and destructive trials on two experimental plots at the Experimental Farm of the University of Southern Colombia (USCO). These plots evaluated direct wet broadcasting in a plot where it was not advisable to introduce the seeder machine, against a plot where direct dry seeding was performed with the SEMEATO SSM-23 Seeder. It was verified that mechanised direct seeding caused higher planting density, but this affected grain filling, resulting in similar production. It was concluded that mechanised seeding is better but with lower density; it was also determined that monitoring with satellite images and vegetation indices is a useful, non-destructive method that is easy to implement.

Materials and Methods

Study area and crop management

Figure 1 shows the experimental plots studied at the Experimental Farm of the Universidad Surcolombiana, located at coordinates 2°53'9.12"N, 75°18'26.09"W in the municipality of Palermo (Huila), in the Vereda of San Miguel, in the Irrigation District of El Juncal.

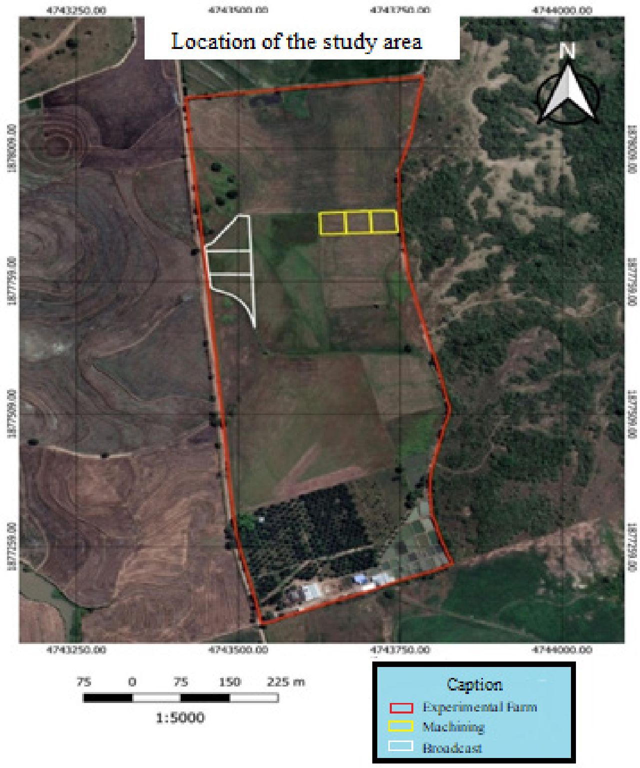

Figure 1: *Location of experimental plots. source of reference: authors.*

Soil preparation involved three passes of disc ploughing (harrowing) to a working depth of up to 20cm, followed by two passes of micro-levelling and ridging with contour lines for the installation of flood irrigation. Four days after sowing, irrigation was applied, saturating the plot for two consecutive days with a water level maintained between 2 and 3 cm. During the vegetative stage of the rice, rapid wetting was conducted, ensuring a thin sheet of water to provide both moisture and heat to the seeds.

The recommended sowing density was 150 kg ha^{-1} using certified seed of the short-cycle variety Fedearroz FL 2020. The sowing methods evaluated in this study were (1) broadcasting, with an initial expectation of a 10% loss due to the irregularity and non-uniform germination of broadcast sowings, and (2) using a Semeato SSM-23 fine-grain mechanical seed drill. During the population count, it was considered that, according to Coronado *et al.* (2024), Rezaei *et al.* (2025) and Villalba *et al.* (2017), between 250 and 300 plants m^{-2} should be established to achieve between 450 and 500 panicles m^{-2}, knowing that for the established sowing density of 150 kg ha^{-1}, there are an estimated 500 seeds m^{-2}.

The fertilisation plan, weed control, fungicide applications, and the schedule of activities were uniformly implemented across the entire experimental area, as detailed in Table 1, with the only variable being the sowing technique. Due to the effectiveness of these treatments, no pests or diseases were observed that could affect the production during the project's development

Table 1: *Fertilisation plan*.

Application (date)	Product	Dose
First subscriber (10/01/22)	Urea Granulated 46-0-0®	10 g m^{-2}
	Olafos – S®	5 g m^{-2}
	Agrimins Granulated ®	5 g m^{-2}
Second subscriber (21/02/22)	Urea Granulated 46-0-0®	10 g m^{-2}
	Olafos – S®	5 g m^{-2}
	KCL Granulated ®	7.5 g m^{-2}
	Terrabiol®	7.5 g m^{-2}
Third subscriber (16/03/22)	SAM®	5 g m^{-2}
	Dap Granulated ®	10 g m^{-2}
	KCL Granulated ®	10 g m^{-2}
	Sulcamag®	5 g m^{-2}
Fourth subscriber (23/03/22)	Urea Granulated 46-0-0®	10 g m^{-2}
	SAM®	5 g m^{-2}
	KCL Granulated ®	7.5 g m^{-2}
Herringbone protection (24/03/22)	Agrostick®	0.03 cm^3 m^{-2}
	Amistar Top®	0.05 cm^3 m^{-2}
	Cumbia (Triciclazol)®	0.03 g m^{-2}
	Engeo®	0.03 cm^3 m^{-2}

Source of reference: *Authors.*

Finally, the harvest was carried out on 14/04/2022 with Massey Ferguson 5650 combine harvester with respective calibrations and field measurements.

Experimental design

The working area of 1.5 ha was divided into two plots, one of 1 ha and the other of 0.5 ha, corresponding to the two sowing methods: mechanised direct seeding on dry soil (0.5 ha) and manual broadcasting on wet soil (1 ha). The size allocation was determined by the operability of the mechanised seeder, which required a minimum area to perform uniform sowing, while the broadcasting plot was adjusted to the usable space not accessible to the machine. Each plot was then subdivided into three subplots of equal area to allow for replication within treatments and to account for intra-plot variability. This subdivision also supported the spatial analysis of the vegetation indices and phenological variables. Within each subplot, three random sampling points were selected using the Conditional Latin Hypercube (cLH) algorithm, ensuring an optimal spatial distribution of sampling locations. This method preserved the randomness required for statistical validity while ensuring representativeness of each subplot (Tipas *et al*., 2021). In total, this design yielded 18 sampling points (3 subplots × 3 points × 2 treatments), as shown in Figure 2, which served as the basis for both destructive field measurements and remote sensing validation. The replication through subplots allowed for ANOVA-based comparison between treatments and subplots, reducing spatial bias and increasing the robustness of the results. This distribution was achieved using a free Geographic Information System (GIS) software (QGIS®) and a free software programming compiler (RStudio®). This method generates the optimal geographical distribution of continuous covariates when estimating statistical parameters from spatial data, applying a stratified random procedure, thus becoming an efficient way to sample variables over a given area (Júnior *et al*., 2014; Liu *et al*., 2015).

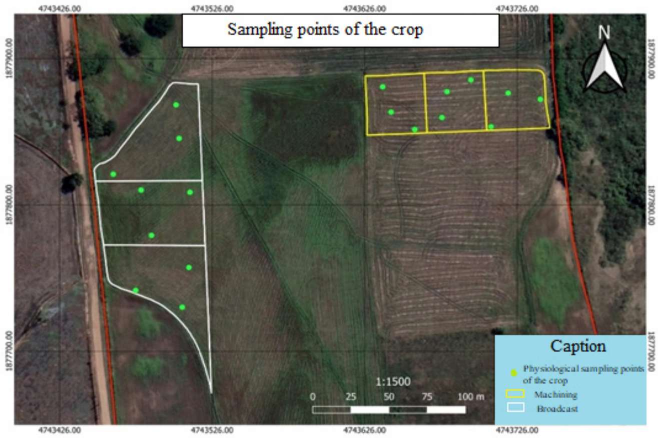

Figure 2: *Phenology sampling points established by cHL.*
Source of reference: *Authors.*

In situ measurement of biophysical variables

The yield parameters were monitored using 50x50cm gauges at the established points, according to the schedule presented in Table 2: population count and height measurement at the different stages of the crop (germination 12 days after germination (ddg), tillering 52 ddg, Stuffing 73 ddg, flowering 89 ddg, and maturity 108 ddg), while panicle count and harvest yield were carried out at the maturity stage.

Table 2: *Crop monitoring schedule.*

Activy	Date	Observation
Sowing	18/12/2021	
Initial population count	01/01/2022	Germination stage.
Cane counting – Heigth measurement	28/01/2022	Maximum tillering: Measurement of the height of the aerial part of three random plants from the base to the highest leaf.
First observation	22/02/2022	Maximum tillering: First low cloud day after maximum tillering - acquisition of satellite images for analysis.
Cane counting – Heigth measurement	4/03/2022	Maximum stuffing.
Second observation	14/03/2022	Maximum cloud cover: First day of low cloud cover after maximum cloud cover.
Panicle counting – Heigth measurement	24/03/2022	Flowering stage: Measurement of the height of the aerial part of three random plants from the base to the last grain of the panicle.
Third observation	03/04/2022	Maturity stage: Last day of low cloud cover prior to harvest.
Cutting and shelling	13/04/2022	Maturity stage: The whole is husked. The empty kernels are separated. The full grains are set aside and weighed.

Source of reference: *Authors.*

Measurement of vegetation indices

To obtain the images in the study area (Figure 1), the Land Viewer® of EOS Data Analytics was utilised to download the spectral bands available for cloud-free days, according to the temporal resolution of the Sentinel-2 sensor. Considering the phenological monitoring dates, the dates of 22 February (tillering), 14 March (Stuffing), and 3 April (maturity) were deemed suitable. Post-processing was then conducted using QGIS® software. To derive the indices, the image data were first transformed to reflectance using the Semi-Automatic Classification Plugin (SCP), followed by atmospheric correction. The Raster-Calculator and SCP tools were then employed to programme the NDVI and GNDVI index equations. Subsequently, a layer of regular points spaced every 10 metres was created to coincide with the centroids of the pixels, given the spatial resolution of the sensor used. The points established for the evaluation of the equations are presented in Figure 3.

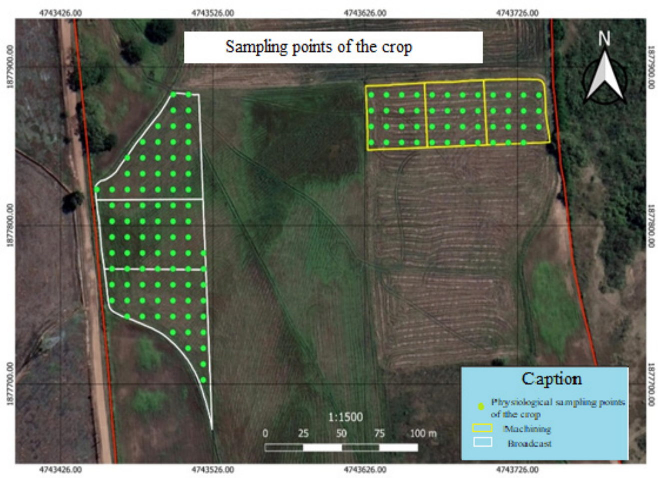

Figure 3: *Spectral index sampling points.*
Source of reference: *Authors.*

Among the typical vegetation spectral indices, NDVI is one of the most suitable for tracking the dynamics of vegetation development, as it measures the photosynthetically active biomass of plants. Its first use is reported by Rouse *et al.* (1976). NDVI is the most common vegetation index in remote sensing, with its values being most accurate in mid-crop during the active growth phase. It should not be used when the vegetation and its canopy are too sparse, as its spectral reflectance is too low, making this index quite sensitive to ground light and atmospheric effects. The model used in this study is described by Equation 1.

$$NDVI = \left(\frac{NIR - RED}{NIR + RED}\right) = \left(\frac{B8A - B04}{B8A + B04}\right)$$

The GNDVI is a modification of the NDVI that also uses the near-infrared but substitutes visible green for visible red (540 to 570 nm). It measures chlorophyll content more accurately than NDVI. It is used to detect and monitor wilted or aged crops and to measure nitrogen content in leaves when an extreme red channel is not available. The model used in this study is described by Equation 2, as proposed by Gitelson *et al.* (1996).

$$GNDVI = \left(\frac{NIR - GREEN}{NIR + GREEN}\right) = \left(\frac{B8 - B3}{B8 + B3}\right)$$

Statistical analysis

Once the data were obtained, a box-whisker plot was created for each sample in Excel to identify and eliminate outliers. The Kolmogorov-Smirnov normality test was performed on the chosen samples, as several samples had more than 50 data points, while the Levene test was performed on the smaller samples to verify their homoscedasticity. The analysis of variance (ANOVA) enabled the identification and quantification of the effect of the experimental study with a confidence level of 95%, determining the existence of significant differences in the parameters analysed between subplots and then between treatments (plots), thus conducting a spatial and then temporal analysis. Finally, Fisher's Least Significant Difference (LSD) was calculated between samples as a post hoc test to determine the statistical difference, and the Z-test for two-sample means was performed for large samples (Pulido and Salazar, 2008). Given the large sample sizes and the nature of satellite-derived NDVI data, the Z-test was preferred over ANOVA and Levene's test. The Z-test is more efficient and appropriate for comparing two means when sample sizes are large and variances are stable or known, especially in remote sensing applications where data distributions are often well-behaved and homogeneity of variance is less critical. The data and the results of the different analyses carried out with Excel can be found in the annexes.

Results

Biophysical data results

Figure 4 shows the yield curves of the crop in the two treatments of the present investigation. In the population count, the broadcast sowing density was

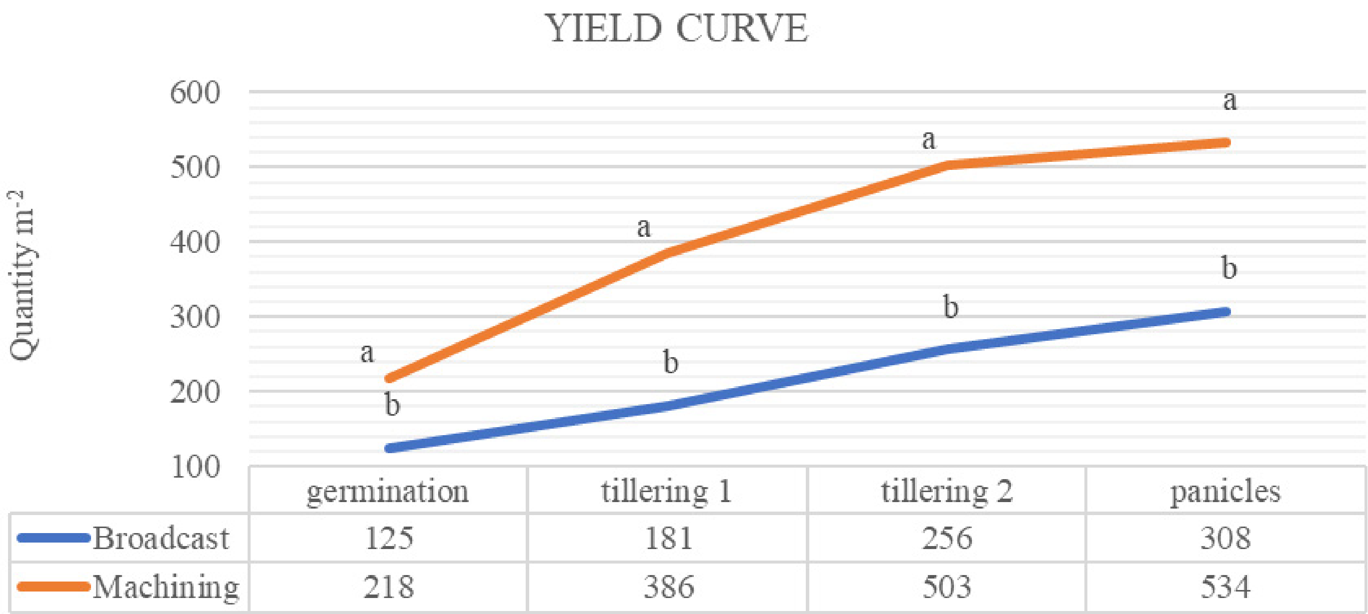

Figure 4: *Yield parameters of rice crop under broadcast and mechanised sowing methods. Equal letters: no significant difference, different letters: significant difference.*
Source of reference: *Authors.*

only 125 plants m^{-2}, whereas in the mechanised sowing, an average of 218 germinated plants were counted. An average of 534 panicles m^{-2} was also reported for mechanical sowing, while the results for broadcast sowing were 308 panicles m^{-2}.

The samples reported in Figure 4 were tested for normality, where the value of the theoretical test statistic (KSt) for nine data points was 0.273 and 0.316, and for seven data points excluding outliers was 0.303 and 0.35 for a confidence level of 95% and 90%, respectively. Specifically, the Kolmogorov-Smirnov test yielded a KSc of 0.314 for broadcast sowing and 0.145 for mechanised sowing. While mechanised sowing met the normality assumption at all tested confidence levels, broadcast sowing only satisfied the condition at α = 1.035 (KSt = 0.350), confirming the need for a higher confidence threshold due to the reduced sample size after excluding outliers. Furthermore, the ANOVA performed for the homoscedasticity test ranged between 0.134 and 0.87, ensuring that the p-value was greater than the established significance of α = 0.05. Fisher's LSD test calculated a minimum significant difference of 29 seedlings, while the observed difference between treatments was 93 seedlings, confirming statistical significance.

For the first tiller count, statistical analysis was conducted using 9 replicates per treatment. The Kolmogorov-Smirnov test confirmed normality for both treatments, with KSc values of 0.213 for broadcast sowing and 0.145 for mechanised sowing, both below the critical thresholds (KSt = 0.250, 0.273, and 0.316). Levene's test for homoscedasticity yielded an F-statistic of 2.49 and a p-value of 0.134, confirming equal variances. The ANOVA test produced an F-statistic of 14.02, exceeding the critical value of 4.49, with a p-value of 0.0018, indicating a statistically significant difference in tiller count between treatments. Fisher's LSD test calculated a minimum significant difference of 124 tillers, while the observed difference between treatments was 247 tillers, confirming statistical significance.

For the second tiller count, statistical analysis was conducted using 9 replicates per treatment. The Kolmogorov-Smirnov test confirmed normality for both treatments, with a KSc of 0.208 for broadcast sowing and 0.134 for mechanised sowing, both below the critical thresholds at multiple confidence levels (KSt values: 0.250, 0.273, and 0.316). Levene's test for homoscedasticity yielded an F-statistic of 0.50 and a p-value of 0.489, which did not exceed the critical value of 4.49, confirming equal variances. The ANOVA test produced an F-statistic of 17.77, exceeding the critical value of 4.49, with a p-value of 0.0007, indicating a statistically significant difference between treatments. Fisher's LSD test calculated a minimum significant difference of 116 tillers, while the observed difference between treatments was 204 tillers, confirming statistical significance.

For the panicle count, statistical analysis was conducted using 9 replicates per treatment. The Kolmogorov-Smirnov test confirmed normality for mechanised sowing (KSc = 0.129), and confirmed normality at α = 0.01 for broadcast sowing (KSc = 0.303), which below the critical thresholds (KSt = 0.250, 0.273, and 0.316). Levene's test for homoscedasticity yielded an F-statistic of 0.027 and a p-value of 0.870, confirming equal variances. The ANOVA test produced an F-statistic of 15.90, exceeding the critical value of 4.49, with a p-value of 0.0011, indicating a statistically significant difference between treatments. Fisher's LSD test calculated a minimum significant difference of 120 panicles, while the observed difference between treatments was 226 panicles, confirming statistical significance.

On the other hand, Figure 5 presents the results in box plots and the yield parameters of the 1000-grain weight. The KSt values obtained for the normality test were 0.273 for broadcast sowing with 9 data points and 95% confidence, and 0.287 for mechanised sowing with 8 data points and 90% confidence. Meanwhile, the results of the calculated statistic (KSc) were 0.247 for broadcast sowing and 0.242 for mechanised sowing.

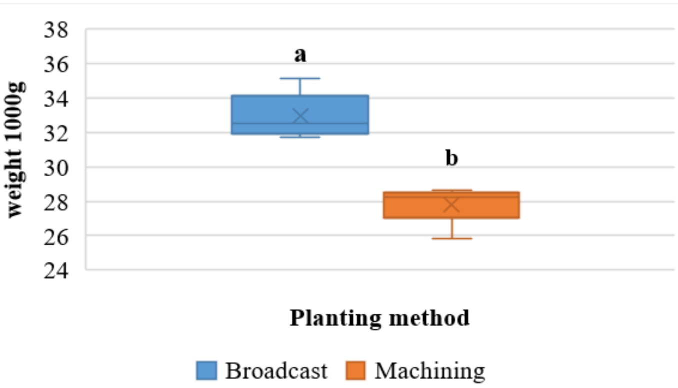

Figure 5: *Box plots weight [g] of 1000 kernels. Equal letters: no significant difference, different letters: significant difference.*
Source of reference: *Authors.*

As previously described in the methodology section, yield data were obtained from a total of 18 sampling points – nine per treatment – distributed across three subplots and three sampling points per subplot. The statistical analysis included verification of ANOVA assumptions – normality via the Kolmogorov-Smirnov test and homoscedasticity via Levene's test – as well as post-hoc comparison using Fisher's Least Significant Difference (LSD). The results are summarised below. When extrapolating the results of the 1000 grains to bulks per hectare as shown in Figure 6, the results obtained were 93.22 and 106.73 bulks per hectare for broadcast and mechanised sowing, respectively. On the other hand, the results obtained in the ANOVA between samples were 2.64 for F and 4.49 for critical F, and in the post hoc test, an LSD of 17.63 g was calculated. For this case, a KSt of 0.273 was obtained for nine data points with 95% confidence, and for KSc, the results were 0.149 and 0.143 for broadcast and mechanised sowing, respectively. Meanwhile, for the homoscedasticity test, the p-value of the ANOVA performed on the variances was 0.7.

Vegetation index results

Figure 7 shows the box plots of the data observed in the two experimental plots on the 3 dates where it was possible to obtain good images.

In the broadcast plot, 87 points were located for satellite tracking (Figure 3), while in the mechanised plot, there were 47 points due to its smaller area. During tillering, the NDVI averages were 0.47 for broadcast sowing and 0.63 for mechanised sowing. During lodging, they rose to 0.78 and 0.84, respectively, and at maturity, they dropped to 0.68 and 0.8. The Z-statistic values between each pair of means were 10.68, 8.77, and 14.76 at each evaluation stage, respectively, with a critical F of only 1.96 for two tails at 95%.

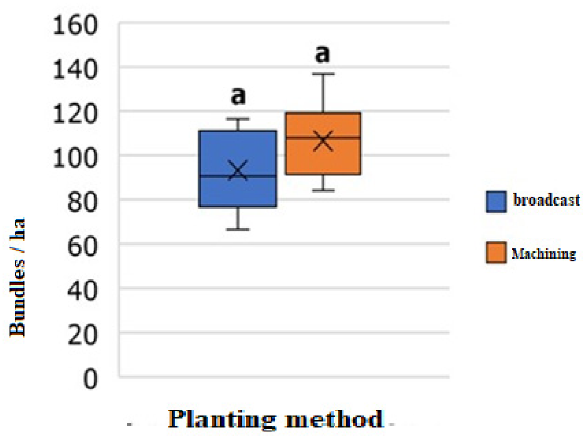

Figure 6: *Box plots of total yield between sub-plots: broadcast sown; mechanised sown. Equal letters: no significant difference, different letters: significant difference.*
Source of reference: *Authors.*

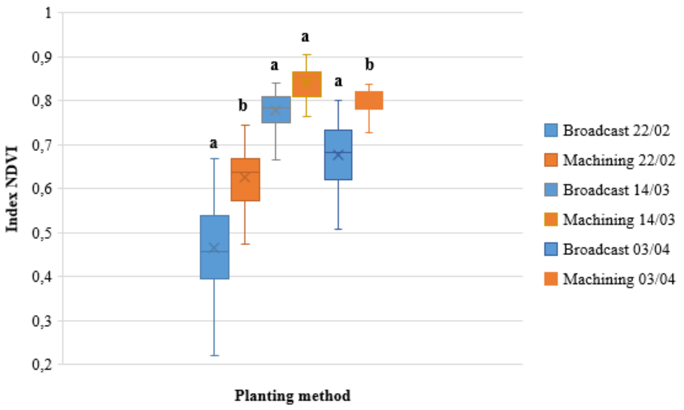

Figure 7: *NDVI index box plots in experimental plots during rice crop development. Equal letters: no significant difference, different letters: significant difference.*
Source of reference: *Authors.*

The normality results for the samples with more than 80 data points reported a KSt of 0.095 for 95% confidence and 0.113 for 90%, and the maximum errors found were 0.058, 0.066, and 0.107. For the samples with fewer than 50 data points, the KSt was 0.13 with 95% confidence, while KSc reported values of 0.105, 0.113, and 0.126 (see Annex 4). Figure 8 shows the map of NDVI distribution at each monitoring time.

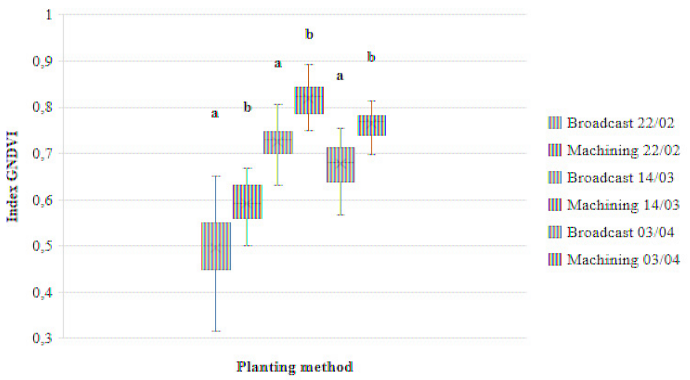

Figure 8: *NDVI maps in experimental plots during rice crop development.*
Source of reference: *Authors.*

To assess the practical significance of the differences in NDVI values between broadcast and mechanised sowing methods, Cohen's d was calculated for each phenological stage. This metric quantifies the magnitude of the difference between two means, normalized by the pooled standard deviation of both groups. For NDVI, the effect sizes were 0.37 at tillering (moderate), 1.63 at heading, and 2.36 at maturity (both of which are considered very large effects). These results indicate that mechanised sowing consistently produced higher NDVI values, reflecting greater vegetative vigor and canopy development. The large effect sizes at heading and maturity suggest that the differences are not only statistically significant but also agronomically meaningful, reinforcing the superiority of mechanised sowing in promoting biomass accumulation and photosynthetic activity during critical growth phases.

Figure 9 shows the results of the monitoring of the GNDVI index. During tillering, the averages were 0.50 for broadcast sowing and 0.59 for mechanised sowing. During lodging, they increased to 0.72 and 0.82, respectively, and at maturity, they decreased to 0.68 and 0.76.

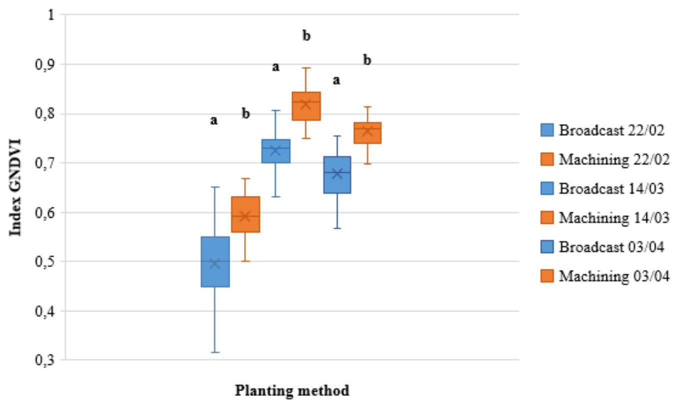

Figure 9: **G***NDVI index box plots in experimental plots during rice crop development. Equal letters: no significant difference, different letters: significant difference.*
Source of reference: *Authors.*

The critical Z value for the GNDVI index was 1.96, and the values of the Z test statistic at each evaluation stage were 9.32, 14.03, and 12.47, respectively. For samples with more than 80 data points, the critical KS was calculated between 0.095 and 0.098 for 95% confidence, with calculated KS values of 0.051, 0.069, and 0.075 at each stage, respectively. For samples with fewer than 50 data points, the critical KS was between 0.128 and 0.132 for 95% confidence, while the calculated KS values were 0.103, 0.107, and 0.108, respectively

Cohen's d was also applied to GNDVI values to evaluate the magnitude of differences between sowing treatments across phenological stages. GNDVI, which is more sensitive to chlorophyll content and nitrogen status, showed effect sizes of 0.24 at tillering (small), 2.60 at heading, and 2.13 at maturity (both indicating very large effects). These findings suggest that mechanised sowing substantially enhanced chlorophyll concentration and nitrogen uptake

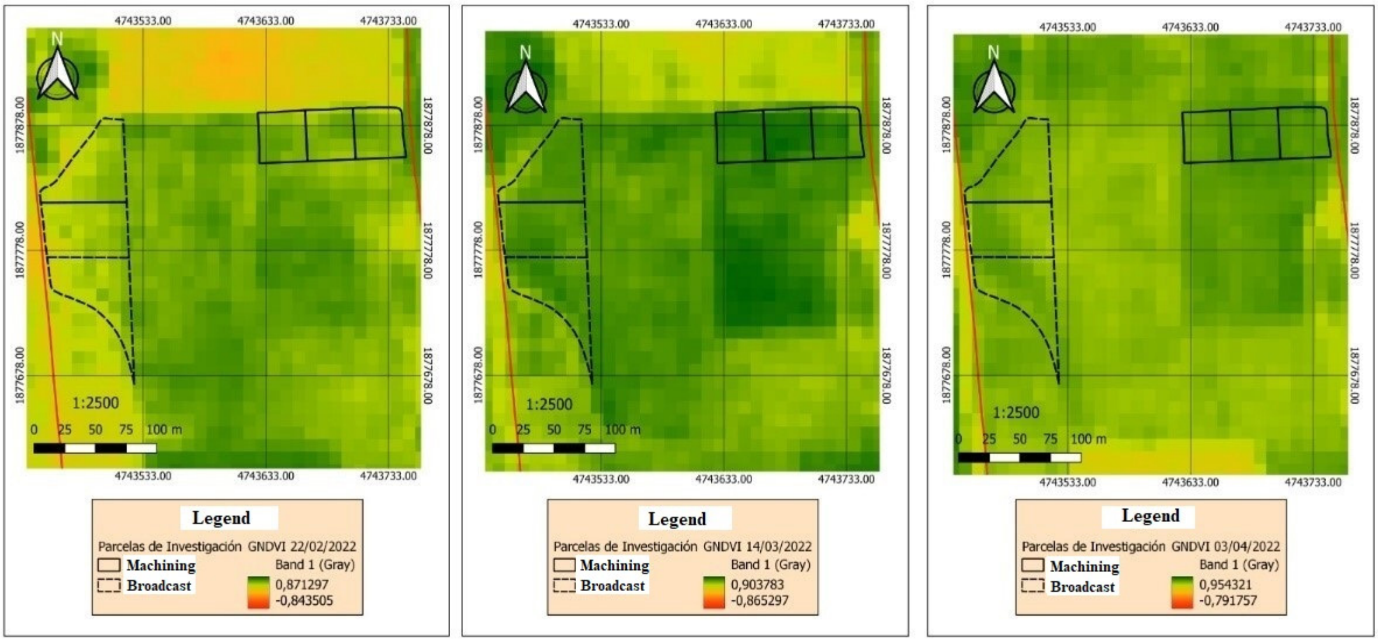

Figure 10: *GNDVI maps in experimental plots during rice crop development.*
Source of reference: *Authors.*

during the reproductive and senescence stages. The pronounced differences in GNDVI values highlight the physiological advantages conferred by mechanised sowing, particularly in optimizing nutrient assimilation and maintaining canopy health. The very large effect sizes confirm that the observed spectral differences are robust and agriculturally relevant, supporting the use of remote sensing indices as reliable indicators of crop performance. Figure 10 shows the map of the distribution of the GNDVI at each monitoring point.

Discussion

Temporal analysis of biophysical variables.
Initially, the inefficiency of the broadcast sowing method was verified. The seed losses that normally occur were amplified by the phenomenon of rainfall with seed washing and by birds that consumed them as food, resulting in much lower than the expectation of at least 250 plants per square metre, phenomena already reported by Al-Khayri *et al.* (2019). Mechanised sowing was also considered to have low emergence, taking into account that it was estimated that approximately 500 seeds were spread per square metre. Even so, it was achieved during phenological development by exceeding 450 panicles per square metre. In the initial broadcast count, two outliers resulting from measurement errors were eliminated, while the KSc for each sample ranged between 0.129 and 0.314, always lower than the theoretical one (KSt), so the normal distribution hypothesis was accepted. Furthermore, the KSc values ranged between 14.02 and 42.54, always higher and therefore statistically different. Fisher's LSD was also calculated for each pair, and it was verified that the difference between samples always exceeded it (see Annex 1).

Figure 4 shows that the measurements corresponding to the mechanised sowing treatment represent higher yields compared to broadcast sowing, as mentioned by Vance *et al.* (2021). For greater clarity, Table 3 shows the relationships between the initial plant count and the counts of tillers and panicles. It can be seen how the indicator increases with each measurement and how they are similar. This is due, initially, to the number of plants that germinated. However, it is difficult to explain considering that both treatments received the same fertilisation and irrigation management, and it is possible that the lack of uniformity in the distribution of the plants in the broadcast sowing treatment had a negative influence on this aspect, coinciding with what was found by Thet (2019).

Table 3: *Ratio of increment of tillers and/or panicles against initial plant count.*

Factor	Broadcasting	Mechanised
Macrolling 1	1.45	1.77
Macrolling 2	2.05	2.31
Panicles	2.46	2.45

Source of reference: *Authors.*

The normality test for Figure 5 indicated that one datum was atypically low according to the sample whisker plot, while the KSc values were both lower than the KSt, allowing the hypothesis of normal distribution to be accepted. The homoscedasticity test yielded a p-value of 0.511, greater than the established 0.05 confidence level, so equality was also established. An ANOVA was performed, which confirmed the difference between means, then an LSD of 1.159 was calculated while the difference was 5.196 g, significantly greater than the minimum significant difference (see Annex 2). The higher average of 30 g in the broadcast sowing treatment is consistent with the expectation for a well-nourished crop, but the lower reading for the mechanised sowing treatment contradicts the phenological evolution reported in Figure 4 and Table 3, where the treatment reported good tillering and lodging but showed deficiencies in grain filling, although, as explained, it received the same agronomic management. However, that grain filling in the crop with lower sowing density was better than in the crop with higher sowing density had already been discovered in studies such as that of Jia *et al*. (2018).

These results led to the fact that, when extrapolating the weight of filled grains from each gauger, discounting the empty grains, to units of bulks per hectare of each subplot, taking into account that the weight of each bulk is 62.5 kg, as reported in Figure 6, no significant difference was found between the treatments. Curiously, the slight difference between averages of production in packages per hectare for the two sowing methods was not significant according to the results presented by the ANOVA, with the difference between samples being only 13.51 g, less than the minimum significant, favouring the mechanised sowing treatment. Again, the lack of uniformity in the distribution and the difference in sowing density could favour the performance of broadcast sowing by decreasing competition for nutrients and increasing the area available for plant growth; This relationship between planting density and yield was previously reported by Khan *et al*. (2017). The normality test determined that both values were lower than the reference statistic, so the normality hypothesis was accepted for both samples. The ANOVA test showed that the variances of the samples were much higher than the established significance of 0.05, which demonstrated the equality of variances (see Annex 3).

Physiological and agronomic interpretation of yield parity

The use of the spectral indices NDVI and GNDVI, obtained with the free software QGIS® from Sentinel-2 observations, supported the results presented in Figure 4, but it was not possible to predict the yield recorded after the harvest, which was also contradictory. In the first measurement (NDVI), the vigour of the plants was low due to the early age of the crop in which part of the pixel has soil. During the lodging period, maximum vigour is evident, but at maturity, senescence has already begun and the leaves are already chlorotic, so the vigour index of the crop drops again; This behavior had already been detected via aerial images according to Barbedo (2019). What Figure 4 reinforces is that, in the three moments, these averages are significantly different as established by the Z-test for the pair of samples at each moment, being 34% higher for the mechanised plot at tillering, 7.8% at heading, and 17.6% at maturity.

Regarding the lack of significant yield difference despite higher plant density and NDVI/GNDVI values in mechanised seeding, we offer the following physiological and agronomic interpretation. First, excessive plant density can lead to intra-specific competition for light, water, and nutrients, which may reduce individual plant performance and limit grain filling. Second, although higher NDVI and GNDVI values indicate greater vegetative vigor, they do not necessarily correlate with final yield, especially when senescence and canopy structure affect spectral reflectance. Third, lower density in broadcast sowing may have allowed better spatial distribution and resource allocation, resulting in more efficient panicle development and grain filling. These mechanisms have been previously reported by Hayashi *et al*. (2006), Jia *et al*. (2018) and Shimono (2011), who demonstrated that reduced density can enhance root development, stress tolerance, and grain filling efficiency, ultimately balancing yield outcomes despite lower biomass indicators.

Conclusions and Recommendations

The experimental study, conducted in the alluvial soils of the Irrigation District of El Juncal (Palermo, Huila), showed that broadcast sowing on wet soil results in significant seed losses, lower emergence rates, and irregular plant distribution, leading to less uniform crop development. These effects are accentuated in poorly structured or uneven terrain, which is typical of the region.

In contrast, mechanised direct seeding on dry soil using a precision drill demonstrated better seed placement, greater initial emergence, and higher plant density. However, excessive density can lead to competition for resources and suboptimal grain filling, as observed in this study. Hence, adjusting the seeding rate downward in mechanised systems is advisable to promote efficient use of aerial and soil resources, enhancing individual plant performance and improving panicle formation.

Given the regional conditions and the predominance of clay-loam soils with good irrigation infrastructure, mechanised dry direct seeding emerges as a more efficient and sustainable alternative for rice growers in northern Huila. This method not only reduces seed costs and facilitates weed control but also ensures better crop uniformity and potentially higher yields if density is properly managed.

Furthermore, the use of NDVI and GNDVI indices obtained from Sentinel-2 satellite imagery proved to be a reliable tool for monitoring vegetative vigour across phenological stages, supporting in situ measurements. However, while these indices captured differences in canopy development, they did not accurately predict final yield, indicating the need for complementary ground-based data for precise yield estimation.

In conclusion, for growers in the Irrigation District of El Juncal and similar agroecological zones, mechanised direct seeding with optimised seed rates, supported by remote sensing for monitoring crop development, constitutes a promising strategy for sustainable rice production under current climatic and economic conditions.

Acknowledgements

The authors would like to thank the Universidad Surcolombiana for sponsoring this research at its experimental farm, as well as the staff who work there

Novelty Statement

This study provides a combined analysis of phenological field measurements and Sentinel-2 spectral vegetation indices (NDVI and GNDVI) to compare mechanised dry direct seeding and wet broadcast sowing of rice in alluvial soils of southern Colombia. Unlike previous work, this research integrates destructive sampling, spatial statistics, and remote sensing to demonstrate that mechanised seeding increases vegetative vigor but does not necessarily translate into higher yield due to density-driven competition. The study highlights the need to adjust seeding rates in mechanised systems and demonstrates the agronomic usefulness of satellite-based monitoring under real farming conditions.

Author's Contribution

Juan Gonzalo Ardila Marín: Designed the research, coordinated fieldwork, performed data analysis, and led the manuscript writing.
Diana Carolina Polania Montiel: Contributed to data collection, processing of vegetation indices, and review of methodological sections.
Luis Manuel Navas Gracia: Supervised the research design, statistical validation, and manuscript revision.
Jordan Alexis Castillo Coronado and Jean Carlos Acosta Vargas: Contributed to data collection, supported field sampling, agronomic interpretation, and preparation of figures and tables.
All authors reviewed and approved the final manuscript.

Generative AI or AI assisted technology statement
The authors declare that no generative AI and AI assisted technology was used in the creation of this manuscript.

Conflict of interest
The authors have no conflict of interest.

References

Abanco, L.V.E. and J.M.B.Q. Valle. 2020. Costos de producción y rentabilidad del cultivo de arroz de los productores del Valle Jequetepeque periodo 2019-2020. Thesis, Universidad Señor de Sipán, Pimental, Perú. https://hdl.handle.net/20.500.12802/7777

Ahmed, S., V. Kumar, A.U. Zaman, M.R. Dewan, A. Khatun, K. Hossain, S. Singh, J. Timsina, T.J. Krupnik. 2025. Dry direct-seeded and broadcast rice: A profitable and climate-smart alternative to puddled transplanted *aus* rice in

Bangladesh. Field Crops Res., 322: 109739. https://doi.org/10.1016/j.fcr.2025.109739

Andriatsiorimanana A., G. Mujawamariya, I.A. Tefy, N.F. Harison, K. Saito, K. Senthilkumar. 2024. Labour-saving sowing tolos for direct dry seeding of rice in Madagascar. Experimen. Agric., 60: 24. https://doi.org/10.1017/S0014479724000188

Al-Khayri, J.M., S.M. Jain and D.V. Johnson. 2019. Advances in plant breeding strategies: Cereals. In Advances in Plant Breeding Strategies: Cereals. 1st edn. Volum 5, Switzerland. Spring. Int. Publishing. https://doi.org/10.1007/978-3-030-23108-8

Barbedo, J.G.A. 2019. A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses. Drones., 3(2): 40. https://doi.org/10.3390/drones3020040

Candiago, S., F. Remondino, M.D. Giglio, M. Dubbini and M. Gattelli. 2015. Evaluating multispectral images and vegetation indices for precision farming applications from UAV images. Remote Sens., 7(4): 4026–4047. https://doi.org/10.3390/rs70404026

Cárdenas, D.A.G., J.A.R. Valencia, D.F. Alzate and J.R.P. Gonzalez. 2019. Dynamics of the indices NDVI and GNDVI in a rice growing in its reproduction phase from multi-spectral aerial images taken by drones. In: Corrales JC, Angelov P, Iglesias JA, editors. Advances in information and communication technologies for adapting agriculture to climate change II. Cham: Springer International Publishing. p. 106–119.

Coronado, J.A.C., D.C.P. Montiel and J.G.A. Marin. 2024. Evaluación del rendimiento de arroz (*Oryza sativa L.)* comparando dos métodos de preparación del suelo. Rev. de Inv. Agra. Y Amb., 15(2): 91-112. https://doi.org/10.22490/21456453.6886

Das, Y., N. Halder and M. Barman. 2020. Studies on the Effect of Sowing Techniques and Seed rate on the Growth, Yield Components and Yield of Direct Seeded Rice (*Oryza sativa* L.) under Rainfed Medium Land Situation. International J. Current Microbiol. Appl. Sci., 9(5): 751-764. https://doi.org/10.20546/ijcmas.2020.905.083

Fukai, S., P. Xangsayasane, D. Manikham and J. Mitchell. 2019. Research strategies for mechanised production of rice in transition from subsistence to commercial agriculture: a case study from Khammouan in Lao PDR. Plant Prod. Sci., 22(1): 1–11. https://doi.org/10.1080/1343943X.2018.1561199

Gai D., Y. Wang, H. Li, B. Shi, Y. Liu, Q. Zhang, Y. Geng, D. Ji, L. Guo and X. Shao. 2025. Appropriate seeding rate facilitates the simultaneous enhancement of population yield and lodging resistance in direct-seeded rice. Front. Plant Sci., 16. https://doi.org/10.3389/fpls.2025.1622993

Gitelson, A.A., Y.J. Kaufman and M.N. Merzlyak. 1996. Use of a green channel in remote sensing of global vegetation from EOS- MODIS. Remote Sens. Environ., 58(3): 289–298. https://doi.org/10.1016/S0034-4257(96)00072-7

Hayashi, S., A. Kamoshita and J. Yamagishi. 2006. Effect of planting density on grain yield and water productivity of rice (*Oryza sativa* L.) grown in flooded and non-flooded fields in Japan. Plant Prod. Sci., 9(3): 298–311. https://doi.org/10.1626/pps.9.298

Jat, R.K., V.S. Meena, M. Kumar, V.S. Jakkula, I.R. Reddy and A.C. Pendey. 2022. Direct Seeded Rice: Strategies to Improve Crop Resilience and Food Security under Advise Climatic Conditios. Land., 11(3): 382. https://doi.org/10.3390/land11030382

Jia, Q., L. Sun, H. Mou, S. Ali, D. Liu, Y. Zhang, P. Zhang, X. Ren and Z. Jia. 2018. Effects of planting patterns and sowing densities on grain-filling, radiation use efficiency and yield of maize (Zea mays L.) in semi-arid regions. Agric. Water Manage., 201: 287–298. https://doi.org/10.1016/j.agwat.2017.11.025

Júnior, W.de C., W., C.daS. Chagas, A. Muselli, H.S.K. Pinheiro, N.R. Pereira and S.B. Bhering 2014. Método do hipercubo latino condicionado para a amostragem de solos na presença de covariáveis ambientais visando o mapeamento digital de solos. Revista Brasileira de Ciencia Do Solo., 38(2): 386–396. https://doi.org/10.1590/S0100-06832014000200003

Khan, A., U. Najeeb, L. Wang, D.K.Y. Tan, G. Yang, F. Munsif, S. Ali and A. Hafeez. 2017. Planting density and sowing date strongly influence growth and lint yield of cotton crops. Field Crop. Res., 209: 129–135. https://doi.org/10.1016/j.fcr.2017.04.019

Kimura, R., S. Okada, H. Miura and M. Kamichika.

2004. Relationships among the leaf area index, moisture availability, and spectral reflectance in an upland rice field. Agric. Water Manage., 69(2): 83–100. https://doi.org/10.1016/j.agwat.2004.04.009

Liu, Z.Z., W. Li and M. Yang. 2015. Two General Extension Algorithms of Latin Hypercube Sampling. Mathemat. Prob. Engineer., v.2015: Article ID 450492. https://doi.org/10.1155/2015/450492

Negi, P., J. Rane, R.S. Wagh, T.J. Bhor, D.D. Godse, P. Jadhav, C. Anilkumar, D. Sreekanth, K.S. Reddy, S.R. Gadakh, K.M. Boraih, C.B. Harisha, and P.S. Basavaraj. 2024. Direct-Seeded Rice: Genetic Improvement of Game-Changing Traits for Better Adaption. Rice Sci., 31(4): 417-433. https://doi.org/10.1016/j.rsci.2024.04.006

Phadikar, S. and J. Goswami. 2016. Vegetation indices based segmentation for automatic classification of brown spot and blast diseases of rice. 2016 3rd Int. Conferen. Recent Advan. Inf. Technol., RAIT 2016: 284–289. https://doi.org/10.1109/RAIT.2016.7507917

Pulido, H.G. and R. de la V. Salazar. 2008. Análisis y diseño de experimentos. In Turkish Journal of Medical Sciences: 2a ed. México, McGraw-Hill.

Rezaei, E., M.S. Daliri, H.R. Mobasser, A.A.M. Mirkolaei and M. Moballeghi. 2025. Assessment of plant density and interactions with soil types and transplanting methods in rice cultivation. Chilean J. Agric. Anim. Sci., 41(1): 59-75. https://doi.org/10.29393/CHJAAS41-7PDEM50007

Rouse, J., R.H. Haas, J.A. Scheel and D.W. Deering. 1976. Monitoring Vegetation Systems in the Great Plains with ERTS. 3rd Earth Resource Technology Satellite (ERTS) Symposium, 24(1): 48–62. https://doi.org/10.1021/jf60203a024

Shi, M., K.P. Paudel and F. Chen. 2021. Mechanization and efficiency in rice production in China. J. Integrat. Agric., 20(7): 1996-2008. https://doi.org/10.1016/S2095-3119(20)63439-6

Shimono, H. 2011. Rice genotypes that respond strongly to elevated CO2 also respond strongly to low planting density. Agric. Ecosys. Environ., 141(1–2): 240–243. https://doi.org/10.1016/j.agee.2011.02.028

Singh, P.K, R.K. Naresh, R. Bhatt, H. Tiwari, O. Singh, A. Singh, R. Hota and R. Kumar. 2023. Efficient crop management strategies to improve crop resilience and crop-water productivity enhacement under direct seeded rice cultivation system in adverse climatic conditions: A review. Pharma Innov., 12(4): 1988-1997.

Thet, K., K.M.M. Ko, K. Ngwe, T.D. Min and K.K. Win. 2019. Performance of different verieties in direct seeded rice (*Oryza sativa* L.) as affected by different sowing methods. J. Agric. Res., 6(1): 65-71.

Tian, J., S. Li, Z. Xing, S. Cheng, Q. Liu, L. Zhou, P. Liao, Y. Hu, B. Guo, H. Wei and H. Zhang. 2022. Seedling Establishment and Yield Performance of Dry Direct-Seeded Rice after Wheat Straw Returning Coupled with Early Nitrogen Application. Agric. (Switzerland)., 12(4): 565. https://doi.org/10.3390/agriculture12040565

Tian, Y.C., X. Yao, J. Yang, W.X. Cao, D.B. Hannaway and Y. Zhu Y. 2011. Assessing newly developed and published vegetation indices for estimating rice leaf nitrogen concentration with ground- and space-based hyperspectral reflectance. Field Crop. Res., 120(2): 299–310. https://doi.org/10.1016/j.fcr.2010.11.002

Tipas, J.F.P., E.I. Mondragon and M.C. Gomez. 2021. Aplicación del método de hipercubo latino para la estimación de parámetros de modelos matemáticas desde una perspectiva pedagógica. Revista Boletín Redipe., 10(5): 208-219. https://dialnet.unirioja.es/servlet/articulo?codigo=8116440

Vance, W. H., R.W. Bell, C. Johansen, M.E. Haque, A.M. Musa and A.K.M. Shahidullah. 2021. Soil disturbance levels, soil water content and the establishment of rainfed chickpea: Mechanised seeding options for smallholder farms in north-west Bangladesh. J. of Agron. Crop Sci., 207(2): 208–223. https://doi.org/10.1111/jac.12455

Villalba, J.V, A.J. Jarma, and E.M. Combatt. 2017. Physiological response of on rice cultivars in different sowing times in Cordoba, Colombia. Temas Agrarios., 22(2): 9–19.

Wang, F., J. Huang, Y. Tang and X. Wang. 2007. New Vegetation Index and Its Application in Estimating Leaf Area Index of Rice. Rice Sci., 14(3): 195–203. https://doi.org/10.1016/

s1672-6308(07)60027-4

Yawata, K., T. Yamamoto, N. Hashimoto, R. Ishida, and H. Yoshikawa. 2019. Mixed model estimation of rice yield based on NDVI and GNDVI using a satellite image. Proc. SPIE,, 11149: 1114918. https://doi.org/10.1117/12.2532108

Yuan, R., Y. Mao, D. Zhang, S. Wang, H. Zhang, M. Wu, M. Ye and Z. Zhang. 2024. The Formation of Rice Tillers and Factors Influencing It. Agron., 14(12): 2904. https://doi.org/10.3390/agronomy14122904

Zhang, H., K. Mi, M. Ma, T. Chen, H. Zhang and Y. Yang. 2025. Effects of planting density on population characteristics and yield formation in conventional *japonica* rice with different yield levels. Agron. J., 117(6): 70233. https://doi.org/10.1002/agj2.70233

Zhong, X., S. Peng, J.E. Sheehy, R.M. Visperas and H. Liu. 2002. Relationship between tillering and leaf area index: quantifying critical leaf area index for tillering in rice. The J. Agric. Sci., 138(3): 269-279. https://doi.org/10.1017/S0021859601001903

Zhu X.Y. 2025. Optimizing planting density to enhance rice productivity. Rice Genomics and Genetics, 16(2): 71-85. https://doi.org/10.5376/rgg.2025.16.0007