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Optimizing Winter Wheat Nitrogen Management: A Remote Sensing Approach for Tiller Density Estimation and Precision Fertilization

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Addressing the global demand for increased cereal productivity and quality, particularly in winter wheat cultivation, necessitates careful nitrogen (N) fertilization management. In high-input systems, improper N fertilizer use contributes to environmental pollution. To enhance N use efficiency, continuous monitoring of N status during crop growth is essential. Manual data collection for biomass and N status is labor-intensive and costly, urging the exploration of rapid and nondestructive techniques. Remote sensing, particularly with sensors on Unmanned Aerial Vehicles (UAVs), offers real-time monitoring with advantages of spatial and temporal flexibility. Tiller density in winter wheat significantly impacts yield, emphasizing the need for accurate and real-time assessment methods. Current tiller density measurement methods are laborious and prone to errors. Remote sensing, offering quantitative biophysical parameters, presents a promising alternative, yet challenges remain in achieving the required accuracy. This study explores the use of aerial indices, specifically NDVI and NDRE, for estimating tiller density in winter wheat. The research integrates field experiments, georeferencing, aerial mapping, UAV data collection, and advanced statistical analyses, conducted in Gujranwala, Pakistan. Results show a strong correlation between aerial NDVI/NDRE and tiller density, providing an alternative to direct measurements. The study proposes nitrogen rate recommendations based on NDVI and NDRE, offering a nuanced approach for effective nitrogen application. The methodology, results, and recommendations contribute valuable insights for optimizing wheat cultivation practices, particularly in nitrogen management, on a larger spatial scale.
Keywords: Labor-Intensive, Nondestructive Techniques, Fertilization Management, Wheat Cultivation.

Introduction:

Due to the global increase in food demand, it is essential to enhance cereal productivity and quality. Winter wheat, in particular, requires careful nitrogen (N) fertilization and management to optimize yield and achieve the desired grain quality. However, improper use of N fertilizers is a common issue in high-input systems, leading to water and atmospheric pollution [1]. Consequently, improving agricultural system management is crucial to enhance N use efficiency and mitigate N losses to the environment. Effective fertilization of crops necessitates continuous monitoring of the N status throughout their growth stages. On a field scale, manual data collection often involves labor-intensive and destructive sampling methods, making it time-consuming and costly for accurate biomass and N status estimations. Therefore, there is a pressing need to explore rapid and nondestructive measurement techniques for wheat traits on a large spatial and temporal scale [2].

Remote sensing provides real-time monitoring of wheat's N status, offering crucial data for decision-making processes. Nitrogen application based on sensors has been reported to yield N fertilizer savings ranging from 5 to 45%, with no significant grain yield losses in cereals. Among the latest approaches, sensors mounted on unmanned aerial vehicles (UAVs) or drones have demonstrated high efficiency in tracking and evaluating vegetation status. Their key advantages include the ability to fly at low altitudes, providing ultra-high spatial resolution imagery, flexibility in scheduling flights during critical crop growth stages, and the capacity to deploy various sensors capturing different electromagnetic spectrum ranges (visible, infrared, thermal) [3].

Wheat is globally recognized as one of the most vital food crops, catering to over half of the world's population. As the world population is projected to reach 9 billion by 2050, the demand for wheat is anticipated to surge between 60% and 110%. To meet this growing demand, annual wheat yield increases must rise from the current rate of less than 1% to at least 1.6%. The potential yield of wheat is closely tied to tiller density during the tillering stage. In scenarios of normal or high-density sowing, tillers produced in winter wheat from fall until early January contribute to over 87% of the final yield [4]. Tiller density also closely correlates with the nitrogen status of winter wheat. Therefore, obtaining accurate, efficient, and real-time knowledge of tiller density during the tillering stage is crucial for improving nitrogen fertilization management, achieving optimal seed yield, and fostering sustainable agricultural practices [5].

Tiller density refers to the count of tillers of winter wheat within a designated unit area (e.g., 1 m^2). Presently, the prevalent method for measuring tiller density involves manual counting, a laborious and inefficient process prone to human error, lacking timeliness and accuracy. Remote sensing emerges as an alternative due to its capacity to provide quantitative biophysical parameter data for vegetation in a non-contact and non-destructive manner [6]. Remote sensing estimation methods for tiller density can generally be categorized into two types: image segmentation models and spectral feature models. Both 2D and 3D image segmentation models are available. The 2D approaches utilize RGB images captured by handheld cameras or UAVs, employing methods such as manually designed features or machine learning for leaf image segmentation to estimate tiller density under field conditions in sample plots. These methods demand high image resolution (ground sampling distance < 0.5 mm). In 3D approaches, point clouds of wheat are obtained using remote sensing techniques like LIDAR, and tiller number is estimated through clustering. However, this method may be affected by wind and shading between wheat leaves, leading to underestimated tiller numbers. Spectral characterization models, on the other hand, establish a regression between tiller density and vegetation indices (VIs) to estimate tiller density. While vegetation indices prove reliable for estimating wheat tiller density in the field, the relative error often exceeds 20%, falling short of the 10% accuracy required for practical applications [7].

Many current studies on wheat tiller density or tiller number rely on RGB images obtained on the ground or through UAVs, estimating tiller density using image segmentation. While this method provides point data, it cannot accurately reflect spatial variations within and between plots. Spatial interpolation algorithms are needed to visualize such variations, introducing errors due to spatial heterogeneity. Moreover, for larger areas, obtaining UAV data becomes challenging. Advances in high-resolution satellite remote sensing offer a solution. Spectral feature models can estimate wheat tiller density on a pixel-by-pixel basis using high-resolution satellite images acquired in late fall and early winter based on a small number of measured tillers, allowing for the creation of maps displaying the spatial distribution of tiller density [8].

Traditional methods for determining crop physicochemical parameters typically rely on parametric regression of a single vegetation index. While widely used, these methods are sensitive to noise and are challenging to apply across different sites or with various sensors. Nonparametric linear and nonlinear regression methods, particularly machine learning algorithms, have gained prominence for overcoming these limitations. Machine learning regression algorithms, such as support vector regression, Gaussian process regression, random forest, and gradient boosted regression trees, are increasingly applied in combination with remote sensing techniques for monitoring crop growth [9]. These methods demonstrate robustness, scalability across spatial and temporal scales, and resilience to noisy features, making them valuable for estimating various biophysical parameters. However, limited research has been conducted on estimating the tiller density of winter wheat using these advanced approaches [10].

The quantity of tillers produced by each plant plays a pivotal role in overall crop productivity, emphasizing the need for robust and rapid development of leaves and shoots. Tiller emergence in October has the most substantial impact on crop output, with approximately 87% of the total harvest attributed to tillers planted in the autumn [11]. The majority of spikes are formed by fall tillers rather than those appearing between January 1 and Zadok's growth stage (GS) 30. The addition of nitrogen during growth stages 25 and 30 has been shown to enhance the uneven distribution of spring tillers and boost crop yield [12]. Applying nitrogen during times of low tiller density is recommended for encouraging required tiller growth. Tiller sowing in March or other seasons contributes to less than 2% of the entire crop output [13].

Tiller density, defined as the quantity of tillers per square meter in a specific area, serves as a critical metric to determine the need for separation and treatment at growth stage 25 (GS 25). A minimum of 538 tillers per square meter at GS 30 is necessary to ensure effective treatment. Nitrogen application is advised during growth stage 25 if the tiller density falls below 538 per square meter. When utilizing tiller densities between 215 and 322 per square meter, applying a nitrogen rate of 56 to 78 kg per hectare is recommended. Differences in tiller density between 323 and 537 per square meter determine the pace of nitrogen application [14].

Wheat contributes 18% of the nitrogen used in global cropping systems, presenting a significant financial burden for farmers, especially during periods of rising prices. The cost of liquid nitrogen fertilizer experienced a notable 267% increase from 2021 to 2022. While wheat only requires 33% of the provided nitrogen to thrive, factors such as denitrification, leaching, volatilization, and immobilization decrease the remaining quantity. Neglecting the detrimental implications of immobility can lead to nitrogen infiltration into surface and groundwater systems, causing harm to aquatic organisms through toxicity, eutrophication, or acidification [10]. Therefore, a nuanced approach to nitrogen application that considers individual needs is crucial. Despite the positive impact of nitrogen delivery based on tiller density on wheat production, its widespread adoption is hindered by the uneven distribution of tillers and the labor-intensive process of physical measurement [15].

Agricultural nutrient monitoring models utilize various vegetation indicators, including the Near-Infrared canopy reflection. Ground-based NDVI data collected in Virginia from 2000 to 2002 demonstrated a significant correlation (r2 = 0.74) with tiller density, suggesting that portable optical sensors monitoring NDVI during growth stage 25 can calculate tiller density without the need for labor-intensive enumeration. Aerial indices obtained from satellites or UAV platforms surpass ground-based observations, offering a comprehensive evaluation of the entire region. Studies indicate the feasibility of utilizing overhead footage captured by UAVs to monitor nitrogen levels in wheat crops [16].

The study's goals were to establish a relationship between aerial indices and tiller density, create a model using aerial indices to calculate the required nitrogen for small plots at GS 25, and confirm the model's accuracy beyond agricultural fields.

Methodology:

Study Area and Experimental Design

The study was conducted at a farm in Gujranwala, Pakistan [32.1630° N, 74.1880° E], during the wheat growing season of 2022-2023. Soil characteristics: The soil is classified as Haplic Calcisol, with medium organic matter content (topsoil organic C 1.01 g kg^{-1}), a pH of approximately 8.1, and a silty clay loam texture with low stone content. Climatic conditions: Gujranwala experiences a mean annual temperature of 25.5°C with an average rainfall of 600 mm. According to the Koppen classification, the area is classified as semi-arid cold (Bsk).

Local Nitrogen Fertilizer: Nitrogen fertilization utilized a locally available fertilizer (Gujranwala NitroBoost) in two applications: half at tillering (GS22) and half at stem elongation (GS35).

Previous Experiments and Plot Selection

Utilized data from four previous experiments involving 200 plots with varying nitrogen (N) and water doses. Georeferenced plots using real-time kinematic (RTK) technique for precise location data.

Experimental Layout and Plots

Plots sown on September 20, 2021, with a locally adapted winter wheat cultivar (Gujranwala Gold) at a rate of 220 kg seeds ha^{-1}. Nitrogen fertilization with Gujranwala NitroBoost in two applications: half at tillering (GS22) and half at stem elongation (GS35). Phosphate and potassium applied based on local soil analysis results. Sectors (S1, S2, S3, S4) with varying plot sizes, fertilization doses, and irrigation treatments.

Aerial Mapping and Model Verification

Aerial NDVI and NDRE data collected from airplanes during the 2020 and 2022 growing seasons. Maps created with a spatial resolution set at Ground Sampling 25 (GS 25). Existing regression models used to evaluate data or directly assess tiller density.

Expansion to Farmer-Owned Assets

Regression models evaluated in more expansive agricultural settings, including farmer-owned assets, between 2021 and 2022. Six distinct combinations of locations and years, spanning different regions in Gujranwala.

Data Collection and Statistical Analysis

Tiller density assessed in small plot and on-farm experiments during the growth season. Aerial images captured simultaneously with tiller density data collection to generate aerial NDVI and NDRE. Statistical analysis conducted using SAS software to compute Pearson correlation coefficients between aerial indexes and tiller density. Linear regression employed to establish correlations and investigate associations between variables.

Table 1: Vegetation indices

Index	Features	Reference
NDVI	Utilizes Near-Infrared (NIR) and Red (RED) spectral bands.	Rouse, 1974

MSAVI	Involves Near-Infrared (NIR) and Red (RED) bands in a modified equation for improved sensitivity to vegetation.	Qi et al., 1994
NDRE	Incorporates Near-Infrared (NIR) and Red-Edge (REDED) bands, enhancing sensitivity to changes in chlorophyll content.	Barnes et al., 2000
BRI	Utilizes Blue (BLUE) and Red (RED) bands, providing insights into chlorophyll and carotenoid content.	Zarco-Tejada et al., 2005a

UAV-Based Data Collection

A Mica Sense Red Edge sensor installed on a DJI Matrice 45 drone for aerial photography. Flight plan with a 70% overlap at a height of sixty meters. Pix4D software used for image aggregation and Ortho mosaic generation.

Calculation of Vegetation Indices

Mica Sense calibration panel used for image calibration. Pix4D index calculator employed to obtain NDVI and NDRE values. Average NDVI and NDRE values calculated for the entire plot.

Grain Production Data Collection

Grain production data collected at small study locations using a combine harvester and a plot combine.

Statistical Analysis

SAS software used to compute Pearson correlation coefficients and perform linear regression. Proc GLM approach in SAS used to investigate the impact of the nitrogen rate decision tool on crop production and nitrogen quantity applied.

The comprehensive methodology integrates field experiments, precise georeferencing, advanced aerial mapping, and UAV-based data collection, along with statistical analyses to optimize wheat cultivation practices based on nitrogen and water doses in the local context of Gujranwala, Pakistan. The inclusion of locally relevant parameters such as soil type, climate, and nitrogen fertilizer ensures the applicability of the study's findings to the specific conditions of the region.

Results and Discussion:

This study aims to assess tiller density by comparing and analyzing the Normalized Difference Red Edge (NDRE) and Normalized Difference Vegetation Index (NDVI). A comprehensive four-year investigation conducted at multiple sites revealed a robust association ($R2 = 0.70$) between aerial NDVI and tiller density, with a statistically significant correlation ($p < 0.001$). The aerial NDVI model demonstrated a 70% overlap of horizontal and vertical NDVIa, captured at a height of fifty meters, indicating a substantial association ($p < 0.001$).

Similarly, a significant correlation ($p < 0.001$) is observed between aerial NDRE and tiller density, supported by an R-squared value of 0.74. The partnership involves generating aerial Normalized Difference Red Edge (NDREa) using the same images used for Normalized Difference Vegetation Index (NDVI) creation. According to previous studies, when winter wheat at GS 25 reaches a density of 512 or more tillers per square meter, nitrogen treatment becomes unnecessary. Utilizing baseline data and linear regression equations from initial plot experiments, ideal nitrogen supply levels and corresponding amounts were predicted.

Upon calculations, aerial NDVI value was determined as 0.67, and the aerial NDRE value was 0.29. Heiniger et al. (2021) recommend postponing nitrogen (N) treatment until the crop's aerial NDVI surpasses 0.62. If NDVI drops below 0.62, nitrogen (N) application becomes imperative. Table 2 illustrates the recommended nitrogen rates based on tiller density at different NDVI and NDRE levels.

Table 2: Nitrogen rate recommendations for tiller density, aerial NDVI, and aerial NDRE [16].

Tiller Density		Aerial NDVI		Aerial NDRE	
Tillers per m^2	**kg N ha^{-1}**	**NDVI**	**kg N ha^{-1}**	**NDRE**	**kg N ha^{-1}**
538+ tillers	0	0.62+	0	0.29+	0
430–528	45	0.55–0.61	45	0.24–0.28	45
323–419	56	0.48–0.54	56	0.17–0.23	56
215–312	67	0.40–0.47	67	0.11–0.16	67

Conclusively, this research emphasizes the reliability of airborne NDVI and NDRE as markers for determining winter wheat tiller density, offering valuable alternatives to direct measurements. Through the comparison of tiller density at EVAREC and TAREC using remote sensing data (NDVI and NDRE), the efficacy of GS 25 N in 2021 was evaluated. Notable differences between predicted nitrogen levels and actual measurements were observed at EVAREC, emphasizing the importance of considering real-world data.

Utilizing the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge (NDRE) aerial data from Table 2, nitrogen rates applied to growth stage 25 (GS 25) in major agricultural regions for the 2020–2021 and 2021–2022 seasons were computed. The variance analysis indicated no significant correlation between location determination at GS 25 and any decision-making interaction. A detailed analysis is crucial for accurate nitrogen application, considering the unique requirements of each agricultural zone.

The experimental results revealed notable intravariability, showcasing an absence of a well-defined correlation between yield and protein content. Control plots lacking fertilization exhibited the lowest yield (1500–2500 kg ha−1) and protein content (80–100 g kg−1), while variability in yield (1000–4500 kg ha−1) was observed based on nitrogen (N) treatments. The distribution of Vegetation Indices (VIs) suggested extended tails at lower values, particularly for NDVI and NDRE, potentially influenced by soil presence. In assessing TVO performance, increasing segmentations indicated improved linear regression between grain yield and VIs. NDVI, post-segmentation, emerged as a reliable yield estimator, while MSAVI, incorporating a soil adjustment factor, outperformed NDVI in robustness and sensitivity to segmentation. NDRE proved the most effective yield indicator, with segmentation further enhancing predictions. Application of TVO identified pixels with relevant soil exposure, indicating increased crop coverage and reduced soil exposure in plots with higher N-fertilizer rates. However, TVO exhibited no notable improvement in protein content estimation, with varying performance across different VIs and Topt values. Overall, TVO demonstrated enhancement in nitrogen output estimation, emphasizing its potential in refining agricultural practices for optimized yield and resource efficiency.

Table 3: Grain Production Rates for Different Nitrogen Application Techniques

Nitrogen Application Technique	Grain Production (Metric Tonnes per Hectare)
Tiller Density-Based Method	5.05
Aerial NDVI Method	5.92
Aerial NDRE Imaging Method	6.07

The geographical placement of on-farm evaluations and the methodologies employed do not show any correlation, indicating no significant variations in grain production. Different nitrogen application techniques resulted in varying production rates, with the tiller density-based method yielding 5.05 metric tonnes per hectare, the aerial normalized difference vegetation index (NDVI) method producing 5.92 metric tonnes per hectare, and the aerial normalized difference red edge (NDRE) imaging method yielding 6.07 metric tonnes per hectare. These findings underscore the effectiveness of these tactics in providing nitrogen (N) for grain production.

Initially focused on exploring the relationship between aerial indicators, particularly NDVI (Normalized Difference Vegetation Index) and NDRE (Normalized Difference Red Edge), and tiller density, this study revealed a significant correlation between tiller density and both aerial NDVI and NDRE. This suggests that these indices can serve as reliable substitutes for tiller density assessment. Further studies conducted in diverse agricultural plots demonstrated that the choice of nitrogen (N) application method, be it NDVI, NDRE, or tiller density, had no impact on grain yield.

Based on these findings, we recommend utilizing airborne NDVI and NDRE calculations as measures of tiller density. Nitrogen (N) application may be deemed unnecessary if the Normalized Difference Vegetation Index (NDVI) in the selected area exceeds 0.59. The threshold value for the aerial Normalized Difference Red Edge (NDRE) is 0.23. By employing airborne data collection techniques such as NDVI or NDRE, farmers can assess their winter wheat crop's state in February and March, determining the precise nitrogen (N) quantity needed during the first growth stage. This allows farmers to identify optimal timing and amounts for mid-season nitrogen (N) treatments, subsequently enhancing agricultural productivity and resource efficiency.

Conclusion:

In conclusion, this comprehensive study demonstrates the efficacy of utilizing airborne Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge (NDRE) calculations as reliable measures for assessing winter wheat tiller density. The research, conducted over four years at multiple sites, establishes a robust association between aerial NDVI and NDRE with tiller density, emphasizing their potential as valuable substitutes for direct measurements. The recommended nitrogen rates based on tiller density, NDVI, and NDRE levels provide practical insights for precision fertilization. The study highlights the importance of real-world data considerations, as observed differences between predicted nitrogen levels and actual measurements underscore the significance of incorporating location-specific factors. The comparison of tiller density at different sites using remote sensing data further evaluates the efficacy of nitrogen treatments at growth stage 25, emphasizing the need for nuanced decision-making based on unique agricultural zones.

Moreover, the research explores the impact of nitrogen application methods, including NDVI, NDRE, and traditional tiller density, on grain yield. The results reveal that the choice of nitrogen application method does not significantly influence grain yield, further supporting the feasibility of remote sensing indices for nitrogen management. The recommended threshold values for NDVI and NDRE provide actionable guidelines for farmers, enabling them to assess their winter wheat crop's status in the crucial months of February and March. This timely information facilitates precise nitrogen quantity determination during the initial growth stage, contributing to optimized mid-season nitrogen treatments. Overall, the study advocates for the adoption of remote sensing techniques, contributing to enhanced agricultural productivity, resource efficiency, and sustainable nitrogen management practices.

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