OPTIMIZING DURUM WHEAT NITROGEN NUTRITION INDEX (NNI) PREDICTION THROUGH SENTINEL-2 VEGETATION INDICES INTEGRATIONS

#11335

[1]N.H Boughattas, [1,2]M. Kadri, [2]M. Zekri, [3]S. Ayadi, [4]S. Arraouadi, [5]H. Hajlaoui, [3]Y. Trifa, [2]I. Hbiri

[1] University of Sousse, Higher Institute of agronomy of chott-Meriem (ISA-CM), Sousse, Tunisia; [2] Robocare, Sfax, Tunisia; [3] National Agronomic Institute of Tunisia (INAT), Tunis, Tunisia; [4] Regional Center of Agriculture Research of Sidi Bouzid (CRRA), Sidi Bouzid, Tunisia; [5] Faculty of Sciences and Technology of Sidi Bouzid, Tunisia.

e-mail: nourelhoudaboughattas@yahoo.fr; 00216 2921361

ABSTRACT

Nitrogen is crucial for durum wheat growth and productivity, but excess or insufficient levels can harm both the environment and farmers' finances. Remote sensing offers rapid, cost-effective, and nondestructive ways to assess crop nutrition, with vegetation indices (VIs) indicating plant health. This study aims to enhance the accuracy of durum wheat nitrogen status prediction by investigating modified formulations of Nitrogen Nutrition Index (NNI) coupled with various VIs, such as NDVI Sentinel-2, NDVI by GreenSeeker, GNDVI, NDRE, NRI, RESAVI, REDVI, and MCARI. Two experimental plots of durum wheat were selected, one in the Medjez El Bab region in the Beja governorate (Z30) and the other in the Sadaguia region in the Sidi Bouzid governorate (Z60). A nitrogen dilution curve (Nc) was established for each plot at a specific growth stage to determine the NNI index. Statistical analysis was performed using RStudio software to obtain a predictive model for NNI and the VIs extracted by CropCare application established by Robocare. The performance of this model was evaluated using the coefficient of determination, R^2. The correlation analysis allowed us to identify a significant correlation between NNI and VIs. The GNDVI index proved to be the best indicator for estimating NNI (R^2=0.972), while the NDVI was excluded (R^2=0.221). In summary, this study underscores the effectiveness of integrating modified NNI formulations with diverse VIs from remote sensing, offering improved precision in fertilizer management for precision agriculture.

INTRODUCTION

Nitrogen is a fundamental nutrient for plant growth, playing a pivotal role in photosynthesis, protein synthesis, and overall crop productivity (Nino et al., 2024). In the case of durum wheat (Triticum durum), a staple in many agricultural systems, nitrogen management is critical for achieving optimal yields and grain quality. However, the delicate balance between sufficient and excessive nitrogen application poses a challenge (P. Chen, 2015) (C. Chen et al., 2023). Over-application can lead to environmental issues such as nitrate leaching and greenhouse gas emissions, while under-application can result in reduced yields and economic losses for farmers (Denora et al., 2023). Traditionally, nitrogen management has relied on soil tests and fixed fertilizer application rates, which often fail to account for spatial and temporal variability in crop nitrogen needs (Diacono et al., 2012). This has driven the development of more precise, dynamic approaches, among which remote sensing has emerged as a powerful tool (Piikki et al., 2022). Remote sensing technologies offer the ability to monitor crop nutrition over large areas with high spatial and temporal resolution (Yu et al., 2023). By analyzing specific spectral bands, VIs can be derived to assess plant stress levels, and nutrient status (Xue & Su, 2017) (Fabbri et al., 2020). The Nitrogen Nutrition Index (NNI) is a widely used indicator for assessing the nitrogen status of crops, providing insights into whether a crop is experiencing nitrogen deficiency or sufficiency (Gée et al., 2023). However, the accuracy of NNI predictions can vary depending on the methods and indices used. Recent advancements in remote sensing, particularly with the availability of high-resolution satellite data like Sentinel-2, have opened new avenues for enhancing NNI prediction accuracy (Zha et al., 2020) (Gée et al., 2023) (Yu et al., 2023) (Nino et al., 2024). This study explores the integration of various VIs, including those derived from Sentinel-2, to optimize the prediction of NNI in durum wheat. By analyzing the performance of different VIs and their relationship with NNI, this research aims to refine nitrogen management practices, ultimately contributing to more sustainable and efficient agriculture.

MATERIALS AND METHODS

Site descriptions

During the 2023-2024 durum wheat growing season, this study was conducted at two experimental sites in Tunisia (Fig.1a), chosen to represent different agro-climatic zones and key phenological stages Z30 and Z60, per the Zadoks scale (Zadoks et al., 1974). Both sites followed actual field practices, reflecting the methods and techniques used by farmers in their daily agricultural activities. The first site, a 47 ha field located in Medjez El Bab, Beja Governorate (Fig.1b), typically receives 550-600 mm of annual rainfall. However, during the 2023 hydrological year, the region faced significant challenges due to adverse climatic conditions. From September 2022 to June 2023, the area experienced severe drought, with only 80 mm of rainfall.

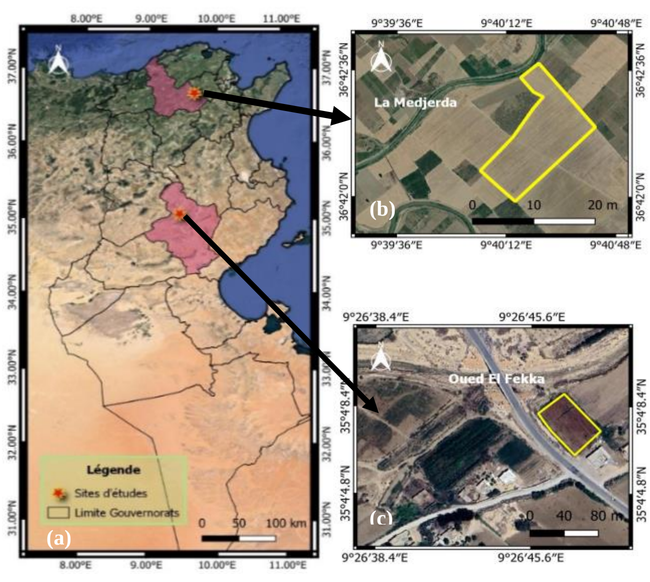

Figure 7. (a) Location of study plots in Tunisia. (b) Delineation of the study plot in Medjez el Bab. (c) Delineation of the study plot in Sadaguia, Sidi Bouzid.

The second site is in the Sadaguia region, Sidi Bouzid Governorate (Fig.3c), with an area of 0.278 ha. This site, cultivating Maali durum wheat, is situated in a semi-arid climate characterized by lower annual rainfall, averaging between 200 and 300 mm. The site features sandy loam soils, which pose specific challenges for water retention and nutrient management.

Experimentation

Sample collection points were chosen using the CropCare application, based on NDVI VI maps. In the field, one-square-meter plots were sampled to determine fresh weight. Chlorophyll content was measured with a SPAD 502Plus (SPAD), and NDVI values were recorded using a GreenSeeker (NDVI Green). In the laboratory, samples were dried at 60°C for 48 hours, then ground and analyzed for total nitrogen (%N measured) using the Kjeldahl method. Critical nitrogen levels (%Nc) were derived from dry matter values, and the NNI was calculated as the ratio of actual nitrogen absorption to critical nitrogen absorption.

Data collection and analysis

Sentinel-2 spectral bands were used to derive those traditional VIs commonly used in the literature (Tab.1) (Hatfield et al., 2019). These indices were computed over plant sample locations and at two phenological stages Z30 and Z60 using the CropCare application established by Robocare (Robocare, 2024). Measured variables (SPAD, NDVI Green, %N measured, %Nc, NNI) and VIs (Table 1)) were analyzed using descriptive statistics, correlation analysis, and multiple linear regression to determine NNI based on other parameters, all performed with R 4.4.1 statistical software.

Table 1. Vegetation Index extracted from Sentinel-2 images.

VIs	Definition	Formula	Application	References
NDVI	Normalized Difference Vegetation Index	$(NIR - Red)/(NIR + Red)$	Chlorophyll content	(Rouse et al., 1974)
NRI	Nitrogen Reflectance Index	$(Green - red)/(Green + Red)$	N content	(Diker & Bausch, 2003)
NDRE	Normalized Difference Red Edge	$(NIR - Red_{edge})/(NIR\ +\ Red_{edge})$	N content	(Barnes et al., 2000)
RESAVI	Red Edge Soil Adjusted Vegetation Index	$1{,}5\ x((NIR - Red_{edge})/NIR\ +\ Red_{edge} - 0.5))$	NNI	(Cao et al., 2013)
REDVI	Red Edge Difference Vegetation Index	$(2xNRI + 1)^2 - 8x(NRI - Red_{edge})$	NNI	
GNDVI	Green Normalized Difference Vegetation Index	$(NIR - Green)/(NIR + Green$	NNI	(Gitelson et al., 1996)
MCARI	Modified Chlorophyll Absorption Ratio Index	$(Red_{edge} - Red)/(Red_{edge} + Red)$	NNI	(Daughtry et al., 2000)

RESULTS AND DISCUSSION

Descriptive Statistical Analysis

The descriptive statistical analysis revealed notable differences between the Z30 and Z60 growth stages, particularly in key VIs and measured variables. The t-test results indicated significant variations in NDVI, SAVI, and NDVI Green, with higher values generally observed at the Z60 stage, reflecting more advanced plant development and increased biomass. Additionally, SPAD values, which measure chlorophyll content, showed a marked increase at Z60, aligning with the period of peak nitrogen demand. The %N measured and %Nc also differed significantly between stages, with higher nitrogen content observed at Z60. The NNI index was significantly higher at Z60, indicating better nitrogen status. These findings align with recent studies showing that these indicators increase with plant development and peak nitrogen demand, supporting their use for optimizing nitrogen management in durum wheat (Yu et al., 2023) (Al-Shammari et al., 2024) (Nino et al., 2024).

Correlation Analysis

The correlation analysis between various VIs and measured variables at the Z30 and Z60 stages for the Medjez El Bab and Sidi Bouzid plots revealed several key relationships. At Z30, strong positive correlations were observed between NDVI and GNDVI, NDVI and NDRE, and NDVI and RESAVI, indicating a close relationship between these indices. Additionally, NDVI Green showed strong correlations with SPAD, %N mesuré, and %Nc, while %Nc exhibited negative correlations with these variables. In contrast, the Z60 stage showed different correlation patterns, with NDRE strongly correlating with NDVI and RESAVI, while GNDVI and NRI also showed high positive correlations. Notably, the correlation between NDVI and GNDVI was positive at Z30 but negative at Z60, indicating a shift in their relationship across stages. Overall, these results highlight the varying strength and direction of correlations between VIs and N related variables at different phenological stages, underscoring the complexity of crop-nutrient interactions over time (Nino et al., 2024) (Yu et al., 2023). The shift in correlation patterns between NDVI and GNDVI across growth stages reflects similar trends reported in studies of crop development and nutrient uptake (Zha et al., 2020).

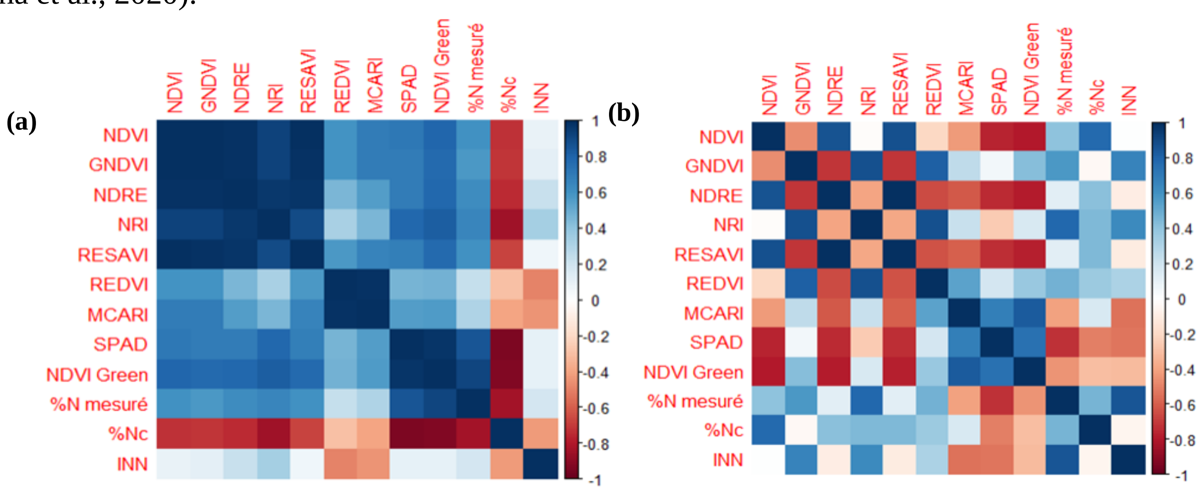

Figure 8. Correlation Matrix Between Different Variables, (a) of the Medjez El Bab Site (Z30), (b) of the Sidi Bouzid Site (Z30).

Relationship between NNI and VIs, Multiple Linear Regression Analysis

The multiple linear regression analysis focused on predicting the NNI Index using various VIs derived from the CropCare application. The model (Eq.1) achieved a high R^2 value of 0.975, explaining 97.5% of the variation in NNI. This indicates a strong predictive capability, with most

VIs contributing significantly to the model. The residuals were randomly distributed around zero, suggesting that the model accurately captured the relationships between the VIs and NNI.

$$INN = 220.60 \text{ NDVI} - 19.10 \text{ GNDVI} - 160 \text{ NDRE} + 6.27 \text{ NRI} - 48.19 \text{ RESAVI} + 0.0376 \text{ REDVI} - 0.0001456 \text{ MCARI} - 8.16 \quad \textbf{Eq.1}$$

CONCLUSION

This study demonstrates the effectiveness of VIs and regression models in optimizing nitrogen management for durum wheat. Statistical analysis revealed significant differences in VIs between stages Z30 and Z60, along with strong correlations among the indices. The linear regression model accounted for 97.5% of the variability in the NNI at stage Z30. Future research should focus on incorporating additional data sources to improve model accuracy. Additionally, conducting field validation trials to evaluate practical applicability and developing new VIs could further enhance nitrogen management strategies.

REFERENCES

Al-Shammari, D., Fuentes, I., Whelan, B. M., Wang, C., Filippi, P., & Bishop, T. F. A. 2024. Combining Sentinel 1, Sentinel 2 and MODIS data for major winter crop type classification over the Murray Darling Basin in Australia. Remote Sensing Applications: Society and Environment, 34, 101200. https://doi.org/10.1016/j.rsase.2024.101200

Barnes, E., Clarke, T. R., Richards, S. E., Colaizzi, P., Haberland, J., Kostrzewski, M., Waller, P., Choi, C., Riley, E., & Thompson, T. L. 2000. Coincident detection of crop water stress, nitrogen status, and canopy density using ground based multispectral data.

Cao, Q., Miao, Y., Wang, H., Huang, S., Cheng, S., Khosla, R., & Jiang, R. 2013. Non-destructive estimation of rice plant nitrogen status with Crop Circle multispectral active canopy sensor. Field Crops Research, 154, 133-144. https://doi.org/10.1016/j.fcr.2013.08.005

Chen, C., Zhou, S., Afshar, R. K., Franck, W., & Zhou, Y. 2023. Durum wheat yield and protein influenced by nitrogen management and cropping rotation. Journal of Plant Nutrition. https://www.tandfonline.com/doi/abs/10.1080/01904167.2022.2068432

Chen, P. 2015. A Comparison of Two Approaches for Estimating the Wheat Nitrogen Nutrition Index Using Remote Sensing. Remote Sensing, 7(4), Art. 4. https://doi.org/10.3390/rs70404527

Daughtry, C. S. T., Walthall, C. L., Kim, M. S., de Colstoun, E. B., & McMurtrey, J. E. 2000. Estimating Corn Leaf Chlorophyll Concentration from Leaf and Canopy Reflectance. Remote Sensing of Environment, 74(2), 229-239. https://doi.org/10.1016/S0034-4257(00)00113-9

Denora, M., Candido, V., D'Antonio, P., Perniola, M., & Mehmeti, A. 2023. Precision nitrogen management in rainfed durum wheat cultivation: Exploring synergies and trade-offs via energy analysis, life cycle assessment, and monetization. Precision Agriculture, 24(6), 2566-2591. https://doi.org/10.1007/s11119-023-10053-5

Diacono, M., Rubino, P., & Montemurro, F. 2012. Precision nitrogen management of wheat. A review. Agronomy for Sustainable Development, 33(1), 219-241. https://doi.org/10.1007/s13593-012-0111-z

Diker, K., & Bausch, W. C. 2003. Potential Use of Nitrogen Reflectance Index to estimate Plant Parameters and Yield of Maize. Biosystems Engineering, 85(4), 437-447. https://doi.org/10.1016/S1537-5110(03)00097-7

Fabbri, C., Mancini, M., dalla Marta, A., Orlandini, S., & Napoli, M. 2020. Integrating satellite data with a Nitrogen Nutrition Curve for precision top-dress fertilization of durum wheat. European Journal of Agronomy, 120, 126148. https://doi.org/10.1016/j.eja.2020.126148

Gée, C., Denimal, E., de Yparraguirre, M., Dujourdy, L., & Voisin, A.-S. 2023. Assessment of Nitrogen Nutrition Index of Winter Wheat Canopy from Visible Images for a Dynamic Monitoring of N Requirements. Remote Sensing, 15(10), Art. 10. https://doi.org/10.3390/rs15102510

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

Hatfield, J. L., Prueger, J. H., Sauer, T. J., Dold, C., O'Brien, P., & Wacha, K. 2019. Applications of Vegetative Indices from Remote Sensing to Agriculture : Past and Future. Inventions, 4(4), Art. 4. https://doi.org/10.3390/inventions4040071

Nino, P., D'Urso, G., Vanino, S., Di Bene, C., Farina, R., Falanga Bolognesi, S., De Michele, C., & Napoli, R. 2024. Nitrogen status of durum wheat derived from Sentinel-2 satellite data in central Italy. Remote Sensing Applications: Society and Environment, 36, 101323. https://doi.org/10.1016/j.rsase.2024.101323

Piikki, K., Söderström, M., & Stadig, H. 2022. Remote sensing and on-farm experiments for determining in-season nitrogen rates in winter wheat – Options for implementation, model accuracy and remaining challenges. Field Crops Research, 289, 108742. https://doi.org/10.1016/j.fcr.2022.108742

Robocare. 2024. RoboCare—We Tech-Care Of your Land. RoboCare - We Tech-Care Of your Land. https://robocare.tn/

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering. 1974. Monitoring Vegetation Systems in the Great Plains with ERTS. Third ERTS-1 Symposium NASA, 309-317.

Xue, J., & Su, B. 2017. Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. Journal of Sensors, 2017, 1-17. https://doi.org/10.1155/2017/1353691

Yu, F., Bai, J., Jin, Z., Zhang, H., Yang, J., & Xu, T. 2023. Estimating the rice nitrogen nutrition index based on hyperspectral transform technology. Frontiers in Plant Science, 14. https://doi.org/10.3389/fpls.2023.1118098

Zadoks, J. C., Chang, T. T., & Konzak, C. F. 1974. A decimal code for the growth stages of cereals. Weed Research, 14(6), 415-421. https://doi.org/10.1111/j.1365-3180.1974.tb01084.x

Zha, H., Miao, Y., Wang, T., Li, Y., Zhang, J., Sun, W., Feng, Z., & Kusnierek, K. 2020. Improving Unmanned Aerial Vehicle Remote Sensing-Based Rice Nitrogen Nutrition Index Prediction with Machine Learning. Remote Sensing, 12(2), Art. 2. https://doi.org/10.3390/rs12020215