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Machine learning-based in-season nitrogen status prediction using unmanned aerial vehicle remote sensing

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Abstract

Objective

The uniformity of fertilizer application across fields is a common practice, driven by local legislation or by expert opinion. However, this approach might lead to over-application of nitrogen in areas with poor yields. Human health, ecological functions, biodiversity, climate change, and long-term stability are all adversely affected by the increasing release of reactive nitrogen into the environment that may result from the excessive use of fertilizers. The purpose of this work was to show that throughout the growth season, location-specific N proposals may be generated using non-invasive crop status monitoring that is built on Remote Sensing Technologies (RST). This tracking system can accurately assess the position of crop N.

Materials and methods

In this study, two frameworks—Support Vector Machine (SVM) and Artificial Neural Networks (ANN)—that rely solely on data collected from crop sensors, with the goal of improving our ability to predict crop N Nutrition Index (NNI) and crop yield throughout the growing season were compared. This was performed by combining data from soil, weather, and cultivation with information from present detectors using Random Forest (RF).

Results

Through RST, a simple and low-cost tool known as a fixed-wing Unmanned Aerial Vehicle (UAV) may capture wavelength reflection images. This collection of images is invaluable to polystyrene nanoparticles (PNSP). Applying ML techniques enhanced the NNI estimate, as seen by the results.

Conclusions

Utilizing machine learning techniques presents a valuable opportunity to maximize the use of RST data, enabling more effective monitoring of agricultural production factors and directing PNSP strategies.

Keywords: ML, Nitrogen, Unmanned Aerial Vehicle, Remote Sensing Technologies, RF Model

Paper Type: Research Paper.

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Introduction

The uniformity of fertilizer application across fields is a common practice, driven by local legislation or by expert opinion. However, this approach might lead to over-application of nitrogen in areas with poor yields. Human health, ecological functions, biodiversity, climate change, and long-term stability are all adversely affected by the increasing release of reactive nitrogen into the environment that may result from the excessive use of fertilizers (Dong et al. 2024). polystyrene nanoparticles (PNSP) can potentially increase farmers' income, reduce groundwater and soil pollution, and significantly improve nitrogen usage efficiency. For the PNSP approach to be executed successfully, technology that can quickly and in-seasonally measure N levels across large areas is essential (Havlin 2020). Nitrate (NO_3^-) and ammonium (NH_4^+) are plant-accessible forms of nitrogen that, when applied to agricultural regions, must first undergo a conversion process before crops may absorb them (Radhika & Masood 2022). The time required for these changes to occur depends on several variables, including but not limited to fertilizer type, field humidity, temperature, pH, and soil air circulation (Havlin 2020; Raschka et al. 2022).

Applying N fertilizers in multiple stages is advised for crop production to enhance Nitrogen Use Efficiency (NUE). These phases include application fertilizer before growing or transferring (known as normal N fertilizer), during the harvesting phase (known as cultivator N fertilizer), during the panicle entry or Stem Lengthening (SL) phase (known as panicle N fertilizer), and during the Heading (Hd) phase (known as grain N fertilizer). Diagnosing the N condition of the crop at various phases of the growth season is crucial to accurately alter the rates of covering N administration (Veerasamy & Fredrik 2023). This allows for a more precise fulfillment of the crop's N requirements (Radhika & Masood 2022; Chlingaryan et al. 2018).

The NNI is a dependable indication of the N level. It is calculated by dividing the Crop N Content (CNC) by the key N content (Nc), which is the minimal CNC required for maximal Aerial Biomass (ABM) generation (Huang et al. 2018). A value of NNI more than 1 suggests an excess of N supply, whereas an NNI value less than 1 suggests a shortage in N. An NNI value around 1 denotes an ideal N intake (Padilla et al. 2020). Nevertheless, the detection of NNI necessitates the use of destructive samples and chemical examination, hence restricting its use in PNSP. Consequently, there is a growing interest in technology that enables non-invasive NNI measurement in extensive regions.

Nearest and distant sensing methods are often used to effectively and inexpensively estimate the N status of crops (Surendar et al. 2024). Several studies have utilized local canopy detectors to assess the NNI of different crops (Mumtaj 2022; Kapoor et al. 2021; Barbedo 2019; Brinkhoff et al. 2021; Dong et al. 2024). Nevertheless, the use of proximate sensors proves inefficient when applied to expansive crop fields, and installing these detectors on vehicles on the ground is unsuitable for crop cultivation. Satellite RST has been employed to track the development of crops and assess the nitrogen condition across extensive regions (Kapoor et al. 2021). The FORMOSAT-2 pictures have been employed to assess NNI and identify N state. The findings revealed that a pragmatic method included using satellite imagery to gauge crop ABM and plant absorbance of N, which was then utilized to compute Nc and NNI (Aula et al. 2020).

Most of this research concentrated on determining the most effective vegetation rating (VR) while employing the LR technique to predict NNI or additional signs of N availability. The study should progress through incorporating more substantial VRs and applying non-linear approaches to enhance the diagnostic of N level utilizing UAV-RST (Wang et al. 2022). Data generation in biology and biotechnology has greatly increased in recent years due to the very rapid development of high-performance technologies (Mohammadabadi et al. 2024). These data are obtained from studying biological molecules, such as metabolites, proteins, RNA, and DNA, to understand the role of these molecules in determining the structure, function, and dynamics of living systems (Pour Hamidi et al. 2017). Functional genomics is a field of research that aims to characterize the function and interaction of all the major components (DNA, RNA, proteins, and metabolites, along with their modifications) that contribute to the set of observable characteristics of a cell or individual (i.e., phenotype). Furthermore, in a breeding program, genetic improvement can be maximized through accurate identification of superior animals that are selected as parents of the next generation, thereby achieving breeding goals (Mohammadabadi et al. 2024). Artificial neural networks have been proposed to alleviate this limitation of traditional regression methods and can be used to handle nonlinear and complex data, even when the data is imprecise and noisy (Pour Hamidi et al. 2017). Omics data can be too large and complex to handle through visual analysis or statistical correlations. This has encouraged the use of machine intelligence or artificial intelligence (Ghotbaldini et al. 2019). In the last ten years, ML techniques have been extensively used in complicated and information-intensive fields, including healthcare, astrophysics, life sciences, and precision farming (Ghotbaldini et al. 2019). ML approaches can uncover undetected details within the information (Zoran et al. 2022). ML has a crucial benefit in effectively addressing complex non-linear issues by employing information from many sources (Angin et al. 2020). Applying ML has shown to be an effective method for solving the non-linear issue of farm RST tilting, with favorable outcomes (Liakos et al. 2018).

This research aimed to investigate the potential improvement in predicting crop NNI and crop yield during the growing season by merging soil, weather conditions, and cultivation evidence with current sensor information using RF compared to LR and SR frameworks, which rely only on crop sensor data (Mohammadabadi et al. 2024). Furthermore, the objective of this study was to illustrate that non-invasive monitoring of crop health using RST can effectively assess the N status of crops (Kapoor et al. 2021; Camgözlü & Kutlu 2023).

Materials and methods

The investigation was done during the years 2019 and 2020. Four research locations were chosen, and the soil characteristics for PNSP using UAV-RST were shown in Figure 1. Locations 1, 2, and 3 all exhibit black dirt with pH levels ranging from 5 to 5.5. These places have elevated levels of soil organic content, ranging from 18.1 to 26.3 g/kg, and total nitrogen concentrations ranging from 0.94 to 1.36 g/kg. On the other hand, site four exhibits sandy soil characterized by a higher pH level of 6, although much lower levels of soil organic content (9.8 g/kg) and total N (0.66 g/kg). These findings suggest that black soil areas often exhibit greater fertility, as seen by higher amounts of organic content and nitrogen, compared to the sandy soil location.

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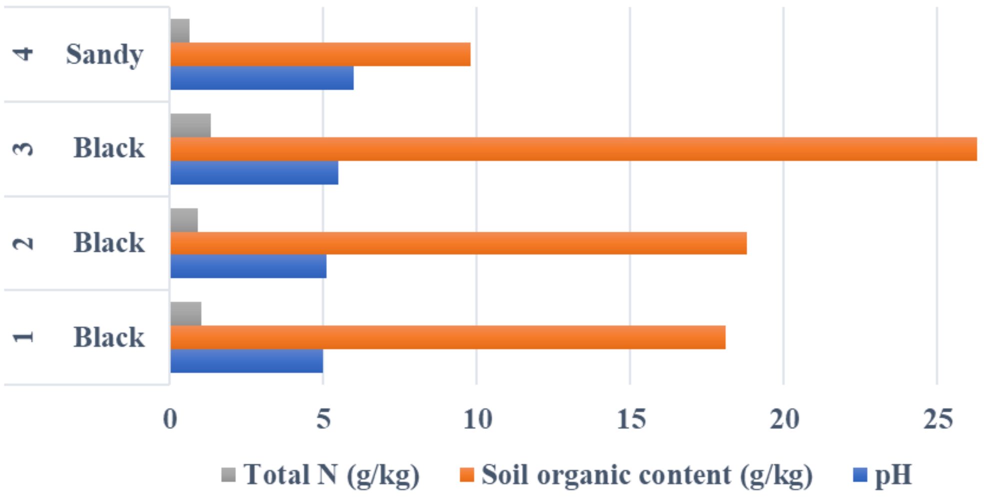

Figure 1. Properties of soil at 4 locations for PNSP using UAV-RST

The GreenSeeker ACS quantifies the electromagnetic energy returned from the plant canopy throughout the SL and Hd development stages (Wang et al. 2022). The detector was positioned roughly 0.7 m above the crop canopy in every area (specifically, four rows in the center of the fields) while the worker maintained a consistent strolling pace. The information collected from sensors from various rows within a location was computed to get the mean values that reflect the location for every site year. The GreenSeeker sensor's internal software instantly computed the Standardized Difference VR (SDVR) and Ratio VR (RVR) values. The In-season Yield forecast (INSY) was determined by dividing the SDVR and RVR values (INSYSDVR and INSYRVR) by the number of days from crop embedding to device information gathering, respectively.

Furthermore, crops were chosen to serve as representatives. The stem and leaf were divided and dehydrated in an oven at a temperature of 100 °C for 40 minutes. They were then further dried at 75 °C until a consistent weight was achieved. Lastly, the crop's ABM was measured by weighing the samples. Subsequently, the samples were crushed into a powder to evaluate the content of N in the crop using an altered Kjeldahl digestion technique. Subsequently, the NNI was generated based on the estimated concentrations of N in the crop, both real and vital, utilizing the critical N diffusion curve. During the Hd growth phase, the crop production was assessed by physically reaping two meters of 8 rows in each location, omitting the boundary rows. The obtained figures were adjusted to account for a crop moisture level of 13.5%.

Data collection and NNI characterization: Following gathering spectral information during the SL and Hd growth phases, three rows of crops were arbitrarily selected based on the mean tilling numbers in every location and uprooted. The objects were rinsed with clear water, and their root systems were eliminated with cutters. The specimens that had been washed were divided into three parts: leaves, stems, and panicles (at the Hd phase). These parts were then kept in an oven at 105℃ for 30 minutes to turn off the enzymes. Subsequently, they were dried until a consistent mass was achieved at about 80 ◦C. This process was carried out to calculate the dry ABM. The N amounts in leaves, stems, and panicles were measured with the usual Kjeldahl technique. The determination of CNC was calculated using the mean of the N of all crop sections. The Crop N Acceptance (CNA) was calculated by combining the CNC and ABM.

The NNI was computed using Equation (1)

$$NNI = Nm/Nc \quad (1)$$

where Nm is the computed N content.

The NNI was otherwise computed using CNA, as shown in Equation (2)

$$NNI = CNA/(Nc \times ABM) \quad (2)$$

CNA is the crop N acceptance (kg/ha), and ABM is represented in t/ha.

UAV-RST: This research used the eBee SQ fixed-wing UAV system manufactured by SenseFly. The UAV was equipped with a camera. This camera is equipped with a three-band multidimensional camera that has a resolution of 1.4 MP and a pixel count of 1285 × 970. The four bands include a green band with a wavelength of 560 + 25 nm, a red band with a λ of 665 + 25 nm, a red edge band with a λ of 740 + 5 nm, and a near-infrared band with a λ of 785 + 25 nm. It also has a Red Green Blue (RGB) camera with a resolution of 16 MP and a pixel count of 4688 × 3464. The device is fitted with an upward-facing brightness sensor that automatically controls the installation duration on the sensors. Before each flying mission, the camera system was calibrated for the present downwelling energy utilizing a white Spectral panel. The UAV flights were carried out from 11:00 to 15:00 under calm, cloudless weather.

The UAV regulator program eMotion 3.5.0 was used to execute the mission control and picture acquisition for the UAV. The aircraft height was 105 meters, the ground sampling proximity of 0.15 $m/pixel$, and the photos were captured with an advancing overlay of 80% and a lateral overlay of 70%. After collecting information, the geo-tagged photos were combined using Pix4Dmapper software to create a reflectivity image of the whole location, including the full test region. The combined image was rectified in ENVI 5.1 software, employing the ground control locations obtained from a high-precision GNSS receiver (Chen et al. 2019). Four orthoimages of UAV reflectance were acquired throughout the SL and Hd growth phases between 2019 and 2020. The plot borders have been recorded and utilized as areas of interest for selecting

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and averaging picture pixels at a specific collection point to establish a relationship with the ground truth information.

Results and discussion

In this study, reflectivity information (RI) from four wavelengths was used to calculate 72 VRs. Additionally, both the original RI from three wavelengths and VRs were included in the analysis. The VRs were rated based on their R^2 values concerning ABM, CNA, and NNI. The metrics that performed the best were then examined extensively. The information acquired in 2019 and 2020 was consolidated and then partitioned into a learning database (75%) and a testing database (25%) using randomization. In the years 2019 and 2020, an overall of 385 samples were collected. Of these, 289 were utilized as the learning database, while 96 were employed as the testing database.

The evaluation of the ML frameworks was conducted using three metrics: the reliability coefficient (R^2), Root Mean Square Error (RMSE), and Proportional Error (PE). Increased R^2 values and decreased RMSE and PE values indicate enhanced accuracy and precision in predicting the N status metrics. The scikit-learn and Python ML libraries were employed in this study to generate predictions for estimating AGB, CNA, and NNI. The purpose of this study was to utilize three common ML approaches: RF, SVM, and ANN regressions. The model creation process involved employing tenfold cross-validation and grid search to determine the optimal variables. The testing database was implemented to evaluate the accuracy of the frameworks.

Figure 2 depicts the testing results (R2 and PE) of various ML methods at SL and Hd for PNSP using UAV-RST. It demonstrates the relative effectiveness of three ML algorithms in predicting various crop variables: ABM in t/ha, CNA in kg/ha, and NNI. During the SL phase, the RF model consistently demonstrates higher R^2 values (0.66 for ABM, 0.63 for CNA, and 0.6 for NNI) than the SVM and ANN models. This indicates that RF has greater predictive accuracy. However, SVM often exhibits the biggest PE, indicating worse dependability. The RF model maintains strong performance throughout the Hd phase, particularly for CNA ($R^2 = 0.71$) and NNI ($R^2 = 0.8$), exhibiting low PE values and demonstrating its usefulness. ANN demonstrates strong performance, especially for NNI in the Hd phase, with a coefficient of determination of 0.79 and a PE of 0.09. Generally, the RF algorithm is the most precise method for forecasting N status during both development stages, while the SVM algorithm exhibits more fluctuation in its performance.

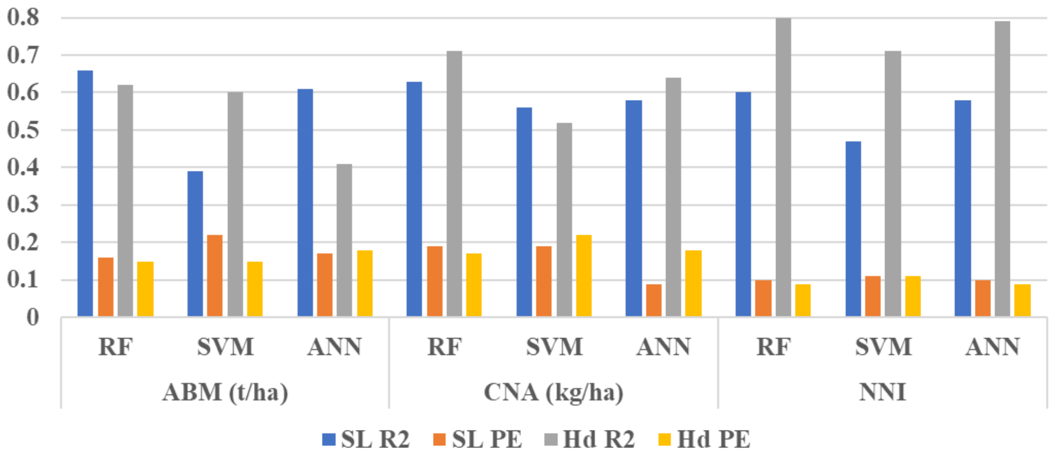

Figure 2. Testing results (R^2 and PE) of various ML algorithms at SL and Hd for PNSP using UAV-RST

Figure 3 shows the testing results (RMSE) of various ML algorithms at SL and Hd for PNSP using UAV-RST. Regarding forecasting ABM, RF demonstrates the lowest RMSE in both the SL (0.59) and Hd (1) phases, showing the best level of accuracy. Following RF, ANN and SVM also exhibit good accuracy. Regarding predicting CNA, the RF method consistently outperforms SVM and ANN regarding RMSE. Specifically, RF obtains lower RMSE values of 10.32 at SL and 15.65 at Hd, making it the most dependable approach for predicting this variable. Regarding NNI, all three algorithms exhibit comparable performance, with both RF and ANN obtaining an RMSE of 0.09 during SL and Hd. Overall, RF consistently exhibits superior predictive performance throughout the variables and development phases, especially minimizing PEs.

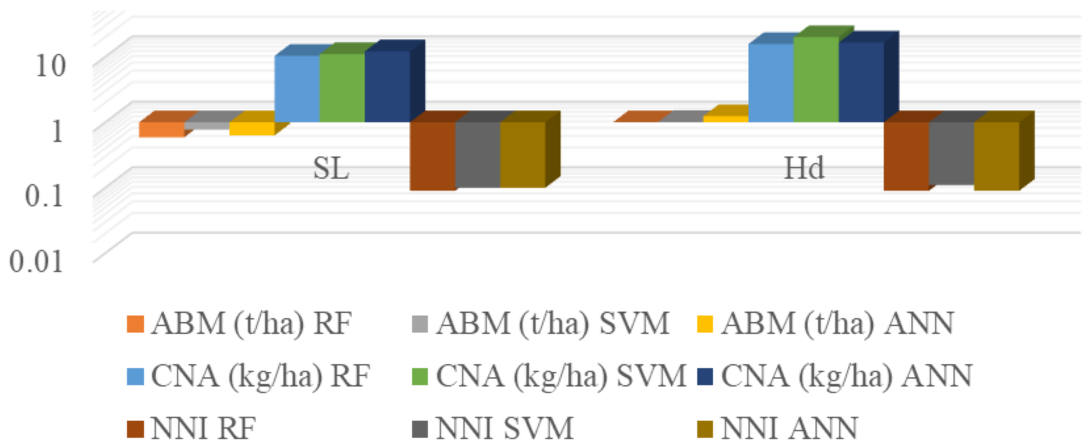

Figure 3. Testing results (RMSE) of various ML algorithms at SL and Hd for PNSP using UAV-RST

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Figure 4 illustrates Nitrogen status prediction in the study location using NNI predicted by RF at SL during 2018 with UAV-RST**.** The N status assessment maps for the research region were generated using fixed-wing UAV-RST photos and RF models during the SE phase of 2019 to anticipate the NNI. During the SL stage, most crop fields had ideal or excess nitrogen levels, with fewer places experiencing nitrogen deficiency.

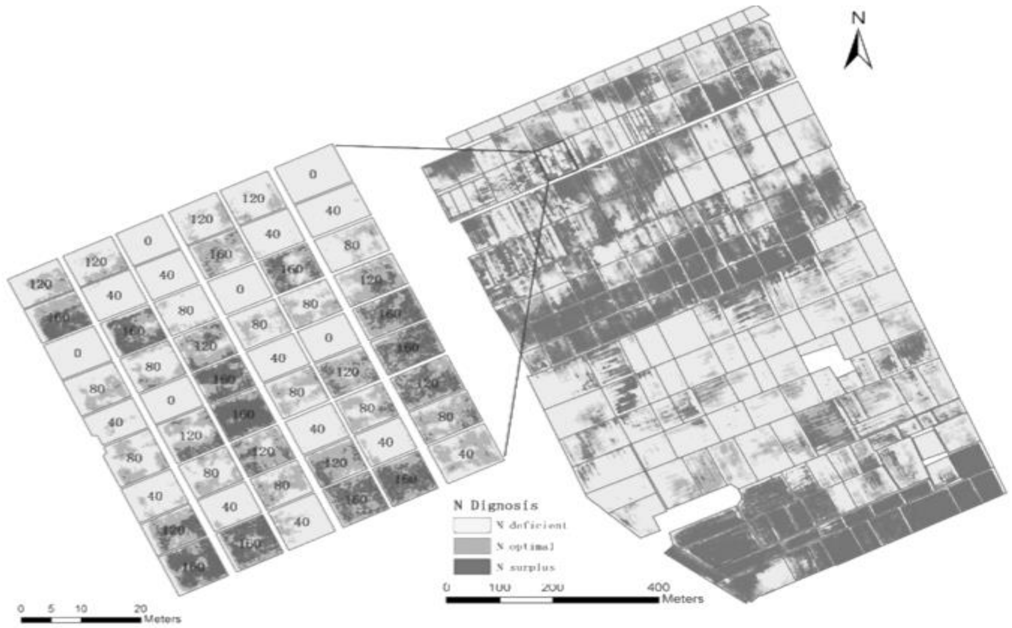

Figure 4 Nitrogen status prediction in the study location using NNI predicted by RF at SL during 2019 with UAV-RST

Soil characteristics, weather, and crop management strategies are some of the variable production parameters that determine the variability in crop growth and grain output. Similarly, the soil nitrogen supply and crop nitrogen demand may be shown by the crop's growth condition and production potential. To enhance crop management, it is crucial to have reliable and up-to-date information on crop growth status and grain production projection. The most popular and user-friendly approach to predicting crop NNI and grain production is the one-factor PNSP model. Of the corn NNI and grain yield variability seen in the test dataset, the PNSP models using RF and SVM were only able to explain 71% and 762% and 65-25% of the variability, respectively.

Conclusion: The PNSP relies heavily on accurate and effective approaches to diagnosis and advice on N levels throughout the growing season. By combining evidence from soil, climate, and culture with current sensor data utilizing the RF method, this study hopes to better forecast NNI and crop output throughout the growing season. This framework will be contrasted with the SVM and ANN frameworks, which exclusively depend on crop sensor data. The aim of this paper

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was to demonstrate that RST can accurately determine the N status of crops without the need for invasive procedures. Throughout the growing season, location-specific N recommendations may be made using the data. The UAV-RST, a fixed-wing vehicle, is a user-friendly and cost-effective technology that captures images through wavelength reflection. These images are an invaluable asset to PNSP. The results showed that ML methods enhanced NNI prediction.

The RF algorithm outperforms the SVM technique in terms of predicting the N status during all the development phases, which shows a greater variation in performance. In 2019, RF models were used during the SE phase to estimate the NNI, and fixed-wing UAV-RST photos were used to generate the N condition assessment maps for the training zone. Nitrogen deficiencies were less common in agricultural fields during the SL stage, whereas most fields showed either optimum or high N levels.

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Conflict of Interest: There is no conflict of Interest.

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پیش‌بینی وضعیت نیتروژن در فصل مبتنی بر یادگیری ماشین با استفاده از سنجش از راه دور هواپیمای بدون سرنشین

پریا ویج

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چکیده

هدف: یکنواختی کاربرد کود در مزارع یک روش معمول است که توسط قوانین محلی یا نظر متخصص هدایت می‌شود. با این حال، این رویکرد ممکن است منجر به استفاده بیش از حد از نیتروژن در مناطق با عملکرد ضعیف شود. سلامت انسان، عملکردهای اکولوژیکی، تنوع زیستی، تغییرات آب و هوا و پایداری درازمدت، همگی تحت تأثیر انتشار فزاینده نیتروژن فعال در محیط هستند که ممکن است در نتیجه استفاده بیش از حد از کودها باشد. هدف از این کار نشان دادن این بود که در طول فصل رشد، پیشنهادات نیتروژن خاص مکان ممکن است با استفاده از نظارت بر وضعیت محصول غیرتهاجمی که بر اساس فناوری‌های سنجش از راه دور (RST) ساخته شده است، تولید شود. این سیستم ردیابی می‌تواند موقعیت محصول نیتروژن را به دقت ارزیابی کند.

مواد و روش‌ها: در این مطالعه، دو چارچوب – ماشین بردار پشتیبان (SVM) و شبکه‌های عصبی مصنوعی (ANN)، که تنها بر داده‌های جمع‌آوری‌شده از حسگرهای محصول متکی هستند، با هدف بهبود توانایی ما در پیش‌بینی شاخص تغذیه N محصول (NNI) و عملکرد محصول در طول فصل رشد مقایسه شدند. این کار با ترکیب داده‌های خاک، آب و هوا و کشت با اطلاعات آشکارسازهای فعلی با استفاده از جنگل تصادفی (RF) انجام شد.

نتایج: از طریق RST، یک ابزار ساده و کم‌هزینه که به عنوان وسیله نقلیه هوایی بدون سرنشین (UAV) با بال ثابت شناخته می‌شود، می‌تواند تصاویر بازتابی با طول موج بگیرد. این مجموعه از تصاویر برای PNSP ارزشمند است. همانطور که در نتایج مشاهده می‌شود، استفاده از تکنیک های ML تخمین NNI را افزایش داد.

نتیجه‌گیری: استفاده از تکنیک‌های یادگیری ماشین فرصتی ارزشمند برای به حداکثر رساندن استفاده از داده‌های RST، امکان نظارت مؤثرتر بر عوامل تولید کشاورزی و هدایت استراتژی‌های PNSP را فراهم می‌کند.

واژه‌های کلیدی: فناوری های سنجش از دور، مدل RF، نیتروژن، وسیله نقلیه هوایی بدون سرنشین، ML

نوع مقاله: پژوهشی.

استناد: پریا ویج، واسانی ویبهاو پراکاش (۱۴۰۳) پیش‌بینی وضعیت نیتروژن در فصل مبتنی بر یادگیری ماشین با استفاده از سنجش از راه دور هواپیمای بدون سرنشین. *مجله بیوتکنولوژی کشاورزی*، ۱۶(۳)، ۲۴۳-۲۵۶.

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