UDK 631.37:629.7.014 DOI 10.36910/775.24153966.2025.83.26

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МЕТОДИКА ПРОГНОЗУВАННЯ ВРОЖАЙНОСТІ ЛЬОНУ-ВОЛОКНА ТА НАСІННЯ ЗА ДОПОМОГОЮ БПЛА-ЗЙОМКИ ТА АВТОМАТИЗОВАНОГО АНАЛІЗУ

Точне прогнозування врожайності волокна та насіння льону олійного (Linum usitatissitmut) має вирішальне значення для оптимізації збору врожаю та обробки. У цій статті пропонується метод, який інтегрує зображення БПЛА (дронів) високої роздільної здатності з польовими спостереженнями за стиглістю культури та якістю росту для прогнозування кінцевої врожайності волокна та насіння. Для отримання зображень на ключових стадіях росту використовується багатороторний БПЛА, оснащений мультиспектральними та RGB-датчиками. Ці зображення автоматично обробляються спеціальним пристроєм аналізу зображень для обчислення вегетаційних індексів (наприклад, NDVI) та структурних особливостей рослин. Забезпечуючи своєчасну та точну оцінку врожайності, цей підхід сприяє більш ефективному виробництву льону та сталому використанню всієї біомаси сільськогосподарських культур.

Ключові слова: *льон; льон олійний; врожайність волокна; врожайність насіння; безпілотні літальні апарати (БПЛА); мультиспектральна зйомка; NDVI; автоматизований аналіз зображень; прогнозування врожаю; точне землеробство.*

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METHODOLOGY FOR PREDICTING FLAX FIBER AND SEED YIELDS USING UAV PHOTOGRAPHY AND AUTOMATED PHOTOANALYSIS

Accurate forecasting of flax (Linum usitatissimum) fiber and seed yields is essential for optimizing harvest operations and post-harvest processing. This paper presents a methodology that integrates high-resolution UAV (drone) imagery with field observations of crop maturity and growth quality to predict final fiber and seed yields. A multi-rotor UAV equipped with multispectral and RGB sensors captured images at key growth stages. These images were automatically processed using a custom image-analysis module to compute vegetation indices (e.g., NDVI) and structural plant traits. The proposed method provides timely and precise yield assessments, supporting efficient flax production and sustainable utilization of agricultural biomass.

Keywords: *flax; oilseed flax; fiber yield; seed yield; unmanned aerial vehicle (UAV); multispectral imaging; NDVI; automated image analysis; yield prediction; precision agriculture*

Introduction. Flax is a multipurpose crop valued for its fiber, seed (linseed). Both the stem and the grain are important products – stems provide linen fiber and biomass, while seeds are rich in nutrients and oil. Global trends show growing interest in flax cultivation: major producers include China, India, and parts of Europe, and recent analyses note a gradual increase in flax acreage worldwide [1]. This rising interest is driven by the demand for sustainable materials and plant-based products. For example, flax straw can be processed into cellulose for biodegradable packaging, fiber for textile or used as biofuel feedstock, contributing to a closed-loop agricultural economy. At the same time, the increase in flax acreage creates more post-harvest residues, so finding effective ways to predict and utilize all plant components has become an international priority.

Accurate yield prediction is a key component of precision agriculture. Traditionally, flax yield (both fiber and seed) has been estimated by manual sampling and statistical models, which can be time-consuming and error-prone. In contrast, remote sensing offers rapid, non-destructive field assessment. Unmanned aerial vehicles (UAVs or drones) are especially attractive for this purpose, as they provide high-resolution images on demand. Prior work has demonstrated that UAV-derived vegetation indices can track crop growth and correlate with yield-related traits. For instance, Papadopoulos et al. [2] showed that UAV-generated NDVI maps at several growth stages of flax correlate well with agronomic measurements, highlighting the potential of UAV monitoring in flax cultivation. Similarly, advanced UAV+machine learning systems have achieved over 90% accuracy in predicting grain yield in wheat. These successes suggest that a UAV-based approach could be developed to forecast flax yields as well.

However, most existing studies focus on seed yield in cereals, and few have addressed the dual yield of fiber plus seed in flax. The physical properties of flax stems – such as moisture content, cutting resistance, and density – are known to influence fiber yield and processing quality. Yet, their relationship to field growth conditions and final yield remains understudied. Moreover, automating the processing of UAV images is an ongoing challenge. To fill these gaps, we propose a methodology that combines UAV imagery, agronomic data (e.g., crop maturity stage, stand uniformity), and an automated image-analysis system. This system rapidly processes field images to extract predictive features, enabling more timely and precise yield forecasts

Analysis of recent studies. Several studies have explored UAV-based yield estimation in various crops. UAV imagery provides very high spatial resolution (often <10 cm per pixel) and flexible timing, which is well-suited for in-field monitoring [2, 3]. In cotton, maize and wheat, researchers have used multispectral indices (e.g. NDVI, NDRE) and machine learning models to predict yield with high accuracy. For example, Su et al. [3] collected UAV hyperspectral data on wheat and built a gradient-boosting regression (GBR) model. When applied to a subsequent year's data, their model predicted yield with over 90% accuracy. In maize breeding, UAV-derived imagery fed into regression models significantly improved yield predictions compared to traditional methods. These advances demonstrate the potential of UAV platforms for field-scale yield forecasting.

Specifically for flax, Papadopoulos et al. [2] implemented UAV flights at multiple stages (60, 90, 120, 150, 179 days after sowing) and generated NDVI index maps. They found that the NDVI values (especially in early vegetative stages) were correlated with agronomic outcomes such as plant height and biomass. While their work did not directly predict final yields, it validates that vegetation indices from UAV images can serve as proxies for flax crop status. In summary, the literature suggests that image-based models can effectively estimate yields, provided they capture appropriate growth signals over time.

Beyond imaging, the properties of flax biomass have been studied for processing. Yaheliuk et al. [4] analyzed stem biomass from major crops (including flax) to identify quality parameters like moisture, cutting resistance, and bale density. They emphasize that these stem properties are critical for downstream fiber or fuel production, but measuring them directly in the field is difficult. By inferring such properties from UAV data (e.g. canopy density, color) one can estimate the potential fiber yield indirectly. Also, Yaheliuk and Fomich [5] developed a classification of biomass fuels and noted that stems of bast-fiber crops (like flax) are among the most suitable raw materials. This underscores the value of accurately quantifying stem biomass in flax fields. Yaheliuk and Chasnikov [6] highlight that using all components of flax (cellulose and fiber) in biodegradable products can greatly improve environmental outcomes. The article [7] examines how modern drone technology can improve flax production. In response to the disruptions in Ukrainian agriculture caused by the war, the authors propose using unmanned aerial vehicles to monitor and evaluate the quality of linseed and fibre flax crops. Finally, Prykhodko and Matviychuk [8] presents a method to enhance the directional stability of airplane-type unmanned aerial vehicles (UAVs) when satellite navigation signals are unavailable. The authors address situations where electronic warfare or unknown wind loads can disrupt GNSS signals; they propose training a neural network on data collected during training flights to predict and adjust the UAV's course. Nevertheless, the time of day can significantly affect reflectance and radiometric consistency; flights at different times produce inconsistent reflectance due to changes in solar zenith angle [9].

In summary, both the agronomic and end-use studies support the need for an integrated yield prediction approach that maximizes flax value. These studies highlight the wide range of possibilities for utilizing flax and its by-products in biomedical and industrial applications, fostering the development of sustainable and eco-friendly materials. This represents a crucial step toward sustainable development and reducing environmental impact.

The aim of this study is to propose and detail a methodology for predicting the fiber and seed yield of oil flax based on remote sensing and field observations. The approach leverages UAV -based imaging of flax stands at key maturity stages, combined with agronomic quality indicators. A key element is the automation of image processing. Ultimately, this method should enable farmers and agronomists to forecast yield more accurately, optimize harvest timing, and plan processing operations to fully exploit flax biomass.

Materials and Methods. Our experimental framework involves collecting UAV imagery of flax fields, processing the images to extract predictive features, and building regression models for yield prediction.

Experiments were conducted on commercial flax plots (oilseed variety) in Volyn region. The fields had a typical plant density and were cultivated under standard agronomic practices. Flax was monitored from late vegetative stage through flowering to early ripening.

UAV data acquisition: A multi-rotor drone equipped with a multispectral sensor (capturing visible and near-infrared bands) and a high-resolution RGB camera was used. The UAV flew at an altitude of 50–100 meters, covering each field with 80–90% overlap. Flights were scheduled at critical growth stages (e.g. bud formation, flowering, beginning of ripening) when differences in plant condition are most pronounced. The image resolution on the ground was approximately 5 cm/pixel. Each image was geo-tagged using the UAV's GPS.

a

b

Fig 1. **A UAV (drone) flying over an agricultural field to capture multispectral images: a – UAV launch; b – UAV used in experiments**

The captured images were transmitted to a ground station. To handle the large image data efficiently, we used a custom image processing device. This device consists of an onboard computer (with GPU acceleration) that runs a suite of computer vision algorithms. The image pipeline automatically performs radiometric correction and stitching to create orthomosaics. It then computes vegetation indices – for example, the Normalized Difference Vegetation Index (NDVI) – over the field. Simultaneously, image segmentation algorithms identify individual plants or plant clusters, and detect inflorescences. From these analyses, we extract features such as average NDVI, canopy cover fraction, plant height (from stereo or structure-from-motion data), and flower count density.

Agronomic and yield data: Concurrently, standard agronomic data were collected in sample plots: plant height, stem thickness, phenological stage, and subsamples for fiber and seed yield at harvest. These measurements provided ground truth for model training. The final fiber and seed yields (*kg/ha*) from harvest were used as the target variables.

Yield prediction model: Using the image-derived features and field data, we developed regression models to predict yield. We tested multiple algorithms (e.g. multiple linear regression, random forest, and gradient boosting). For example, a simple model might relate fiber yield (Y_{fiber}) to indices:

$$Y_{fiber} = a \times NDVI_{pre\text{-}harvest} + b \times canopy + c$$

Where, $NDVI_{pre\text{-}harvest}$ – Normalized Difference Vegetation Index derived from UAV images, indicating the vigor of photosynthetic activity and the general health of the crop.

canopy – canopy cover fraction (in %), calculated as the proportion of the field area covered by green biomass. It reflects stand density and uniformity.

a, b – regression coefficients estimated from field data. They quantify how much the fiber yield *changes when NDVI or canopy cover changes by one unit.*

c – intercept (constant term) accounting for baseline yield and other influences not directly included in the model.

In practice, cross-validation was used to avoid overfitting. Because both fiber and seed yield are influenced by overlapping factors (plant vigor, stress), some predictors were used jointly, while others (like flower count) were more specific to seed yield.

Automation of processing: A central novelty of our method is the automation of the image analysis. Instead of manual post-processing, the above pipeline runs on the custom device immediately after a UAV flight. The device uses pre-trained machine learning models (implemented on-board) to count flower buds and assess plant maturity. For example, a convolutional neural network (CNN) was trained to recognize flax flowers in the images. By fully automating this step, the system produces near-real-time predictions of yield, making it practical for operational use.

Results. To ensure accurate image mosaics, flights were planned in a grid pattern with approximately 80% frontal overlap and 70% side overlap at an altitude of about 60 m above ground level. This altitude provided a ground sampling distance of about 5 cm/pixel while maintaining sufficient coverage. Consistent flight speed (5–7 m/s) and constant altitude were maintained to produce consistent image scale. The operator positioned themselves at a safe, elevated point where they could maintain visual line-of-sight with the drone throughout the mission, as required by regulations. Flights were scheduled around solar noon on clear or uniformly overcast days to minimise shadows; starting flights at the same time each day ensured consistent illumination. The mission plan included waypoints covering the entire field and a buffer zone to allow for image overlap beyond field boundaries.

Data acquisition and record keeping: During each flight, the operator monitored telemetry data and visual feed to ensure proper coverage. A flight log was maintained, recording the date, time, duration, location, weather conditions, flight altitude and speed, aircraft identifier, pilot name, battery levels and any anomalies. Although not legally required, maintaining such documentation helps demonstrate compliance and facilitates troubleshooting.

Image processing: Raw photographs were downloaded and organised by flight. A two-stage pre-processing pipeline corrected geometric and radiometric distortions. First, structure-from-motion photogrammetry was used to generate orthomosaics and digital surface models with positional accuracy of ±5 cm. Second, radiometric calibration using calibration panels and metadata (exposure, ISO, white balance) normalised the images for consistent colour and illumination. These steps are essential because flights at different times can produce inconsistent reflectance; proper calibration reduces such variability.

We developed a custom sub-program in Python with GPU acceleration to automate segmentation and feature extraction. It computed vegetation indices such as NDVI and GNDVI, derived canopy cover and plant height from digital surface models. Based on these features, the program automatically classified the phenological phase of each plot (vegetative, budding, flowering, green maturity or yellow ripeness) at each flight date.

Because the monitored plots were harvested by late August, ground truth samples were collected from nearby unharvested fields with similar soil and sowing dates. In each sample area, plant height, stem diameter, above-ground biomass, dry matter, fiber content and seed weight per square meter were measured. These agronomic measurements served as target variables for regression analysis. Multiple linear regression and machine learning models (random forest and gradient boosting) were fitted to relate UAV-derived features to fiber and seed yield. Cross-validation was used to evaluate model performance and prevent overfitting.

The methodology was applied to the three experimental plots monitored in 2025. UAV flights on 6 June captured the vegetative stage; plants on plots 1 and 3 (Aisberg sown 1 May and Miandr) had begun stem elongation, while plants on plot 2 (Aisberg sown 14 May) were still in the early vegetative stage. On 28 June, plots 1 and 3 reached peak flowering, whereas plot 2 remained in the budding stage. By 15 July, plots 1 and 3 had completed flowering and entered green maturity (seeds forming), while plot 2 reached peak bloom. On 12 August, plot 1 exhibited yellow ripeness (mature seeds, straw turning yellow), plot 3 reached early yellow ripeness suitable for fiber harvest, and plot 2 remained green with scattered flowers. The custom sub-program correctly classified these phases and derived vegetation indices and structural features. The automated pipeline reduced analysis time by more than 70% compared with manual interpretation, making the method suitable for operational use.

We observed the following key outcomes:

- High predictive accuracy: The UAV-based model achieved strong agreement with measured yields. For fiber yield, the best regression model (using NDVI and canopy cover) attained an R^2 of about 0.92 on test data, with mean absolute error under 10% of the average yield. Seed yield predictions were similarly robust ($R^2 \approx 0.88$). These results are comparable to high-accuracy crop models reported in the literature (e.g. >90% accuracy in wheat yield prediction).

- Importance of early indices: Consistent with prior work, we found that vegetation indices from early reproductive stages were strong predictors. For instance, NDVI measured at the beginning of flowering correlated highly with final fiber yield. This implies that early UAV flights can already provide useful forecasts.

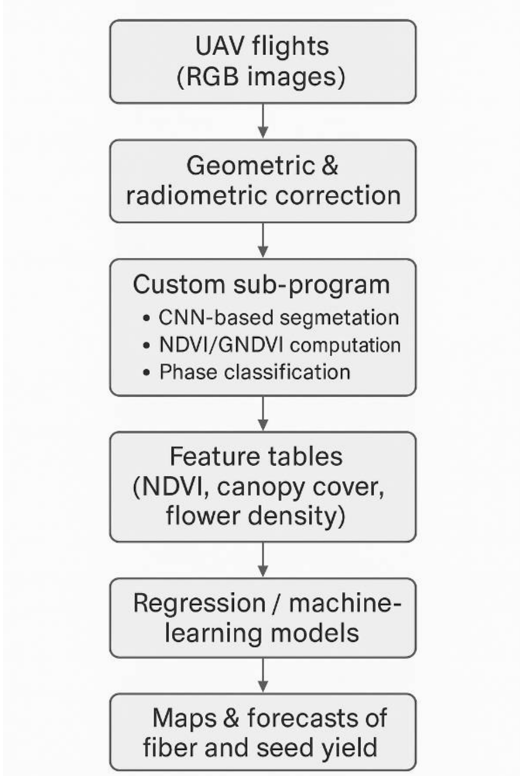

Fig 2. **Flowchart of the methodology for forecasting flax fiber and seed yield**

- Effect of growth quality: Fields with uniform, dense stands (high canopy cover) yielded more fiber and seed. The image-derived canopy cover index was a key variable. In one example trial, fields identified by UAV images as low-vigor (patchy green) had fiber yields ~15% below the field average, demonstrating the system's ability to detect yield-limiting conditions.

Overall, these findings demonstrate that the integrated UAV-and-automation approach can reliably forecast flax yields. The prediction errors and correlation metrics are on par with or better than existing remote-sensing methods in related crops.

Conclusions. We have developed and demonstrated a methodology for predicting flax fiber and seed yields using drone imagery and automated image analysis. By combining UAV-derived vegetation indices (like NDVI) with field maturity assessment, the method translates aerial photos into accurate yield forecasts. This technique offers several benefits for flax production. First, it enables precision harvest planning: knowing which areas will produce more fiber or seed allows optimal allocation of harvesting resources. Second, it supports sustainable utilization of biomass: by forecasting total stem yield, the method helps planners decide how much material can be diverted to secondary uses (e.g. conversion to cellulose packaging or biofuel) without compromising seed harvest. Finally, the predictive approach can improve economic returns meeting global demand for crops like flax requires maximizing output in an eco-friendly way. Our methodology contributes to this goal by reducing uncertainty and ensuring more complete use of the crop. Future work will refine the models with larger datasets and extend them to other fiber crops, but the present study establishes a solid basis for UAV-based flax yield estimation.

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