

FORECASTING WHEAT LEAF DISEASE DEVELOPMENT USING SPECTRAL SIGNATURE DYNAMICS FROM SATELLITE AND GROUND-BASED DATA

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Received: July 22th 2026 / Accepted: July 24th 2026 / Published: October 1st 2026

<https://doi.org/10.24057/2071-9388-2026-4712>

ABSTRACT. In the context of modern agricultural land management systems, precision agriculture is becoming increasingly relevant. Remote sensing is one of the most promising sources of operational crop information. Nevertheless, despite the growing interest, there is still a lack of research to make the transition from theoretical knowledge to the precise practical application of fungicides. This study evaluates whether integrating satellite remote sensing with ground-based spectrometry can reliably predict early-stage development of the pathogenic background in winter wheat, including overall disease pressure and specific pathogens, under real field conditions in both conventional tillage and no-till systems, with the goal of supporting precision farming applications. The experiment was conducted in the experimental fields of the research institute in Krasnodar Krai, Russia. Test plots were created with different methods of pre-sowing soil cultivation (conventional tillage and no-till farming), as well as with an artificial infectious background and disease-free control plots. The study used data from ground-based spectrometry and space imaging by the Planet Scope satellite constellation. The results indicate that spectral data are correlated with pathogen dynamics and allow predicting disease manifestation. Prediction accuracy is likely to improve with denser observations and more reliable input data. The most informative spectral ranges for detecting diseases were 443, 490 and 865 nm. This study describes a methodology for predicting winter wheat diseases and highlights the potential of using spectral data for precision agriculture.

KEYWORDS: winter wheat, wheat pathogen, phytosanitary monitoring, remote sensing, hyperspectral spectrometry, crop disease detection

CITATION: Sereda I. I., Kremneva O. Yu., Danilov R. Yu., Gasiyan K. E., Zimin M. V. (2026). Forecasting Wheat Leaf Disease Development Using Spectral Signature Dynamics From Satellite And Ground-Based Data. *Geography, Environment, Sustainability*, 3 (19), 188-203

<https://doi.org/10.24057/2071-9388-2026-4712>

ACKNOWLEDGEMENTS: The authors gratefully acknowledge the support provided within the State Assignment of the Ministry of Education and Science of the Russian Federation, topic No. FGRN-2025-0007, under which ground-based spectrometry and visual assessment of wheat disease development were carried out. Special appreciation is given to the Center of Collective Usage "Geoportal, Lomonosov Moscow State University" for providing access to the ASD FieldSpec 3 Hi-Res spectroradiometer within the state budgetary theme No. 121051400061-9. We also extend our sincere thanks to the Institute of Geography, Russian Academy of Sciences, for additional support under State Assignment No. FMWS-2024-0009, No. 1023032700199-9, for providing satellite imagery data. These contributions were instrumental in the successful completion of this study.

Conflict of interests: The authors reported no potential conflict of interests.

INTRODUCTION

Precision agriculture is increasingly used as a framework for site-specific crop management. Most of the current research in precision agriculture using space or UAV-based images studies plant abiotic stresses related to water stress, soil properties, or nutrient deficiencies (Liu et al. 2021). Biotic stress factors must also be considered, because effective crop management cannot be achieved if disease pressure is ignored. For example, by 2030, the European Union plans to reduce the use of chemical-synthetic plant protection products up to 50%. To achieve this, it is necessary to develop both biological plant protection products and effective methods for the early detection of disease outbreaks in the fields (Rieker et al. 2023).

Winter wheat is an integral part of the global agricultural system due to its resilience and high climate adaptivity. Wheat production and export are important components of the economies of many countries. Therefore, a significant part of the research on plant diseases using spectral data is aimed at this crop (Abdulridha et al. 2023; Bohnenkamp et al. 2019; Feng et al. 2022; Kremneva et al. 2023).

Modern academic literature analysis proves that, at present, optical remote sensing methods are widely used along with visual disease detection and damage assessment methods. Hyperspectral ones are considered the most promising (Dubrovskaya et al. 2019). However, such technology gives reliable results only in the late stages of disease development, when preventive measures are no longer effective. In this regard, the practical application of hyperspectral data is an open problem, despite the increasing number of studies on this topic (Bravo et al. 2003). Early detection contributes to the timely implementation of protective measures. They, in turn, contribute to increasing the economic efficiency of protective measures and reducing the pesticide pressure on agroecosystems (Bajwa et al. 2017; Lowe et al. 2017; Rumpf et al. 2010) are often obtained only after symptoms become well developed, and papers that combine the following aspects remain rare:

- accurate forecasting of pathogen dynamics both in the context of the general pathogenic background and individual characteristics of each pathogen;
- a series of field spectrometric measurements, accompanied by sub-satellite observations carried out by phytopathology experts;
- the use of large-sized plots suitable for both ground and satellite imaging;
- a sufficient number of experimental plots allowing for modeling using machine learning methods.

Such knowledge is necessary for moving from theoretical remote-sensing diagnostics to practical precision farming (Dubrovskaya et al. 2019).

The transition from detection to prognosis is an important step in the development of practical pathogen field management (Bravo et al. 2003). Early detection contributes to the timely implementation of protective measures. They, in turn, contribute to increasing the economic efficiency of protective measures and reducing the pesticide pressure on agroecosystems (Bajwa et al. 2017; Lowe et al. 2017; Rumpf et al. 2010). In this case, the basis of the predictive model for the pathogen development is the study of the dynamics of the spectral image of agricultural crops against the background of the disease development in the growing season, taking into account the key stages of the ontogenesis of cultivated plants (Li et al. 2020; Singh et al. 2019). In this regard, a number of studies have been conducted on the early diagnosis of agricultural pathogens.

Laboratory and controlled-field studies show that hyperspectral measurements can detect pathogen-related spectral changes several days before visible symptoms, including changes in the visible, SWIR, and NIR ranges and strong responses near 720–1075 nm. However, these results still need to be tested under real field conditions, where several pathogens and stress factors may interact simultaneously (Huang et al. 2015; Jung et al. 2021; Liu et al. 2023; Mahlein et al. 2019; Rieker et al. 2023; Terentev et al. 2023).

Light, weather, and poorly predictable factors in the field experiments differ greatly from the laboratory ones. This poses a number of additional challenges for researchers. One such challenge is the identification of specific pathogens in real field conditions, where multiple stress factors interact simultaneously (Das et al. 2018; Susič et al. 2018). To solve this problem, it is necessary to combine high-resolution satellite data with the results of surveys obtained using sub-satellite ground observations, taking into account the biological aspects of the experiment to construct a consistent time series of remote sensing data (Cheshkova 2022).

Current research into early detection of crop pathogens is mainly based on laboratory data or unmanned aerial vehicle (UAV) imaging. At the same time, the potential of satellite images remains underutilized due to the complexity of such experiments, such as the unreliability of data acquisition due to cloudiness, low resolution, and frequency of sensing. However, space imaging allows scaling up field research experience from small experimental sites to larger territories. This in turn facilitates monitoring over larger areas, including the regional level.

Satellite and multi-scale remote sensing have been successfully applied to several crop diseases and health-monitoring tasks, especially when these data are combined with UAV data and machine-learning models (Bi et al. 2020; Chang et al. 2024; Maimaitijiang et al. 2020; Sagan et al., 2019; Tussupov et al. 2024; Yudarwati et al. 2020). However, comparable studies focused specifically on winter wheat disease forecasting remain scarce.

In winter wheat, foliar disease epidemics are tightly synchronized with host phenology (Ababa 2023). Powdery mildew (*Erysiphe graminis*) commonly intensifies from stem elongation (Z30–39 Zadoks scale) through heading (Z50–59) and flowering–early grain fill (Z60–75); field monitoring of mildew progress is often reported across late stages such as Z49–75, consistent with continued development during reproductive growth (Věchet 2006). Tan spot (*Pyrenophora tritici-repentis*) can infect wheat at any growth stage, including seedlings, but yield-relevant damage is typically linked to the period when infection reaches upper leaves during stem elongation to heading (≈Z30–69) (Ababa 2023). Septoria leaf spot (*Septoria tritici*) is driven by wind-dispersed primary inoculum (ascospores) and rain-splash secondary spread, so the critical window for rapid canopy “laddering” to upper leaves often aligns with Z32–55 under frequent rainy days, with substantial impact when infection reaches the flag-leaf complex around heading/early flowering (Bankina et al. 2018). Compared with conventional ploughing, no-till (or reduced tillage) tends to increase tan spot because infected residues remain near the soil surface and sustain inoculum. For Septoria, tillage effects are more variable and may be outweighed by weather; in some datasets, ploughing did not reduce Septoria severity, supporting the dominant role of rainfall-driven dispersal and external inoculum. In contrast, no-till effects on powdery mildew are often weaker and inconsistent, because the pathogen

is primarily sustained via living hosts and airborne conidia (Bankina et al. 2018).

Previous field experiments in Russia and Bulgaria have shown that ground-based spectrometry can identify informative disease-related spectral features in winter wheat and can help relate these features to UAV and satellite observations (Danilov et al. 2024; Ganeva et al. 2024; Kremneva et al. 2023; Sereda et al. 2023). These studies confirm the general applicability of spectral measurements for detecting biotic stress in wheat crops. However, the transition from detection to forecasting under real field conditions remains insufficiently tested, especially when several pathogens, different tillage systems, and incomplete satellite time series are considered simultaneously. The present study, therefore, extends previous work by evaluating whether satellite imagery combined with ground spectrometry can be used not only to detect disease-related spectral differences but also to forecast pathogen development at the plot level.

Here we aim to evaluate whether satellite remote sensing combined with ground spectrometry can predict the early development of the pathogenic background of wheat agroecosystems, both at the level of overall disease pressure and of individual pathogens, under real-field conditions. The experiments were performed under no-till and conventional tillage to test the approach across contrasting tillage systems and enable its use in precision agriculture. The study design was informed by previously identified gaps in this research area.

MATERIALS AND METHODS

Experimental Design

The experiment was conducted on the fields of the Federal State Budgetary Scientific Institution “Federal Research Center of Biological Plant Protection” (FSBSI FRCBPP; Krasnodar Krai, Russia, 45°2.413' N 38°58.5598' E; Fig. 2A, B). The site is a low-elevation plain field typical of the Western Ciscaucasian agricultural zone. The moisture coefficient is less than 0.25, 450–500 mm of precipitation; the sum of active temperatures is 3200–3400 °C and more (Kremneva et al. 2021). The soil cover of the experimental area is represented by leached mycelial-carbonate chernozem, with a slightly acidic reaction (pH 5.5–6.5). The parent materials are clayey and heavy loamy; humus content in the arable layer is about 3.0–4.5%, total nitrogen is about 0.20%, mobile phosphorus is 18.2 mg/100 g soil, and exchangeable potassium is 30.6 mg/100 g soil (Ponomarev et al. 2025).

The experiments were carried out in 2023, and the processing of the obtained data and analysis were carried out in 2024–2025 (Fig. 1). The studied season was characterized by relatively low precipitation but high relative air humidity during spring vegetation, ranging from 76.6 to 88.6%; spring air temperatures ranged from 8.6 to 16.5 °C, which was above the long-term average. Under these conditions, active vegetation and disease monitoring mainly covered the March–June period (Ponomarev et al. 2025).

Test plots with winter wheat of the Alekseich variety were created. This variety was selected because it is a modern Krasnodar-bred winter wheat cultivar relevant for cultivation in the North Caucasus and already used in experimental phytopathological studies in this region. Alekseich is also suitable for experiments with artificial infectious backgrounds because it combines agronomic relevance with a documented resistance profile (Gulyaeva et al. 2021).

The experimental plots differed in terms of pre-sowing soil cultivation, which significantly affect the pathogen development: conventional tillage (plowing to a depth of 22–25 cm) and no-till farming (shallow non-inversion disk tillage to a depth of 10–12 cm) (Bankina et al. 2018). In the non-till plot, two additional full-field cultivations were carried out on 30 August 2022 and 18 September 2022, followed by pre-sowing cultivation to the seed placement depth of 3–5 cm on 10 October 2022. Sowing was performed on 18 October 2022 using the standard seeding rate of 250 kg ha⁻¹. Within the test plots, zones with an artificial infectious background and zones with fungicide treatment were identified to create clean, undamaged crops (control). The number of recording points for each individual variant of the infectious background (moldboard and non-moldboard methods of soil cultivation) was 20. The total number of recording points was 40. The method of artificial infection of winter wheat with phytopathogen spores was used to create an infectious background in test plots (Kremneva et al. 2021) (Fig. 2C).

Winter wheat was infected with phytopathogen spores on April 18 during the “beginning of tube emergence” phase (phase Z 30–32). A clean background (disease-free) was created by treating control areas with a systemic fungicide twice: 1st treatment – April 27, 2023 (phase “flag-leaf”), 2nd – May 11, 2023 (phase “beginning of flowering” Z 61). The diseases were recorded starting from the moment of initial manifestations, which were noted on May 4, 2023 in the “flag leaf” phase (Z 40–47) and subsequent ones – up to the “milky-wax ripeness of grain” phase (Z 70–80) at intervals of 10–12 days (May 4, 13, 24 and June 8, 2023).

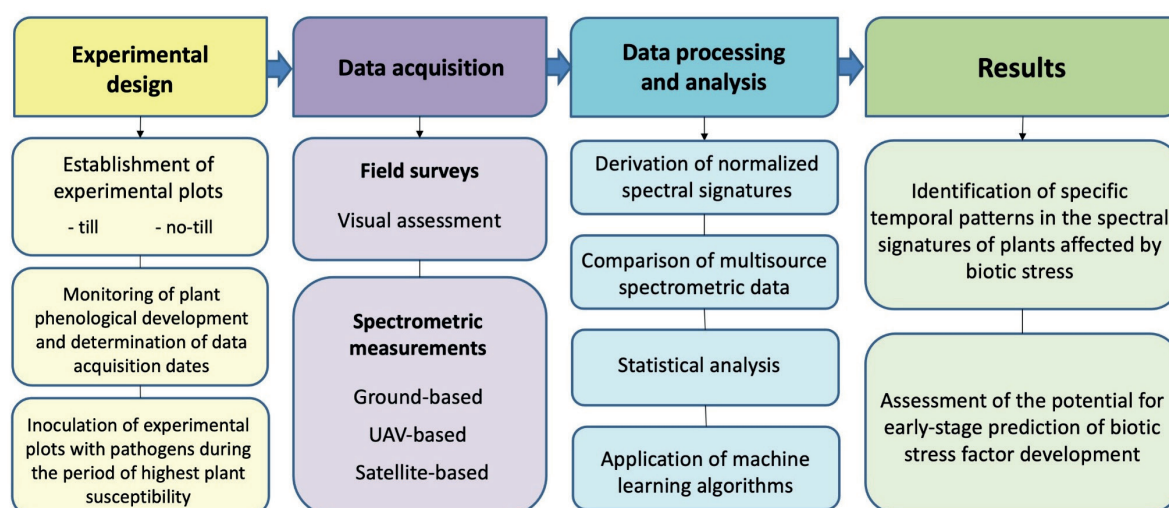


Fig. 1. General flowchart of the study

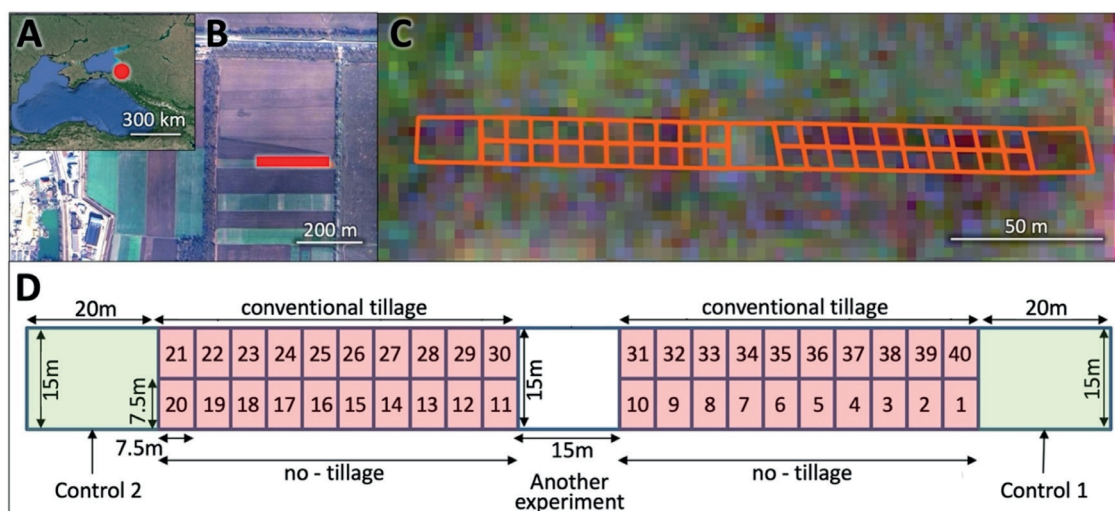


Fig. 2. Location of experimental fields (A, B, C). Layout of experimental plots (C): test plots are shown in red, control plots are shown in green

Data Collection

Disease severity was assessed using methods based on visual accounting of the proportion ratio of the affected leaf blade to its total area. During the survey, 30 plants were selected. Then, for each tier (first, second leaf, etc.), according to international scales, a percentage assessment of leaf damage was given (Eyal et al. 1987; Roelfs et al. 1992). As a result of the studies conducted on control crops of winter wheat, the following diseases were identified: powdery mildew (*Erysiphe graminis*), tan spot (*Pyrenophora tritici-repentis*), and septoria leaf spot (*Septoria tritici*) (Appendix A).

Data on the dynamics of the spectral imaging of crops were collected on the basis of ground-based spectrometry and satellite sensing.

Ground-based spectrometry was carried out on May 4, 12 and 23, as well as June 1 and 9, 2023. The measurements were carried out contactlessly at a height of 1.2–1.4 m from the earth's surface in the electromagnetic radiation range from 350 to 2500 nm with a spectral resolution of 1–10 nm (Fig. 3A). For this purpose, the ASD FieldSpec 3 Hi-Res spectroradiometer was used. It is designed to measure absolute and relative values of radiance. Fig. 3B depicts the measurement technique using this device.

Ten ground-based spectrometric measurements of vegetation were performed within the test plots. The sensor was placed approximately 70 cm away from other objects, including people, to eliminate the effect of light re-reflection, and was directed orthogonally downwards. Since spectrometry outside laboratory conditions is associated with constant variability in light conditions, every 5 measurements were supplemented by measurements of a control white panel (reference reflector). The control panel helped to convert physical units of reflectivity measurements of the studied objects into absolute reflectance values.

The size of the test plots allowed the use of ultra-high-resolution satellite remote sensing data. For the experiment, images were obtained for the following dates: April 15, 26, May 4, June 3, 8 and 25, 2023 (Fig. 4). The satellite images were carried out by the Planet Scope satellite images¹. All downloaded scenes were previously processed to top-of-atmosphere (TOA) reflectance and atmospherically corrected to surface reflectance. The spatial resolution of the obtained images is 3 m. The spectral resolution is 8 channels with central spectrum values of 443 nm, 490 nm, 531 nm, 565 nm, 610 nm, 665 nm, 705 nm, and 865 nm.

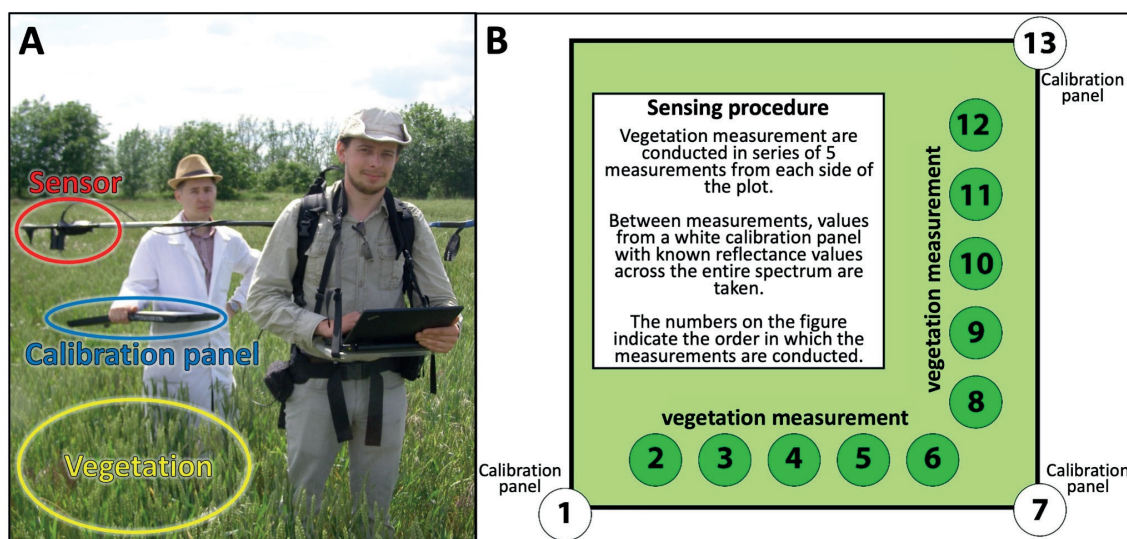


Fig. 3. A: Workflow of ground-based spectrometry; B: Scheme of ground-based spectrometry

¹European Space Agency, PlanetScope, ESA Earth Online. Available at: <https://earth.esa.int/eogateway/missions/planetscope> (accessed 28 June 2026);

Planet Labs PBC, Planet Imagery Product Specifications, June 2026. Available at: https://assets.planet.com/docs/Planet_Combined_Imagery_Product_Specs_letter_screen.pdf (accessed 28 June 2026).

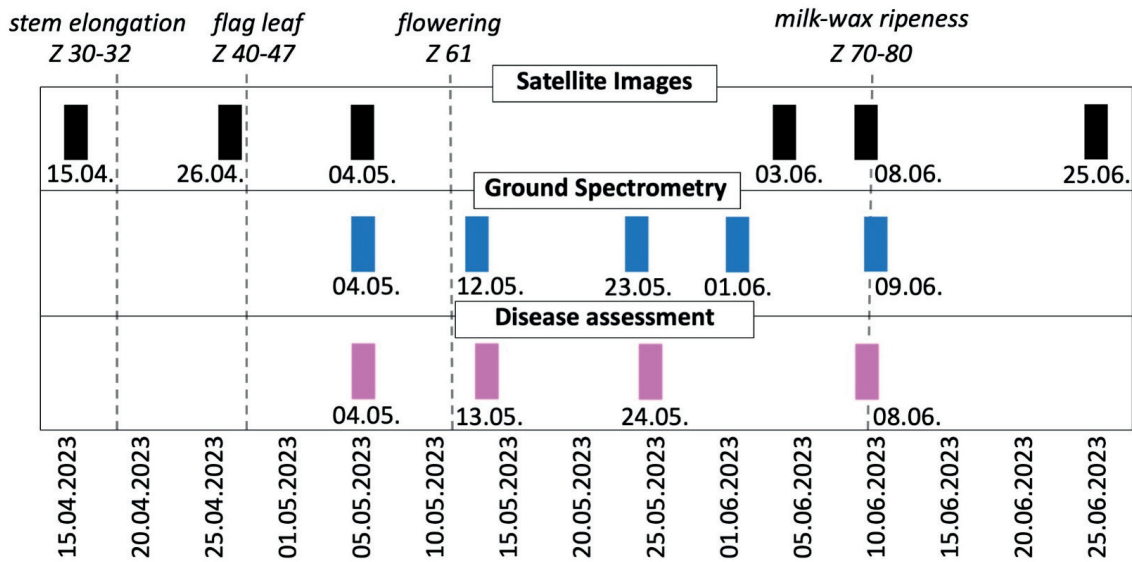


Fig. 4. Periods of the experiment and data acquisition

Planet Scope data were selected because their high revisit frequency, 3 m resolution, and eight spectral bands make it possible to analyze plot-level temporal dynamics while limiting pixel mixing.

Pre-Processing

Ground measurements were converted to reflectance using a standard relative calibration scheme with a reference panel (Eq. 1):

$$\rho_{tar}(\lambda) = \frac{L_{tar}(\lambda)}{L_{ref}(\lambda)} \times \rho_{ref}(\lambda) \quad (1)$$

where L_{tar} and L_{ref} — are the measured spectral radiances (or sensor signals) of the target and the reference, and ρ_{ref} is the calibrated reflectance of the panel (Peddle et al. 2001).

Satellite data were converted to surface reflectance using a standard atmospheric correction workflow. The images were then georeferenced and co-registered with the plot boundaries. For each plot and acquisition date, mean surface reflectance values were extracted from pixels within the plot polygon (Zhu & Woodcock 2012) using zonal statistics tools implemented as scripts in the GDAL Python package. This processing yielded the median reflectance and the standard deviation of pixel values for each spectral band and date.

Because the study compares satellite imagery with ground-based spectrometry, the central wavelengths of the Planet Scope bands were used as reference wavelengths. Therefore, the central wavelengths of the Planet Scope satellite images were used as the main ones for analysis and comparison with ground-based spectrometry data. In this case, for ground-based spectrometry, the average values of each wavelength included in the spectral band of the space imaging channel were taken.

Fig. 4 summarizes the timing of phytopathological surveys, ground spectrometry, and satellite acquisitions. Cloudiness caused gaps in the satellite time series, including a 30-day gap, but May 4 and June 8 contained all three types of measurements, allowing the approach to be tested under realistic, imperfect observation conditions.

Ground spectrometry was performed within one day of the corresponding satellite acquisitions, which is acceptable for comparing temporal dynamics rather than exact one-to-one observations (Kayastha et al. 2022). Missing satellite observations were therefore supplemented with satellite-equivalent values recalculated from ground spectra.

Spectral harmonization was then performed by converting narrowband ground spectra into band-equivalent values for the target satellite sensor using the sensor relative spectral response (RSR) (Eq. 2):

$$g, b = \frac{\int g(\lambda) S_b(\lambda) d\lambda}{\int S_b(\lambda) d\lambda} \quad (2)$$

where $S_b(\lambda)$ is the spectral response of band b and $g(\lambda)$ is the ground-measured reflectance. This reduces bias caused by different band definitions.

For cloud-free dates, a per-band transfer function between ground and satellite reflectance was fitted using a simple linear relationship (Eq. 3):

$$sat, b = b + bg, b \quad (3)$$

Model performance was assessed by cross-validation using R^2 , bias, and $RMSE_b$ (Eq. 4):

$$RMSE_b = \sqrt{\frac{1}{n} \sum_{i=1}^n (sat, b, i - \hat{sat, b, i})^2} \quad (4)$$

The transfer produced $RMSE = 0.021$, $MAPE = 10.8$, and $R^2 = 0.97$.

The fitted coefficients were then used to reconstruct missing satellite-equivalent reflectance values for cloudy dates when ground spectra were available (Eq. 5):

$$\hat{sat, b}(t) = b + bg, b(t) \quad (5)$$

for all bands b (Milton et al. 2009).

Data Analysis

Pearson correlation analysis was performed to determine the most informative and promising spectral ranges for test plots (Pearson 1895).

The statistical significance of the disease influence on winter wheat spectral characteristics, as well as the significance of using spectral channels of space imaging data, was tested using one-factor analysis of variance with the Fisher criterion (Fisher 1992).

The analysis was built on ground-based surveys and ground-based spectrometry data, as they were performed on dates closest to each other.

We therefore based the correlation analysis on temporal dynamics rather than on same-date reflectance–disease relationships. This approach is due to the fact that, as similar experiments in previous years have shown, it is much more effective to assess the development of pathogenic background for crops using dynamic indicators (Kremneva et al. 2023; Sereda et al. 2023). The analysis was implemented in Python using the SciPy library.

Based on the pathogen development graphs, two dates of maximum development can be identified: May 4 (powdery mildew and septoria leaf spot) and May 24 (tan spot). It was decided to use the pathogen development rates on these dates as a forecasting target. A total of 3 dates were selected to predict the development of diseases: May 4, May 13 and May 24. Spectral data obtained for one of them were used for forecasting. That is, if on May 4 a forecast of tan spot development by May 24 is modeled, then we cannot use the data obtained on May 12 or 23 (Fig. 5).

Since remote sensing data were not always acquired on the same days as ground-based measurements, spectral data for specific ground-based survey dates were calculated using linear interpolation between the two closest measurements or images.

Eight forecasting algorithms were tested: Linear Regression, Decision Tree, Random Forest, Bagging, Huber Regression, Bayesian Ridge, Lasso, and AdaBoost (Breiman 1996, 2001; Freund & Schapire 1997; Huber 1964; MacKay 1992; Seber & Lee 2012; Tibshirani 1996).

480 possible models for predicting pathogen development were calculated since various combinations of initial data were considered: source of data acquisition (ground-based spectrometry, satellite sensing), type of soil cultivation (all types, moldboard, non-moldboard), pathogens (all pathogens, powdery mildew, tan spot, septoria leaf spot), forecasting algorithms (8 algorithms), forecast execution dates (2–3 depending on the pathogen).

The implementation of forecasting models, as well as the assessment of their accuracy, statistical significance, and the preparation of graphical materials were carried out with Python scripts and the Sklearn, SciPy, Yellowbrick, and Matplotlib libraries.

Forecasting models were evaluated using 5-fold cross-validation, which allowed all available observations to be used for both training and testing while reducing the risk of overfitting (Stone 1974).

RESULTS

General Overview

The results of a comparative assessment of the dynamics of pathogenic background development in control winter wheat grown using two different pre-sowing soil cultivation technologies revealed the following: the pathogenic background of crops cultivated using no-till farming significantly exceeded that of crops with conventional tillage practices, which confirms the findings of the scientific studies cited in the Introduction (Appendix A).

The most intensive development of powdery mildew and septoria leaf spot was observed in the “flag leaf” phase Z 40–47. On the no-till plot it was 9.65% and 5.91%, respectively, but on the conventional tillage plot it was 2.85% and 4.57%, respectively. Tan spot (pyrenophora) severity was 0.25% on the no-till plot and 0.52% on the conventional tillage plot. Thus, the manifestation of powdery mildew and septoria leaf spot on the no-till plot was higher than that on the conventional tillage plot. The differences in pyrenophorosis between the two practices are not significant due to the weak development of the disease at this stage. The development of powdery mildew and septoria leaf spot decreased during subsequent phases of the winter wheat vegetation period. However, disease manifestation on the no-till plot was always higher than that on the conventional tillage plot. Tan spot (pyrenophora) severity increased sharply starting from the Z 50–59 “earring” phase. In the research period it was as well higher on the no-till plot than on the conventional one.

Fig. 6 shows reflectance values for the satellite-equivalent bands on May 4 and June 1, 2023, including variance ranges for tillage types and dashed curves for control plots.

The spectra indicate that tillage type strongly affected wheat reflectance: on May 4, control curves clearly separated no-till and conventional tillage plots, while by June 1 this separation weakened but remained partly visible, with no-till plots generally showing lower brightness.

Thus, we cannot claim that at the beginning of the experiment all experimental plots had equal starting conditions. Some preservation of groups according to the soil cultivation practices towards the end of the experiment may be a consequence of this factor directly or may be associated with the peculiarities of pathogen

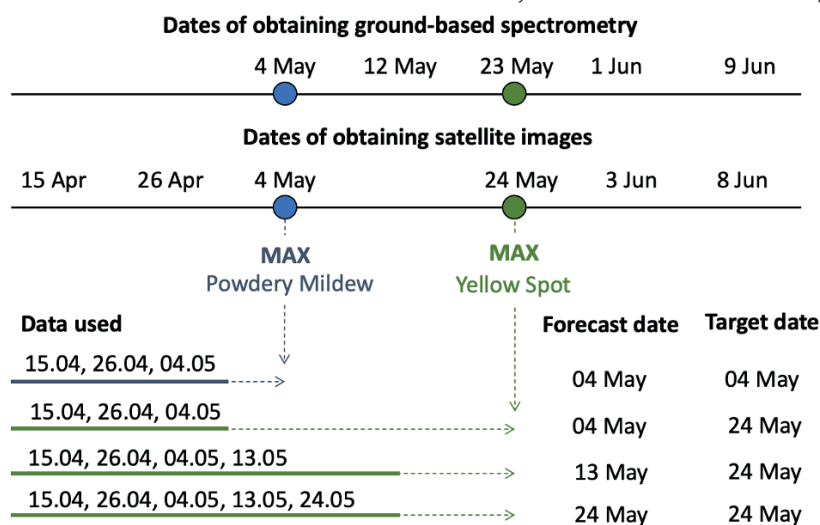


Fig. 5. Forecasting scheme, including dates of remote sensing materials used; composition of spectral data for training models and algorithms used

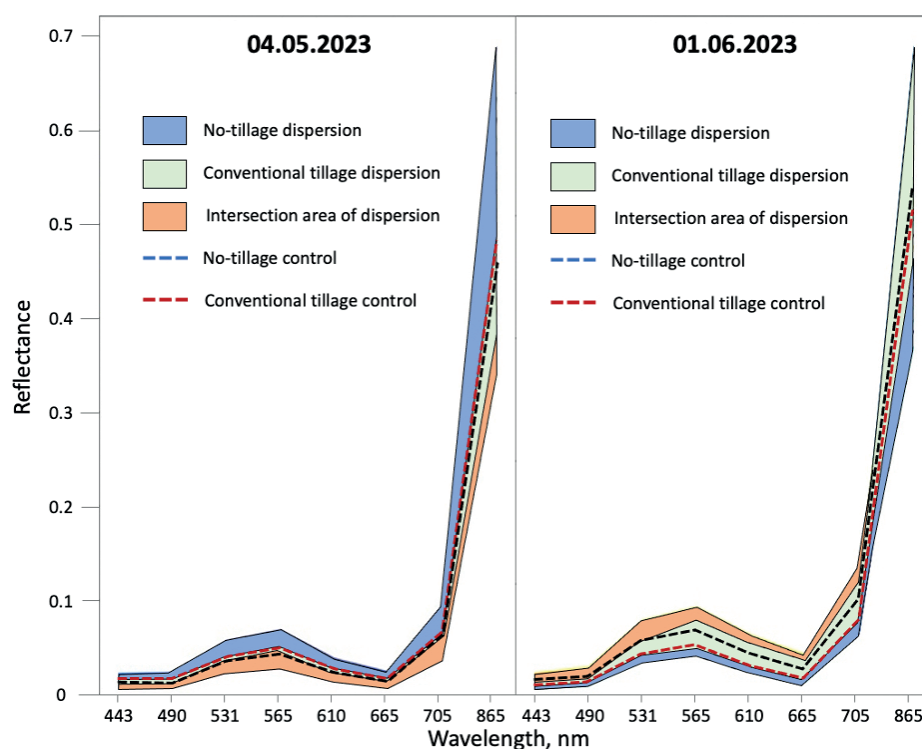


Fig. 6. Reflectance values for space imaging ranges based on ground-based spectrometry data on May 4, 2023 and June 1, 2023

development under different initial conditions. In this regard, for further analysis it is advisable to consider three separate data groups: conventional tillage, no-till farming, and their combination.

Statistical Data Analysis Results

Although cloudiness limited the number of satellite images, several acquisitions coincided closely with ground measurements. Fig. 7 compares May 4–June 1 reflectance changes from both data sources for six Planet Scope bands and shows that the two systems are similar enough for analysis but still differ noticeably. Ground measurements were generally slightly lower than satellite reflectance values.

This may be due to technical reasons: differences in sensor sensitivity and their calibration. The difference in spectrum change between plots during ground-based spectrometry is more pronounced than during satellite sensing. It is important to note the following observation. Despite some similarity in the trends of spectral changes for conventional tillage plots, the changes for no-till plots differ significantly. In this case, for ground-based spectrometry, the change in the spectrum for different types of soil cultivation can have opposite dynamics, but for space survey data, they have a common direction. Pearson correlation coefficients confirm that, depending on the wavelength, the similarity degree of these types of remote sensing varies greatly (from 0.29 to 0.79).

In this regard, despite some similarity of the obtained data, we cannot unambiguously claim the accuracy and methods of assessing plant diseases according to data from one of the systems based on data from another remote sensing system. They also need to be considered separately when analyzing. Since our study is focused on space imagery data, the results of these data analysis were recognized as a priority.

The Fisher criterion was used to test statistical significance at $p < 0.05$, with a critical F value of 4.1. Significance was not confirmed for the closely behaving

531, 565, and 610 nm bands or between powdery mildew and septoria leaf spot, but the relationship between disease presence and spectral characteristics was confirmed overall.

Table 1 in Appendix B summarizes Pearson correlations between pathogen dynamics and spectral ranges for individual plots and for the total pathogenic background.

Correlation analysis showed that spectral ranges can be arranged in the following order: (from highest correlation to lowest): 443, 865, 490, 531, 565, 665, 610, 705 nm. Simultaneously, despite the rather high arithmetic mean and median values for 40 plots, some of them may have significantly lower correlation coefficient values. Thus, for powdery mildew, the median value for the 865 nm channel is 0.62; it is 0.37 for plot 5, but 0.31 for plot 3.

Let us point out that when considering the general degree of plant damage by all pathogens, the overall correlation coefficient becomes somewhat lower than when considering individual pathogens. At the same time, the standard deviation also increases. High standard deviation values are also observed for tan spot. This is probably due to the fact that tan spot is a dominant pathogen in the conducted experiment.

The obtained results prove that individual spectral ranges demonstrate a low but still significant correlation dependence on the dynamics of the winter wheat pathogen development.

Forecasting Pathogen Development

Fig. 8 presents model residuals, R^2 values, and Q-Q plots used to compare the distributions of training and test samples.

The importance of using certain spectral ranges was calculated when executing the modeling algorithms. The results differed slightly depending on the combinations of the input data. But, in general, they corresponded to the same order that was revealed in the correlation analysis: high values for the 443, 490, 865 nm channels and low values for the 610, 665, 705 nm channels.

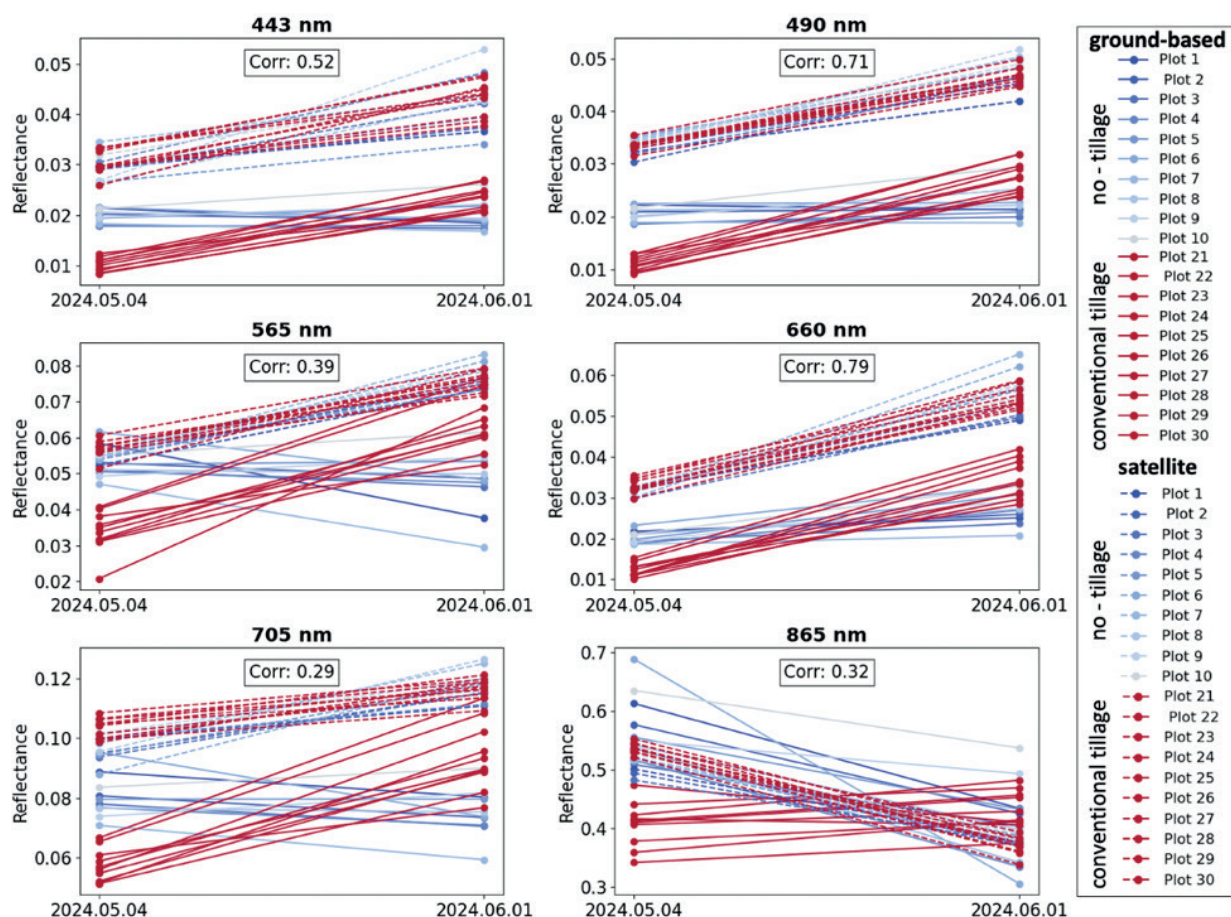


Fig. 7. Comparison of spectral brightness based on ground-based spectrometry data (solid lines) and satellite imagery (dashed lines) for different wavelength ranges, taking into account soil cultivation practices: red indicates conventional tillage, and blue indicates no-till

Most models did not provide reliable forecasts, but several combinations produced meaningful results. Tables 2 and 3 in Appendix B report the best test-sample R^2 values for different data sources, tillage groups, pathogens, and forecasting dates.

Disease prediction models are generally more accurate the later they are implemented and, accordingly, the closer they are to the disease maximum and the more spectral data are used in training. In this case, R^2 values above 0.5 are observed only on the actual day of the onset of the disease maximum.

We assume that this is due to the fact that tan spot was a dominant pathogen in the experiment. Simultaneously, the influence of powdery mildew and septoria leaf spot, especially in the later stages, did not play a significant part in the formation of the plant spectral response.

Forecasting accuracy was higher for no-till plots than for conventional-tillage plots, whereas combining both tillage systems reduced model performance. This suggests that tillage-specific models are preferable.

DISCUSSION

The results support three main interpretations. First, winter wheat spectral response was affected not only by pathogen development but also by tillage system. No-till plots showed a higher pathogenic background than conventional tillage plots, and this difference was also reflected in the spectral data. Therefore, tillage should not be treated only as an agronomic background factor; it must be included as a separate modeling condition or predictor when disease forecasting models are developed.

Second, the most informative PlanetScope bands were concentrated in the blue, green-blue, and near-infrared

regions, especially 443, 490, and 865 nm. This indicates that pathogen development was associated with both pigment-related changes and changes in canopy structure or plant physiological status. At the same time, the relationship was not uniform across pathogens. Correlations were generally clearer for individual diseases than for the total pathogenic background, whereas some forecasting models performed better when the total disease pressure was used as the target variable. This suggests that disease detection and disease forecasting may require different modeling strategies.

Third, ground-based spectrometry and satellite imagery showed broadly comparable temporal patterns, but they were not interchangeable. Ground spectrometry provided more detailed and stable spectral information, whereas satellite imagery offered spatial coverage and practical scalability. The differences between these data sources explain why models trained on one type of data cannot be directly transferred to another without harmonization and validation.

In this study, we lacked the desired amount of satellite data for the required time period. The models developed here cease to produce statistically significant results if even a single day of measurements is removed. This indicates that the dataset used in this study represents the theoretical minimum necessary to enable any meaningful forecasting of the development of the winter wheat pathogens under consideration.

The recommended data frequency for disease forecasting should be higher than it was available during the described experiment. Presumably, not less than every 5 days during the period of active manifestation of winter wheat diseases.

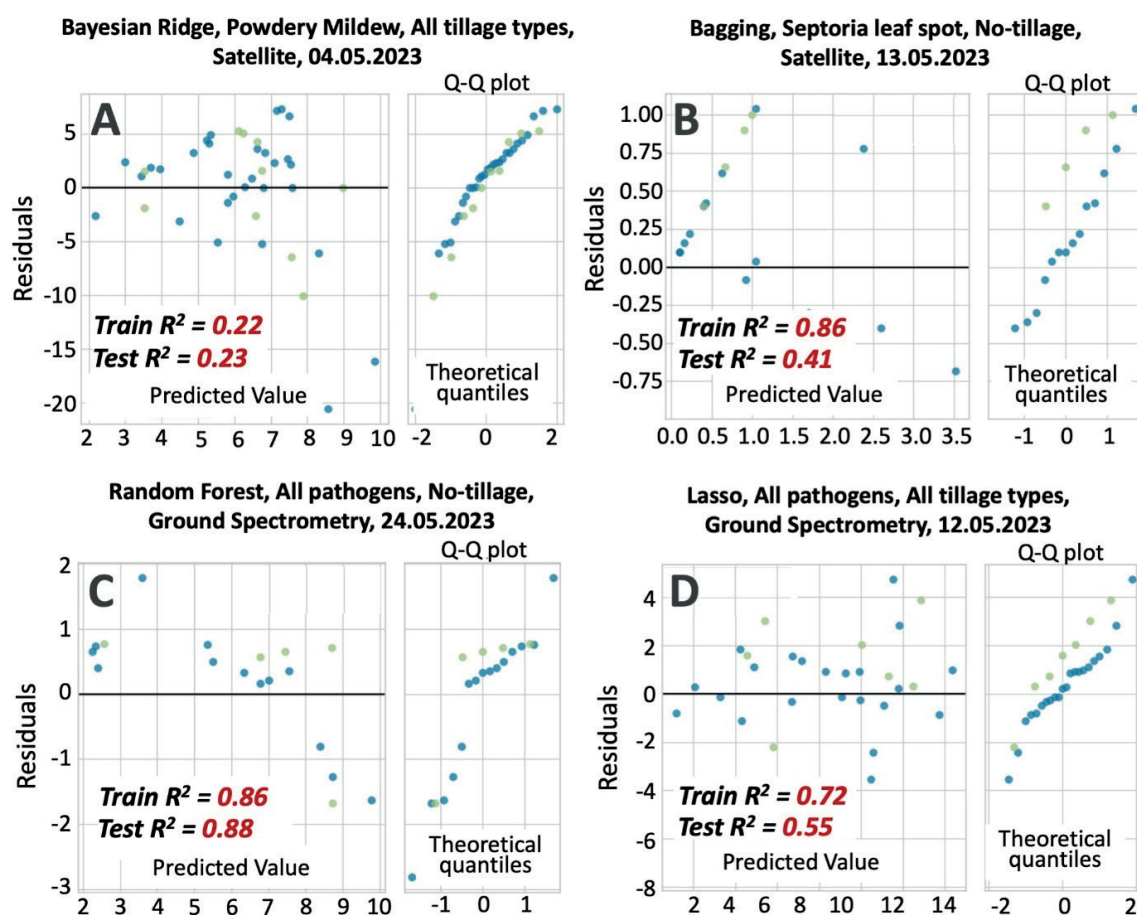


Fig. 8. Residual plots and corresponding Q-Q plots for pathogen development forecasts on experimental plots: (A) Bayesian Ridge model for powdery mildew, all tillage types, satellite data, 4 May 2023; (B) Bagging model for Septoria leaf spot under no-tillage, satellite data, 13 May 2023; (C) Random Forest model for all pathogens under no-tillage, ground spectrometry data, 24 May 2023; (D) Lasso model for all pathogens, all tillage types, ground spectrometry data, 12 May 2023

Therefore, persistent cloud cover during the period of active satellite monitoring may completely preclude the application of this approach. A potential solution could be the use of multiple satellite systems. Additionally, unmanned aerial vehicles with a sufficient number of spectral channels can be used for increased detection accuracy and prediction of maximum pathogen development.

We used the Planet Scope Ultra-High-Definition Imaging System to have sufficient statistical data within small-scale experimental plots. We suppose that systems with lower spatial but similar or higher spectral resolution will be suitable for regional monitoring (Kremneva et al. 2023; Sereda et al. 2023).

Advanced processing methods such as wavelet transforms, feature-band selection, gradient boosting, neural networks, SVM, and Random Forest have proven useful for crop disease monitoring and remain promising for further development of winter wheat disease forecasting (Bevers et al. 2022; Feng et al. 2022; Filipovics 2023; Gao et al. 2023; Rahman et al. 2020; Shi et al. 2018; Wang et al. 2015; Zhelezova et al. 2023).

The study attempted not only to determine the manifestation degree of certain pathogens based on spectra but also to predict their further development based on the dynamics of spectral images.

Forecasting accuracy increased as the date of maximum disease manifestation approached, and the available data confirmed a stable link between plant spectra and disease development. However, the dataset did not support accurate prediction even one week before the maximum, so future work should test denser spectral observations and the integration of meteorological variables.

Of particular note is the difference in modeling using space imagery and ground-based spectrometry. Ground-based spectrometry showed slightly better results for powdery mildew and tan spot, while space imagery is more effective in predicting septoria leaf spot.

It is peculiar that when searching for the most informative spectral ranges, a higher correlation and a low standard deviation value were observed for individual diseases, but not for their total. While forecasting crop yields, the highest determination coefficients were obtained by models calculating the sum of all pathogenic diseases.

Unlike precision herbicide systems, fungicide decision-making cannot usually rely on a single spectral measurement (Jensen 2015; Komives & Reisinger 2012; Sangeetha et al. 2024; Yang 2020). It requires multi-temporal monitoring and task maps. Combining UAV and satellite data is promising, but differences in spectral characteristics complicate the creation of universal models for winter wheat disease forecasting (Maimaitijiang et al. 2020; Sagan et al. 2019).

The scalability of the proposed approach should be interpreted primarily at the workflow level rather than as direct transferability of the fitted models. The general sequence of risk assessment, selection of the most informative phenological window, repeated spectral monitoring, and local model calibration can be applied to other winter wheat varieties and other physical-geographical conditions. However, the numerical model coefficients obtained in this study are specific to the Alekseich variety, the Western Ciscaucasian lowland environment, the 2023 growing season, and the observed pathogen complex. Transfer to other varieties or regions

would require recalibration because cultivar resistance, canopy architecture, sowing dates, soil background, humidity regime, disease pressure, and cloud conditions can all affect spectral response. For broader application, future studies should test the workflow across several varieties, contrasting soil-climatic zones, and multiple seasons, preferably with additional meteorological and phenological predictors. Thus, the approach is scalable as a methodological framework, but operational models should be locally validated before being used for fungicide decision-making.

For applying this methodology in precision agriculture, a combined approach is suggested. It includes assessing risk factors, choosing the best observation periods, and directly monitoring crops. First, weather data and phytopathological references are used to check whether current seasonal conditions favor the development of certain pathogens. Then, the most informative time window for active imaging is identified, helping to avoid unnecessary monitoring throughout the season. This step should consider weather, terrain elevation, field boundaries and characteristics, and sowing dates. Seasonal NDVI trends can serve as indicators of crop growth stages, supported by local studies linking NDVI to specific phenological phases (Dížková et al. 2022; F. Zhao et al. 2021; Y. Zhao et al. 2022). During active monitoring, satellite images should be complemented with UAV data. Results should be processed quickly and presented as maps for farm managers and digital layers for site-specific pesticide application.

The resulting framework can support more timely protective measures, reduce costs and pesticide pressure, and improve crop-management decisions.

CONCLUSIONS

The study showed that spectral data have a good correlation with both pathogenic background development in general and individual diseases in particular. However, with the current number of measurements, effective disease prediction is relevant in the final stages of pathogen development. Nevertheless, predicting diseases using spectral data is not without promise. It is necessary to obtain spectral data more frequently and achieve an increase in their accuracy and reliability.

In the presented experimental configuration, it was found that the pathogenic background of no-till crops significantly exceeds that of the conventional tillage ones. At the same time, soil cultivation method significantly affects the spectral image of plants. It was determined that when detecting and predicting winter wheat diseases using the Planet Scope survey system, the most informative spectral ranges are 443, 490, 865 nm, and less informative are 610, 665, 705 nm. Forecasting for no-till plots, where disease development was greater, is somewhat more effective than for conventional tillage. The maximum forecasting accuracy for diseases on the day of their maximum manifestation based on space data using the R^2 metric was 0.46 for powdery mildew, 0.37 for septoria leaf spot, 0.7 for tan spot, and 0.64 for the entire pathogenic background as a whole.

The proposed methodology can be scaled to other fields and regions as a monitoring workflow, but the fitted forecasting models should not be transferred without local calibration. Application to other winter wheat varieties or physical-geographical conditions requires additional validation because cultivar resistance, phenology, soil background, climate, and pathogen composition may change the spectral response. Future work should therefore include multi-season experiments across contrasting environments and combine spectral, meteorological, and phenological predictors. ■

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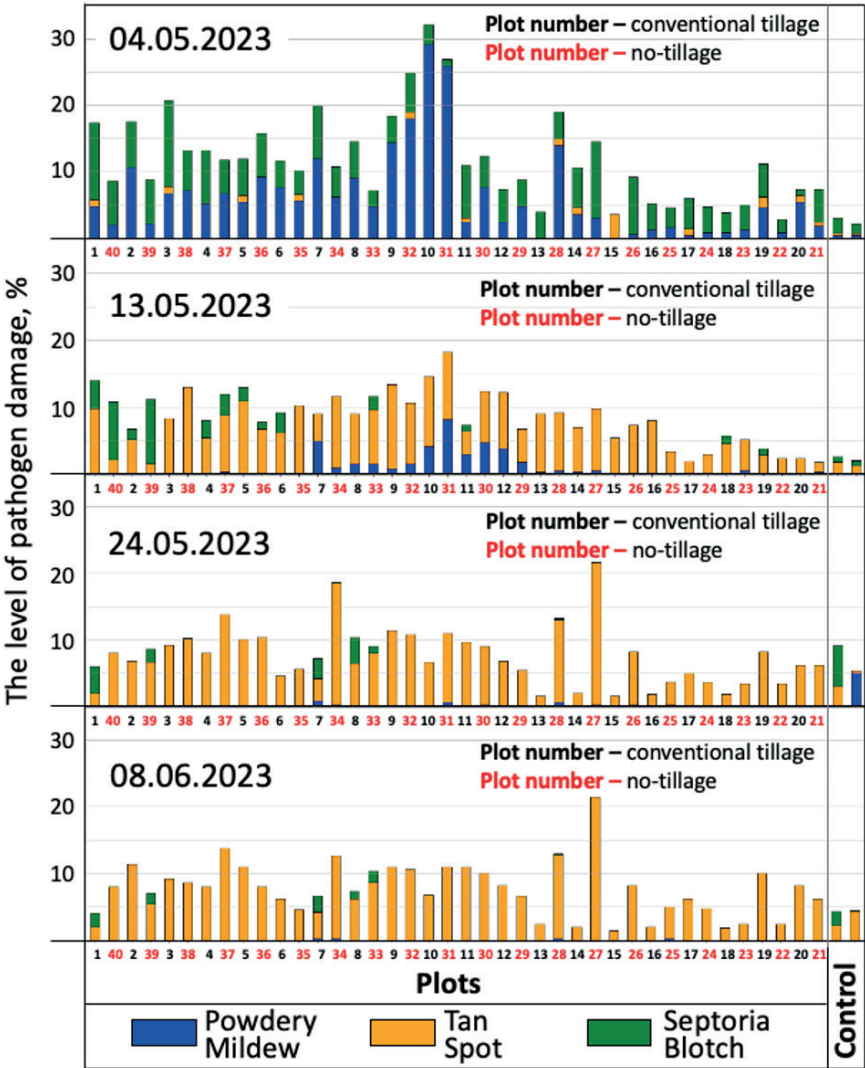
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APPENDIX A

Dynamics of pathogen development in test plots in 2023. The order of the plots was arranged according to their proximity to one another.



APPENDIX B

Quantitative indicators of spectrometric data analysis regarding the informativeness of spectral bands and the accuracy of yield prediction models

Table 1. Case studies and used methods. Pearson correlation coefficients of pathogens on individual test plots for different spectral ranges (ground-based spectrometry data)

Powdery Mildew	Plot 1	Plot 2	Plot 3	Plot 4	Plot 38	Plot 39	Plot 40	mean	median	std
443 nm	0.62	0.59	0.72	0.71	0.69	0.44	0.75	0.68	0.69	0.15
490 nm	0.57	0.58	0.54	0.5	0.54	0.53	0.6	0.61	0.6	0.11
531 nm	0.61	0.51	0.51	0.5	0.51	0.55	0.62	0.59	0.57	0.1
565 nm	0.6	0.51	0.51	0.46	0.53	0.53	0.58	0.58	0.56	0.09
610 nm	0.48	0.43	0.43	0.41	0.49	0.46	0.47	0.51	0.5	0.09
665 nm	0.49	0.47	0.47	0.46	0.47	0.47	0.51	0.55	0.52	0.1
705 nm	0.41	0.43	0.43	0.38	0.44	0.43	0.46	0.48	0.46	0.09
865 nm	0.77	0.44	0.31	0.61	0.46	0.66	0.67	0.62	0.62	0.21
Yellow Spot	P1	P2	P3	P4	P38	P39	P40	mean	median	std
443 nm	0.23	0.94	0.77	0.86	0.42	0.55	0.94	0.56	0.69	0.39
490 nm	0.25	0.94	0.59	0.64	0.27	0.65	0.82	0.49	0.59	0.36
531 nm	0.24	0.9	0.56	0.65	0.24	0.67	0.84	0.47	0.55	0.36
565 nm	0.24	0.9	0.56	0.61	0.26	0.64	0.8	0.47	0.56	0.36
610 nm	0.26	0.85	0.48	0.55	0.22	0.56	0.7	0.41	0.5	0.34
665 nm	0.26	0.88	0.52	0.6	0.2	0.58	0.74	0.44	0.53	0.35
705 nm	0.27	0.85	0.48	0.51	0.18	0.53	0.69	0.38	0.48	0.33
865 nm	0.06	0	0.3	0.62	0.54	0.72	0.63	0.52	0.56	0.27
Septoria Blotch	P1	P2	P3	P4	P38	P39	P40	mean	median	std
443 nm	0.79	0.7	0.72	0.86	0.69	0.65	0.84	0.67	0.7	0.15
490 nm	0.74	0.7	0.54	0.64	0.54	0.7	0.76	0.58	0.56	0.11
531 nm	0.78	0.61	0.51	0.65	0.51	0.71	0.77	0.56	0.54	0.11
565 nm	0.77	0.62	0.51	0.61	0.53	0.7	0.75	0.55	0.53	0.11
610 nm	0.67	0.53	0.43	0.55	0.49	0.66	0.67	0.48	0.47	0.11
665 nm	0.68	0.57	0.47	0.6	0.47	0.66	0.7	0.51	0.49	0.11
705 nm	0.61	0.54	0.43	0.51	0.44	0.64	0.67	0.44	0.42	0.11
865 nm	0.69	0.43	0.31	0.62	0.46	0.33	0.46	0.62	0.68	0.21
Total	P1	P2	P3	P4	P38	P39	P40	mean	median	std
443 nm	0.91	0.2	0.68	0.71	0.97	0.74	0.48	0.36	0.5	0.48
490 nm	0.86	0.2	0.51	0.5	0.91	0.73	0.48	0.3	0.48	0.48
531 nm	0.9	0.1	0.47	0.5	0.9	0.72	0.48	0.29	0.47	0.47
565 nm	0.89	0.1	0.48	0.46	0.91	0.73	0.48	0.29	0.46	0.47
610 nm	0.8	0	0.4	0.41	0.89	0.74	0.46	0.25	0.41	0.46
665 nm	0.81	0.05	0.44	0.46	0.88	0.74	0.47	0.27	0.44	0.47
705 nm	0.73	0.01	0.4	0.38	0.86	0.74	0.46	0.23	0.41	0.46
865 nm	0.71	0.73	0.32	0.61	0.02	0.13	0.11	0.29	0.34	0.37

Table 2. Average determination coefficient (R^2) for test samples of plant disease forecasting models based on ground-based spectrometry data in various combinations of features

Ground-based spectrometry		Powdery Mildew 04.05.2023	Powdery Mildew 13.05.2023	Yellow Spot 04.05.2023	Yellow Spot 13.05.2023	Yellow Spot 24.05.2023	Septoria Leaf Spot 04.05.2023	Septoria Leaf Spot 13.05.2023	Total 04.05.2023	Total 13.05.2023	Total 24.05.2023
All Data	Lasso	-0.25	0.52	-1.20	0.48	-6.81	0.37	-3.66	-0.24	0.55	-5.69
	Bagging Regressor	0.02	0.23	-0.94	-0.27	0.71	-0.44	-0.38	-0.20	0.09	0.16
	Random Forest Regressor	-0.08	0.22	-1.04	0.10	0.47	-0.46	-0.28	-0.27	0.21	0.42
	Ada Boost Regressor	-0.18	0.22	0.30	-0.01	0.29	-0.29	-0.39	-0.14	0.12	0.35
No-tillage	Lasso	-2.58	-0.45	-14.37	-0.60	-9.99	0.25	-3.78	-1.49	0.24	-2.09
	Bagging Regressor	0.42	-0.08	-7.28	-0.13	0.83	-0.75	-0.33	-0.87	-0.13	0.55
	Random Forest Regressor	0.30	-0.01	-8.29	-0.13	0.84	-0.23	-0.19	-0.42	0.14	0.88
	AdaBoost Regressor	0.34	-0.24	-16.39	-0.19	0.73	-0.80	-0.50	-0.92	-0.22	0.59
Conventional tillage	Lasso	-26.01	-0.48	-0.64	-0.49	0.20	-5.26	-	-1.19	0.14	0.02
	Bagging Regressor	-0.14	0.70	-0.46	-0.02	-0.10	-6.47	-	-0.18	-0.22	0.28
	Random Forest Regressor	-0.09	0.25	-0.30	-0.07	0.13	-5.60	-	-0.30	-0.23	0.25
	Ada Boost Regressor	0.01	0.06	-3.66	-0.47	0.69	-5.16	-	0.07	-0.66	-0.03

Table 3. Average determination coefficient (R^2) for test samples of plant disease forecasting models based on space imagery data in various combinations of features

Satellite images		Powdery Mildew 04.05.2023	Powdery Mildew 13.05.2023	Yellow Spot 04.05.2023	Yellow Spot 13.05.2023	Yellow Spot 24.05.2023	Septoria Leaf Spot 04.05.2023	Septoria Leaf Spot 13.05.2023	Total 04.05.2023	Total 13.05.2023	Total 24.05.2023
All Data	Lasso	-1.33	-24.16	-17.41	-9.88	-19.11	-53.76	-14.82	-7.01	-4.87	-14.37
	Bagging Regressor	-0.11	0.10	-0.18	-0.11	0.22	0.13	0.01	-0.02	0.38	0.49
	Random Forest Regressor	-0.06	0.04	-0.39	-0.12	0.70	0.37	0.43	0.10	0.15	0.36
	Ada Boost Regressor	0.00	-0.03	-0.51	-0.22	0.70	0.12	0.13	0.15	0.22	0.64
No-tillage	Lasso	-22.87	-2.64	-4.67	-0.19	-0.27	-1.34	0.28	-12.08	-0.79	0.48
	Bagging Regressor	0.35	0.21	-0.36	-0.75	-0.07	-0.13	0.41	0.09	0.08	0.59
	Random Forest Regressor	0.26	-0.01	-1.68	-0.59	-0.03	-0.15	0.49	0.52	-0.07	0.57
	Ada Boost Regressor	-0.15	-0.32	-1.83	-0.72	-0.18	-0.08	-0.43	-0.03	-0.41	0.39
Conventional tillage	Lasso	0.46	-18.83	-2.69	-2.26	-6.64	-26.26	-1.12	-0.68	-7.04	-6.54
	Bagging Regressor	-0.50	-0.16	-0.51	-0.27	0.09	0.20	0.17	-0.37	-0.94	-3.73
	Random Forest Regressor	-0.15	-2.98	-0.59	-0.59	-1.71	-0.15	0.44	-0.27	-0.05	-1.99
	Ada Boost Regressor	-0.21	-0.12	-0.67	-0.81	-4.62	-0.41	0.21	-0.45	0.24	-4.29