

Analysis of photoluminescent parameters of oat seeds infected by *Fusarium*

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Abstract: Fluorescence spectroscopy and imaging are widely used for the analysis various biological objects. In crop production, these methods can be applied to reduce grain losses due to pathogens during post-harvest cleaning using non-invasive optical methods for assessing infestation. The excitation and photoluminescence spectra of the oat grain (*Avena sativa* L.) were measured on the diffraction spectrofluorimeter. A frequency analysis method with Gaussian decomposition was used to process the results. Primary excitation maxima at wavelengths of 232 nm, 362 nm, 424 nm, and 485 nm are revealed in the spectra. The greatest change in the integral flux Φ is 232 nm for the excitation. In infected oat seeds, the amplitude of the left Gaussian wave decreases by 2.5-5 times upon excitation with radiation at wavelengths of 232 nm, 362 nm, and 485 nm, while the amplitude of the right Gaussian wave remains unchanged. Luminescence spectroscopy with excitation by short-wave radiation with a wavelength of 232 nm can be used for effective and timely diagnosis of *Fusarium* diseases based on analyzing the integral photoluminescence fluxes and Gaussian decomposition in the frequency spectrum.

Keywords: fluorescence spectroscopy, oat grain, optical properties, pathologies of plant organisms.

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1 Introduction

Fusarium ssp. infections of cereal plants are serious problems worldwide due to the mycotoxins potentially produced by these fungi. This fact has led to the need to develop tools for early detection of infections. The widespread occurrence of mycotoxic fusaria highlights the need for comprehensive monitoring and integrated management strategies to reduce the risks associated with mycotoxins and ensure the safety and quality of oat products. Infection identification is based on the identification of mycotoxins, rather than on the direct identification of fungi. Existing surveillance systems mainly focus on testing end products for mycotoxins, rather than monitoring *Fusarium* at the production level.

This gap between mycotoxin detection and fungal disease monitoring is of particular concern, given that climate change may lead to changes in the composition of the *Fusarium* community, resulting in species with different mycotoxin profiles entering the food chain (Bucur et al., 2025). Common diagnostic methods are visual, as well as mycological analysis, enzyme-linked immunosorbent assay, real-time Polymerase Chain Reaction (PCR) and quantitative digital PCR (Natarajan et al., 2025), and detection using markers based on intergenic spacers, ultra-high performance liquid chromatography with mass spectrometry (Dick et al., 2024; Qu et al., 2024).

Optical sensors have shown good potential for improving detection and monitoring of plant diseases

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(Moskovsky et al., 2023). Image processing and machine learning technologies are used to classify seeds by quality. The images are analyzed for texture, morphology, and grain color. A solution for quality analysis using machine learning is presented (Kini and Bhandarkar, 2023). Much attention is paid to hyperspectral imaging as a non-destructive and simple method for assessing seed quality and safety. Modern hyperspectral imaging systems generate huge amounts of data containing a huge amount of information that can be converted into practical conclusions (Dhanya et al., 2024). In the research by Atta et al. (2023), the use of fluorescence spectroscopy along with advanced statistical methods and confocal microscopy was studied for the early detection of stripe rust infection in wheat grown under field conditions. Due to the combination of exceptional antibody specificity and high sensitivity of the fluorescent method, fluorescence-based immunosensors have recently become one of the most promising developments for the detection of mycotoxins (Jia et al., 2021).

As noted by Rigler and Widengren (2018), the use of fluorescence correlation spectroscopy (FCS), begun over 50 years ago, due to technological developments has led now to the use of FCS for monitoring the state of biological objects. FCS measurements are used to research proton exchange mechanisms at biomembranes, which are essential for bioenergetics and signal transduction. The system has been developed for real-time fluorescent recordings of changes in the cell membrane caused by electroporation (Tivig et al., 2020).

Luminescent proteins such as green fluorescent protein (GFP) have proven to be powerful tools in plant genetic transformation and gene expression researches due to their excellent sensitivity and rapid response. GFP also has the significant advantage that it does not require a substrate and its expression can be detected in living cells in real time by light excitation (Himuro et al., 2009).

Most plant tissues exhibit high autofluorescence. Synchronous fluorescence spectroscopy provides the specificity and sensitivity to detect fluorescence changes in a single grain of rice that occur in the presence of carotenoids. Developed a non-destructive method for

screening individual rice grains for the presence of carotenoids in their bran (Belefant-Miller et al., 2005).

For the spectroscopic research of E/Z photoisomerization of the new cyrethrenyl acylhydrazone, absorption spectres in the ultraviolet range were recorded on an Agilent Cary 8454 diode spectrophotometer in the range of 250-600 nm. Emission spectra were measured on an Ahoriba Jobin Yvon FluoroMax-4CP spectrophotometer (Toro et al., 2021). Optical absorption and fluorescence techniques were used to draw conclusions about how Brazilian green propolis artepillin C interacts with amphiphilic aggregates commonly used as model membranes. The optical absorption spectra represented the protonation state dictated by the local pH at the surface of micelles and lipid vesicles (Camuri et al., 2019).

Using pH-dependent UV-vis spectroscopy and spectral decomposition modeling, interactions between neighboring amino acids and bilin in the phytochrome family are studied (Rumfeldt et al., 2019). The fluorometric method allows one to estimate the concentration of chlorophyll a contributed by individual algal groups in a real sample by fitting its fluorescence excitation spectrum to a linear combination of the normal spectra of the corresponding algal groups (Gsponer et al., 2018). The photochemistry of the oat photosystem during herbicide treatment was assessed by measurements of chlorophyll a fluorescence. The parameters measured were steady-state fluorescence, steady-state maximum fluorescence, and overall photochemical quantum yield (Lehnhoff et al., 2013). Fluorescent tags have been used to directly monitor auxin transport at the cellular and tissue level (Pařízková et al., 2021; Balcerowicz et al., 2021).

Analyzers and screening systems have been developed taking into account the optical properties of oats in the infrared range, analyzers and screening systems have been developed. An analyzer has been created which collects near-infrared reflectivity data. This approach has the potential to provide a low-cost solution for quickly and accurately measuring morphological traits of individual oat seeds and possibly other crop species, allowing seed screening of multiple genotypes in breeding programs (Clohessy et al., 2018).

Non-destructive screening of beta-glucan, protein and oil content in individual hulled oat kernels using the near-infrared spectrum can be successfully used in breeding programs (Gracia et al., 2017).

This paper proposes the hypothesis that during infection, the frequency characteristics and parameters of the luminescence spectra of plant seed surfaces change significantly. The relevance of the research is due to the need to create a new method for diagnosing seeds in the development of technologies for high-

precision monitoring of the condition of biological objects and the development of ecological agriculture.

The paper shows the method of frequency analysis of photoluminescence spectra of seeds and the results of analysis of the spectra of healthy and *Fusarium graminearum* inoculated oat (*Avena sativa* L.) seeds.

2 Materials and methods

2.1 Research methodology

The research methodology is shown in Figure 1.

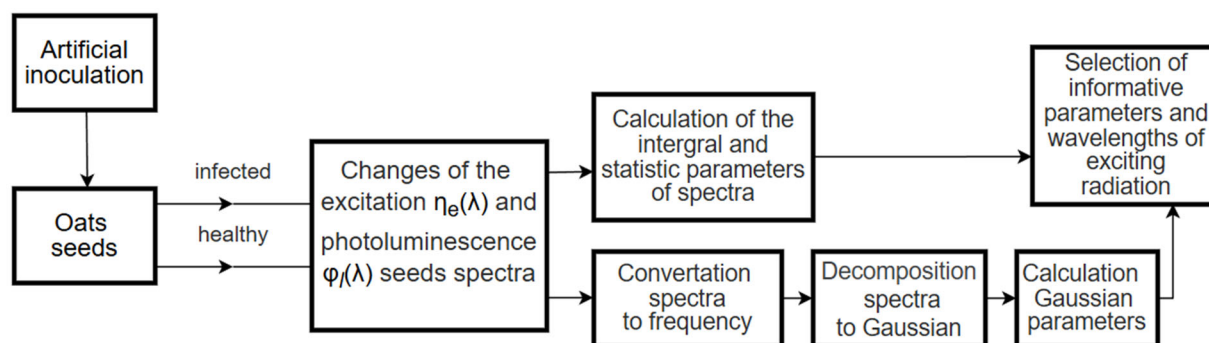


Figure 1 Flow chart of the methodology for the study of luminescent parameters of oats infected with fusarium

The selected oat seeds were inoculated with *Fusarium graminearum* spores (the process is described in more detail in Section 2.2). The spectral characteristics of excitation and photoluminescence were measured in samples of healthy and infected seeds of 250 grains each (spectral measurements are described in more detail in Section 2.3). Excitation maxima were determined for the obtained spectra and the integral photoluminescence flux and statistical parameters of the excitation spectra were calculated (the calculation procedure is described in more detail in Section 2.4). The obtained spectra were also converted from wave to frequency spectra and decomposed into Gauss curves. The parameters of the obtained curves were calculated. Further analysis of the obtained results made it possible to identify the best informative parameters of the spectra for possible optical detection of infected grains, as well as the wavelengths of photoluminescence excitation, the use of which makes it possible to determine these parameters.

2.2 Biological objects

Oat seeds of the Zalp variety were studied from the Peschanokopskaya agricultural holding (Rostov region, Russia).

The process of seed infection by mycopathogens

occurred as follows. Oat grains were weighed and packaged in four bags of 7.0 - 7.5 grams each, and then disinfected. Seeds were placed in sterile glass Petri dishes, then 3 ml of solution with *F. Graminearum* spores were added using separate clean Pasteur pipettes. After these steps, the Petri dishes were sealed with Paraphylum, packed in sealed bags and stored in a thermostat at a temperature of 28°C.

The weight of the average sample is 2.0 ± 0.1 kg, the weight of the sample is not less than 25 g. Infected with *Fusarium* grains were selected based on their external characteristics: the grain shape and structure must be small. Spots and deposits are present of the grain surface, endosperm structure – significant loss of glassiness, endosperm – loose; color of the embryo – the embryo on the cut is dark in color (brown); there is a coating of fungus on the embryonic part and in the groove. Additionally, the thin-layer chromatography method was used to detect T-2 toxin by fluorescence in long-wave ultraviolet light (365 nm) after treatment with an alcohol solution of sulfuric acid, followed by heating at 100°C-105°C. This method can detect up to 100 ng of T-2 toxin in infected spot grains.

2.3 Spectral measurements

The spectral characteristics of excitation and

luminescence of seeds were measured according to a previously developed method (Bashilov et al., 2021) using a Fluorat-02-Panorama spectrofluorometer (manufactured by Lumex, Russia) with PanoramaPro software. The spectrofluorimeter includes an optical circuit with a radiation source - a pulsed xenon lamp and a radiation receiver - a photomultiplier. The lamp operates in short pulse mode with a repetition frequency of 25 Hz. To isolate the required spectral range, monochromators with a concave diffraction grating are used.

The excitation (absorption) spectra $\eta_e(\lambda)$ were measured during synchronous scanning with excitation and registration monochromators, and on their basis, the luminescence spectra $\varphi(\lambda)$. Based on the measurement results, statistical processing was carried out, where averaging was carried out over 250 spectra. Two-dimensional photoluminescence spectra were also measured using simultaneous excitation and luminescence scanning.

2.4 Processing the results

The integral parameters of the photoluminescence spectra, which are fluxes Φ , expressed in relative units (r. u.), were calculated in the Panorama Pro program according to the Equation (1) (Bashilov et al., 2021):

$$\Phi = \int_{\lambda_1}^{\lambda_2} \varphi_l(\lambda) d\lambda \quad (1)$$

Where,

$\varphi_l(\lambda)$ – spectral characteristics of photoluminescence, r.u. nm⁻¹;

$\lambda_1 \dots \lambda_2$ – limits of the working spectral range of photoluminescence, nm.

The photoluminescence spectrum is continuous over the entire measured wavelength range. The mathematical expectation (average value) M_λ , is determined by the integral, according to the Equation (2) (Bashilov et al., 2021):

$$M_\lambda = \frac{\int_{\lambda_{\min}}^{\lambda_{\max}} \lambda \varphi(\lambda) d\lambda}{\int_{\lambda_{\min}}^{\lambda_{\max}} \varphi(\lambda) d\lambda} \quad (2)$$

Where,

$\varphi(\lambda)$ – differential distribution function (probability density distribution);

λ – wavelength, nm;

$\lambda_{\min}, \lambda_{\max}$ – minimum and maximum wavelengths of

the photoluminescence measurement range, nm.

The variance σ^2 is found by the Equation (3):

$$\sigma^2 = \int_{\lambda_{\min}}^{\lambda_{\max}} (\lambda - M_\lambda)^2 \varphi(\lambda) d\lambda \quad (3)$$

The numerical characteristic of asymmetry (skewness) is the central static moment of the 3rd order μ_3 , according to the Equation (4):

$$\mu_3 = \int_{\lambda_{\min}}^{\lambda_{\max}} (\lambda - M_\lambda)^3 \varphi(\lambda) d\lambda \quad (4)$$

In practice, the asymmetry coefficient is used to assess asymmetry As , according to the Equation (5):

$$As = \frac{\mu_3}{\sigma^3} \quad (5)$$

Where,

σ – standard deviation.

For right-sided asymmetry $As > 0$. With left-sided symmetry $As < 0$. The numerical characteristic of the steepness of the spectrum is the estimate of the central static moment of the 4th order μ_4 , according to the Equation (6):

$$\mu_4 = \int_{\lambda_{\min}}^{\lambda_{\max}} (\lambda - M_\lambda)^4 \varphi(\lambda) d\lambda \quad (6)$$

In practice, an artificially created value, which is called kurtosis, is taken as an estimate of the steepness coefficient Ex , according to the Equation (7):

$$Ex = \frac{\mu_4}{\sigma^4} - 3. \quad (7)$$

For curves that are more peaked than the normal distribution curve (bell curve), the kurtosis is positive, and for those that are flatter, the kurtosis is negative.

The largest absolute value of negative kurtosis is 2. With this value, the top of the curve drops to the x-axis and the curve is divided into two independent peaks and their analysis should be considered separately. The positive value of kurtosis can be anything.

To obtain an equation for the numerical characteristic of photoluminescence energy, it should be taken into account that each photoluminescence photon has an energy associated with the radiation wavelength by the relation, according to the Equation 8:

$$E_{\phi} = \frac{1240}{\lambda} \quad (8)$$

where E_{ϕ} measured in eV, a λ measured in nm. If the differential distribution function $\phi(\lambda)$ is known, then the total energy of the spectrum in the wavelength range is found as, according to the Equation 9:

$$E = 1240 \int_{\lambda_{\min}}^{\lambda_{\max}} \frac{1}{\lambda} \phi(\lambda) d\lambda \quad (9)$$

2.5 Decomposition of the resulting curves into Gaussians

The next stage of processing the spectra is their decomposition into elementary stripes. One of the main problems of qualitative photoluminescence analysis is the division of a wide experimental spectrum into elementary stripes and the establishment of parameters of individual emission stripes. For this purpose, methods of decomposing experimental photoluminescence spectra into individual stripes, such as the Alentsev–Fock method, λ -modulation, and derivative spectroscopy, are mainly used (Zienko et al., 2018).

However, each method has its limitations. The Alentsev–Fock method requires significant differences in the photoluminescence spectra while maintaining the unchanged shape of the individual stripes in the spectra. The disadvantage of the λ -modulation method is its low noise immunity. In the derivative spectroscopy method, the accuracy of determining the half-width of the spectrum and the order of the derivative is insufficient. Computer modeling is divorced from real physical processes, and it is difficult to associate the individual bands found with real photoluminescence centers (Zienko et al., 2018).

A method is proposed for decomposing the total of Gaussian functions that make up the experimental photoluminescence spectrum into individual stripes. The method of decomposition of the total of Gaussian functions was tested using the example of solving the problem of identifying the parameters of individual stripes in the photoluminescence spectrum. The parameters of individual stripes are close to those obtained by the Alentsev–Fock and derivative spectroscopy methods (Kovalenko et al., 2021).

Decomposition into Gaussians was carried out according to the method described in Zienko et al. (2018). To obtain Gaussian curves, the spectral

characteristics of luminescence were smoothed, after which, to determine the differential distribution function of the spectrum, it is necessary to divide the ordinates of the luminescence spectrum curve by the numerical value of the area limited by the curve, i. e. perform normalization by area, which will be the future ordinate axis.

After constructing the x-axis and y-axis, using the hardware capabilities of the Microcal Origin program, we carried out multi-peak processing, i.e. direct decomposition of the spectral characteristics of luminescence into Gaussian curves. The error of decomposition into Gaussians is about 0.018%. This error was calculated by Microcal Origin Soft.

3 Results

The luminescent characteristics of infected and uninfected oats obtained from two-dimensional scanning are presented in Figures 2 and 3, respectively.

The spectra highlight the main excitation maxima at wavelengths of 232 nm, 362 nm, 424 nm and 485 nm. In this case, photoluminescence is recorded in the ranges of 290-380 nm, 390-550 nm, 450-600 nm, 520-680 nm, respectively. There is a noticeable quantitative increase in photoluminescence in infected oats.

Statistical parameters of infected and uninfected oat seeds are presented in Table 1.

The value of the mathematical expectation does not change significantly and unsystematically. The dispersion increases for $\lambda_e = 232$ nm, 362 nm and 485 nm, which can be associated with an increase in the spread of seed parameters during infection. The asymmetry module of the graphs changes noticeably, especially for $\lambda_e = 232$ nm and $\lambda_e = 362$ nm. In the latter case, the sign changes, indicating a transition from left- to right-sided asymmetry. The value of kurtosis increases in absolute value by 14%-28% for excitation by radiation of 232 nm and 362 nm, but decreases for long-wave excitation (424 nm and 485 nm) by 5%-15%. The energy of the photoluminescence spectrum changes slightly (by 1%-2%).

The photoluminescence flux Φ increases when infected with *Fusarium*: for excitation 232 nm – by 1.71 times, 362 nm – by 1.09 times, 424 nm – by 1.30 times, 485 nm – by 1.14 times.

As an example, the normalized luminescence characteristic of uninfected oat seeds at $\lambda_e = 424$ nm and its decomposition by Gaussian curves are presented in Figure 4.

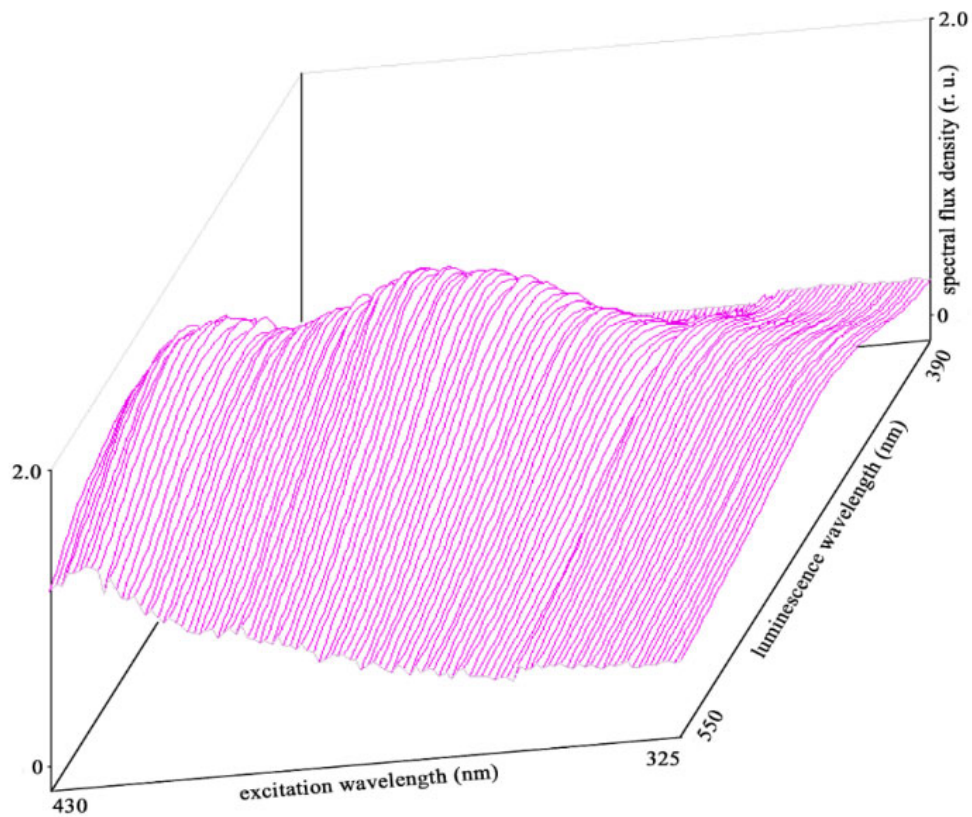


Figure 2 Photoluminescence spectrum of uninfected oat seeds during two-dimensional scanning

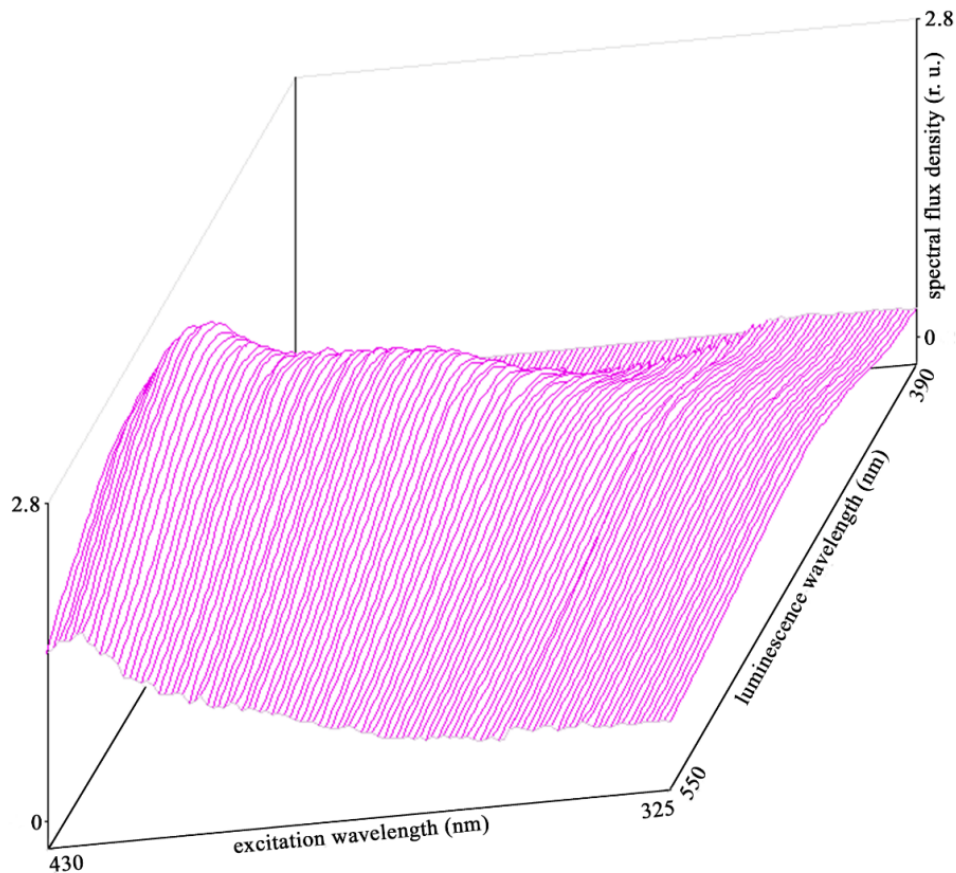


Figure 3 Photoluminescence spectrum of fusarium-infected oat seeds during two-dimensional scanning

Table 1 Statistical characteristics of uninfected and infected oat seeds

λ_e , nm	M_{λ} , nm	σ^2	As	Ex	E , eV	Φ , r. u.
uninfected seeds						
232	338	555	-0.07	-0.93	3.68	21
362	473	1348	0.10	-0.76	2.64	586
424	516	1491	0.31	-0.86	2.41	1312
485	576	1763	0.33	-0.87	2.16	652
infected seeds						
232	340	659	-0.47	-1.06	3.75	36
362	470	1412	-0.15	-0.97	2.65	641
424	512	1448	0.42	-0.75	2.43	1706
485	574	1788	0.41	-0.83	2.17	745

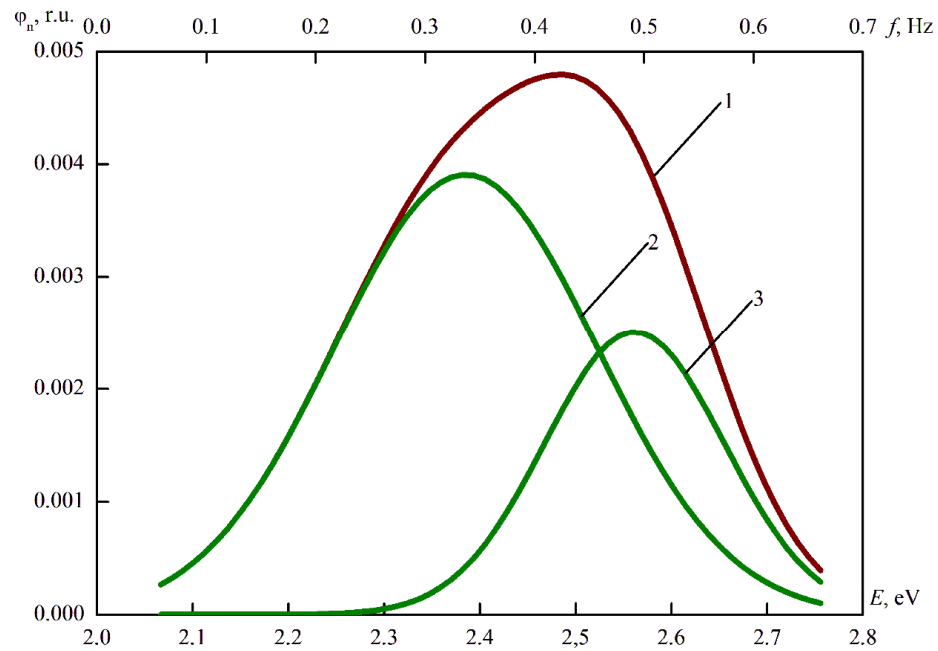


Figure 4 The normalized luminescence characteristic of uninfected oat seeds at $\lambda_e = 424$ nm (1), decomposition by Gauss curves (2), (3), where ϕ_n is the normalized luminescence intensity, f is the frequency, E is the photon energy

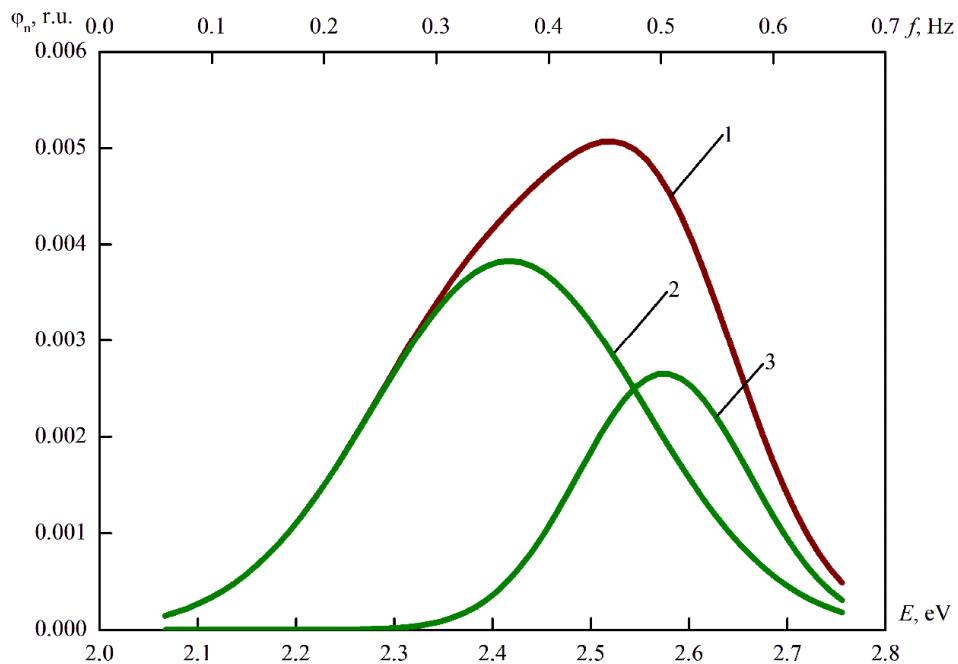


Figure 5 Normalized luminescence characteristic of fusarium-infected oat seeds at $\lambda_e = 424$ nm (1), decomposition by Gauss curves (2), (3)

The normalized luminescence characteristic of infected oat seeds at $\lambda_e = 424$ nm and its decomposition by Gaussian curves are presented in Figure 5.

All normalized spectral characteristics, including those not presented in the main part of the paper, are decomposed into two Gaussians - left (curve 2) and right (curve 3). Probably, all changes parameters ratio of the left and right Gaussians, during Fusarium infection, are connected with changes of luminescence quenching in the grain water system disturbance (Al Masri et al., 2017). The coefficients of determination, which evaluate the accuracy of approximation, are very high $R^2 > 0.98$ (Table 2).

To decompose the spectrum into elementary components, there were used the analytical Gaussian function, according to the Equation 10:

$$\varphi_n = \frac{A}{\sigma\sqrt{\pi/2}} e^{-2\left(\frac{f-f_c}{\sigma}\right)^2} \quad (10)$$

Where,

A – amplitude,

σ – dispersion,

f_c – mathematical expectation (along the frequency axis).

The values of A , σ , f_c , as well as the coefficients of determination are presented in Table 2.

Table 2 Coefficients for Gaussian decomposition of luminescence frequency spectra

Gaussian		A , 10^{-3} r. u.	Σ	f_c , Hz	R^2
uninfected seeds					
$\lambda_c = 232$ nm	curve 2	2.18±0.05	0.291±0.008	3.690±0.004	0.986
	curve 3	0.25±0.04	0.158±0.025	4.025±0.013	
$\lambda_c = 362$ nm	curve 2	4.18±0.10	0.267±0.015	2.512±0.025	0.997
	curve 3	2.03±0.16	0.268±0.036	2.717±0.052	
$\lambda_c = 424$ nm	curve 2	1.35±0.19	0.275±0.018	2.385±0.020	0.994
	curve 3	0.59±0.19	0.187±0.014	2.561±0.009	
$\lambda_c = 485$ nm	curve 2	0.56±0.09	0.226±0.021	2.121±0.015	0.992
	curve 3	0.14±0.06	0.125±0.015	2.260±0.005	
infected seeds					
$\lambda_c = 232$ nm	curve 2	0.44±0.12	0.193±0.028	3.601±0.028	0.983
	curve 3	0.23±0.12	0.135±0.019	3.745±0.016	
$\lambda_c = 362$ nm	curve 2	1.04±0.29	0.261±0.016	2.535±0.022	0.998
	curve 3	2.41±0.29	0.302±0.013	2.763±0.017	
$\lambda_c = 424$ nm	curve 2	1.32±0.23	0.275±0.021	2.417±0.025	0.995
	curve 3	0.58±0.23	0.175±0.017	2.574±0.006	
$\lambda_c = 485$ nm	curve 2	0.22±0.06	0.162±0.017	2.092±0.020	0.980
	curve 3	0.23±0.06	0.151±0.014	2.238±0.016	

The amplitude of the left curve for excitation $\lambda_e = 232$ nm decreases significantly (5 times) when seeds are infected, while for the right curve it does not change. The variance is reduced for both curves by 51% and 17%, respectively. The value of the mathematical expectation also decreases when seeds are infected.

For excitation $\lambda_e = 362$ nm, the amplitude of the left curve also decreases significantly (4 times). The variance and mathematical expectation change less significantly. For excitation $\lambda_e = 424$ nm, the parameters of the Gaussian functions practically do not change. For excitation $\lambda_e = 485$ nm, the amplitude of curve 1 decreases by 2.5 times upon infection. The variance is reduced by 39%.

4 Discussion

The main effects of fusarium blight on wheat spikelets are chlorosis, breakdown of spikelet tissue and disruption of the water system of the ear and ear. The degree and dynamics of symptom development depend on the resistance of the host plant (Al Masri et al., 2017). The characteristic spectral characteristics in the visible region are caused by changes in pigment composition, tissue structure and water content in plants. The development of fusarium, associated with a decrease in water content in infected spikelets, leads to an increase in luminescence flux compared to the uninfected control. This can be explained by a decrease in luminescence

quenching, which was previously confirmed by the author for seeds (Belyakov and Kulikova, 2020).

Similarly, the studied wheat plants (Atta et al., 2023) show two types of fluorescence in their emission spectra, namely blue-green fluorescence (range 400–600 nm) and chlorophyll fluorescence (range 650–800 nm). Earlier studies also noted an increase in photoluminescent flux during *Fusarium* infection with a shift in the spectrum to short wavelengths, especially with excitation $\lambda_e = 232$ nm. This trend was established for winter wheat (Bashilov et al., 2021) and barley (Moskovsky et al., 2023).

Spectral reflectance is influenced by plant cultivar susceptibility (Alisaac et al., 2018). There was a minimum of reflection and, as a consequence, a maximum of absorption of radiation in the range of less than 500 nm due to the rapid penetration of the pathogen, which led to the decomposition of chlorophyll. Plant aging and chlorophyll decomposition lead to an increase in reflectance intensity in the spectral ranges of 400–530 nm and 550–740 nm.

Also, in a study by Mahlein et al. (2019), using wheat as an example, high sensitivity to fusarium monitoring was shown by analysis of fluorescence and quantum yield for chlorophyll.

5 Conclusion

The optical properties of oat seeds change qualitatively and quantitatively when infected with fusarium. The largest change is in the integral flux Φ for excitation at 232 nm. The asymmetry and peakedness of the photoluminescence spectra change. When oat seeds are infected, the amplitude of the left Gaussian curve decreases several times for excitation by radiation of wavelengths of 232 nm, 362 nm and 485 nm, while the amplitude of the right Gaussian does not change. The change in dispersion during seed infection is noticeable only at excitation wavelengths of 232 nm and 485 nm. The change in the mathematical expectation f_c during infection occurs within the error.

Thus, the most informative parameters are when excitation of oat seeds with 232 nm radiation.

It is assumed that luminescence spectroscopy, along with chemometrics, helps in the effective and timely diagnosis of fusarium, and the detected signs provide the

basis for the development of sensing methods and technical means.

References

- Al Masri, A., B. Hau, H. W. Dehne, A. K. Mahlein, and E. C. Oerke. 2017. Impact of primary infection site of *Fusarium* species on head blight development in wheat ears evaluated by IR-thermography. *European Journal of Plant Pathology*, 147: 855–868.
- Alisaac, E., J. Behmann, M. T. Kuska, H. W. Dehne, and A. K. Mahlein. 2018. Hyperspectral quantification of wheat resistance to *Fusarium* head blight: comparison of two *Fusarium* species. *European Journal of Plant Pathology*, 152: 869–884.
- Atta, B. M., M. Saleem, M. Bilal, A. Rehman, and M. Fayyaz. 2023. Early detection of stripe rust infection in wheat using light-induced fluorescence spectroscopy. *Photochemical & Photobiological Sciences*, 22(1): 115–134.
- Balcerowicz, M., K. N. Shetty, and A. M. Jones. 2021. Fluorescent biosensors illuminating plant hormone research. *Plant Physiology*, 187(2): 590–602.
- Bashilov, A. M., I. Y. Efremenko, M. V. Belyakov, A. V. Lavrov, A. A. Gulyaev, S. A. Gerasimenko, S. I. Borzenko, and A. A. Boyko. 2021. Determination of Main Spectral and Luminescent Characteristics of Winter Wheat Seeds Infected with Pathogenic Microflora. *Photonics*, 8(11): 494.
- Belefant-Miller, H., G. H. Miller, and J. N. Rutger. 2005. Nondestructive Measurement of Carotenoids in Plant Tissues by Fluorescence Quenching. *Crop Science*, 45: 1786–1789.
- Belyakov, M. V., and M. G. Kulikova. 2020. Control of bulk products' humidity and grinding size by the photoluminescent method photoluminescent quality control. *Journal of Food Processing and Preservation*, 44: e14640.
- Bucur, D. E., F. Doohan, and S. Kildea. 2025. Prevalence and Diversity of *Fusarium* Species in Oat Grains Harvested From Commercial Oat Fields in Ireland in 2022. *Plant Pathology*, 74(9): 2818–2829.
- Camuri, I. J., A. B. da Costa, A. S. Ito, and W. M. Pazin. 2019. pH and Charge Effects Behind the Interaction of Artepillin C, the Major Component of Green Propolis, With Amphiphilic Aggregates: Optical Absorption and Fluorescence Spectroscopy Studies. *Photochemistry and Photobiology*, 95(6): 1345–1351.
- Clohesy, J. W., D. Pauli, K. M. Kreher, E. S. Buckler, P. R. Armstrong, T. Wu, O. A. Hoekenga, J. L. Jannink, M. E.

- Sorrells, and M. A. Gore. 2018. A Low-Cost Automated System for High-Throughput Phenotyping of Single Oat Seeds. *The Plant Phenome Journal*, 1(1): 180005.
- Dick, F., A. Dietz, S. Asam, and M. Rychlik. 2024. Development of a high-throughput UHPLC-MS/MS method for the analysis of *Fusarium* and *Alternaria* toxins in cereals and cereal-based food. *Analytical and Bioanalytical Chemistry*, 416: 5619–5637.
- Dhanya, V. G., A. Subeesh, C. Susmita, Amaresh, S. J. Saji, C. Dilsha, C. Keerthi, A. Nunavath, A. N. Singh, and S. Kumar. 2024. High throughput phenotyping using hyperspectral imaging for seed quality assurance coupled with machine learning methods: principles and way forward. *Plant Physiology Reports*, 29(4): 749–768.
- Gracia, M. B., P. R. Armstrong, H. Rongkui, and S. Mark. 2017. Quantification of betaglucans, lipid and protein contents in whole oat groats (*Avena sativa* L.) using near infrared reflectance spectroscopy. *Journal of Near Infrared Spectroscopy*, 25(3): 172–179.
- Gsponer, N. S., M. C. Rodríguez, R. E. Palacios, and C. A. Chesta. 2018. On the Simultaneous Identification and Quantification of Microalgae Populations Based on Fluorometric Techniques. *Photochemistry and Photobiology*, 94(5): 875–880.
- Himuro, Y., T. Gondo, K. Yamakawa, and R. Akashi. 2009. Genetic transformation of bahiagrass (*Paspalum notatum* Flüge) by visually screening cells expressing green fluorescent protein. *Grassland Science*, 55: 216–220.
- Jia, M., X. Liao, L. Fang, B. Jia, M. Liu, D. Li, L. Zhou, and W. Kong. 2021. Recent advances on immunosensors for mycotoxins in foods and other commodities. *TrAC Trends in Analytical Chemistry*, 136: 116193.
- Kini, M. G., and R. Bhandarkar. 2023. Quality Assessment of Seed Using Supervised Machine Learning Technique. *Journal of Institution of Engineers (India): Series B*, 104: 901–909.
- Kovalenko, A. V., S. M. Vovk, and Y. G. Plakhtii. 2021. Sum Decomposition Method for Gaussian Functions Comprising an Experimental Photoluminescence Spectrum. *Journal of Applied Spectroscopy*, 88(2): 357–362.
- Lehnhoff, E. A., B. K. Keith, W. E. Dyer, R. K. Peterson, and F. Menalled. 2013. Multiple Herbicide Resistance in Wild Oat and Impacts on Physiology, Germinability, and Seed Production. *Agronomy Journal*, 105: 854–862.
- Mahlein, A. K., E. Alisaac, A. Al Masri, J. Behmann, H. W. Dehne, and E. C. Oerke. 2019. Comparison and Combination of Thermal, Fluorescence, and Hyperspectral Imaging for Monitoring *Fusarium* Head Blight of Wheat on Spikelet Scale. *Sensors*, 19(10): 2281.
- Moskovsky, M. N., Y. H. Shogenov, A. V. Lavrov, A. A. Gulyaev, I. Y. Efremkov, D. S. Pyatchenkov, and M. V. Belyakov. 2023. Spectral Photoluminescent Parameters of Barley Seeds (*Hordéum vulgare*) Infected with *Fusarium* ssp. *Photochemistry and Photobiology*, 99(1): 29–34.
- Natarajan, S., D. Bucur, S. Kildea, and F. Doohan. 2025. Digital PCR assays for quantifying trichothecene-producing *Fusarium* species, including *Fusarium langsethiae*, *F. poae*, and *F. sporotrichioides*, in oats. *Analytical and Bioanalytical Chemistry*, 417(13): 2957–2969.
- Pařízková, B., A. Žukauskaitė, T. Vain, P. Grones, S. Raggi, M. F. Kubeš, M. Kieffer, S. M. Doyle, M. Strnad, S. Kepinski, R. Napier, K. Doležal, S. Robert, and O. Novák. 2021. New fluorescent auxin probes visualise tissue-specific and subcellular distributions of auxin in Arabidopsis. *New Phytologist*, 230(2): 535–549.
- Qu, Z., X. Ren, Z. Du, J. Hou, Y. Li, Y. Yao, and Y. An. 2024. *Fusarium* mycotoxins: The major food contaminants. *mLife*, 3(2): 176–206.
- Rigler, R., and J. Widengren. 2018. Fluorescence-based monitoring of electronic state and ion exchange kinetics with FCS and related techniques: from T-jump measurements to fluorescence fluctuations. *European Biophysics Journal*, 47(4): 479–492.
- Rumfeldt, J. A., H. Takala, A. Liukkonen, and J. A. Ihalainen. 2019. UV-Vis Spectroscopy Reveals a Correlation Between Y263 and BV Protonation States in Bacteriophytochromes. *Photochemistry and Photobiology*, 95(4): 969–979.
- Tivig, I., T. Savopol, E. Kovacs, and M. G. Moisesescu. 2020. An experimental system for real-time fluorescence recordings of cell membrane changes induced by electroporation. *European Biophysics Journal*, 49(1): 105–111.
- Toro, P. M., D. H. Jara, A. H. Klahn, D. Villaman, M. Fuentealba, A. Vega, and N. Pizarro. 2021. Spectroscopic Study of the E/Z Photoisomerization of a New Cyretrenyl Acylhydrazone: A Potential Photoswitch and Photosensitizer. *Photochemistry and Photobiology*, 97(1): 61–70.
- Zienko, S., M. Belyakov, and V. Malyschkin. 2018. Investigation of luminescence spectra of the plant tissue cover tissue. *Applied Physics*, 3: 43–48.