

SPECTRAL FEATURES OF THE MAIN SPRING WHEAT PESTS (*EURYGASTER INTEGRICEPS* AND *ALIA ACUMINATA*) IN MACHINE RECOGNITION

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Annotation. For the first time, the article presents the spectral characteristics of the entomofauna of Kazakhstan, using the wheat pests *Eurygaster integriceps* and *Aelia acuminata* as examples. Spectral analysis revealed how insects reflect and absorb light. Patterns in the formation of spectral curves and key factors associated with morphological features, pigmentation, and exoskeleton structure were identified. Differences in spectral intensity are attributed to variations in melanin and chitin content among different parts of the insects and between different insect species. It is shown that in the 550 nm range, reflectance is determined by pigment composition, while in the 700-750 nm region, it is determined by the structural components of the integument; at the same time, the reflectance coefficients of *Aelia acuminata* are higher than those of *Eurygaster integriceps*. Based on spectral and morphological characteristics, a classification model was developed using the Random Forest algorithm, achieving an identification accuracy of 89 %. The results obtained expand the understanding of the ultrastructure of the insect exoskeleton and demonstrate the potential of using hyperspectral imaging in agriculture for monitoring cereal crop pests. Furthermore, the generated spectral profiles can serve as references for the creation of regional spectral libraries of insects. The study opens up new opportunities for implementing sustainable practices in the agro-industrial sector.

Keywords: hyperspectral imaging, spectral characteristics, wheat pests, entomofauna of Kazakhstan, remote sensing.

Introduction. Hyperspectral imaging is a remote sensing data processing technique that expands and refines the capabilities of multispectral image analysis [1]. This technology effectively differentiates between plant diseases and pests, ensuring agricultural product quality and reducing crop losses [2]. Hyperspectral imaging enables the identification of similar insect species and field surveys to detect crops infested with harmful insects. Near-infrared hyperspectral imaging (NIR-HSI) is an effective method for detecting *Tetramesa caespitum* and *Tetramesa impurum* [3], *Halyomorpha halys* [4], *Tetranychus urticae* [5], *Oulema melanopus* [6], the brown marmorated stink bug [7], and *Phenacoccus solenopsis* [8]. Hyperspectral imaging allows for the detection of pest damage in soybeans [9], rice [10], mangoes [11], and sweet peppers even before visually noticeable signs appear [12], for automatic pest recognition based on neural networks [13], and for identifying damage to mangrove leaves [14]. The use of UAVs enhances the efficiency of this technology for field monitoring [15] [16] [17]. Thus, hyperspectral imaging technology can increase the economic efficiency of the agricultural sector. To implement hyperspectral imaging in agriculture for pest identification or damage assessment, more data are needed on the spectral characteristics of the entomofauna and the potential applications of this technology under the agricultural conditions of Kazakhstan. The identification and classification of insects require an analysis of their spectra, which reveal unique optical properties – such as reflectance or absorption of light at specific wavelengths – enabling accurate differentiation even between similar species.

Therefore, our goal was to study the spectral characteristics of spring wheat pests in

northeastern Kazakhstan using hyperspectral imaging for their identification and the assessment of crop infestation. Samples of *Eurygaster integriceps* and *Aelia acuminata* were selected for the study, as they cause significant economic damage by reducing cereal yields and deteriorating grain quality.

Materials and methods of research. The collection of phytophagous insects was carried out during the summer months of 2025 in the northeastern region of Kazakhstan (Pavlodar region). The primary objects of the study were *Eurygaster integriceps* and *Aelia acuminata*, which pose a significant threat to spring wheat crops. The body of an adult *Eurygaster integriceps* is oval, convex, and approximately 10–13 mm long. The scutellum is greatly expanded and covers most of the abdomen and wings; its colouration is greyish-cream with brown spots, and the body is covered by a chitinous cuticle. The body length of an adult *Aelia acuminata* is about 7–10 mm. The body is elongated, with a pointed, narrow head section and an oblong scutellum. Its colouration is light with brown longitudinal stripes on the pronotum and scutellum. Standard methods were used for the quantitative accounting of the insects [18].

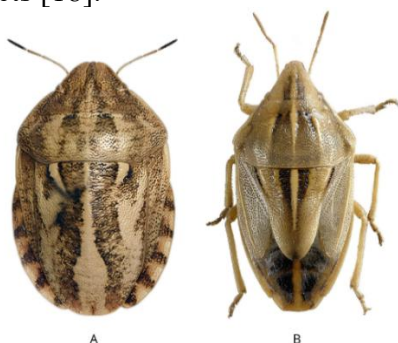


Figure 1 – Study objects: *Eurygaster integriceps* (A) and *Aelia acuminata* (B)

Imaging and acquisition of hyperspectral images were conducted at the Biological Research Laboratory of Toraighyrov University (Pavlodar, Kazakhstan) using an FS-13 scanning camera operating in the 400–1000 nm range (Hangzhou, China). The camera utilised a CMOS detector across 1200 spectral channels with a resolution of 2.5 nm.

Image processing and the conversion of hypercubes into two-dimensional images to optimise the visualisation process were performed using Breeze software (v2024.2.0). We used PCA model analysis for dimensionality reduction. Using the tools in Pixel Explore mode, the optical characteristics of different body parts of the studied phytophagous species were obtained. The pixel distribution density allowed for the analysis of their scatter on variance diagrams according to the distribution of spectral data across the principal components of the dimensionality-reduced images, allowing the identification of major patterns and interrelations between the studied characteristics. Data visualisation across spectral channels enabled the selection of the most relevant samples. These numbered 36 for the Train set and 120 for the Train+Test set. Their extraction was preceded by stages of calibration, standard normalisation, and centering. The overall working range of the model was defined between 391.51 and 1006.8 nm (Figure 2).

The classification model was trained for the two insect species based on the Random Forest algorithm, using a pixel prediction classification type based on the average spectral indices of the object. The model's performance was tested on seven insect species, five of which were unknown to the classification model, while training was conducted only on the two known subsets of cereal pests. The spectral data results were subjected to statistical processing using descriptive statistics and ANOVA methods. To assess the model's performance, the results of basic quality metrics for the classification model operating on the basis of the machine learning algorithm were analysed.

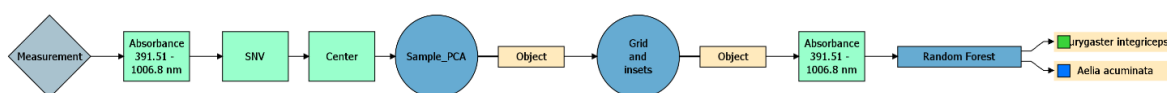


Figure 2 – Classification model for harmful insect species

Results and Discussion. The figures present hyperspectral images of the wheat pests (*Eurygaster integriceps* and *Aelia acuminata*), Raw Spectrum graphs, and Variance Scatter diagrams. The hyperspectral images are coloured in false colours, which correspond to the intensity level of light reflectance. Cool colours (blue, light blue) indicate areas with low reflectance, while warm colours (red, orange) show areas of high reflectance. The curves on the Raw Spectrum graph reflect the spectral characteristics of different insect body parts in terms of reflectance coefficient and wavelength. All figures include legends; for example, the red curve corresponds to the top of the head, and the green curve corresponds to the pronotum. The Variance Scatter diagram shows the distribution of spectral data after dimensionality reduction, where each point corresponds to one pixel of the hyperspectral image, transformed into principal component coordinates.

Eurygaster integriceps

Figure 3 presents data on *Eurygaster integriceps*. On the Raw Spectrum graph, the red curve corresponds to the top of the head. The first peak of the curve is at the 25% level of the reflectance scale, the second at 22.5%. The green curve, with reflectance within 20% at the first peak and 10% at the second peak, represents the pronotum. The blue spectrum belongs to the scutellum, where the reflectance of the first and second peaks is recorded at 35% and 20%, respectively. The yellow curve represents the elytra and has a reflectance of 22.5% at the first peak and 15% at the second. The light blue spectrum belongs to the wing membrane, where the reflectance at the first peak is recorded at 22.5% and at the second at 14%. The purple curve describes the forelegs, with reflectance coefficients of 16% and 37% sequentially for the two peaks. The ochre-coloured curve represents the hind legs, with the first peak having a reflectance of 25% and the second 17%. The beige curve describes the spectrum of the antennae, with maximum reflectance values prevailing from 22.5% at the first peak to 30% at the second peak. The grey spectrum belongs to the underside of the head, with reflectance reaching maximum values of 30% and 20% depending on the increase in wavelength. The black curve represents the insect's thorax, with reflectance coefficients of 38% and 22.5% for the first and second peaks, respectively. The light green spectrum describes the reflective and absorptive characteristics of the abdomen and demonstrates a 44% reflectance at the first peak and 25% at the second peak. A cumulative analysis shows the first maximum is in the wavelength range of 550-750 nm, the second in 750-780 nm. Distinctive characteristics were identified for the purple and beige curves, where the first peak lies within the 550-700 nm wavelength range, and the second within 700-780 nm.

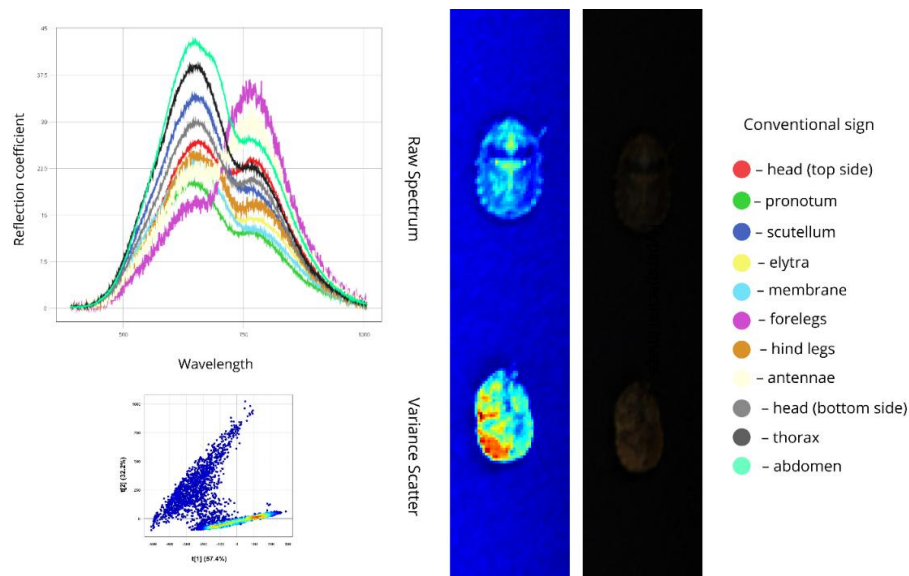


Figure 3 – Spectral features of *Eurygaster integriceps*

On the Variance Scatter diagram, the first component $t[1]$ (57.4%) reflects the majority of data variation and differences between spectra, while the second component $t[2]$ (32.2%) shows

additional variations for the studied insect species. Together, the first two components explain 89.6% of the total variance, indicating high informativeness of the two-dimensional representation for this species. The main cloud of points forms an elongated diagonal structure, explaining most of the variation. A separate grouped distribution is located closer to the bottom of the graph, characterised by lower variability and a narrower range of values belonging to specific morphological features of the species.

Aelia acuminata

Figure 4 presents the spectral data for *Aelia acuminata*. On the Raw Spectrum graph, the red curve corresponds to the top of the head, where the first maximum of the curve is at the 55% level of the reflectance scale, and the second at 40%. The green spectrum is characterised by reflectance of 75% at the first peak and 45% at the second, representing the pronotum. The blue curve belongs to the scutellum, with reflectance coefficients of 90% and 45% for the first and second peaks, respectively. The yellow curve clearly demonstrates the reflective properties of the elytra and has maximum reflectance values of 75% and 40% for the two peaks. The light blue spectrum belongs to the wing membrane, where the reflectance at the first peak is recorded at 80%, and for the second at 40%. The purple curve describes the forelegs, where the reflective-absorptive properties of the morphological structures and integuments vary from 25% to 40%.

The ochre-coloured curve represents the middle legs, where both peaks have approximately similar values; the first peak has a reflectance of 45%, and the second 49%. The beige curve describes the spectrum of the hind legs, with reflectance values varying in the range of 40-48%. The grey spectrum belongs to the underside of the head, the first peak having a reflectance with a total contribution around 70%, and the second peak around 45%. The black curve corresponds to the reflective characteristics of the insect's thorax, with maximum reflectance of the first and second peaks corresponding to 90% and 52%, respectively. The light green curve describes the spectrum of the abdomen with reflectance indicators within 90% at the first peak and 55% at the second. In general, it was established that the first peak lies in the wavelength range of 550-750 nm, while the limits of the second peak are lower and correspond to the range of 750-780 nm. The spectra for the ochre, purple, and beige curves differ in ranges; the first peak is observed within the 550-700 nm wavelength, and the second in the 700-780 nm range.

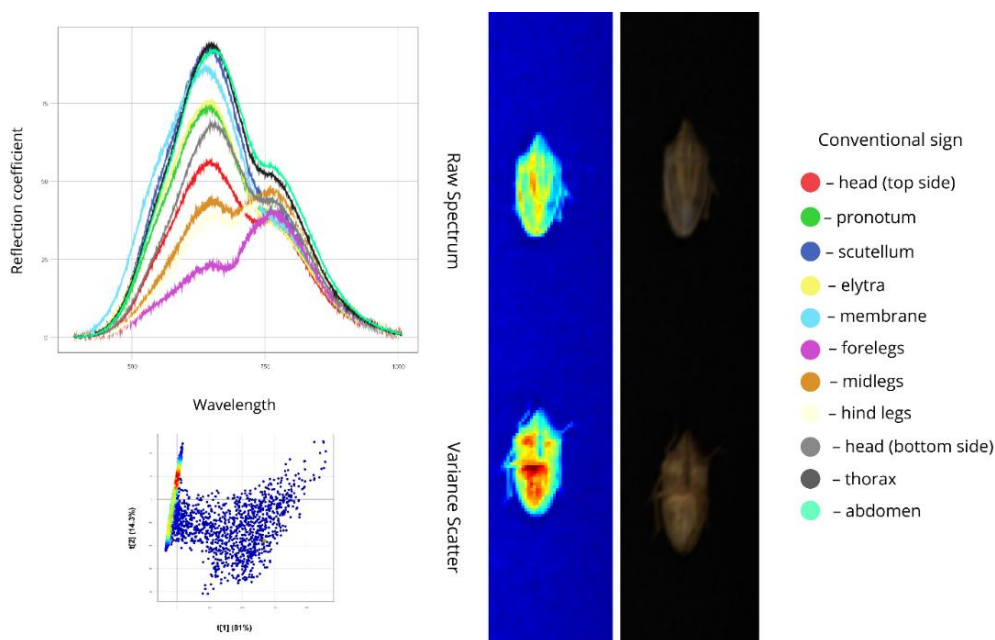


Figure 4 – Spectral features of *Aelia acuminata*

On the variance diagram, the first component t[1] (81%) explains the main share of data variability and displays key differences between spectra, while the second component t[2] (14.3%)

also shows significant variable characteristics not covered by PC1 but contributing to the overall image. Together, the first two components explain 95.3% of the variability, indicating the high informativeness of the two-dimensional PCA model. The main data variation is concentrated along the horizontal axis; the main contribution to spectral differences comes from the overall level of reflectance and the shape of the spectral curve. The second component reflects secondary differences related to the texture of the integuments, cuticle thickness, and pigmentation.

Figure 5 presents a general Raw Spectrum graph showing the spectral characteristics of the upper and lower parts of the insects. The red curve reflects the upper part, and the green curve the lower part of *Eurygaster integriceps*. The red spectrum has two peaks: the first with a reflectance of 20%, the second with a reflectance of 18%. For the green curve, the peaks correspond to reflectance values of 35% and 25%. The blue curve belongs to the upper part of *Aelia acuminata* with a reflectance of 80% at the first peak and 40% at the second. The yellow spectrum describes the lower part and has reflectance coefficients with maxima within 90% and 55%. In general, the first peak of the curves lies in the 550-750 nm range, while the second peak falls in the 750-780 nm range.

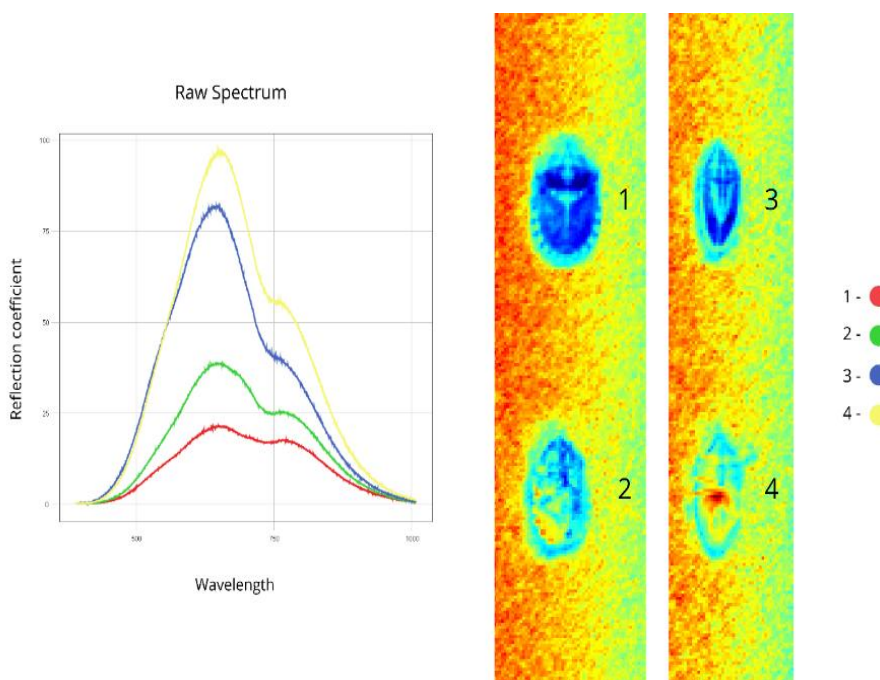


Figure 5 – Comparison of spectra of *Eurygaster integriceps* and *Aelia acuminata*

Statistical analysis

In accordance with the main values of the spectral characteristics obtained during the hyperspectral imaging, key reflectance indicators were calculated and are presented in Table 1. It was established that for *Eurygaster integriceps*, the reflectance coefficient for various body parts varied from 10 to 35%, with an overall average value reaching 24.3%. The pronotum (15%) and the membranous part of the elytra (18.3%) possessed the lowest reflective capabilities. The reason for this may be the high degree of radiation absorption within the VNIR range due to the dark colouration of these areas, which is confirmed by the insignificant deviation (1.3%), as well as the average coefficient of variation of 5.4%, indicating moderate variability in the spectral characteristics. Maximum variability was noted for the forelimbs (10.06%), which may be due to the heterogeneity of the surface structures of the integuments, as well as changes in the angle of incident radiation. A low level of spectral contrast and, consequently, a smoother spectral profile is noted due to the average Δ Reflectance value within 7.4% (Table 1, Figure 6).

In *Aelia acuminata*, conversely, higher reflectance values were recorded, ranging from 20% to 90%, where the average value of the reflective characteristics exceeds half the possible range (57.7%). This indicator is almost twice as high as that for *Eurygaster integriceps*. Maximum

reflectance values were noted for the lower part of the body as a whole, the thorax, and the abdomen (71.0-72.5%), which is a result of the high reflectivity of the cuticle due to its light colouration, and is also confirmed by comparable relative variability when recording higher reflectance indicators in absolute value ($\sigma=3.6$, $CV=5.9$). The manifestation of both light and dark areas in the visualisation of hyperspectral imaging results explains the fact that Δ Reflectance in *Aelia acuminata* exceeds that of *Eurygaster integriceps* by almost 2.7 times (19.8%), which clearly demonstrates more pronounced spectral differences between different parts of the insect's body.

Table 1 – Spectral data of crops pests: reflectance indicators

№	Spec ies	Body part	Reflectance (%)		Mean Reflectan ce	Standard Deviation	CV	Rate of Chan ge	ΔReflectance
			min	max					
1	<i>Eurygaster integriceps</i>	Body (top side)	18	20	19.0	0.25	1.34	1.41	2.0
		Body (bottom side)	25	35	30.0	1.27	4.23	7.05	10.0
		Head (top side)	22.5	25	23.8	0.32	1.34	1.76	2.5
		Pronotum	10	20	15.0	1.27	8.47	7.05	10.0
		Scutellum	20	35	27.5	1.91	6.93	10.58	15.0
		Elytra	15	22.5	18.8	0.95	5.08	5.29	7.5
		Membrane	14	22.5	18.3	1.08	5.92	5.99	8.5
		Forelegs	16	37	26.5	2.67	10.06	14.81	21.0
		Hind legs	17	25	21.0	1.02	4.84	5.64	8.0
		Antennae	22.5	30	26.3	0.95	3.63	5.29	7.5
		Head (bottom side)	20	30	25.0	1.27	5.08	7.05	10.0
		Thorax	22.5	38	30.3	1.97	6.51	10.93	15.5
		Abdomen	25	44	34.5	2.41	6.99	13.40	19.0
Average			19.0	29.5	24.3	1.3	5.4	24.3	7.4
2	<i>Aelia acuminata</i>	Body (top side)	40	80	60.0	5.08	8.47	28.21	40.0
		Body (bottom side)	55	90	72.5	4.45	6.13	24.68	35.0
		Head (top side)	40	55	47.5	1.91	4.01	10.58	15.0
		Pronotum	45	75	60.0	3.81	6.35	21.15	30.0
		Scutellum	45	90	67.5	5.72	8.47	31.73	45.0
		Elytra	40	75	57.5	4.45	7.73	24.68	35.0
		Membrane	40	80	60.0	5.08	8.47	28.21	40.0
		Forelegs	25	40	32.5	1.91	5.86	10.58	15.0
		Midlegs	45	49	47.0	0.51	1.08	2.82	4.0
		Hind legs	40	48	44.0	1.02	2.31	5.64	8.0
		Head (bottom side)	45	70	57.5	3.18	5.52	17.63	25.0
		Thorax	52	90	71.0	4.83	6.80	26.79	38.0
		Abdomen	55	90	72.5	4.45	6.13	24.68	35.0
Average			43.6	71.7	57.7	3.6	5.9	57.7	19.8

Analysis of the spectral contrast indicators shows the minimum and maximum wavelength coverage from 550 to 780 nm, with a spectral band width of 230 nm. Table 2 also notes that the reflectance contrast values were identical for both species ($C=1.4$, $B_{rel}=0.2$, $C_{norm}=0.3$) due to the peaks covering the same wavelength ranges, indicating an average level of spectral distinguishability.

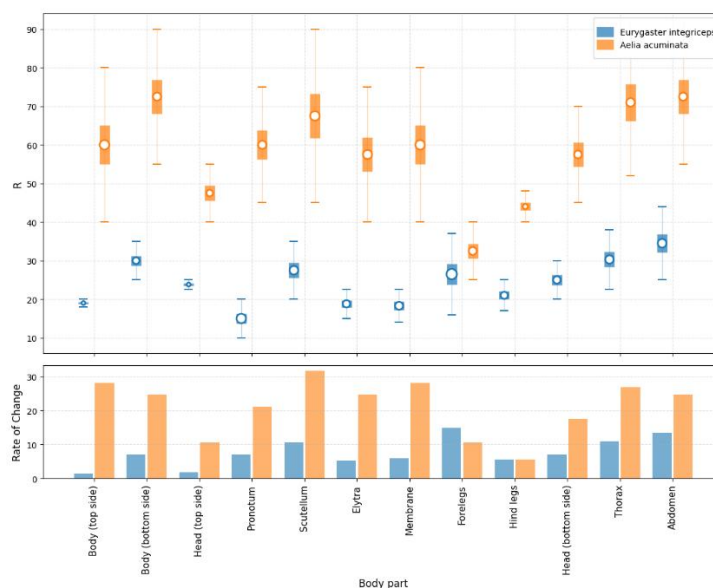


Figure 6 – Statistical indicators of different body parts reflectance of *Eurygaster integriceps* and *Aelia acuminata*

This is effectively determined by the optical and morphological properties of their integuments, features of the integument microstructure, and pigment composition.

Table 2 – Indicators of spectral contrast in the studied VNIR range

№	Species	Wavelength (nm)		Spectral Bandwidth	Contrast ratio	Relative bandwidth	Normalised contrast
		$\lambda_{\min}$	$\lambda_{\max}$				
1	<i>Eurygaster integriceps</i>	550	780	230	1.4	0.2	0.3
2	<i>Aelia acuminata</i>	550	780	230	1.4	0.2	0.3

Statistical differences in the form of more pronounced spectral variations and high reflectance values in *Aelia acuminata* create conditions for automatic identification of this species. In contrast, for *Eurygaster integriceps*, the features of a smooth spectral profile create a condition for their potential merging with other monitoring objects, especially in dense agro-phytocenosis conditions. Accordingly, in general, the spectral properties of the main cereal pests of wheat within the 550-780 nm range are informative identifiers used for analysing interspecific differences among the studied pests, which may have practical application for the classification of harmful entomofauna in agroecosystems.

Classification model

A classification model was built based on the spectral data. To test the model, 2 known species (*Eurygaster integriceps* and *Aelia acuminata*) and 5 unclassified species were used. The Random Forest algorithm was employed to train the model. Figure 7 presents the statistical indicators of the model. According to the macro and micro accuracy metrics, the model correctly classifies 89% of objects on average. Based on the log loss and log loss reduction metrics, the model exhibits good probabilistic predictions compared to a random model. Cross-validation indicates a slight overfitting during model testing, resulting in lower performance metrics on new data.

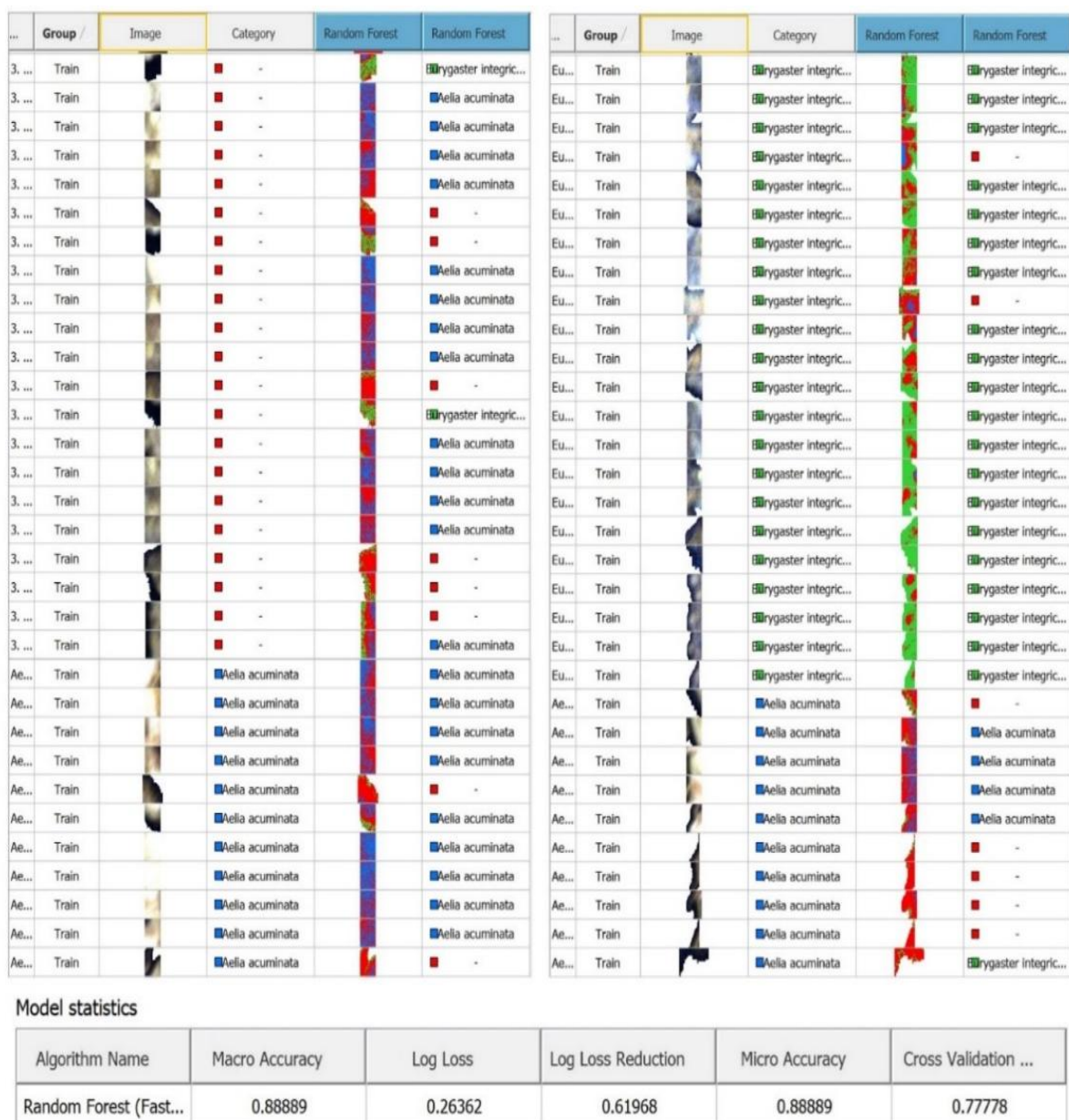


Figure 7 – Results and classification model statistics

Figure 8 shows the Confusion matrix for the trained model and the model during testing. The sample consisted of 120 objects, of which 36 belonged to the two known species, and the remainder to insect species unknown to the system. During model training, 72.2% of *Eurygaster integriceps* and 83.3% of *Aelia acuminata* were correctly classified, whereas during testing with unknown classes, these figures were 46.9% and 57.1%, respectively.

Due to training the model alongside unclassified insect samples, there is a large percentage of unidentified samples during model testing (40.8%). Minor classification errors occur due to similar spectral characteristics of the *Eurygaster integriceps* and *Aelia acuminata* samples (3.57% and 10.9% errors, respectively). Precision indicates how accurate the model's predictive capability is for a given class. For *Eurygaster integriceps*, precision is 93.8%; for *Aelia acuminata*, it is 82.1%. Recall represents the proportion of actual class objects correctly identified, where for *Eurygaster integriceps* it is 46.9%, and for *Aelia acuminata* 57.1%. The F1-score is a comprehensive metric balancing the previous two indicators; accordingly, for *Eurygaster integriceps* it is 62.5%, and for *Aelia acuminata* 67.4%. Under conditions of limited data and a small sample size, the model demonstrated good results for pest identification.

Since *Eurygaster integriceps* and *Aelia acuminata* belong to the same family, *Scutelleridae*, they share similar morphological traits, which is reflected in their spectral properties.

Actual classes	Total	Eurygaster integriceps	Aelia acuminata	No class
Eurygaster integriceps	64 (53.3%)	30 (46.9%)	7 (10.9%)	27 (42.2%)
Aelia acuminata	56 (46.7%)	2 (3.57%)	32 (57.1%)	22 (39.3%)
# Predicted	120 (100%)	32 (26.7%)	39 (32.5%)	49 (40.8%)
Correctly	62 (51.7%)			
Incorrectly	58 (48.3%)			
Precision		93.8%	82.1%	
Recall		46.9%	57.1%	
F-score		62.5%	67.4%	

Actual classes	Total	Eurygaster integriceps	Aelia acuminata	No class
Eurygaster integriceps	18 (50%)	13 (72.2%)		5 (27.8%)
Aelia acuminata	18 (50%)		15 (83.3%)	3 (16.7%)
# Predicted	36 (100%)	13 (36.1%)	15 (41.7%)	8 (22.2%)
Correctly	28 (77.8%)			
Incorrectly	8 (22.2%)			
Precision		100%	100%	
Recall		72.2%	83.3%	
F-score		83.9%	90.9%	

Figure 8 – Confusion matrix of classification model results (Train+Test set and Train set)

Due to the light shade of the integuments, epicuticle, and waxy components of the exoskeleton, these pests exhibit high reflectance intensity, with the highest reflectance intensity observed from the abdomen, sternum, and forelegs of the insect. The pronotum shows the lowest reflectance due to its dark colouration. The ventral part of the insects has a smooth structure with fewer melanins, ommochromes, pterines, and other pigments, especially in the form of brown spots, resulting in a higher reflectance coefficient compared to the dorsal part. The insect tarsi are characterised by a thin cuticle, contain numerous sensilla and articular structures, and possess high surface anisotropy; therefore, their spectral bands differ from other parts, with the first peak reflectance intensity being lower than the second. Within the NIR range, reflectance originates from setae on the legs, which scatter light and increase the reflectance of the second peak. In other body parts, the first peak has a higher reflectance coefficient than the second due to pigment activity within the 550-750 nm range and reflectance from the cuticle within the 750-780 nm range. All insect parts, except the legs, exhibit a red edge around 750 nm, while in the 700-750 nm region, a transition occurs from light absorption by pigments to reflectance by the cuticle. It was also established that *Aelia acuminata* collectively has more light-coloured areas compared to *Eurygaster integriceps*, which has more brown spots in its colouration. Consequently, due to lower pigment content and lighter colouration (as confirmed by other studies [19]), as well as a smoother structure, *Aelia acuminata* has a higher reflectance coefficient in the VIS and NIR ranges. Evidently, such differences in insect morphology serve as markers for their identification against a background of other pests. Accordingly, the most significant differences in the reflectance properties of the integuments of the studied species and their spectral characteristics are depicted in Figure 9.

Based on the identified spectral data, a classification model was developed. The Random Forest algorithm builds many decision trees on different subsets of data and features, which reduces the risk of overfitting and increases robustness given a small sample size, unknown classes, and a large number of morphological and spectral features of living objects such as insects. Unlike neural networks, the algorithm does not require a large dataset or feature scaling.

Despite this, classification errors exist between *Eurygaster integriceps* and *Aelia acuminata* in the model, which is due to their morphological and spectral similarity, the limited size of the training sample, and the insufficient informativeness of the features used. As a result, the feature

distributions of the two classes overlap significantly, reducing the accuracy of their identification. The presence of a large number of samples classified as 'No class' indicates high model reliability, as most test objects belonged to other insect species (for which the model was not trained).

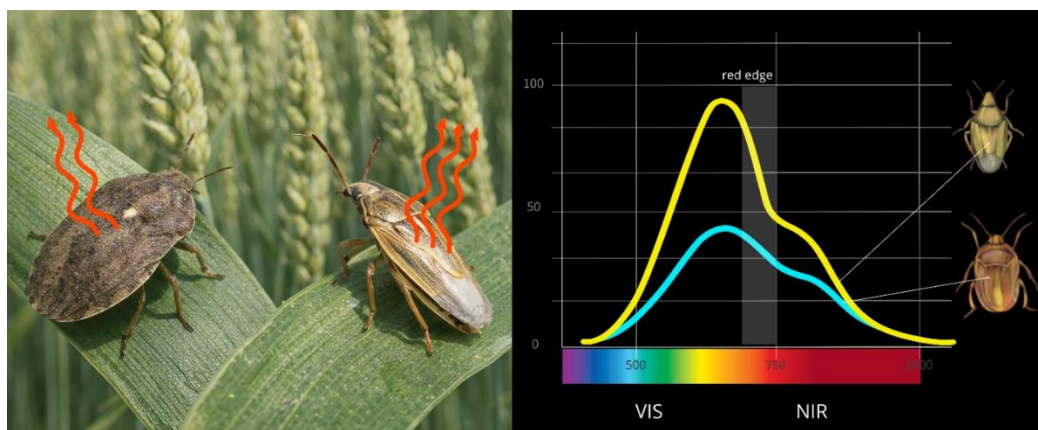


Figure 9 – Reflectance characteristics of *Eurygaster integriceps* and *Aelia acuminata*

Conclusion. This study provides the first description of entomofaunal spectra in Kazakhstan, specifically the wheat pests *Eurygaster integriceps* and *Aelia acuminata*. Analysis of the spectra revealed how these insects reflect, transmit, and absorb light, information that can be utilised in agricultural practice for pest damage assessment. The work identified patterns and determined key factors influencing the spectral curves of different insect species, demonstrating the possibility of distinguishing similar species through hyperspectral imaging based on spectral differences.

Despite variations, the spectral curves of the species share a similar form, yet specific differences emerge due to the reflectance properties of the exoskeleton. The diversity in intensity reflects variability among different body parts and morphological features of individuals, such as pigmentation, density, and structure of the chitinous integument. In the range around 550 nm, reflectance depends on pigment composition; from 700-750 nm, reflectance originates from the structural components of the insect exoskeleton. Furthermore, reflectance intensity in the VIS range depends on pigment colouration: the darker the pigment, the more light it absorbs, resulting in a lower reflectance coefficient for the spectral curve. Consequently, *Aelia acuminata* exhibits higher reflectance coefficients than *Eurygaster integriceps*. Based on morphological differences and identified patterns in spectral characteristics, a classification model was developed to identify *Eurygaster integriceps* and *Aelia acuminata* with an accuracy of 89%, leveraging the ability of the Random Forest algorithm to model complex nonlinear relationships between features and classes, making it suitable for biological objects.

Thus, this work provides new insights into the ultrastructure of the insect exoskeleton and opens up possibilities for applying hyperspectral imaging in agriculture. The research contributes to the study of hyperspectral technology applications in agriculture. The implementation of remote sensing technologies in the agro-industrial sector for the identification of crop pests and diseases holds promise for promoting sustainable agricultural practices and precision farming.

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ЖАЗДЫҚ БИДАЙДЫҢ НЕГІЗГІ ЗИЯНКЕСТЕРІ (*EURYGASTER INTEGRICEPS* ЖӘНЕ *AELIA ACUMINATA*) ҮШІН МАШИНАЛЫҚ ТАҢУ КЕЗІНДЕ СПЕКТРЛІК СИПАТТАМАЛАРЫ

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Аңдатпа. Мақалада алғаш рет *Eurygaster integriceps* және *Aelia acuminata* бидай зиянкестерінің мысалында Қазақстан энтомофаунасының спектрлік сипаттамалары ұсынылған. Спектрлерді талдау барысында жәндіктердің жарықты қалай шағылыстырып, жұтатыны анықталды. Спектрлік қисықтардың қалыптасу заңдылықтары және экзоскелеттің морфологиялық ерекшеліктеріне, пигментациясына және құрылымына байланысты негізгі факторлар анықталды. Спектр қарқындылығының айырмашылығы жәндіктің әртүрлі бөліктері мен әртүрлі жәндік түрлеріндегі меланин мен хитин мөлшерінің әркелкі болуына байланысты. 550 нм диапазонында шағылысу пигменттің құрамына, ал 700–750 нм аймағында жабындардың құрылымдық компоненттеріне тәуелді екені анықталды; *Aelia acuminata*-да *Eurygaster integriceps*-ке қарағанда шағылысу коэффициенттері жоғары. Спектрлік және морфологиялық белгілерге сүйене отырып, Random Forest алгоритміне негізделген және 89 % сәйкестендіру дәлдігін қамтамасыз ететін жіктеу моделі құрылды. Алынған нәтижелер жәндіктердің экзоскелетінің ультрақұрылымы туралы түсініктерді кеңейтеді және ауыл шаруашылығында астық дақылдарының зиянкестерін тиімді мониторингтеу үшін заманауи гиперспектрлік түсірілімді қолдану мүмкіндіктерін айқындайды, сондай-ақ қалыптастырылған спектрлік профильдер жәндіктердің аймақтық спектрлік кітапханаларын құру кезінде эталон ретінде пайдаланылуы мүмкін. Зерттеу агроөнеркәсіптік секторда тұрақты тәжірибелерді іске асыру үшін жаңа мүмкіндіктер ашады.

Тірек сөздер: гиперспектралды визуализация, спектрлік сипаттамалар, бидай зиянкестері, Қазақстанның энтомофаунасы, қашықтықтан зондтау.

СПЕКТРАЛЬНЫЕ ХАРАКТЕРИСТИКИ ОСНОВНЫХ ВРЕДИТЕЛЕЙ ЯРОВОЙ ПШЕНИЦЫ (*EURYGASTER INTEGRICEPS* И *ALIA ACUMINATA*) ПРИ МАШИННОМ РАСПОЗНАВАНИИ

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Аннотация. В статье впервые представлены спектральные характеристики энтомофауны Казахстана на примере вредителей пшеницы *Eurygaster integriceps* и *Aelia acuminata*. Анализ спектров показал, как насекомые отражают и поглощают свет. Выявлены закономерности формирования спектральных кривых и ключевые факторы, связанные с морфологическими особенностями, пигментацией и структурой экзоскелета. Разница в интенсивности спектра обусловлена разным содержанием меланина и хитина между частями насекомого и между разными видами насекомых. Показано, что в диапазоне 550 нм отражение определяется пигментным составом, а в области 700-750 нм – структурными компонентами покровов; при этом у *Aelia acuminata* коэффициенты отражения выше, чем у *Eurygaster integriceps*. На основе спектральных и морфологических признаков построена классификационная модель с использованием алгоритма Random Forest, обеспечившая точность идентификации 89 %. Полученные результаты расширяют представления об ультраструктуре экзоскелета насекомых и демонстрируют перспективы применения гиперспектральной съемки в сельском хозяйстве для мониторинга вредителей злаковых культур, а сформированные спектральные профили могут служить эталонными при создании региональных библиотек спектров насекомых. Работа открывает новые возможности для реализации устойчивых практик в агропромышленном секторе.

Ключевые слова: гиперспектральная визуализация, спектральные характеристики, вредители пшеницы, энтомофауна Казахстана, дистанционное зондирование.