

Article

Spectral Stability Assessment of an nJ-Class Ultrafast Femtosecond Fiber Laser Using Ensemble Statistics and Principal Component Analysis

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Abstract

This article presents a structured spectral-stability assessment of an nJ-class ultrafast fiber laser generating femtosecond pulses with an approximate pulse duration of 115 fs, based on an ensemble of 61 consecutively acquired optical spectra. The study is motivated by the practical need to extract reliable short-sequence stability information from routine compact-spectrometer exports without requiring a separate pulse-diagnostic instrument at the initial assessment stage. For each spectrum, peak wavelength, centroid wavelength, FWHM bandwidth, integrated spectral area, correlation with the ensemble mean spectrum, and RMS deviation were calculated. Principal component analysis (PCA) was then applied to reduce the full spectral ensemble into a compact diagnostic space and to identify the dominant modes of residual spectral variation. The analyzed spectra yielded a peak wavelength of 775.31 ± 0.19 nm, a FWHM bandwidth of 7.95 ± 0.20 nm, an integrated spectral area of 10.43 ± 0.42 a.u.·nm, and a correlation with the mean spectrum of 0.99957 ± 0.00019 , confirming a highly repeatable spectral envelope. PCA showed that PC1 and PC2 explained 66.50% and 12.60% of the variance, respectively, while PC3 contributed only 1.90%, indicating that the measured variability was weak and largely low-dimensional. These results demonstrate that consecutively exported optical spectra can provide a defensible and physically interpretable short-sequence stability assessment of ultrafast femtosecond fiber lasers, offering a practical route for routine monitoring, early-stage diagnostics, and future integration with simultaneous temporal and spectral characterization.

Keywords: ultrafast femtosecond fiber laser; spectral stability; compact optical spectrometer; wavelength jitter; bandwidth stability; ensemble statistics; residual heat map; principal component analysis



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1. Introduction

Ultrafast femtosecond fiber lasers are increasingly used as compact and reliable sources for nonlinear optics [1,2], ultrafast spectroscopy [3], optical frequency conversion [4], micromachining [5], LiDAR and remote sensing applications [6], biomedical imaging [7], and as seed sources for amplifier systems [8]. In these applications, the optical spectrum is not only a basic output characteristic, but also an indirect indicator of pulse quality, compressibility, dispersion sensitivity, nonlinear phase accumulation, and operational stability. For an nJ-class femtosecond fiber laser producing pulses with a duration of

approximately 115 fs, even small spectral changes may be important because they can indicate wavelength jitter, bandwidth variation, amplitude instability, coupling fluctuation, or weak spectral reshaping [9].

In many laboratories, spectral stability is commonly assessed by visually overlapping multiple optical spectra [10]. Although this visual inspection provides a useful first indication of repeatability, it is not sufficient for a quantitative stability assessment. Strong overlap between spectra can hide weak but systematic deviations, especially near the spectral peak or in the spectral wings. Similarly, a laser may appear stable in an overlay plot while still showing small changes in centroid wavelength, full width at half maximum, integrated spectral area, or normalized spectral shape [11,12]. Therefore, a more structured approach is required in which the spectral ensemble is converted into quantitative stability descriptors and diagnostic plots.

The present work addresses this need by analyzing 61 consecutively acquired spectra from an nJ-class 115-fs ultrafast fiber laser using ensemble statistics, normalized shape comparison, residual difference mapping, and principal component analysis (PCA). The uniqueness of this work lies in developing a spectrum-only stability assessment workflow from routine compact-spectrometer exports. Instead of relying only on visual spectral overlap or isolated spectral parameters, the study combines descriptor-based statistics, correlation/RMS shape analysis, residual heat mapping, and PCA score-loading interpretation in a single diagnostic framework. Conventional spectral descriptors [13], including peak wavelength, centroid wavelength, FWHM bandwidth, and integrated spectral area, are first extracted from each spectrum. Shape-sensitive quantities, including correlation to the ensemble mean and RMS deviation from the mean, are then calculated after normalization [14]. Finally, PCA is applied to represent the spectral ensemble in a compact monitoring space, allowing weak variations, clustering, and possible outliers to be identified more clearly than from spectral overlays alone.

This approach is useful because it does not require a separate pulse-diagnostic instrument during the initial spectral assessment stage. Instead, it shows how a spectrum-only dataset can provide a defensible first-level evaluation of source stability. The method also provides a practical route toward future real-time monitoring, where each newly acquired spectrum can be compared with a reference ensemble, projected into PCA space, and checked against predefined stability limits. In this way, the study contributes both a practical analysis of the present femtosecond fiber laser dataset and a general workflow for spectral monitoring of ultrafast laser sources.

2. Experimental Setup and Spectral Acquisition

A set of 61 optical spectra was acquired from an Erbium-doped ultrafast femtosecond fiber laser under identical experimental conditions to ensure a consistent spectral stability assessment. The spectra were recorded consecutively at one-minute intervals. The acquisition was limited to this short sequence because extended operation of the laser system produced pump-diode heating and gradual performance degradation. Therefore, the measurement was intended to evaluate short-sequence spectral repeatability rather than long-term environmental drift. The laser operated near a central wavelength of 775 nm, with a repetition rate of 71 MHz and a pulse duration of approximately 115 fs, delivering pulse energy in the nJ range [14].

The measured output corresponds to the second-harmonic spectral region of a commercial Er: fiber femtosecond laser system. In this type of source, the fundamental Er: fiber emission near the 1.55 μm wavelength region is frequency-doubled through an internal second-harmonic-generation stage, producing an output near 775 nm. Since the laser is a commercial integrated system (EFOA[M4.1]-SH, Avesta Inc., Troitsk, Moscow, Russia),

detailed internal design parameters of the SHG module, such as the exact nonlinear crystal configuration and proprietary mechanical mounting, are not specified by the manufacturer and were not independently modified in the present study. However, the observed second-harmonic spectral stability is expected to depend on the stability of the fundamental spectrum, the phase-matching condition of the nonlinear conversion stage, and the mechanical and thermal stability of the SHG assembly. Therefore, the measured 775 nm spectral sequence represents the combined short-term stability of the fundamental Er: fiber laser and its internal frequency-doubling stage.

The spectral output was recorded using a compact optical spectrometer (CCS200/M, Thorlabs, Inc., Newton, NJ, USA), which provided wavelength-intensity data for each measurement. The spectrometer operates over the 200–1000 nm wavelength range with a spectral resolution of less than 2 nm, and this instrumental resolution was considered when interpreting the extracted peak wavelength, centroid wavelength, and FWHM bandwidth values. All spectra were exported using the same acquisition configuration and wavelength grid, allowing the spectral traces to be directly stacked without interpolation.

During acquisition, the laser was kept in the same operating state, and no intentional adjustment was made to the laser cavity, coupling optics, or spectrometer settings. This fixed acquisition condition was used to minimize measurement-induced changes, although small systematic contributions from spectrometer resolution, coupling stability, background level, and environmental conditions cannot be completely excluded. The recorded spectral sequence, therefore, represents the natural short-term variation in the source under routine operating conditions. The 61 spectra were later analyzed as an ensemble to extract peak wavelength, centroid wavelength, FWHM bandwidth, integrated spectral area, correlation to the mean spectrum, RMS deviation from the mean, residual difference map, and PCA-based diagnostic coordinates [15–17].

The complete experimental and analytical workflow is summarized in Figure 1. The figure outlines the path from laser-output measurement to spectral-data processing and statistical interpretation. In the present study, the ultrafast femtosecond fiber laser output was first measured using the compact optical spectrometer and exported as wavelength-intensity data. The exported spectra were then pre-processed using baseline shifting and normalization, followed by extraction of the main stability metrics and PCA score coordinates [18]. This workflow converted the measured spectra from individual spectral traces into an ensemble dataset suitable for statistical analysis, residual mapping, and low-dimensional PCA-based interpretation. The individual processing steps shown schematically in Figure 1 are demonstrated on the measured spectra used in the ensemble analysis, with a representative single spectrum shown in the inset of Figure 2.

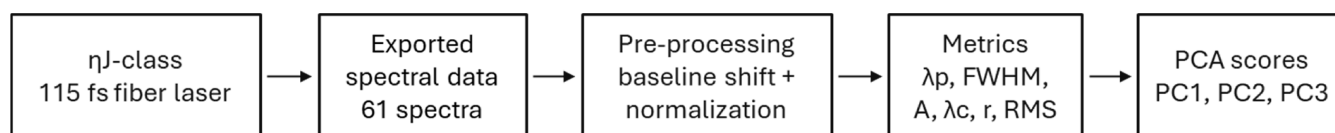


Figure 1. Present offline workflow for spectral acquisition, pre-processing, stability-metric extraction, residual mapping, and PCA-based observation.

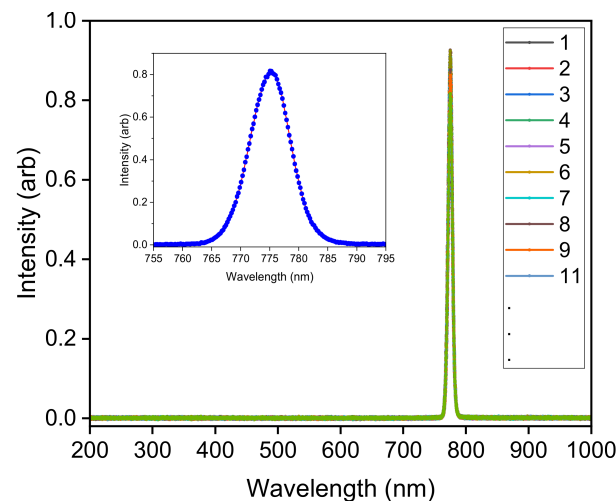


Figure 2. Overlay of all 61 measured spectra, with an inset showing a representative single-shot spectrum.

3. Data Processing and Analysis Methods

3.1. Dataset

The dataset consists of 61 consecutive optical spectra, exported as two-column wavelength-intensity files. Since all spectra were recorded on the same wavelength grid, they could be stacked directly for point-by-point comparison without interpolation. This direct stacking avoids interpolation-related numerical artifacts and preserves the measured spectral relationship between consecutive acquisitions.

3.2. Pre-Processing

For each measured spectrum $S_i(\lambda)$, a zero-level-corrected signal was first constructed as $S_i^*(\lambda) = S_i(\lambda) - \min_{\lambda}[S_i(\lambda)]$. This operation shifts the minimum intensity of each spectrum to zero and should not be interpreted as a full background-averaged baseline subtraction. It removes small offset differences while preserving the measured spectral envelope. Since the minimum value of each spectrum is shifted to zero, the processed spectrum remains non-negative over the measured wavelength range. For shape-only analysis, the zero-level-corrected spectrum was then max-normalized according to $x_i(\lambda) = S_i^*(\lambda) / \max_{\lambda}[S_i^*(\lambda)]$. The zero-level-corrected spectra $S_i^*(\lambda)$ were used for descriptors related to spectral position, width, and integrated area, whereas the normalized spectra $x_i(\lambda)$ were used for correlation, RMS deviation, residual mapping, and PCA. This separation allowed shape variation to be examined independently of absolute intensity scaling [19]. The representative single spectrum shown in the inset of Figure 2 illustrates the type of measured spectrum to which the zero-level correction and max-normalization steps described above were applied.

3.3. Spectral Descriptors

For each zero-level-corrected spectrum $S(\lambda)$, the peak wavelength λ_p was defined as $\lambda_p = \arg \max_{\lambda} S(\lambda)$, meaning the wavelength at which the measured spectral intensity reaches its maximum value. The half-maximum level was calculated as $S_{\text{half}} = 0.5 \max_{\lambda} S(\lambda)$. The full width at half maximum was obtained from the two half-maximum crossing wavelengths, λ_{left} and λ_{right} , as $\Delta\lambda_{\text{FWHM}} = \lambda_{\text{right}} - \lambda_{\text{left}}$. The crossing positions were determined by linear interpolation between neighboring sampled points. The integrated spectral area A and centroid wavelength λ_c were calculated as $A = \int S(\lambda) d\lambda$ and $\lambda_c = \int \lambda S(\lambda) d\lambda / \int S(\lambda) d\lambda$, respectively. To avoid artificial displacement of the centroid by low-signal background regions, the centroid wavelength was

calculated only over the meaningful spectral region of interest containing the measured laser spectrum, rather than over the full exported spectrometer wavelength range. For the discrete spectrometer data, these integrals were evaluated numerically over the measured wavelength grid. The shape similarity of the i -th normalized spectrum $x_i(\lambda)$ relative to the normalized ensemble mean spectrum $\bar{x}(\lambda)$ was quantified using the correlation coefficient $r_i = \text{corr}[x_i(\lambda), \bar{x}(\lambda)]$ and the RMS deviation $\text{RMS}_i = \sqrt{\left(\sum_{j=1}^m (x_{ij} - \bar{x}_j)^2\right)}$, where m is the number of sampled wavelength points [20].

3.4. PCA and Residual Mapping

The normalized spectra were arranged in a data matrix X of size $n \times m$, where $n = 61$ is the number of spectra and m is the number of sampled wavelength points. Each row of X represents one normalized spectrum, while each column represents the normalized intensity at a specific wavelength. After mean-centering, the matrix was written as $X_c = X - \mathbf{1}\bar{x}^T$, where X_c is the centered data matrix, $\mathbf{1}$ is a column vector of ones, and $\bar{x}^T$ is the row vector of the mean-normalized spectrum. The covariance matrix was then calculated as $C = (1/(n-1))X_c^T X_c$. The eigenvectors of C provided the PCA loading vectors p_1, p_2 , and p_3 , which are associated with the leading principal components. For the i -th spectrum, the PCA score coordinates were obtained by projecting the centered spectrum onto these loading vectors. Thus, the first three scores were calculated as $PC1_i = t_{i1} = \sum_{j=1}^m (x_{ij} - \bar{x}_j)p_{j1}$, $PC2_i = t_{i2} = \sum_{j=1}^m (x_{ij} - \bar{x}_j)p_{j2}$, and $PC3_i = t_{i3} = \sum_{j=1}^m (x_{ij} - \bar{x}_j)p_{j3}$. The score vector $t_i = [PC1_i, PC2_i, PC3_i]$ therefore represents the reduced PCA-space coordinates of the i -th spectrum. The PC1-PC2 scatter plot was generated from the coordinate pairs $(PC1_i, PC2_i)$, whereas the score-trend plots were obtained by plotting $PC1_i, PC2_i$, and $PC3_i$ individually against the acquisition index. The corresponding loading curves indicate the wavelength regions that contribute most strongly to each principal component.

In addition to PCA, the residual difference map was generated as $D_i(\lambda) = x_i(\lambda) - \bar{x}(\lambda)$. In this map, the horizontal axis represents wavelength, the vertical axis represents spectrum index, and the color scale represents the positive or negative deviation from the normalized mean spectrum. This residual map provides a direct wavelength-resolved view of the small deviations that remain after normalization.

4. Results and Discussion

4.1. Ensemble Overlay and Qualitative Stability

Figure 2 overlays the 61 spectra acquired consecutively at one-minute intervals. The number of spectra was limited by the practical operating condition of the fiber laser system, where extended acquisition led to pump-diode heating and gradual performance degradation. Therefore, this dataset represents a short-sequence stability measurement rather than a long-term drift study.

The strong overlap of the spectral traces indicates that the laser remained in a stable operating state during the acquisition period, with no large spectral excursions, mode changes, or abrupt wavelength shifts. Figure 2, therefore, serves as an initial qualitative stability check and provides a visual reference for the measured spectral envelope before applying the quantitative analysis. The representative single spectrum shown in the inset also helps identify the main spectral shape used for the subsequent descriptor extraction. However, because small variations in peak position, bandwidth, intensity distribution, or spectral shape may not be easily visible in an overlay plot, additional quantitative descriptors were calculated in the following analysis. These descriptors provide a clearer assessment of the weak spectral variations that are hidden within the strongly overlapping traces.

The spectral overlay is further supported by the descriptor trends shown in Figure 3. The peak wavelength remains stable, with $\lambda_p = 775.31 \pm 0.19$ nm and a total range of

774.83 to 775.78 nm. Monitoring the peak wavelength is a common way to evaluate wavelength jitter and short-term spectral stability in laser sources [21]. It should be noted that the peak wavelength in this study was obtained from the measured maximum intensity point of each spectrum rather than from a fitted peak curve. Therefore, small peak-position variations may include contributions from the spectrometer wavelength sampling, finite spectral resolution, detector noise, and local intensity fluctuations near the spectral maximum. For this reason, the peak-wavelength trend is interpreted here as a practical indicator of short-term spectral repeatability rather than as an absolute high-precision measurement of wavelength jitter. The centroid wavelength and FWHM bandwidth trends were also considered to support the interpretation of spectral stability beyond the single maximum point.

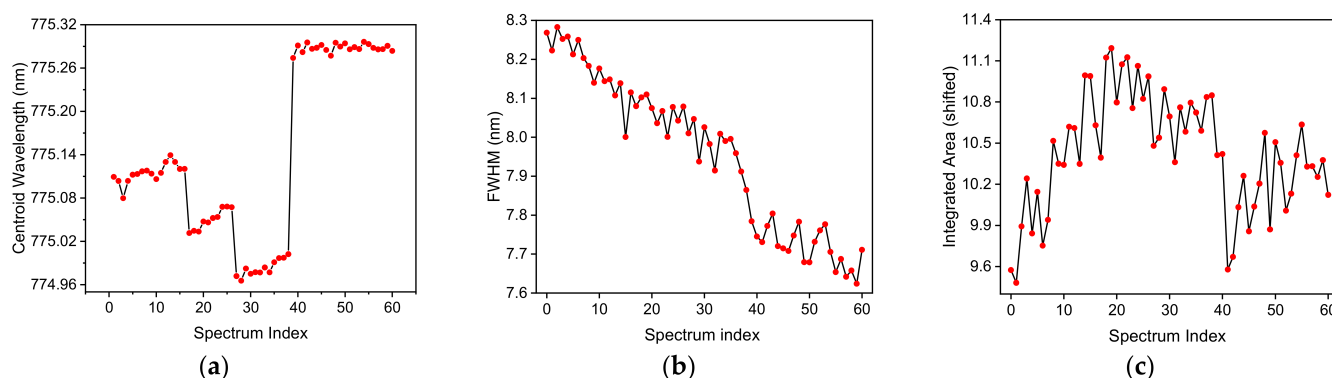


Figure 3. Descriptor trends across the 61 spectra: (a) centroid wavelength, (b) FWHM bandwidth, and (c) integrated spectral area. Red points show measured values, and black lines connect consecutive points only for visual guidance.

The centroid wavelength is calculated within the spectral signal region of interest, excluding low-signal background regions outside the useful laser spectrum. The centroid wavelength is ($\lambda_c = 775.14 \pm 0.12$) nm, which is physically consistent with the peak wavelength and confirms that the spectral mass remains centered around the main laser emission band. The FWHM bandwidth is (7.95 ± 0.20) nm, showing only modest bandwidth variation across the 61 spectra. Since the optical bandwidth is directly related to the transform-limited pulse duration and pulse compressibility, the FWHM trend provides useful information about the stability of the ultrafast pulse source [22]. The integrated spectral area is (10.43 ± 0.42) a.u.·nm, corresponding to a coefficient of variation of about 4.06%, which indicates weak amplitude- or coupling-related fluctuation. Since no simultaneous external power-meter measurement was recorded during the spectral acquisition, the integrated-area variation is interpreted as a relative indicator of amplitude stability in the spectrometer signal and may include contributions from both laser output power variation and coupling fluctuation into the spectrometer. The centroid wavelength trend in Figure 3a provides a relative measure of spectral-mass displacement, while Figure 3b tracks bandwidth stability and Figure 3c follows the integrated spectral strength. Together, these descriptors show that the laser remained within a narrow short-term operating window during the acquisition sequence.

4.2. Shape Stability, Correlation, RMS, and Residual Heat Mapping

Shape consistency was evaluated by comparing each max-normalized spectrum with the max-normalized ensemble mean spectrum. As shown in Figure 4a, the correlation to the mean remains very high across the full sequence, with an average value of 0.99957 ± 0.00019 and a minimum value of 0.99933. This confirms that the normalized spectral envelope is highly reproducible during the short acquisition period. The RMS deviation from the mean is 0.00262 ± 0.00063 , indicating that the remaining point-by-point differences are very small

in magnitude. Although the coefficient of variation in the RMS deviation appears relatively high, this mainly results from the very small mean RMS value. In absolute terms, the RMS deviations remain low, showing that the normalized spectra stay close to the ensemble mean. These two quantities provide complementary information: the correlation coefficient describes the similarity of the overall spectral shape, while the RMS deviation quantifies the residual difference from the mean spectrum.

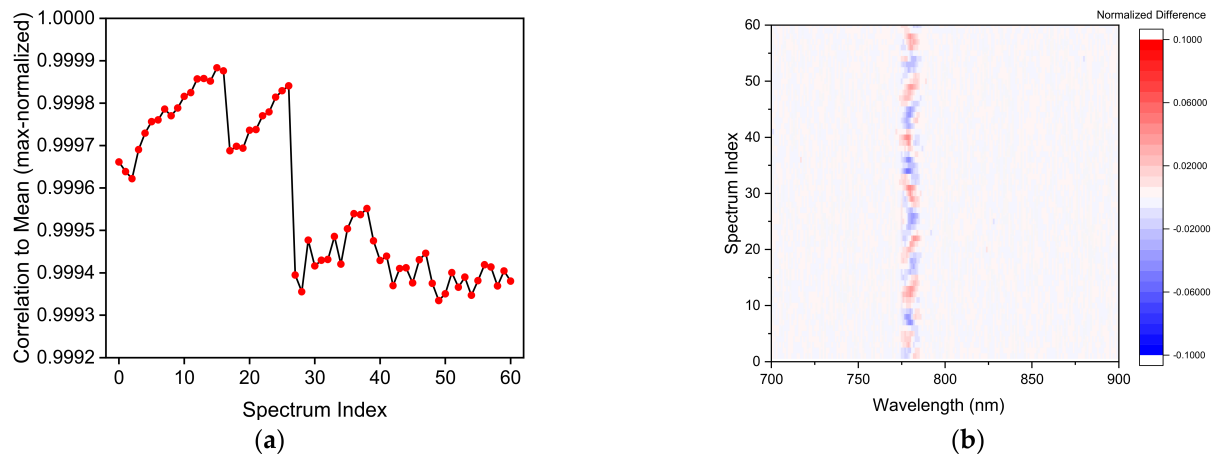


Figure 4. Shape stability and residual mapping: (a) correlation of each max-normalized spectrum with the normalized ensemble mean and (b) residual difference heat map shown over the spectral region of interest around the measured laser emission.

Figure 4b presents the residual difference heat map, calculated as $D_i(\lambda) = x_i(\lambda) - \bar{x}(\lambda)$, where $x_i(\lambda)$ is the i -th normalized spectrum and $\bar{x}(\lambda)$ is the normalized ensemble mean spectrum. The map is shown over the spectral region of interest around the measured laser emission rather than over the full spectrometer wavelength range, so that the weak residual variations near the main spectral band can be seen more clearly. In this map, the horizontal axis represents wavelength, the vertical axis represents spectrum index, and the color scale represents positive or negative deviation from the mean spectrum. The mostly uniform background and weak color contrast indicate that the spectra remain close to the ensemble mean. The small localized red and blue features near the central spectral region show that the residual variation is mainly associated with weak reshaping around the main peak rather than broad spectral distortion. This result supports the interpretation that the laser remained spectrally stable, with only low-amplitude residual deviations during the measured sequence.

4.3. PCA Diagnostics and Low-Dimensional Spectral Variability

PCA was applied as a compact stability diagnostic rather than as a classification method. Each measured spectrum contains intensity values over many wavelength points, and therefore direct comparison of all spectra becomes difficult when only the raw traces are considered. PCA reduces this high-dimensional spectral information into a small number of score coordinates that represent the dominant modes of variation within the spectral ensemble. If the laser remains stable, the PCA scores are expected to remain clustered within a compact region. In contrast, spectral drift, a change in operating state, or an abnormal spectrum would appear as a directional movement or an outlier in the PCA score space.

For the present dataset, PC1 explains 66.50% of the total variance, PC2 explains 12.60%, and PC3 explains 1.90%, as shown in Figure 5. Thus, the first two principal components account for 79.10% of the variance, while the first three components account for 81.00%. This result shows that most of the weak residual spectral variability can be

represented by only a few principal components, confirming the low-dimensional nature of the measured variations.

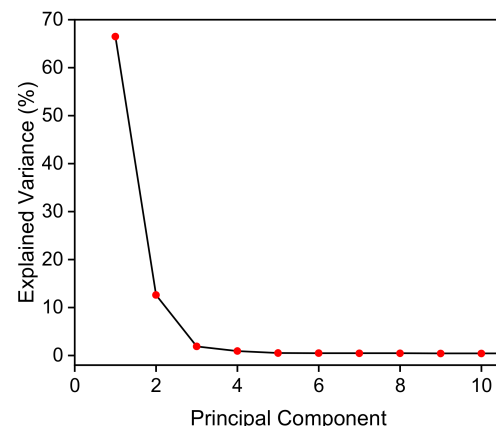


Figure 5. PCA explained variance for the first 10 principal components.

The PCA score plots are shown in Figure 6. Figure 6a presents the PC1-PC2 score scatter plot, where each point represents one measured spectrum. The dashed boundary lines indicate the observed score limits of the measured dataset and provide practical reference bounds for the present short-sequence stability assessment. The compact grouping of the points indicates that the spectra occupy a limited region in reduced dimensional space, supporting the conclusion that the laser remained within a stable operating regime during the acquisition sequence. Figure 6b–d shows the PC1, PC2, and PC3 score trends as a function of spectrum index. In these trend plots, the connecting lines are used only to link consecutive measured score values for visual guidance and do not represent fitted or predictive curves. The upper and lower dashed lines show the observed score bounds for each principal component. These plots extend the score-space interpretation into the acquisition sequence and help identify whether the dominant modes of spectral variation evolve gradually, fluctuate randomly, or contain isolated deviations. In the present case, the score trends remain within the observed bounds, indicating that the variations are small and do not correspond to a clear transition to another spectral state.

The loading curves in Figure 7a–c provide the spectral interpretation of the principal components. These loading curves identify the wavelength regions that contribute most strongly to PC1, PC2, and PC3. A strong loading feature near the main spectral peak indicates that the corresponding component is associated with local peak reshaping, slight spectral displacement, or bandwidth-related modulation. In this interpretation, PC1 represents the dominant residual spectral variation around the strongest part of the normalized spectrum. PC2 represents a weaker secondary mode, which can be associated with slight intensity redistribution, peak asymmetry, or weak reshaping around the central spectral region. PC3 explains only a small fraction of the total variance and mainly represents minor localized residual deviations or measurement-level features remaining after the dominant PC1 and PC2 variations are removed. In the present dataset, the dominant loading features are concentrated around the strongest part of the spectrum. This agrees with the residual heat-map result and confirms that the main spectral variations are small perturbations near the central peak rather than broad distortions across the entire spectral envelope.

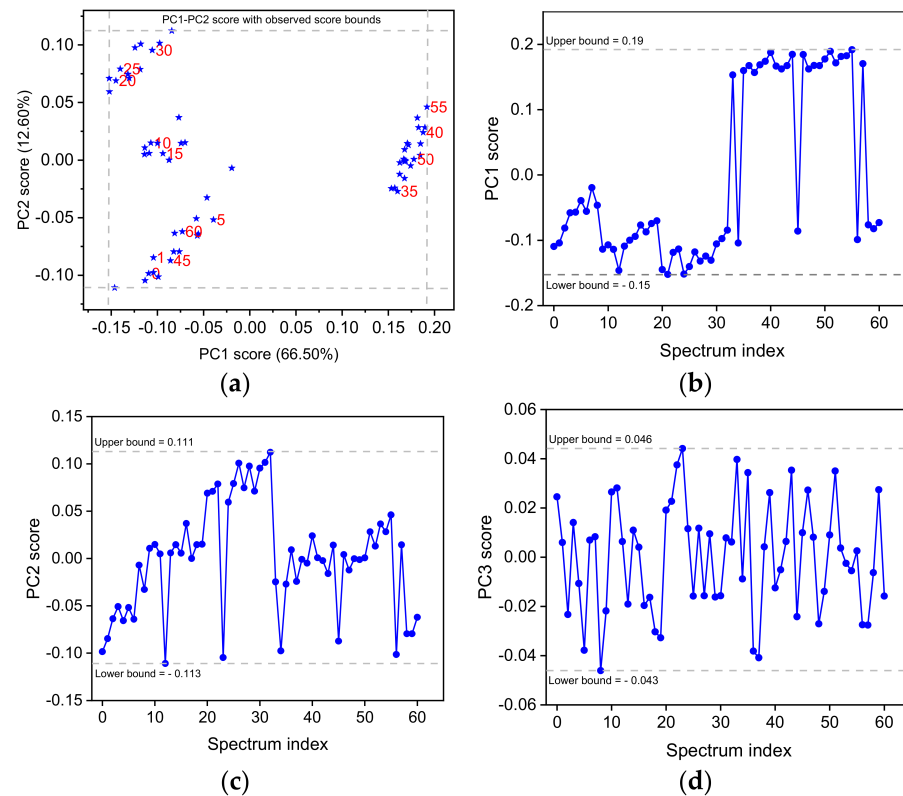


Figure 6. PCA score diagnostics with observed score bounds: (a) PC1 versus PC2 score plot; (b) PC1 score; (c) PC2 score; and (d) PC3 score versus spectrum index. Dashed lines show observed score bounds, and connecting lines are only for visual guidance.

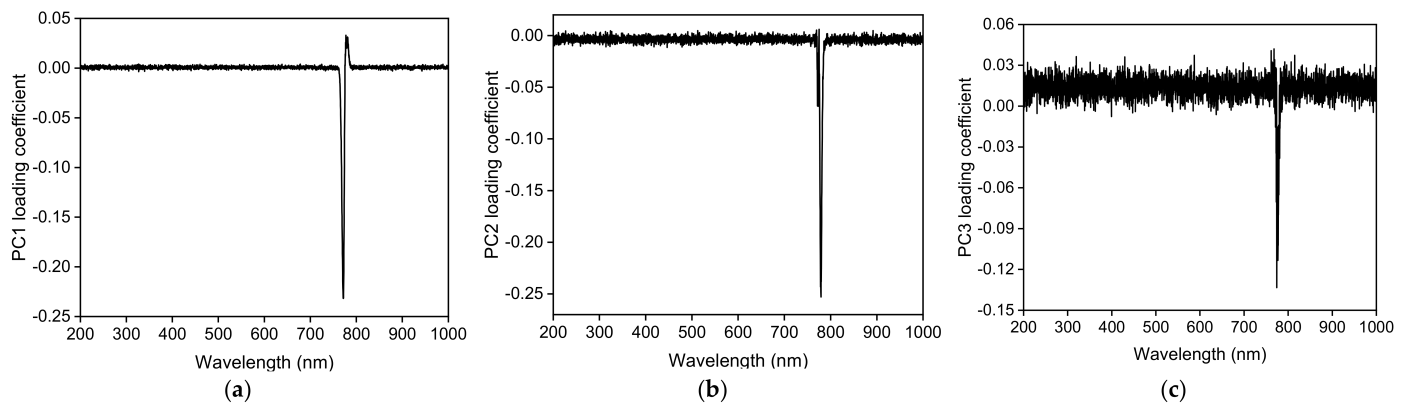


Figure 7. PCA loading coefficients as a function of wavelength: (a) PC1, (b) PC2, and (c) PC3.

Additional summary plots are provided in Figure 8 to support the overall interpretation. Figure 8a compares the coefficients of variation in the extracted stability metrics and identifies which parameters show the largest relative dispersion. Figure 8b summarizes the PCA variance partition together with the cumulative variance. These plots provide a compact statistical overview of the stability descriptors and confirm that the measured spectral variability is weak, bounded, and mainly represented by the leading principal components.

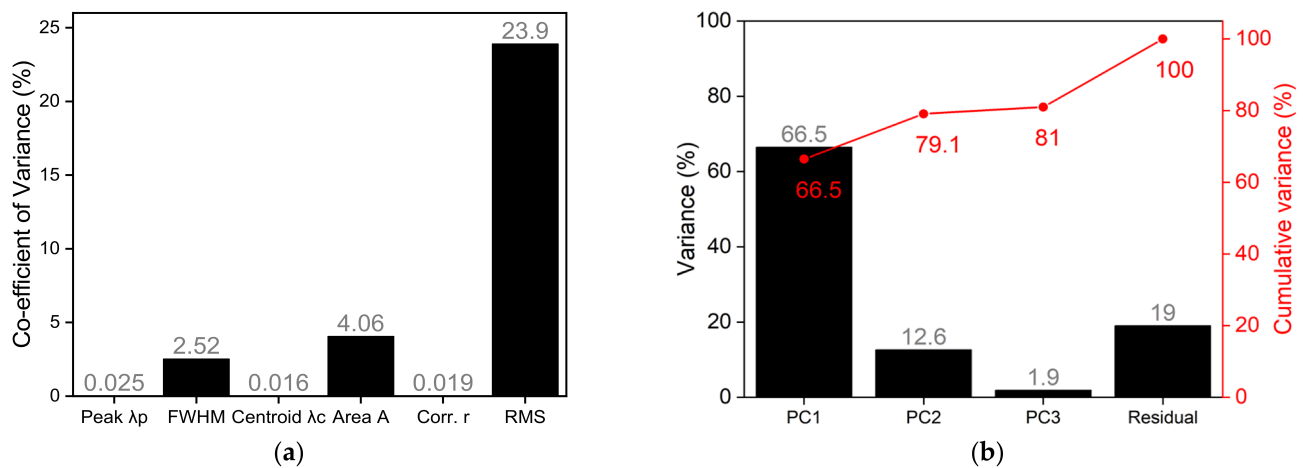


Figure 8. Summary of stability indicators: (a) coefficient of variation in the extracted metrics and (b) PCA variance partition with cumulative explained variance.

4.4. Integrated Interpretation and Future Monitoring Workflow

The ensemble overlay, descriptor trends, shape metrics, residual difference map, PCA scores, and loading curves together provide a consistent indication of stable short-sequence operation. The numerical values supporting this interpretation are summarized in Table 1, which lists the mean, standard deviation, minimum, maximum, and coefficient of variation for the main extracted stability parameters. The peak wavelength varies only weakly, the FWHM bandwidth remains within a narrow range, the integrated spectral area fluctuates at only a few-percent level, and the correlation to the mean spectrum remains very high. The PCA variance values summarized in Table 2 further show that most of the weak spectral variability is captured by the first few principal components, confirming that the residual changes are low-dimensional. These observations indicate that the laser remained in one dominant spectral regime throughout the acquisition sequence. Although the present analysis confirms stable short-sequence spectral behavior, possible measurement-related systematic effects should also be considered. These may include spectrometer wavelength calibration uncertainty, detector noise, baseline/background offsets, finite spectral resolution, and small coupling variations between the laser output and the spectrometer input. In addition, external changes to the laser system, such as pump-diode heating, thermal drift of the fiber laser or SHG module, mechanical vibration, and environmental temperature fluctuations, can produce slow spectral displacement, bandwidth variation, or amplitude fluctuation. In the present experiment, all spectra were acquired consecutively under the same measurement configuration, and no intentional adjustment was made to the laser cavity, coupling optics, or spectrometer settings. Therefore, the reported variations should be interpreted as the combined short-term behavior of the laser source, frequency-doubling stage, optical coupling, and spectrometer measurement chain, rather than as a fully separate measurement of only the intrinsic laser drift. At the same time, the residual difference map and PCA loading curves show that the small remaining variability is not purely random but is mainly localized near the central spectral region.

Table 1. Summary stability metrics for the analyzed spectral ensemble ($n = 61$).

Metric	Mean	Std	Min	Max	CV (%)
Peak wavelength, λ_p (nm)	775.31	0.19108	774.83	775.78	0.025
FWHM bandwidth, $\Delta\lambda_{FWHM}$ (nm)	7.95481	0.20054	7.62393	8.28275	2.521
Centroid wavelength, λ_c (nm)	775.14	0.122	774.97	775.30	0.016
Integrated area, A (a.u.·nm)	10.4277	0.42354	9.4813	11.1924	4.062
Correlation to mean, r (-)	0.99957	0.00019	0.99933	0.99988	0.019
RMS to mean (-)	0.00262	0.00063	0.00127	0.00362	23.946

Table 2. PCA variance explained for the leading principal components.

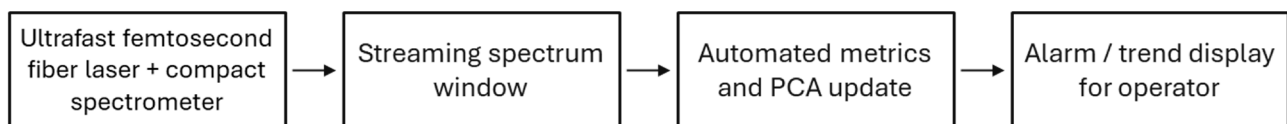
Principal Component	Variance Explained (%)	Cumulative (%)
PC1	66.50	66.50
PC2	12.60	79.10
PC3	1.90	81.00

The measured spectral variations may also include small contributions from the measurement system itself. These can arise from spectrometer wavelength drift, detector noise, coupling fluctuations between the laser output and the spectrometer input, and short-term environmental changes. In the present measurement, the same spectrometer, acquisition interval, coupling condition, and wavelength grid were used for all 61 spectra, which helped maintain a consistent measurement chain. For future real-time monitoring, a faster acquisition cycle, comparison with a second identical spectrometer, or periodic referencing to a calibrated spectral lamp could further separate instrument-related drift from laser-related spectral changes.

From an applied perspective, the present work also provides a clear path toward future implementation. The diagnostic role of each figure is summarized in Table 3, which connects the graphical results with their physical meaning and usefulness for laser monitoring. In this study, the spectra were first acquired and then analyzed offline as a batch. As illustrated in Figure 9, the same computational workflow could later be linked to a live acquisition routine, where every newly recorded spectrum would be compared immediately with the baseline ensemble, projected into PCA space, and checked against predefined limits for λ_p , $\Delta\lambda_{FWHM}$, A , r , and RMS. Figure 9 summarizes the proposed future monitoring concept by showing the sequential path from live spectral acquisition to automatic pre-processing, metric extraction, residual comparison, PCA projection, stability-limit checking, and operator feedback. Because the workflow is based on standard spectral exports, descriptor extraction, residual comparison, and PCA projection, it can also be adapted for routine stability monitoring of other ultrafast laser sources and compact spectrometer-based diagnostic systems. In future feedback-control implementation, deliberate changes in operating conditions, such as ambient temperature, pump-diode current, or optical coupling, could be introduced to evaluate how the extracted spectral descriptors respond to controlled perturbations. Such controlled tests would help define practical response thresholds and improve the use of the workflow for automated laser monitoring and feedback stabilization. In this future mode, spectral acquisition and observation would occur simultaneously, allowing the method to move from retrospective assessment toward real-time ultrafast femtosecond laser monitoring and operator feedback.

Table 3. Diagnostic significance of the main plots used in the study.

Plot(s)	Primary Quantity	Diagnostic Significance
Figure 1	Acquisition and observation workflow	Connects the present offline batch analysis with the future pathway toward simultaneous acquisition, observation, and automated monitoring.
Figure 2	Spectral overlay	Provides the first qualitative impression of repeatability and reveals whether large drifts or mode hops are present.
Figure 3a–c	Centroid, FWHM, integrated area	Quantify slow drift, bandwidth stability, and amplitude-related variation versus acquisition index.
Figures 4 and 5	Correlation and residual heat map	Assess shape reproducibility and localize weak wavelength-dependent deviations that may be hidden in the overlay.
Figures 6 and 7	Explained variance and PCA scores	Compress the spectral ensemble into compact monitoring coordinates and highlight clustering, drift, or outliers.
Figures 8 and 9	PCA loadings, metric dispersion, and variance partition	Identify the wavelength regions responsible for the dominant variability and summarize relative metric dispersion and PCA variance.

**Figure 9.** Future workflow for simultaneous spectral acquisition, automated stability analysis, PCA-based monitoring, and operator feedback.

5. Conclusions

A structured analysis of 61 consecutively acquired spectra from an nJ-class ultrafast femtosecond fiber laser with a pulse duration of approximately 115-fs confirms stable short-sequence spectral operation. The residual variations observed in the spectral ensemble are small, localized, and mainly low-dimensional. The results show that routine spectral exports, when analyzed as an ensemble dataset, can provide a reliable stability assessment by combining descriptor-based statistics, shape-sensitive comparison, residual difference mapping, and PCA. The spectral overlay provided the initial qualitative evidence of repeatability, while the centroid wavelength, FWHM bandwidth, and integrated spectral area trends quantified wavelength-, bandwidth-, and amplitude-related variations. The statistical results summarized in Table 1 support this interpretation by showing low variation in the main spectral descriptors and a very high correlation to the ensemble mean spectrum. The PCA variance summary in Table 2 further confirms that the remaining spectral variability is mainly captured by the leading principal components. In addition, the residual difference map and PCA loading curves show that the weak deviations are concentrated primarily near the central spectral region rather than distributed broadly across the full spectrum.

Overall, the proposed workflow converts a sequence of spectra measured with a Thorlabs compact optical spectrometer into a compact diagnostic framework for assessing ultrafast femtosecond laser spectral stability. Although the present work was performed as an offline short-sequence analysis, the same approach can be extended toward real-time monitoring, where newly acquired spectra are automatically compared with a reference ensemble, projected into PCA space, and evaluated using predefined stability indicators.

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References

1. Liu, X.; Dai, M.; Pan, D.; Lin, K.; Malomed, B.A.; Li, Q.; Fu, H.Y. Robust mode-locking in a hybrid ultrafast laser based on nonlinear multimodal interference. *Opt. Laser Technol.* **2023**, *159*, 108941.
2. Ma, W.; Li, X.; Qin, Y.; Chen, W.; Hu, G. High-power spatiotemporal mode-locked Yb-doped fiber laser based on transverse modes division control. *Opt. Lett.* **2025**, *50*, 5202–5205. [[CrossRef](#)] [[PubMed](#)]
3. Deng, J.; Gong, N.; Ma, L. Capturing Ultrafast Carrier and Exciton Transport: Advances in Wide-Field Transient Absorption Microscopy. *J. Phys. Chem. Lett.* **2025**, *16*, 11183–11195. [[CrossRef](#)] [[PubMed](#)]
4. Su, X.; Zhu, R.; Wang, B.; Bai, Y.; Ding, T.; Sun, T.; Zheng, Y. Generation of 8–20 μm mid-infrared ultrashort femtosecond laser pulses via difference frequency generation. *Photonics* **2022**, *9*, 372. [[CrossRef](#)]
5. Zhang, Z.; Yang, Z.; Wang, C.; Xu, W. Accelerating ultrashort pulse laser micromachining process comprehensive optimization using a machine learning cycle design strategy integrated with a physical model. *J. Intell. Manuf.* **2024**, *35*, 449–465.
6. Zhou, G.; Liu, Z.; Zhou, X.; Zhang, H.; Xu, C.; Zhao, D.; Wu, G. Internal Stray Light Suppression for Single-Band Bathymetric LiDAR Optical System. *IEEE Trans. Instrum. Meas.* **2024**, *73*, 1–12.
7. Chen, J.; Li, Q.; Zhang, Z.; Bratchenko, I.A.; Su, H.; Wang, S. A Femtosecond Fiber Laser-Based Compact Label-Free Multimodality Nonlinear Optical Microscopy and Its Ex Vivo Bioimaging. *Microsc. Res. Tech.* **2025**, *88*, 1078–1086. [[PubMed](#)]
8. Tomaszewska-Rolla, D.; Lindberg, R.; Pasiskevicius, V.; Laurell, F.; Soboń, G. A comparative study of a Yb-doped fiber gain-managed nonlinear amplifier seeded by femtosecond fiber lasers. *Sci. Rep.* **2022**, *12*, 404. [[PubMed](#)]
9. Zhou, Y.; Lai, T.; Li, H.; Lu, W.; Chen, F.; Wang, J.; Guan, C.; Chen, S.; Peng, X.; Liu, J. Cross-Scale High-Precision Characterization for Three-Dimensional Profiles of Curved Diffractive Microstructures. *Small Methods* **2026**, *10*, e01775. [[PubMed](#)]
10. Guardalben, M.J.; Barczys, M.; Kruschwitz, B.E.; Spilatro, M.; Waxer, L.J.; Hill, E.M. Laser-system model for enhanced operational performance and flexibility on OMEGA EP. *High Power Laser Sci. Eng.* **2020**, *8*, e8. [[CrossRef](#)]
11. Zhang, Y.; Luo, S.; Zhang, B.; Cui, Y.; Ling, Q.; Yu, Z.; Chen, D. Spectral-temporal transient dynamics of dissipative soliton molecules in mode-locking fiber lasers. *Opt. Laser Technol.* **2022**, *153*, 108286.
12. Edreira, I.B.; Slavík, R.; Sahu, J.K.; Núñez-Velázquez, M.; Wright, L.; Schioppo, M.; Marra, G. Frequency drift characterization of a laser stabilized to an optical fiber delay line. *Opt. Express* **2024**, *32*, 16823–16830. [[CrossRef](#)] [[PubMed](#)]
13. Stoica, P.; Moses, R.L. *Spectral Analysis of Signals*; Pearson Prentice Hall: Upper Saddle River, NJ, USA, 2005; Volume 452, pp. 25–26.
14. Imran, T.; Naeem, M. Image-based laser-beam diagnostics using statistical analysis and machine learning regression. *Photonics* **2025**, *12*, 504.
15. Meza Ramirez, C.A.; Greenop, M.; Ashton, L.; Rehman, I.U. Applications of machine learning in spectroscopy. *Appl. Spectrosc. Rev.* **2021**, *56*, 733–763.
16. Grant-Jacob, J.A.; Zervas, M.N.; Mills, B. Spatial analysis of femtosecond laser generated plasma using principal component analysis. *Sci. Rep.* **2024**, *14*, 30301. [[CrossRef](#)] [[PubMed](#)]
17. Hong, X.; Xie, J.; Sheng, J.; Xie, F.; Zhang, J.; Wang, K.; Wu, C. Single-view neural illumination estimation and editing for dynamic light field display. *Light Sci. Appl.* **2026**, *15*, 147. [[CrossRef](#)] [[PubMed](#)]
18. Shaik, A.K.; Epuru, N.R.; Syed, H.; Byram, C.; Soma, V.R. Femtosecond laser induced breakdown spectroscopy based standoff detection of explosives and discrimination using principal component analysis. *Opt. Express* **2018**, *26*, 8069–8083. [[CrossRef](#)] [[PubMed](#)]
19. Shen, X.; Ye, S.; Xu, L.; Hu, R.; Jin, L.; Xu, H.; Liu, W. Study on baseline correction methods for the Fourier transform infrared spectra with different signal-to-noise ratios. *Appl. Opt.* **2018**, *57*, 5794–5799. [[CrossRef](#)] [[PubMed](#)]
20. Chen, W.; Du, Y.; Zhang, F.; Zhang, R.; Ding, B.; Chen, Z.; Xiong, Q. Sampling error profile analysis (SEPA) for model optimization and model evaluation in multivariate calibration. *J. Chemom.* **2018**, *32*, e2933.

21. Xia, Y.; Cheng, X.; Li, F.; Wang, J.; Yang, Y.; Lin, X.; Gong, S. Long-term wavelength drift compensation of tunable pulsed dye laser for sodium detection lidar. *Opt. Commun.* **2015**, *354*, 52–58. [[CrossRef](#)]
22. Lassonde, P.; Mironov, S.; Fourmaux, S.; Payeur, S.; Khazanov, E.; Sergeev, A.; Mourou, G. High energy femtosecond pulse compression. *Laser Phys. Lett.* **2016**, *13*, 075401. [[CrossRef](#)]

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