

Fusion of Synchronous Fluorescence Spectra with Application to Argan Oil for Adulteration Analysis



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Abstract

When synchronous fluorescence (SyF) spectroscopy is used for quantitative and qualitative analysis, selection of a useful wavelength interval between the excitation and emission wavelengths ($\Delta\lambda$) is needed. Presented is a fusion approach to combine $\Delta\lambda$ intervals thereby negating the selection process. This study uses the fusion of SyF spectra for the quantitative analysis of the corn oil adulterant content. The SyF spectra were acquired by varying the excitation wavelength in the region 300-800 nm using $\Delta\lambda$ wavelength intervals from 10 to 100 nm in steps of 10 nm producing 10 sets of SyF spectra. For quantitative analysis, two calibration approaches are evaluated with these 10 SyF spectral datasets. Multivariate calibration by partial least squares (PLS) and a univariate calibration process where the SyF spectra are summed over respective SyF spectral ranges, the area under the curve (AUC) method. For adulteration detection and quantitation of the corn oil, prediction errors decrease with fusion compared to individually using the 10 $\Delta\lambda$ interval SyF spectral data sets. For this data set, the AUC method generally provides smaller prediction errors than PLS at individual $\Delta\lambda$ intervals as well as with fusion of all 10 $\Delta\lambda$ intervals.

Objectives

- Develop and showcase a fusion approach to bypass the $\Delta\lambda$ selection process required when using synchronous fluorescence spectroscopy (SyF) for multivariate analysis
- Showcase an effective method for quantitating corn oil adulterants in Argan Oil

Synchronous Fluorescent Spectroscopy (SyF)

- When a SyF spectrum is measured a $\Delta\lambda$ interval is maintained
 - $\Delta\lambda$ interval: a linearly increasing wavelength difference between the emission and excitation wavelengths
- Currently $\Delta\lambda$ intervals are individually evaluated and selected for multivariate analysis
 - Slows down the classification and/or calibration and prediction processes

Modeling Approach

Partial Least Squares (PLS)

$$\mathbf{y} = \mathbf{X}\mathbf{b} \rightarrow \hat{\mathbf{b}} = \mathbf{X}^+ \mathbf{y}$$

$$\hat{\mathbf{y}} = \mathbf{X}\hat{\mathbf{b}}$$

- \mathbf{X}^+ is calculated by decomposing \mathbf{X} and \mathbf{y}
- The number of PLS models is dependent on the rank of \mathbf{X} , i.e. the minimum number of rows or columns in
- Requires latent variable selection

Area Under the Curve (AUC)

$$\mathbf{y} = \mathbf{x}\mathbf{b} \rightarrow \hat{\mathbf{b}} = (\mathbf{x}^T \mathbf{x})^{-1} \mathbf{x}^T \mathbf{y}$$

$$\hat{\mathbf{y}} = \mathbf{x}\hat{\mathbf{b}}$$

- Spectral responses are summed across the measured spectral ranges
- \mathbf{X} : calibration samples
- \mathbf{y} : actual analyte concentration
- $\hat{\mathbf{y}}$: analyte concentration prediction
- $\hat{\mathbf{b}}$: estimated model regression vector

Model Measures

- Bias:**
 - R^2
 - Root Mean Square Error (RMSE)
 - RMSEC, RMSEV
- $$RMSE = \sqrt{\frac{\sum_{k=1}^n (y_k - \hat{y}_k)^2}{n}}$$

Model Measures Cont'd

- Variance:**
 - Euclidean 2-norm ($\|\hat{\mathbf{b}}\|_2$)
- U-Curves:**
 - Bias-variance trade-off
 - C1 $C1_i = \frac{\left(\|\mathbf{b}_i\| - \left(\|\mathbf{b}_i\|_{\min}\right)\right)}{\left(\|\mathbf{b}_i\|_{\max} - \left(\|\mathbf{b}_i\|_{\min}\right)\right)} + \frac{\left(RMSEC_i - RMSEC_{\min}\right)}{\left(RMSEC_{\max} - RMSEC_{\min}\right)}$
 - C2 $C2_i = \frac{\left(\|\mathbf{b}_i\| - \left(\|\mathbf{b}_i\|_{\min}\right)\right)}{\left(\|\mathbf{b}_i\|_{\max} - \left(\|\mathbf{b}_i\|_{\min}\right)\right)} + \frac{\left(1 - R_i^2\right) - \left(1 - R_{\min}^2\right)}{\left(1 - R_{\max}^2\right) - \left(1 - R_{\min}^2\right)}$

MV Model Selection

- The PLS approach creates numerous models with latent variables (LV).
- A set of LV must be selected to form the model from the calibration set and then predict the validation set.
- To automate the LV selection a U-curve approach was used

$$\text{Selected LV} = \min[\text{mean}(C1 + C2)]$$

- C1 balances prediction error for the calibration set, RMSEC, in conjunction with the model regression vector \mathbf{b} .
- C2 balances the calibration model fit with the variance indicator
- C1 and C2 guard against selecting an over fitted or under-fitted model

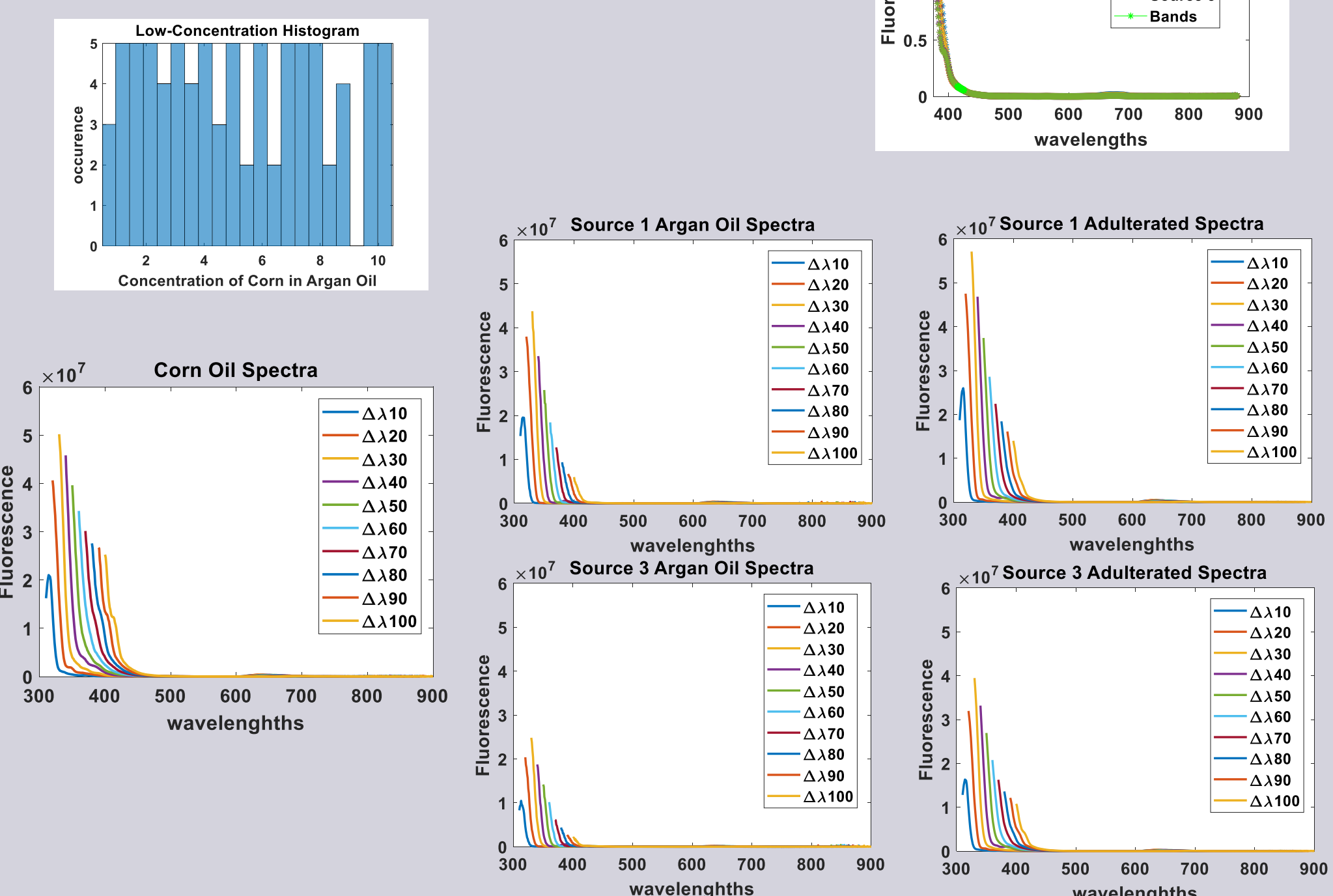
Argan Oil Data Set

- 5 sources from separate Moroccan farms
- Each source was adulterated with corn oil purchased from a local store
- Source 1: 27 samples
- Source 2: 30 samples
- Source 3: 29 samples
- Source 4: 33 samples
- Source 5: 34 samples



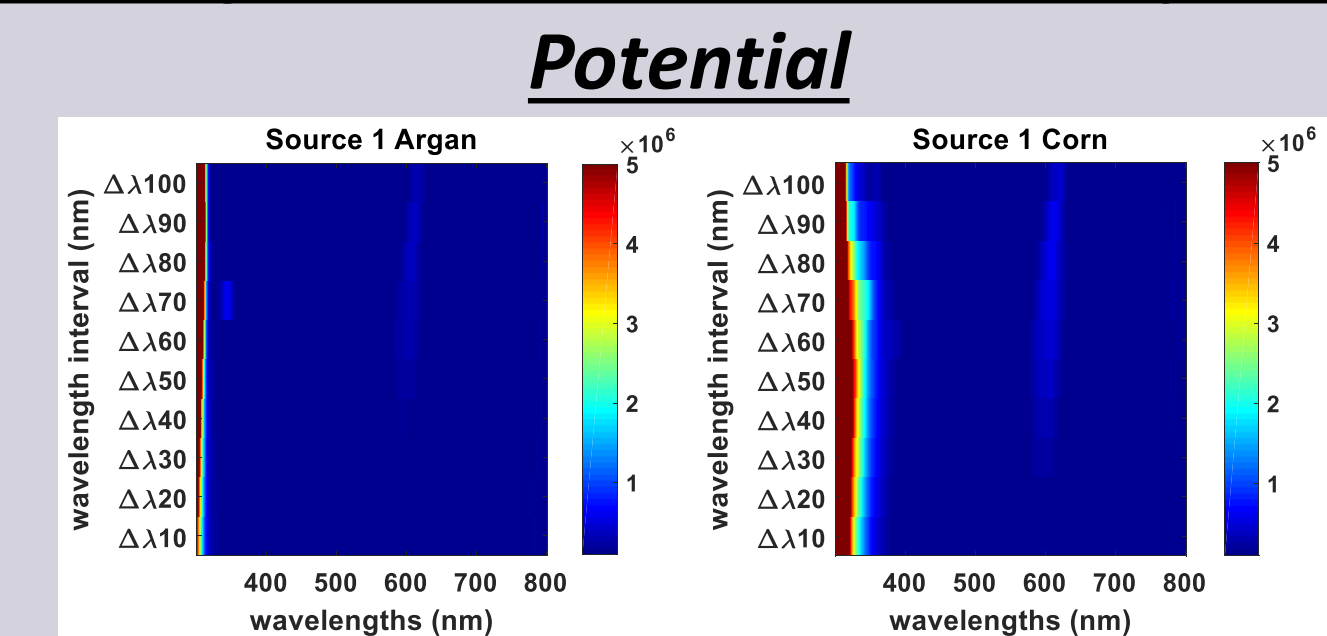
Full Range	Wavelengths (nm)		$\Delta\lambda$ Interval
	Selected Band		
310-710	365-375		10
320-720	345-355		20
330-730	360-370		30
340-740	360-370		40
350-750	380-390		50
360-760	385-395		60
370-770	410-420		70
380-780	415-425		80
390-790	415-425		90
400-800	435-445		100

- SyF spectra obtained by simultaneously measuring excitation and emission wavelengths in the range 300 to 800 nm varying the $\Delta\lambda$ interval from 10 to 100 nm in increments of 10 nm.



- Each source is from a unique farm in Morocco
- Argan spectra differentiates from Corn spectra

Total Synchronous Fluorescence Spectra



- Argan Excitation Region: 300 – 330 nm
- Corn Excitation Region: 300 – 410 nm
- Potential for differentiation within 300 – 410 nm range

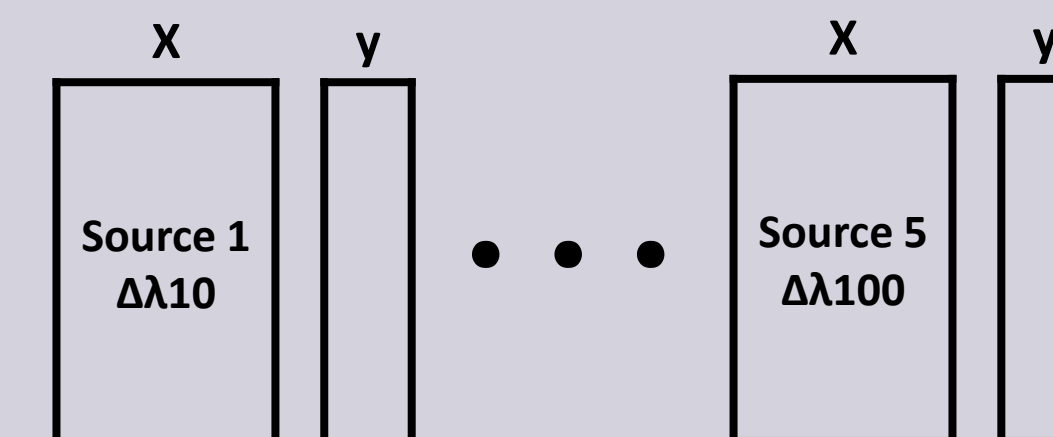
Organizational Techniques

- $\Delta\lambda$ -Wise, Source-Wise: $\Delta\lambda$ and sources separate
- All $\Delta\lambda$, Source-Wise: $\Delta\lambda$ combined and sources separate
- $\Delta\lambda$ -Wise, All Sources: $\Delta\lambda$ separate and sources combined
- All $\Delta\lambda$, All Sources: $\Delta\lambda$ combined and sources combined

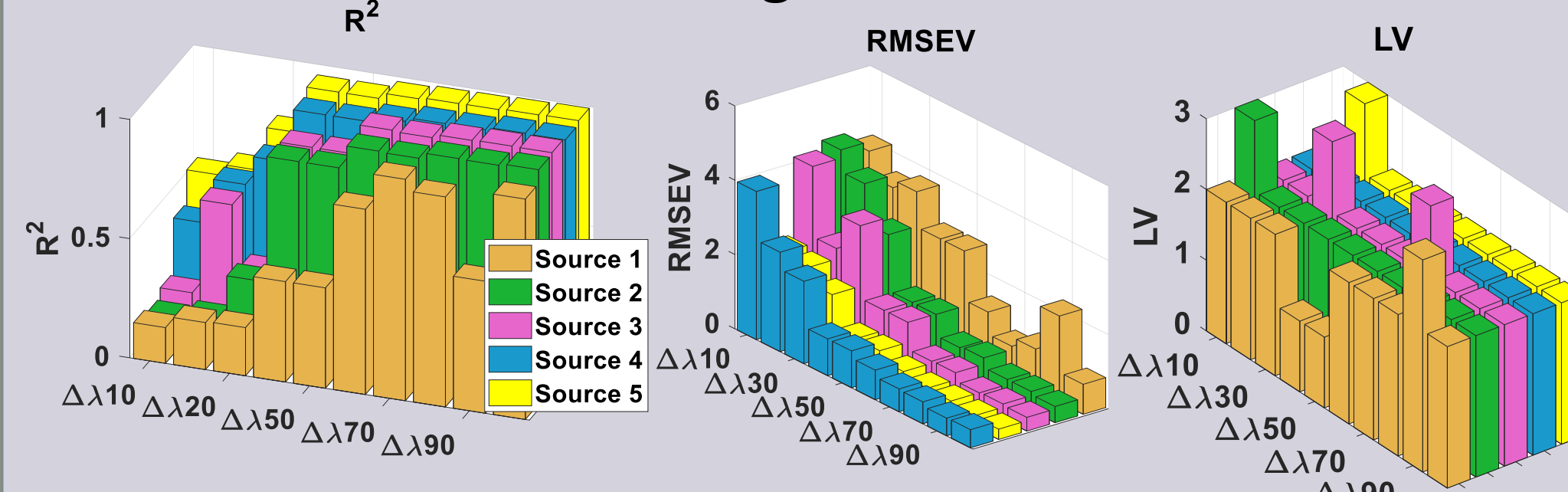
Experimental Results

(1) $\Delta\lambda$ -Wise, Source-Wise

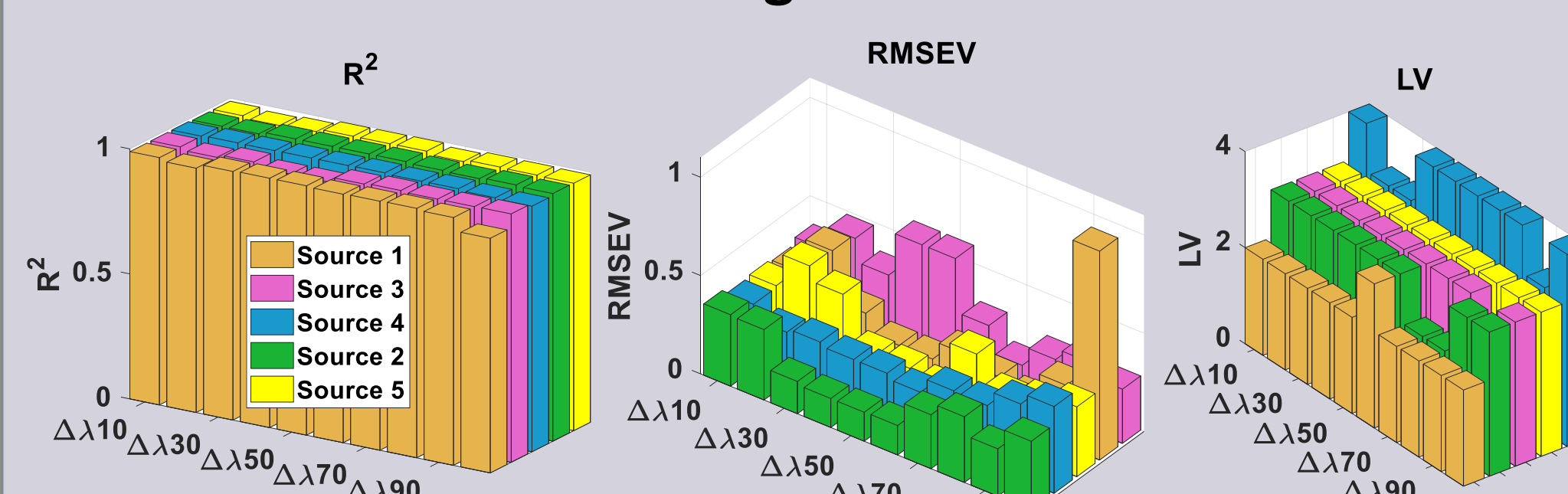
$\Delta\lambda$ separate and Sources separate



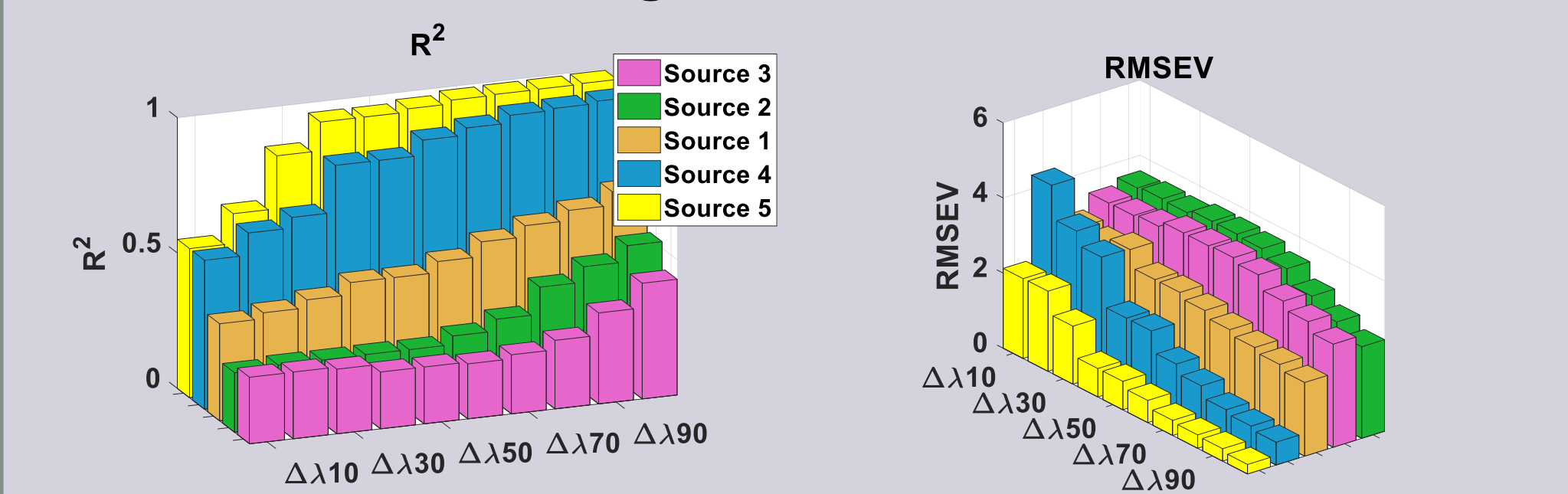
All Wavelengths Multivariate



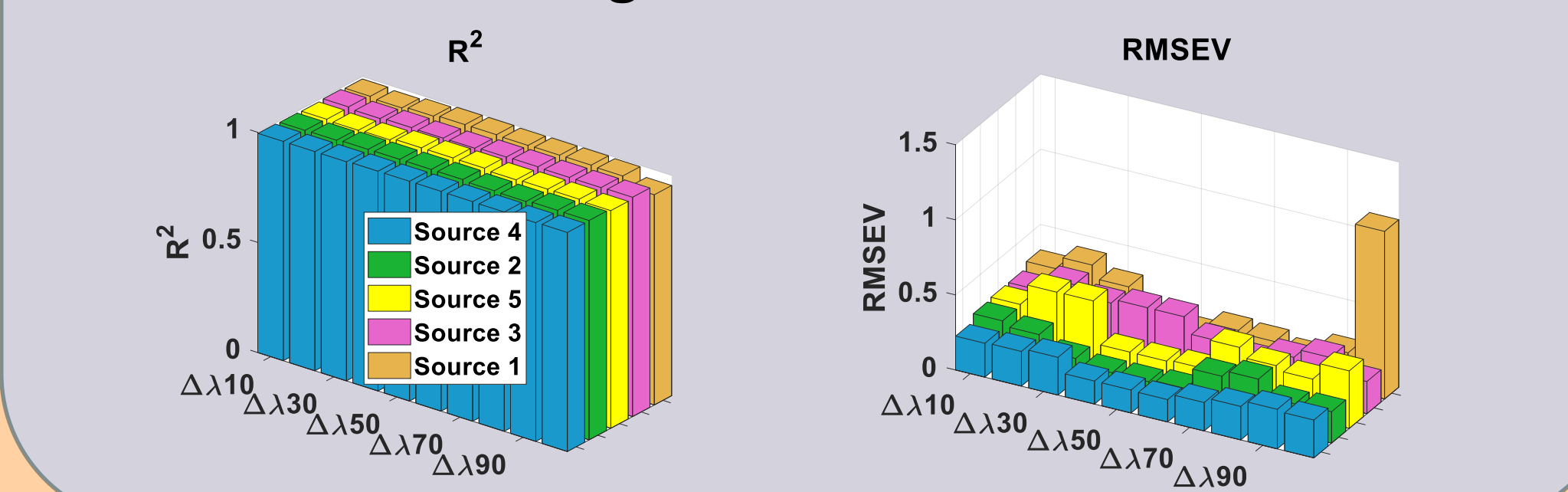
Selected Wavelength Bands Multivariate



All Wavelengths Area Under the Curve

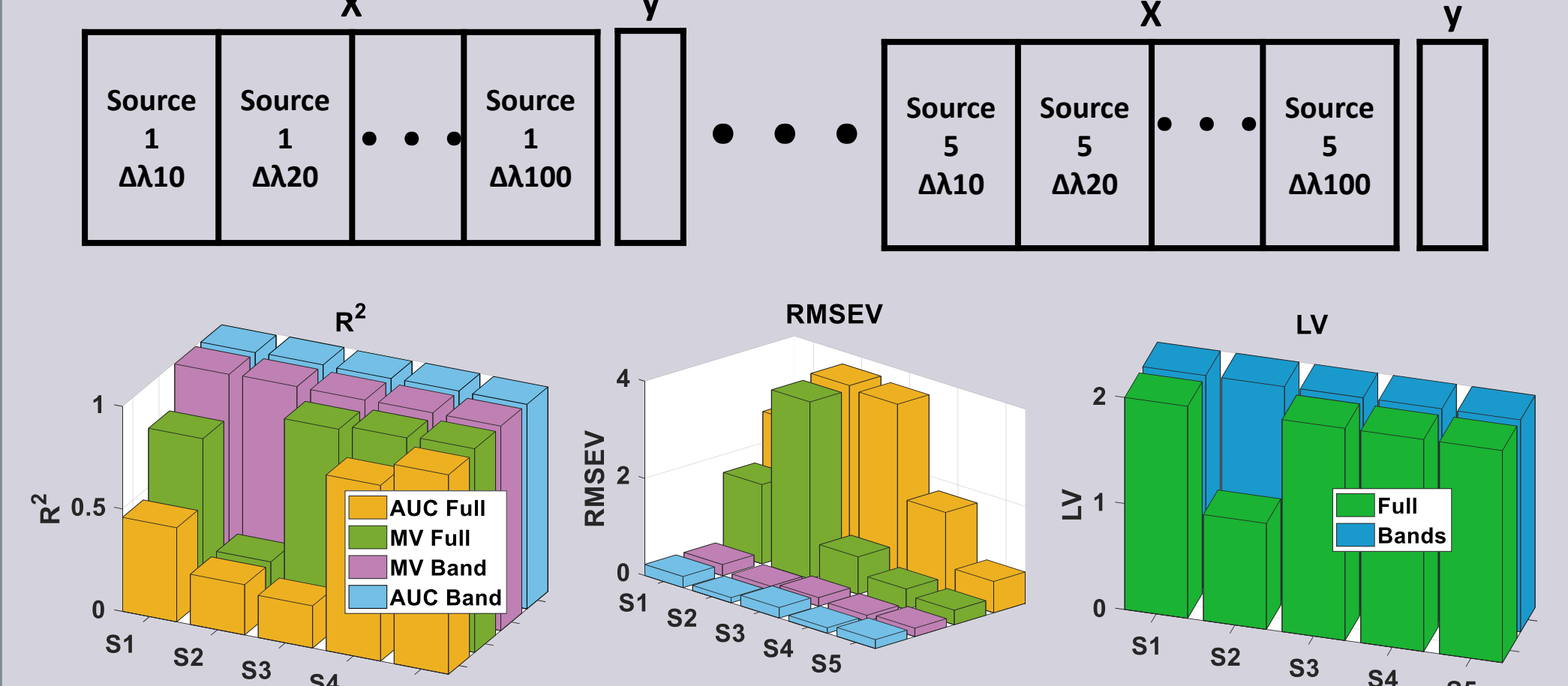


Selected Wavelength Bands Area Under the Curve



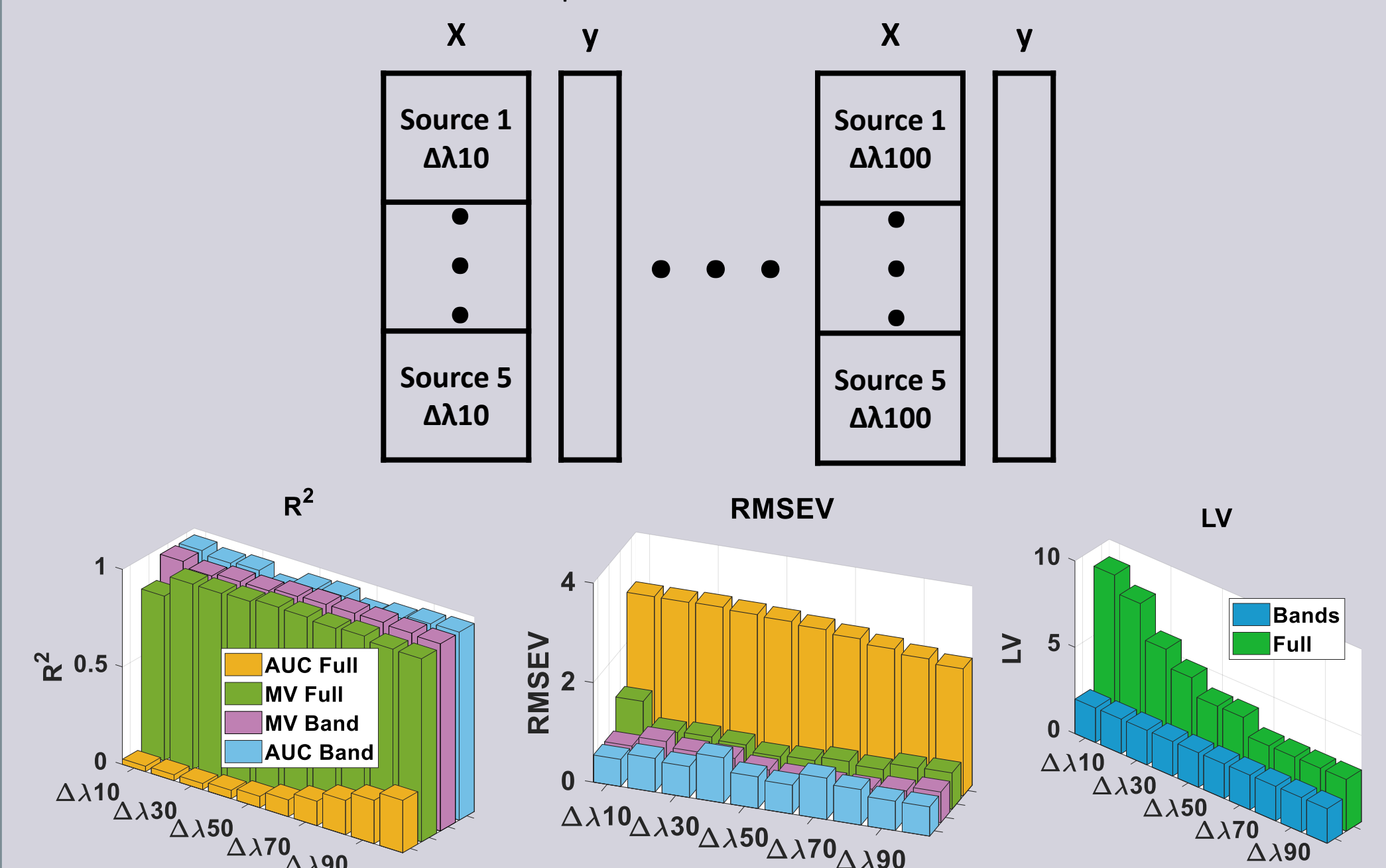
(2) All $\Delta\lambda$, Source-Wise

$\Delta\lambda$ combined and Sources separate



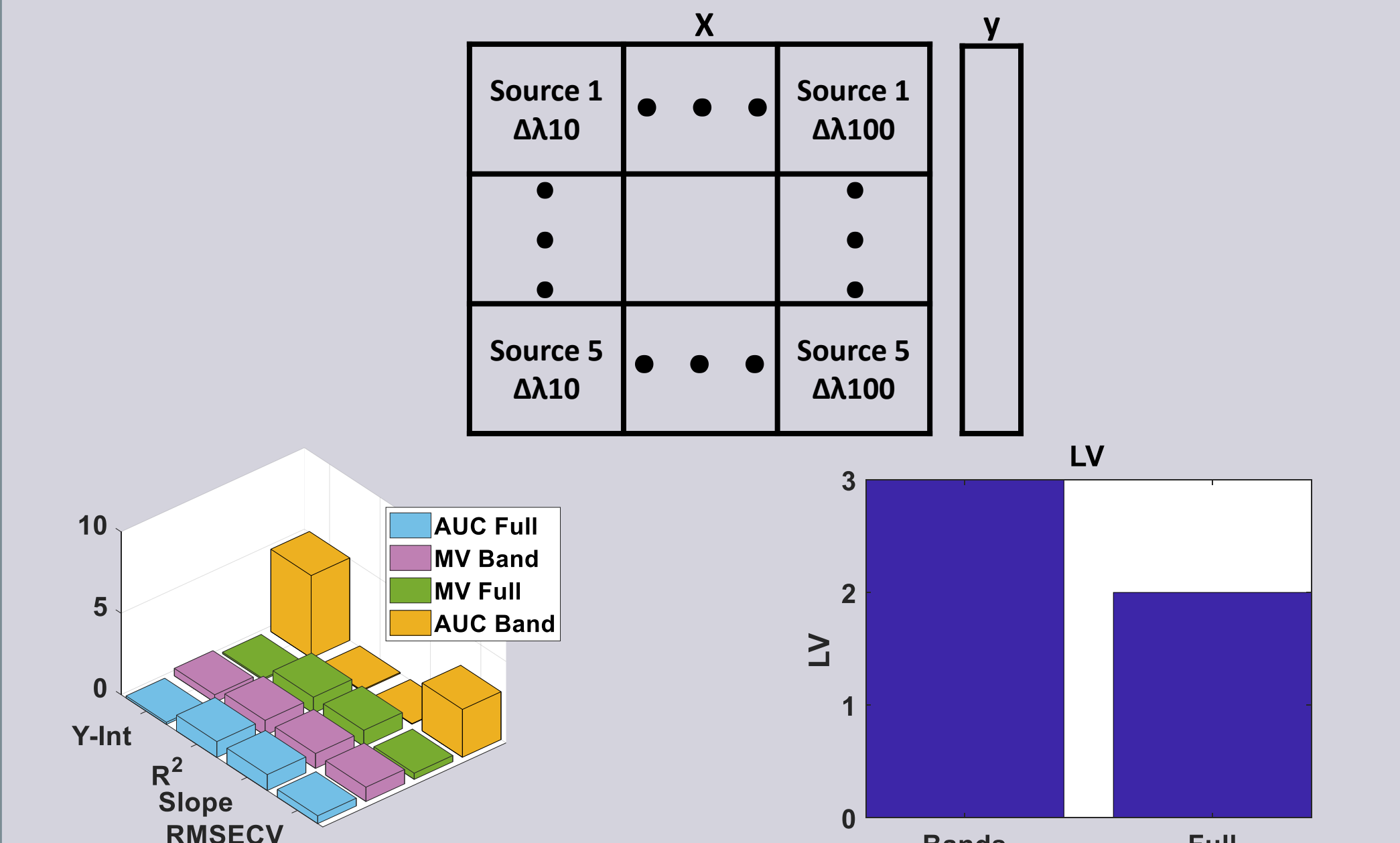
(3) $\Delta\lambda$ -Wise, All Sources

$\Delta\lambda$ separate and Sources combined



(4) All $\Delta\lambda$, All Sources

$\Delta\lambda$ fused and Sources fused



Conclusions

- Low level fusion provided lower prediction errors
- The bands provided more consistent prediction errors for individual $\Delta\lambda$
 - Full wavelength results were $\Delta\lambda$ independent when the sources are fused
- AUC performed better than PLS at the bands, in general
- Low level fusion was showcased to be an effective means to bypass the $\Delta\lambda$ selection process

Acknowledgement

This material is based upon work supported by the National Science Foundation under Grant No. CHE-1506417 (co-funded by CDS&E) and is gratefully acknowledged by the authors.