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FACULTY OF INFORMATION TECHNOLOGY

SPECTRAL IMAGING LABORATORY

REMOTE SENSING AND GREEN TECHNOLOGIES

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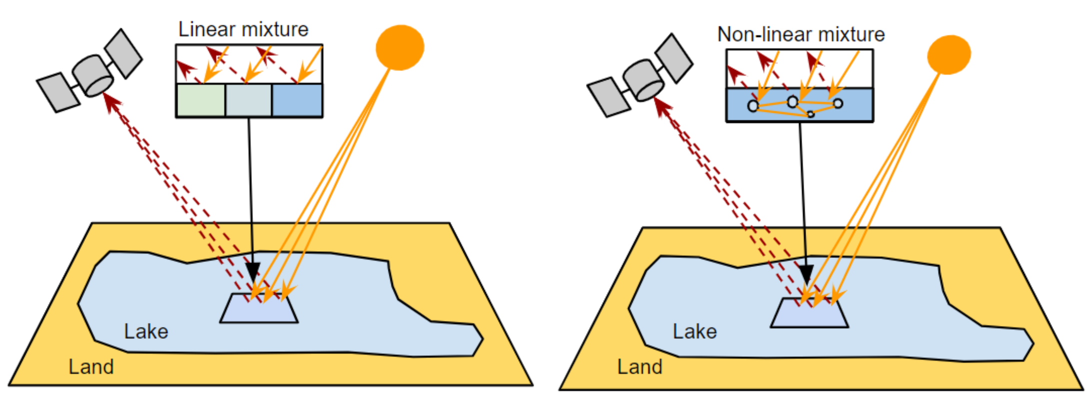
PHYTOPLANKTON PIGMENT CONCENTRATIONS USING HYPERSPECTRAL UNMIXING AND AUTOENCODERS

This study proposes a novel protocol for efficient Phytoplankton monitoring in inland waters. It combines a mobile spectral imager and autoencoder to assess Chlorophyll-a, Fucoxanthin, and Phycocyanin pigments. Tested in 20 Scottish lakes the protocol adapts well to varied environments. High-performance liquid chromatography and spectrophotometry methods are used to extract the ground truth. The proposed autoencoder is initialized using fixed endmembers from the literature to improve the accuracy of abundance estimation. The protocol shows a strong correlation between abundance estimates obtained from autoencoders and the ground truth data.

INTRODUCTION

Phytoplankton, critical to the global carbon cycle and Earth's photosynthesis, are vital for ecological monitoring and understanding biogeochemical cycles and climate dynamics[1]. Phytoplankton are detectable in water bodies' euphotic layer using hyperspectral imagers[2]. The remote sensing data analysis of phytoplankton depends on their optical properties, influenced by pigment composition, concentration, cell structure, and geometry [3, 4].

A hyperspectral image captures a wide spectrum of light for each pixel. Hyperspectral Unmixing is a method to decompose the measured pixel spectrum of hyperspectral data into a collection of endmembers and a set of corresponding fractional abundances. This unmixing is a challenging problem because of low spatial resolution, particulate mixtures, and multiple light scatterings.[5]

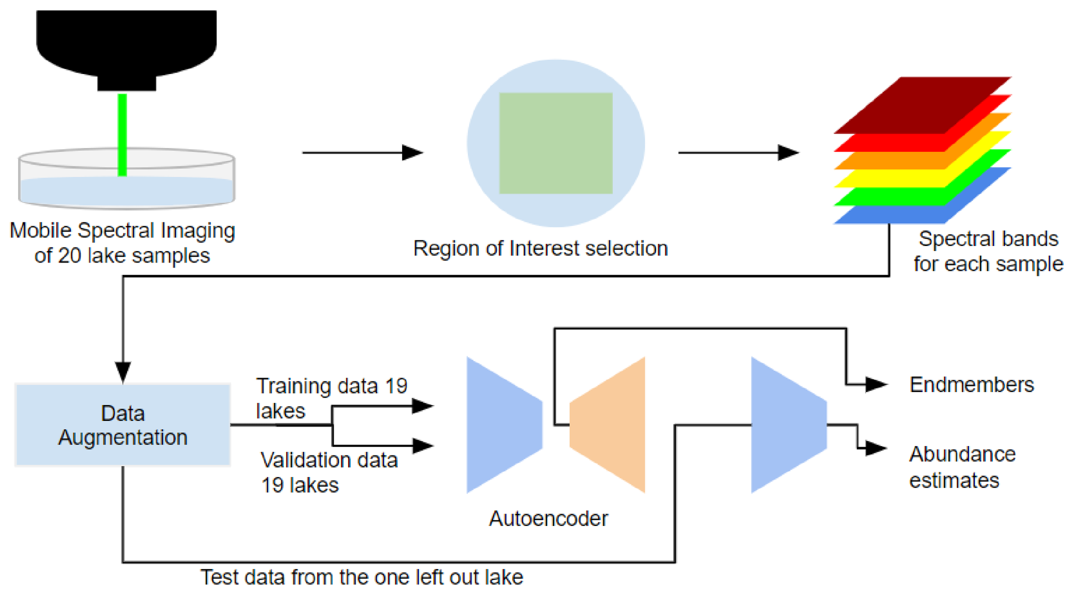


Linear (left) and Non-linear(right) spectral unmixing

Traditional methods involve linear and nonlinear unmixing models and algorithms to extract and estimate component proportions. However, they face limitations from modeling errors and observational noise [6]. The recent deep learning advancements, particularly autoencoders, are being explored for abundance estimation and nonlinear unmixing, thereby increasing accuracy in identifying endmembers .[7, 8].

METHODS

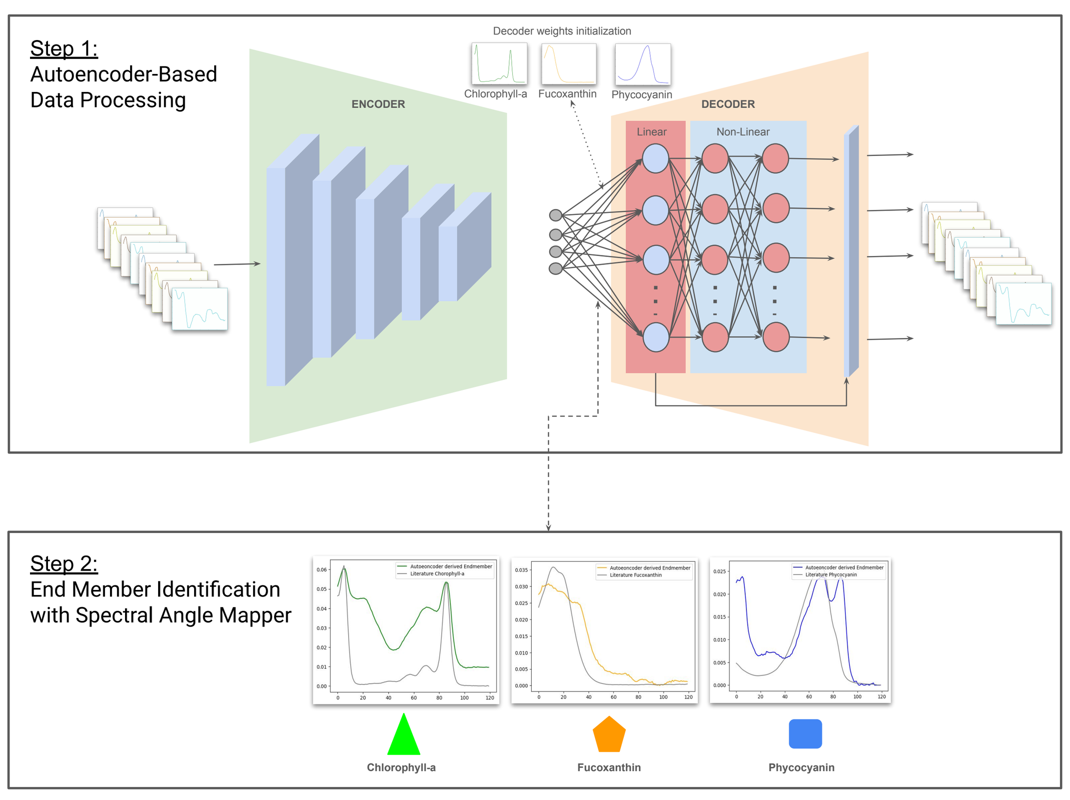
We acquire hyperspectral images of water samples of 20 different lake in Scotland using a mobile imager and augment our dataset. The data for 19 lakes serve for training and validation, leaving one exclusively for testing. This approach generates 20 sets of training and testing data, each excluding one lake, ensuring a thorough evaluation of model performance for robustness and accuracy.



Schematic Overview of 20 Scottish Lake Sample Analysis: Mobile Spectral Imaging to Autoencoder-Based Estimation

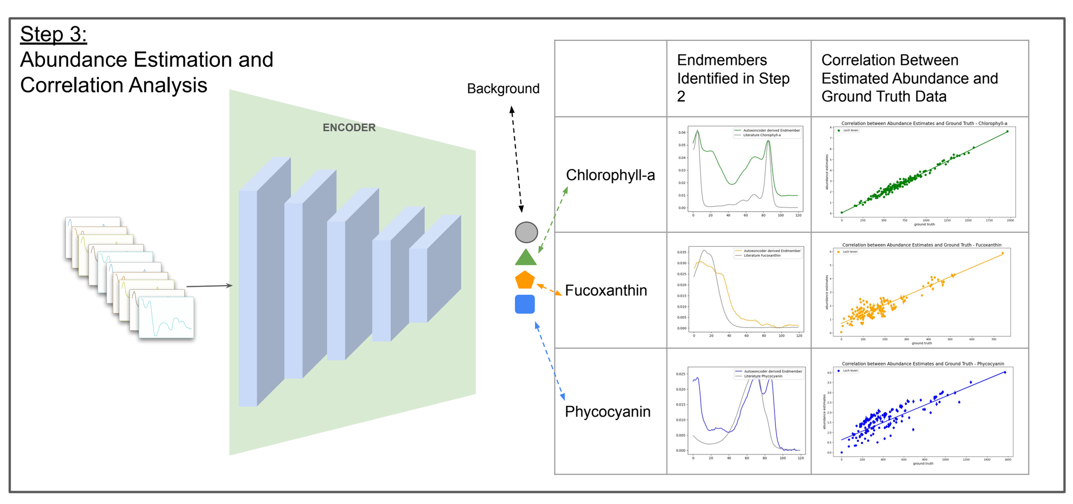
Step 1 (Autoencoder Initialization and Data Processing): Methodology employs an autoencoder to process training data, extracting abundance estimates and endmembers. The autoencoder derives abundance estimates from its latent space and obtains endmembers using its decoder's weights. The decoder's weights are initialized with fixed endmember data for Chlorophyll-a, Phycocyanin, and Fucoxanthin from existing literature.[9]

Step 2 (End Member Identification with Spectral Angle Mapper): We identify the endmembers for Chlorophyll-a, Fucoxanthin, Phycocyanin pigments using the spectral angle mapper. It compares the endmembers derived for autoencoder's decoder weights with reference spectra for each pigment from the literature[9], ensuring proper identification of endmembers and their related abundance estimates.



Autoencoder Initialization and Endmember Identification with Spectral Angle Mapper.

Step 3 (Abundance Estimation and Correlation Analysis): We apply the encoder to a separate, left-out lake sample to acquire its abundance estimates linked to each pigment. Finally, we compare these abundance estimates with actual pigment concentrations from the left-out lake using the correlation coefficient.

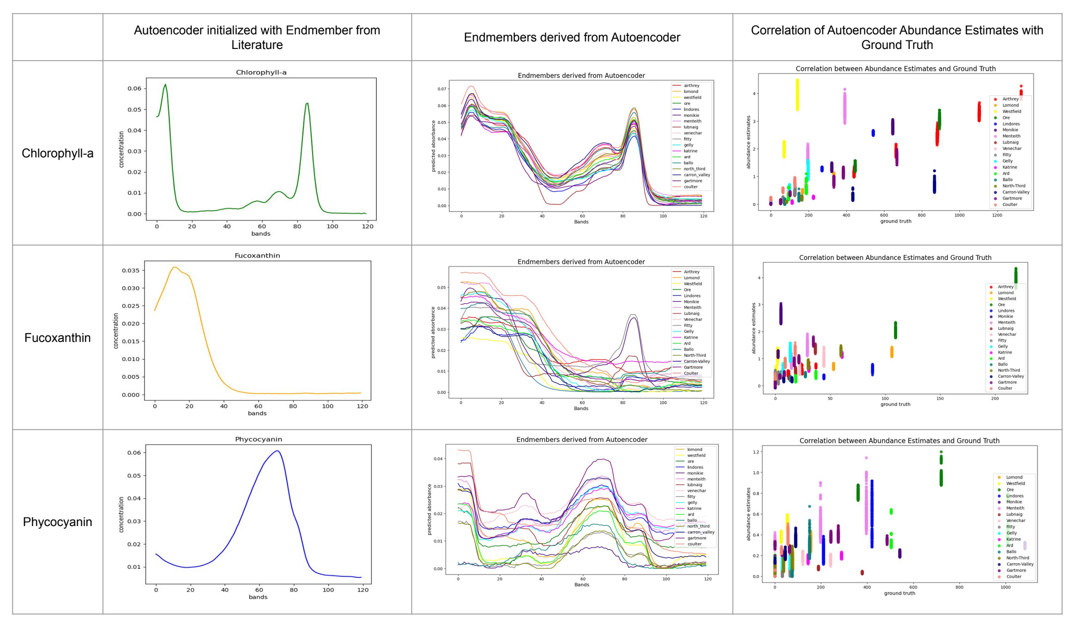


Abundance Estimation and Correlation Analysis for Loch Leven

RESULTS

For Loch Leven lake, the pigment concentration analysis revealed high accuracy in autoencoder estimates with ground truth, showing correlation coefficients of 0.98 for Chlorophyll-a, 0.91 for Fucoxanthin, and 0.84 for Phycocyanin.

For other lakes, Chlorophyll-a levels exhibited strong correlations across most sites, including Lomond, Lindores, and Monikie, with coefficients between 0.89 to 0.99. Fucoxanthin showed a wider coefficient range from 0.38 to 0.99, but mostly remained above 0.90. Phycocyanin presented the most variability, with coefficients as low as 0.17 up to 0.97, suggesting location-dependent distribution.



Autoencoder Analysis of Phytoplankton Pigments for lakes except Loch Leven: Literature Initialization[9], Endmember Derivation, and Ground Truth Correlation

CONCLUSIONS

- Hyperspectral unmixing combined with Autoencoders effectively resolves phytoplankton pigment concentrations.
- Initializing the decoder's weights with fixed endmember data for Chlorophyll-a, Phycocyanin, and Fucoxanthin, as sourced from literature, enhances result accuracy.
- The current results were obtained using laboratory-based spectrography. Future work will focus on validating and enhancing the autoencoder model by applying it to hyperspectral unmixing with satellite-derived hyperspectral imagery. This will enable us to test the model's efficacy and applicability in a broader, real-world context.

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