Quantitative and qualitative evaluation of microplastic contamination of shrimp using Vis-NIR multispectral imaging technology combined with a modified self-organizing map

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Presented by
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❑ INTRODUCTION

Microplastic (MPs) in the seafood can have several negative effects

- **Disruption of Marine Ecosystems**
  MPs can cause harm to various species through ingestion, altered feeding and reproductive behaviors, leading to declines in biodiversity and the overall health of marine environments.

- **Chemical Contamination**
  MPs can adsorb and concentrate toxic chemicals from the surrounding environment. This bioaccumulation of toxins poses risks to both wildlife and humans.

- **Human Health Concerns:**
  It is possible that MPs could carry harmful chemicals into human body, although the extent of these health risks is not yet fully understood.

- **Economic Costs**
  MPs in seafood can impact the fishing industries, leading to decreased consumer confidence and economic losses.

❑ INTRODUCTION

Why PET, PE, PP and PS

Prevalence

They are widely used in consumer products. PE and PP are the most widely used worldwide.

Environmental Persistence

PET, PE, PP, and PS are known for their durability and resistance to degradation

Toxicity Concerns

They can absorb harmful pollutants from the environment, posing risks to marine life.

Analytical Techniques

Their detection is well-supported by existing analytical methods, such as spectroscopy and imaging techniques

Why Shrimp

Ecological Importance

Shrimps are a key food source. Studying MP in shrimp helps assess marine food chains

Bioaccumulation Potential

Shrimps can accumulate MPs in their bodies, which may transfer to food chain

Human Consumption

Shrimps are widely consumed, making it essential to evaluate their safety

Research Gap

There is a need for more studies on MP contamination in seafood, to fill knowledge gaps and support future monitoring.

Note: PET (Polyethylene Terephthalate), PE (Polyethylene), PP (Polypropylene), and PS (Polystyrene)

Ref: [1] Unuofin, J.O. et al., 2023.. *Journal of Sea Research*, *194*, p.102410

❑OVERVIEW

01

INTRODUCTION

Background of MP detection in seafood, as well as the study's objective

02

EXPERIMENTAL

Sample collection and MSI acquisition. Modified supervised SOMs and its application in qualitative and quantitative analysis

03

RESULTS AND DISCUSSION

Results and discussion of modified SOMs and comparison with PCA

04

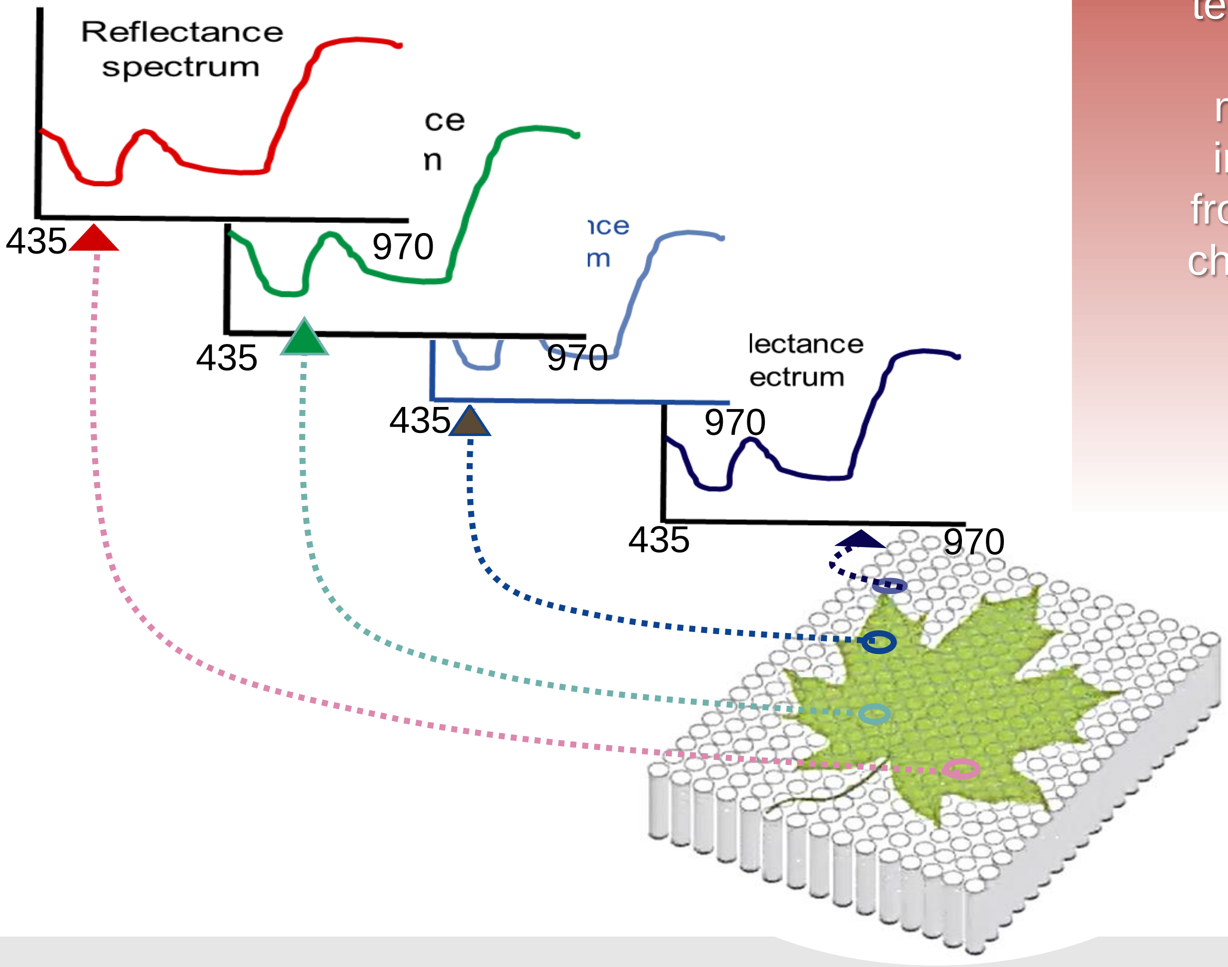
CONCLUSION

Conclusion and future perspectives to improve this work

❑ INTRODUCTION

Visible-Near Infrared Multispectral Imaging (Vis-NIR MSI) technology

It captures image data across specific wavelength ranges and is widely used for MP detection because it captures spatial and spectral data and provides fast and non-destructive measurements.



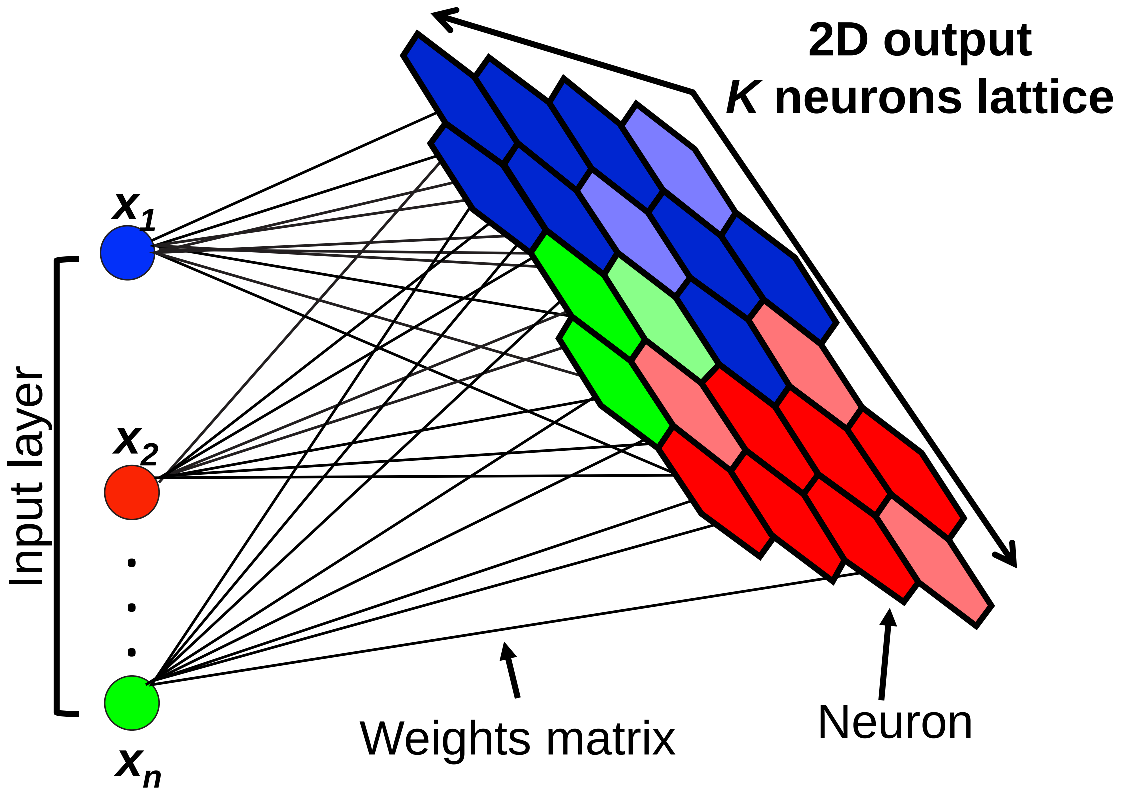
Chemometrics

Mathematical and statistical techniques to extract meaningful information from complex chemical data

Reference: Jianwei Qin, et al,. 2008

❑ INTRODUCTION

" Self-organizing map (SOMs) "



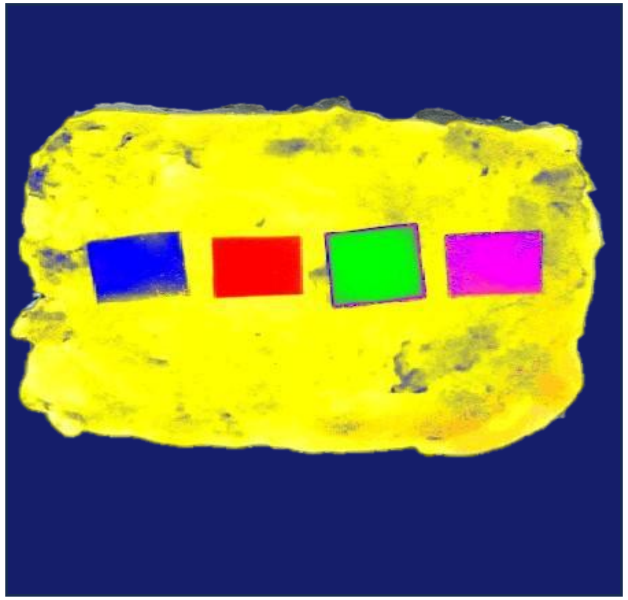
MATLAB R2019b
Using an in-house coded algorithm

SOMs is an unsupervised machine learning technique used to provide a topology-preserving mapping from the high dimensional space to map units.

- Dimension reduction method
- No need to determine the number of latent variables
- Linearity and nonlinearity of the underlying information are not affected by SOMs calculation

❑ OBJECTIVES

To classify and predict MPs (PET, PE, PP, and PS) contamination in minced shrimp



Rapid

Just taking only one photo

Non-invasive

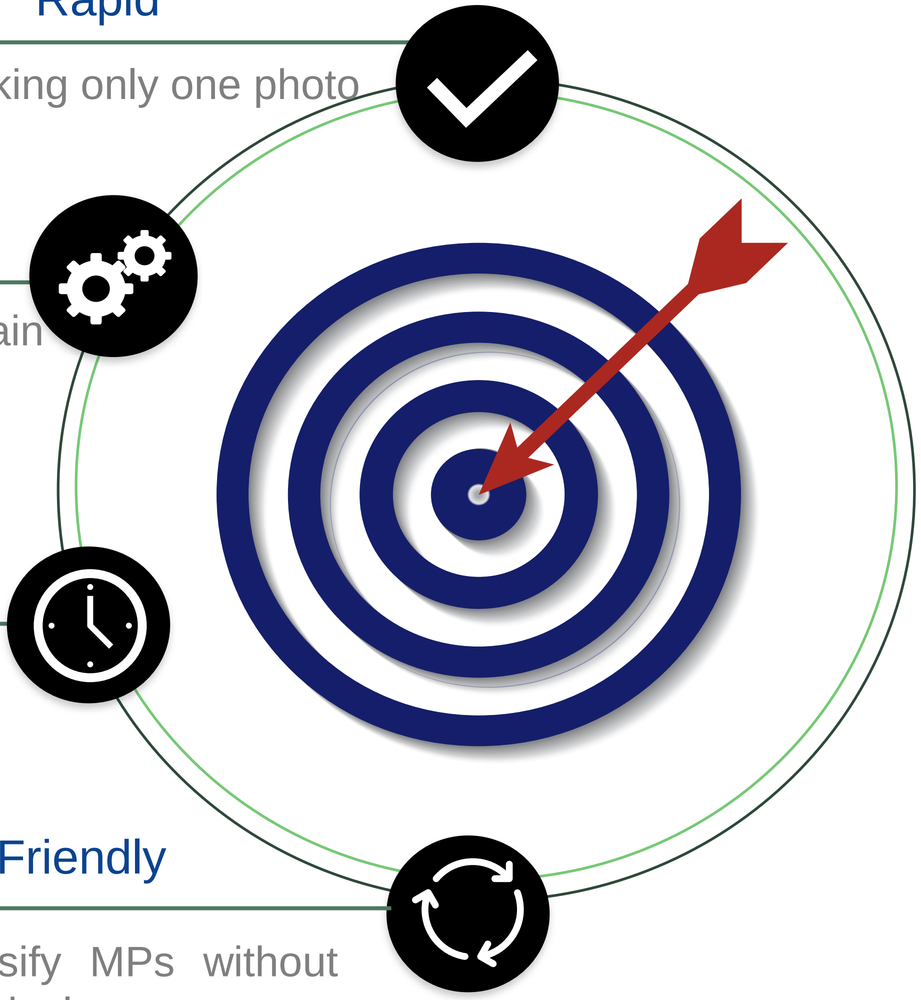
Sample be used again

Quantitative

Predict MPs in %

Environmental Friendly

SOMs can classify MPs without the need of chemicals



Note: PET (Polyethylene Terephthalate), PE (Polyethylene), PP (Polypropylene), and PS (Polystyrene)

❑ EXPERIMENTAL

01 Sample collection & MSI acquisition

Different varieties of microplastic in range size 1-4 mm contaminated in minced shrimp were scanned in reflectance mode in the wavelength range of 435-970 nm using multispectral imaging

02 Modified supervised self-organizing map (SOM)

A modified SOM algorithm is used to classify unknown microplastics (MPs) by adjusting key parameters such as map size, scaling values, and the number of iterations. This is then applied to multispectral imaging (MSI) to classify MPs and compared to other conventional chemometric methods

03 Application in qualitative and quantitative

In qualitative, the results allow visual identification. In quantitative, MPs were contaminated with minced shrimp at concentrations from 0.04% to 1% w/w.

❑ EXPERIMENTAL

Raw MSI spectra extraction → **Preprocessing using smooth+SNV** → **Modified SOM map** → **Classification of unknown MP**

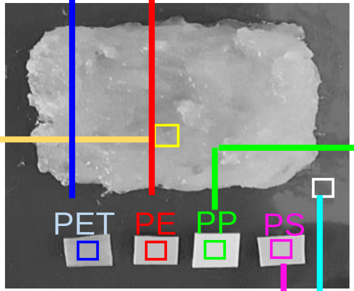
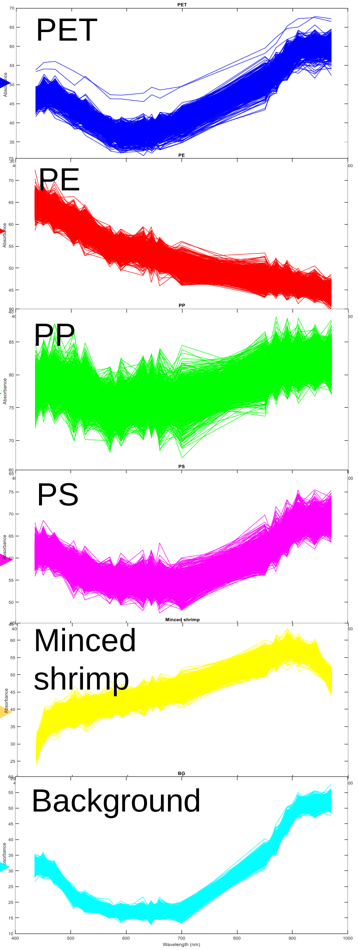
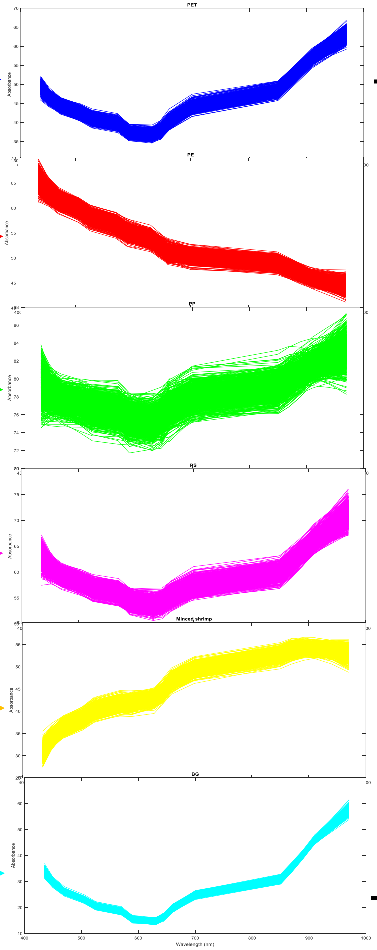


Figure shows MSI spectra from a 30 × 30 pixel ROI, with reflectance spectra representing each microplastic (MP). Data was preprocessed PET, PE, PP, PS, shrimp, and background are color-coded as blue, red, green, magenta, yellow, and cyan, respectively.

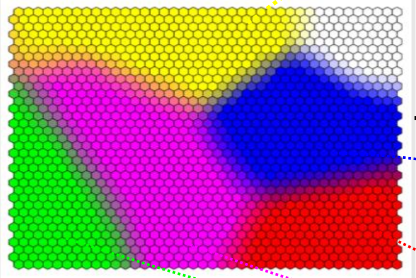
900 spectra
900 spectra
900 spectra
900 spectra
900 spectra
900 spectra



852 spectra
890 spectra
890 spectra
884 spectra
884 spectra
884 spectra



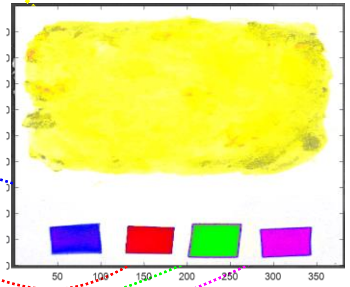
Legends:
- PET
- PE
- PP
- PS
- Shrimp
- background



Condition
Data from smooth
Map size = 35x40
Scaling value = 2

Euclidean distance between map unit ($\boldsymbol{k}$) and sample $\boldsymbol{Xs}$

$$d_{sk} = \sqrt{(x_s - w_k)(x_s - w_k)^{\mathrm{T}}}$$



The BMU of each pixel was determined with the smallest Euclidean distance. After the BMU was determined, the color RGB vector of the map unit was extracted and projected onto the pixel.

Note: $\boldsymbol{x_s}$: Sample vectors
$\boldsymbol{w_k}$: Weight vector of each unit ($\boldsymbol{w_k}$) on the initial SOM map
$\boldsymbol{d_{ks}}$: Euclidean distance e between $\boldsymbol{x_s}$ and $\boldsymbol{w_k}$ for each map unit k

Note: Preprocessing is Savitzky-Golay smoothing, standard normal variate (SNV)
Best map unit (BMU)

Ref: [1] Makmuang, S., et al., 2023. *Microchemical Journal*, 190, p.108599.
[2] Makmuang, S., et al. *Computers and Electronics in Agriculture*, 191, p.106522.

RESULT AND DISCUSSION

❑ RESULT AND DISCUSSION

Qualitative analysis

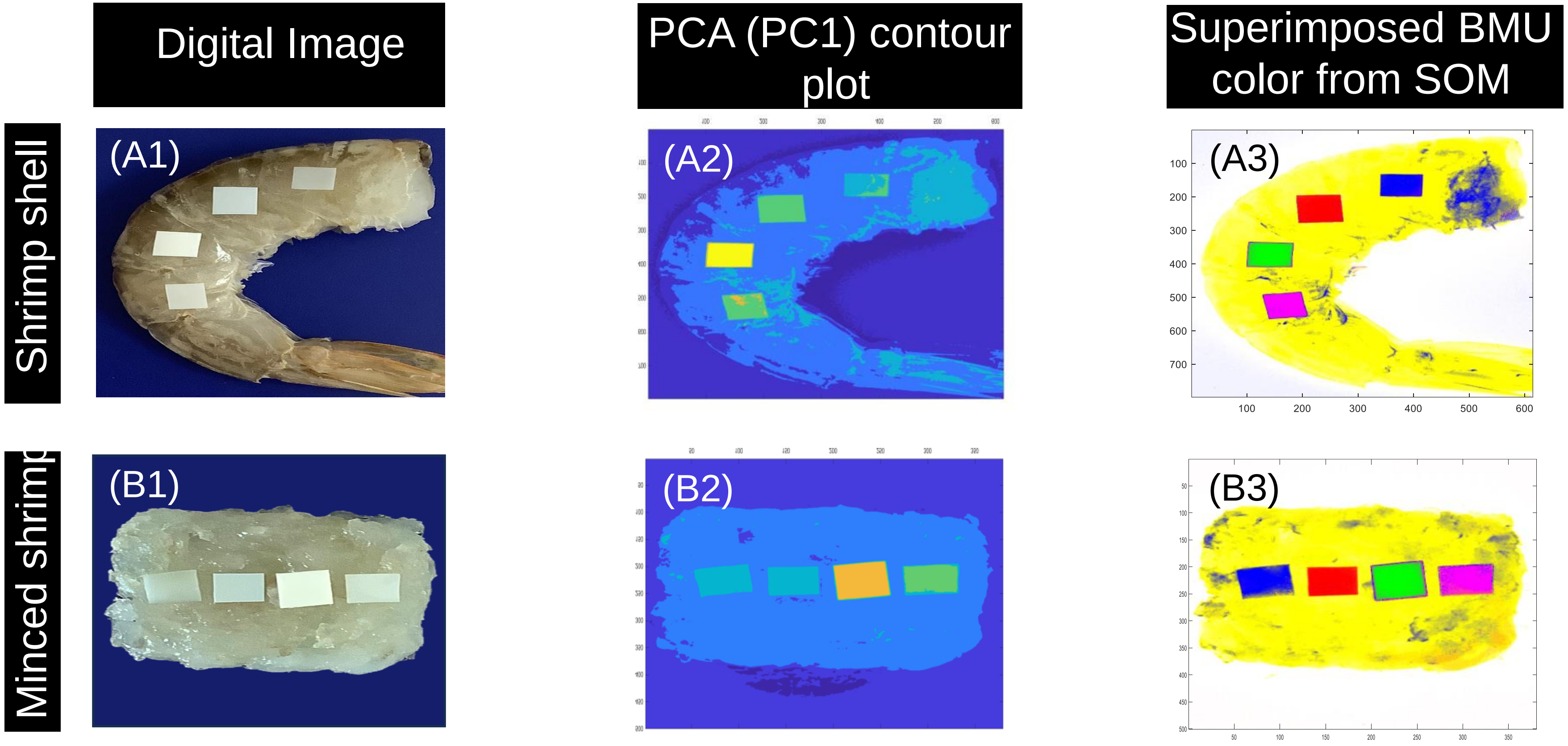
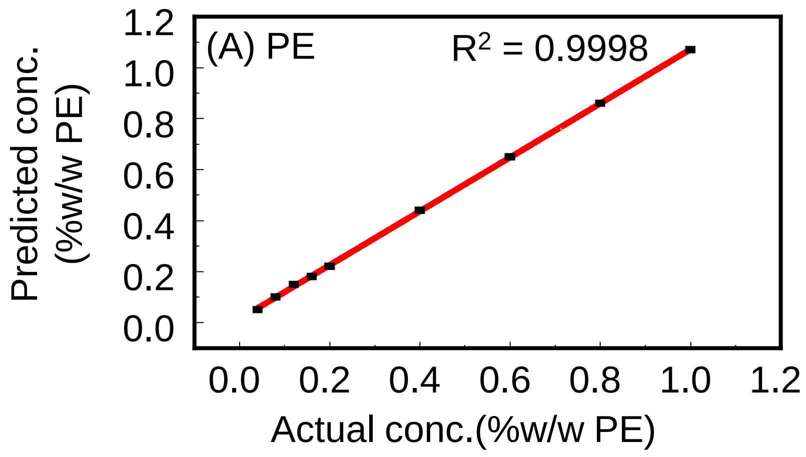


Figure shows four types of MPs (PET, PE, PP, PS) on a shrimp shell: (A1) digital image, (A2) PCA contour plot of PC1, and (A3) superimposed BMU color map from the global SOM. The corresponding images are also shown, with (B1) digital image, (B2) PCA contour plot, and (B3) superimposed BMU color map which the colors blue, red, green, magenta, yellow, and white represent PET, PE, PP, PS, shrimp shell (A3), minced shrimp (B3), and background, respectively.

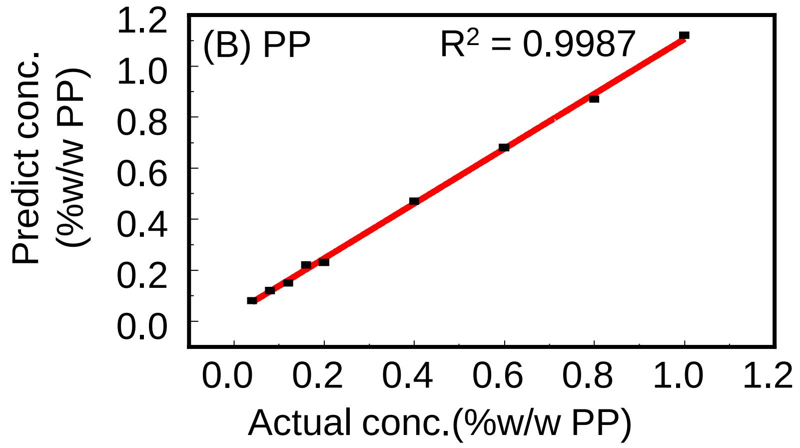
"In qualitative analysis, the SOM results offer clearer visual identification and distinction of the four types of microplastics (PET, PE, PP, and PS) compared to PCA, giving better insights into the types and distribution of MPs within the samples"

❑ RESULT AND DISCUSSION

Quantitative analysis



Actual conc. (%w/w PE)	Predicted conc. (%w/w PE)
0.04	0.05
0.08	0.1
0.12	0.15
0.16	0.18
0.2	0.22
0.4	0.44
0.6	0.65
0.8	0.86
1	1.07



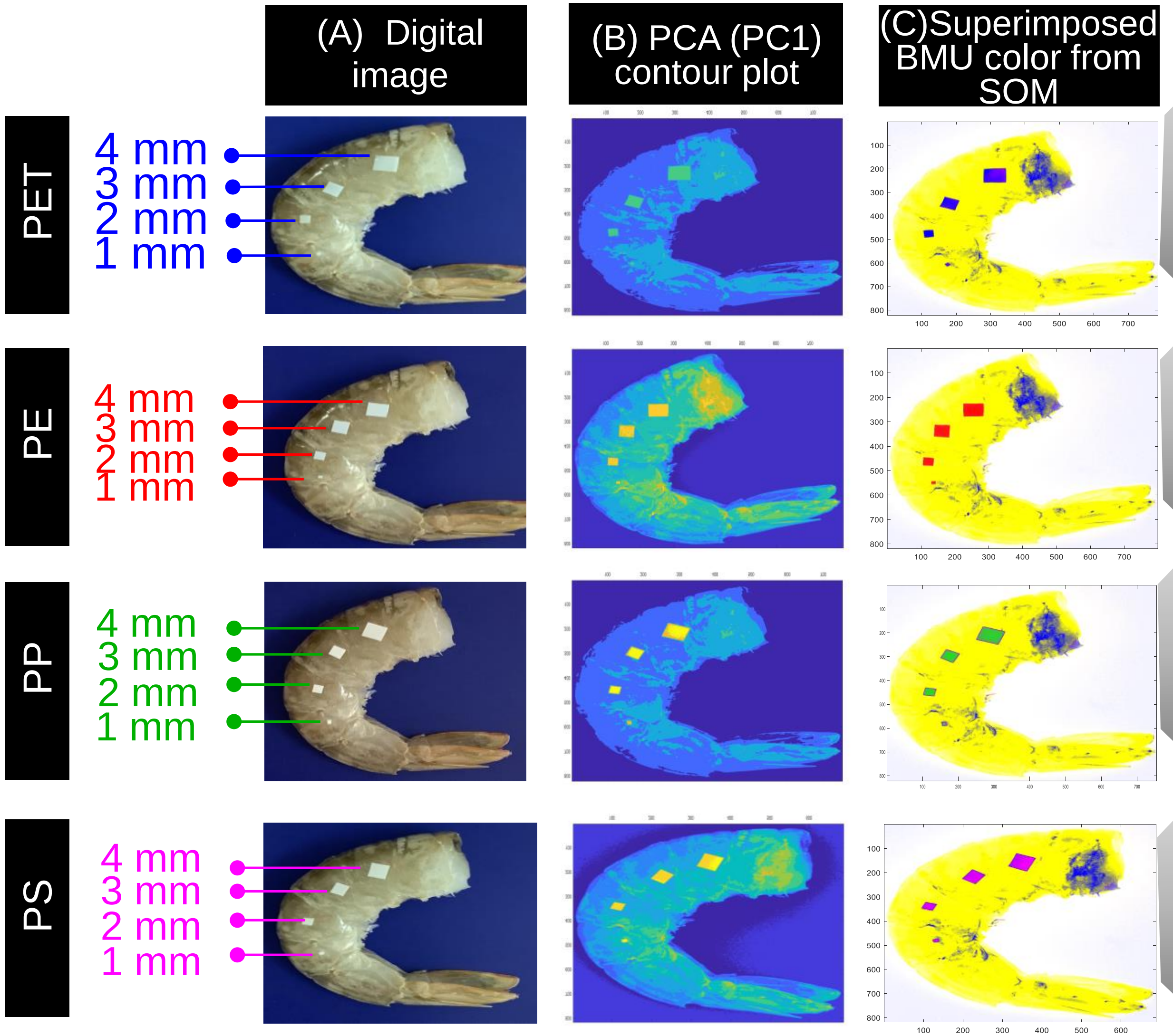
Actual conc. (%w/w PP)	Predict conc. (%w/w PP)
0.04	0.08
0.08	0.12
0.12	0.15
0.16	0.22
0.2	0.23
0.4	0.47
0.6	0.68
0.8	0.87
1	1.12

Fig. 3 presents the R^2 plots for predicting MPs on minced shrimp using modified SOMs: (A) PE, (B) PP. The inset table shows the percentage of actual versus predicted MPs concentrations on minced shrimp, ranging from a limit of quantification (LOQ) of 0.04% to 1% w/w.

"In quantitative analysis, the results show that modified SOMs achieved a high R^2 over 0.99, suggesting a strong correlation between the predicted and actual concentrations, indicating that the model can accurately predict concentrations of MPs in shrimp samples"

❑ RESULT AND DISCUSSION

Size analysis



PET	Blue pixel	Red pixel	Green pixel	Magenta pixel	%Proportion of blue pixels
	3453	0	0	399	89.64
	1999	0	0	0	100
	869	0	0	0	100
	269	0	0	48	84.85

PE	Blue pixel	Red pixel	Green pixel	Magenta pixel	%Proportion of red pixels
	31	3113	0	69	96.89
	1	2227	0	73	96.78
	24	1013	0	37	94.32
	129	129	0	12	47.78

PP	Blue pixel	Red pixel	Green pixel	Magenta pixel	%Proportion of green pixels
	198	10	3360	340	85.98
	141	0	1411	228	79.27
	94	1	780	167	74.86
	221	0	110	84	26.51

PS	Blue pixel	Red pixel	Green pixel	Magenta pixel	%Proportion of magenta pixels
	267	0	0	2807	91.31
	193	0	0	1707	89.84
	127	0	0	783	86.04
	157	0	0	153	49.35

"
- ❑ If any piece has a relevant pixel proportion greater than 25%, it will be classified in its respective class
- ❑ E.g. PET, all four PET pieces have a blue pixel proportion exceeding 84%, indicating that all are classified as PET.
- ❑ This suggests that SOMs is effective in classifying MP particles as small as 1 mm and perform better than PCA
"

Figure illustrates the size-independent analysis of MPs ranging from 1-4 mm for the four types on the shrimp shell: (A) digital image, (B) PCA contour plot of PC1, and (C) superimposed BMU color map from the global SOM. In these maps, the colors blue, red, green, magenta, yellow, and white represent PET, PE, PP, PS, shrimp shell, and background, respectively. The inset table show the number of RGB pixel count from superimposed BMU color map.

❑CONCLUSION

The modified SOMs can effectively identify MP contamination in shrimp, both qualitative and quantitative assessments within a contamination range of 0.04-1% w/w, and R^2 >0.99. However, the prediction performance depends on the type of MPs.

Future research could focus on determining the limit of detection (LOD) for MP contamination and extend studies to various seafood types and MP varieties to enhance food safety and protect consumer health

Note: correlation coefficient (R^2)

❑ ACKNOWLEDGMENT

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MOPGA (Make Our Planet Great Again)
Postdoctoral fellowship from the French Ministry for Europe and Foreign Affairs

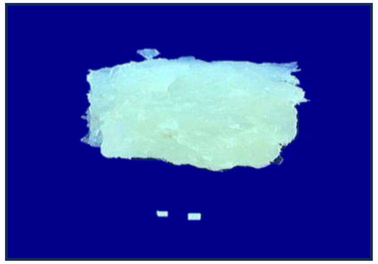
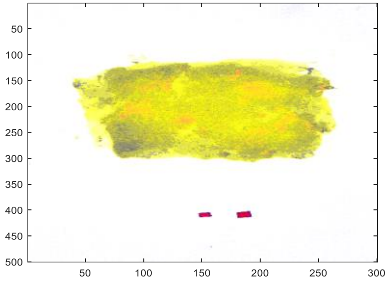
THANK YOU

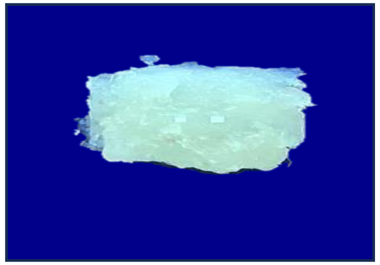
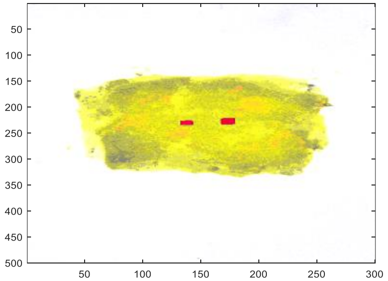
Q & A

❑ QUANTITATIVE ANALYSIS OF PE

Reference | **Prediction**

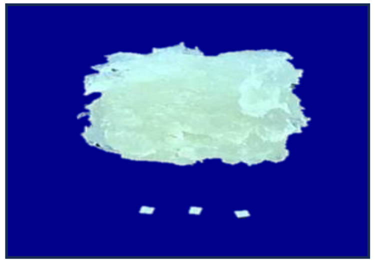
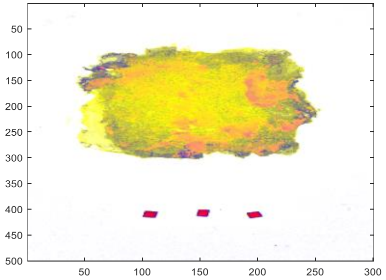
0.04 %w/w

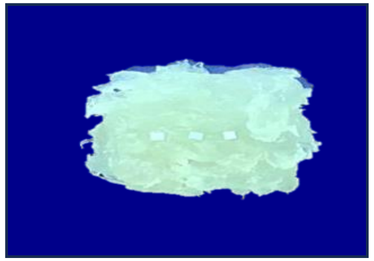
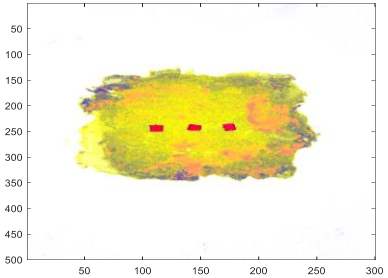



	Number of PS pixels	% w/w
Ref	169	0.04
Predict	221	0.05

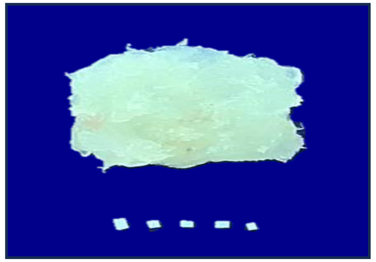
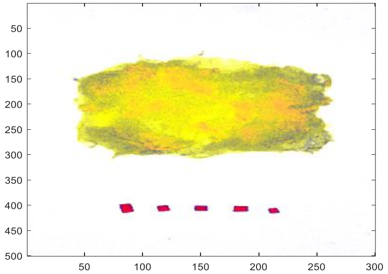
0.08 %w/w

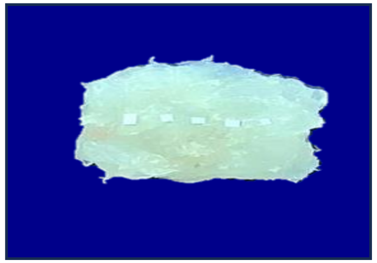
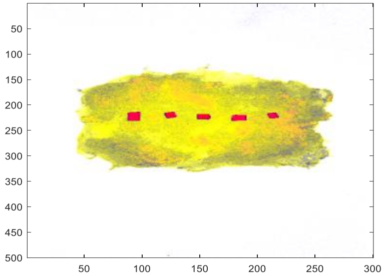



	Number of PS pixels	% w/w
Ref	296	0.08
Predict	363	0.10

0.12 %w/w

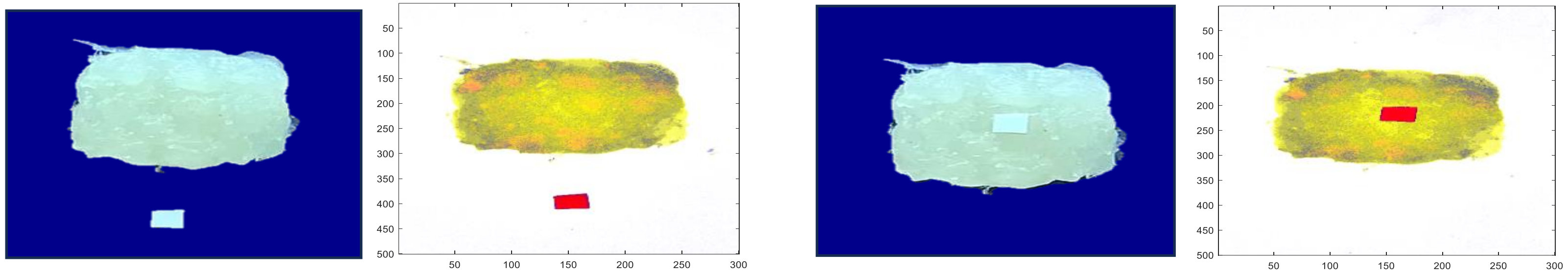



	Number of PS pixels	% w/w
Ref	477	0.12
Predict	580	0.15

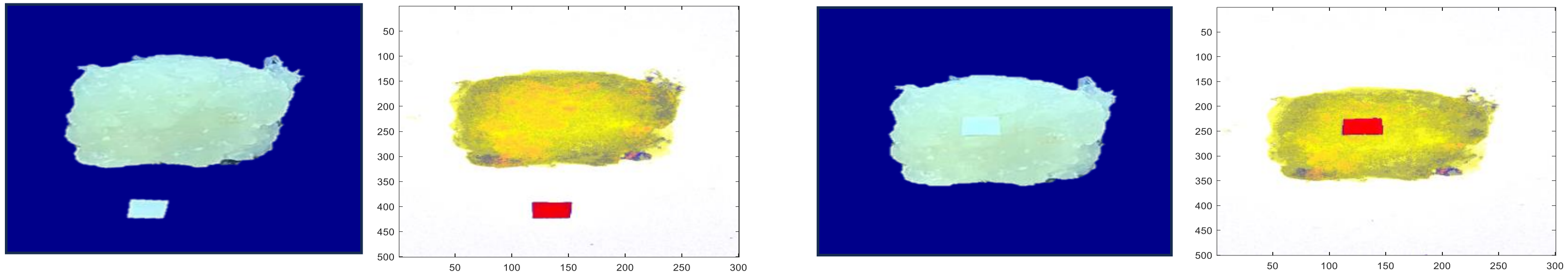
❑QUANTITATIVE ANALYSIS OF PE

0.16 %w/w



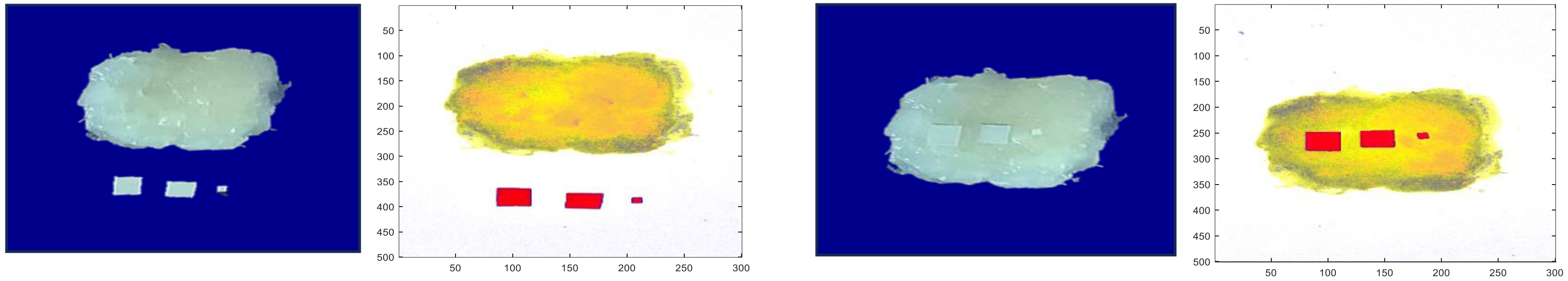
	Number of PS pixels	% w/w
Ref	769	0.16
Predict	868	0.18

0.20 %w/w



	Number of PS pixels	% w/w
Ref	999	0.2
Predict	1095	0.22

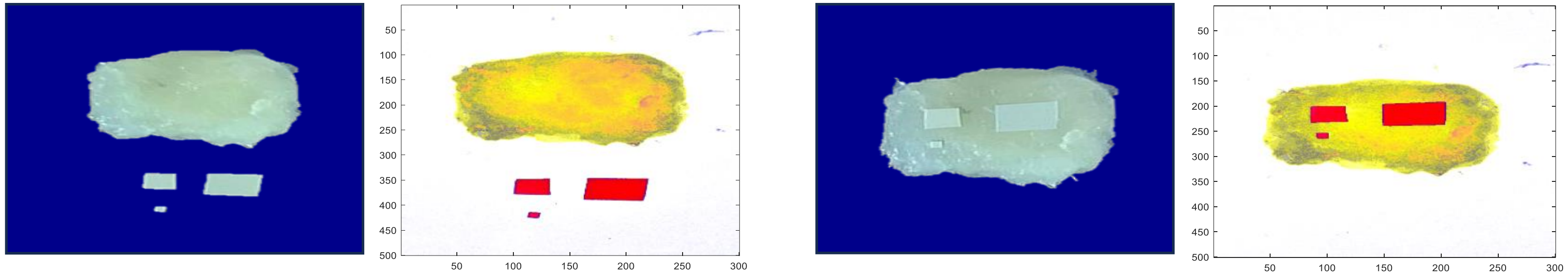
0.40 %w/w



	Number of PS pixels	% w/w
Ref	1984	0.4
Predict	2187	0.44

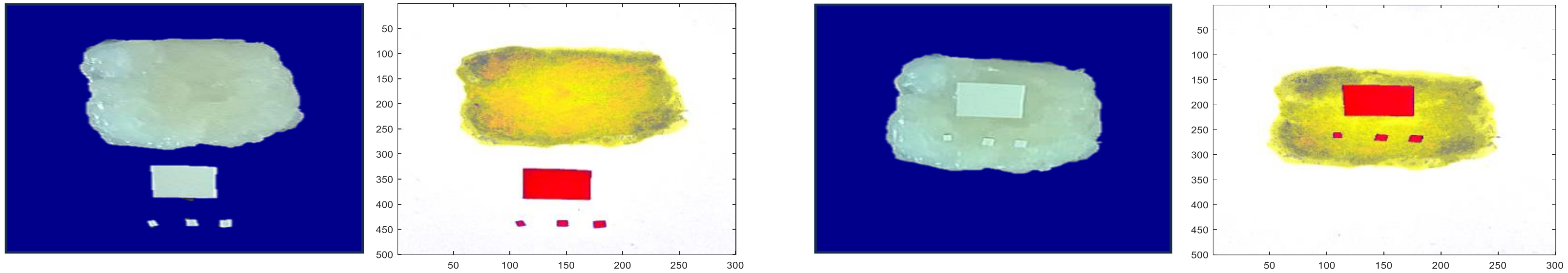
❑QUANTITATIVE ANALYSIS OF PE

0.60 %w/w



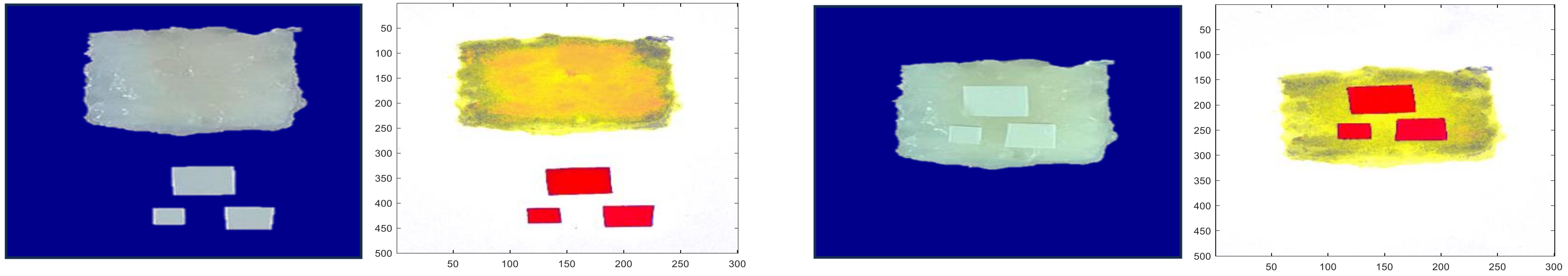
	Number of PS pixels	% w/w
Ref	3209	0.60
Predict	3483	0.65

0.80 %w/w



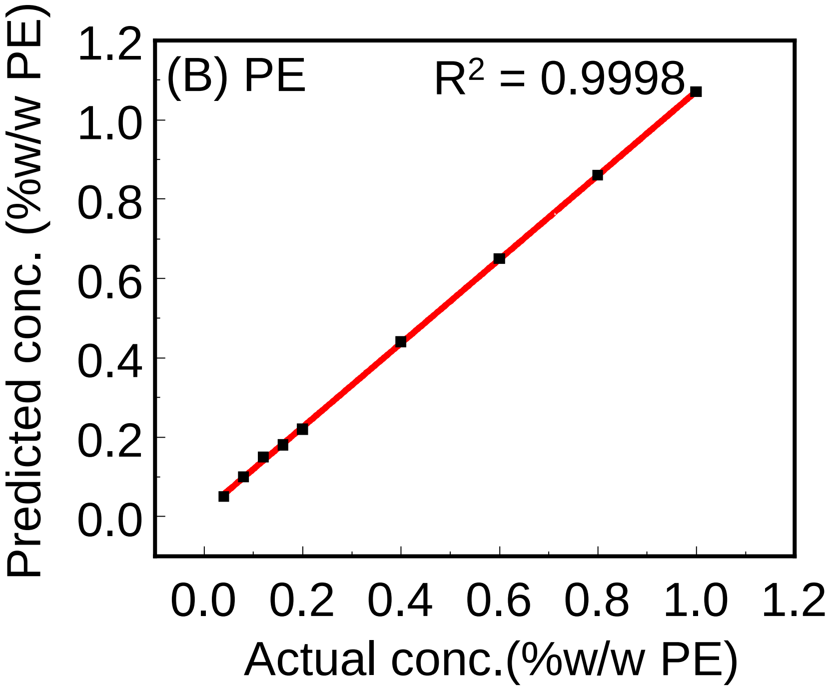
	Number of PS pixels	% w/w
Ref	3743	0.80
Predict	4041	0.86

1 %w/w



	Number of PS pixels	% w/w
Ref	5464	1
Predict	5854	1.07

❑QUANTITATIVE ANALYSIS OF PE



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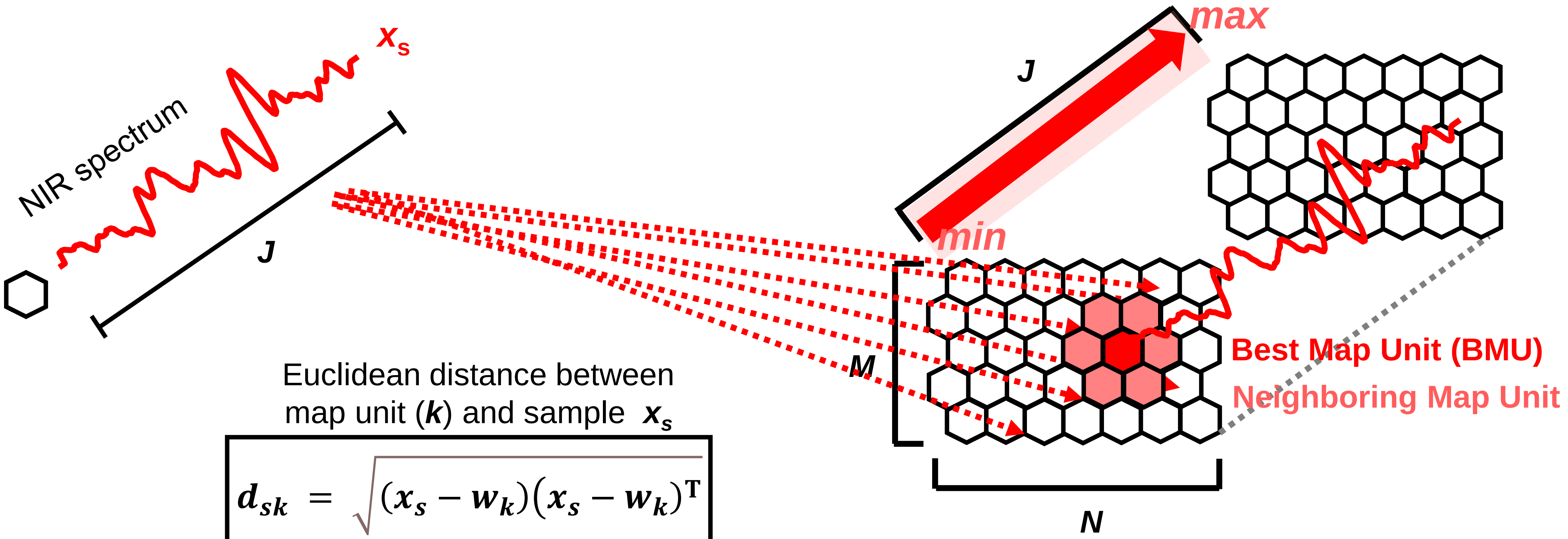
0.08	0.1
0.12	0.15
0.16	0.18
0.2	0.22
0.4	0.44
0.6	0.65
0.8	0.86
1	1.07

❑ SELF-ORGANIZING MAP (SOMs)

Generation of unsupervised SOM map

where X_s: Sample vectors
W_k: Weight vector of each unit (w_k) on the initial SOM map
d_{ks}: Euclidean distance e between x_s and w_k for each map unit k



Euclidean distance between map unit (k) and sample x_s

$$d_{sk} = \sqrt{(x_s - w_k)(x_s - w_k)^{\mathrm{T}}}$$

❑ SELF-ORGANIZING MAP (SOM)

Generation of unsupervised SOMs

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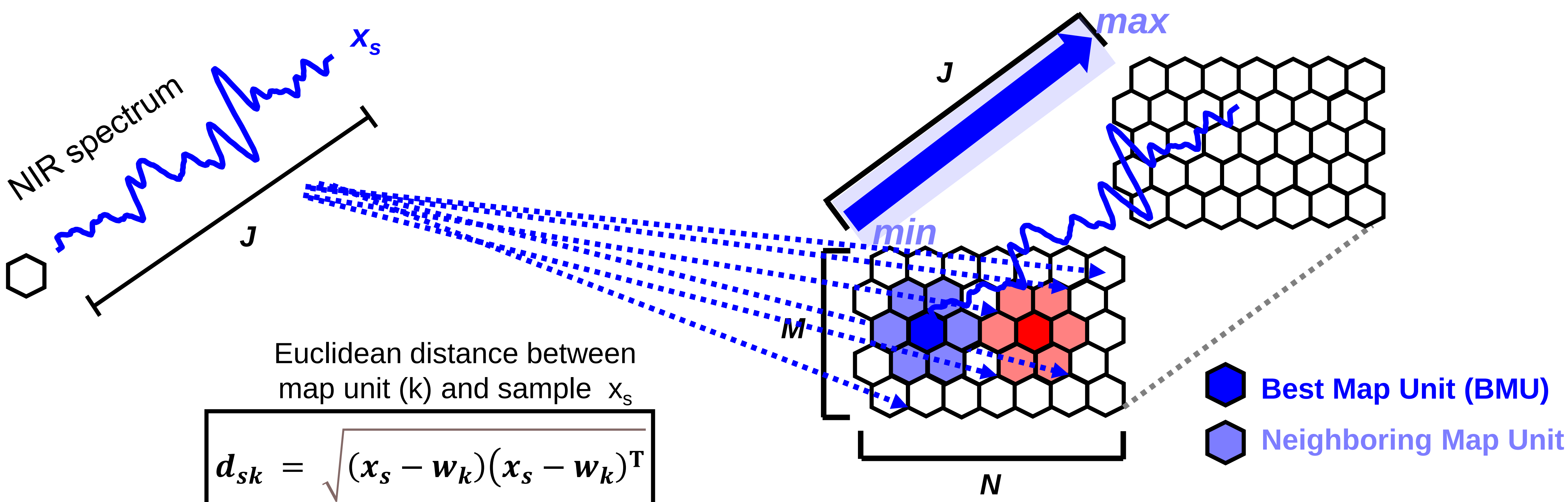

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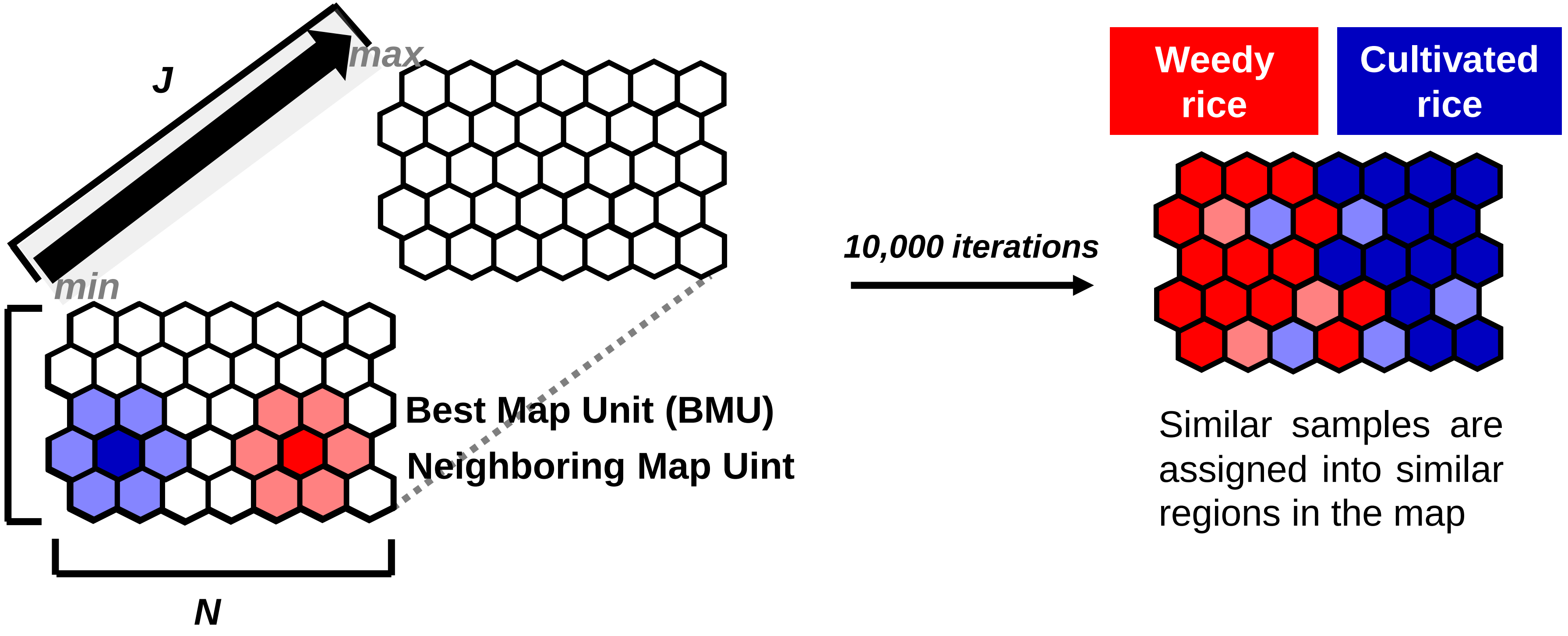
References Wongravee *et al.*, 2010
Richard G Brereton, 2012

❑ SELF-ORGANIZING MAP (SOM)

Determination of unsupervised SOM



Similar samples are assigned into similar regions in the map

References Wongravee *et al.*, 2010
Richard G Brereton, 2012

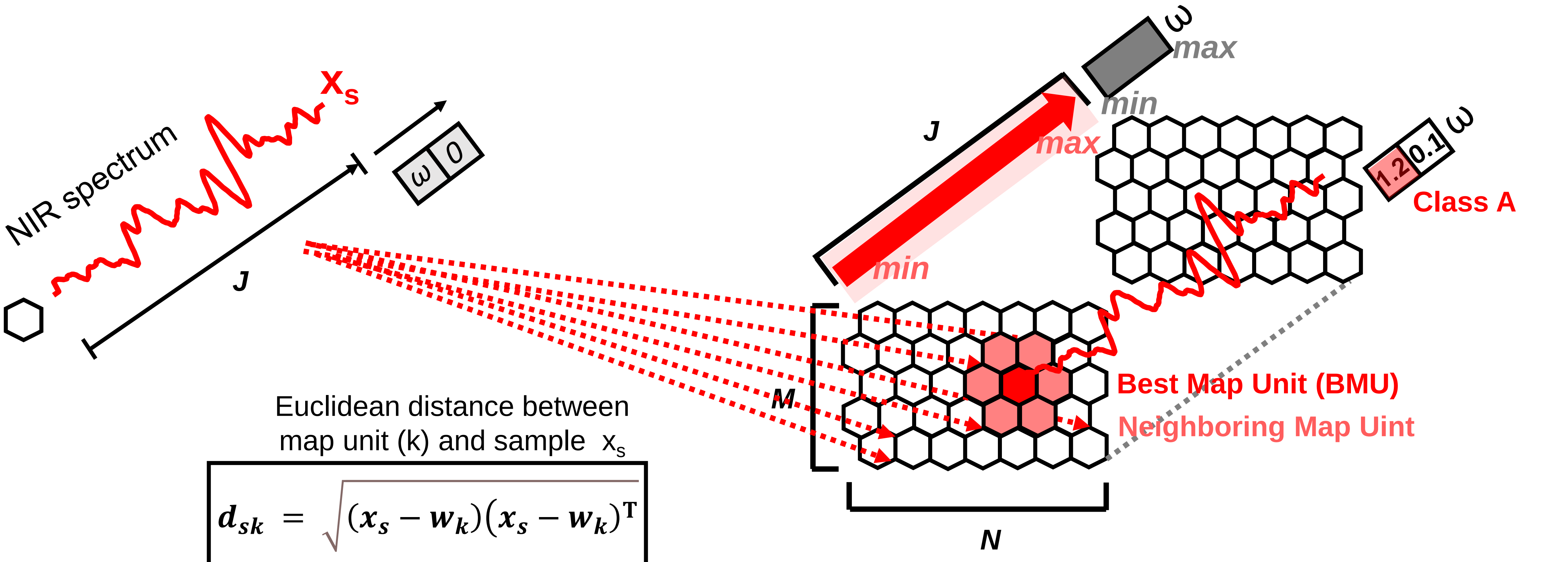
❑ SELF-ORGANIZING MAP (SOM)

Generation of supervised SOM

Scaling value (ω)

= $[\ \omega\ \ 0\ ]$ for class A

$[\ 0\ \ \omega\ ]$ for class B



Euclidean distance between map unit (k) and sample x_s

$$d_{sk} = \sqrt{(x_s - w_k)(x_s - w_k)^{\mathrm{T}}}$$

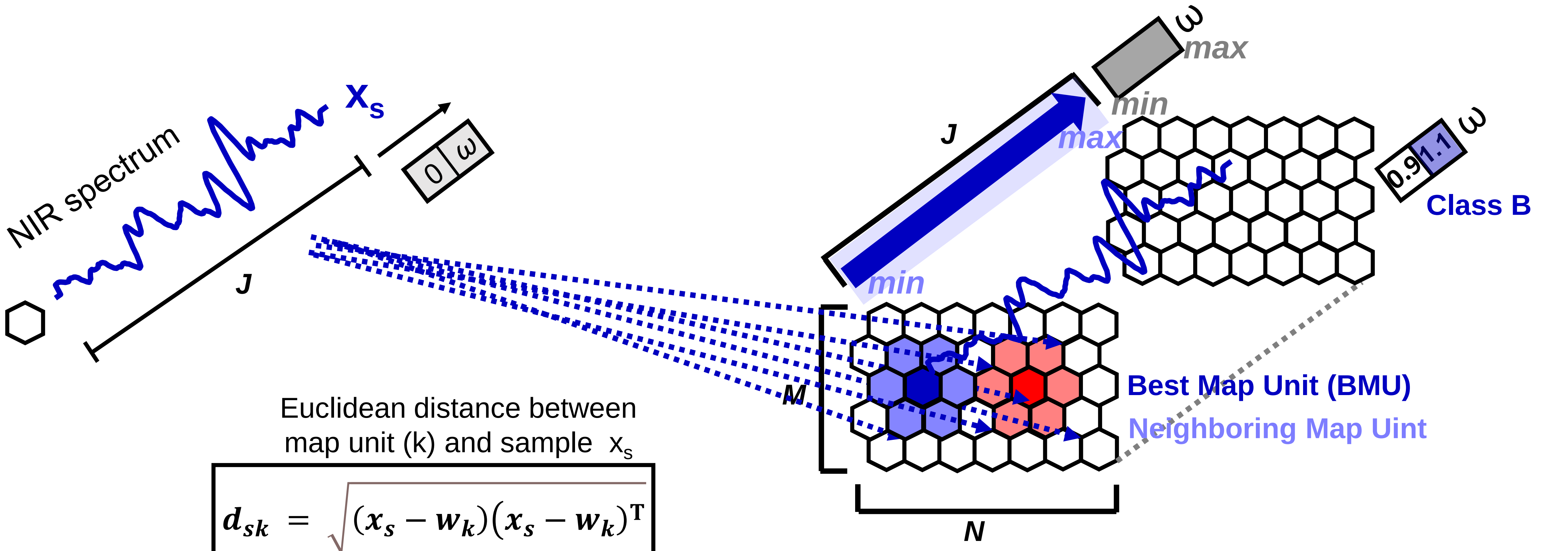
❑ SELF-ORGANIZING MAP (SOM)

Generation of supervised SOM map

Scaling value (ω)

= [ω 0] for class A

[0 ω] for class B

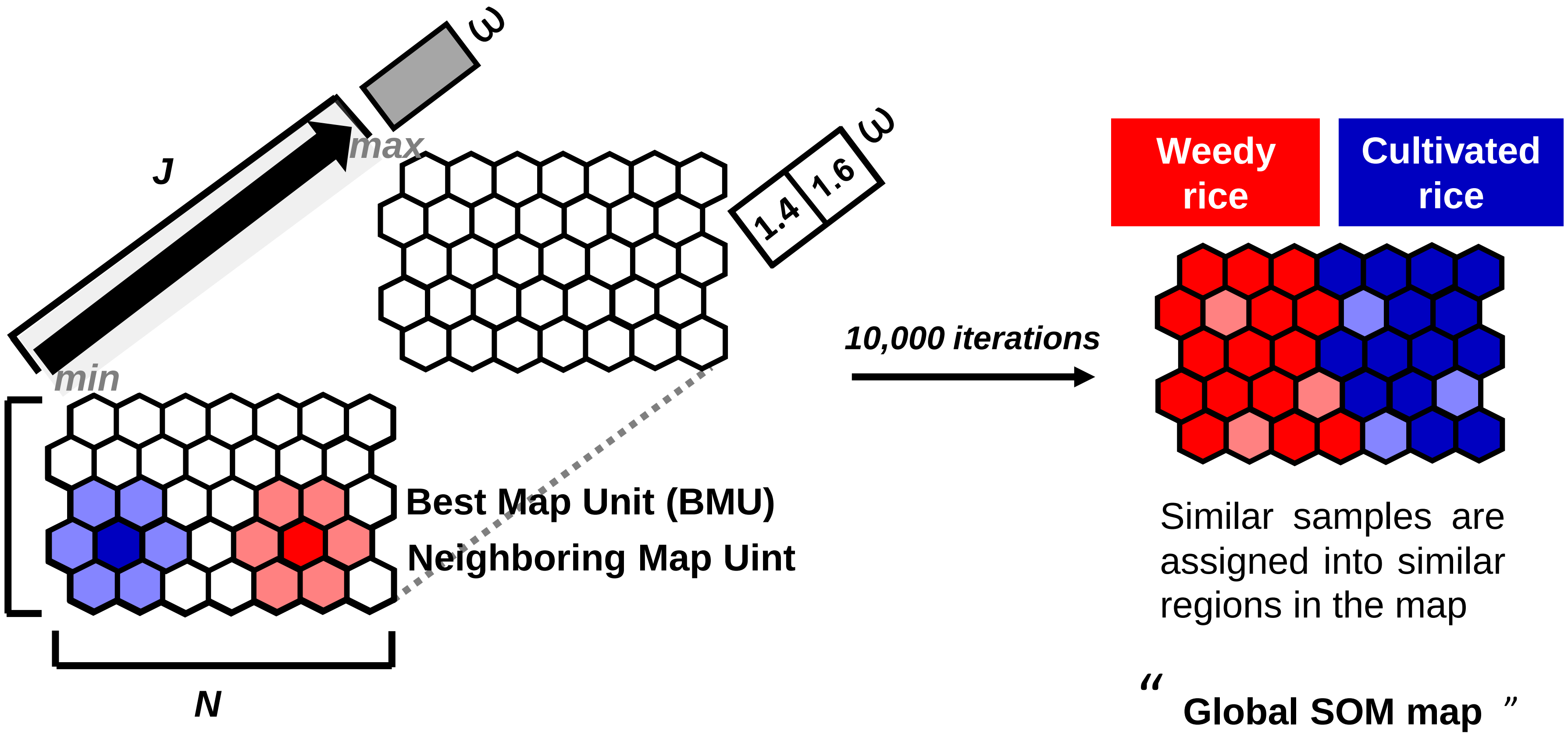


Euclidean distance between map unit (k) and sample x_s

$$d_{sk} = \sqrt{(x_s - w_k)(x_s - w_k)^{\mathrm{T}}}$$

❑ SELF-ORGANIZING MAP (SOM)

Determination of supervised SOM



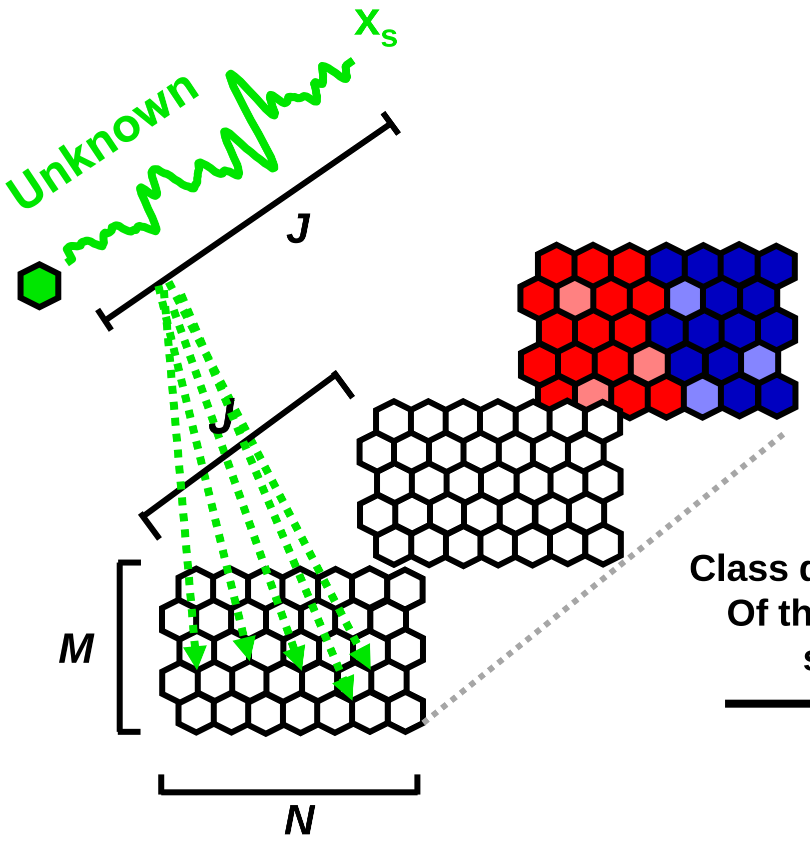
Similar samples are assigned into similar regions in the map

" Global SOM map "

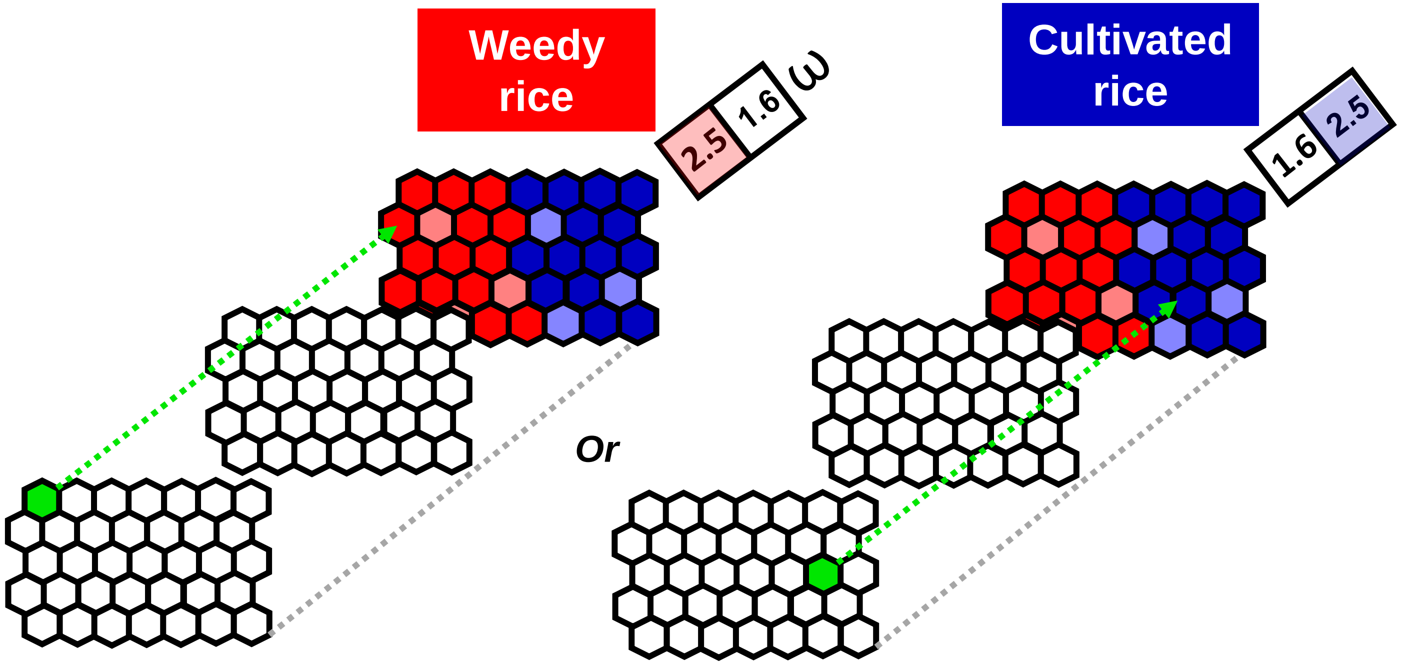
❑ SELF-ORGANIZING MAP (SOM)

Determination of an unknown

Scaling value (ω) is impact factor for SOM performance



Class determination Of the unknown sample

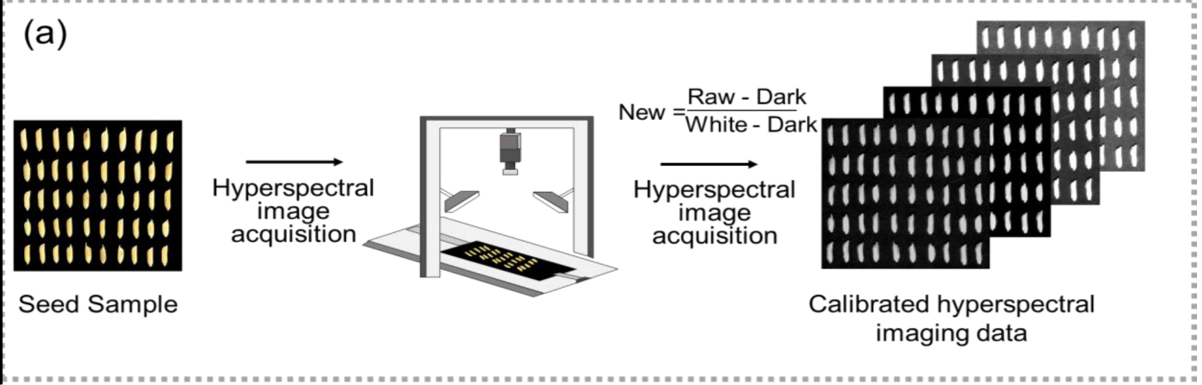


BMU of an unknown sample is determined and
Give the larger value in the region of **"weedy rice"**
Unknown sample is assigned to be **"weedy rice"**

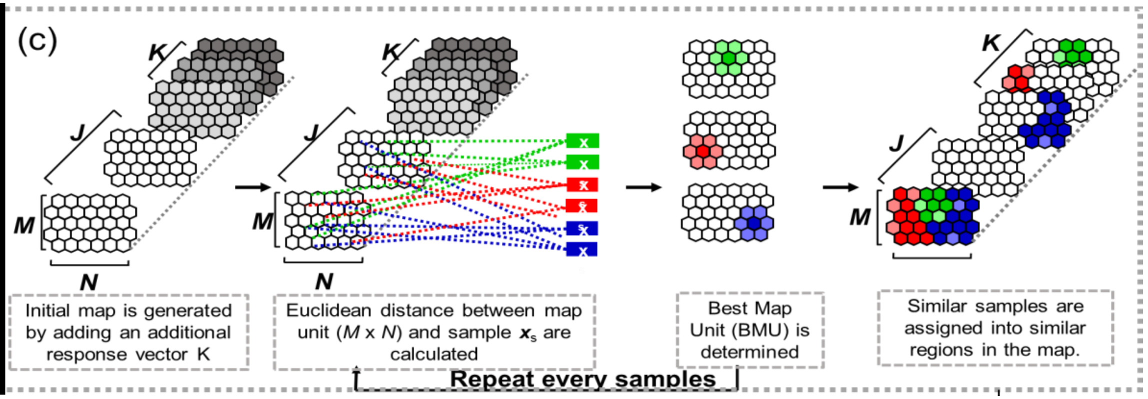
BMU of an unknown sample is determined and
Give the larger value in the region of **"cultivated rice"**
Unknown sample is assigned to be **"cultivated rice"**

❑ RESULTS AND DISCUSSIONS

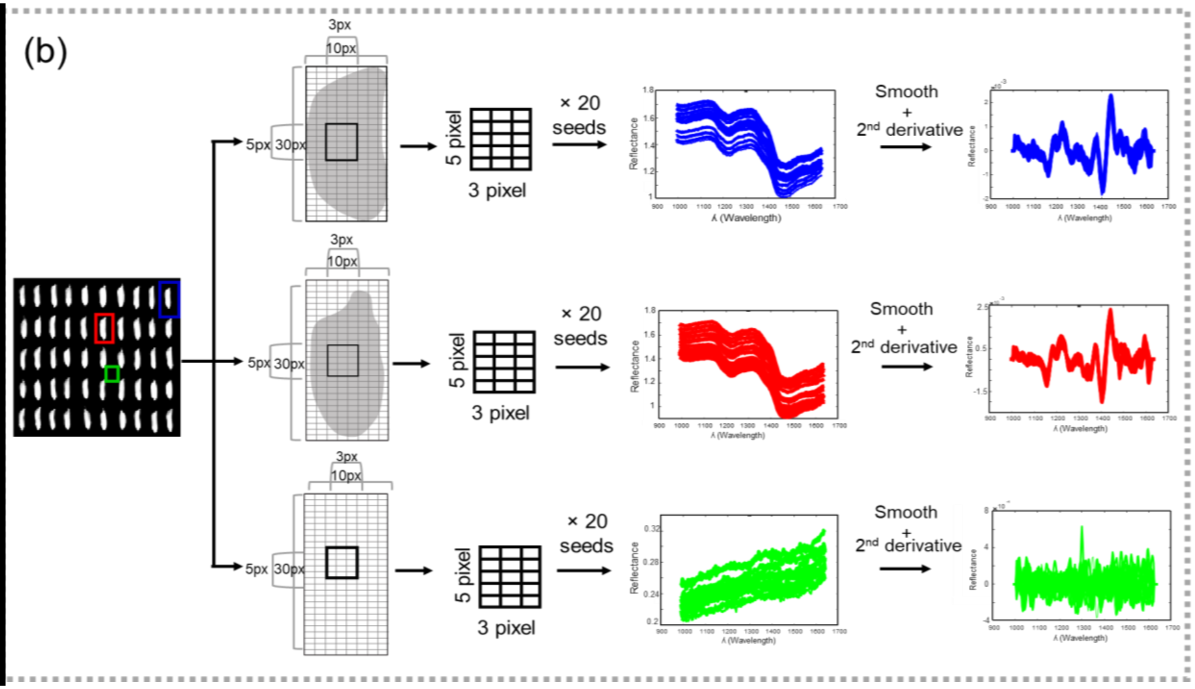
Data acquisition



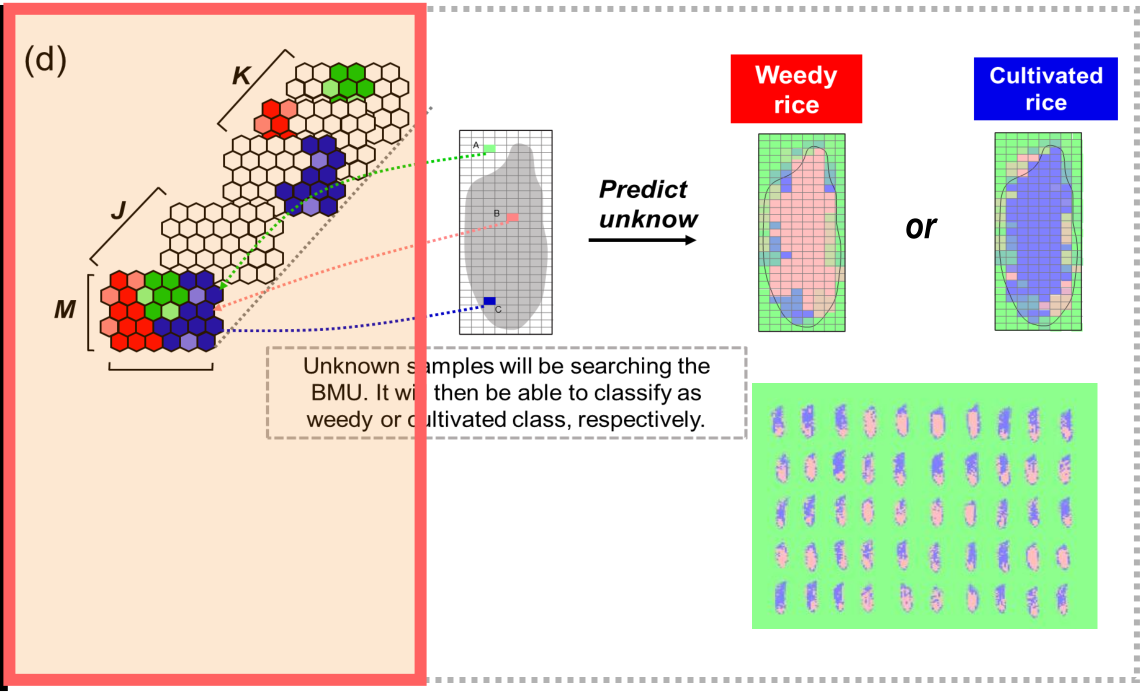
Global SOM map



Sample Segmentation



Determination unknow seed



❑ RESULTS AND DISCUSSIONS