Quantitative comparison of independent single-beam, sidescan and multibeam benthic habitat maps, Te Matuku Marine Reserve, New Zealand

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Introduction: benthic habitat mapping

Systems:

- Single-beam
- Sidescan sonar
- Multibeam
- Other sonars

- LIDAR
- Airborne imagery

- Divers
- Video/camera
- Sampling/coring

- Hindcast ocean conditions modelling

- …

Measured variables:

- Bathymetry
  - Depth, slope, roughness
  - TPI
  - Fourier/Wavelet analysis
- Reflectivity
  - Echo shape
  - First order moments
  - Spectral features
  - Textures (GLCM)
- Angular response
  - mean level, slope, intercept
  - Geoacoustic model fitting
- Aerial image analysis
- Temperature, wave exposure, currents, seasonal variations
- …

Classification methods:

- Supervised/unsupervised, “bottom-up”/”top-down”

- QTC View, RoxAnn, EchoPlus…

- MB-System, QTC Multiview, SonarScope, Geocoder…

- k-means, decision tree, neural network, Bayes decision rule,…

- Object-oriented

- …

Introduction

• Varied approaches imply varied results in habitat maps
→ Need for a **quantitative** estimation of a **map accuracy**, or two **maps similarity**

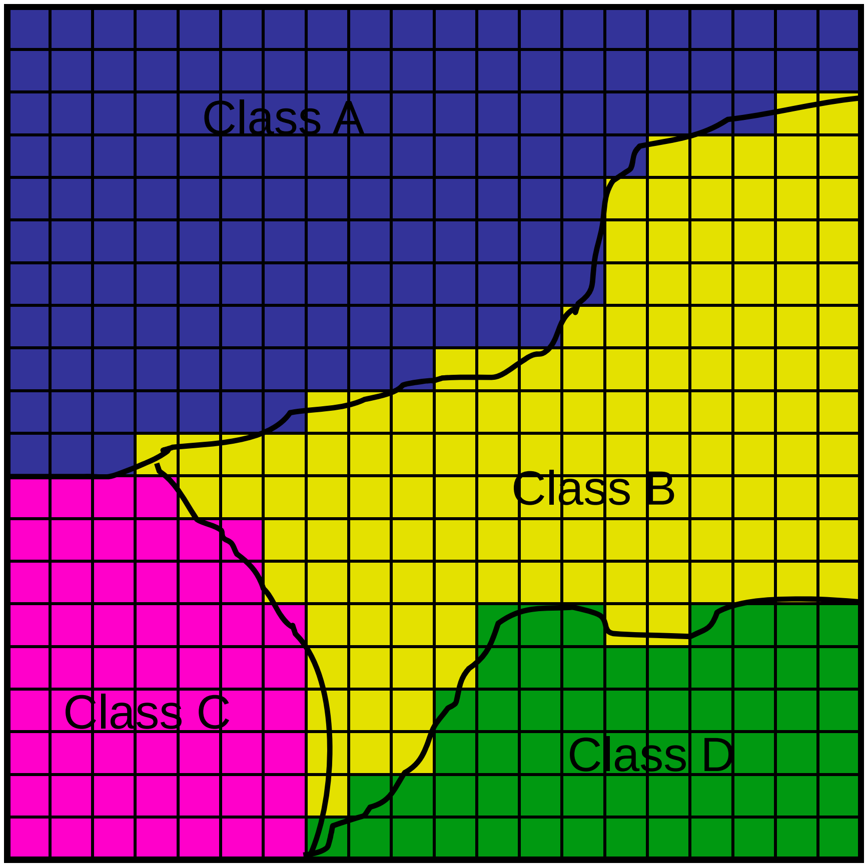
• Quantitative data → wide range of measures of correlation between datasets

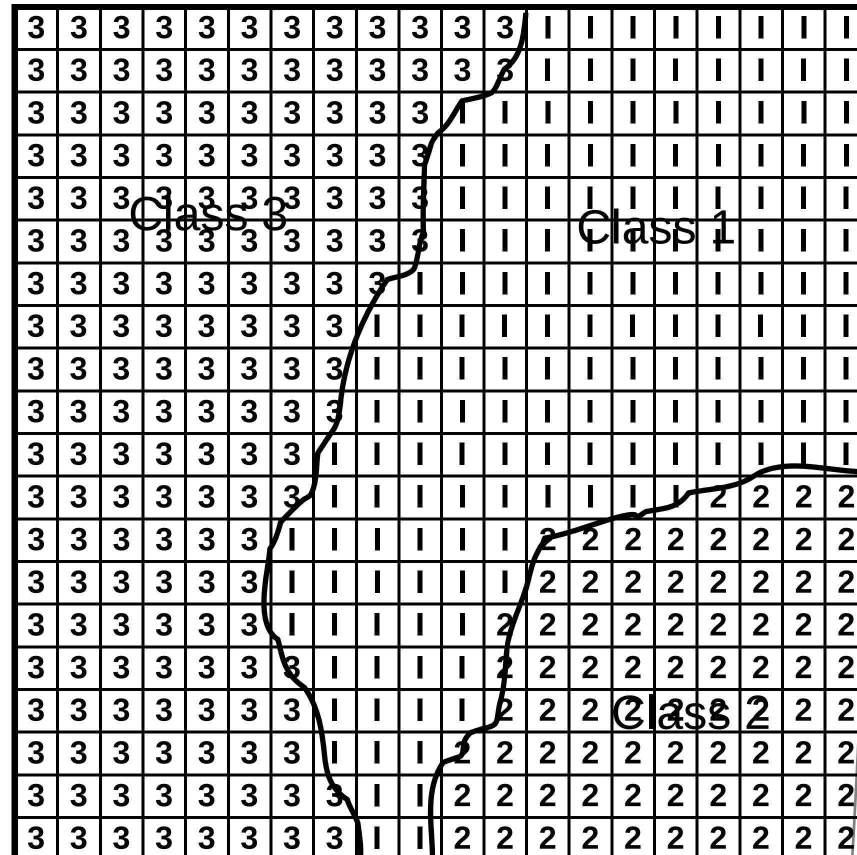
• **Maps: Categorical data** → field much less developed (at least in underwater remote sensing)

→Concepts and measures for the estimation of similarity between two maps.

→Application to a case study

The confusion matrix





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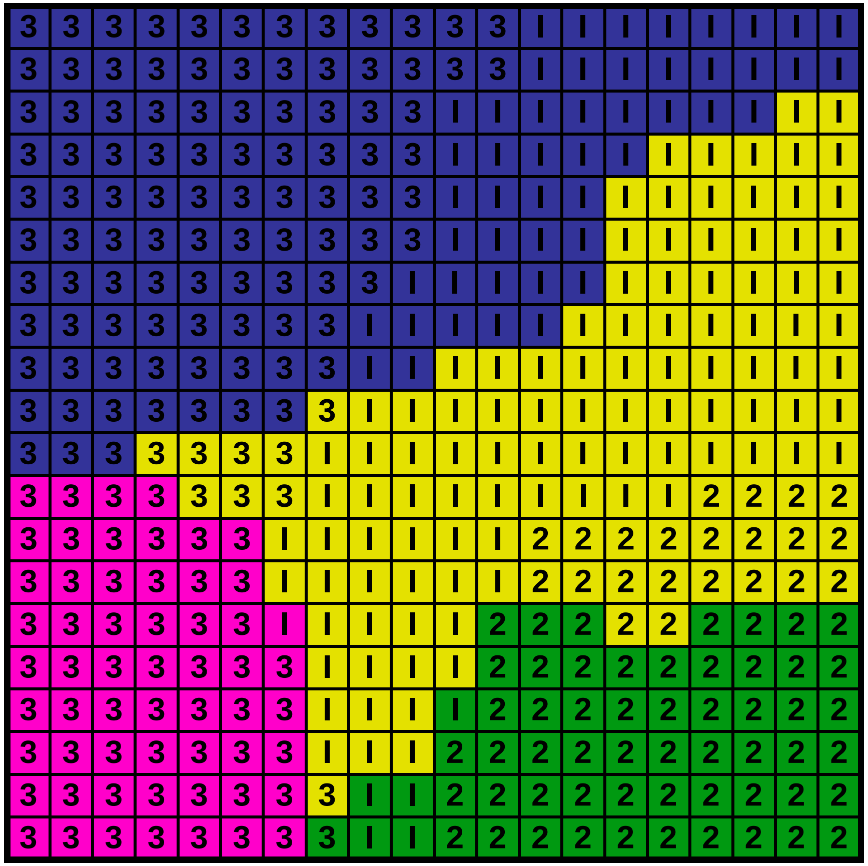


	1	**2**	**3**	tot
A	49	0	99	148
B	102	22	9	133
C	1	0	57	58
D	5	55	1	61
tot	157	77	166	400

Measures of Categorical Association

- Mathematical tools to assess the dependence of two different categorical variables

	1	2	3	tot
A	c_{11}	c_{12}	c_{13}	c_{1+}
B	c_{21}	c_{22}	c_{23}	c_{2+}
C	c_{31}	c_{32}	c_{33}	c_{3+}
D	c_{41}	c_{42}	c_{43}	c_{4+}
tot	c_{+1}	c_{+2}	c_{+3}	N

$$U = \frac{2[H(A) + H(B) - H(A,B)]}{H(A) + H(B)}$$

$$H(A) = -\sum_{i=1}^{m} \frac{c_{i+}}{N} \log\left(\frac{c_{i+}}{N}\right)$$

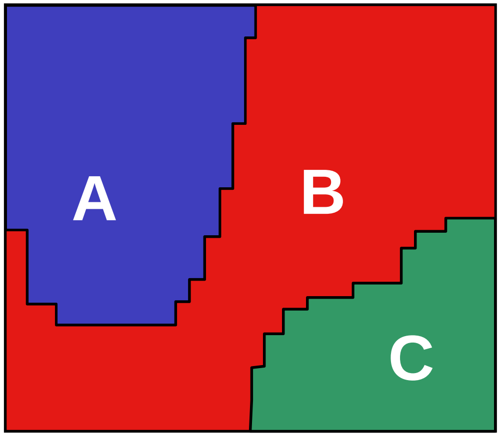
$$H(B) = -\sum_{j=1}^{n} \frac{c_{+j}}{N} \log\left(\frac{c_{+j}}{N}\right)$$

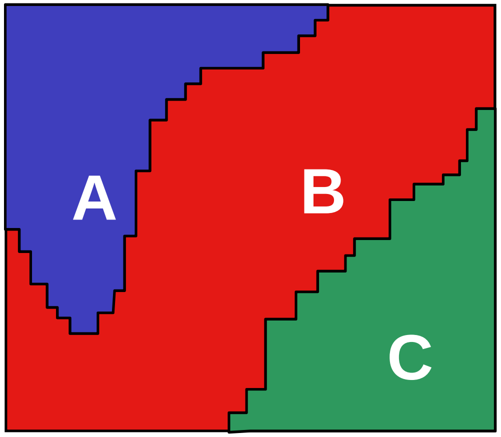
$$H(A,B) = -\sum_{i=1}^{m}\sum_{j=1}^{n} \frac{c_{ij}}{N} \log\left(\frac{c_{ij}}{N}\right)$$

$$\lambda = \frac{\sum_{i=1}^{m} \max_j (c_{ij}) + \sum_{j=1}^{n} \max_i (c_{ij}) - }{2N - \max_j (c_{+j}) - \max_i (c_{i+})}$$

Measures of Categorical Agreement

- Same measures as in estimation of accuracy
- Only if both maps are realized with the same legend





	A	B	C	tot
A	c_{11}	c_{12}	c_{13}	c_{1+}
B	c_{21}	c_{22}	c_{23}	c_{2+}
C	c_{31}	c_{32}	c_{33}	c_{3+}
tot	c_{+1}	c_{+2}	c_{+3}	N

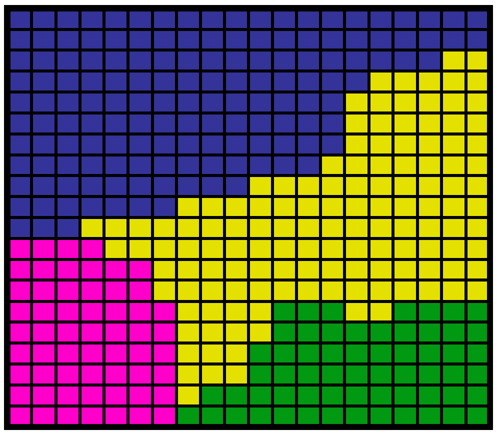
$$OA = \frac{1}{N}\sum_{i=1}^{n} c_{ii}$$

$$\kappa = \frac{OA - \frac{1}{N}\sum_{i=1}^{n}\frac{c_{i+}c_{+i}}{N}}{1 - \frac{1}{N}\sum_{i=1}^{n}\frac{c_{i+}c_{+i}}{N}}$$

$$\kappa_n = \frac{n \times OA - 1}{n - 1}$$

Measures of Categorical Agreement

- What if the two maps are not realized with the same legend?



3	3	3	3	3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	I	I	I	I
3	3	3	3	3	3	3	I	I	I	I	I	I	I	I	I	2	2	2	2
3	3	3	3	3	3	I	I	I	I	I	I	2	2	2	2	2	2	2	2
3	3	3	3	3	3	I	I	I	I	I	I	2	2	2	2	2	2	2	2
3	3	3	3	3	3	I	I	I	I	I	2	2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	I	I	I	I	2	2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	I	I	I	I	2	2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	I	I	I	2	2	2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	3	I	I	2	2	2	2	2	2	2	2	2	2
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	3	**2**	**1**	tot
A	99	0	49	148
B	9	22	102	133
C+D	58	55	6	119
tot	166	77	157	400
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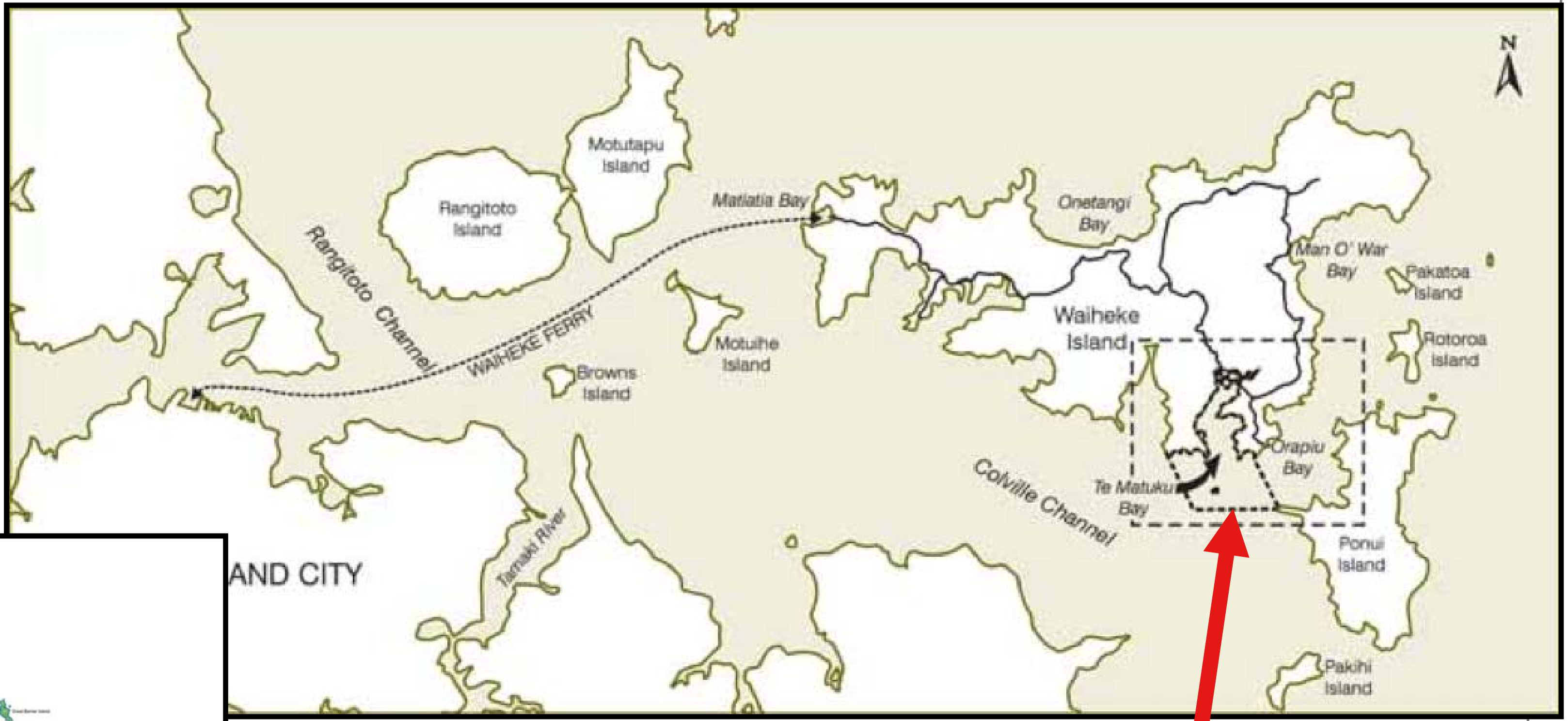
Solutions summary

- Use **measures of categorical association**:
  - Cramer's ***V***
  - Goodman-Kruskal's λ
  - Theil's ***U***
- Realize all possible aggregation/permutation possibilities, and use **measures of categorical agreement**:
  - Overall accuracy ***OA***
  - Cohen's κ
  - Brennan-Prediger's κ_n

Application: Te Matuku Marine Reserve



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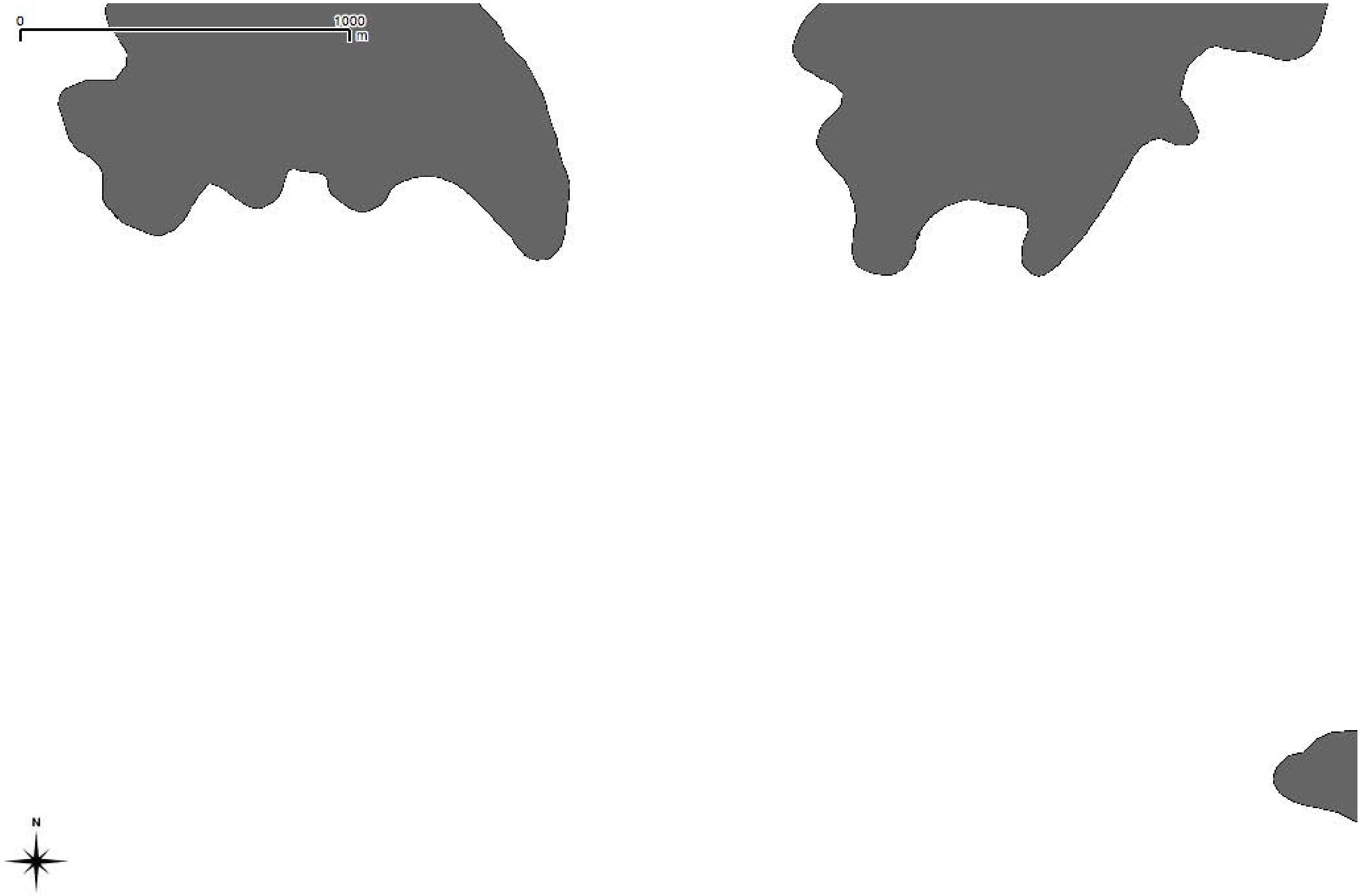
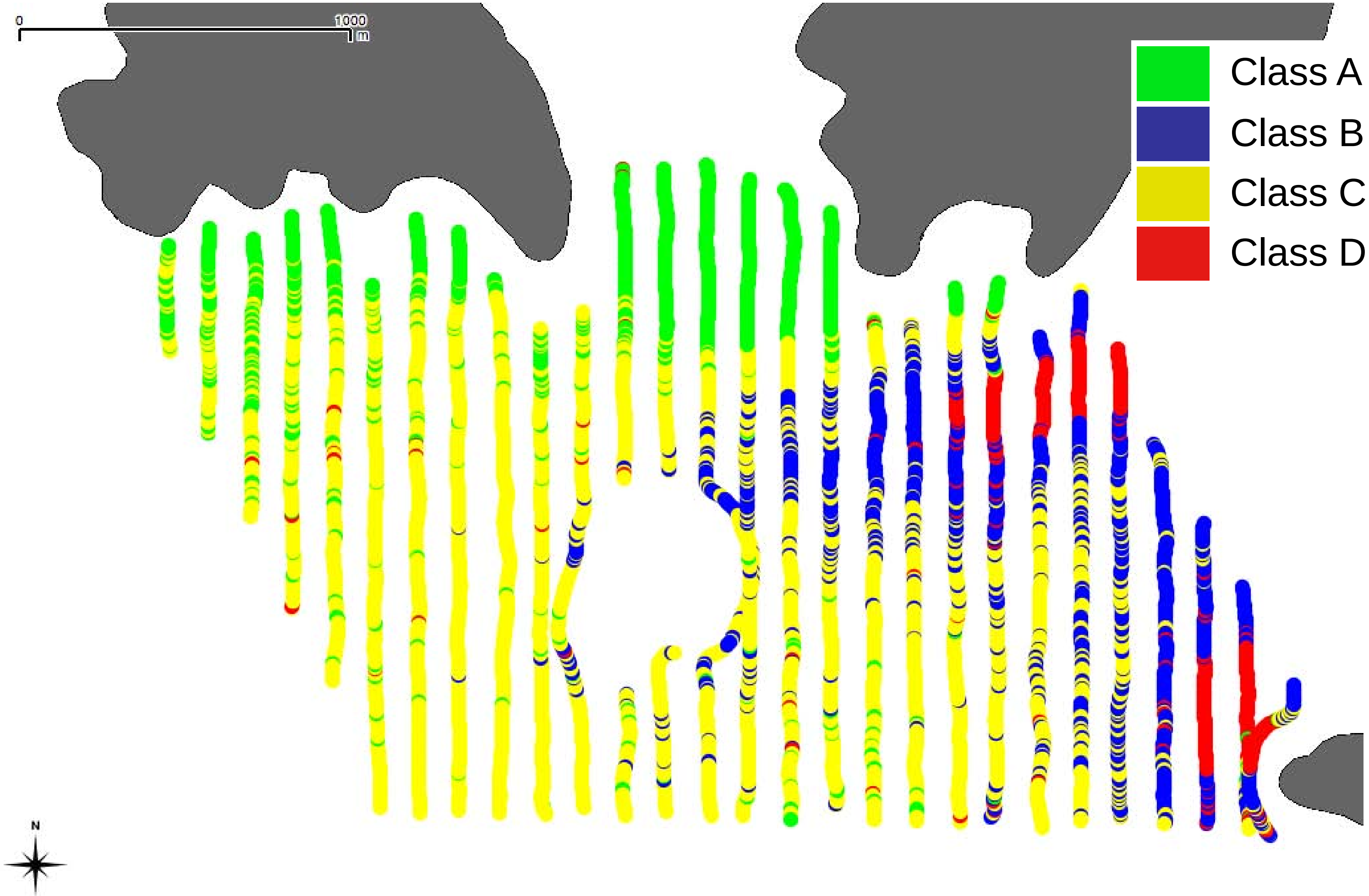


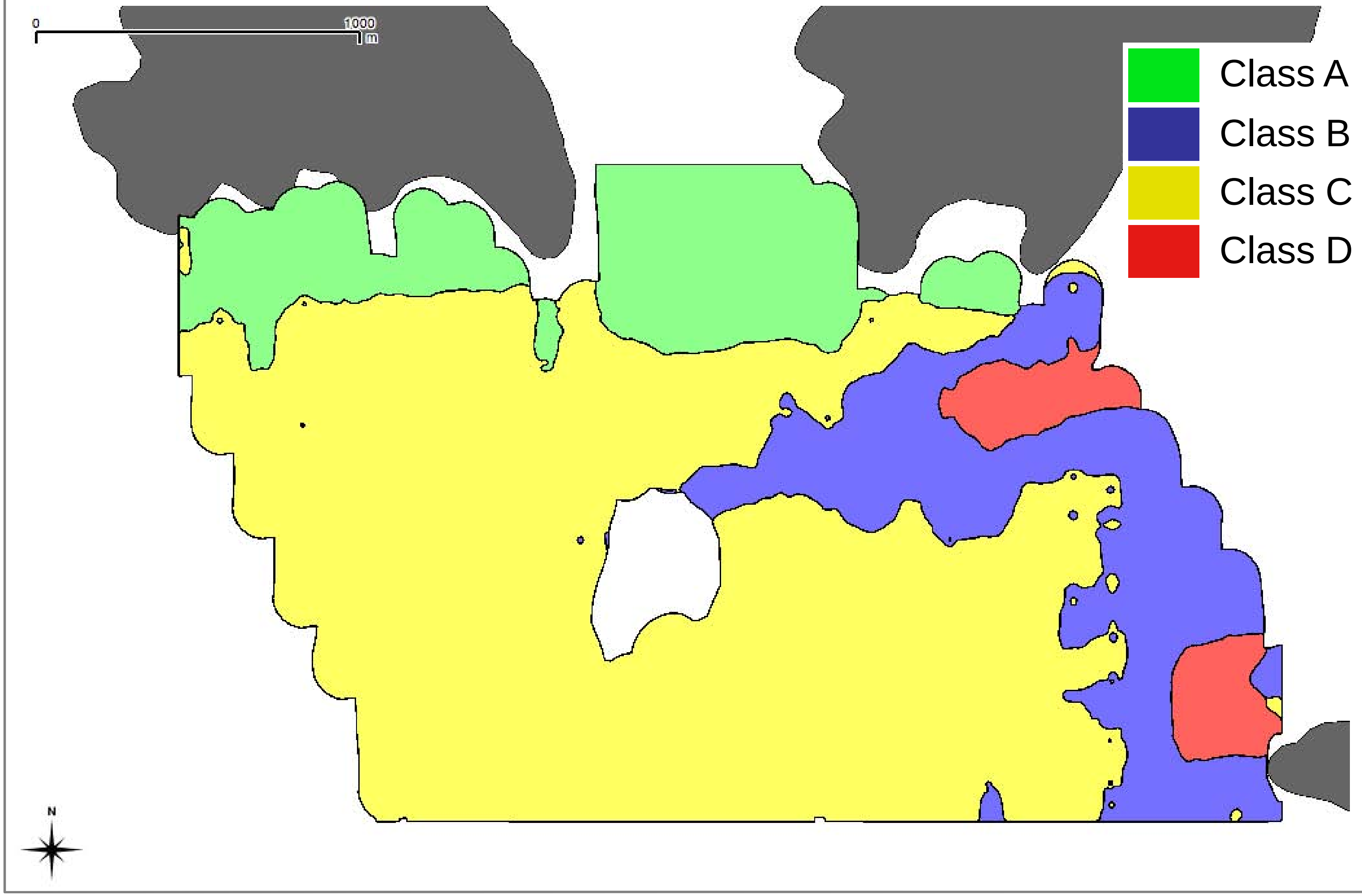
Application: Te Matuku Marine Reserve

2002 QTC View classification (NIWA)
SBES Simrad EA501P, 200kHz, resolution ~ 6/120m



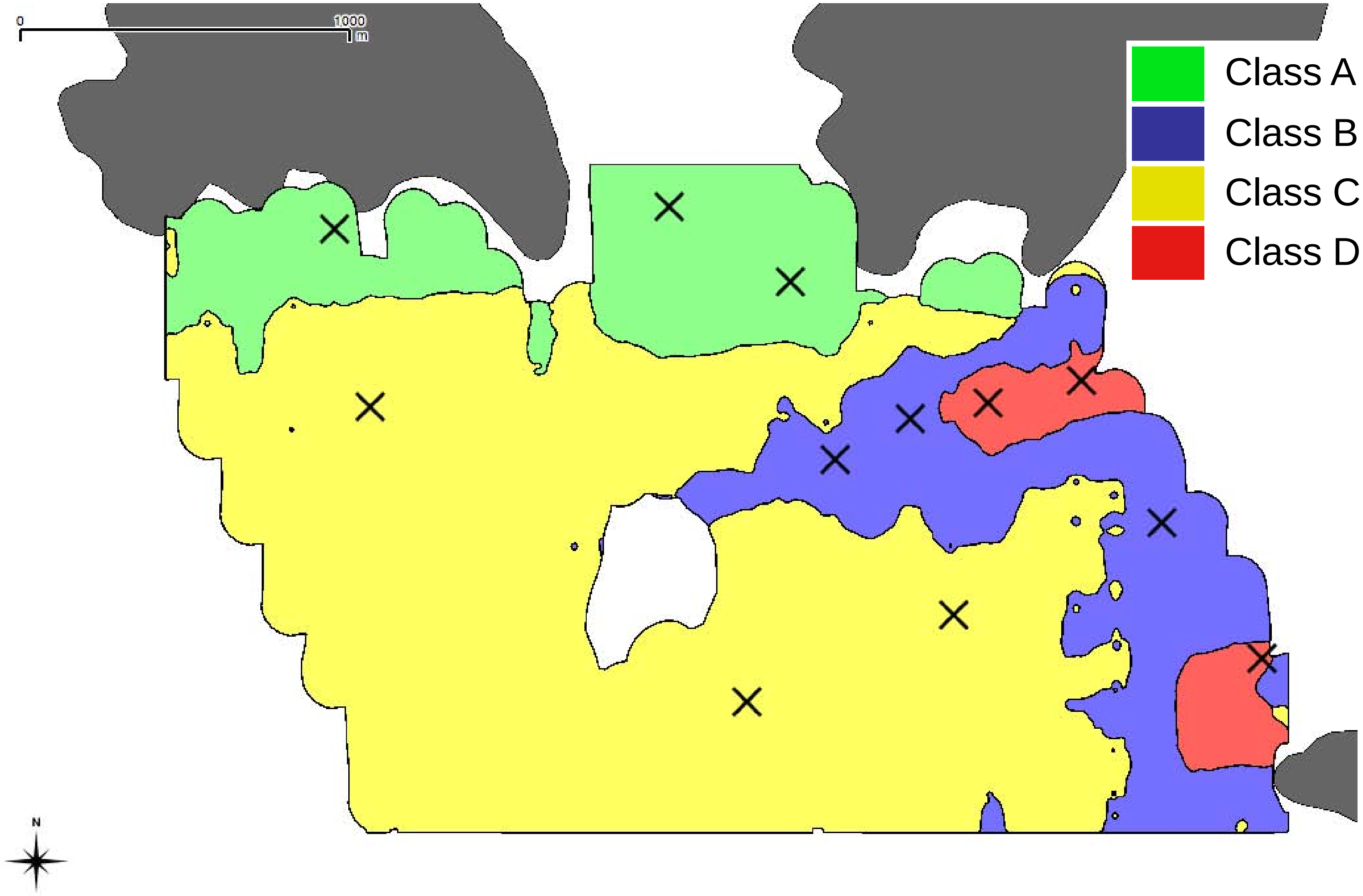
Application: Te Matuku Marine Reserve

2002 QTC View classification
After interpolation



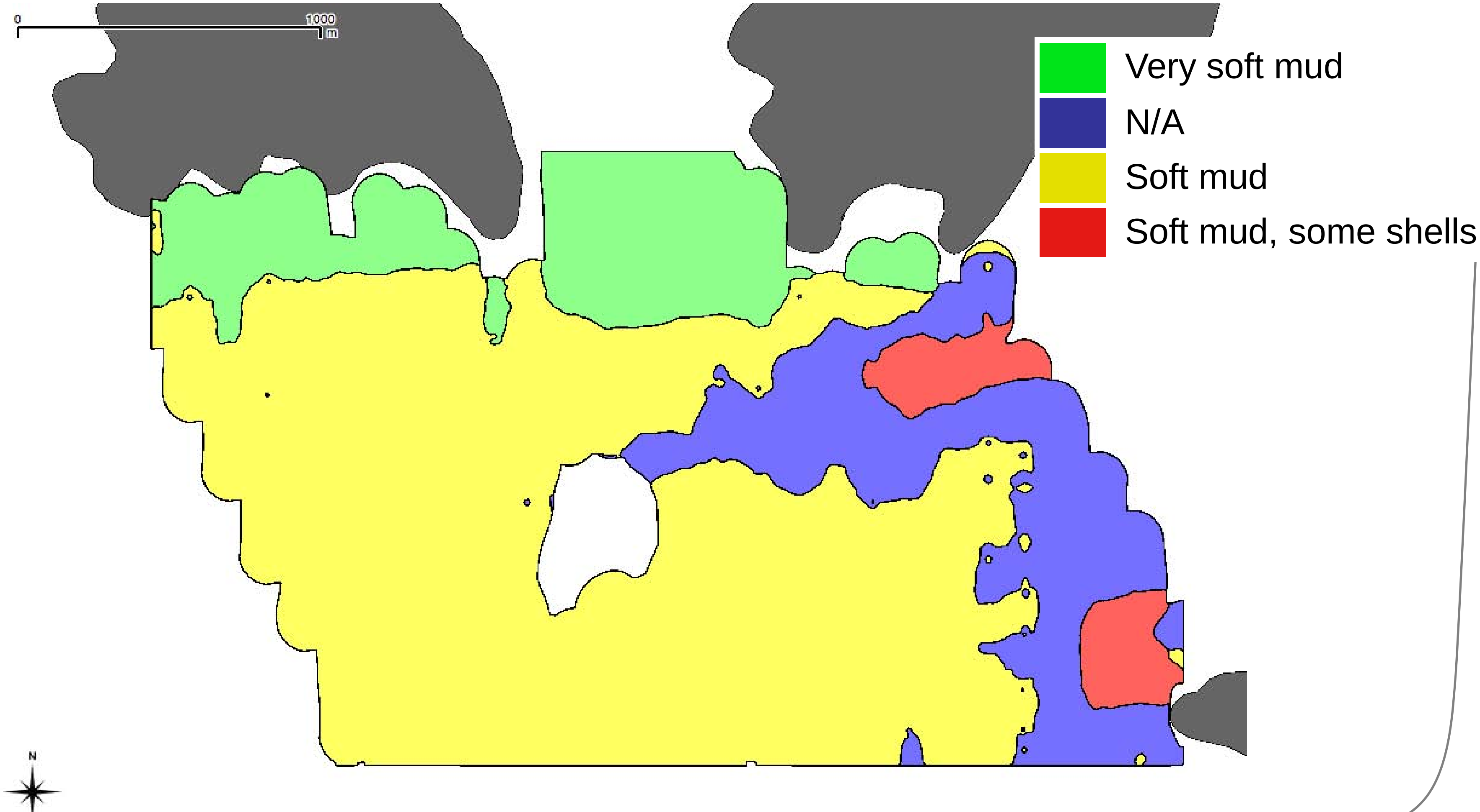
Application: Te Matuku Marine Reserve

2002 video + sampling stations (NIWA)

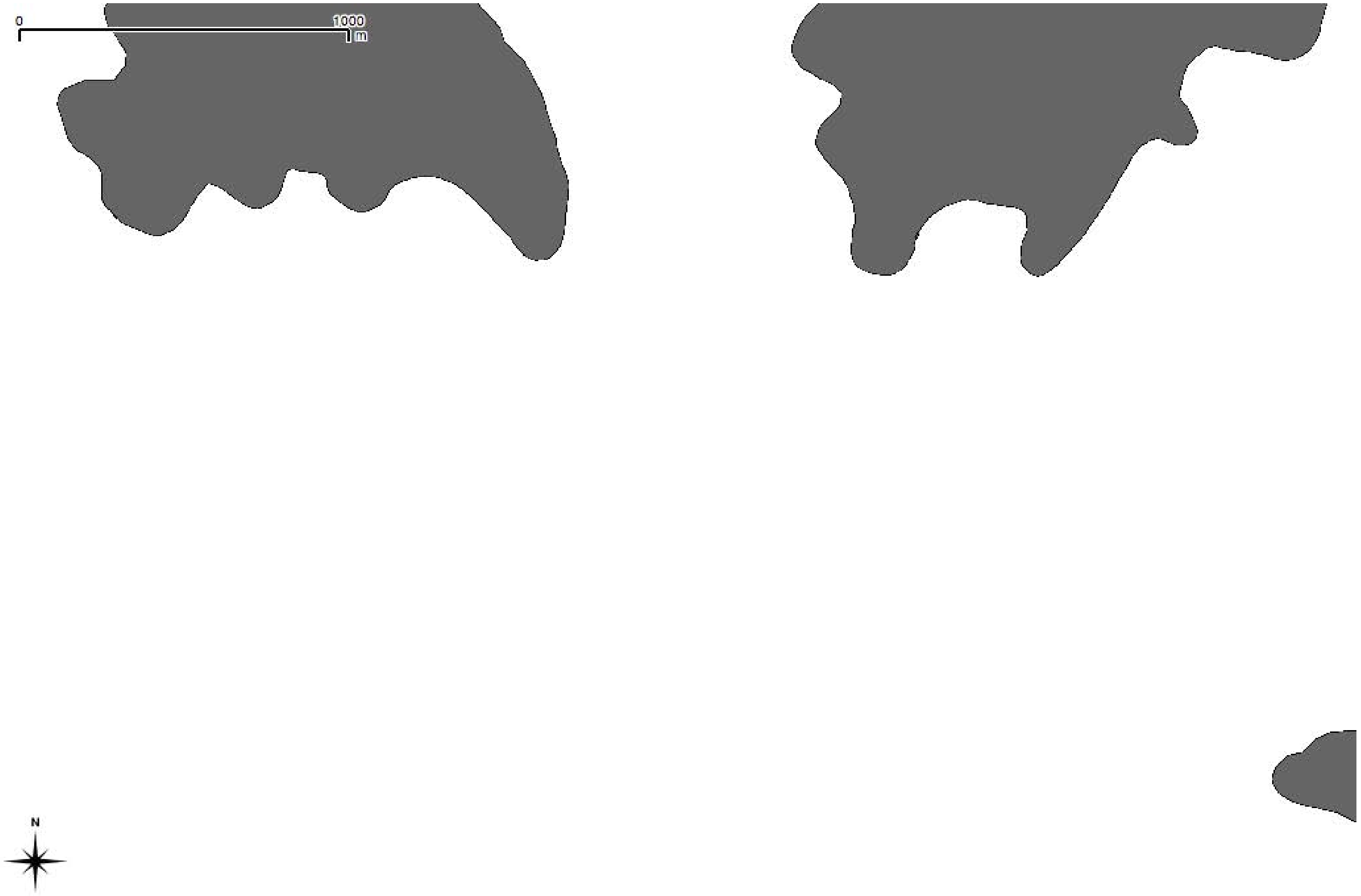


Application: Te Matuku Marine Reserve

2002 QTC/video-based benthic habitat map

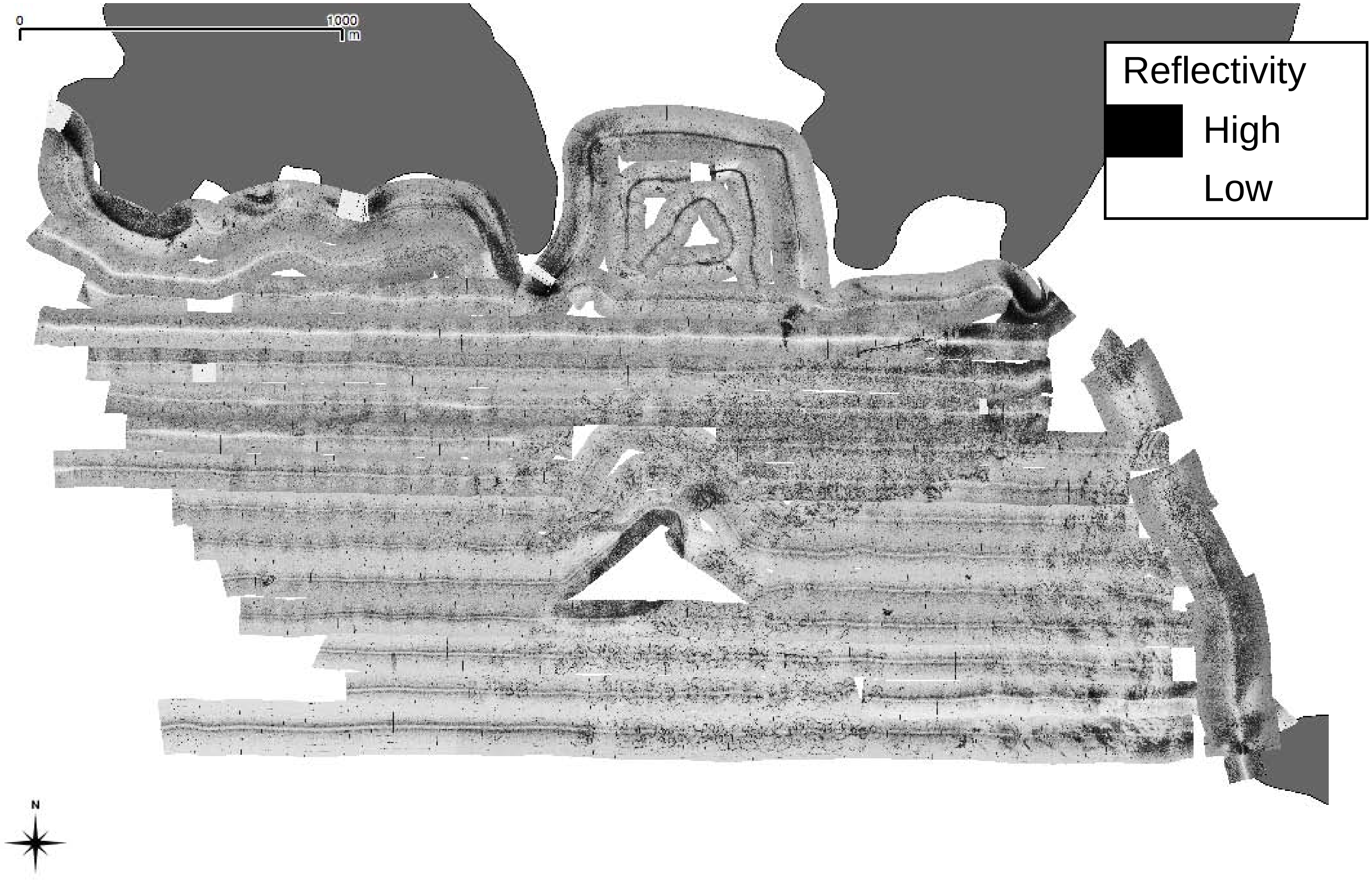


Application: Te Matuku Marine Reserve



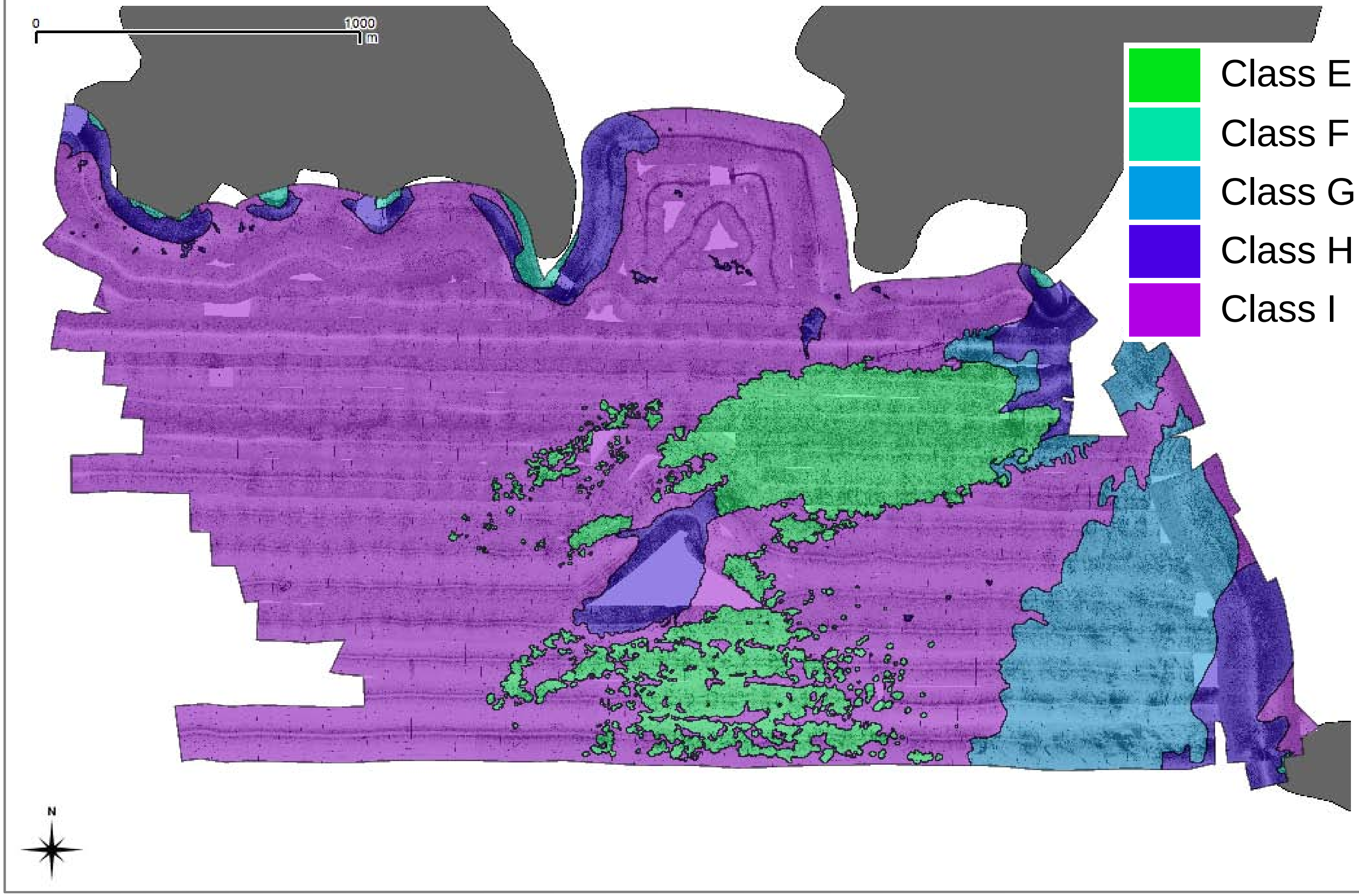
Application: Te Matuku Marine Reserve

2002 Sidescan sonar imagery (UoW)
Klein 595, 100kHz, resolution 0.2m



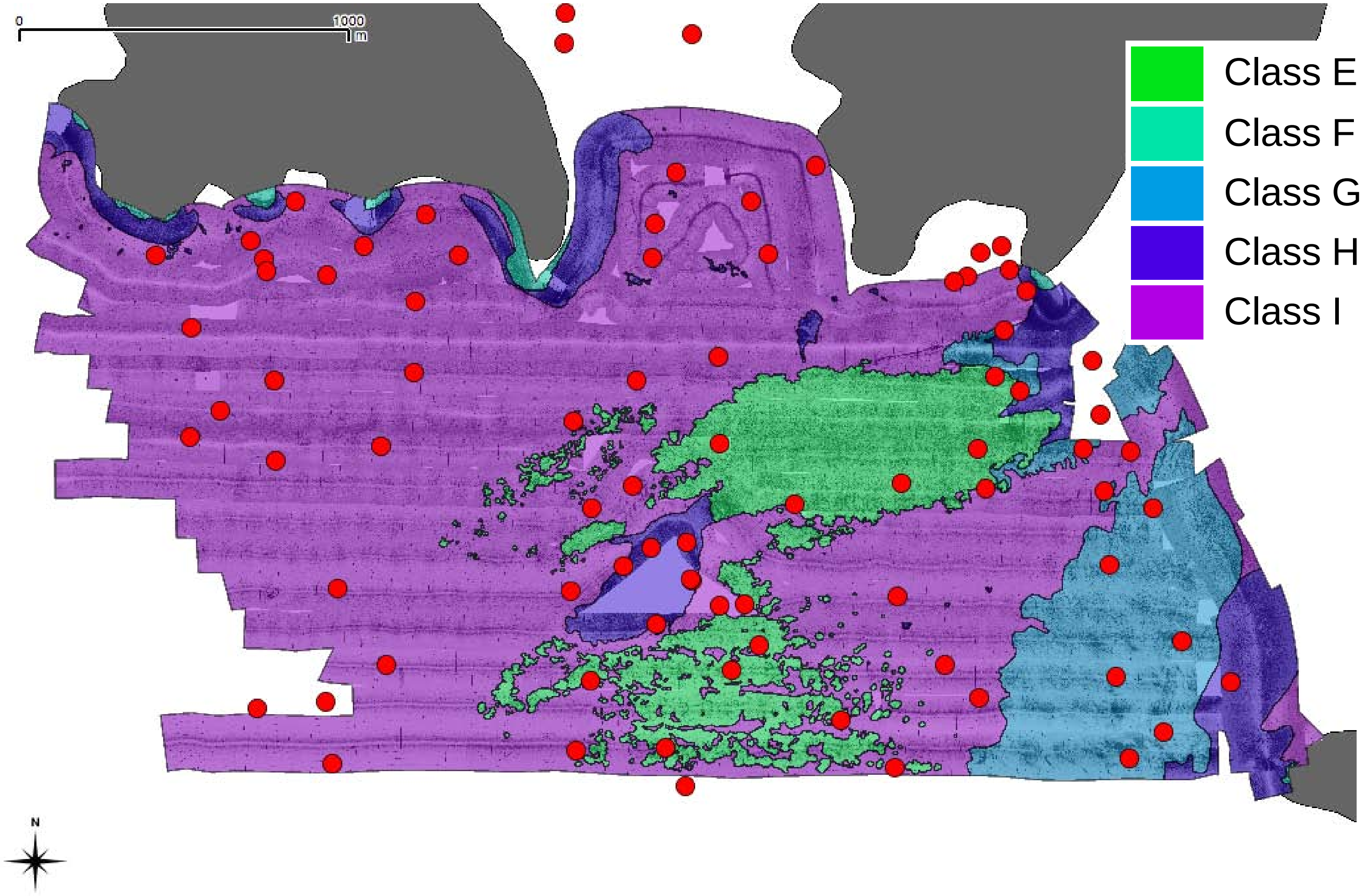
Application: Te Matuku Marine Reserve

SSS imagery manual classification

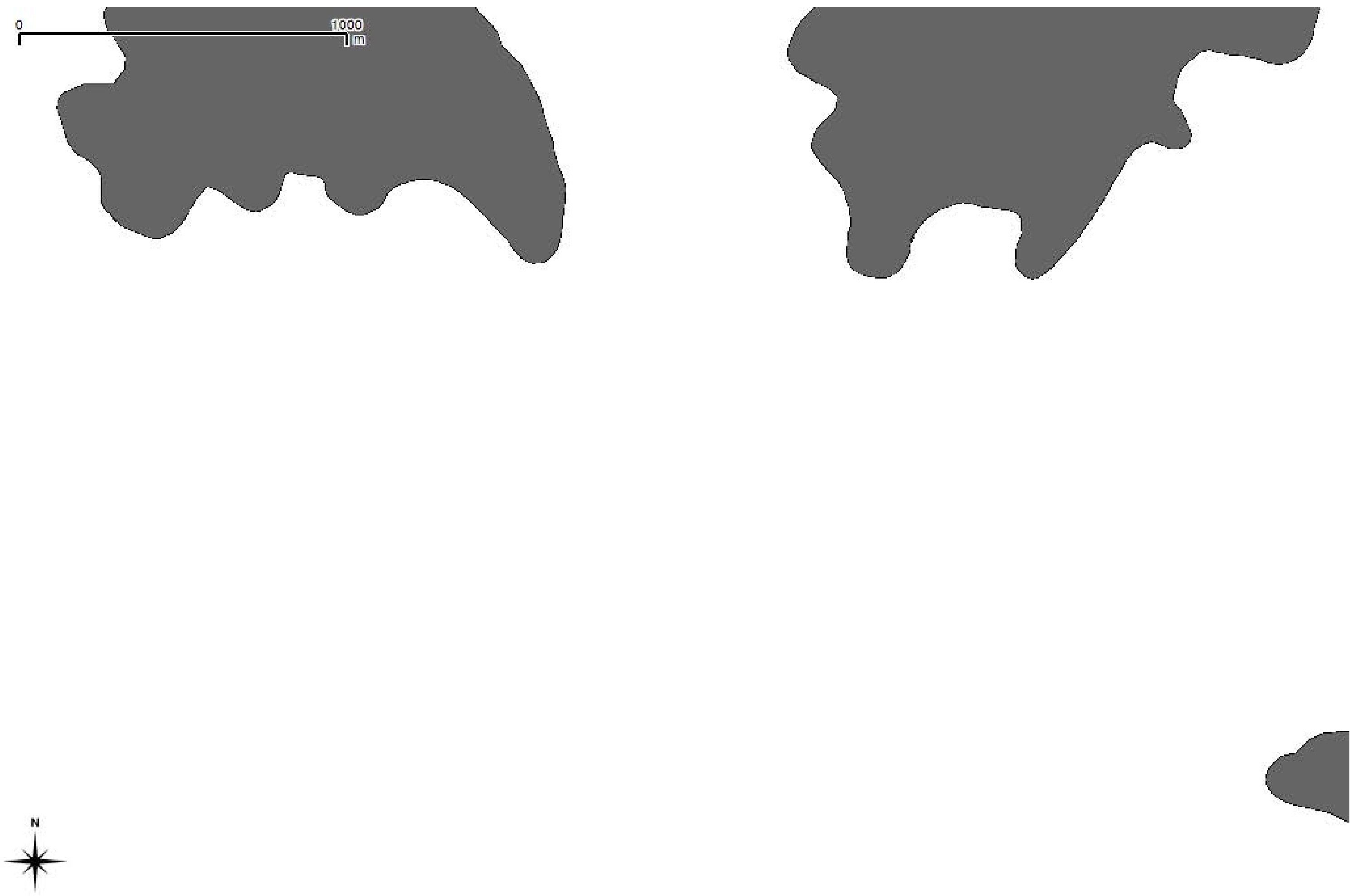


Application: Te Matuku Marine Reserve

2005 sampling stations (DoC)



Application: Te Matuku Marine Reserve

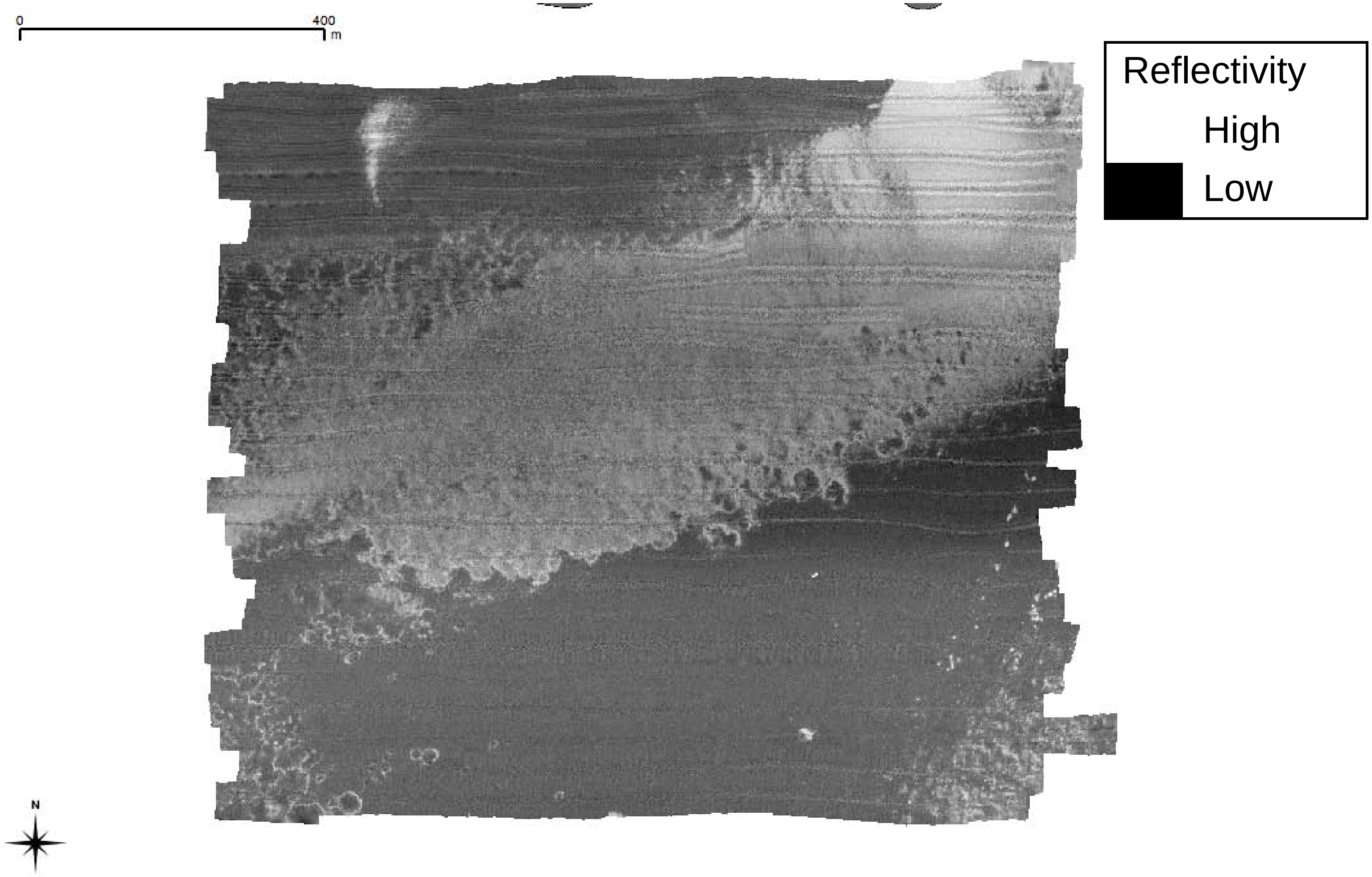


Application: Te Matuku Marine Reserve

2007 Multibeam backscatter (UoW)
SIMRAD EM3000, 300kHz, resolution 1m

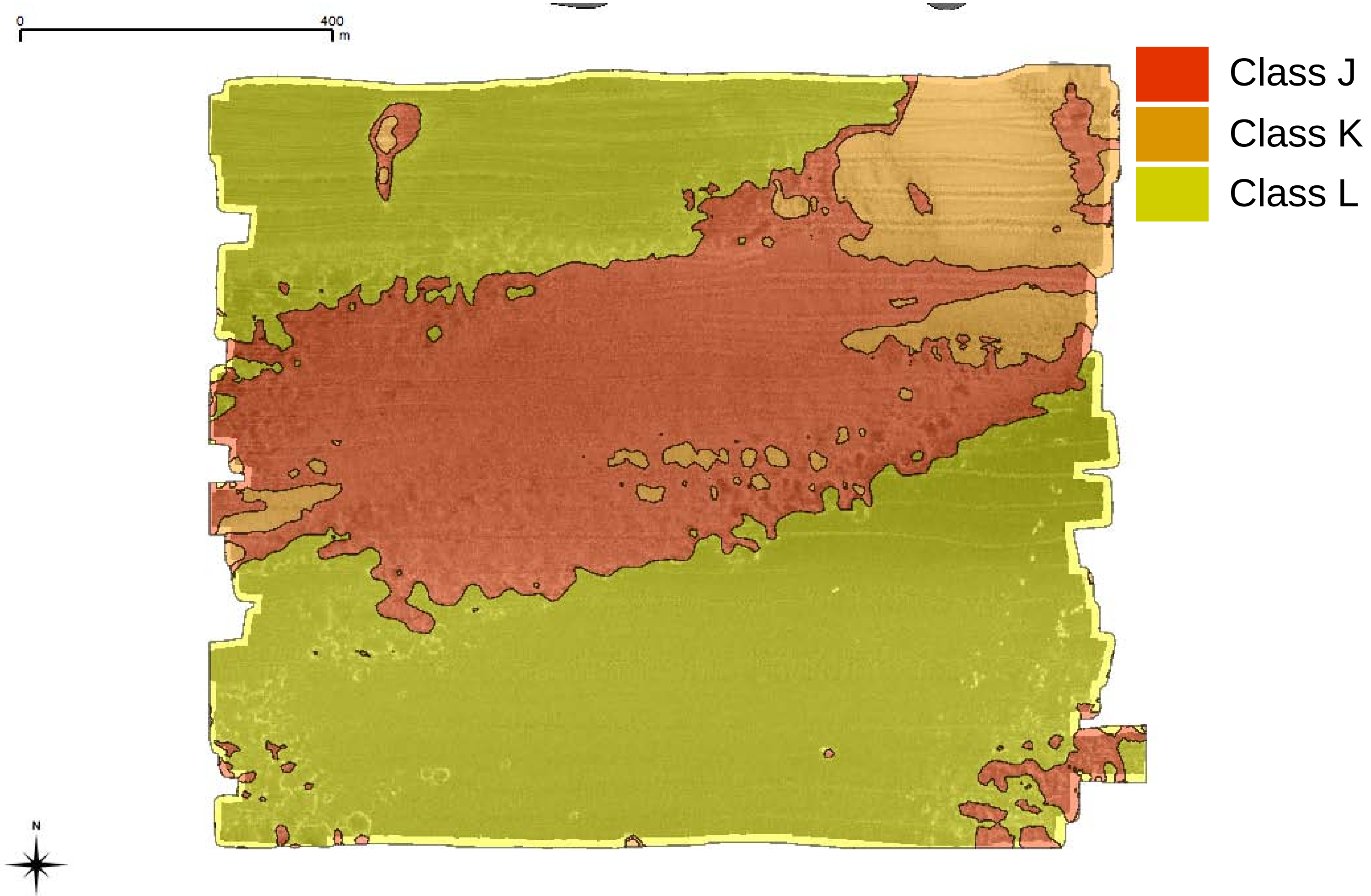
Application: Te Matuku Marine Reserve

2007 Multibeam backscatter (UoW)
SIMRAD EM3000, 300kHz, resolution 1m



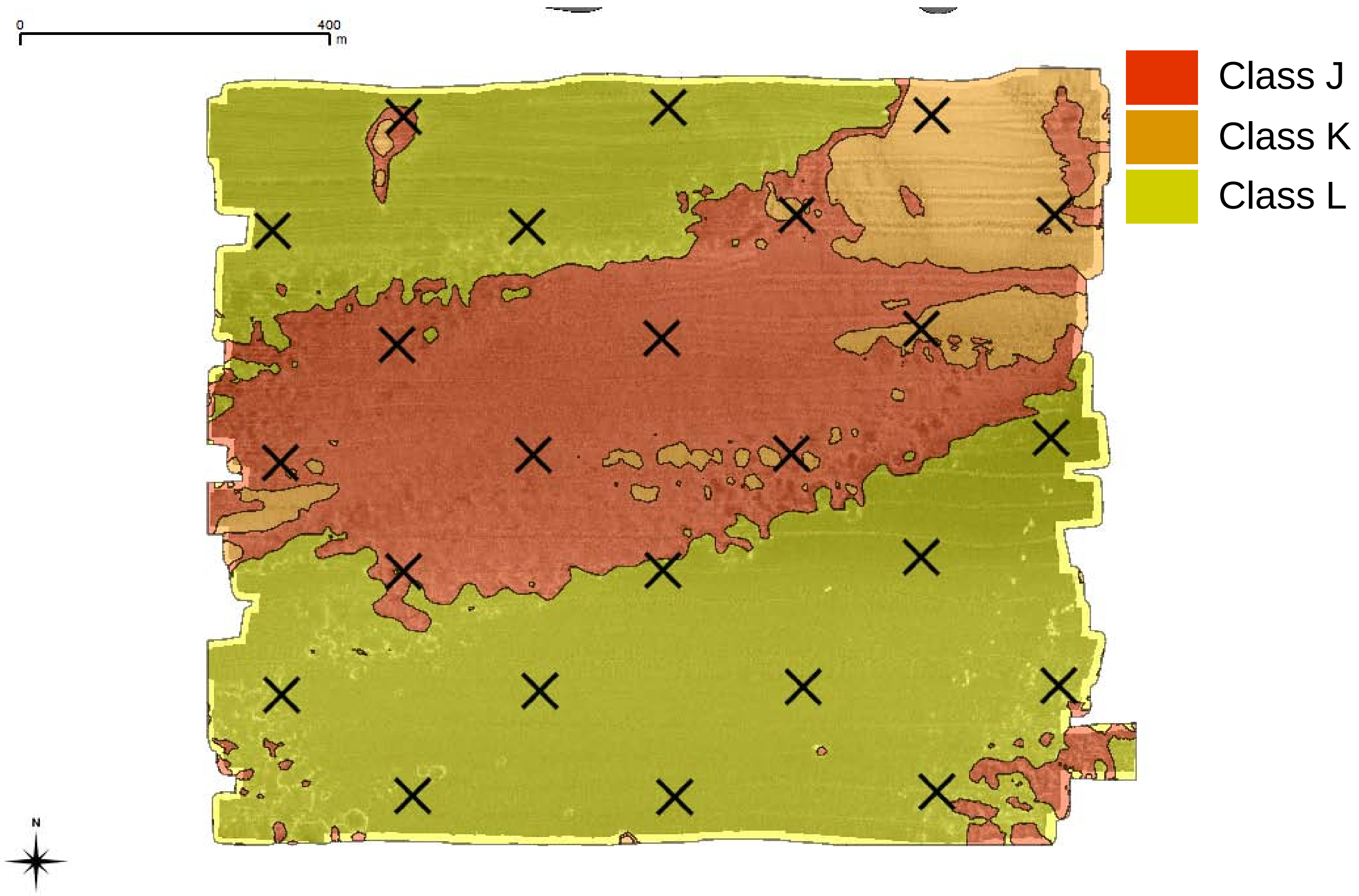
Application: Te Matuku Marine Reserve

2007 Multibeam backscatter classification
k-means clustering of median BS in 20m neighborhood



Application: Te Matuku Marine Reserve

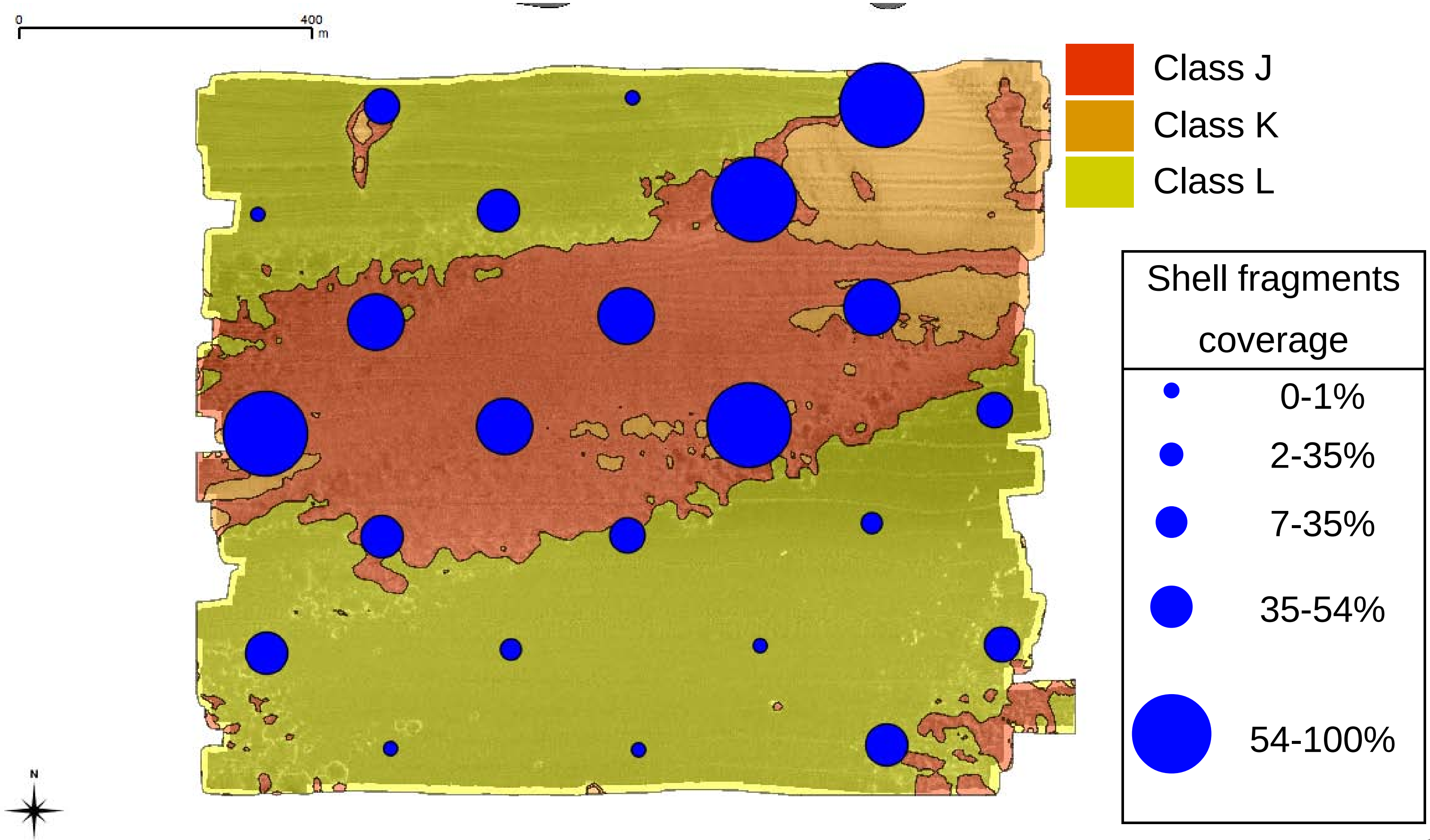
2008 video stations (UoW)



Application: Te Matuku Marine Reserve

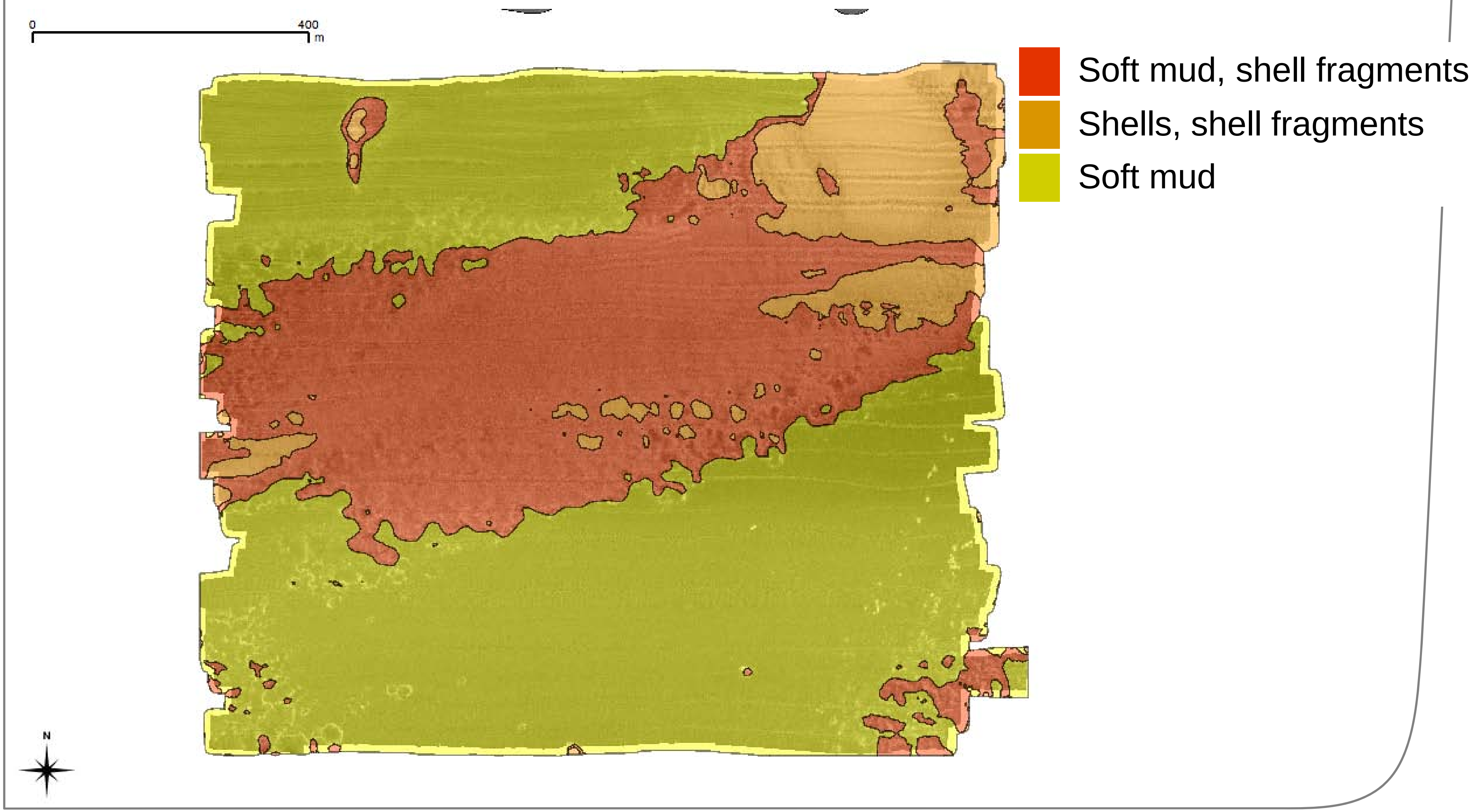
2008 video stations (UoW)

All stations: soft mud + variable cover in shell fragments



Application: Te Matuku Marine Reserve

2007/2008 MBES/video-based benthic habitat map



Application: Te Matuku Marine Reserve

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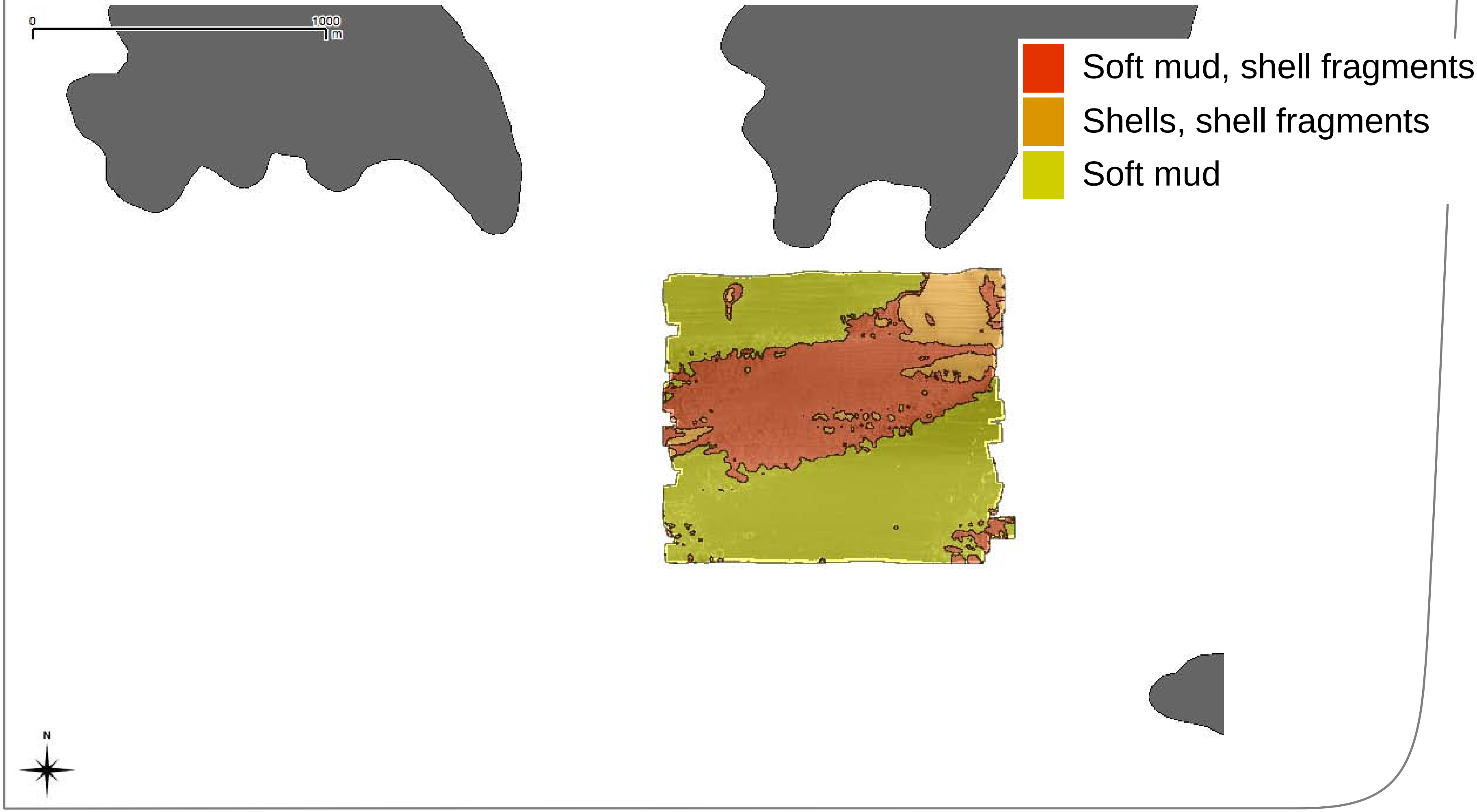
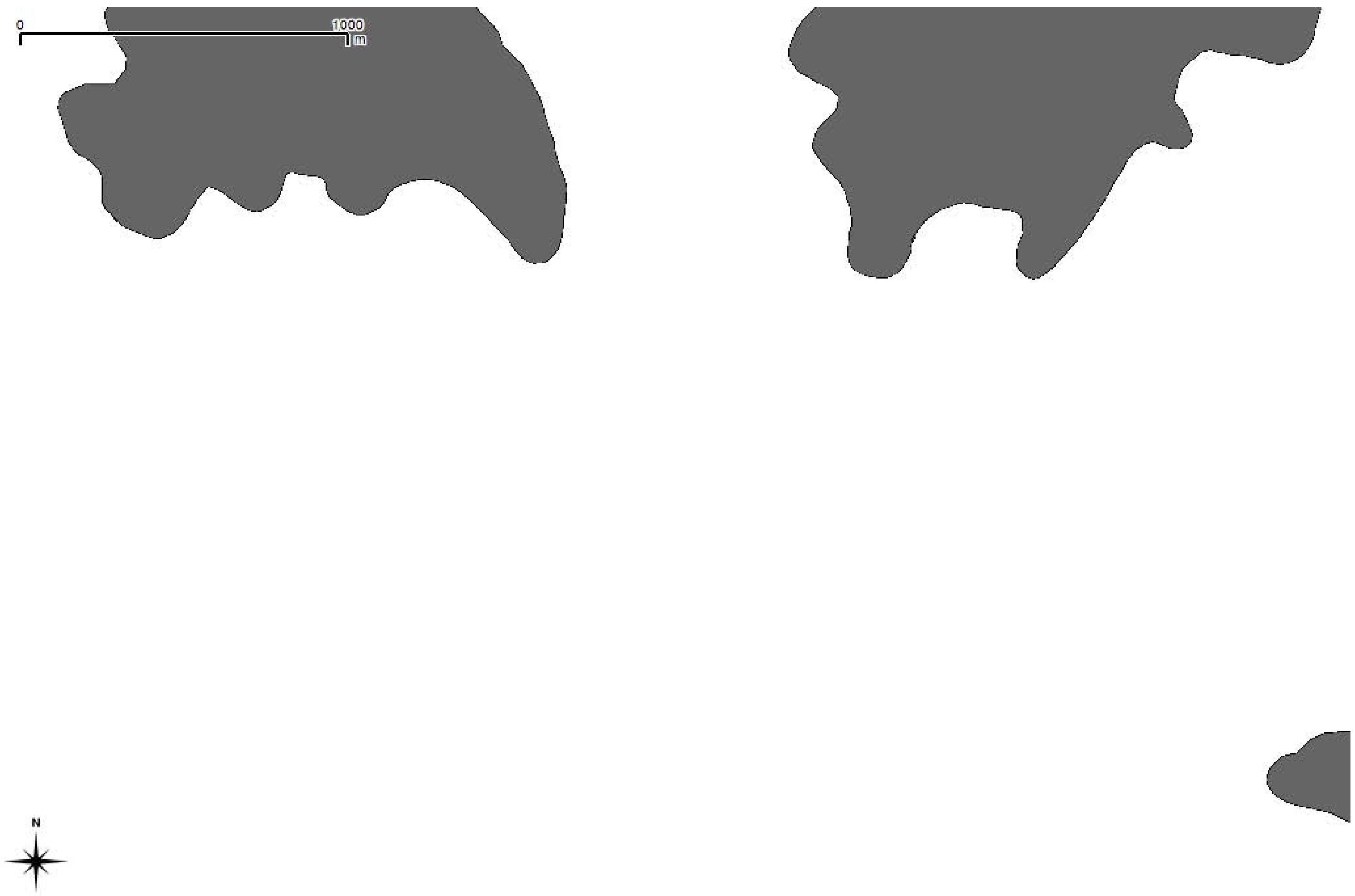
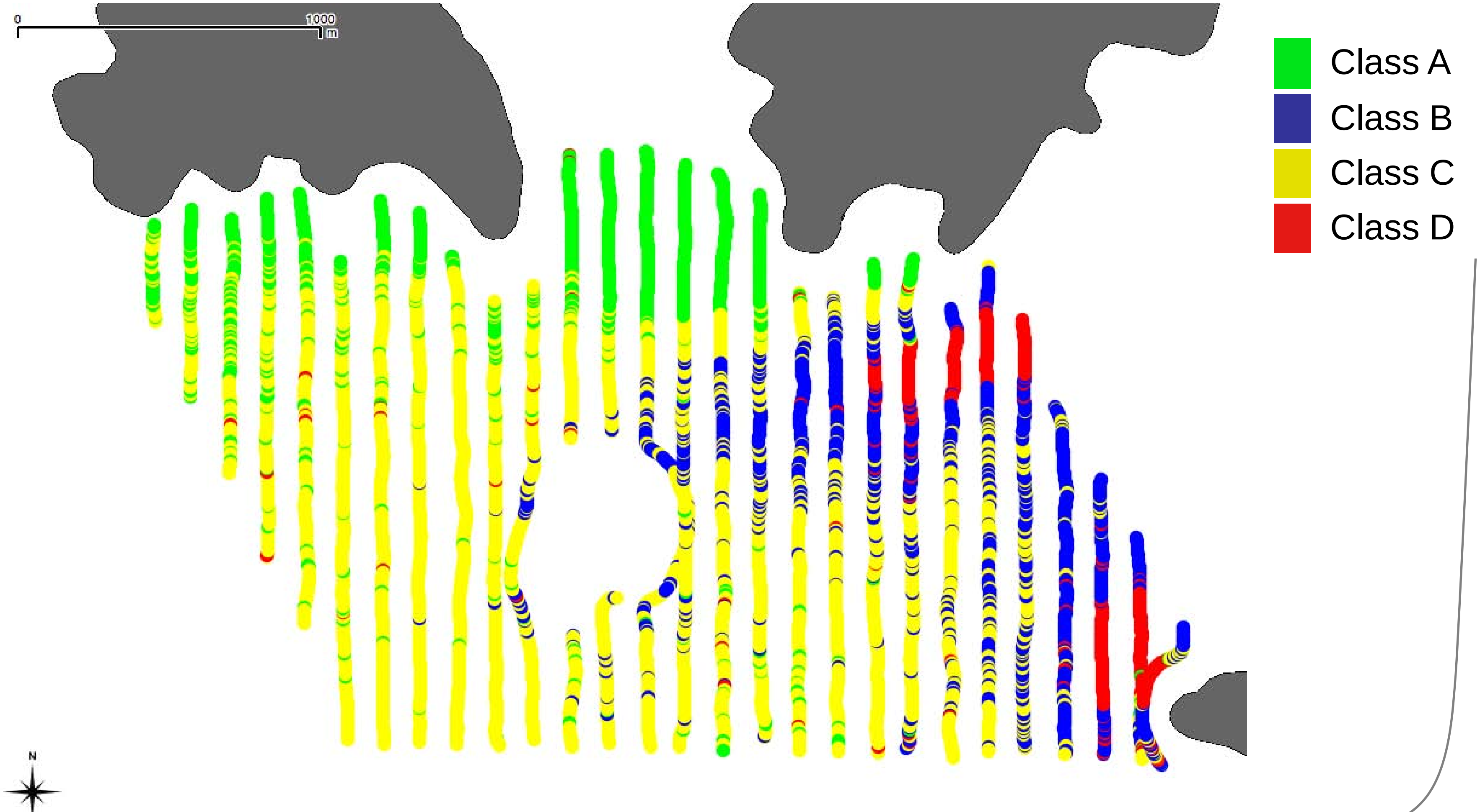


Application: Te Matuku Marine Reserve



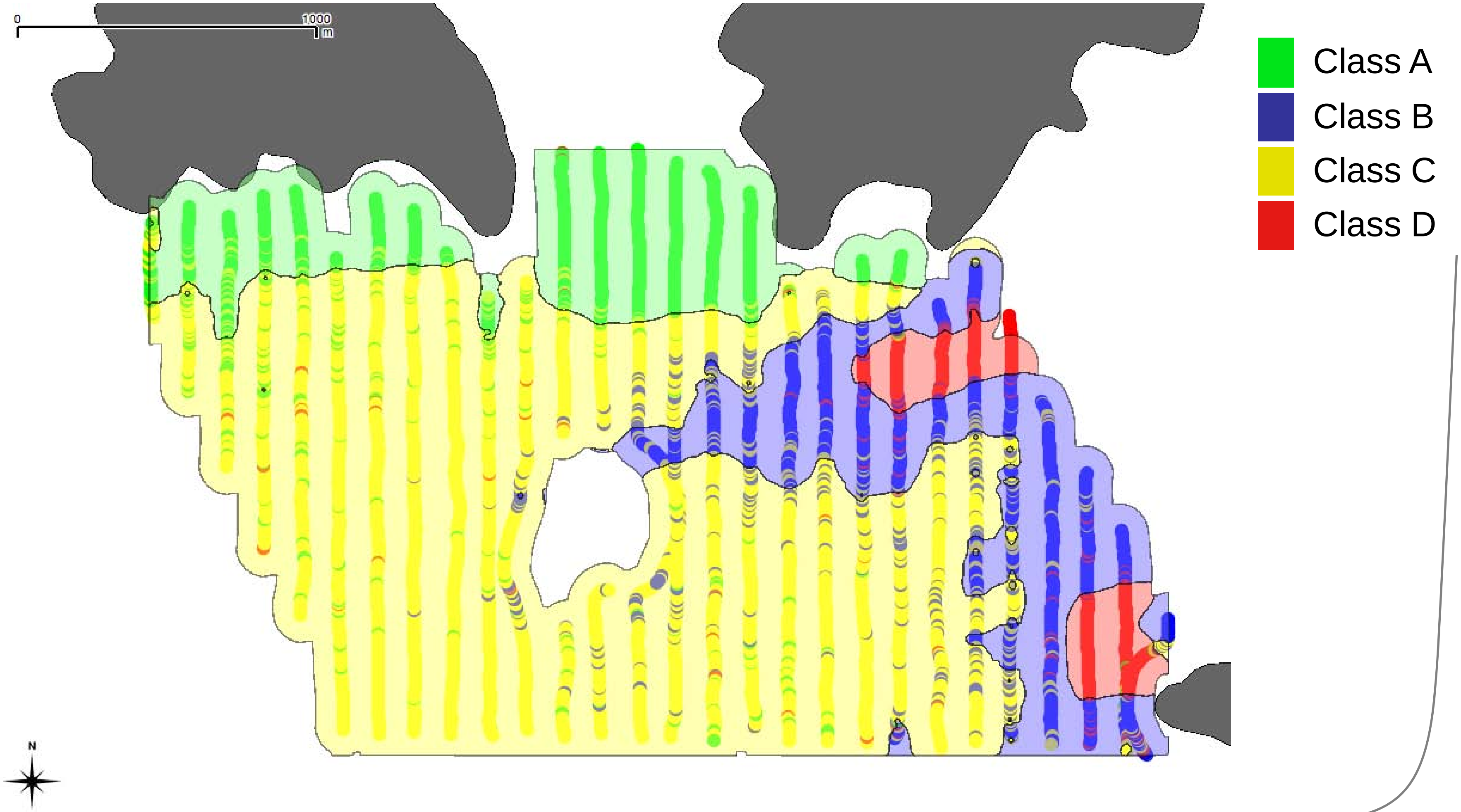
Application: Te Matuku Marine Reserve

QTC View classification



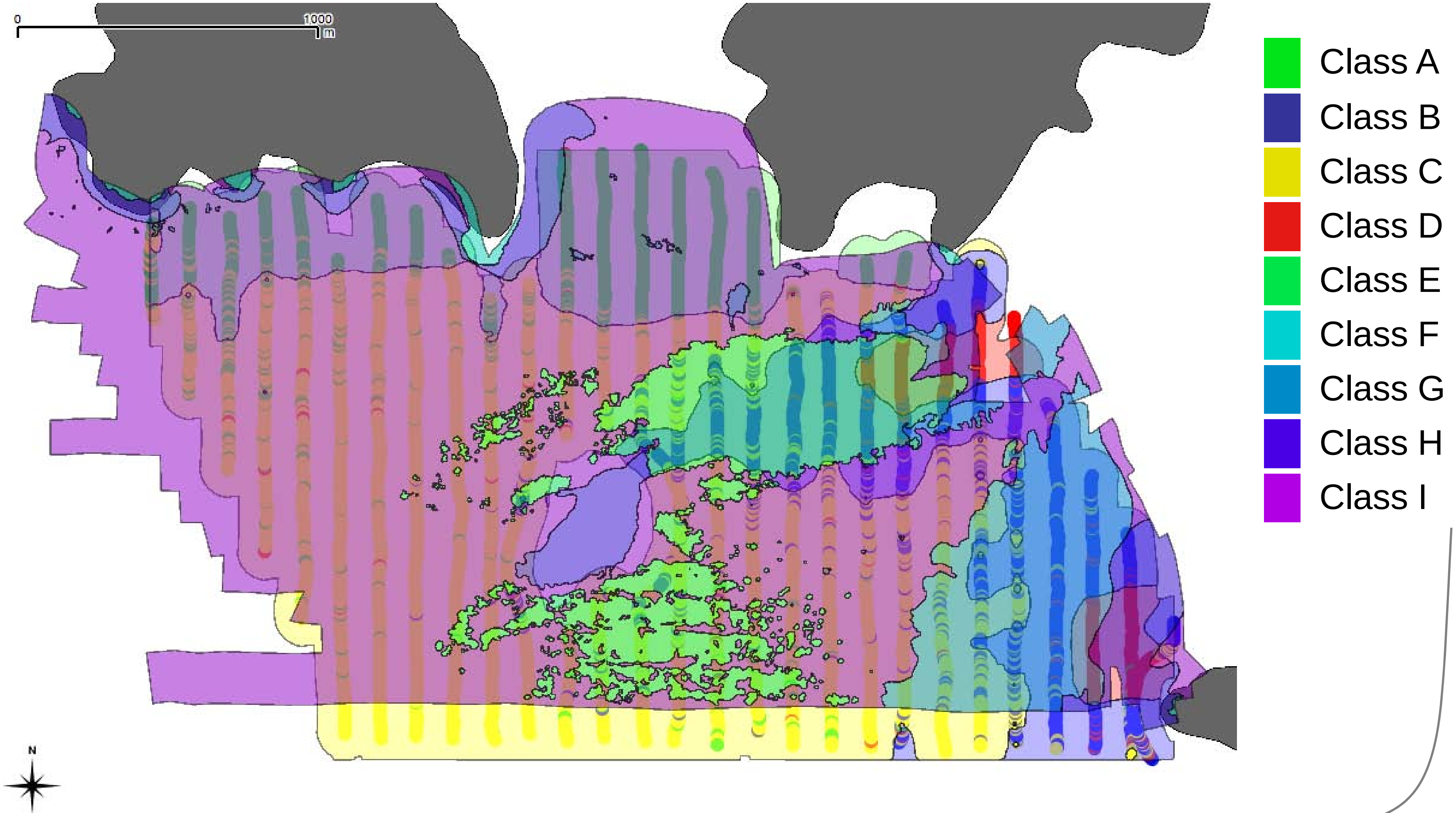
Application: Te Matuku Marine Reserve

QTC View classification + Interpolated QTC View classification



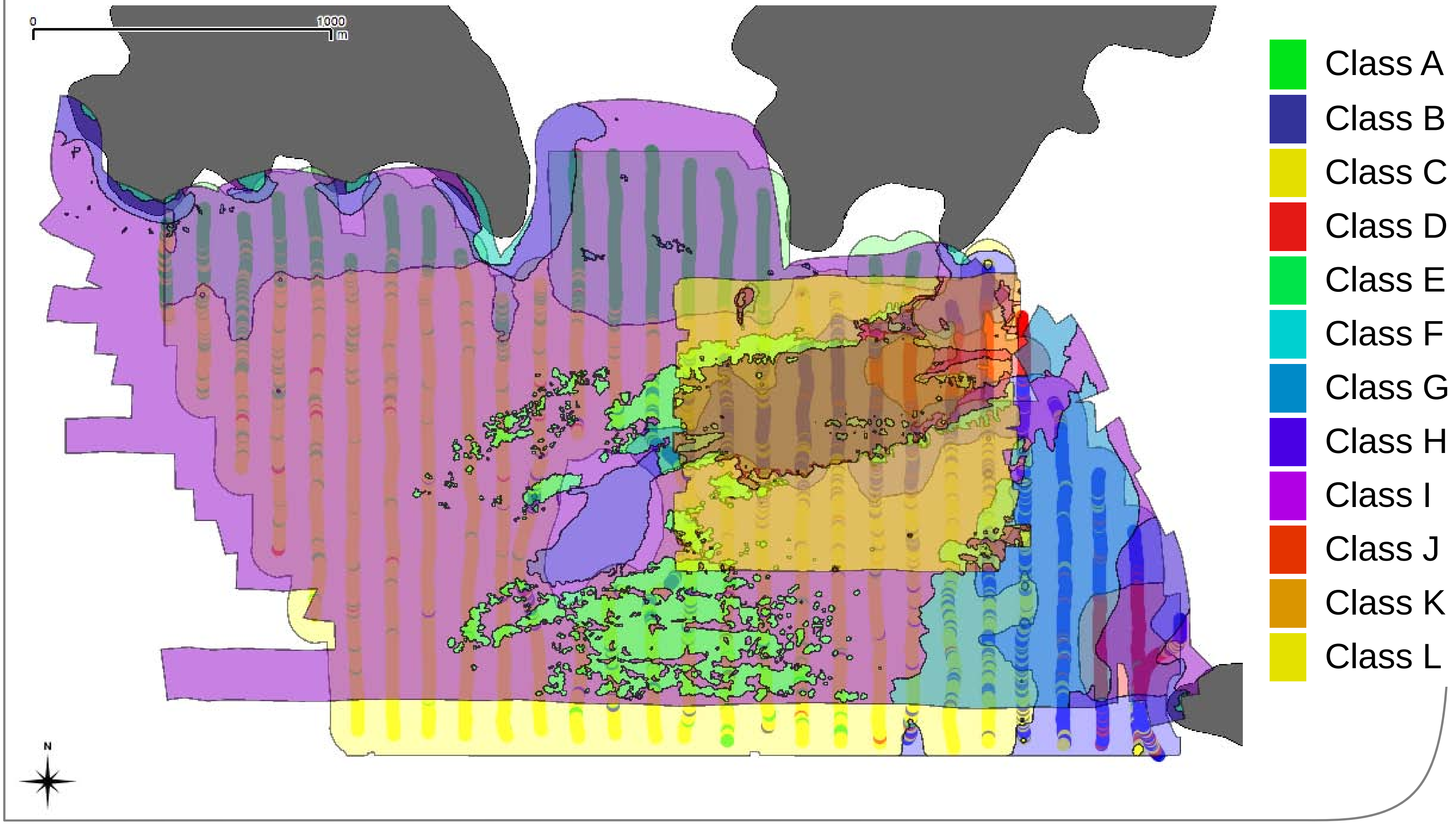
Application: Te Matuku Marine Reserve

QTC View classification + Interpolated QTC View classification + SSS imagery classification



Application: Te Matuku Marine Reserve

QTC View classification + Interpolated QTC View classification + SSS imagery classification + MBES backscatter classification



Application: similarity study results

	Map comparison					
	Raw QTC interp. QTC	Raw QTC SSS	Raw QTC MBES	interp. QTC SSS	interp. QTC MBES	MBES SSS
Measures of association						
V						
λ						
U						
Measures of agreement						
max OA						
max κ						
max κ_n						

Application: similarity study results

	Map comparison					
	Raw QTC interp. QTC	Raw QTC SSS	Raw QTC MBES	interp. QTC SSS	interp. QTC MBES	MBES SSS
Measures of association						
V	**0.8376**	**0.4103**	**0.4871**	**0.4123**	**0.5333**	**0.7310**
$\boldsymbol{\lambda}$	**0.7394**	**0.1208**	**0.4123**	**0.1498**	**0.4552**	**0.6292**
U	**0.6389**	**0.2304**	**0.2650**	**0.2484**	**0.3202**	**0.4691**
Measures of agreement						
max *OA*	**0.9007**	**0.5528**	**0.7362** [ª]	**0.6643** [ªª]	**0.7474** [ª]	**0.8486** [¤¤]
max $\boldsymbol{\kappa}$	**0.8219**	**0.1966**	**0.5140** [ª]	**0.3053** [¤]	**0.5488** [ª]	**0.7187** [¤¤]
max $\boldsymbol{\kappa_n}$	**0.8677**	**0.4038**	**0.6043** [ª]	**0.5523** [ªª]	**0.6211** [ª]	**0.7729** [¤¤]

: A=A, B=B, C=C, D=D

: A=E, B=G, C=I, D=H

: A=H, B=G, C=I, D=E

[ª]: J=B, K=D, L=A+C

[ªª]: A=F, B=G, C=E+I, D=H

[¤]: A=F, B=E+G, C=I, D=H

[¤¤]: J=E, K=H, L=G+I

Application: similarity study results

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All measures consistent with one another

Application: similarity study results

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All measures consistent with one another

➡ QTC interpolation in agreement with QTC raw data

Application: similarity study results

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U	**0.6389**	**0.2304**	**0.2650**	**0.2484**	**0.3202**	**0.4691**
Measures of agreement						
max OA	**0.9007**	**0.5528**	**0.7362** [ª]	**0.6643** [ªª]	**0.7474** [ª]	**0.8486** [¤¤]
max κ	**0.8219**	**0.1966**	**0.5140** [ª]	**0.3053** [¤]	**0.5488** [ª]	**0.7187** [¤¤]
max κ_n	**0.8677**	**0.4038**	**0.6043** [ª]	**0.5523** [ªª]	**0.6211** [ª]	**0.7729** [¤¤]

: A=A, B=B, C=C, D=D
: A=E, B=G, C=I, D=H
: A=H, B=G, C=I, D=E
[ª]: J=B, K=D, L=A+C
[ªª]: A=F, B=G, C=E+I, D=H
[¤]: A=F, B=E+G, C=I, D=H
[¤¤]: J=E, K=H, L=G+I

All measures consistent with one another

QTC interpolation in agreement with QTC raw data

MBES and SSS have highest inter-classification agreement

Application: similarity study results

	Map comparison					
	Raw QTC interp. QTC	Raw QTC SSS	Raw QTC MBES	interp. QTC SSS	interp. QTC MBES	MBES SSS
Measures of association						
V	**0.8376**	**0.4103**	**0.4871**	**0.4123**	**0.5333**	**0.7310**
λ	**0.7394**	**0.1208**	**0.4123**	**0.1498**	**0.4552**	**0.6292**
U	**0.6389**	**0.2304**	**0.2650**	**0.2484**	**0.3202**	**0.4691**
Measures of agreement						
max *OA*	**0.9007**	**0.5528**	**0.7362** [ª]	**0.6643** [ªª]	**0.7474** [ª]	**0.8486** [¤¤]
max κ	**0.8219**	**0.1966**	**0.5140** [ª]	**0.3053** [¤]	**0.5488** [ª]	**0.7187** [¤¤]
max κ_n	**0.8677**	**0.4038**	**0.6043** [ª]	**0.5523** [ªª]	**0.6211** [ª]	**0.7729** [¤¤]

: A=A, B=B, C=C, D=D
: A=E, B=G, C=I, D=H
: A=H, B=G, C=I, D=E
[ª]: J=B, K=D, L=A+C
[ªª]: A=F, B=G, C=E+I, D=H
[¤]: A=F, B=E+G, C=I, D=H
[¤¤]: J=E, K=H, L=G+I

All measures consistent with one another

QTC interpolation in agreement with QTC raw data

MBES and SSS have highest inter-classification agreement

Interpolating QTC improves agreement with image-based maps

Application: similarity study results

	Map comparison					
	Raw QTC interp. QTC	Raw QTC SSS	Raw QTC MBES	interp. QTC SSS	interp. QTC MBES	MBES SSS
Measures of association						
V	**0.8376**	**0.4103**	**0.4871**	**0.4123**	**0.5333**	**0.7310**
λ	**0.7394**	**0.1208**	**0.4123**	**0.1498**	**0.4552**	**0.6292**
U	**0.6389**	**0.2304**	**0.2650**	**0.2484**	**0.3202**	**0.4691**
Measures of agreement						
max *OA*	**0.9007**	**0.5528**	**0.7362** [a]	**0.6643** [aa]	**0.7474** [a]	**0.8486** [¤¤]
max κ	**0.8219**	**0.1966**	**0.5140** [a]	**0.3053** [¤]	**0.5488** [a]	**0.7187** [¤¤]
max κ_n	**0.8677**	**0.4038**	**0.6043** [a]	**0.5523** [aa]	**0.6211** [a]	**0.7729** [¤¤]

: A=A, B=B, C=C, D=D

: A=E, B=G, C=I, D=H

: A=H, B=G, C=I, D=E

[a]: J=B, K=D, L=A+C

[aa]: A=F, B=G, C=E+I, D=H

[¤]: A=F, B=E+G, C=I, D=H

[¤¤]: J=E, K=H, L=G+I

All measures consistent with one another

QTC interpolation in agreement with QTC raw data

MBES and SSS have highest inter-classification agreement

Interpolating QTC improves agreement with image-based maps

QTC agrees more with MBES than SSS

Conclusions

• **Accuracy estimation** is highly dependent on ground-truth data quality. It is hazardous to compare the “% success rate” of different case studies. **Similarity estimation** is less meaningful but more reliable.

• Using similarity measures to compare **classifications from several different datasets** allows finding which datasets are redundant or complementary.

• Using similarity measures to compare **several classification methodologies of a unique dataset** allows finding which methodology proves the more adapted to the data.

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Any questions ?

- Contact
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- References and related publications

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Appendices

Aggregation/Permutation

- Total number of possibilities of aggregation *n* columns into *m*:

$$S(n,m) = \frac{1}{m!}\sum_{k=0}^{m}(-1)^{m-k}\frac{m!}{k!(m-k)!}k^n$$

- Total number of possibilities of aggregation/permutation:

$$m!S(n,m)$$

Estimation of similarity: What if the two maps' classification schemes are different?

- Example 1: Two independent unsupervised classifications, but ground-truthed with a common dataset.

- Map 1 (4 classes)
  - Aggregated reef
  - Gravel + cobbles + attached epifauna
  - Sand with bedforms
  - Bioturbated soft sediment

- Map 2 (6 classes)
  - Aggregated reef
  - Gravel + cobbles (undisturbed)
  - Gravel + cobbles (dregdged)
  - Inshore medium sand
  - Offshore fine sand
  - Bioturbated soft sediment

→Subjective **classes aggregation**

Estimation of similarity: What if the two maps' classification schemes are different?

- Example 2: Two independent unsupervised classifications with separate ground-truth surveys.

- Map 1 (4 classes)
  - Cobbles and boulders (Φ <-5)
  - Gravel and pebbles (-5 < Φ < -1)
  - Sand (-1 < Φ < 4)
  - Fine soft sediment (Φ > 4)

?

- Map 2 (4 classes)
  - Aggregated reef + macro-algae
  - Mobile rocky reef (cobbles) + moderate epifauna
  - Mostly gravelly sand with occasional pebbles + shells
  - Bioturbated mud

→Subjective **classes correspondence**

Estimation of similarity: What if the two maps' classification schemes are different?

- Example 3: Two independent unsupervised classifications without ground-truth.

- Sidescan imagery interpretation
  - Acoustic theme A
  - Acoustic theme B
  - Acoustic theme C

???

- Single-beam classification software
  - Cluster 1
  - Cluster 2
  - Cluster 3
  - Cluster 4
  - Cluster 5
  - Cluster 6