

Complex Structures in Arctic Sea Ice and a Note on Walgreen Coast, Antarctica

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Thanks to my collaborators and students ...

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Recent Rapid Changes of the Cryosphere

- Glaciers in most mountain ranges retreat
- Antarctic and Greenland Ice Sheets lose elevation
- Outlet glaciers of ice sheets accelerate and retreat
- Northern Antarctic ice shelves break up
- Arctic sea-ice cover reaches record lows in coverage

Approach

Understanding Environmental Change
through Geomathematical Analysis
of Remote-Sensing Data

Objectives

Glaciologic objective:

Detect and quantify different forms of change in the cryosphere and attribute changes to glaciologic or sea-ice-morphogenetic processes

Remote-sensing objective:

Present and analyze observations from new instruments with a focus on the role of ICESat GLAS data

Geomathematical objective:

- Realize new methodological components for spatial structure analysis
- Identify, characterize and classify forms from hidden information in
 - (a) Undersampled situations
 - (b) Oversampled situations

Measurement objective:

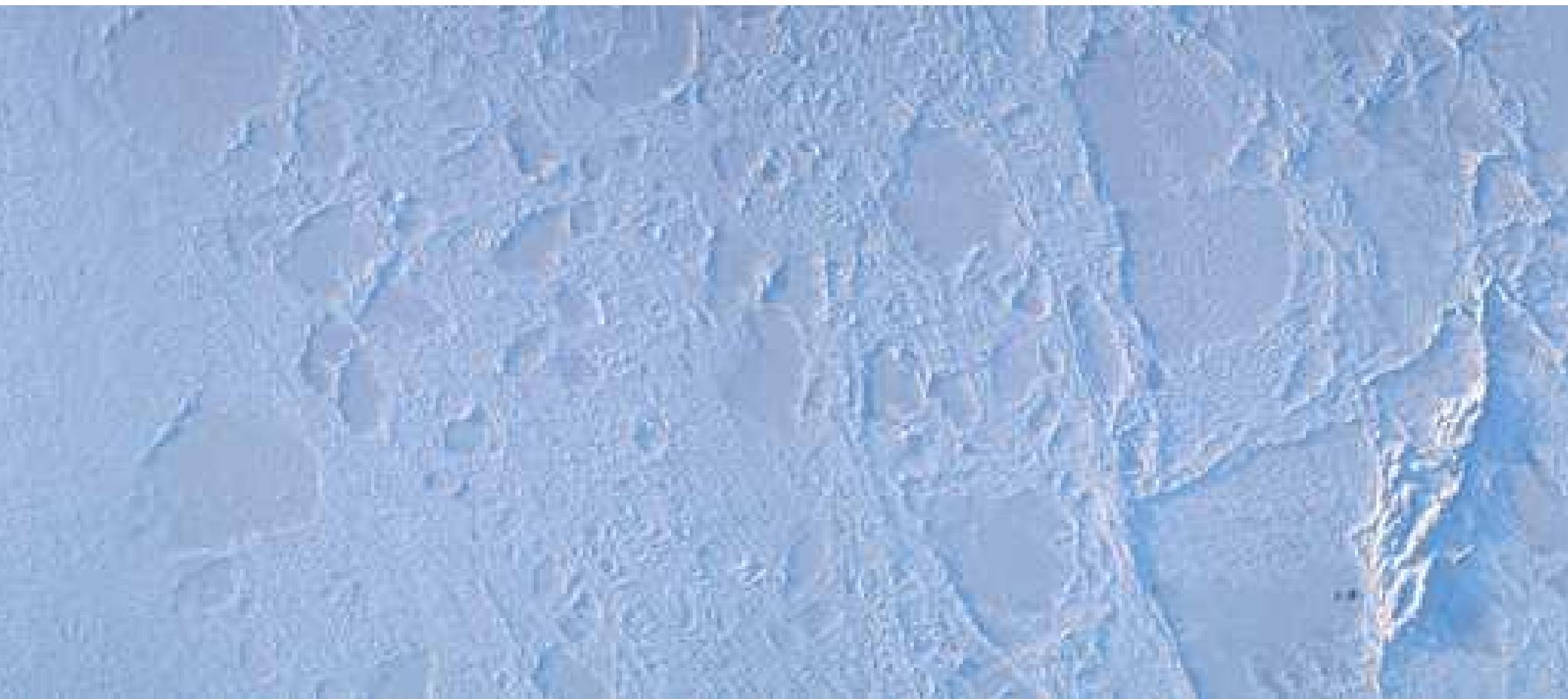
Development of instrumentation to survey
micro-topography and roughness of ice surfaces

- (1) Glacier Roughness Sensor (GRS)
- (2) UAV Laser Profilometer
(UAV- Unmanned Aerial Vehicle)

Objectives of Ice Classification

- (1) **Characterization of sea ice provinces:** Establish a unique quantitative description of each sea ice type
- (2) **Classification:** Assign a given object to a surface class, using the characterization
- (3) **Segmentation:** Create a thematic map by applying the classification operator in a moving window

Beaufort Sea





Beaufort Sea, Ridge (March 2003) (J. Maslanik photo)



Rubbled Ice (March 2003) (J. Maslanik photo)

(1.) What is spatial surface roughness?

- a derivative of (micro)topography
→ characterization of spatial behavior

(2.) Why do we need surface roughness?

- morphologic characteristics are captured in surface roughness (*not* in absolute elevation)
- subscale information for satellite data

(3.) How do we measure surface roughness? — The GRS !



A UAV with laser profilometer over Barrow



Niwot Ridge Snow Surface: Winter ————— Summer





Bering Glacier, 1994, mature surge stage, Khittrov Hills in background

Jakobshavn Isbræ Drainage Basin – Spring Ice Surface

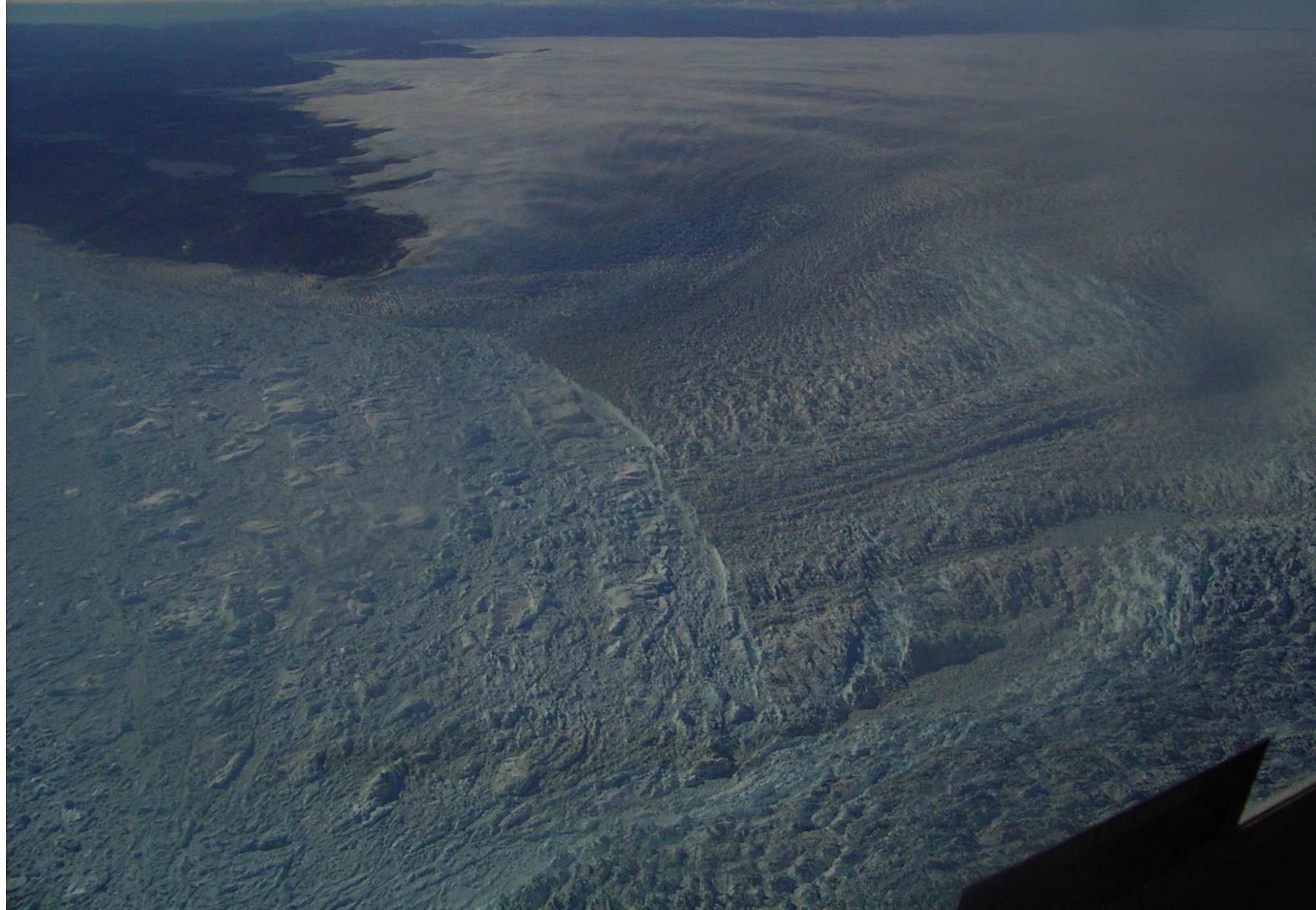


Jakobshavn Isbræ Drainage Basin – Summer Ice Surface



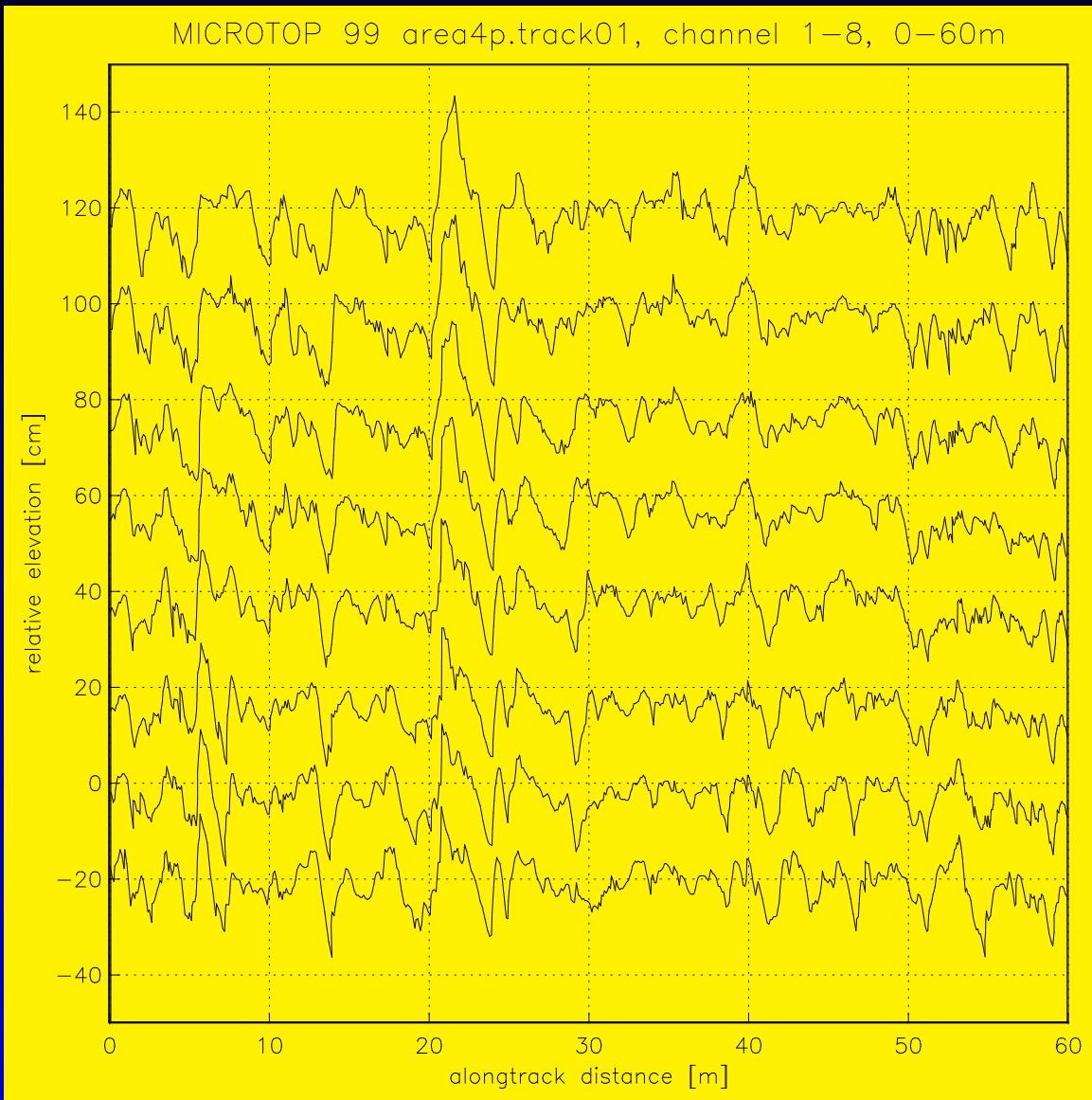


Jakobshavn Isbræ: August 1996



Calving Front of Jakobshavns Isbræ on 16 July 2005

GRS Data – Greenland Ice Sheet



(4.) How do we analyze surface roughness?

The analytically defined spatial derivative needs to be calculated numerically from a data set.

One way to do this:

$$\lim_{x \rightarrow x_0} \frac{z(x_0) - z(x)}{x_0 - x}$$

surface slope in a given location x_0

To characterize morphology, better use averages...

Definition of Vario Functions

$$V = \{(x, z) \text{ with } x = (x_1, x_2) \in \mathcal{D} \text{ and } z = z(x)\} \subseteq \mathcal{R}^3$$

discrete-surface case or

$$V = \{(x, z) \text{ with } x \in \mathcal{D} \text{ and } z = z(x)\} \subseteq \mathcal{R}^2$$

discrete-profile case

Define the *first-order vario function* v_1

$$v_1(h) = \frac{1}{2n} \sum_{i=1}^n [z(x_i) - z(x_i + h)]^2$$

with $(x_i, z(x_i)), (x_i + h, z(x_i + h)) \in \mathcal{D}$ and n the number of pairs separated by h .

Higher-Order Vario Functions

The *first-order vario-function set* is

$$V_1 = \{(h, v_1(h))\} = \underline{v}(V_0)$$

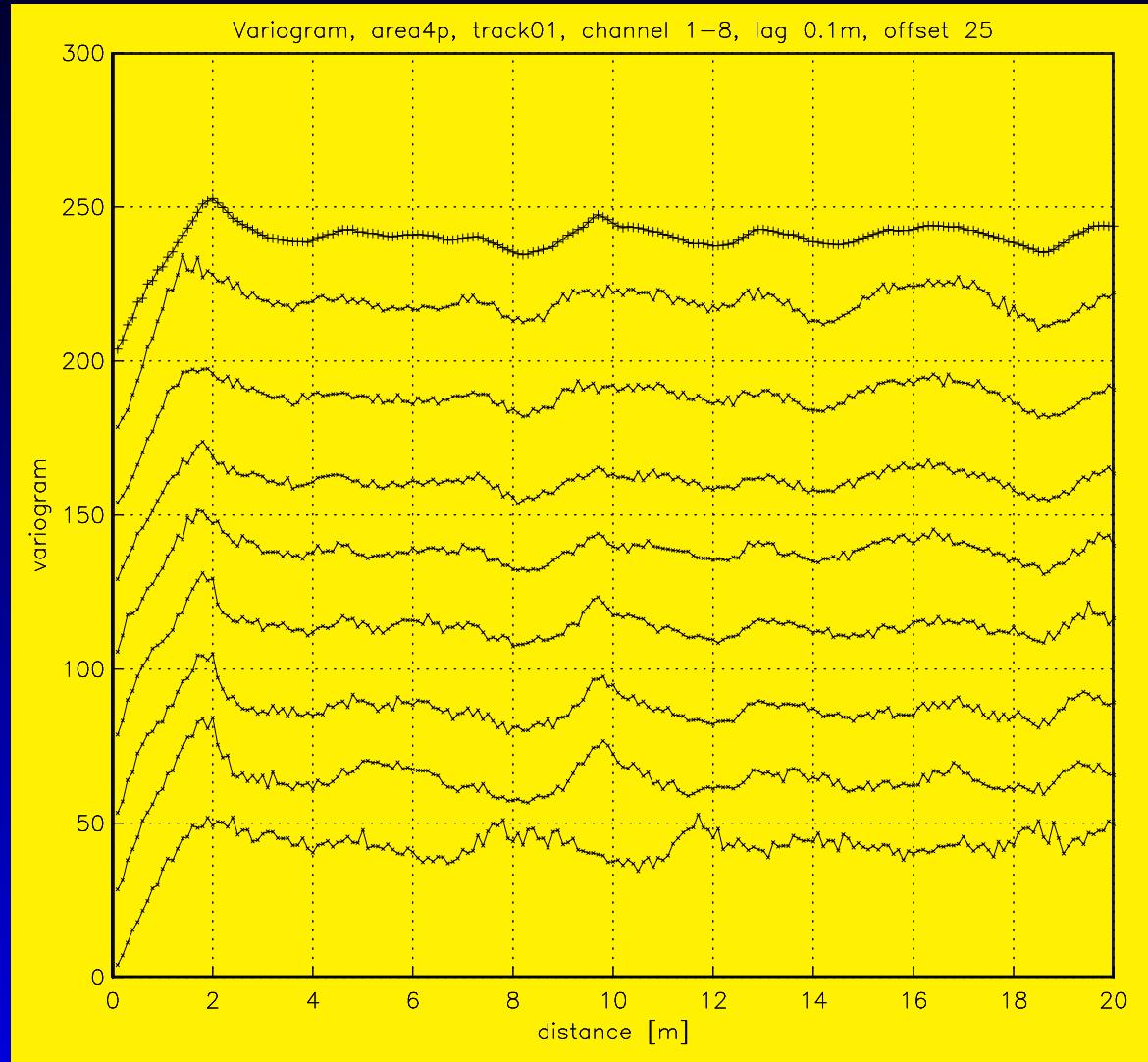
Then: get V_2 from V_1 in the same way you get V_1 from V_0 . The second-order vario function is also called *varvar function*.

Recursively, the *vario function set of order $i + 1$* is defined by

$$V_{i+1} = \underline{v}(V_i)$$

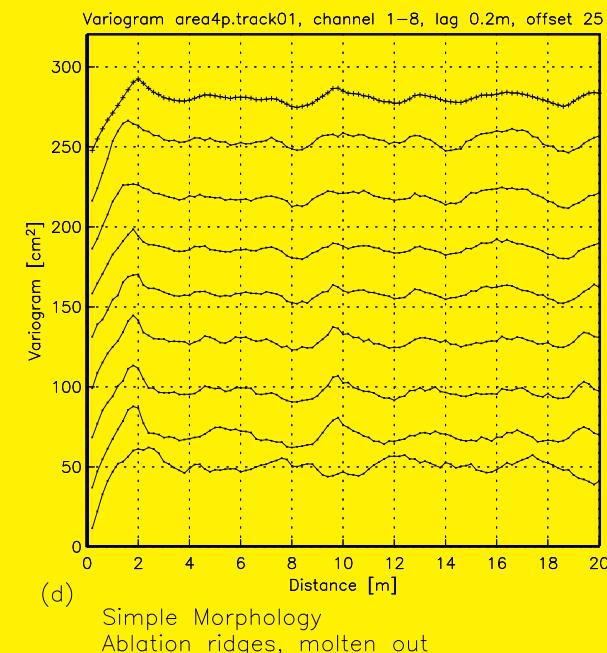
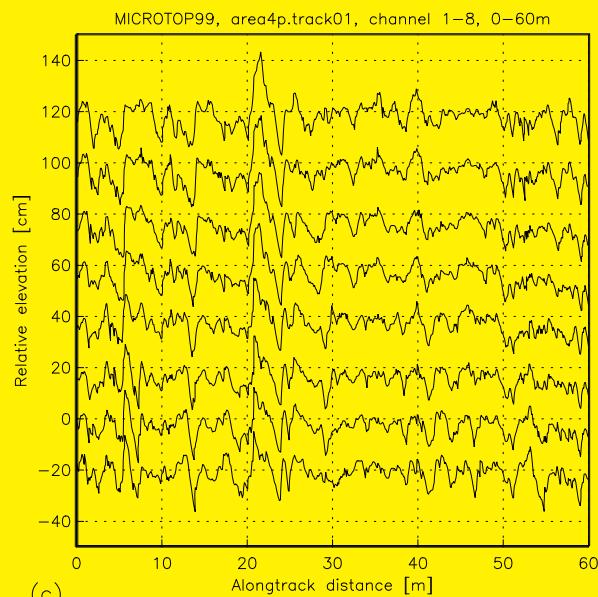
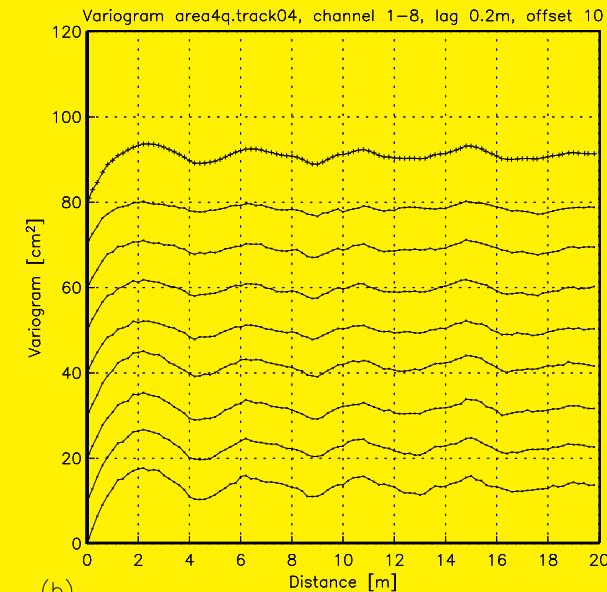
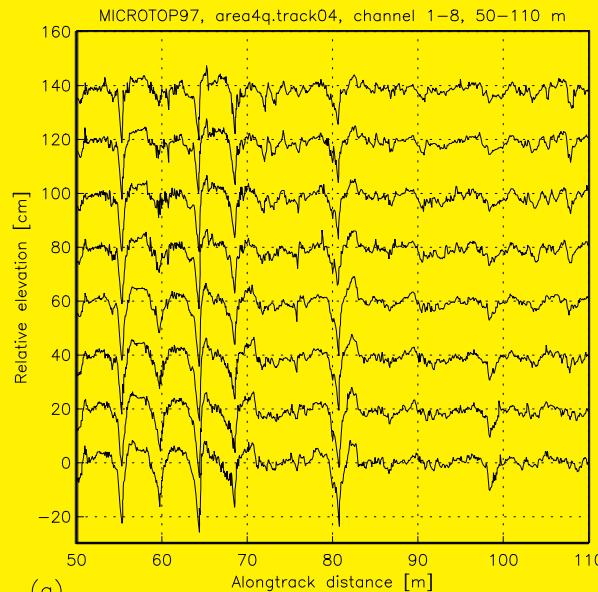
for $i \in \mathbb{N}_0$.

GRS Data – Variogram

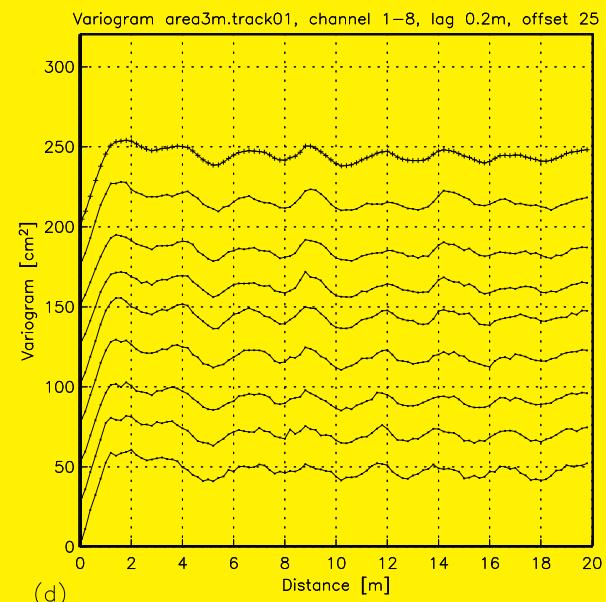
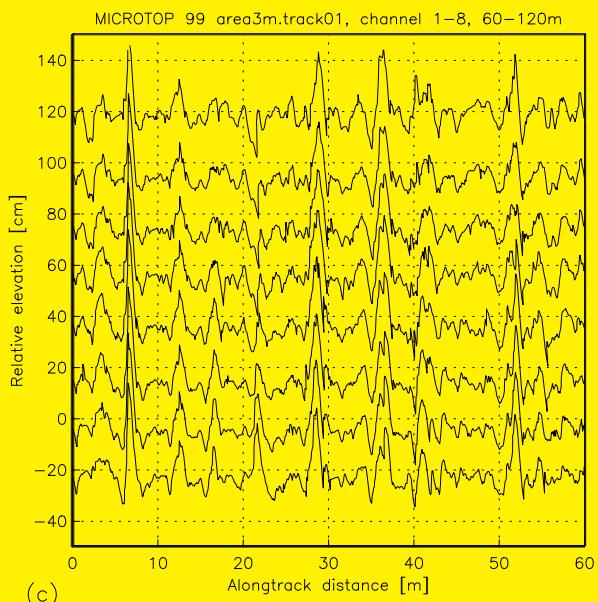
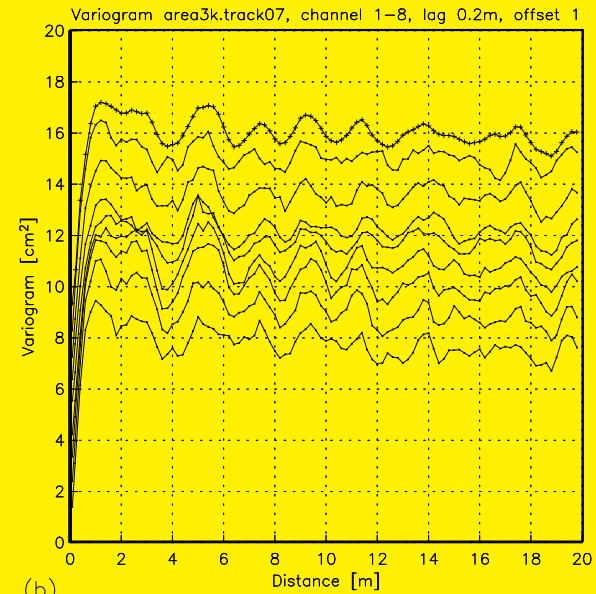
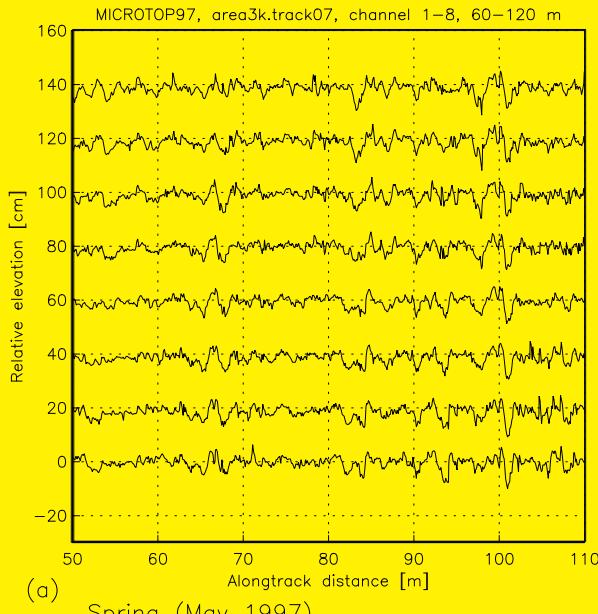


Ice Surface Roughness, Jakobshavn Isbrae Drainage Basin

Seasonal Comparison, Area 4 "RIDGES"



Ice Surface Roughness, Jakobshavn Isbrae Drainage Basin
Seasonal Comparison, Area 3 "ABOVE ICE CAMP"



Geostatistical Classification

Steps:

- (1) Select a window in the study area
- (2) Calculate vario function(s) for data in the window
- (3) Filter the function in (2) [optional]
- (4) Calculate vario parameters (geostatistical classification parameters) from (2) or (3)
- (5) Compose a feature vector of parameters
- (6) Associate the surface in the window (1) to a class by
 - (a) deterministic algorithm
 - (b) connectionist association (neural net)
 - (c) multivariate statistical classification

Geostatistical Classification Parameters

significance parameters:

slope parameter:

$$p1 = \frac{\gamma_{max_1} - \gamma_{min_1}}{h_{min_1} - h_{max_1}}$$

relative significance parameter:

$$p2 = \frac{\gamma_{max_1} - \gamma_{min_1}}{\gamma_{max_1}}$$

pond – maximum vario value

mindist – distance to first min after first max

$$avgspac = \frac{1}{n} \sum_{i=1}^n \frac{1}{i} h_{min_i}$$

Parameters for complex morphology

Define $p2$ -type parameters $pt2(\cdot, \cdot)$ as

$$pt2(max_i, min_j) = \frac{\gamma_{max_i} - \gamma_{min_j}}{\gamma_{max_i}}$$

for $i \leq j$.

With this notation, we define significance parameters for the first few minima in the vario function:

$$p3 = pt2(max_1, min_2)$$

$$p4 = pt2(max_2, min_2)$$

$$p5 = pt2(max_s, min_2)$$

Feature vectors

Parameters are composed into *feature vectors*, on which the classification is based.

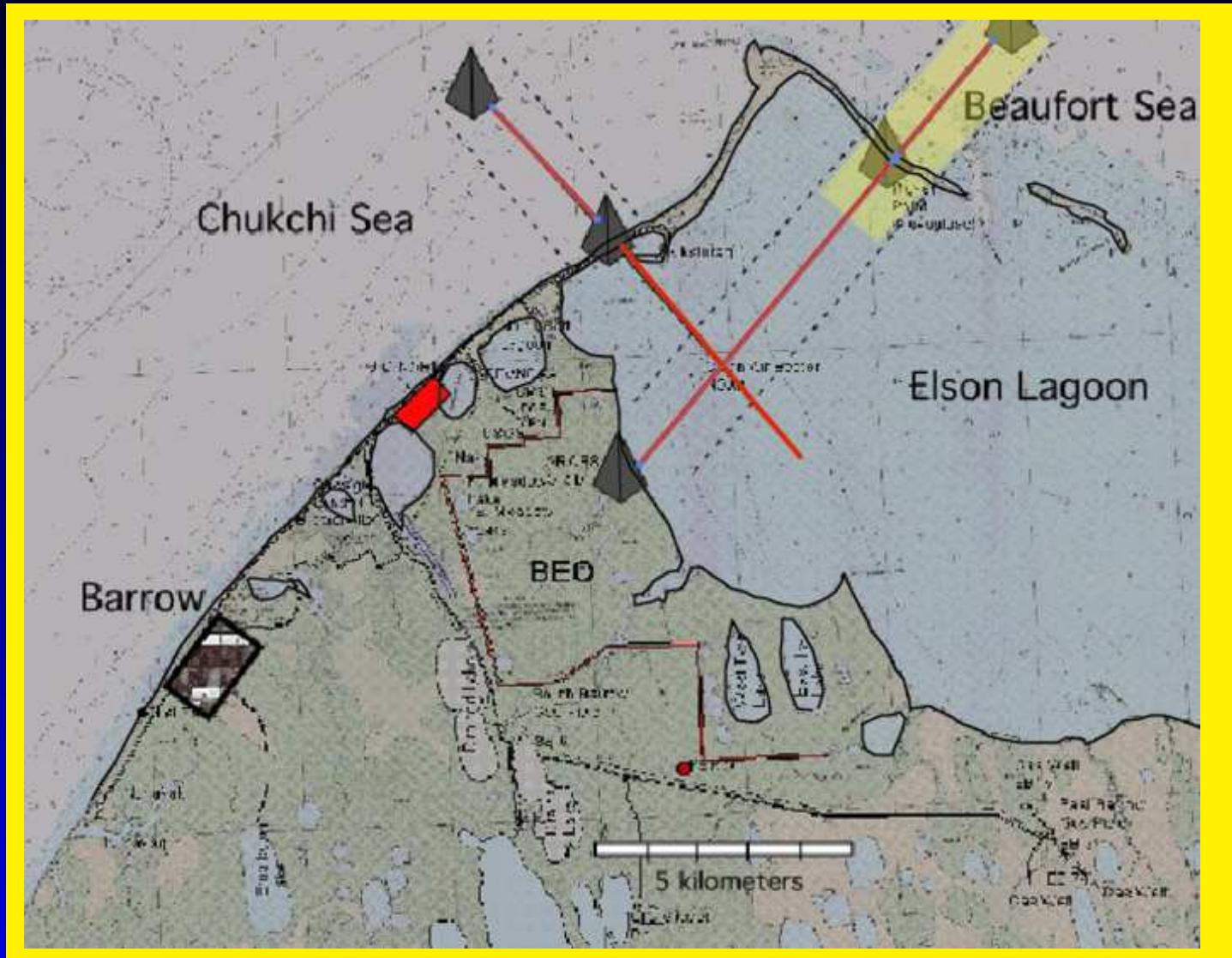
Selection of parameters depends on the applied problem.

Characteristic Snow Forms

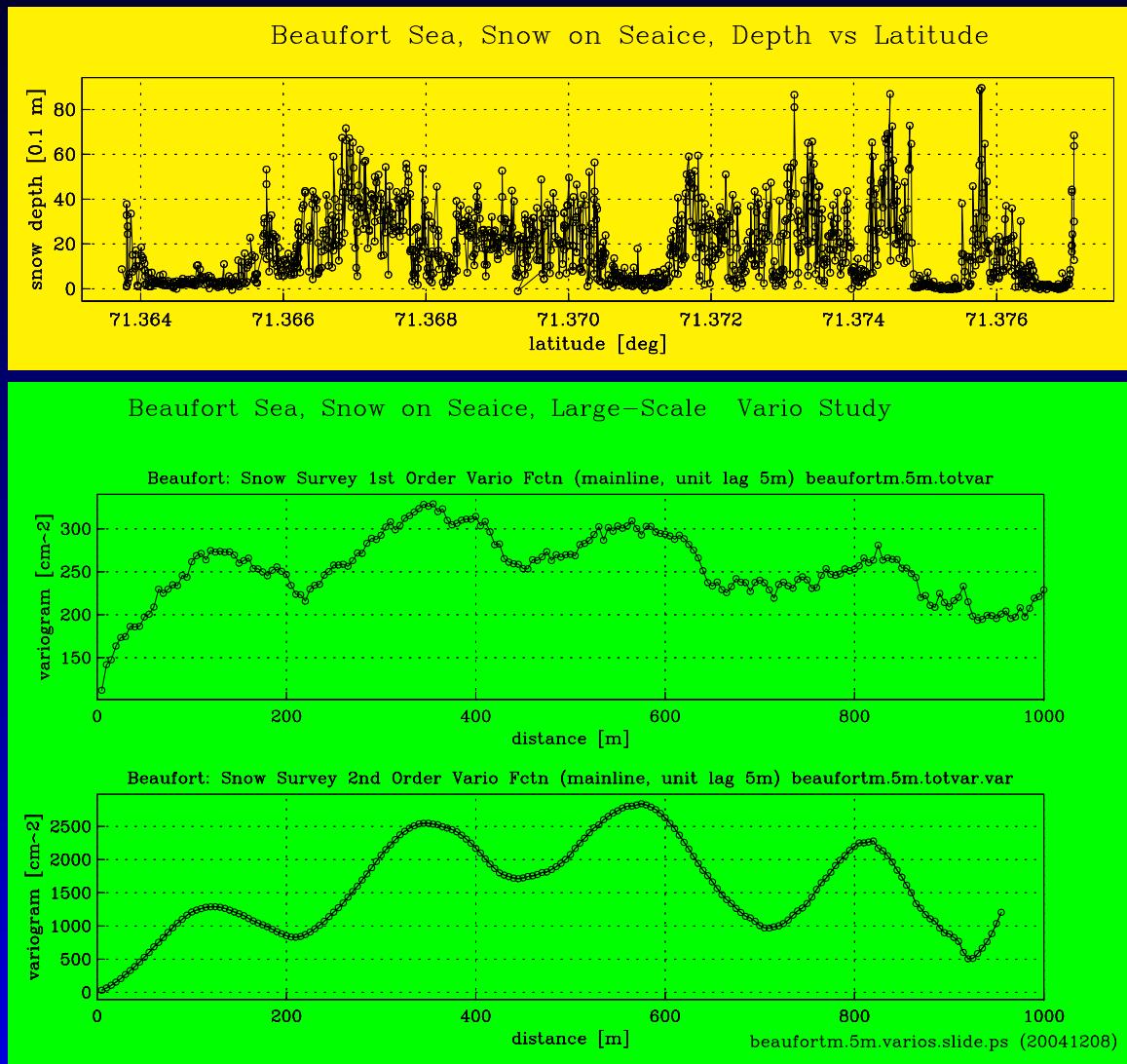
Winter sastrugi	Summer sun cups
rougher	smoother
<i>pond</i> high	<i>pond</i> low
complexely shaped surface	regularly, evenly shaped surface
large size range of features	well-defined characteristic sizes
$min_a = 2 \text{ m}$	$min_a = 0.4\text{-}0.6 \text{ m}$ $min_b = 2.2\text{-}2.4 \text{ m}$ $min_c = 7 \text{ m}$
<i>avgspac</i> often not defined	<i>avgspac</i> well defined
<i>deriv</i> high	<i>deriv</i> low
narrow first <i>max</i> significant first <i>min</i>	<i>min</i> – <i>max</i> sequence with regular multiples

Sea Ice in the Alaskan Arctic

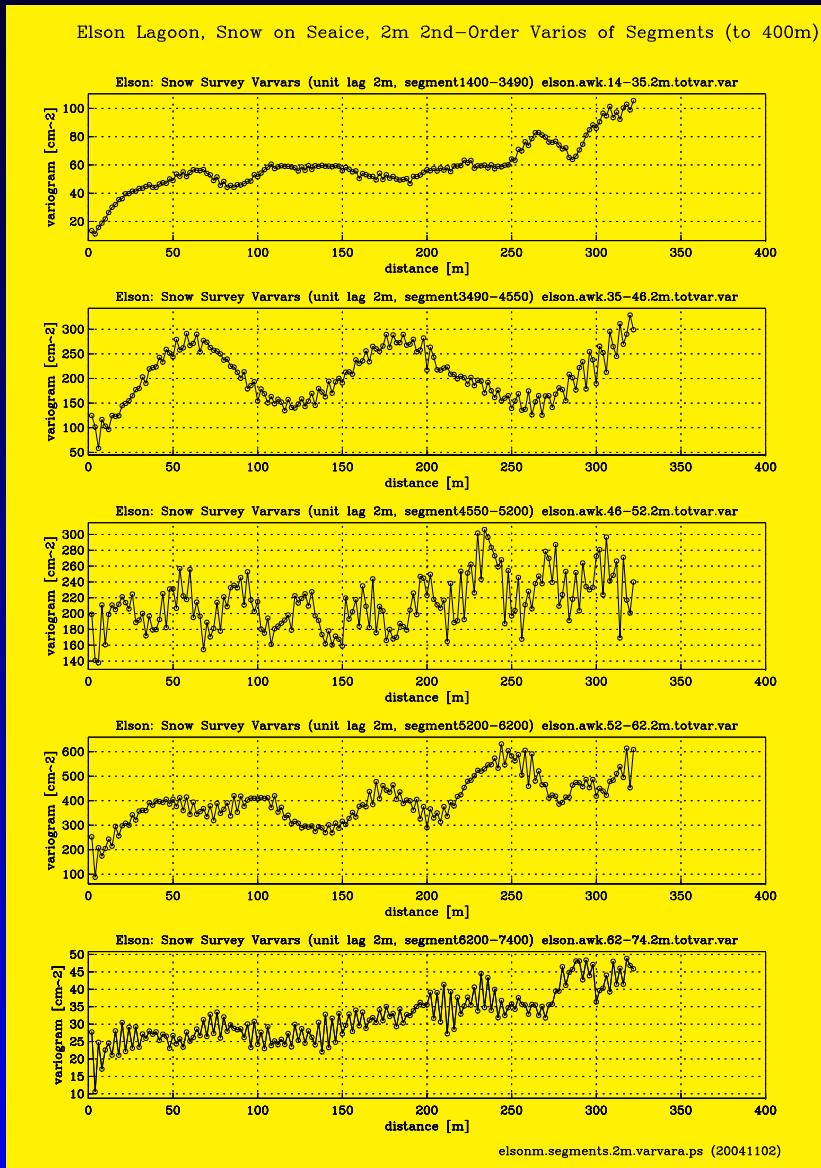
Characterization and Segmentation
of Sea-Ice Provinces
Using Hyperparameters
in Geostatistical Classification



Beaufort Sea



Elson Lagoon Profile: varvar functions



Robust search for hyperparams in complex geo-data sets

Determine bigmax , the largest maximum in a group of g maxima:

$$\gamma_{\text{bigmax}} = \max\{\gamma_{\text{max}_1}, \dots, \gamma_{\text{max}_g}\}$$

say, $\gamma_{\text{bigmax}} = \gamma_{\text{max}_k}$, some $k \in \{1, \dots, g\}$

$$h_{\text{bigmax}} = h_{\text{max}_k}$$

Then determine bigmin , the smallest minimum in a group of g minima following bigmax :

$$\gamma_{\text{bigmin}} = \min\{\gamma_{\text{min}_k}, \dots, \gamma_{\text{min}_{k+g-1}}\}$$

say, $\gamma_{\text{bigmin}} = \gamma_{\text{min}_r}$, some $r \in \{k, \dots, k+g-1\}$

$$h_{\text{bigmin}} = h_{\text{max}_r}$$

Important hyperparameters

Then:

$$pt1(\text{bigmax}, \text{bigmin}) = pt1(\max_k, \min_r)$$

$$pt2(\text{bigmax}, \text{bigmin}) = pt2(\max_k, \min_r)$$

Generalization: Determine all bigmax_i and bigmin_j analogously for a given groupsize g .

$$pt * (\text{bigmax}_i, \text{bigmin}_j) \quad \text{for } * = 1, 2$$

Generalization: Determine the best groupsize automatically

Segmentation of Snow-Depth-on-Sea-Ice Profiles (Complexity)

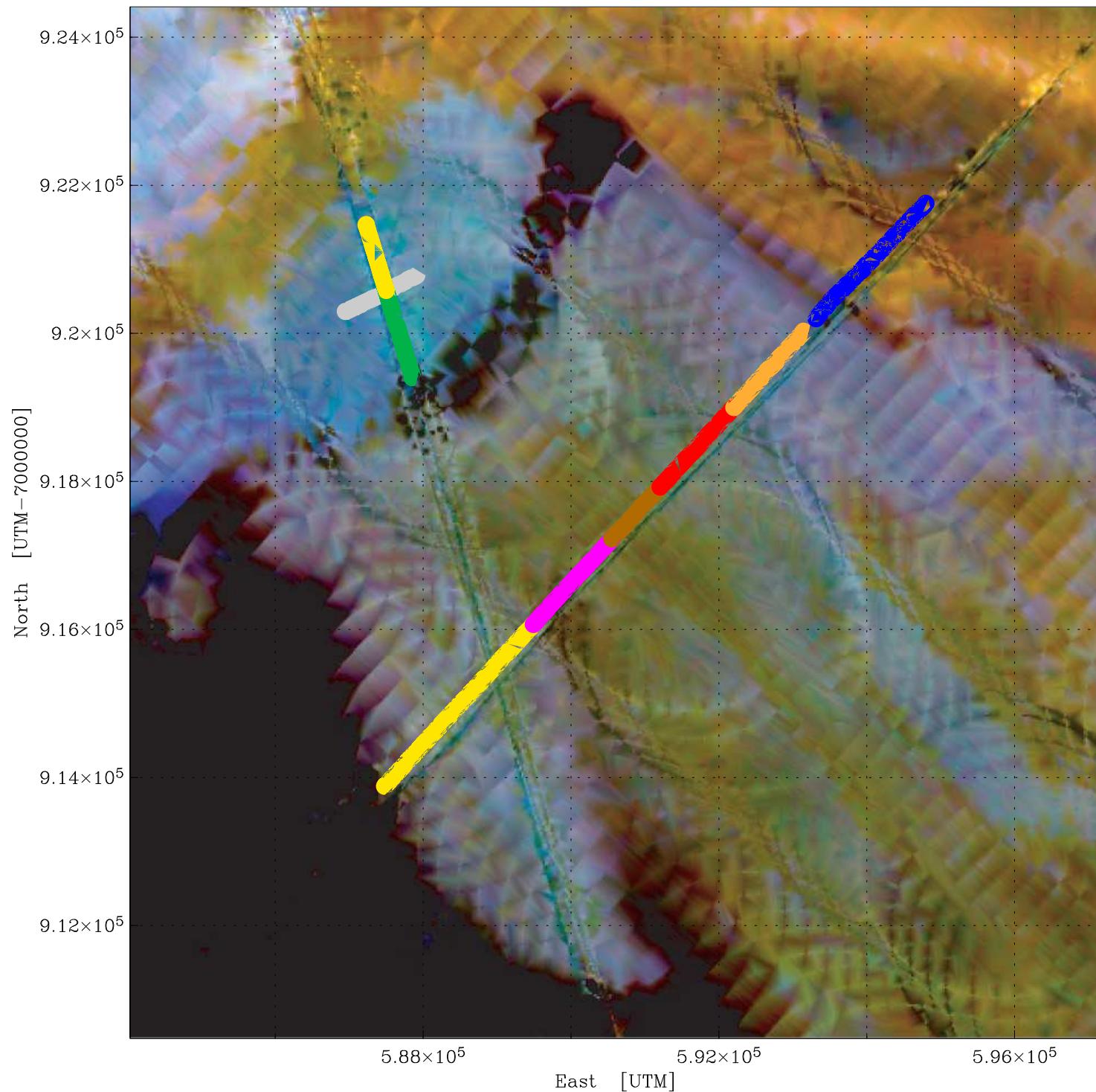
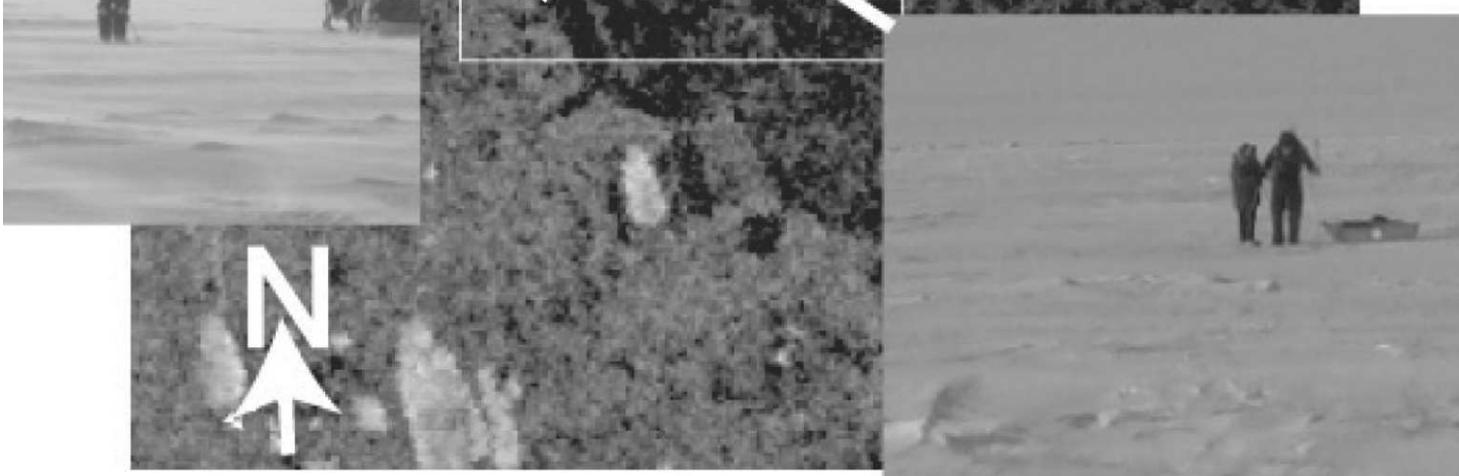
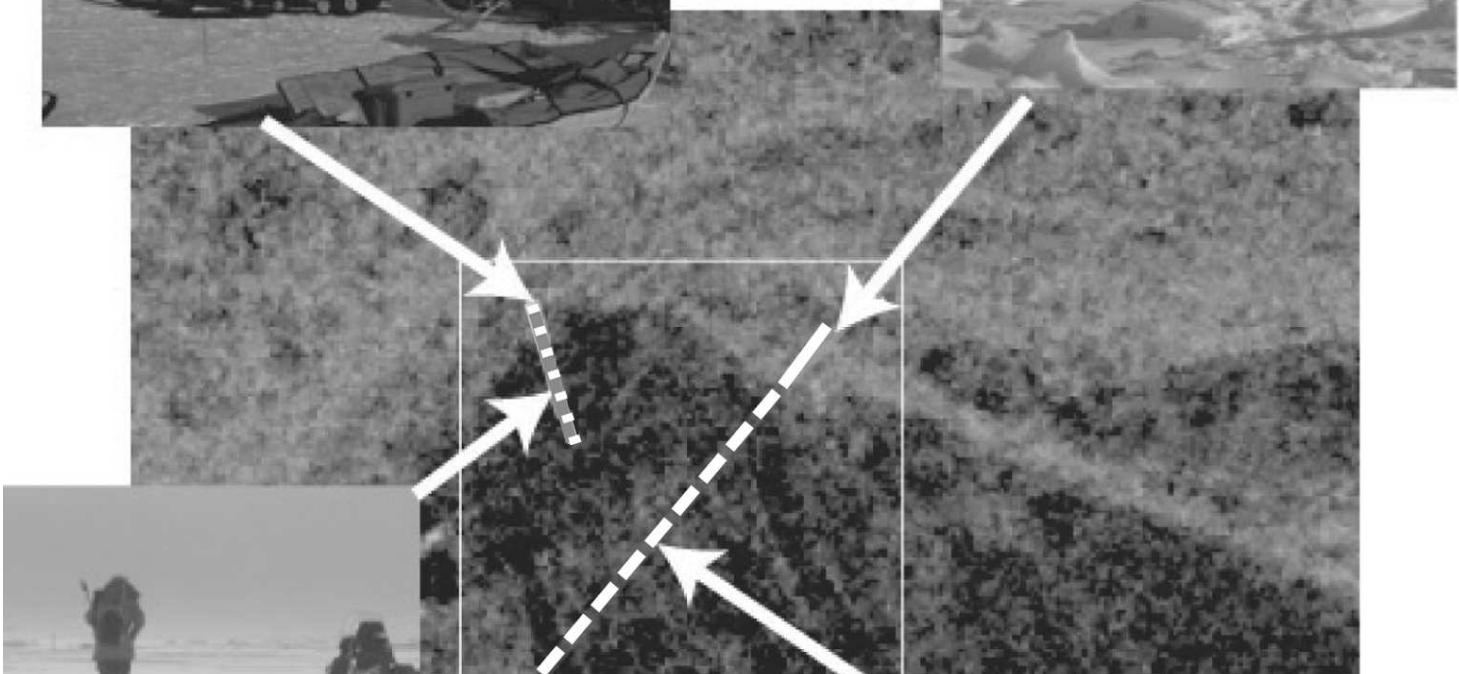


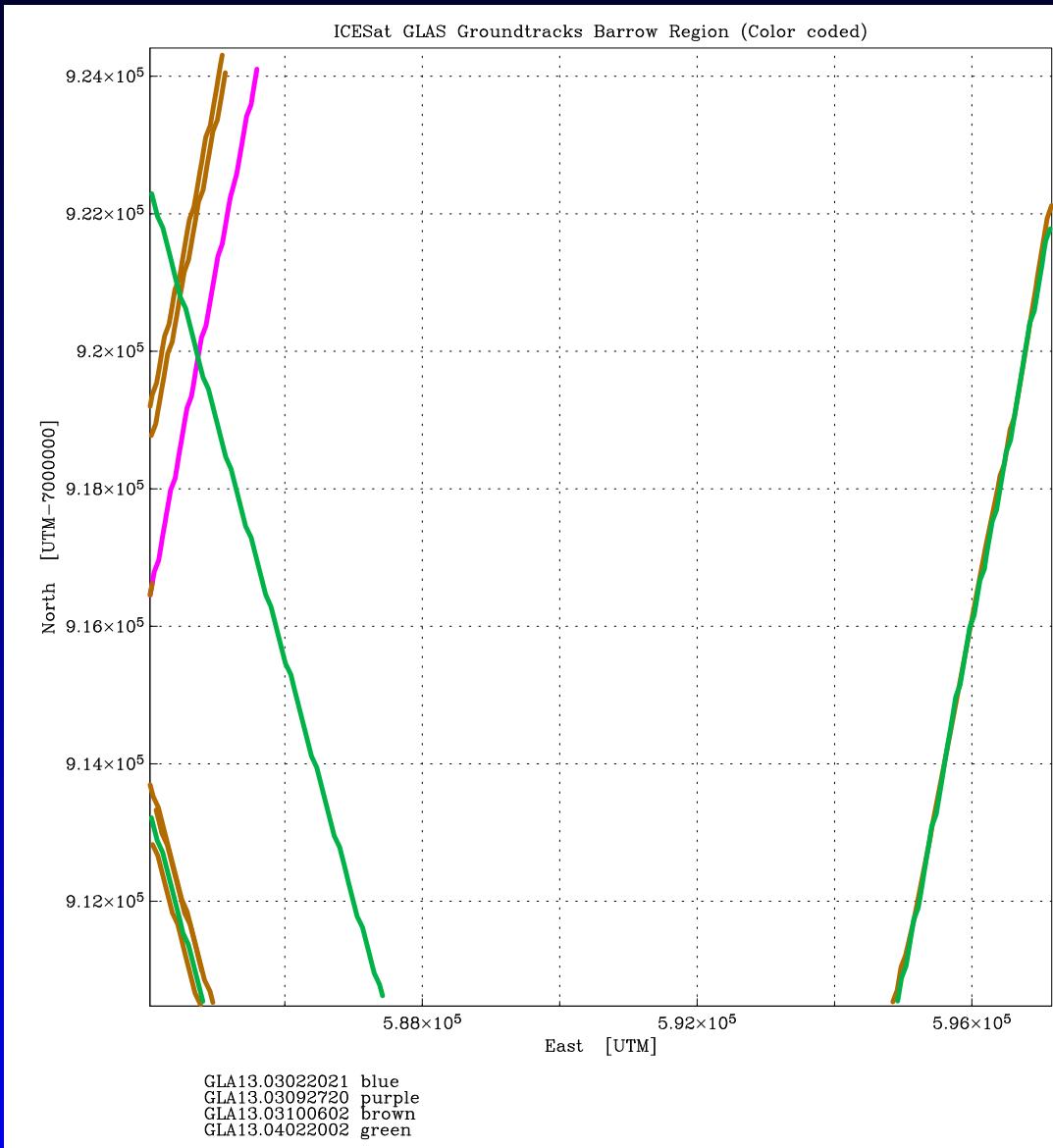
Table 1. Arctic Sea-Ice Classes near Point Barrow — Geostatistical Characterization

	z_0	$z_0(SLT)$	pond	$mindist_{big}$	$p1big$	$p2big$	description	development stage	complexity	sea-ice class
Beaufort Type	6.42	12.83	329	210	5.4	0.35	organization at large scale (210m); highly rubbed / ridged at smaller scale; large small-scale features of intermediate-high significance	late	f+	deformed ice
beaufort.sub1 (75-81)	6.43	12.86	331	25	5.0	0.092	ridges (subunit of Beaufort Type)	late	[subunit]	deformed ice
beaufort.sub2 (82-85)	10.36	20.72	850	50	117.4	0.5	very highly ridged (subunit of Beaufort Type)	late	[subunit]	deformed ice
Elson Type	3.18	6.36	81	—	—	—	small-scale features more significant than large ones, heterogeneous, low roughness	several	several	several
Elson segment 1 (14-35)	3.09	6.18	76.39	86	0.7	0.22	surface disturbed after freezing, no organized large features	early transitional	a	embayment ice
Elson segment 2 (35-46)	3.50	7.0	98.04	116	2.7	0.54	large-scale features dominant, organized at large scale	late	e	grounded ice, dynamically undisturbed
Elson segment 3 (46-52)	3.72	7.43	110.47	68	7.32	0.40	high roughness, highly complex, not much organization	intermediate transitional	c	transitional ice
Elson segment 4 (52-62)	4.46	8.92	159.29	144	2.62	0.36	very high roughness, increasing large-scale organization	later transitional	d	later-stage-transitional ice
Elson segment 5 (62-72)	2.62	5.24	55	138	0.18	0.34	2m and 20m features dominate large-scale (138m) features, relatively large disturbances	early intermediate transitional	b	shore-fast ice (no seaward dynamics)

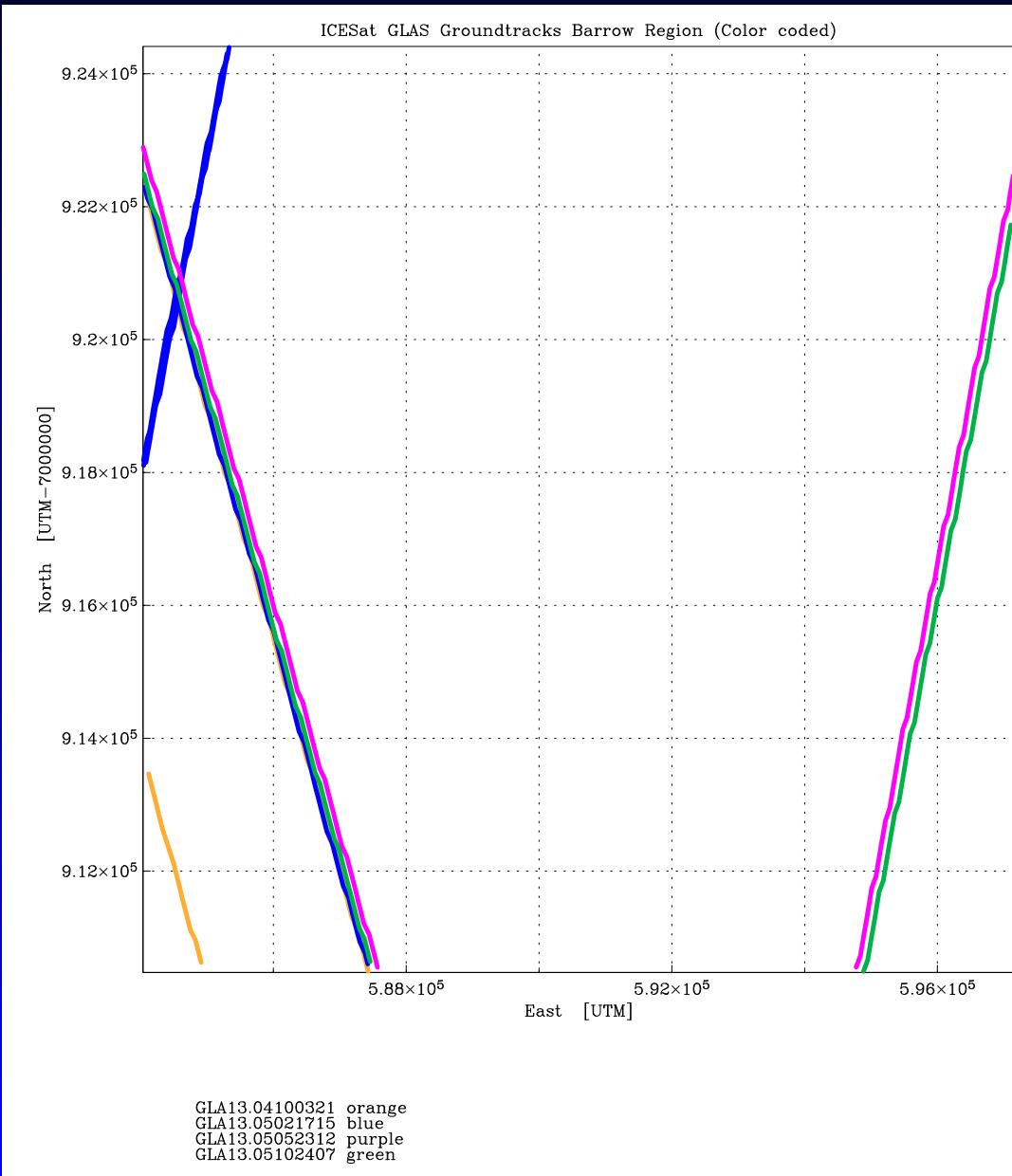


Roughness and Spatial Variability in GLAS Data

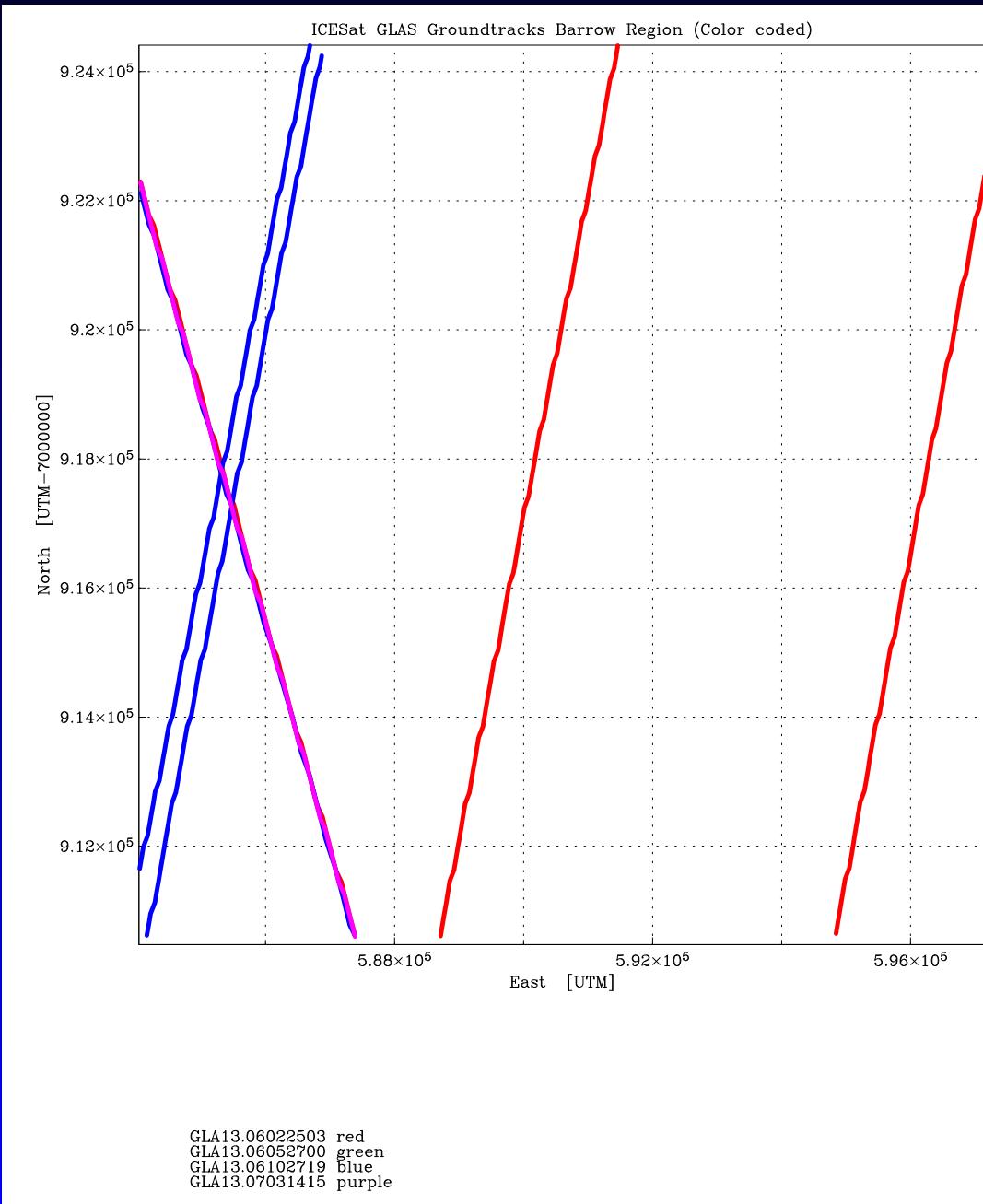
GLAS Tracks: Barrow Area [1]



GLAS Tracks: Barrow Area [2]

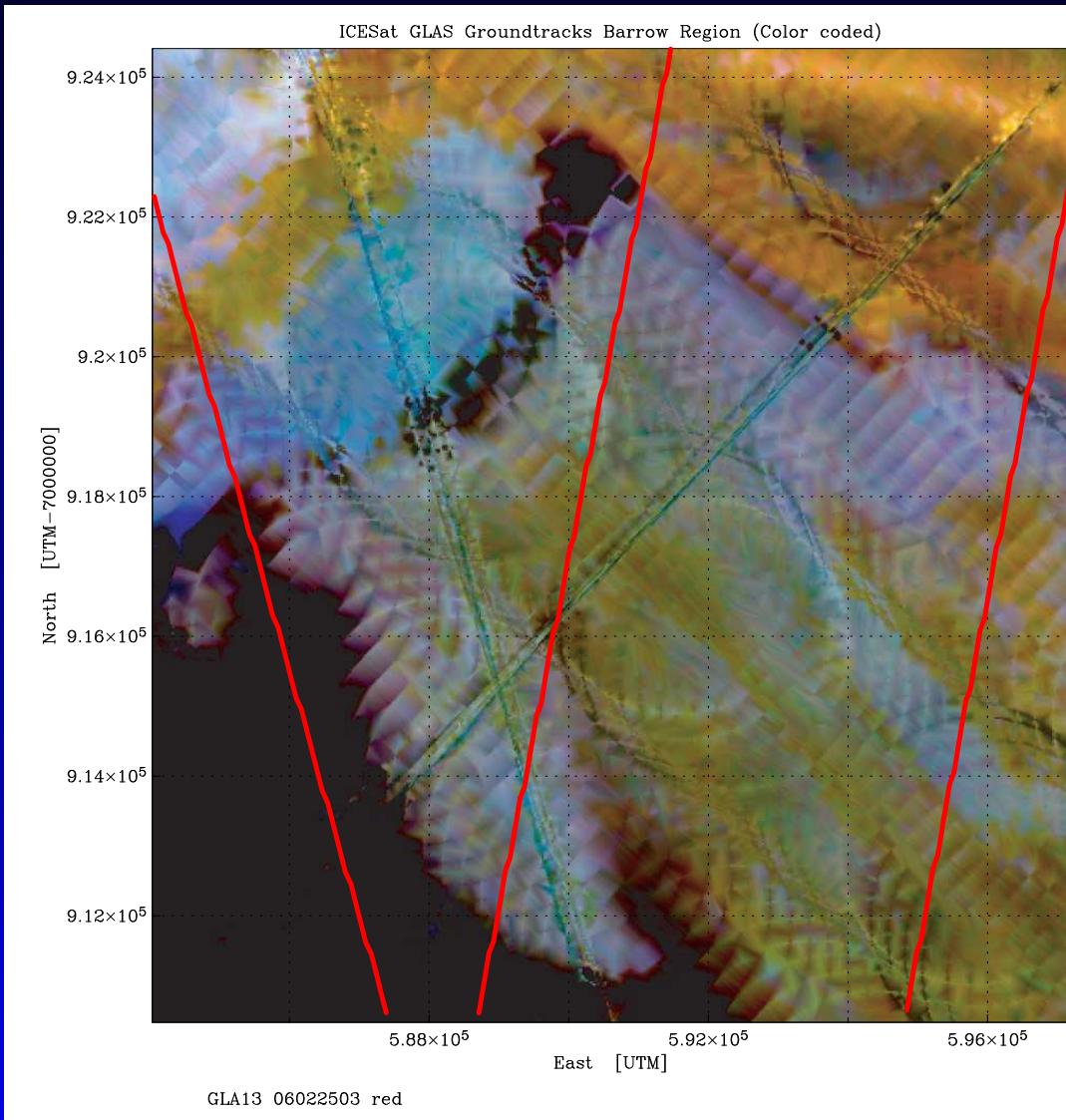


GLAS Tracks: Barrow Area [3]

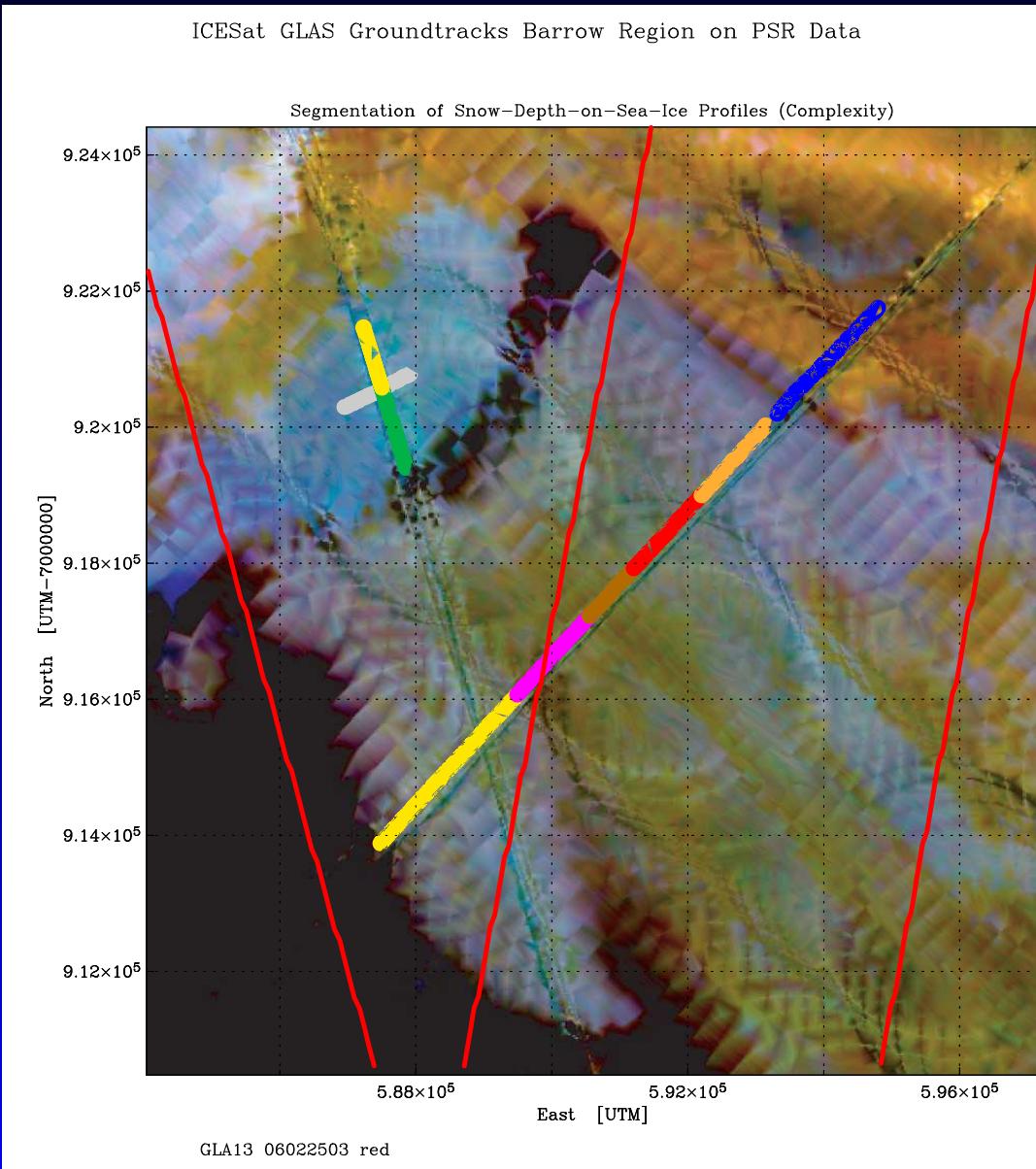


GLAS Tracks: Barrow Area

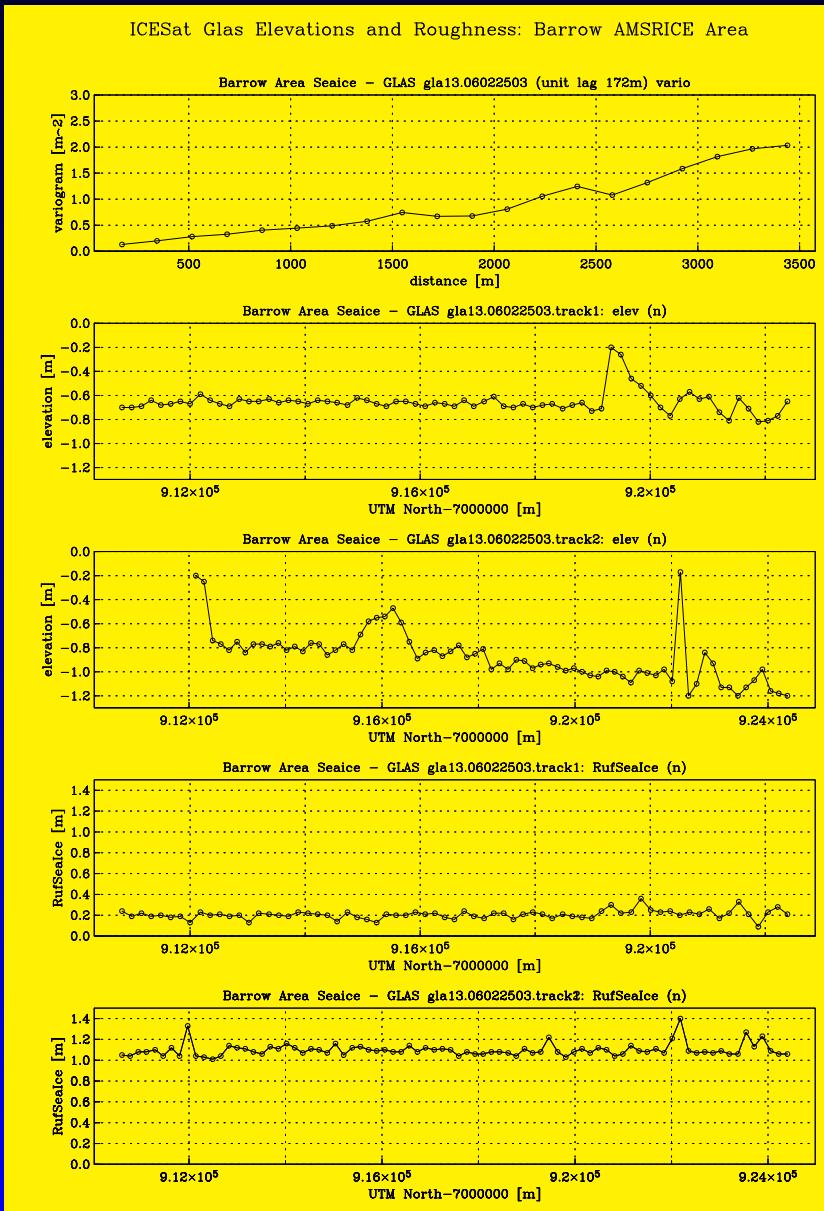
[3.1] Feb/March 2006 L3E



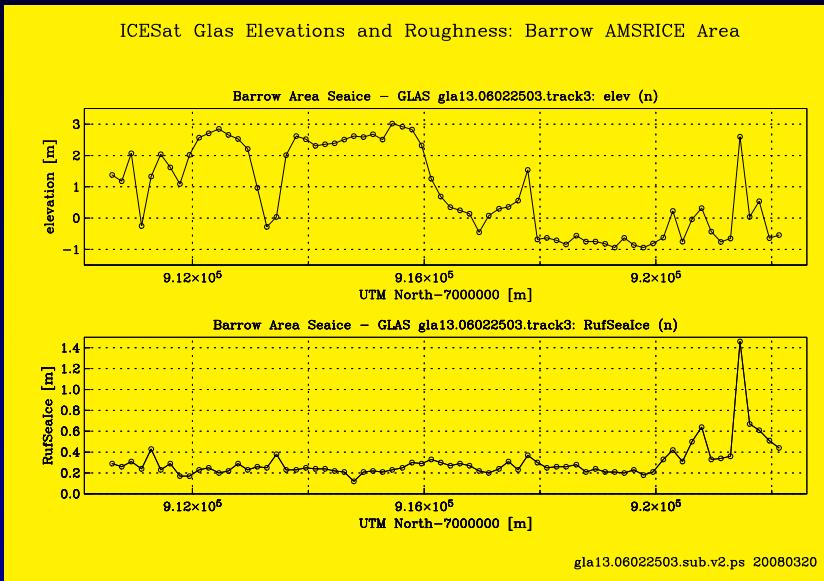
GLAS Tracks L3E with PSR and Snow-Depth Segmentation



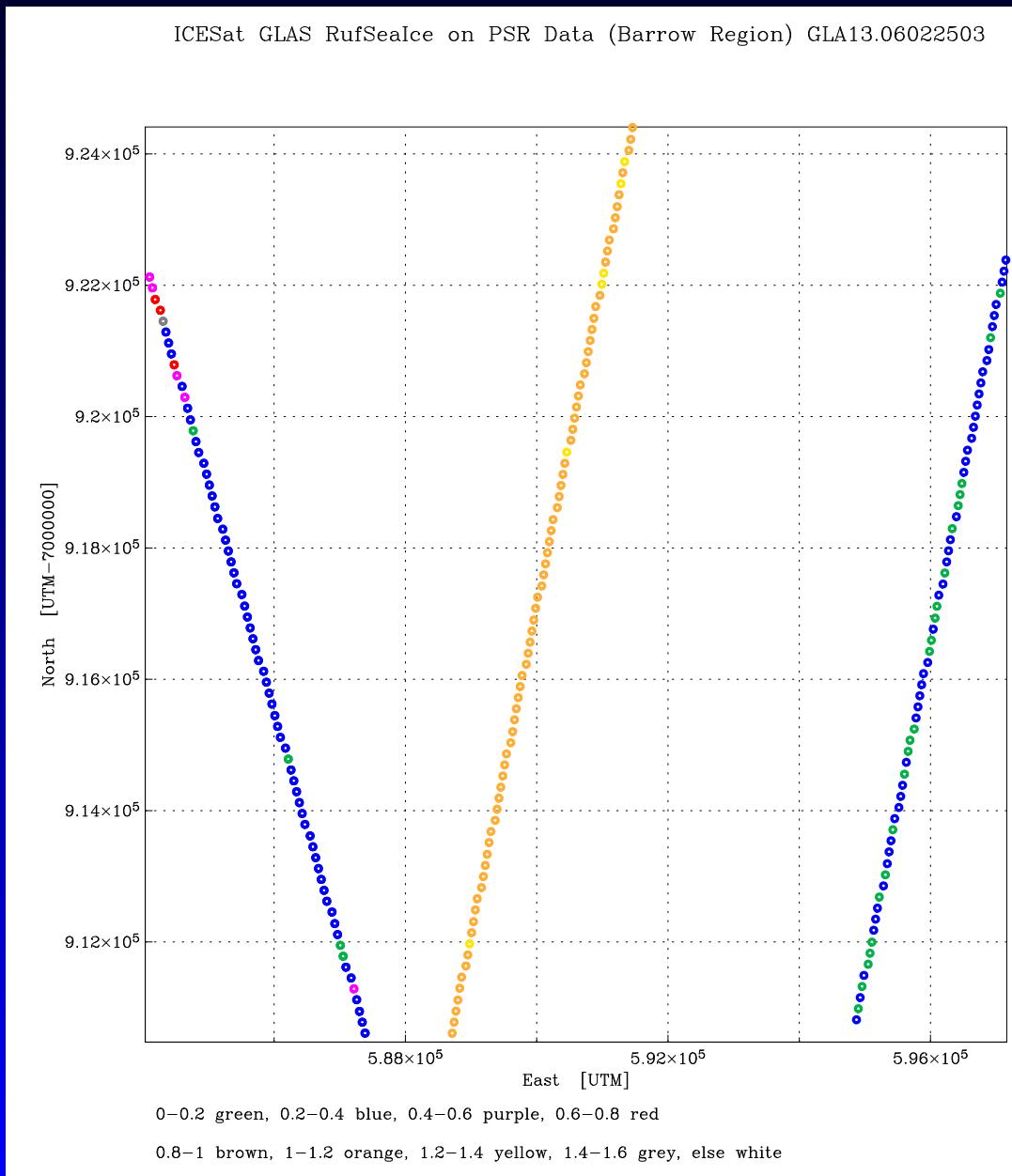
GLA13 Feb/March 2006 Barrow (L3E, rel28): Vario, Elev, RufSeaIce



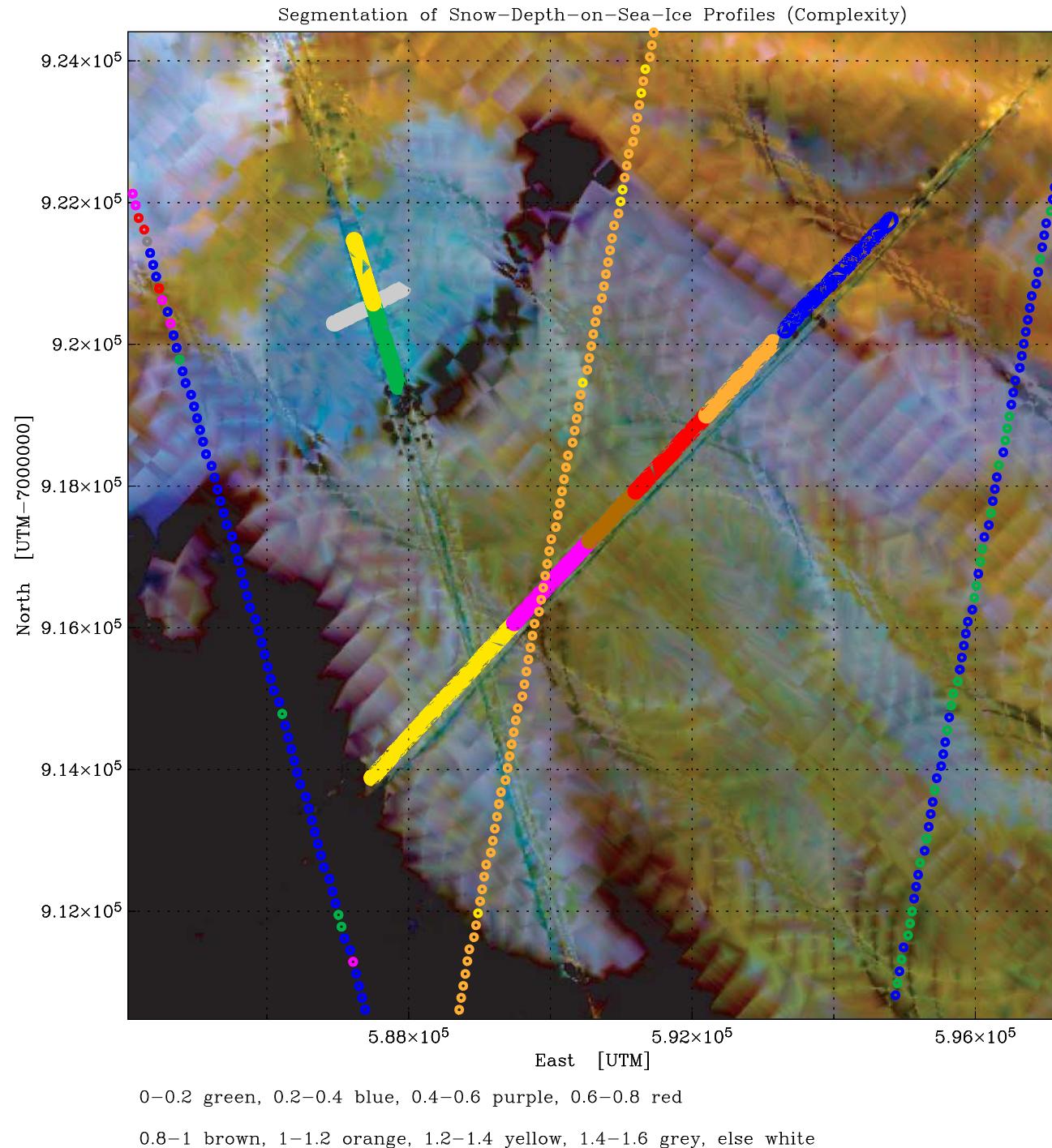
GLA13 Feb/March 2006 Barrow (L3E, rel28): Elev, RufSeaIce



GLAS Tracks L3E: Color By Ruf

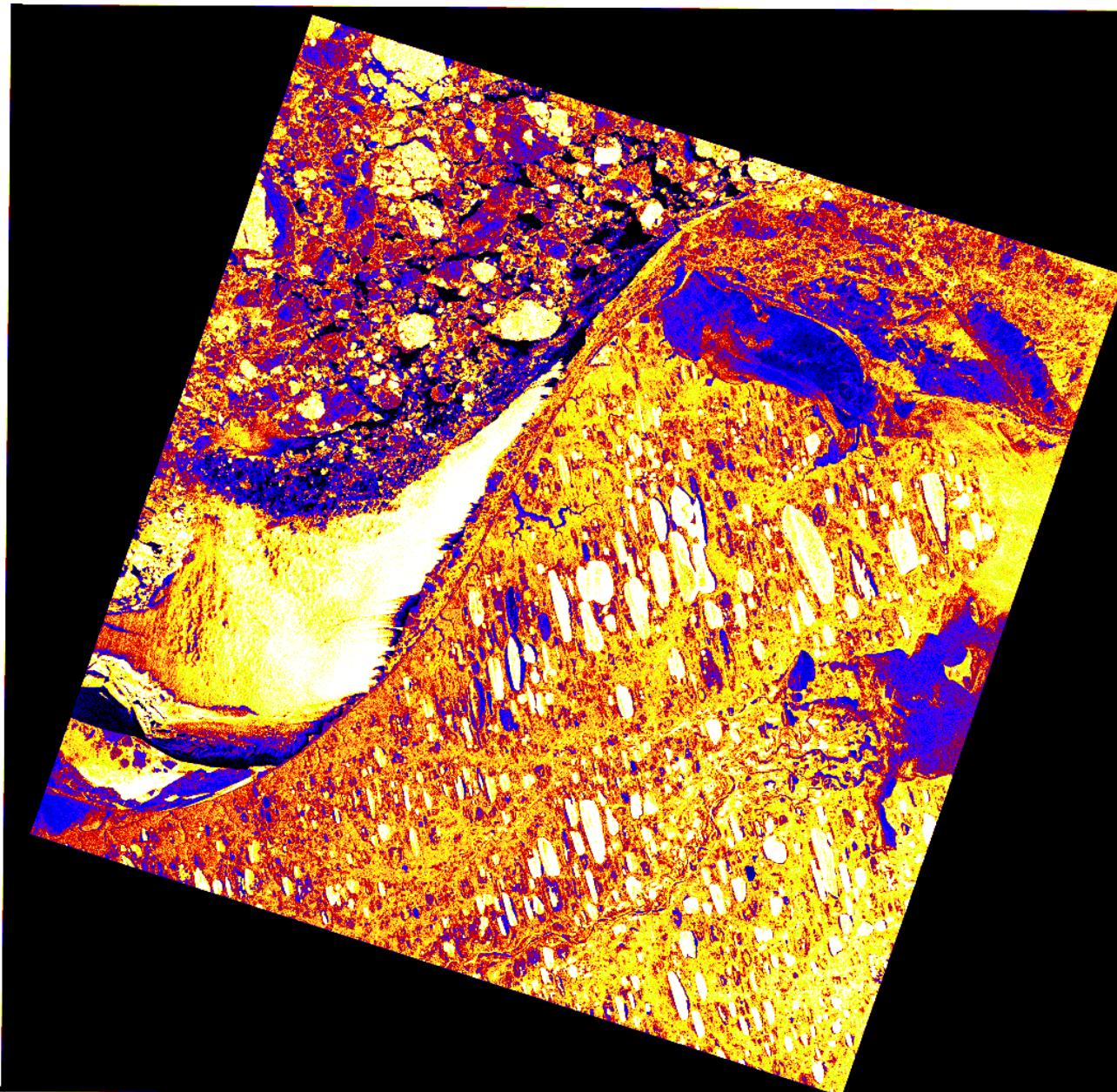


ICESat GLAS RufSealIce on PSR Data (Barrow Region) GLA13.06022503

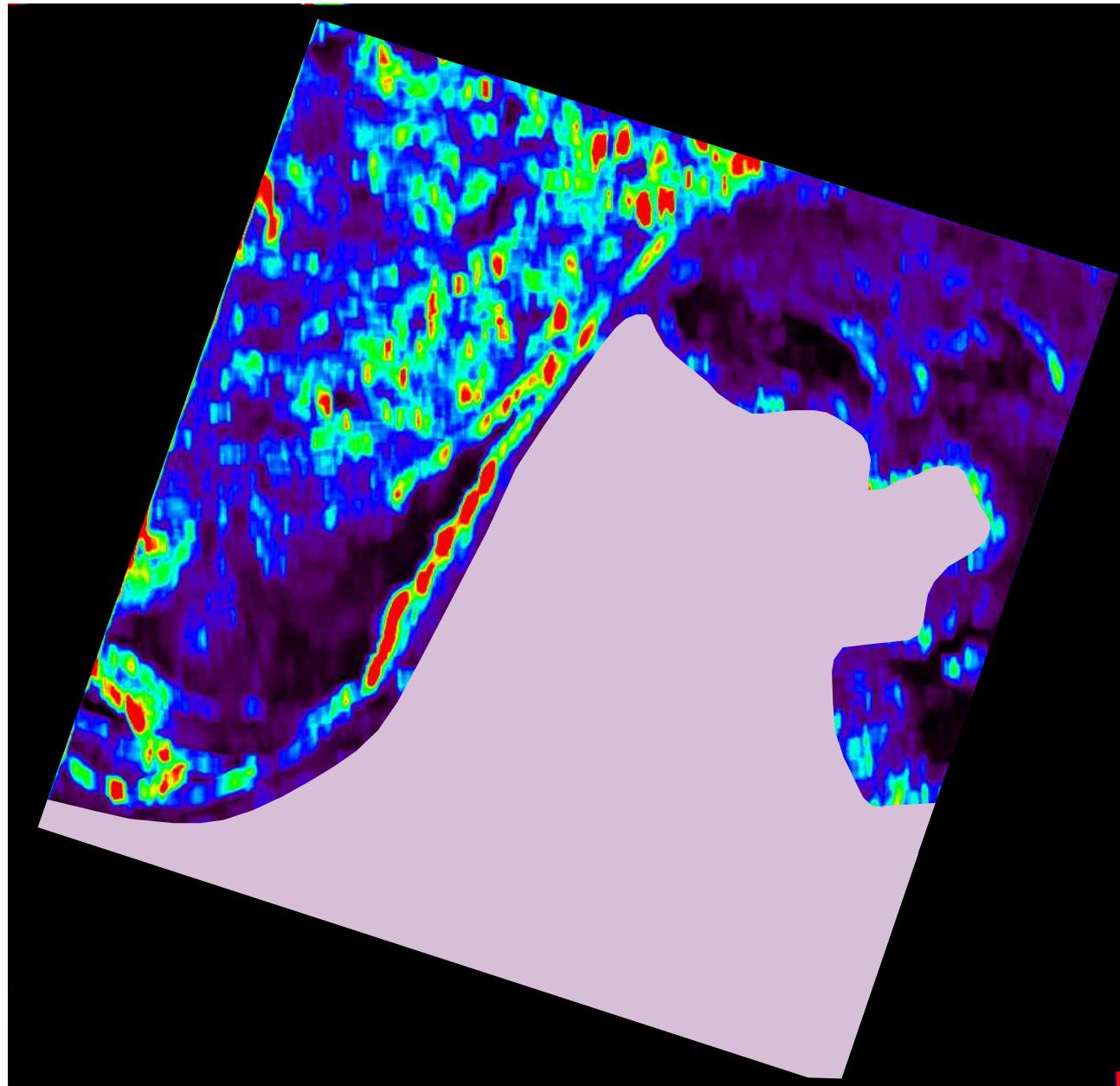


Classification of RADARSAT SAR data

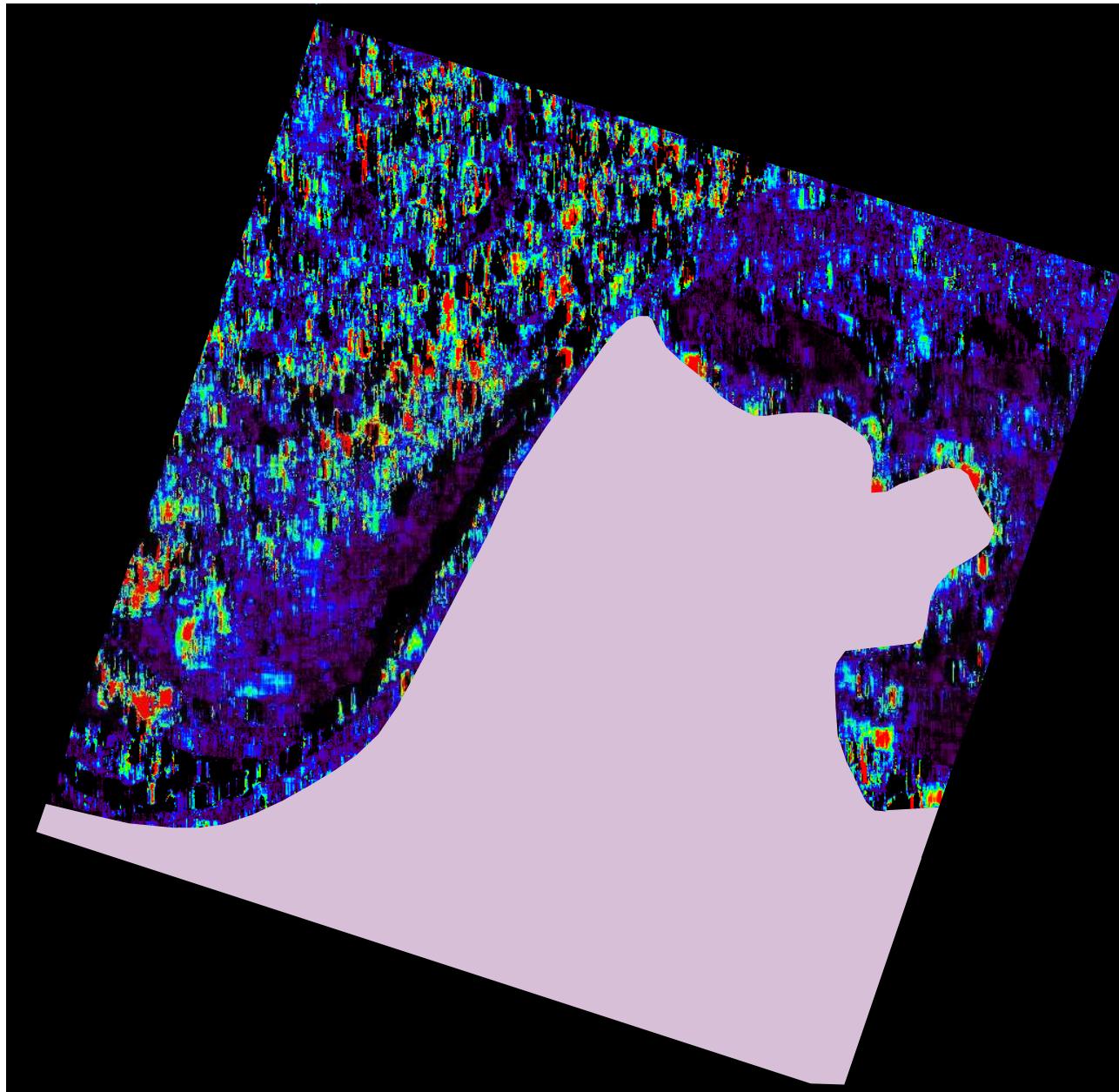
RADARSAT Data (March 2003)



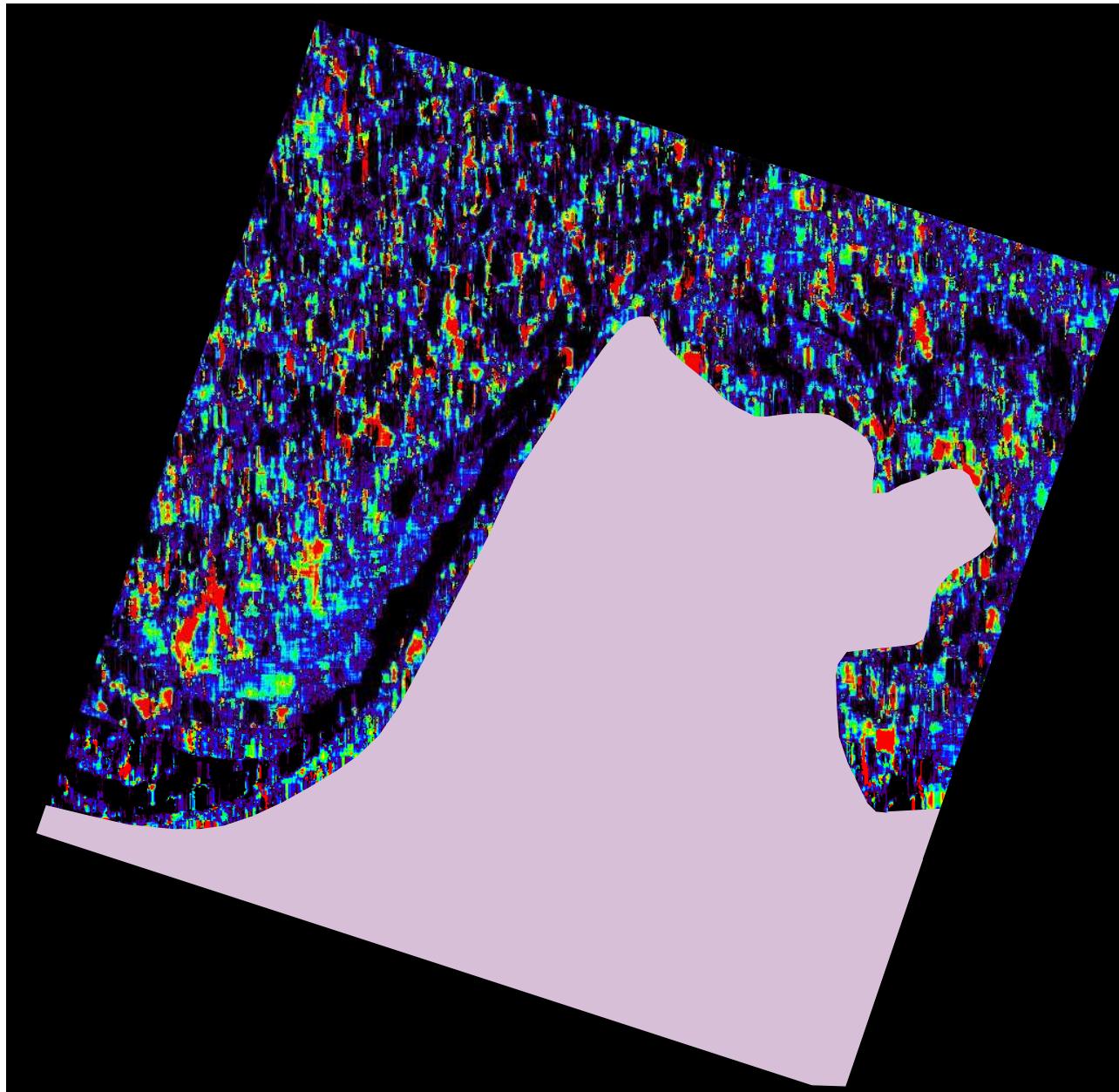
Parameter Map: pond



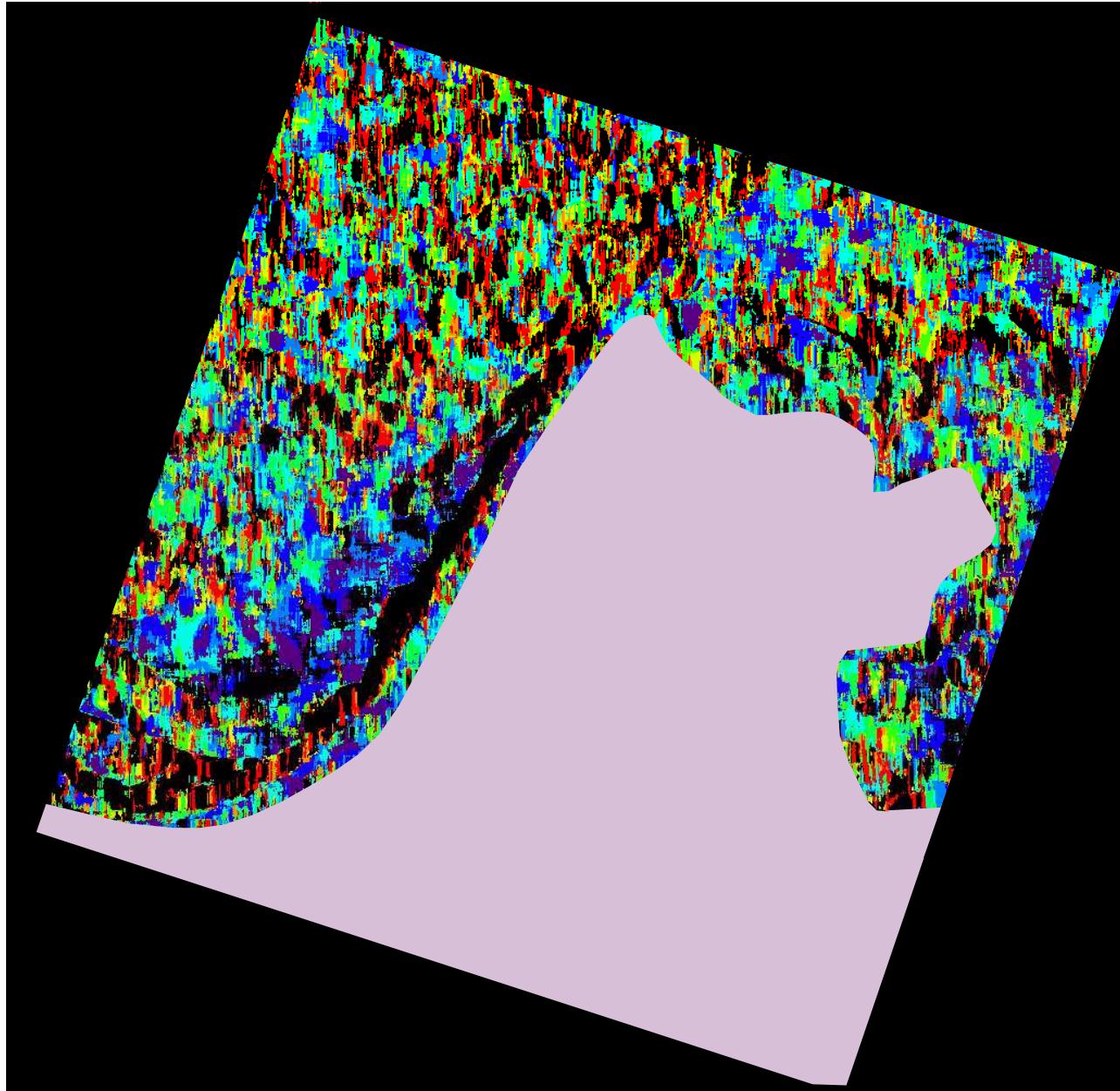
Parameter Map: p1



Parameter Map: p2

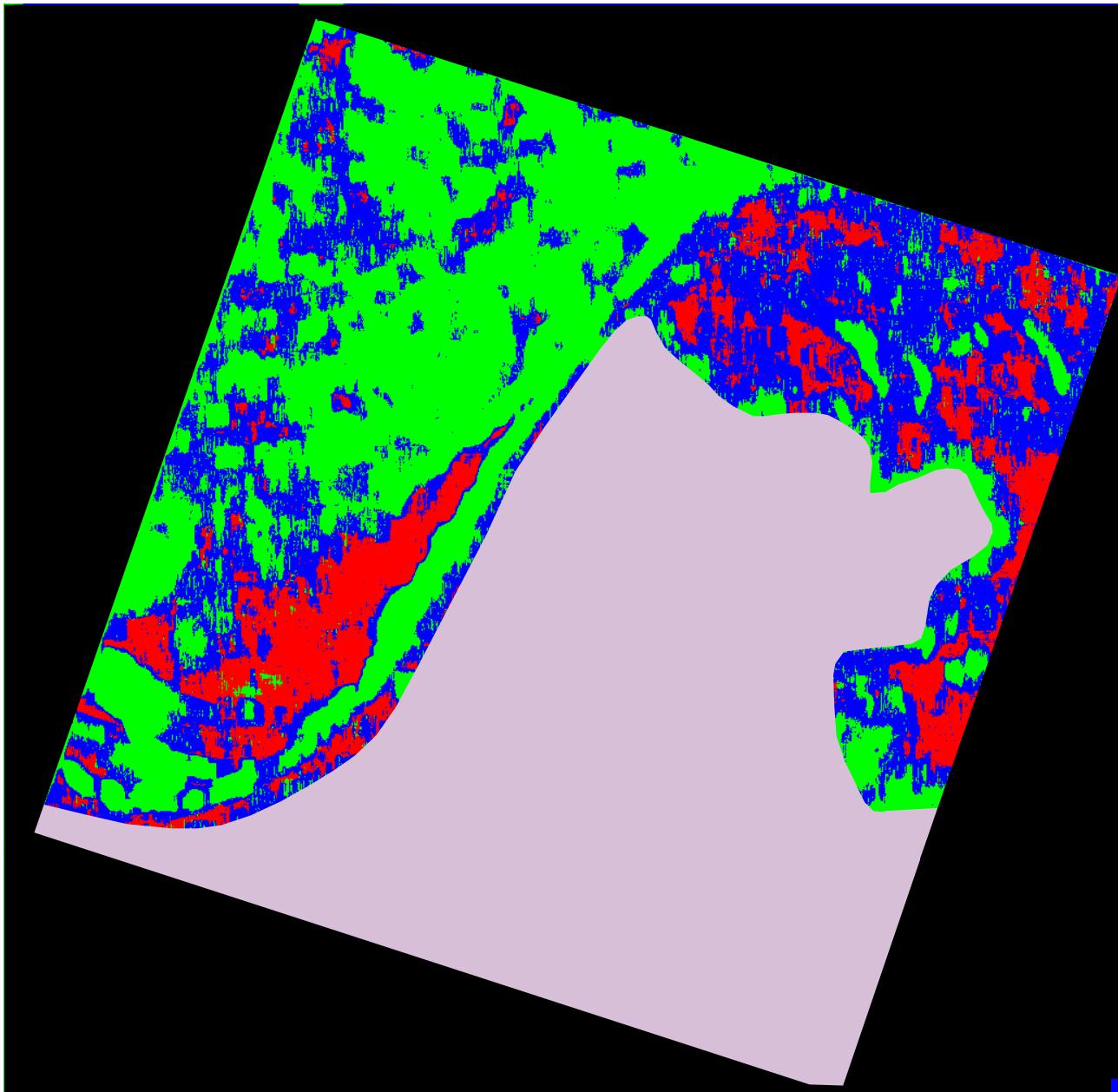


Parameter Map: mindist

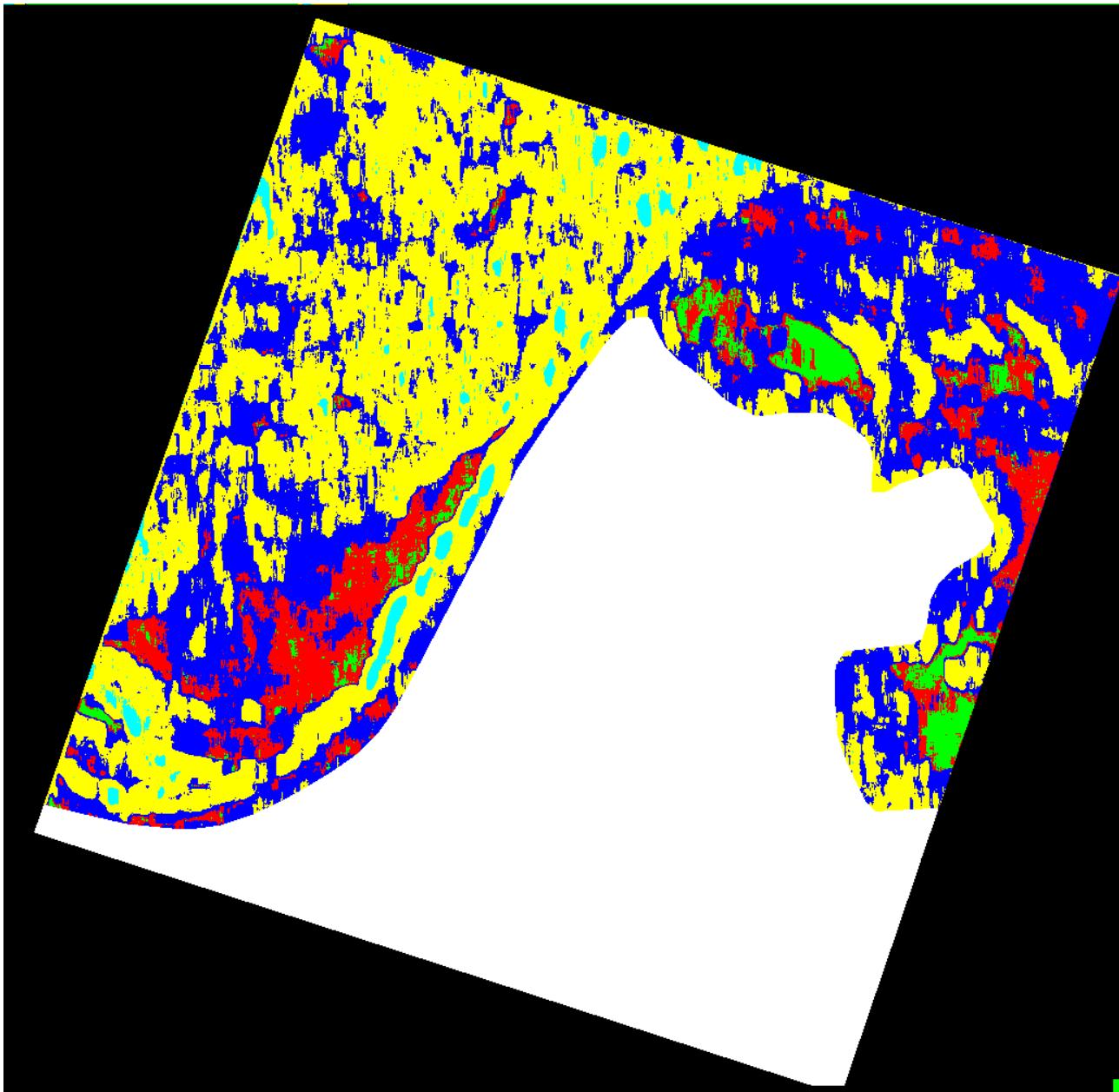


Maximum Likelihood Classification

Based on 4 Parameter Maps (3 Classes)



Maximum Likelihood Classification Based on 4 Parameter Maps (5 Classes)



Applications

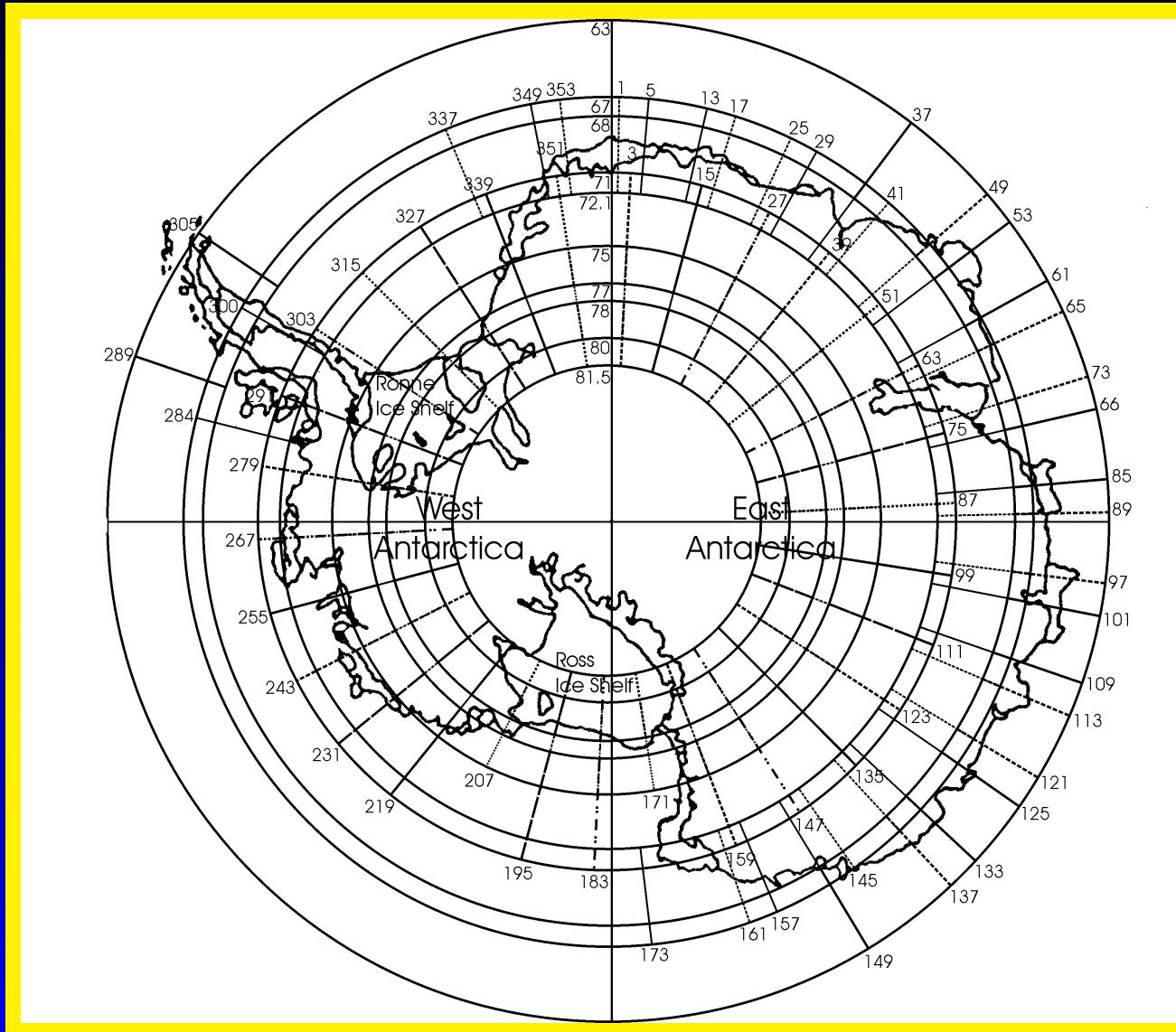
- Subscale information for ground truthing of (new) satellite sensors
- Deformation and dynamics of icestreams
- Characterization of seaice types
- Derivation of aerodynamic roughness length from data
- Importance of surface roughness for ablation

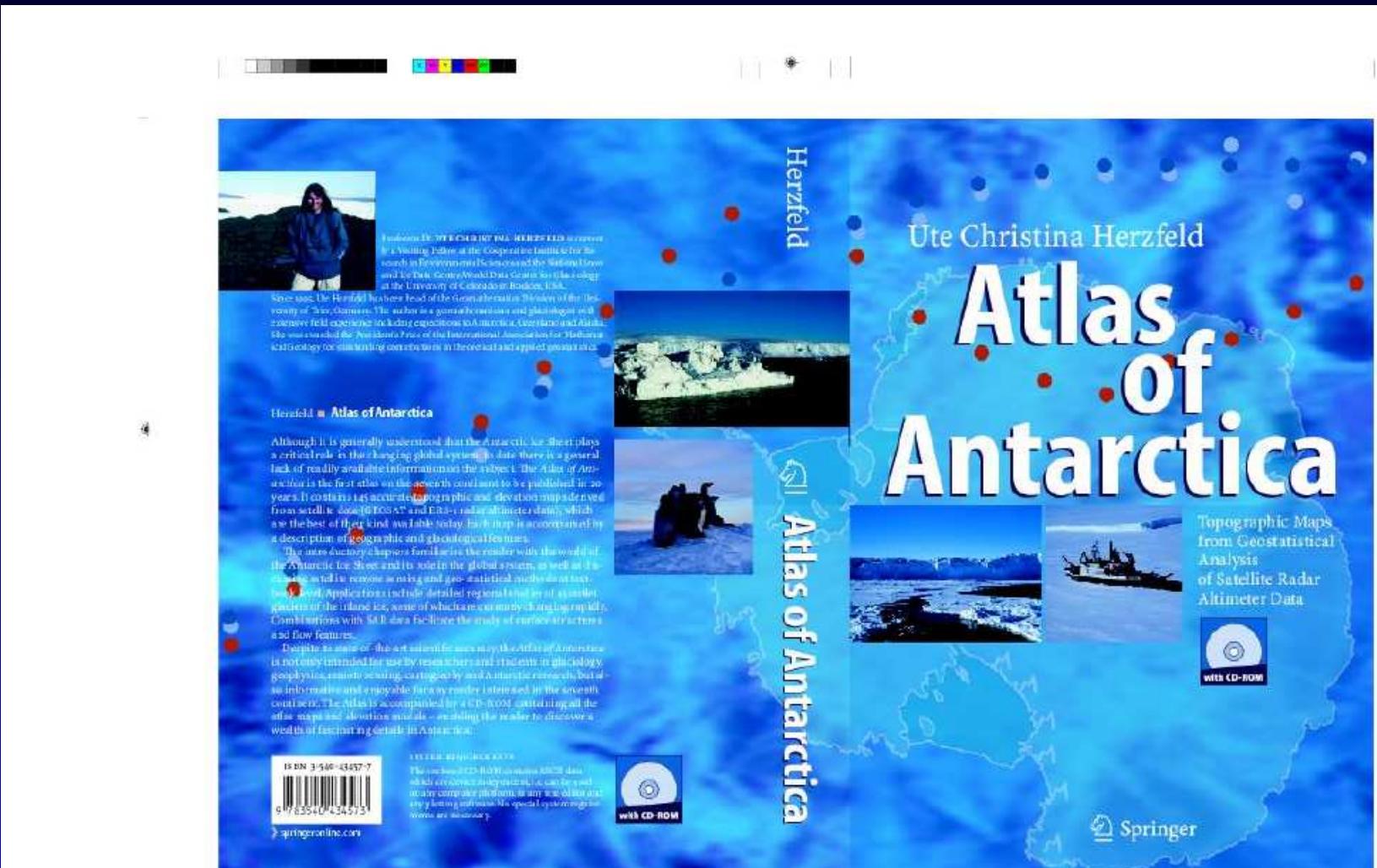
Changes in Amundsen Sea Glaciers, Antarctica

Altimeter Data Sources

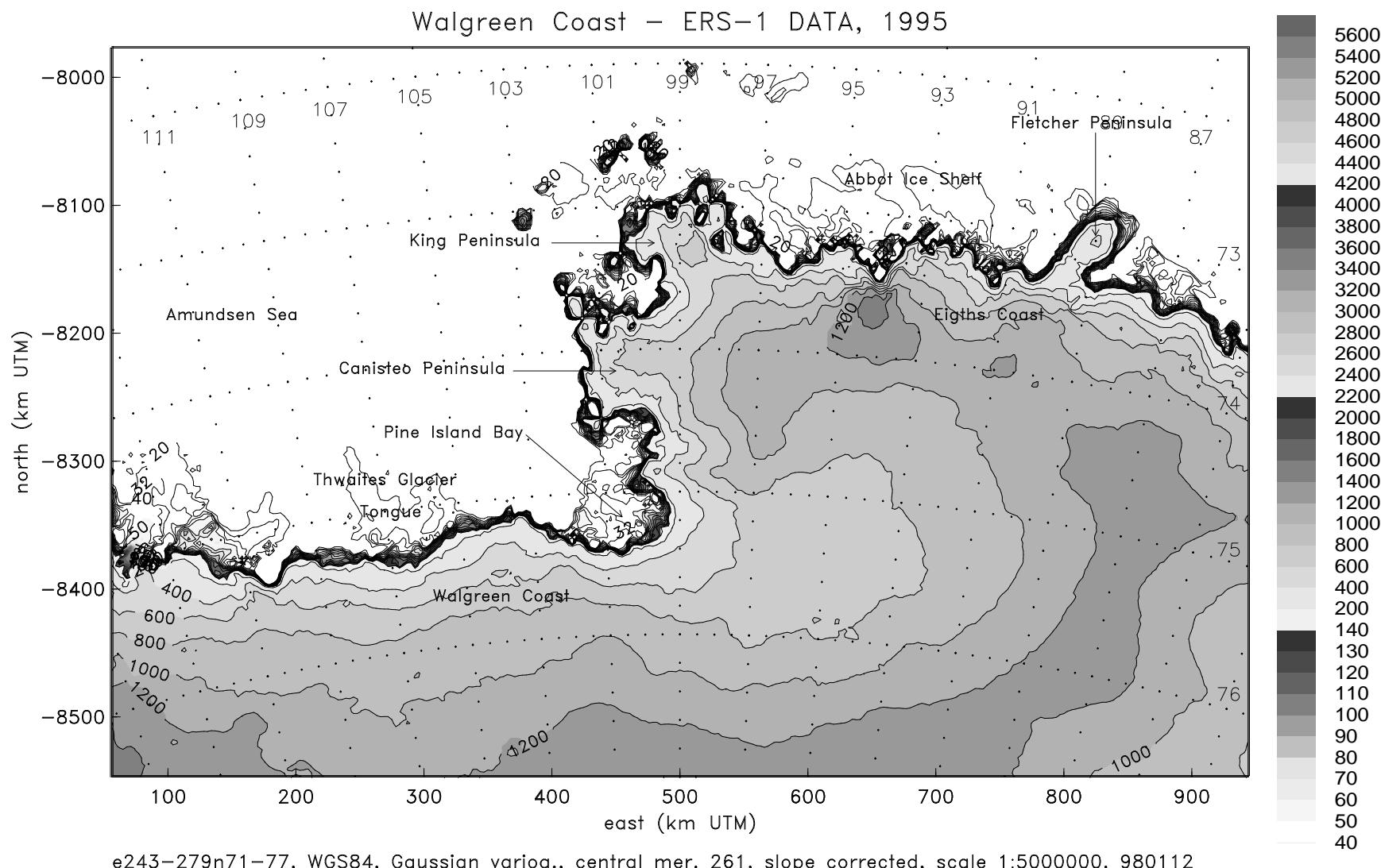
- (a) ERS-1 Satellite Radar Altimeter Data
(01 Feb–01 Aug 1995)
- (b) ICESat GLAS Data (4 Oct–20 Nov 2003;
Laser 2A; rel18)
- (c) ICESat GLAS Data (Oct/Nov 2006; Laser 3G;
rel28)

Antarctic Atlas Mapping Scheme

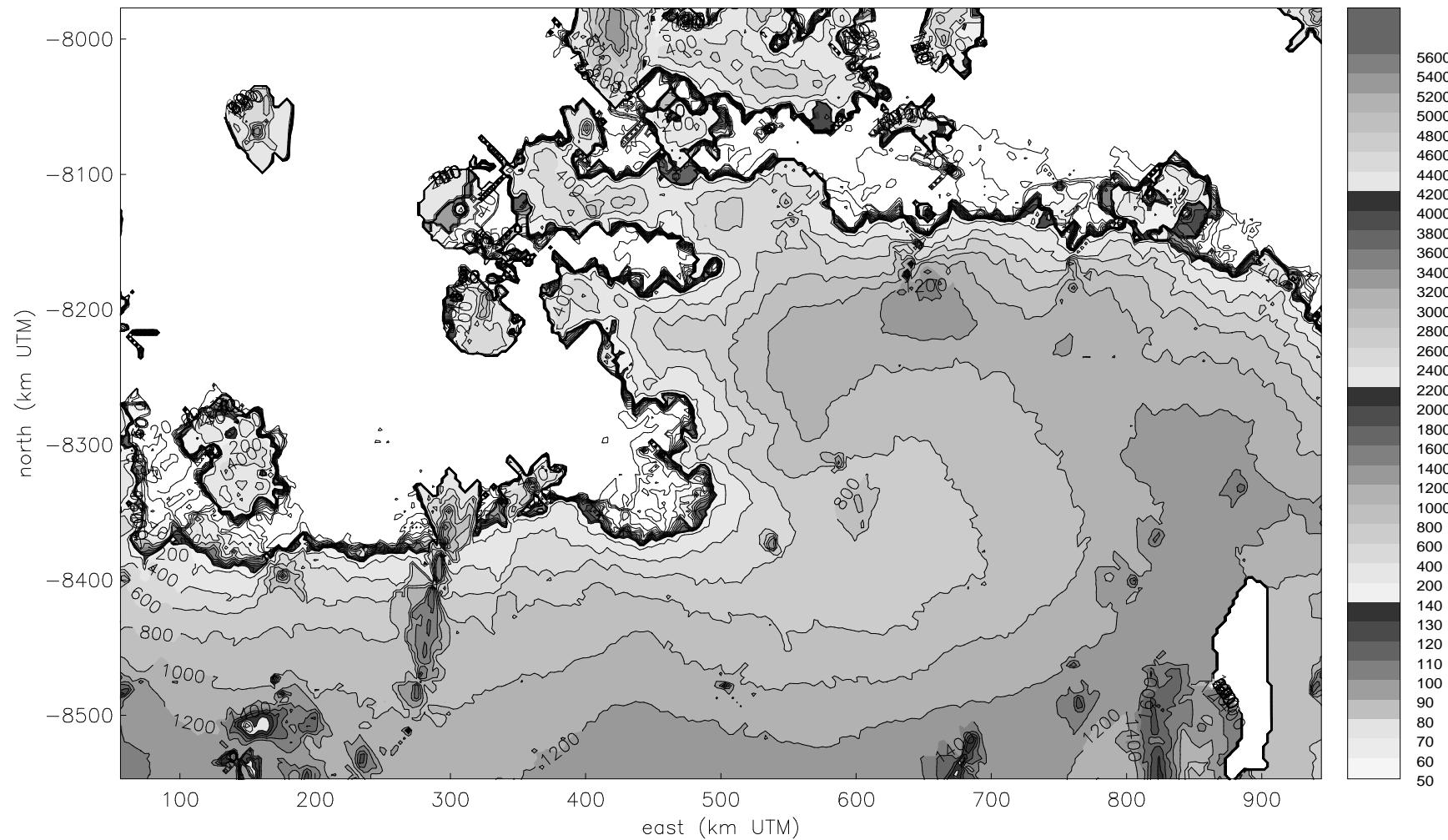




Präsentation Projekt Adressen



e243-279n71-77, WGS84, Gaussian variog., central mer. 261, slope corrected, scale 1:5000000, 980112



```

inuni.last33days.dat 20050225
297, 191, 1, 54500, -8548500, 0, 3000, 3000, 0, 1
30000.,16,10.,1,0,0,0,200.,8
1,1,0,0,0,33
0,0,0,'*'
gla06.last33days.trans
20050407
/data1/ws/pinegl/piggles/rel18/gla06/last33days.totps

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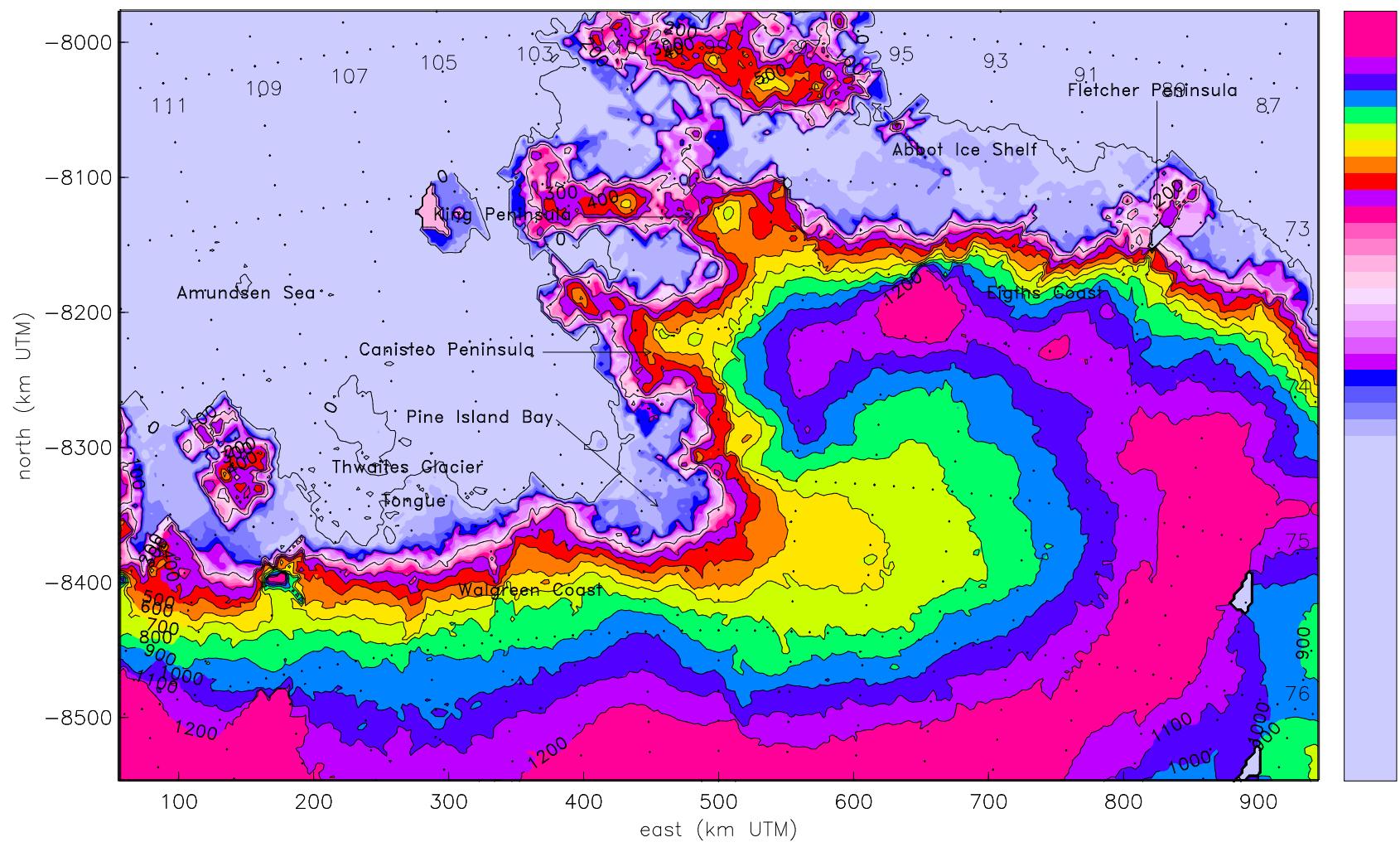
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'*'
last33days.krg
last33days.dtm
last33days.est
1CE ELEV',0,0,0,0,6
350,3100,3468.21,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0

```

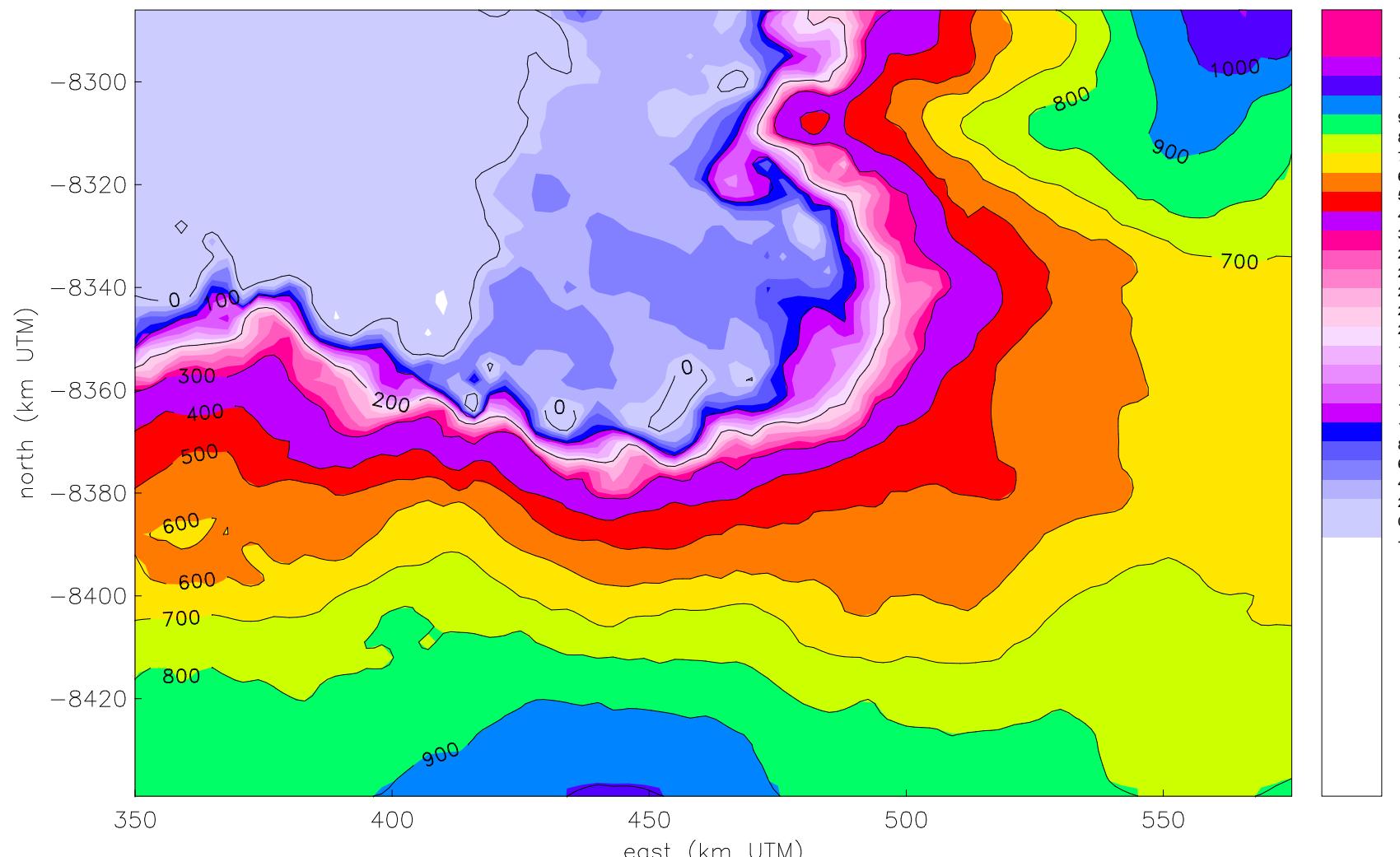
GLA06 (rel18, L2A, last33days) vario1(350,3450,6000m) search-rg 30km

Walgreen Coast – GLAS Data



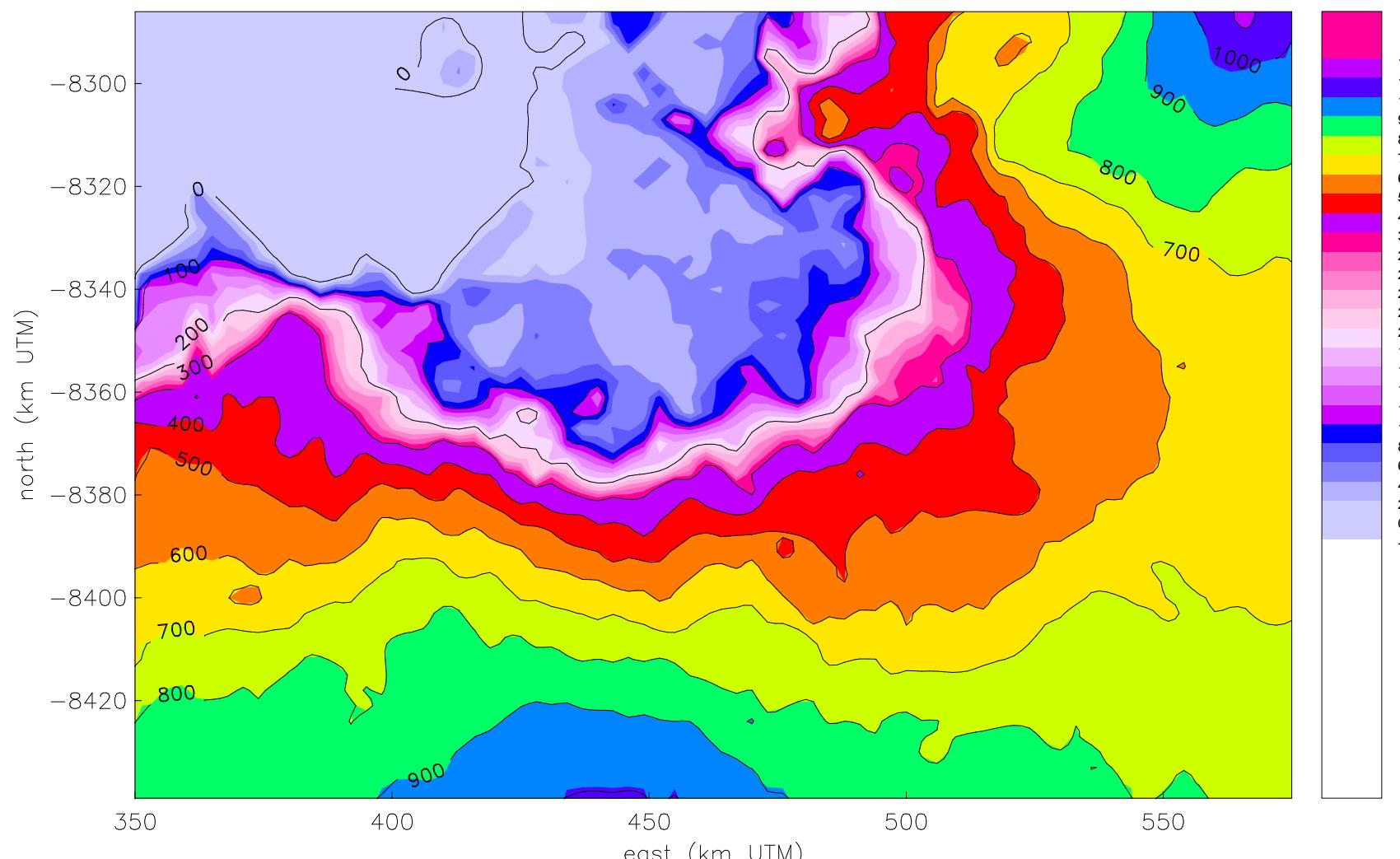
GLA06 Data, (Laser 2A, gain-crit, rel18), Oct/Nov 2003, vario(350,3450,6000m), search-rg 30km, 1:5000000,
gla06.1.gain.0.col8

Pine Island Glacier – ERS-1 Data, 1995



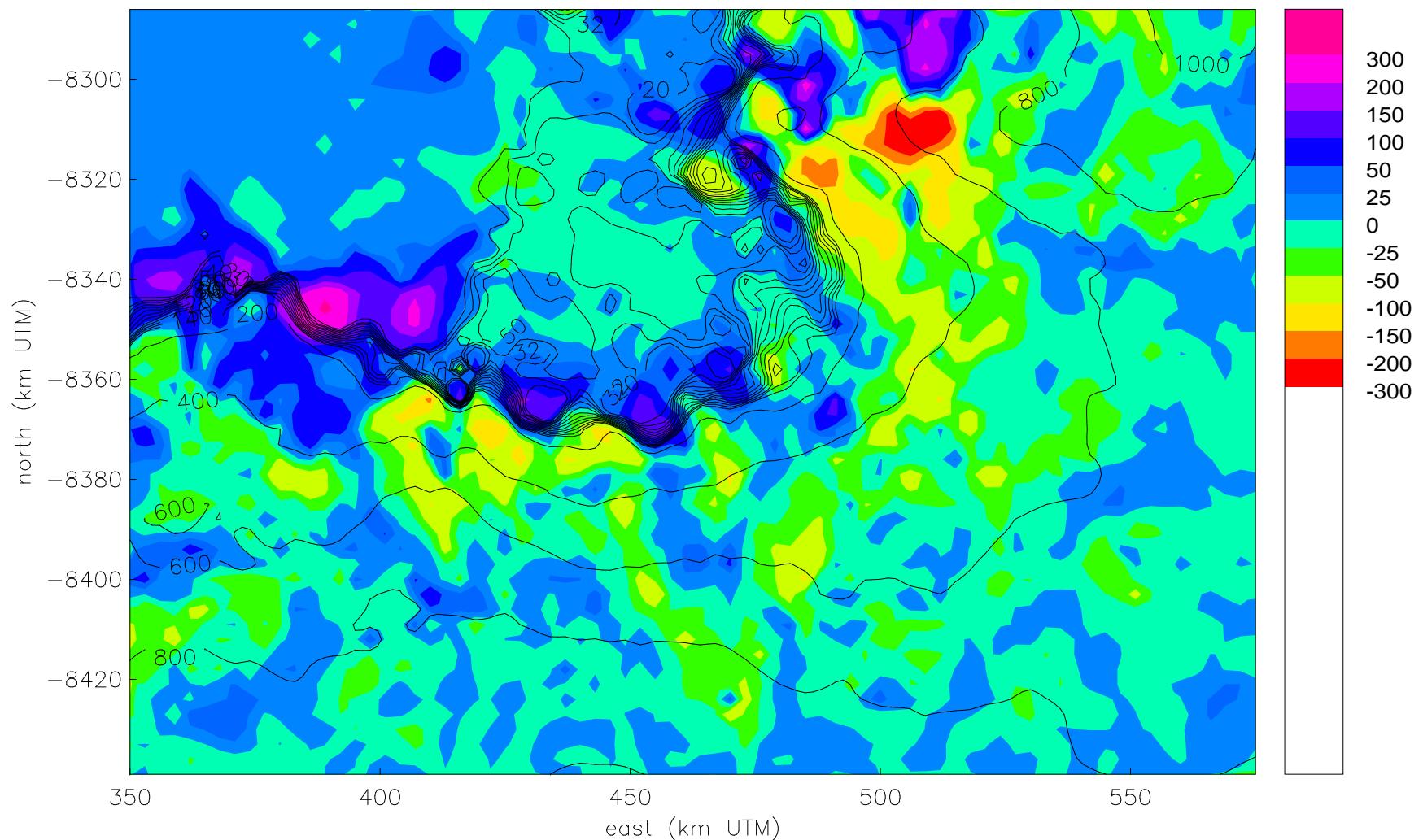
1:2000000, m261e243–279n71–77.e.smallpine2.v2.col8

Pine Island Glacier – GLAS Data



GLA06 Data, (Laser 2A, gain-crit, rel18), Oct/Nov 2003, vario(350,3450,6000m), search-rg
30km, 1:2000000, gla06.1.gain.smallpine2.v2.col8

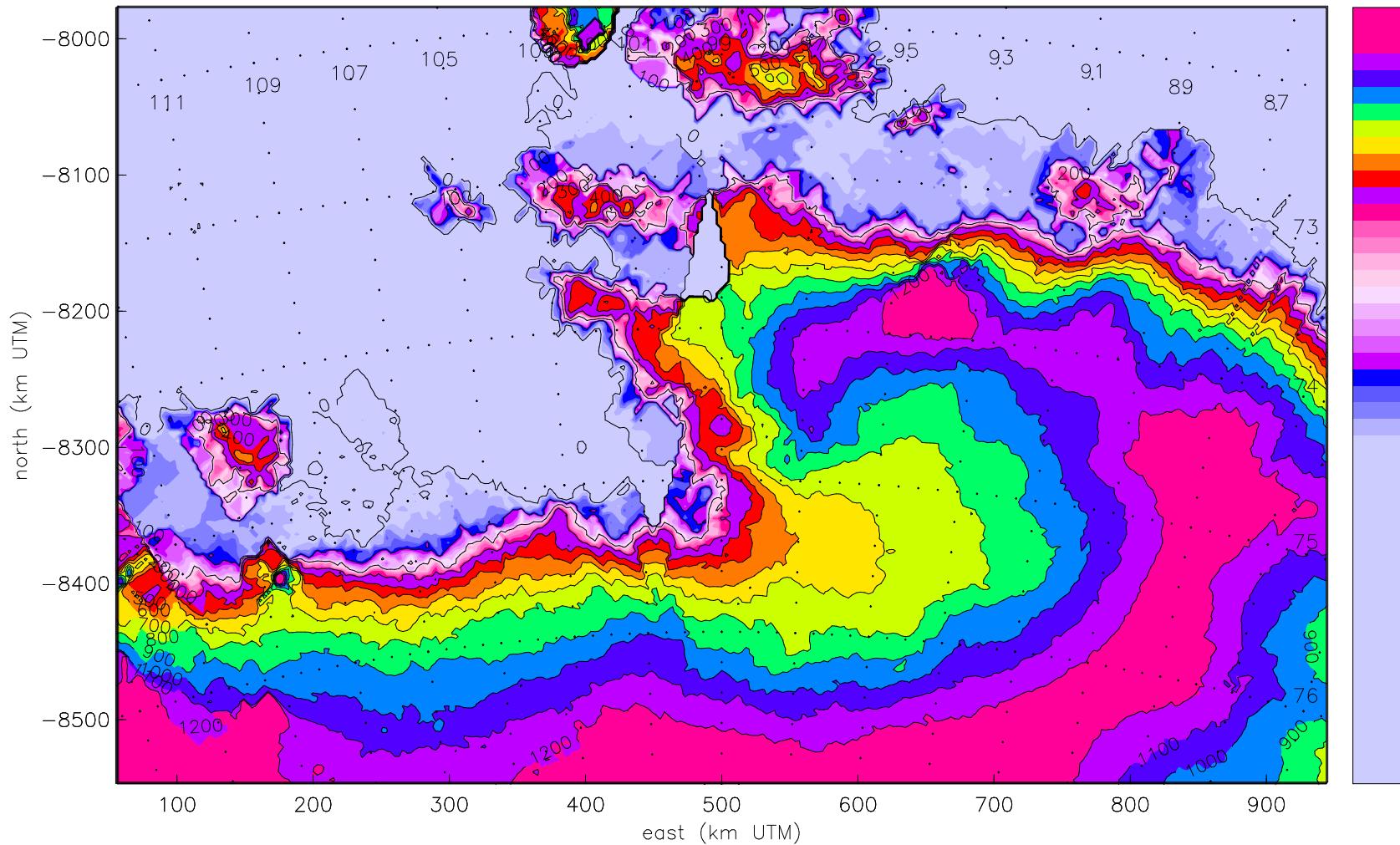
Pine Island Glacier – GLAS (2003) minus ERS–1 (1995) [with ERS–1 contours]



scale 1:2000000 diff glasgain–ers1.wers1cont.smallpine2.col10.v2.totps 20050404

gla06.1.gain.smallpine2.0.dtm minus m261e243–279n71–77.e.smallpine2.0.dtm

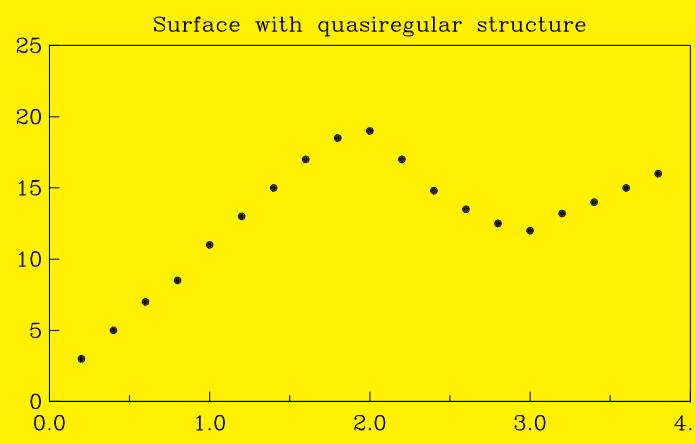
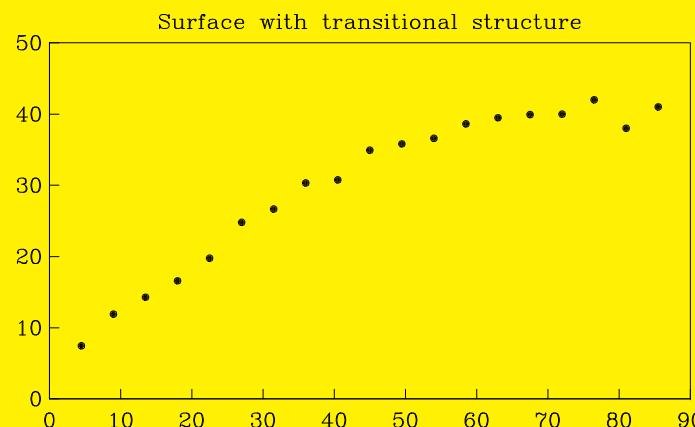
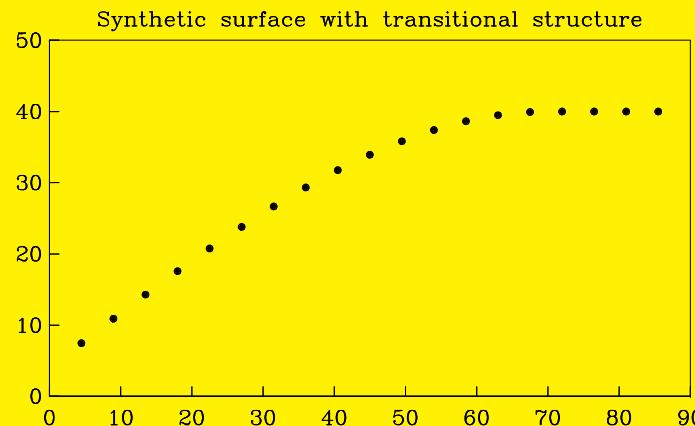
Walgreen Coast, Antarctica: GLA12 2006102512 (L3G, rel28)



Appendix

Geostatistical Classification —
Principles, Parameters, Feature Vectors, Classification
Algorithms

Typical Experimental Variograms



Definition of Vario Functions

$$V = \{(x, z) \text{ with } x = (x_1, x_2) \in \mathcal{D} \text{ and } z = z(x)\} \subseteq \mathcal{R}^3$$

discrete-surface case or

$$V = \{(x, z) \text{ with } x \in \mathcal{D} \text{ and } z = z(x)\} \subseteq \mathcal{R}^2$$

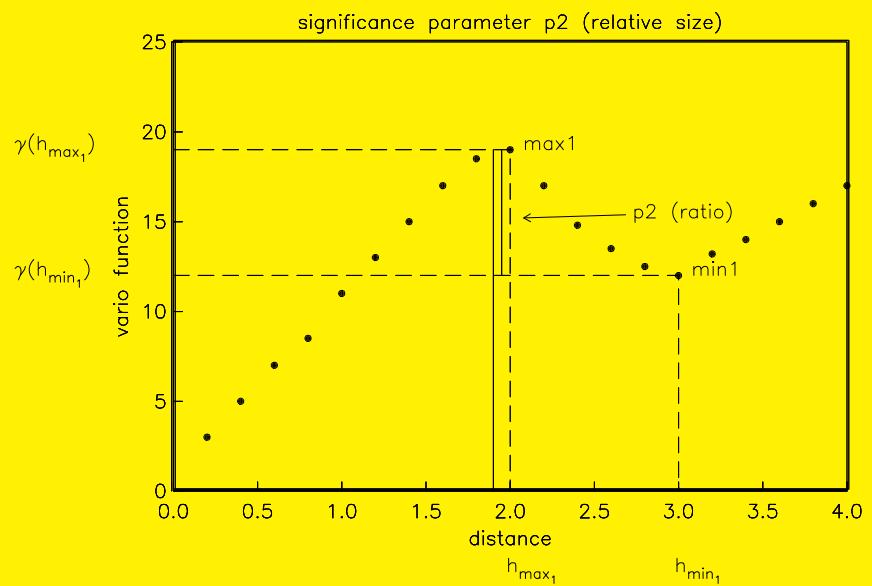
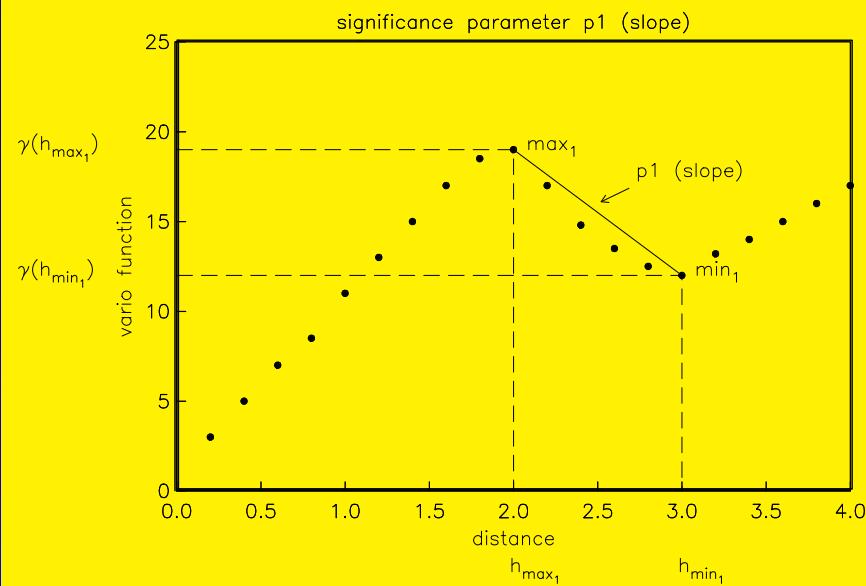
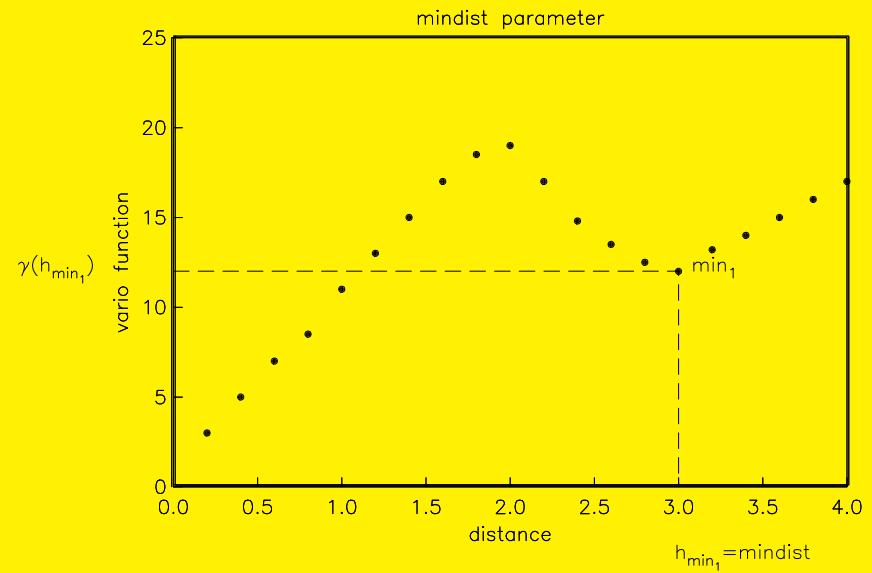
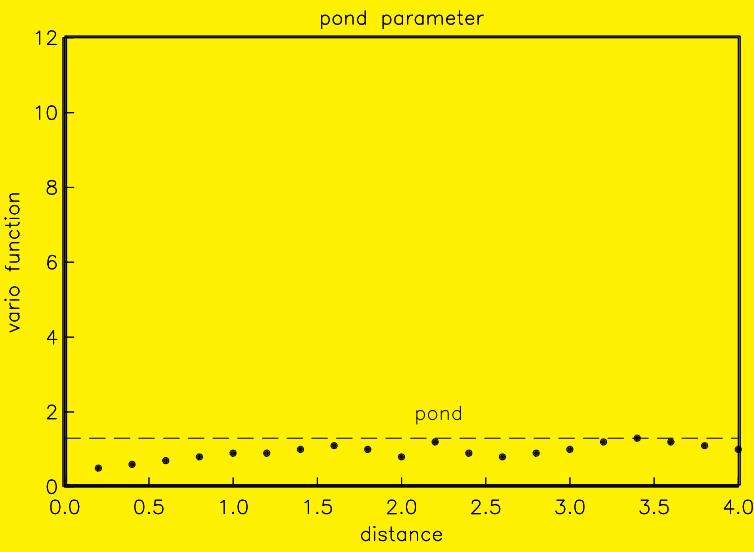
discrete-profile case

Define the *first-order vario function* v_1

$$v_1(h) = \frac{1}{2n} \sum_{i=1}^n [z(x_i) - z(x_i + h)]^2$$

with $(x_i, z(x_i)), (x_i + h, z(x_i + h)) \in \mathcal{D}$ and n the number of pairs separated by h .

Vario Parameters for Geostatistical Classification



Geostatistical Classification Parameters

significance parameters:

slope parameter:

$$p1 = \frac{\gamma_{max_1} - \gamma_{min_1}}{h_{min_1} - h_{max_1}}$$

relative significance parameter:

$$p2 = \frac{\gamma_{max_1} - \gamma_{min_1}}{\gamma_{max_1}}$$

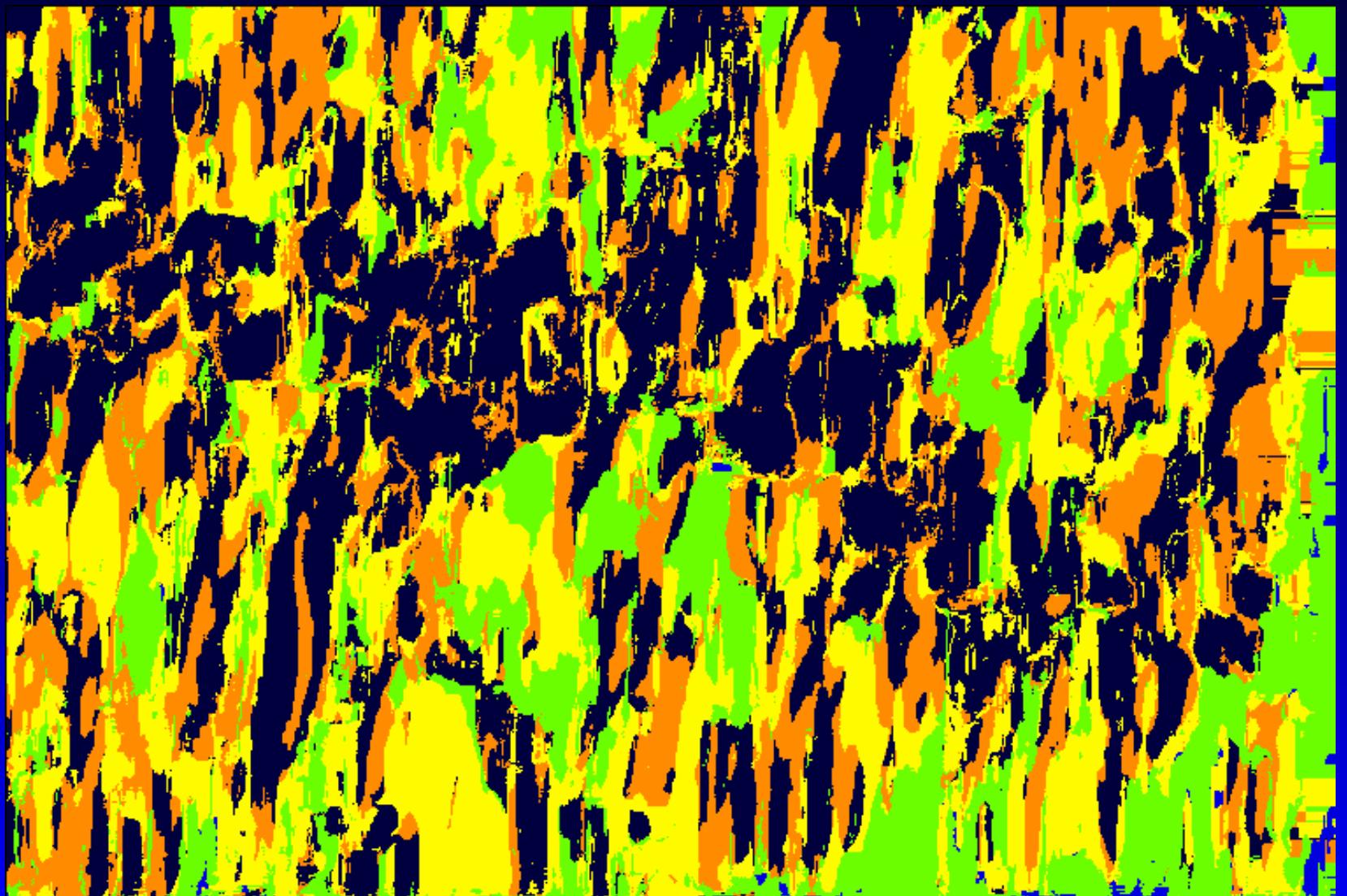
pond – maximum vario value

mindist – distance to first min after first max

$$avgspac = \frac{1}{n} \sum_{i=1}^n \frac{1}{i} h_{min_i}$$

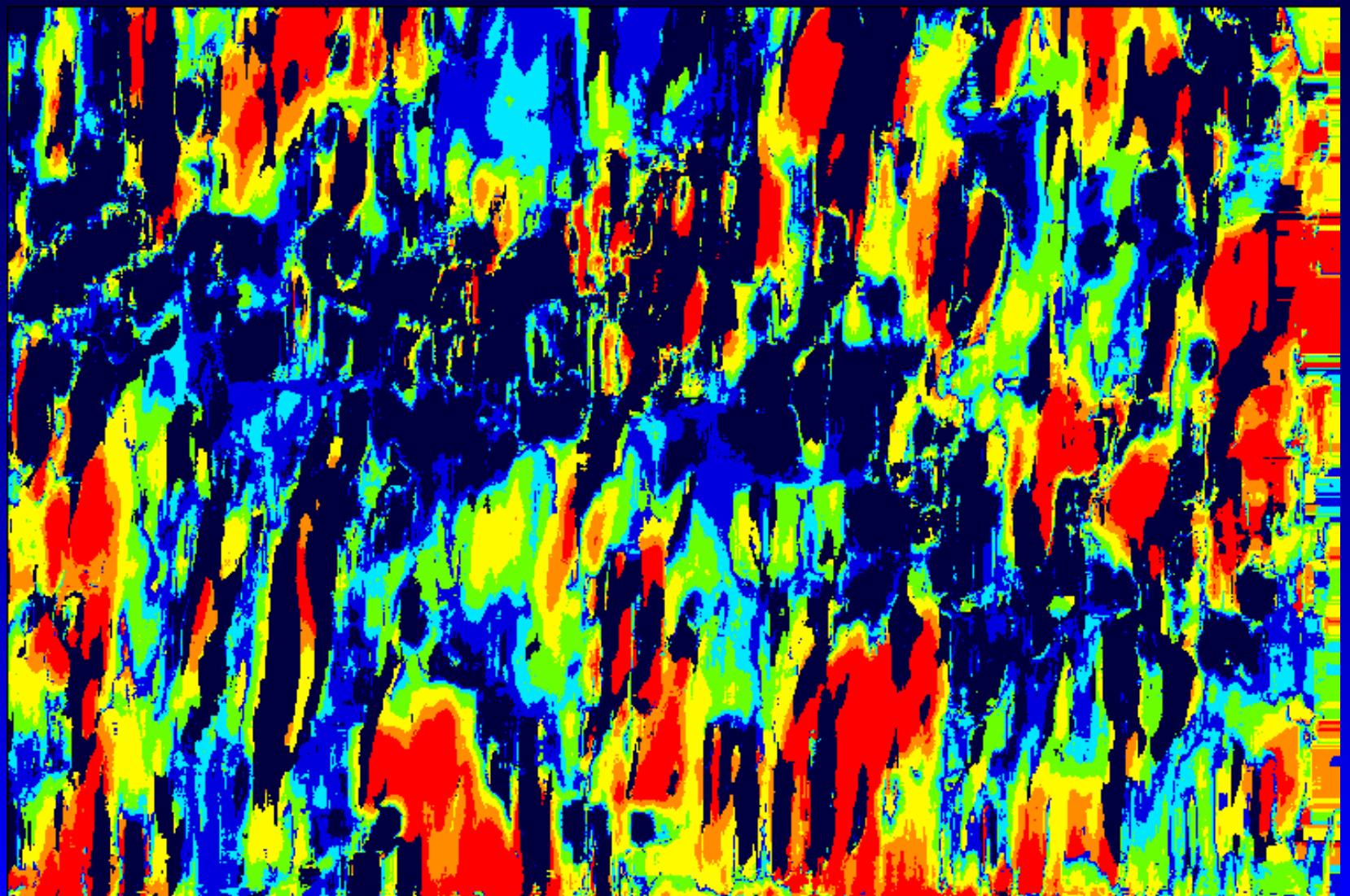
Geostatistical Seafloor Classification

Parameter $mindist$



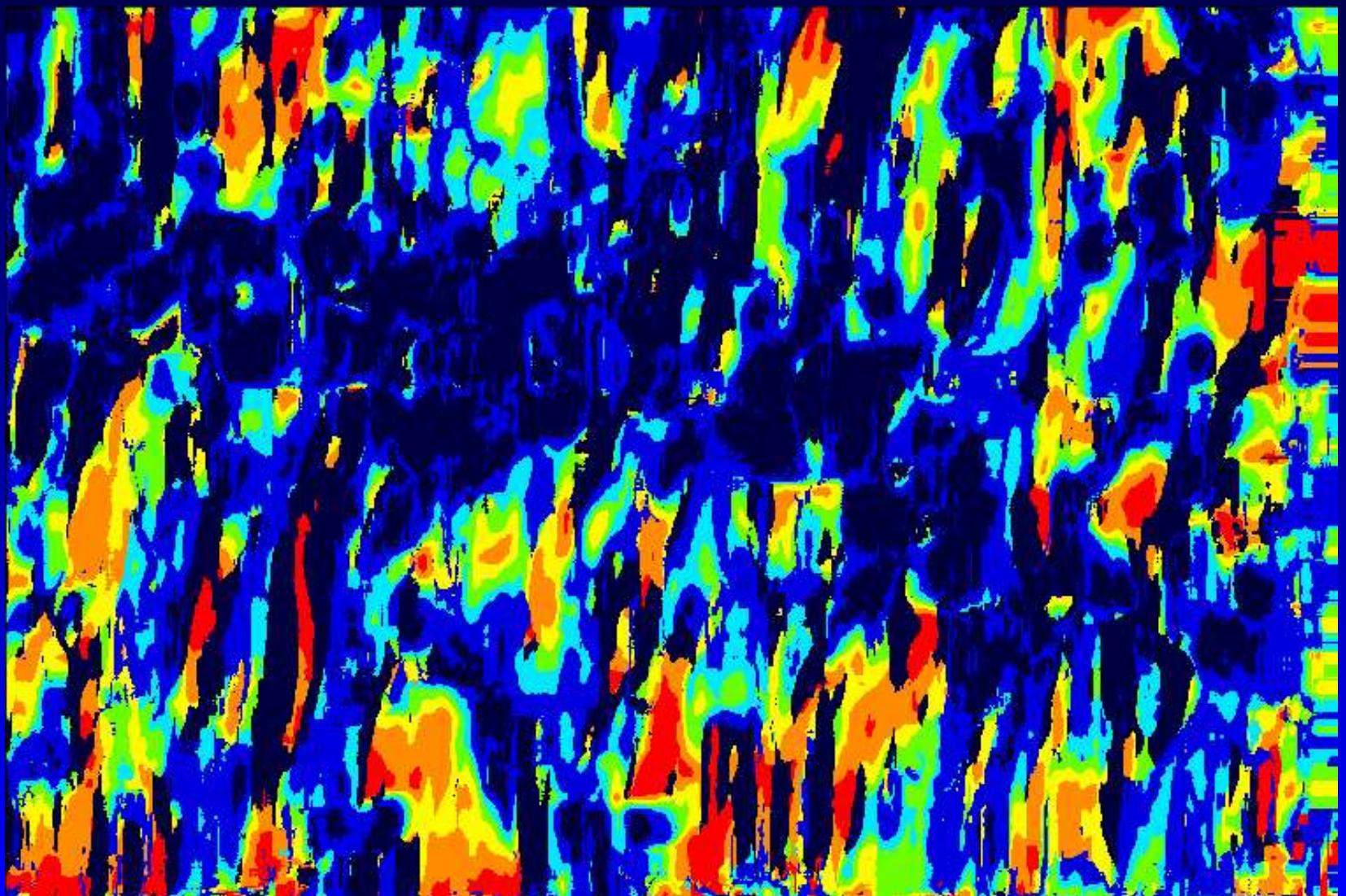
Geostatistical Seafloor Classification

Parameter $p1$:
significance of abyssal hill terrain (slope)



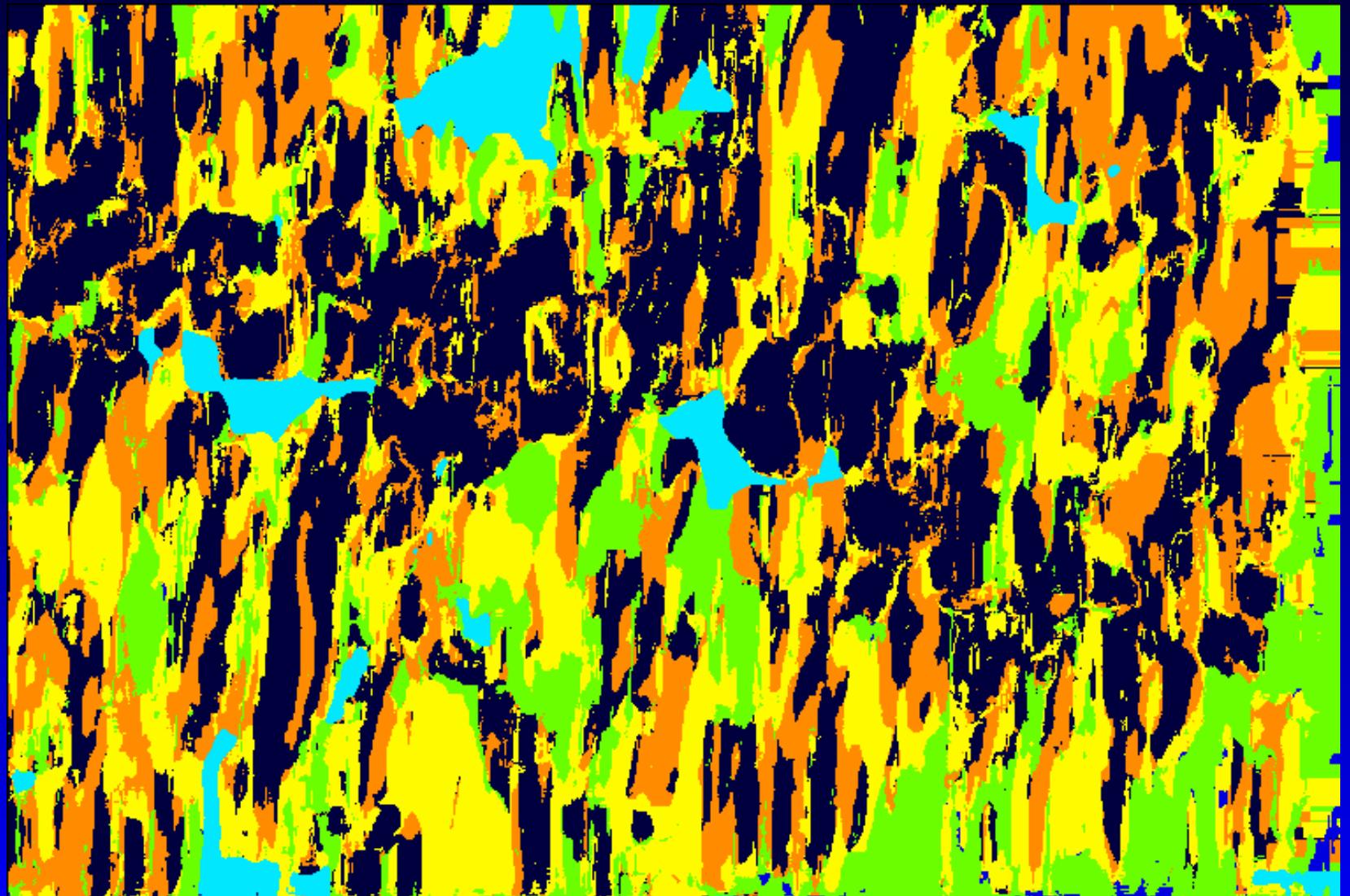
Geostatistical Seafloor Classification

Parameter $p2$:
significance of abyssal hill terrain (relative size)



Geostatistical Seafloor Classification

Parameters *pond* and *mindist*



Vario Parameters for Geostatistical Classification

