

# Geoid Determination by FFT Techniques

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# Contents

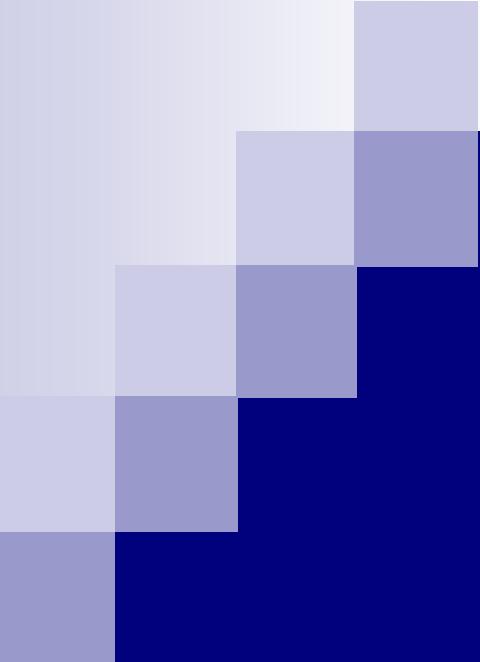
- Introduction: Geoid determination by the remove-restore technique
- The Fourier transform and its properties
- Geoid undulations by **FFT**
- Optimal spectral geoid determination
- Other applications of **FFT**
- Concluding remarks

## Addendum

Matching the gravimetric geoid to the GPS-levelling undulations

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# **Introduction: Geoid Determination by the Remove-Restore Technique**

# Stokes's Boundary Value Problem

Problem definition

$$\nabla^2 T = \frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2} = 0$$

$$\frac{\partial T}{\partial r} + \frac{2}{r} T + \Delta g = 0$$

Solution

$$T = \frac{R}{4\pi} \iint_{\sigma} \Delta g S(\psi) d\sigma \quad \Rightarrow \quad N = \frac{T}{\gamma}$$

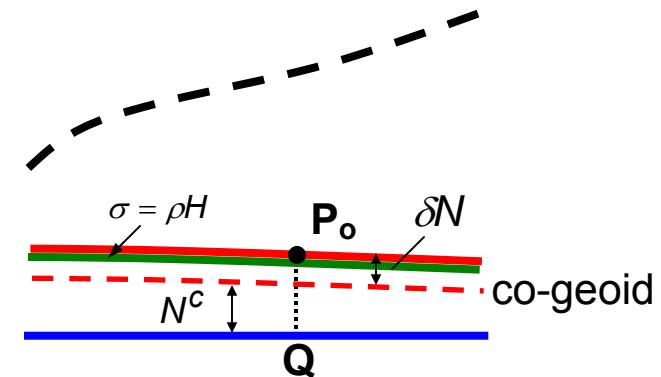
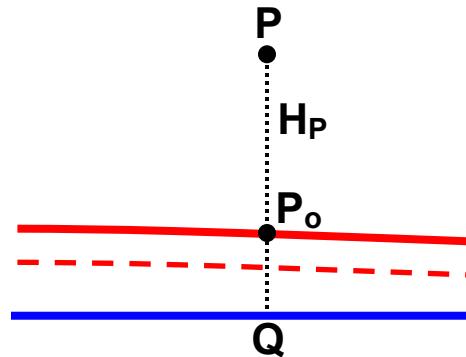
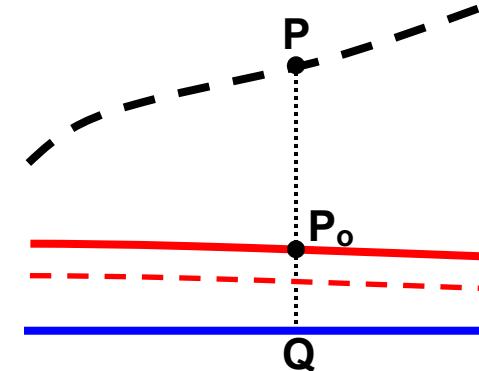
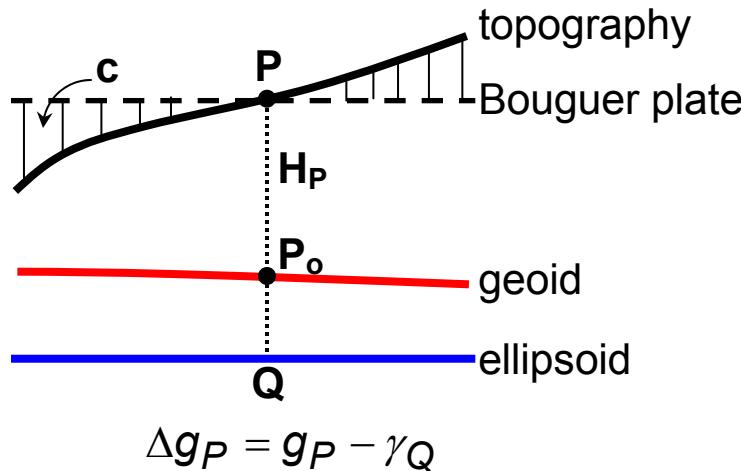
Gravity anomalies given on the geoid

(no masses outside the boundary surface)

**Terrain reductions**

# Terrain Reductions

(example: Helmert's Condensation)



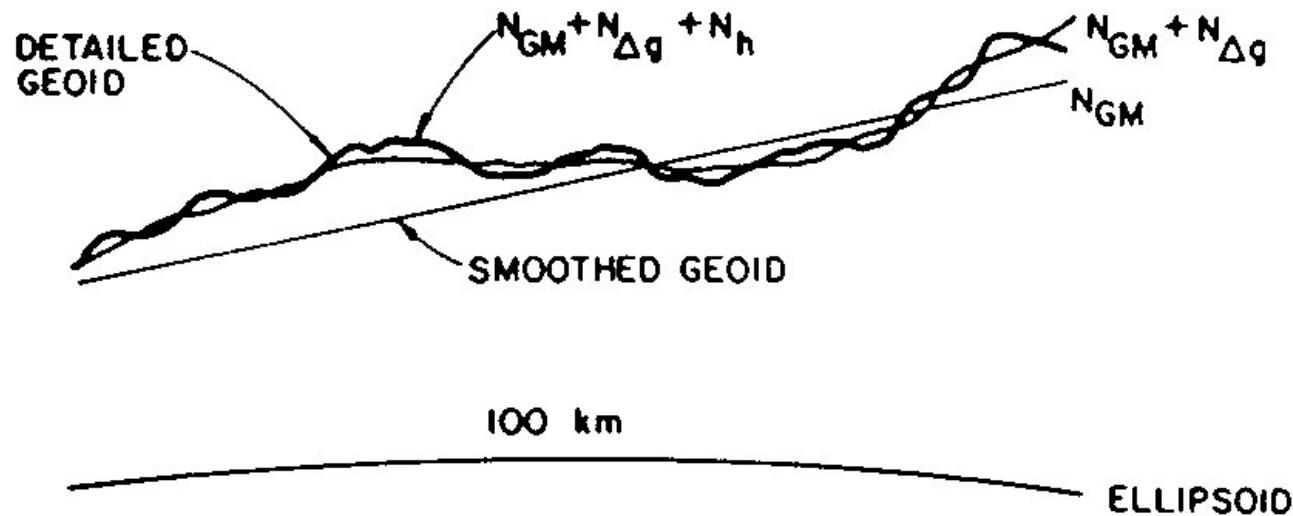
# The Remove-Restore Technique

Separate the different frequency contributions

- GM (long wavelengths)
- local gravity data (medium wavelengths)
- DTM (short wavelengths)

$$\Delta g = \Delta g^{FA} - \Delta g^{GM} - \Delta g^H$$

$$N = N^{GM} + N^{\Delta g} + N^H$$



# Basic Equations

GM-contributions, in spherical approximation

$$\Delta g_P^{GM} = G \sum_{n=2}^{n_{\max}} (n-1) \sum_{m=0}^n [C_{nm} \cos m\lambda_P + S_{nm} \sin m\lambda_P] P_{nm}(\sin \varphi_P)$$

$$N_P^{GM} = R \sum_{n=2}^{n_{\max}} \sum_{m=0}^n [C_{nm} \cos m\lambda_P + S_{nm} \sin m\lambda_P] P_{nm}(\sin \varphi_P)$$

Δg-contributions, in planar approximation

$$N_P^{\Delta g} = \frac{1}{2\pi\gamma} \iint_E \frac{\Delta g}{l} dx dy, \quad l = [(x - x_P)^2 + (y - y_P)^2]^{1/2}$$

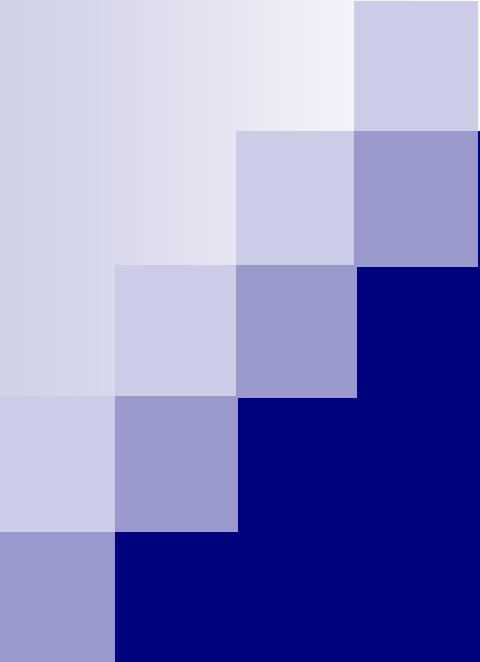
H-contributions, in planar approximation

$$\delta A_P = c_P = -\Delta g_P^H \approx \frac{1}{2} k\rho \iint_E \frac{(H - H_P)^2}{l^3} dx dy$$

$$\delta N_P \approx -\frac{\pi k\rho}{\gamma} H_P^2 - \frac{k\rho}{6\gamma} \iint_E \frac{H^3 - H_P^3}{l^3} dx dy$$

# Why Use FFT?

- FFT provides very fast evaluation of convolution sums/integrals with gridded data
- In planar approximation, the Stokes and terrain correction integrals are convolutions
- In spherical approximation, these integrals are convolutions along the parallels, and so are the summations for the GM-contributions
- Gravity and topography data are usually provided on regular grids
- Computations for very large areas can be performed on a PC



# The Fourier Transform and its Properties

# Real Sinusoids

$$s(t) = A_0 \cos(\omega_0 t + \phi_0) :$$

Sinusoid of frequency  $\omega_0$

$A_0$  ..... amplitude

$\omega_0$  ..... cyclic frequency

$t$  ..... time (or distance)

$\phi_0$  ..... phase angle

Expansion 

$$s(t) = a \cos \omega_0 t + b \sin \omega_0 t$$

where

$$a = A_0 \cos \phi_0, \quad b = -A_0 \sin \phi_0$$

$$A_0 = (a^2 + b^2)^{1/2}$$

$$\phi_0 = \arctan\left(\frac{-b}{a}\right)$$

## Sinusoids in complex form

$$s_c(t) = a \cos \omega_0 t \pm i a \sin \omega_0 t = a e^{\pm i \omega_0 t}$$

## Real sinusoids in complex form

$$s(t) = A_0 \cos(\omega_0 t + \phi_0) =$$

$$A_0 \frac{e^{i(\omega_0 t + \phi_0)} + e^{-i(\omega_0 t + \phi_0)}}{2} = \frac{A_0}{2} e^{i\phi_0} e^{i\omega_0 t} + \frac{A_0}{2} e^{-i\phi_0} e^{-i\omega_0 t}$$

# Fourier Series

If  $g(t) = g(t + T)$ ;  $\int_0^T g(t)dt = \int_{t_0}^{t_0+T} g(t)dt$ , then

$$g(t) = \sum_{n=0}^{\infty} (a_n \cos \frac{2\pi n}{T} t + b_n \sin \frac{2\pi n}{T} t)$$

$$a_n = \frac{2}{T} \int_{t_0}^{t_0+T} g(t) \cos nt dt; \quad b_n = \frac{2}{T} \int_{t_0}^{t_0+T} g(t) \sin nt dt$$

Provided that:  $g(t)$  has a finite numbers of maxima and minima in a period and a finite number of finite discontinuities (Dirichlet's conditions)

Complex form

$$g(t) = \frac{1}{T} \sum_{n=-\infty}^{\infty} G_n e^{i\omega_n t}, \quad \omega_n = \frac{2\pi n}{T}$$

$$G_n = \int_{-T/2}^{T/2} g(t) e^{-i\omega_n t} dt, \quad G_n = \frac{1}{2} (a_n - i b_n), \quad n = 0, \pm 1, \pm 2, \dots$$

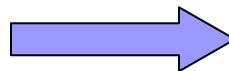
$$\text{Call } \Delta\omega = \frac{2\pi}{T} \Rightarrow \begin{cases} \omega_n = n\Delta\omega \\ \frac{1}{T} = \frac{\Delta\omega}{2\pi} \end{cases} \Rightarrow g(t) = \sum_{n=-\infty}^{\infty} \frac{G_n}{2\pi} e^{i\omega_n t} \Delta\omega$$

# The Continuous Fourier Transform

$$g(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} G(\omega) e^{i\omega t} d\omega \Rightarrow \text{Inverse CFT}$$

$$G(\omega) = \int_{-\infty}^{\infty} g(t) e^{-i\omega t} dt \Rightarrow \text{Direct CFT}$$

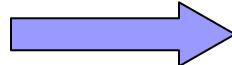
Since  $\omega = 2\pi f$



$$g(t) = \int_{-\infty}^{\infty} G(f) e^{i2\pi ft} df = \mathcal{F}^{-1}\{G(f)\}$$

$$G(f) = \int_{-\infty}^{\infty} g(t) e^{-i2\pi ft} dt = \mathcal{F}\{g(t)\}$$

$G(f)$  is complex



$$G(f) = G_R(f) + iG_I(f) = |G(f)| e^{i\theta(f)}$$

$$\text{Amplitude} \Rightarrow |G(f)| = [G_R^2(f) + G_I^2(f)]^{1/2}$$

$$\text{Phase angle} \Rightarrow \theta(f) = \text{Arg}\{G(f)\} = \arctan \frac{G_I(f)}{G_R(f)}$$

# The CTF (continued)

Conditions for Existence :

---

- The integral of  $|g(t)|$  from  $-\infty$  to  $+\infty$  exists (it is  $< \infty$ )
- $g(t)$  has only finite discontinuities
- If  $g(t)$  is periodic or impulse,  $G(f)$  does not exist

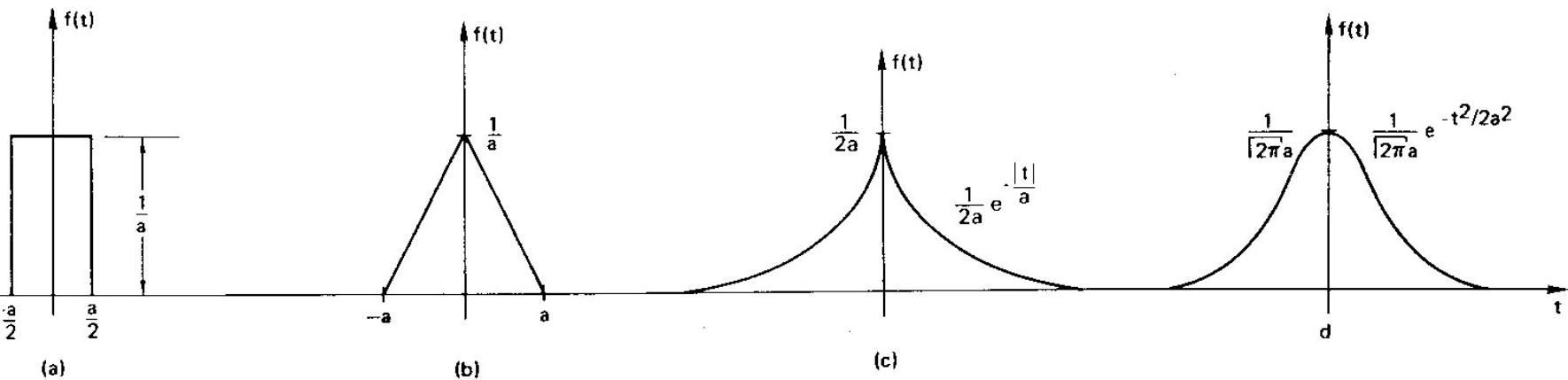
# The Impulse Function

Definition :

$$\left. \begin{array}{l} \delta(t - t_0) = 0, \quad t \neq t_0 \\ \int_{-\infty}^{\infty} \delta(t - t_0) dt = 1 \end{array} \right\} \Leftrightarrow \delta(t) = \lim_{a \rightarrow 0} f(t, a)$$

*Definition as a distribution*

$$\int_{-\infty}^{\infty} \delta(t - t_0) \phi(t) dt = \phi(t_0)$$



# The Impulse Function (continued)

Definition as a generalized limit :

$$\text{If } \lim_{n \rightarrow \infty} \int_{-\infty}^{\infty} f_n(t) \phi(t) dt = \phi(0) \quad \Rightarrow \quad \delta(t) = \lim_{n \rightarrow \infty} f_n(t)$$

Properties :

$$\delta(t_0)h(t) = h(t_0)\delta(t_0)$$

$$\delta(at) = |a|^{-1} \delta(t)$$

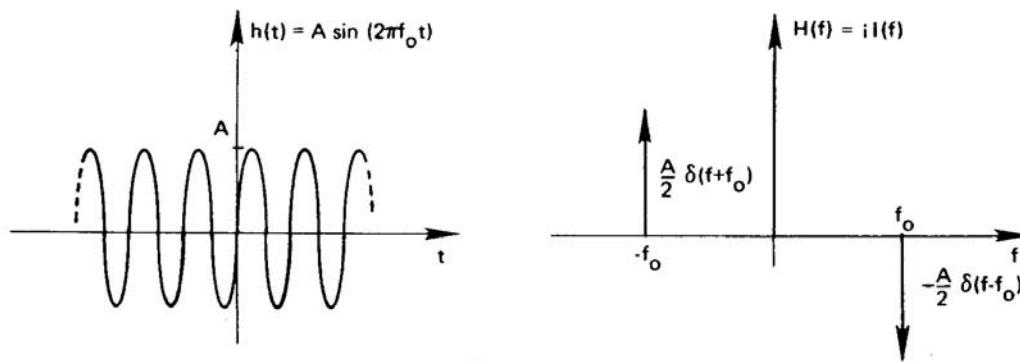
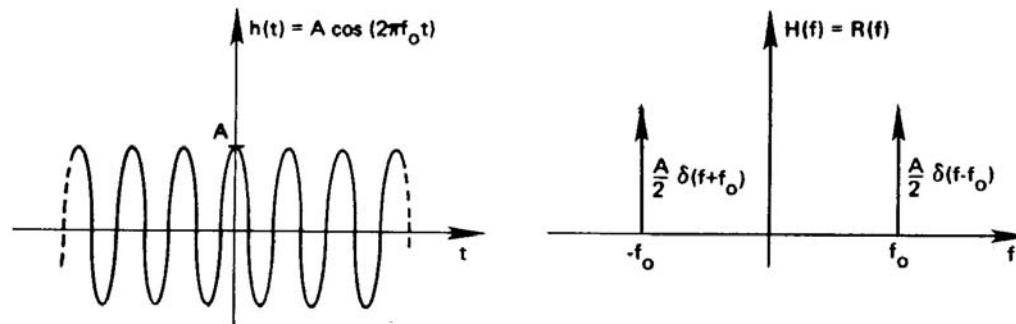
$$F\{K\delta(t)\} = K$$

e.g. If we define it as  $\delta(t) = \lim_{a \rightarrow \infty} \frac{\sin at}{\pi t}$ ,

$$\text{then } \int_{-\infty}^{\infty} \cos(2\pi ft) df = \int_{-\infty}^{\infty} e^{i2\pi ft} df = \delta(t)$$

Used, as a distribution, for the (otherwise nonexistent) CFT of periodic functions

# The CTF of cosine and sine



$$A \cos(2\pi f_o t) \leftrightarrow \frac{A}{2} \delta(f - f_o) + \frac{A}{2} \delta(f + f_o)$$

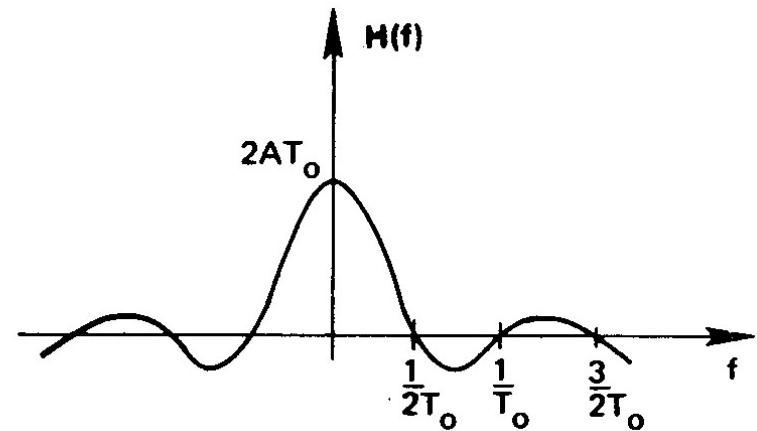
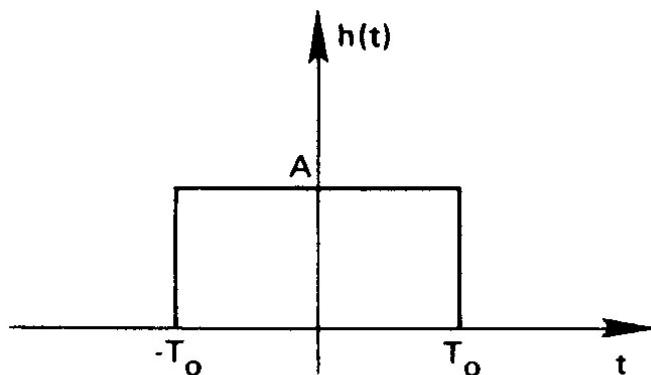
$$A \sin(2\pi f_o t) \leftrightarrow i \frac{A}{2} \delta(f + f_o) - i \frac{A}{2} \delta(f - f_o)$$

# The Sampling Function

$$III(t) = \sum_{n=-\infty}^{\infty} \delta(t - nT) \leftrightarrow F\{III(t)\} = \frac{1}{T} \sum_{n=-\infty}^{\infty} \delta(f - \frac{n}{T})$$

$$III(t)f(t) = \sum_{n=-\infty}^{\infty} f(nT)\delta(t - nT) \Rightarrow \text{Digitization}$$

# The Rectangle and sinc Functions



$$h(t) = \begin{cases} A, & |t| = T_0/2 \\ A/2, & t = \pm T_0/2 \\ 0, & |t| > T_0/2 \end{cases} \leftrightarrow H(f) = 2AT_0 \text{sinc}(2T_0 f),$$

$$\text{sinc}(f) = \frac{\sin(\pi f)}{\pi f}$$

# Properties of the CFT

- Linearity

$$ah(t) + bg(t) \leftrightarrow aH(f) + bG(f)$$

- Symmetry

$$H(t) \leftrightarrow h(-f)$$

- Time scaling

$$h(at) \leftrightarrow \frac{1}{|a|} H\left(\frac{f}{a}\right)$$

- Time shifting

$$h(t - t_o) \leftrightarrow H(f)e^{-i 2 \pi f t_o}$$

- Differentiation

$$\frac{\partial^n h(t)}{\partial t^n} \leftrightarrow (i 2 \pi f)^n H(f)$$

- Integration

$$\int_{-\infty}^t h(x) dx \leftrightarrow \frac{1}{i 2 \pi f} H(f) + \frac{1}{2} H(0) \delta(f)$$

# Properties of the CFT (continued)

- DC-value

$$\int_{-\infty}^{\infty} h(t) dt = H(0)$$

- Even function

$$h_E(t) \leftrightarrow H_E(f) = R_E(f)$$

- Odd function

$$h_O(t) \leftrightarrow H_O(f) = iI_O(f)$$

- Real function

$$h(t) = h_R(t) \leftrightarrow H(f) = R_E(f) + iI_O(f)$$

- Imaginary function

$$h(t) = ih_I(t) \leftrightarrow H(f) = R_O(f) + iI_E(f)$$

# Convolution and Correlation

$$x(t) = \int_{-\infty}^{\infty} g(t') h(t - t') dt' = g(t) * h(t) = h(t) * g(t) = \int_{-\infty}^{\infty} h(t') g(t - t') dt'$$

$$y(t) = \int_{-\infty}^{\infty} g(t') h(t + t') dt' = g(t) \otimes h(t) \neq h(t) \otimes g(t)$$

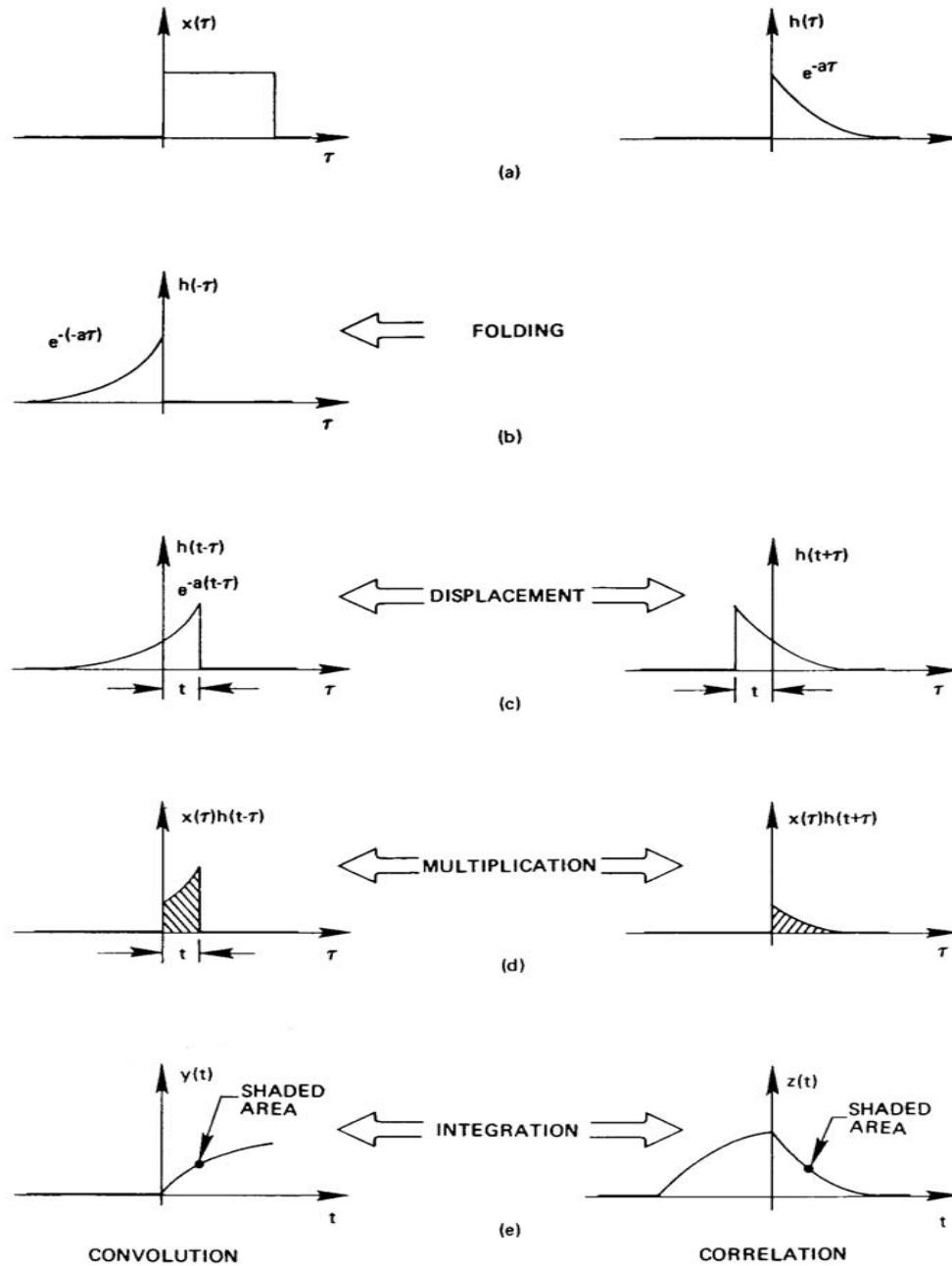
Convolution theorem

$$X(f) = F\{g(t) * h(t)\} = F\{g(t)\}F\{h(t)\} = G(f)H(f)$$

Correlation theorem

$$Y(f) = F\{g(t) \otimes h(t)\} = G(f)H^*(f)$$

# Pictorial Representation of Convolution and Correlation



# Convolution and Correlation (continued)

Properties:

a) If either  $g(t)$  or  $h(t)$  is even, then  $g(t) * h(t) = g(t) \otimes h(t)$

b)  $\delta(t + \tau) * h(t) = h(t + \tau)$ ,  $\delta(t) * h(t) = h(t)$

c)  $x'(t) = (g(t) * h(t))' = g'(t) * h(t) = g(t) * h'(t)$

d)  $F\{h(t)g(t)\} = F\{h(t)\} * F\{g(t)\} = H(f) * G(f)$

e) If  $h(t)$  and  $g(t)$  are time limited functions, i.e, non-zero  
in the domain  $-T_0 \leq t \leq T_0$ , then

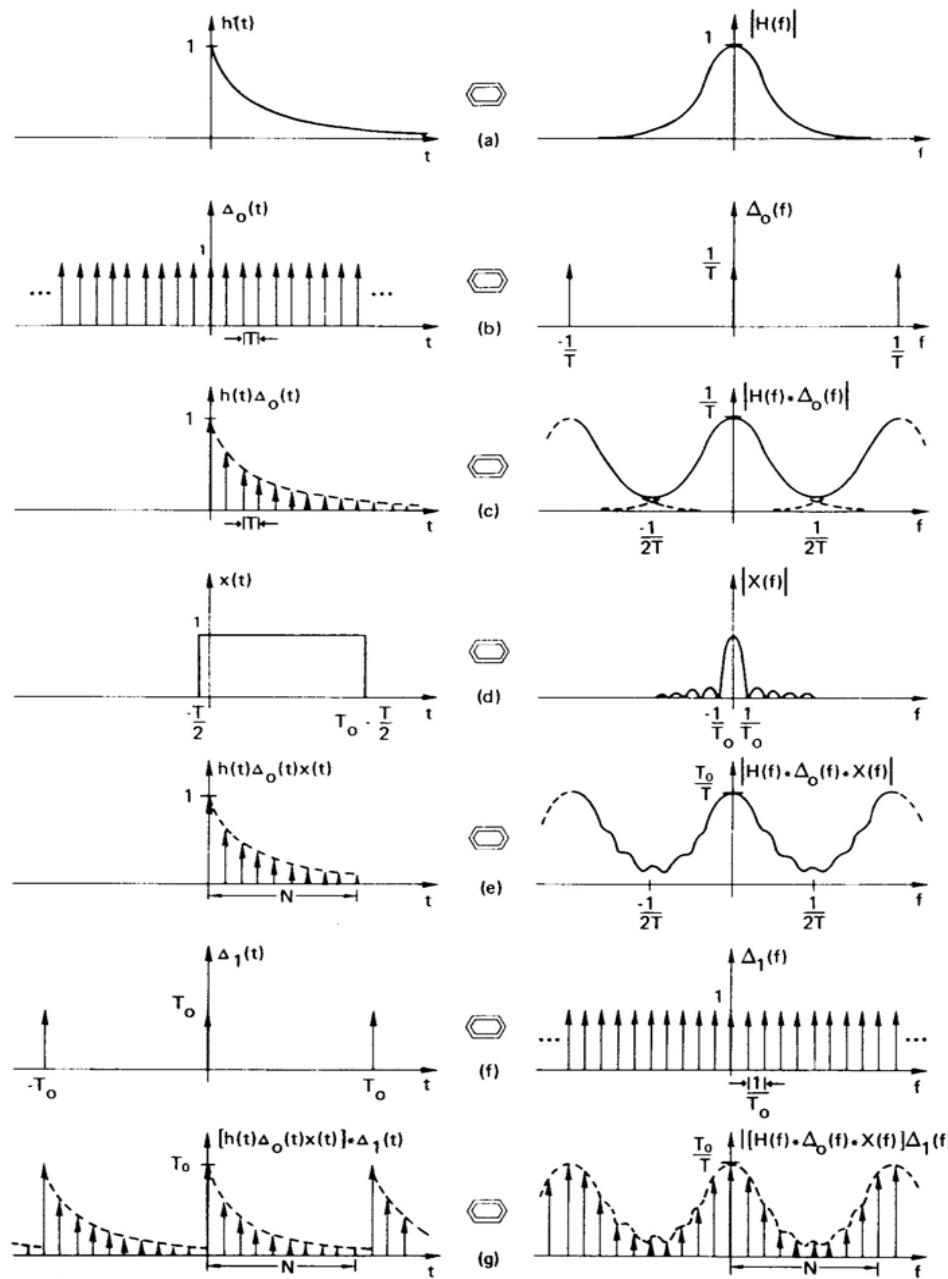
$x(t) = h(t) * g(t)$  is time limited with twice the support of  $h(t)$  or  $g(t)$ ,  
i.e., non-zero in the domain  $-2T_0 \leq t \leq 2T_0$

f) Parseval's theorem:

$$\int_{-\infty}^{\infty} h^2(t) e^{-2\pi\sigma t} dt = \int_{-\infty}^{\infty} H(f) H(\sigma - f) df$$

with  $\sigma = 0$  and for  $h(t)$  real:  $\int_{-\infty}^{\infty} h^2(t) dt = \int_{-\infty}^{\infty} |H(f)|^2 df$

# From the Continuous to the Discrete Fourier Transform



aliasing

leakage

periodic

# The Discrete Fourier Transform

$$H(m\Delta f) = \sum_{k=0}^{N-1} h(k\Delta t) e^{-i2\pi k \Delta t m \Delta f} \Delta t = \sum_{k=0}^{N-1} h(k\Delta t) e^{-i2\pi k m / N} \Delta t$$

$$h(k\Delta t) = \sum_{m=0}^{N-1} H(m\Delta f) e^{i2\pi k \Delta t m \Delta f} \Delta f = \sum_{m=0}^{N-1} H(m\Delta f) e^{i2\pi k m / N} \Delta f$$

$$T_o = \frac{1}{\Delta f} = N\Delta t, \quad F_o = \frac{1}{\Delta t} = N\Delta f, \quad |f_N| = \frac{F_o}{2} = \frac{1}{2\Delta t}$$

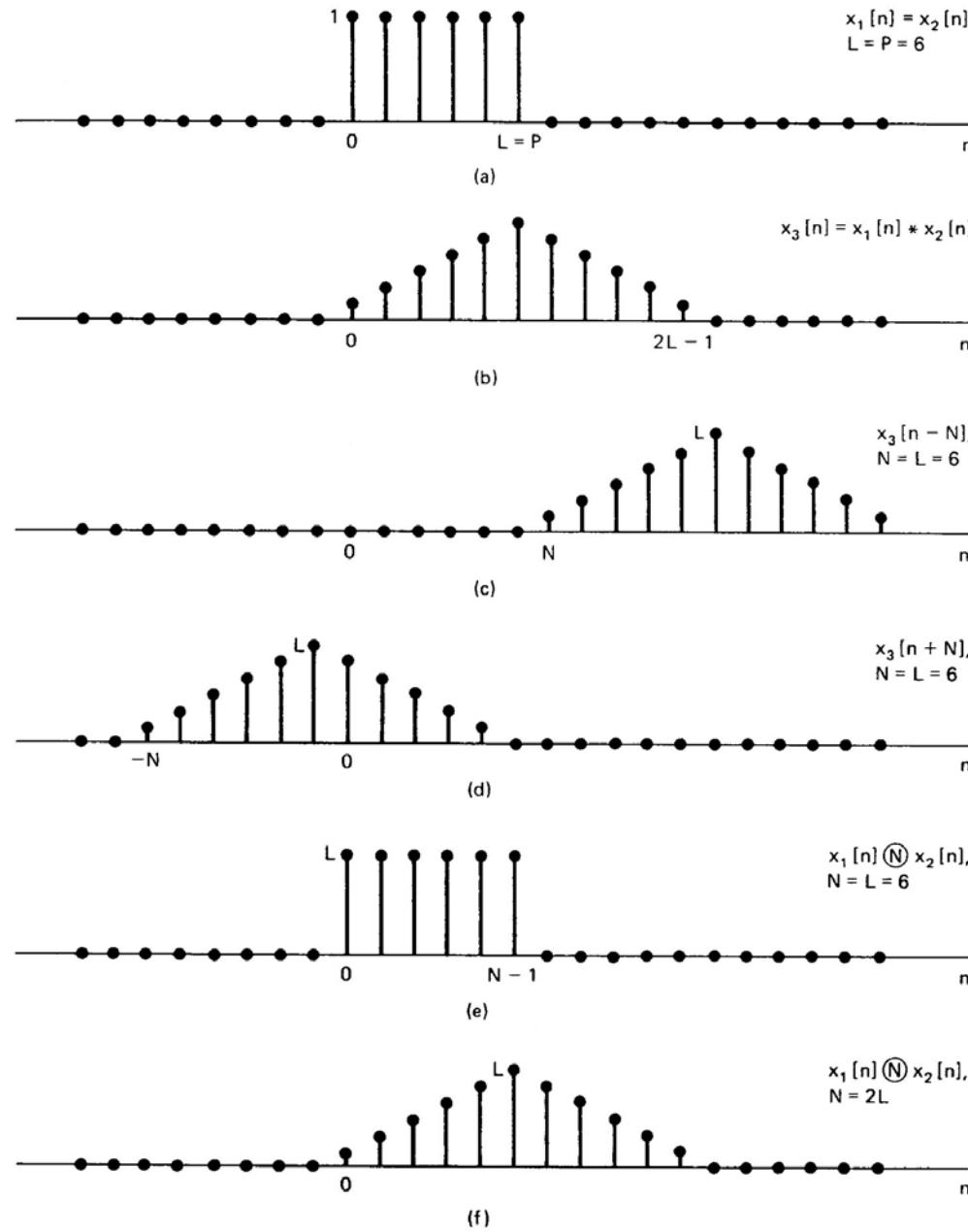
$$h(k\Delta t) \leftrightarrow H(m\Delta f) \quad \text{or} \quad h(t_k) \leftrightarrow H(f_m) \quad \text{or} \quad h(k) \leftrightarrow H(m)$$

## Discrete and circular convolution and correlation

$$x(k) = \sum_{l=0}^{N-1} g(l) h(k-l) \Delta t = g(k) * h(k) \quad y(k) = \sum_{l=0}^{N-1} g(l) h(k+l) \Delta t = g(k) \otimes h(k)$$

$$x(k) = \mathbf{F}^{-1} \{ \mathbf{F}\{g(k)\} \mathbf{F}\{h(k)\} \} \quad y(k) = \mathbf{F}^{-1} \{ \mathbf{F}\{g(k)\} [\mathbf{F}\{h(k)\}]^* \}$$

# Circular Convolution as Linear Convolution Plus Aliasing



# CR, CV and PSD Functions

Definitions:

$$R_{gh}(t_k) = \mathbf{E}\{g(t_l)h(t_k + t_l)\} = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{l=0}^{N-1} g(t_l)h(t_k + t_l) = \lim_{T_o \rightarrow \infty} \frac{1}{T_o} g(t_k) \otimes h(t_k)$$

$$\begin{aligned} C_{gh}(t_k) &= \mathbf{E}\{\{g(t_l) - \bar{g}\}[h(t_k + t_l) - \bar{h}]\} = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{l=0}^{N-1} [g(t_l) - \bar{g}][h(t_k + t_l) - \bar{h}] \\ &= \lim_{T_o \rightarrow \infty} \frac{1}{T_o} g(t_k) \otimes h(t_k) - \bar{g}\bar{h} = R_{gh}(t_k) - \bar{g}\bar{h} \end{aligned}$$

$$P_{gh}(f_m) = \mathbf{F}\{R_{gh}(t_k)\} = \lim_{T_o \rightarrow \infty} \frac{1}{T_o} G(f_m) H^*(f_m)$$

Computation by FFT:

$$\hat{P}_{gh}(f_m) = \frac{1}{\sqrt{T_o}} \sum_{\lambda=1}^v G_\lambda(f_m) H_\lambda^*(f_m)$$

$$\hat{R}_{gh}(t_k) = \mathbf{F}^{-1}\{\hat{P}_{gh}(f_m)\}$$

$$\hat{C}_{gh}(t_k) = \mathbf{F}^{-1}\{\hat{P}_{gh}(f_m) - \bar{g}\bar{h}\delta(f_m)\}$$

# The DFT in Computers

Subroutines usually assume  $\Delta t = 1$  and also ignore  $T_o$ .  
This requires rescaling as follows:

$$H(f_m) = T_o H_c(m) = N \Delta t H_c(m)$$

$$x(t_k) = g(t_k) * h(t_k) = T_o x_c(t_k) = T_o F_c^{-1} \{G_c(m) H_c(m)\}$$

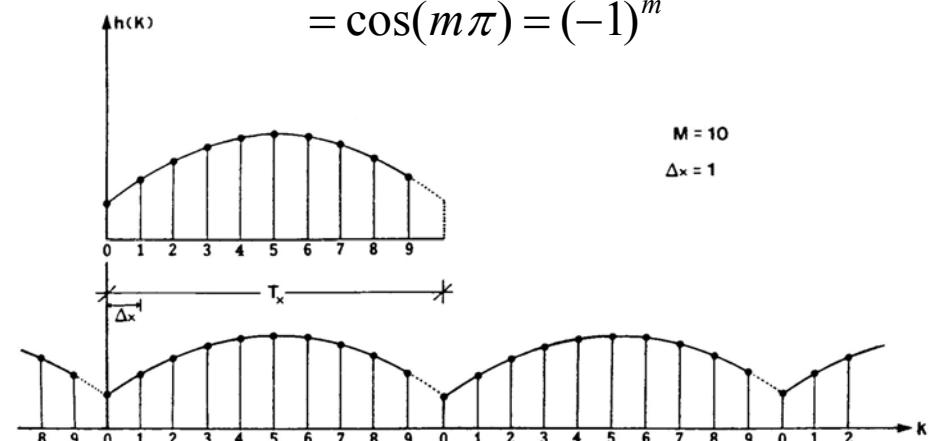
It also yields:  $H_c(0) = \bar{h}$

Subroutines also assume the origin at the left of the record.

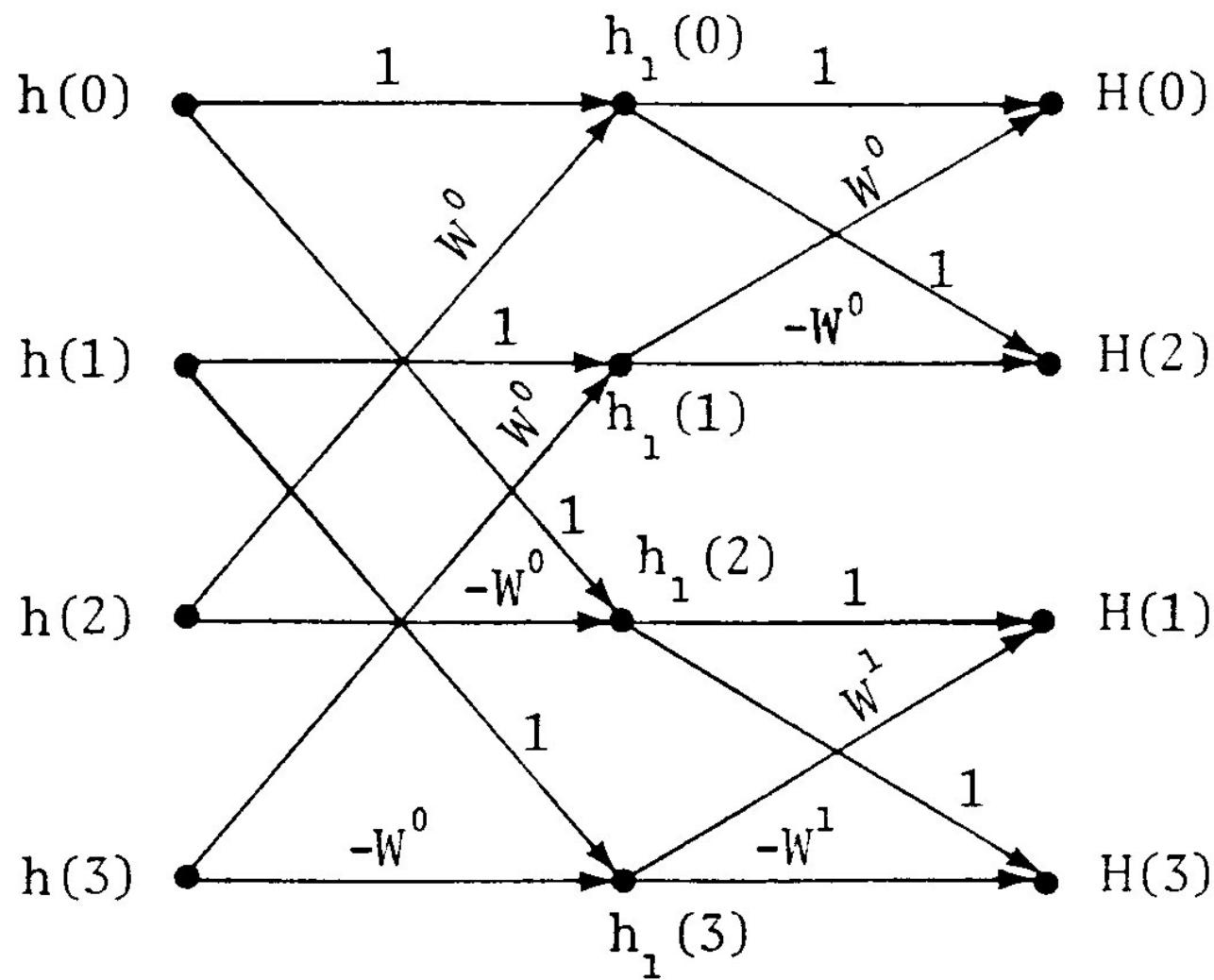
This requires changing the phase of the spectrum by  $e^{-i2\pi m \Delta f T_o / 2} = e^{-i\pi m}$

$$h(t_k - T_o / 2) \leftrightarrow (-1)^m H(f_m)$$

End point of a period  
must be omitted  
(assumed due to periodicity)



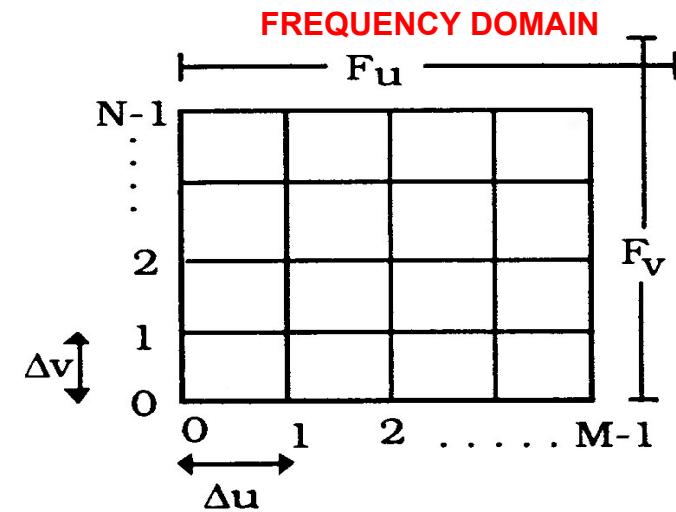
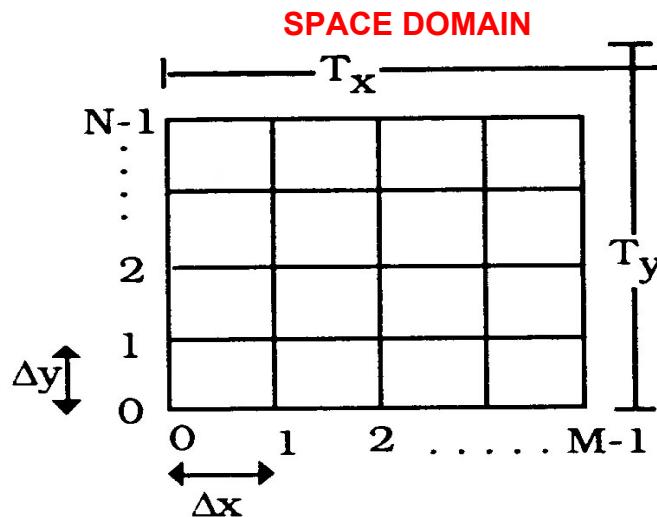
# The FFT - Flow Graph of Operations for N=4



# The Two-dimensional DFT

$$H(u_m, v_n) = \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} h(x_k, y_l) e^{-i2\pi(mk/M + nl/N)} \Delta x \Delta y$$

$$h(x_k, y_l) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} H(u_m, v_n) e^{i2\pi(mk/M + nl/N)} \Delta u \Delta v$$



$$\Delta u = \frac{1}{T_y} = \frac{1}{M \Delta x},$$

$$\Delta v = \frac{1}{T_y} = \frac{1}{N \Delta y}$$

$$\Delta x = \frac{1}{F_u} = \frac{1}{M \Delta u} = \frac{1}{2u_N},$$

$$\Delta y = \frac{1}{F_v} = \frac{1}{N \Delta v} = \frac{1}{2v_N}$$



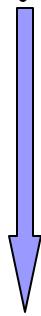
# Geoid Undulations by FFT

# Geoid Undulations by FFT (1/9)

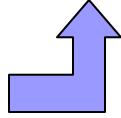
## PLANAR APPROXIMATION OF STOKES'S INTEGRAL

$$N(x_P, y_P) = \frac{1}{2\pi\gamma} \iint_E \frac{\Delta g(x, y)}{\sqrt{(x_p - x)^2 + (y_p - y)^2}} dx dy = \frac{1}{\gamma} \Delta g(x_P, y_P) * l_N(x_P, y_P)$$

FFT: two direct  
and one inverse  
Fourier transform



$$l_N(x, y) = (2\pi)^{-1} (x^2 + y^2)^{-1/2}$$



$$N(x, y) = \frac{1}{\gamma} \mathbf{F}^{-1} \{ \mathbf{F}\{\Delta g(x, y)\} \mathbf{F}\{l_N(x, y)\} \} = \frac{1}{\gamma} \mathbf{F}^{-1} \{ \Delta G(u, v) L_N(u, v) \}$$

# Geoid Undulations by FFT (2/9)

## Point Gravity Anomalies as Input

$$N(x_k, y_l) = \frac{1}{\gamma} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \Delta g(x_i, y_j) l_N(x_k - x_i, y_l - y_j) \Delta x \Delta y$$

FFT: two direct  
and one inverse  
Fourier transform

$$N(x_k, y_l) = \frac{1}{2\pi\gamma} F^{-1} \{ \Delta G(u_m, v_n) L_N(u_m, v_n) \}$$

$$L_N(u_m, v_n) = F\{l_N(x_k, y_l)\} = \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} l_N(x_k, y_l) e^{-j2\pi(mk/M+nl/N)} \Delta x \Delta y$$

$$\Delta G(u_m, v_n) = F\{\Delta g(x_k, y_l)\} = \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} \Delta g(x_k, y_l) e^{-j2\pi(mk/M+nl/N)} \Delta x \Delta y$$

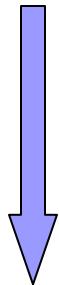
# Geoid Undulations by FFT (3/9)

## Mean Gravity Anomalies as Input

$$N(x_k, y_l) = \frac{1}{2\pi\gamma} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \overline{\Delta g}(x_i, y_j) \overline{l_N}(x_k - x_i, y_l - y_j)$$



$$\begin{aligned}\overline{l_N}(x_k, y_l) &= \int_{x_k - \Delta x/2}^{x_k + \Delta x/2} \int_{y_l - \Delta y/2}^{y_l + \Delta y/2} \frac{1}{\sqrt{x^2 + y^2}} dx dy \\ &= x \ln(y + \sqrt{x^2 + y^2}) + y \ln(x + \sqrt{x^2 + y^2}) \Big|_{x_k - \Delta x/2}^{x_k + \Delta x/2} \Big|_{y_l - \Delta y/2}^{y_l + \Delta y/2}\end{aligned}$$



FFT: two direct  
and one inverse  
Fourier transform

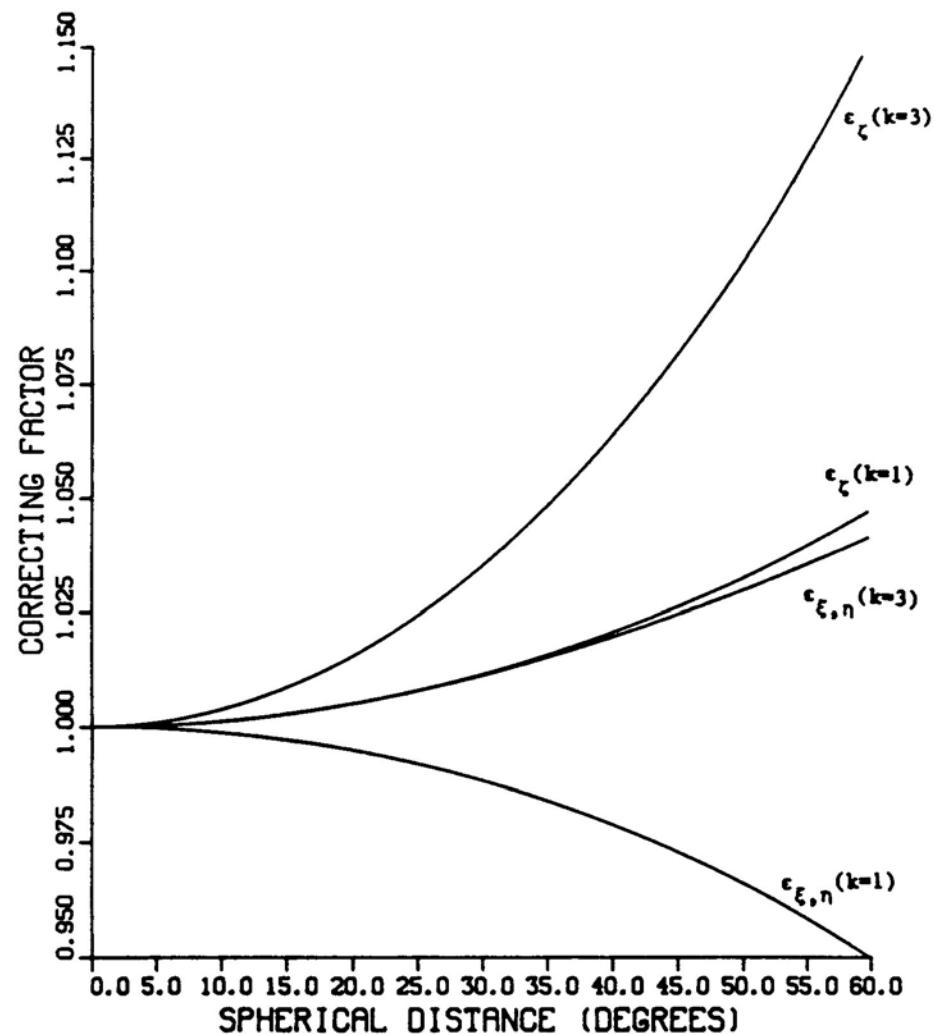
$$N(x_k, y_l) = \frac{1}{2\pi\gamma} \mathbf{F}^{-1} \{ \mathbf{F} \{ \overline{\Delta g}(x_k, y_l) \} \mathbf{F} \{ \overline{l_N}(x_k, y_l) \} \} = \frac{1}{2\pi\gamma} \mathbf{F}^{-1} \{ \overline{\Delta G}(u_m, v_n) \overline{L_N}(u_m, v_n) \}$$

# Geoid Undulations by FFT (4/9)

## Effects of Planar Approximation - Spherical Corrections

Factors for correcting planar  $\xi$ ,  $\eta$ ,  $N$  (or  $T$  or  $\zeta$ ) for the Earth's curvature

To avoid long-wavelength errors, the area of local data should not extend to more than several hundreds of kilometers in each direction.



# Geoid Undulations by FFT (5/9)

## Spherical form of Stokes's Integral

$$N(\varphi_p, \lambda_p) = \frac{R}{4\pi\gamma} \iint_E \Delta g(\varphi, \lambda) S(\varphi_p, \lambda_p, \varphi, \lambda) \cos \varphi d\varphi d\lambda$$

$$N(\varphi_l, \lambda_k) = \frac{R}{4\pi\gamma} \sum_{j=0}^{N-IM-1} \sum_{i=0}^{M-1} \Delta g(\varphi_j, \lambda_i) \cos \varphi_j S(\varphi_l, \lambda_k, \varphi_j, \lambda_i) \Delta\varphi \Delta\lambda$$

With different approximations of Stokes's kernel function on the sphere, geoid undulations can be evaluated at all gridded points simultaneously by means of either the one-dimensional or the two-dimensional fast Fourier transform

# Geoid Undulations by FFT (6/9)

## Approximated Spherical Kernel

$$\cos \phi_P \cos \phi \xrightarrow{\text{approximation}} \cos^2 \bar{\phi} - \sin^2(\phi_P - \phi)/2$$

$$\sin^2 \frac{\psi}{2} = \sin^2 \frac{\varphi_P - \varphi}{2} + \sin^2 \frac{\lambda_P - \lambda}{2} \cos \varphi_P \cos \varphi$$

$$\begin{aligned} \hookrightarrow \quad \sin^2 \frac{\psi}{2} &\approx \sin^2 \frac{\varphi_p - \varphi}{2} + \sin^2 \frac{\lambda_p - \lambda}{2} \cos^2 \bar{\phi} \\ &\approx \sin^2 \frac{\varphi_p - \varphi}{2} + \sin^2 \frac{\lambda_p - \lambda}{2} (\cos^2 \bar{\phi} - \sin^2 \frac{\varphi_p - \varphi}{2}) \end{aligned}$$

$$N(\varphi_l, \lambda_k) = \frac{R}{4\pi\gamma} \sum_{j=0}^{N-IM-1} \sum_{i=0}^{M-1} \Delta g(\varphi_j, \lambda_i) \cos \varphi_j S(\varphi_l - \varphi_j, \lambda_k - \lambda_i, \bar{\phi}) \Delta \varphi \Delta \lambda$$

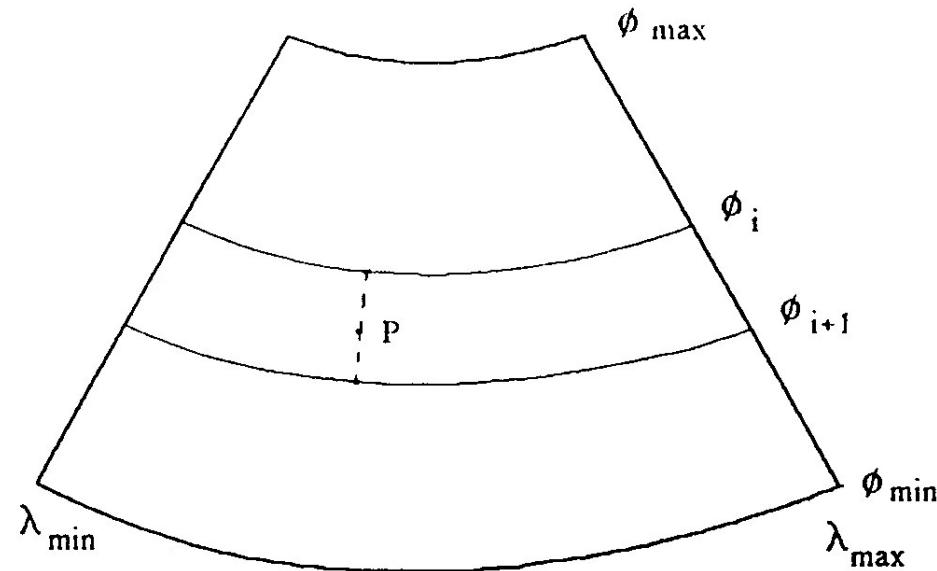
$$= \frac{R}{4\pi\gamma} [\Delta g(\varphi_l, \lambda_k) \cos \varphi_l] * S(\varphi_l, \lambda_k, \bar{\phi}).$$

$$\hookrightarrow N(\varphi_l, \lambda_k) = \frac{R}{4\pi\gamma} \mathbf{F}^{-1} \{ \mathbf{F} \{ \Delta g(\varphi_l, \lambda_k) \cos \varphi_l \} \mathbf{F} \{ S(\varphi_l, \lambda_k, \bar{\phi}) \} \}$$

# Geoid Undulations by FFT (7/9)

Latitude bands used in the multi-band spherical FFT approach

$$\begin{aligned} \sin^2 \frac{\psi}{2} &\approx \sin^2 \frac{\varphi_p - \varphi}{2} + \sin^2 \frac{\lambda_p - \lambda}{2} \cos \bar{\varphi}_t \cos [\bar{\varphi}_t - (\bar{\varphi}_t - \varphi)] \\ &\approx \sin^2 \frac{\varphi_p - \varphi}{2} + \sin^2 \frac{\lambda_p - \lambda}{2} [\cos^2 \bar{\varphi}_t \cos(\bar{\varphi}_t - \varphi) + \cos \bar{\varphi}_t \sin \bar{\varphi}_t \sin(\bar{\varphi}_t - \varphi)] \end{aligned}$$

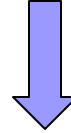


# Geoid Undulations by FFT (8/9)

## Rigorous Spherical Kernel

$$N(\varphi_l, \lambda_k) = \frac{R}{4\pi\gamma} \sum_{j=0}^{N-1} \left[ \sum_{i=0}^{M-1} \Delta g(\varphi_j, \lambda_i) \cos \varphi_j S(\varphi_l, \varphi_j, \lambda_k - \lambda_i) \Delta \lambda \right] \Delta \varphi, \quad \varphi_l = \varphi_1, \varphi_2, \dots, \varphi_N$$

Addition Theorem of DFT



$$N(\varphi_l, \lambda_k) = \frac{R}{4\pi\gamma} \mathbf{F}_I^{-1} \left\{ \sum_{j=0}^{N-1} \mathbf{F}_I \{ \Delta g(\varphi_j, \lambda_k) \cos \varphi_j \} \mathbf{F}_I \{ S(\varphi_l, \varphi_j, \lambda_k) \} \right\}, \quad \varphi_l = \varphi_1, \varphi_2, \dots, \varphi_N$$

The advantage of the 1D spherical FFT approach: it gives exactly the same results as those obtained by direct numerical integration. It only needs to deal with one one-dimensional complex array each time, resulting in a considerable saving in computer memory as compared to the 2D FFT technique discussed before.

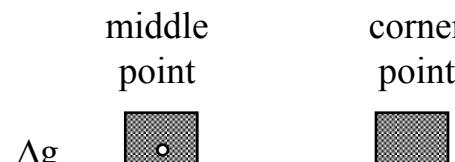
# Geoid Undulations by FFT (9/9)

## Computational procedure:

- Subtract effect of GM from  $\Delta g$  (long wavelength)
- Subtract effect of terrain from  $\Delta g$  (short wavelength)
- Use the reduced  $\Delta g$  in the FFT formulas
- Add to the results (reduced co-geoid) the GM effect
- Add to the results (reduced co-geoid) the indirect terrain effects

# Edge Effects and Circular Convolution - Zero Padding

computation of



kernel



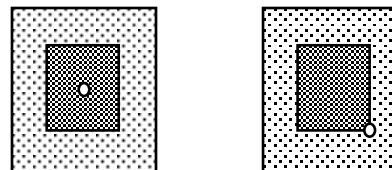
(a) numerical integration

computation of

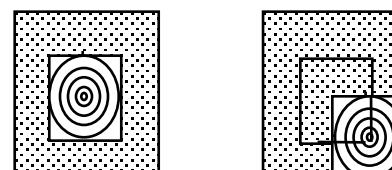


(b) circular convolution  
without zero padding

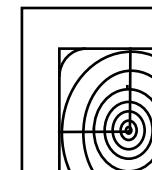
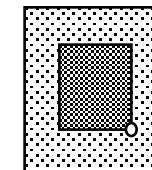
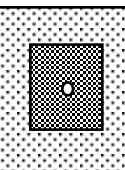
$\Delta g$



kernel



(c) circular convolution  
100% zero-padding on  
both  $\Delta g$  and kernel



(d) circular convolution  
100% zero-padding on  $\Delta g$  only and  
computing kernel in the whole area



# Optimal Spectral Geoid Determination

# Error propagation (1/2)

FFT method can use heterogeneous data, provided that they are given on a grid, and can produce error estimates, provided the PSDs (the Fourier transform of the covariance functions) of the data and their noise are known and stationary

$$(\Delta g + n) * s + \varepsilon = N, \quad s = \frac{l_N}{\gamma}$$

$$\mathbf{F}\{N\} = (\mathbf{F}\{\Delta g\} + \mathbf{F}\{n\})\mathbf{F}\{s\} + \mathbf{F}\{\varepsilon\}$$

Multiplying by the complex conjugate of  $\mathbf{F}\{N\}$  first  
and then by the complex conjugate of  $\mathbf{F}\{\Delta g\}$ , we get :

$$P_{NN} = P_{ee} + S(P_{\Delta g \Delta g} + P_{nn})S^* = P_{ee} + |S|^2(P_{\Delta g \Delta g} + P_{nn}) \quad \leftarrow$$

$$P_{N \Delta g} = S(P_{\Delta g \Delta g} + P_{nn})$$

No correlation  
between signal  
and noise and  
between input  
and output noise

$S$  is the spectrum of  $s$ , and  $P_{\Delta g \Delta g}$  is the PSD of the gravity anomalies

# Error Propagation (2/2)

$$\mathbf{F}\{N\} = \mathbf{F}\{\Delta g\} \mathbf{F}\{s\} = P_{N\Delta g} (P_{\Delta g\Delta g} + P_{nn})^{-1} \mathbf{F}\{\Delta g\} \quad \text{spectral form}$$

$$S = P_{N\Delta g} (P_{\Delta g\Delta g} + P_{nn})^{-1} = S_0 (1 + \frac{P_{nn}}{P_{\Delta g\Delta g}})^{-1}, \quad S_0 = \frac{P_{N\Delta g}}{P_{\Delta g\Delta g}}$$

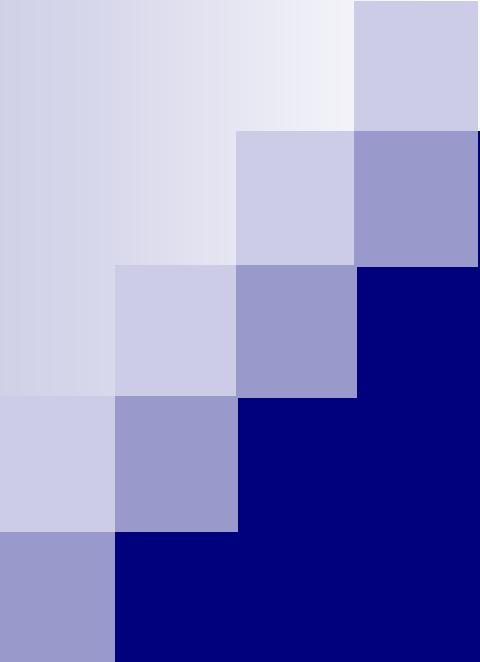


$$\hat{\mathbf{N}} = \mathbf{C}_{N\Delta g} (\mathbf{C}_{\Delta g\Delta g} + \mathbf{C}_{nn})^{-1} \Delta \mathbf{g} \quad \xrightarrow{\text{collocation form}}$$

$$P_{ee} = P_{NN} - P_{N\Delta g} (P_{\Delta g\Delta g} + P_{nn})^{-1} P_{\Delta g N} = |S_0|^2 P_{\Delta g\Delta g} [1 - (1 + \frac{P_{nn}}{P_{\Delta g\Delta g}})^{-1}] \quad \text{spectral form}$$



$$\mathbf{C}_{ee} = \mathbf{C}_{NN} - \mathbf{C}_{N\Delta g} (\mathbf{C}_{\Delta g\Delta g} + \mathbf{C}_{nn})^{-1} \mathbf{C}_{N\Delta g}^T \quad \xrightarrow{\text{collocation form}}$$



## Other Applications of FFT

# Application 1: Terrain Corrections by FFT (1/2)

## Conventional Computation of TC

- Single point computation
- Numerical integration: summation of contributions of compartments (prisms)
- Time consuming:  $t \sim N^2$

## FFT Computation of TC

- Convolution integral
- Homogeneous TC coverage for BVPs
- Height files on regular grid
- Need for faster methods → **FFT approach ideal**
- Reduced computation time:  $t \sim N \log N$
- Handling of large amounts of gridded data
- Spectral analysis; covariance functions

**DATA:** gridded  $h$  (and  $\rho$ )

**OBJECTIVE:** Rigorous and fast evaluation of TC integral

# Terrain Corrections by FFT(2/2)

$$\begin{aligned} c(x_P, y_P) &= \frac{1}{2} k\rho \iint_E \frac{h^2(x, y) - h^2(x_P, y_P)}{[(x_P - x)^2 + (y_P - y)^2]^{3/2}} dx dy \\ &\quad - h(x_P, y_P) k\rho \iint_E \frac{h(x, y) - h(x_P, y_P)}{[(x_P - x)^2 + (y_P - y)^2]^{3/2}} dx dy \\ &= \frac{1}{2} k\rho \{ h^2(x_P, y_P) * l_c(x_P, y_P) - h^2(x_P, y_P) [o(x_P, y_P) * l_c(x_P, y_P)] \\ &\quad - 2h(x_P, y_P) [h(x_P, y_P) * l_c(x_P, y_P) - h(x_P, y_P) [o(x_P, y_P) * l_c(x_P, y_P)]] \} \\ \text{where } l_c(x, y) &= (x^2 + y^2)^{-3/2} \text{ and } o(x, y) = 1 \end{aligned}$$

## PROCEDURE

- Transform  $h, h_2 = h^2, o, l_c$  to  $H, H_2, O, L_c$  (direct FFT) and form  $HL_c, H_2L_c, OL_c$
- Transform  $HL_c, H_2L_c, OL_c$  to  $h * l_c, h_2 * l_c, o * l_c$  (inverse FFT)
- Multiply and add/subtract terms as needed

$$\begin{aligned} c(x, y) &= \frac{1}{2} k\rho \{ F^{-1} \{ H_2(u, v)L_c(u, v) \} - h^2(x, y) F^{-1} \{ O(u, v)L_c(u, v) \} \\ &\quad - 2h(x, y) [F^{-1} \{ H(u, v)L_c(u, v) \} - h(x, y) F^{-1} \{ O(u, v)L_c(u, v) \}] \} \end{aligned}$$

## Application 2:

# Stokes and Vening Meinesz on the plane (1/2)

$$N(x_p, y_p) = \frac{1}{2\pi\gamma} \iint_E \Delta g(x, y) \frac{1}{[(x_p - x)^2 + (y_p - y)^2]^{1/2}} = \frac{1}{2\pi\gamma} \Delta g(x_p, y_p) * l_N(x_p, y_p)$$

$$l_N(x, y) = (x^2 + y^2)^{-1/2}$$

$$\begin{aligned} \begin{Bmatrix} \xi(x_p, y_p) \\ \eta(x_p, y_p) \end{Bmatrix} &= \begin{Bmatrix} -\partial N(x_p, y_p)/\partial y_p \\ -\partial N(x_p, y_p)/\partial x_p \end{Bmatrix} = -\frac{1}{2\pi\gamma} \begin{Bmatrix} \Delta g(x_p, y_p) * \partial l_N(x_p, y_p)/\partial y_p \\ \Delta g(x_p, y_p) * \partial l_N(x_p, y_p)/\partial x_p \end{Bmatrix} \\ &= -\frac{1}{2\pi\gamma} \Delta g(x_p, y_p) * \begin{Bmatrix} l_\xi(x_p, y_p) \\ l_\eta(x_p, y_p) \end{Bmatrix} \\ \begin{Bmatrix} l_\xi(x, y) \\ l_\eta(x, y) \end{Bmatrix} &= -\begin{Bmatrix} \partial l_N(x, y)/\partial y \\ \partial l_N(x, y)/\partial x \end{Bmatrix} = (x^2 + y^2)^{-3/2} \begin{Bmatrix} y \\ x \end{Bmatrix} \end{aligned}$$

$$\begin{Bmatrix} \xi(x_p, y_p) \\ \eta(x_p, y_p) \end{Bmatrix} = \frac{1}{2\pi\gamma} \iint_E \Delta g(x, y) \frac{1}{[(x_p - x)^2 + (y_p - y)^2]^{3/2}} \begin{Bmatrix} y_p - y \\ x_p - x \end{Bmatrix} dx dy$$

# Stokes and Vening Meinesz on the plane (2/2)

Since  $L_N(u,v) = \mathbf{F}\{l_N(x,y)\} = \mathbf{F}\{(x^2 + y^2)^{-1/2}\} = (u^2 + v^2)^{1/2}$

$$\begin{Bmatrix} l_\xi(x,y) \\ l_\eta(x,y) \end{Bmatrix} = -\begin{Bmatrix} \partial l_N(x,y)/\partial y \\ \partial l_N(x,y)/\partial x \end{Bmatrix}$$

then

$$\mathbf{F}\begin{Bmatrix} \xi(x,y) \\ \eta(x,y) \end{Bmatrix} = -\frac{1}{2\pi\gamma} \Delta G(u,v) \begin{Bmatrix} 2\pi i u \\ 2\pi i v \end{Bmatrix} L_N(u,v)$$

$$N(x,y) = \frac{1}{2\pi\gamma} \mathbf{F}^{-1} \left\{ \Delta G(u,v) \frac{1}{(u^2 + v^2)^{1/2}} \right\}$$

**High-frequency attenuation  
(integration)**

$$\begin{Bmatrix} \xi(x,y) \\ \eta(x,y) \end{Bmatrix} = -\frac{1}{\gamma} \mathbf{F}^{-1} \begin{Bmatrix} \Delta G(u,v) \frac{iv}{(u^2 + v^2)^{1/2}} \\ \Delta G(u,v) \frac{i u}{(u^2 + v^2)^{1/2}} \end{Bmatrix}$$

**High-frequency amplification  
(differentiation)**

# Application 3: Analytical Continuation

Upward continuation from  $h=0$  to  $h=z_0$

$$\begin{aligned}\Delta g(x_P, y_P, z_0) &= \frac{1}{2\pi} \iint_E \Delta g(x, y, 0) \frac{z_0}{[(x_P - x)^2 + (y_P - y)^2 + z_0^2]^{3/2}} dx dy \\ &= \Delta g(x_P, y_P, 0) * l_u(x_P, y_P, z_0), \quad l_u(x, y, z_0) = \frac{z_0}{2\pi[(x^2 + y^2 + z_0^2)]^{3/2}} \\ &= F^{-1}\{F\{\Delta g(x_P, y_P, 0)\} F\{l_u(x_P, y_P, z_0)\}\}\end{aligned}$$

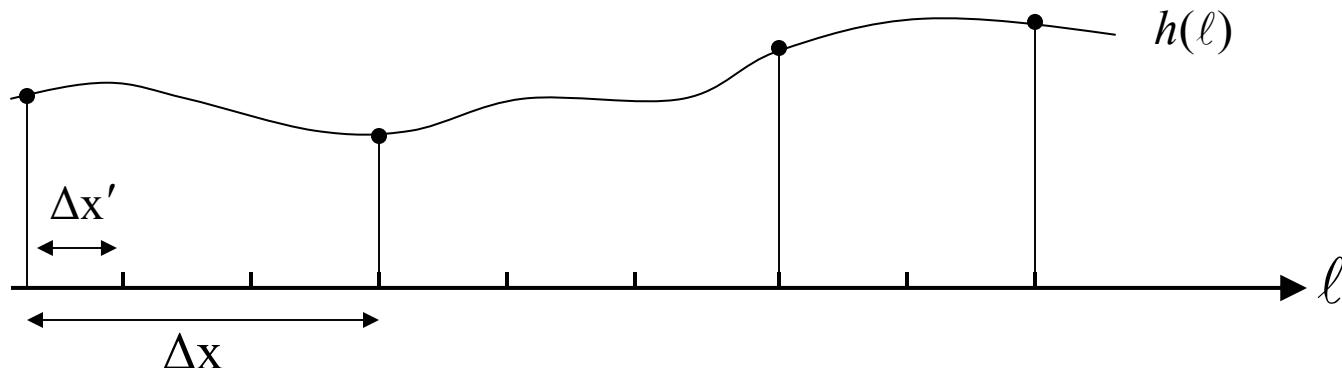
Analytical spectrum of  $l_u$ :  $F\{l_u(x_P, y_P, z_0)\} = L_u(u, v, z_0) = e^{-2\pi z_0(u^2 + v^2)^{1/2}}$   
**High-frequency attenuation**

Downward continuation from  $h=z_0$  to  $h=0$

$$\Delta g(x_P, y_P, 0) = F^{-1}\left\{\frac{F\{\Delta g(x_P, y_P, z_0)\}}{F\{l_u(x_P, y_P, z_0)\}}\right\} = F^{-1}\{F\{\Delta g(x_P, y_P, z_0)\} F\{l_d(x_P, y_P, z_0)\}\}$$

Analytical spectrum of  $l_d$ :  $F\{l_d(x_P, y_P, z_0)\} = 1/L_u(u, v, z_0) = e^{2\pi z_0(u^2 + v^2)^{1/2}}$   
**High-frequency amplification**

# Application 4: Interpolation by FFT



- Want to interpolate with spacing  $\Delta x' = \Delta x / L$
- Zeros are filled at  $L-1$  points between the initial pairs of sampled values

$$g(\ell) = \begin{cases} h(1/L), & \ell = 0 \leq L \leq 2L \\ 0, & \text{elsewhere} \end{cases} \quad G(m) = H(mL) \quad \text{includes } m > \pm \frac{1}{L}$$

- Filter out higher frequencies, so that

$$-\frac{1}{L} \leq m \leq \frac{1}{L} \quad G_1(m) = \begin{cases} c \cdot H(mL), & -\frac{1}{L} \leq m \leq \frac{1}{L} \\ 0, & \text{elsewhere} \end{cases}$$

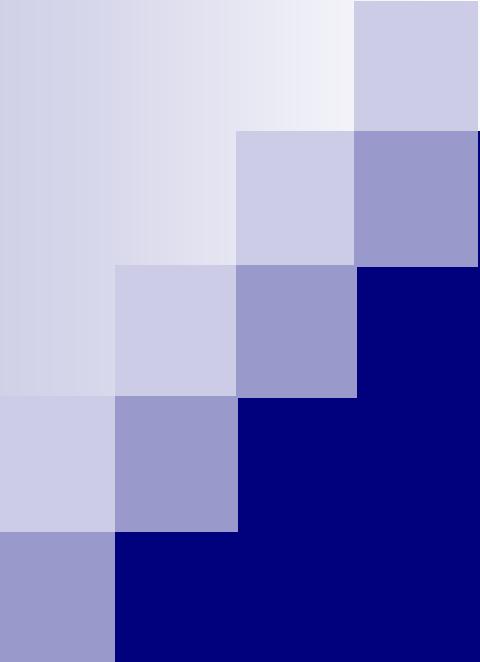
- Match initial amplitudes

$$g_1(0) = \frac{c}{L} h(0) \rightarrow c = L \rightarrow g_1(\ell) = F^{-1}\{G_1(m)\}$$

# Concluding Remarks

# Concluding Remarks

- Spectral methods can efficiently handle large amounts of gridded data and give results on all grid points simultaneously → **indispensable for geoid computations**
- Problems that affect the accuracy of the results: aliasing, leakage, singularity of the kernel functions at the origin, proper handling of mean and point data → **common to all methods using the same data**
- Problems unique to spectral methods:
  - Phase shifting
  - Edge effects and circular convolution
  - Planar approximation
- Drawbacks of FFT-based spectral techniques
  - Gridded data ONLY as input
  - Computer memory
  - Fast error propagation possible only with stationary noise



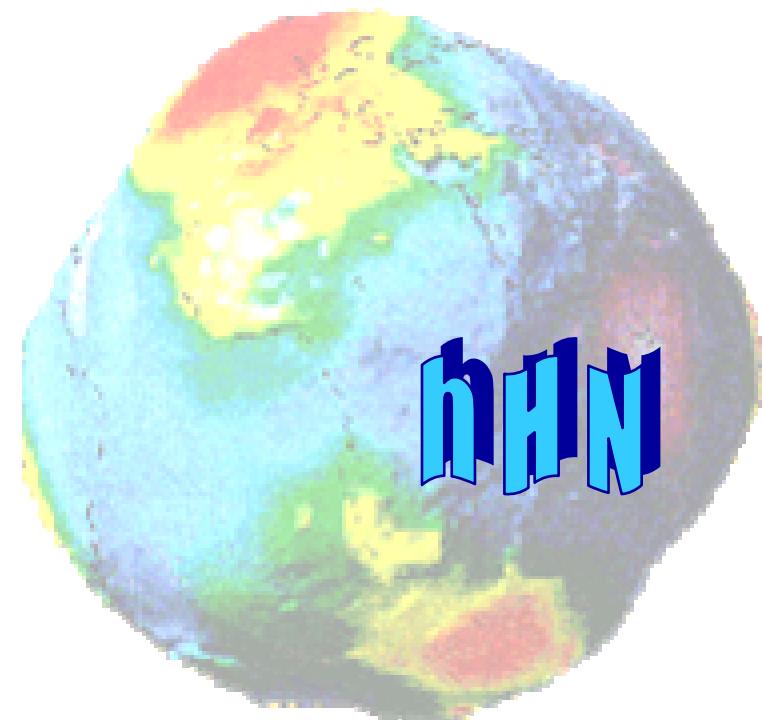
# **Matching the Gravimetric Geoid to the GPS-Levelling Undulations**

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[gfotoiou@ucalgary.ca](mailto:gfotoiou@ucalgary.ca)

Department of Geomatics Engineering  
University of Calgary

# Contents

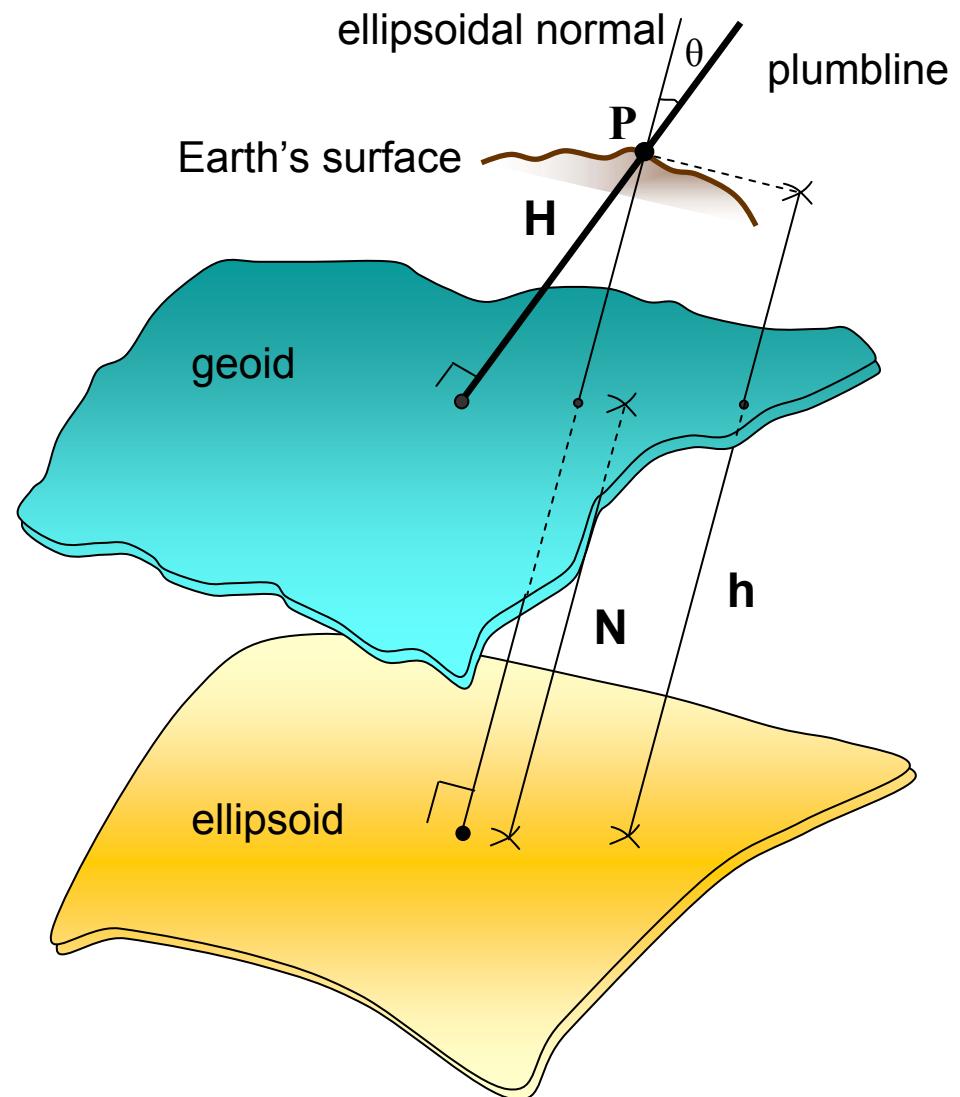
- Introduction to problem
- Why combine  $h$ ,  $H$  and  $N$ ?
- Semi-automated parametric model testing procedure
  - classical empirical approach
  - cross-validation
  - measures of goodness of fit
  - testing parameter significance
- Examples
- Summary



# Introduction

- Traditional means for establishing vertical control ( $H$ ): spirit-levelling
  - costly
  - labourious
  - inefficient, difficult in remote areas, mountainous terrain, over large regions
- With advent of satellite-based global positioning systems (GPS) 3D positioning has been revolutionized

$$h - H - N = 0$$



# Why combine h, H and N?

- modernize regional vertical datums
- unify/connect national regional datums between neighbouring countries
- transform between different types of height data (GPS-levelling)
- refine and test existing gravimetric geoid models
- better understanding of data error sources
  - calibrate geoid error model
  - assess noise in GPS heights, test a-priori error measures
  - evaluate levelling precision, test a-priori error values
- Other applications: sea level change monitoring, post-glacial rebound studies, etc.

# Introduction (continued)

Factors that cause discrepancies when combining heterogeneous heights:

- random errors in the derived heights  $h$ ,  $H$ , and  $N$
- datum inconsistencies inherent among the height types
- systematic effects and distortions (long-wavelength geoid errors, poorly modelled GPS errors and over-constrained levelling network adjustments)
- assumptions/theoretical approximations made in processing observed data (neglecting sea surface topography or river discharge corrections at tide gauges)
- approximate or inexact normal/orthometric height corrections
- instability of reference station monuments over time (geodynamic effects, land uplift/subsidence)

# Problem Formulation

**Standard practice:** Use of a corrector surface to model the datum discrepancies and systematic effects when combining GPS, geoid and orthometric heights

**Theory:**  $h_i - H_i - N_i = 0 \rightarrow N_i^{GPS/levelling} = N_i$

**Practice:**  $h_i - H_i - N_i = l_i \rightarrow N_i^{GPS/levelling} \neq N_i$

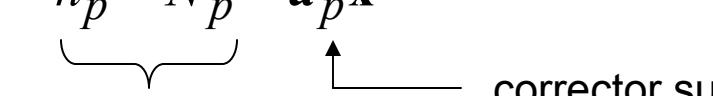
**Model:**  $l_i = h_i - H_i - N_i = \mathbf{a}_i^T \mathbf{x} + v_i$

↑  
parametric model      ↑ residuals

# GNSS-Levelling

- Development of corrector surface models to be used with GPS and gravimetric geoid models for [GPS-Levelling](#)

$$H_p = h_p - N_p - \mathbf{a}_p^T \hat{\mathbf{x}}$$

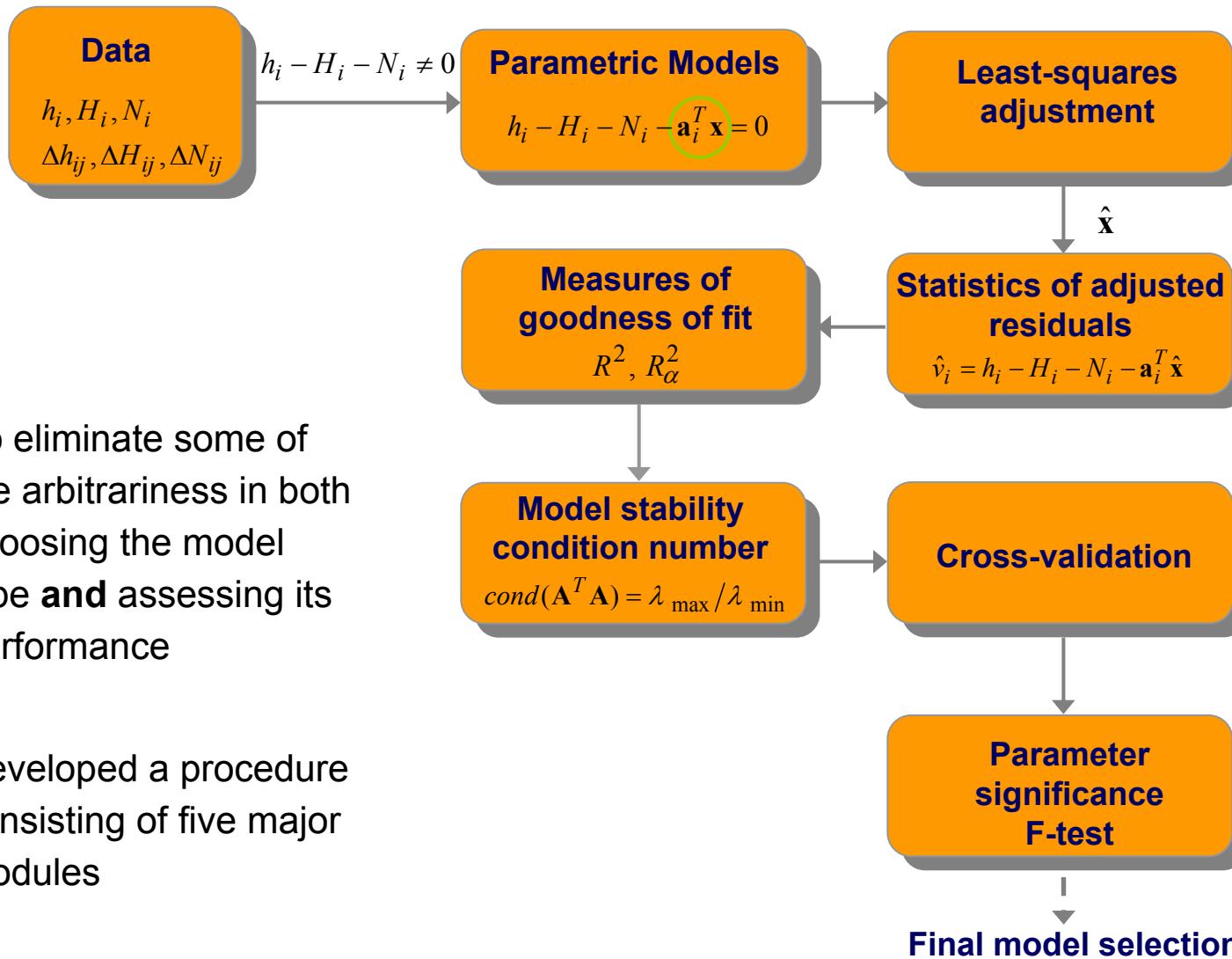

 orthometric height at new point  
 known height data  
 corrector surface

Data

GPS:  $h_i, \Delta h_{ij}$  Orthometric heights:  $H_i, \Delta H_{ij}$  Geoid model:  $N_i, \Delta N_{ij}$

Prediction surface → aim is to derive a surface from data which is to be applied to new data

# Semi-automated Parametric Model Testing Procedure



# Parametric Surface Model Selection

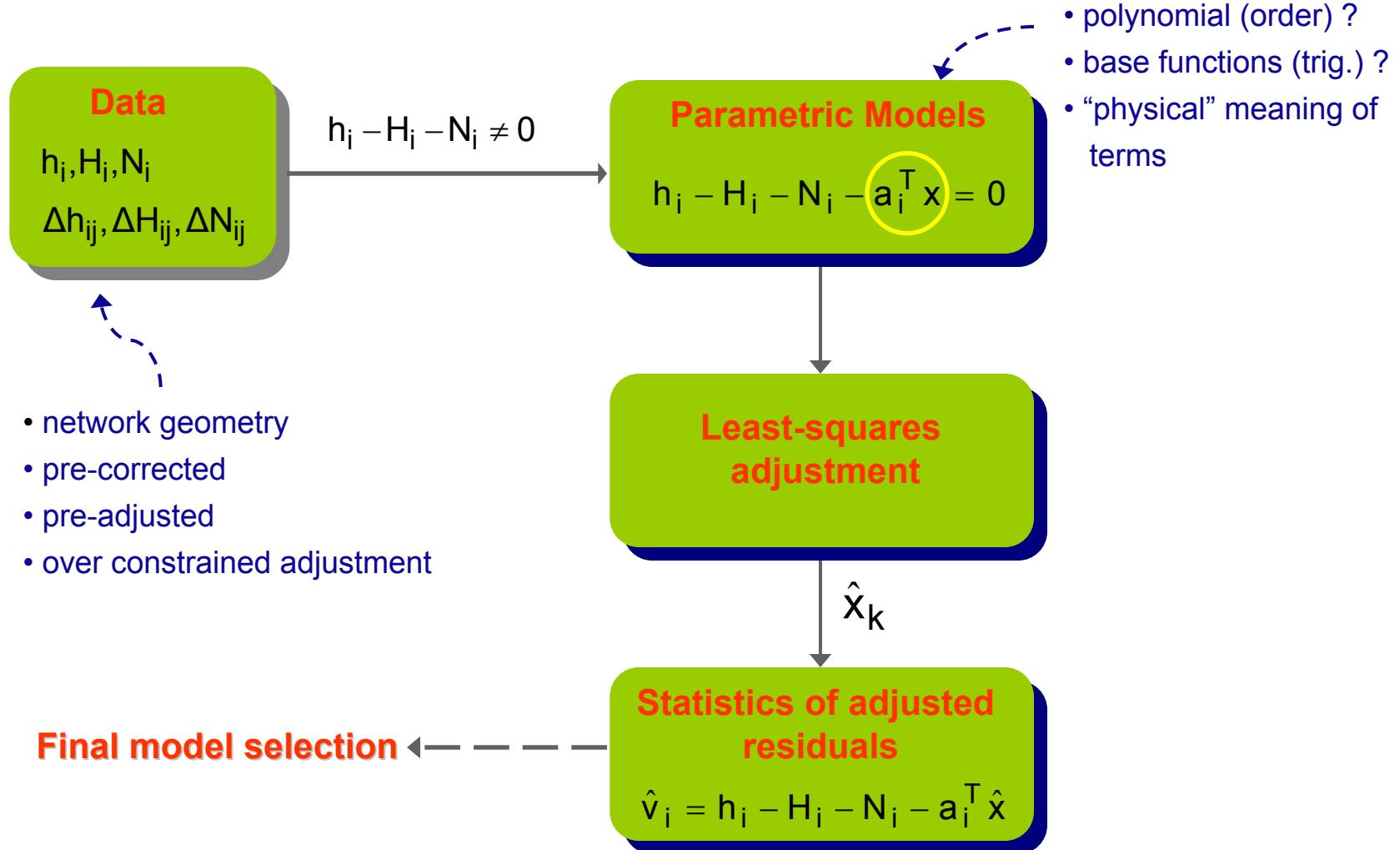
## Parametric Models

$$h_i - H_i - N_i - \mathbf{a}_i^T \mathbf{x} = 0$$

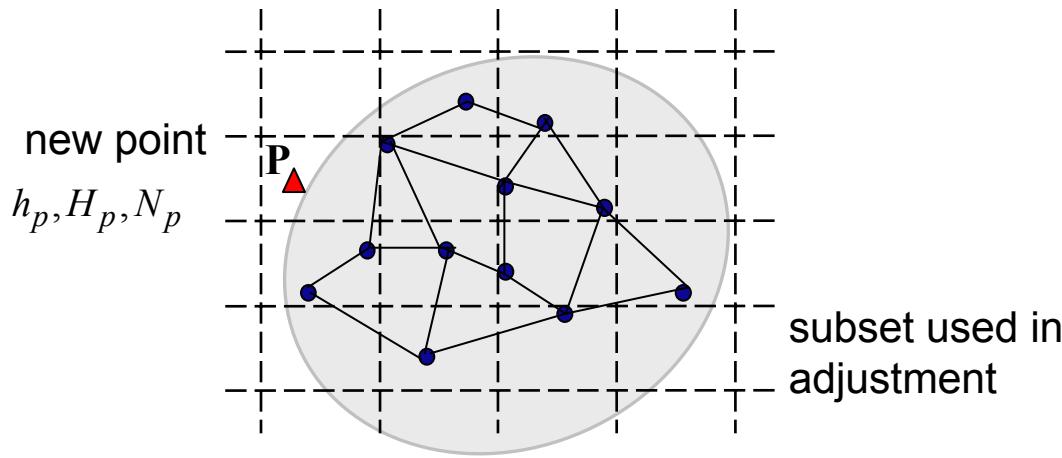
- Selection of analytical model suffers from a degree of arbitrariness (*Why?*)
  - type of model (i.e. polynomial)
  - type of base functions (i.e. trigonometric)
  - number of coefficients
- Need statistical tools to
  - assess choices made
  - compare different models
- Factors for model selection/analysis may vary if
  - nested models
  - orthogonal vs. non-orthogonal models

*No straightforward answer, data dependent (geometry)*

# Classic Empirical Approach

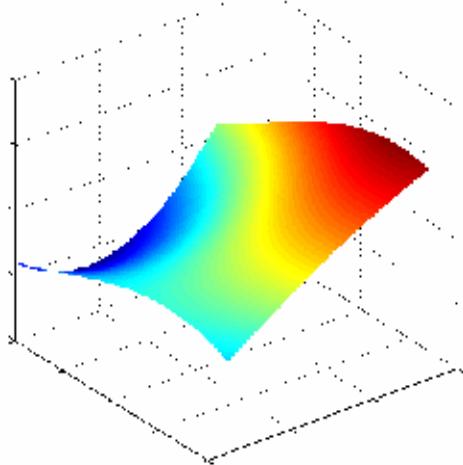


# Cross Validation



Cross-validation  
(empirical approach)

$$\mathbf{a}_p^T \hat{\mathbf{x}}$$



$$\rightarrow \Delta \hat{v}_p = h_p - H_p - N_p - \mathbf{a}_p^T \hat{\mathbf{x}}$$

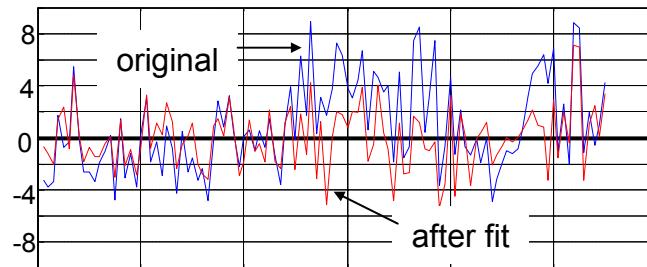
Repeat for each point and compute:

$$\frac{1}{n} \sum_{i=1}^n \sqrt{\mu_i^2 + \sigma_i^2}$$

# Measures of Goodness of Fit

Statistics of adjusted residuals

$$\hat{v}_i = h_i - H_i - N_i - a_i^T \hat{x}$$



Coefficient of determination

$$R^2$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (\ell_i - \hat{v}_i)^2}{\sum_{i=1}^n (\ell_i - \bar{\ell}_i)^2} \quad \ell_i = h_i - H_i - N_i$$

n ... # of observations

Adjusted coefficient of determination

$$\bar{R}^2$$

$$\bar{R}^2 = 1 - \frac{\left[ \sum_{i=1}^n (\ell_i - \hat{v}_i)^2 \right] / (n-m)}{\left[ \sum_{i=1}^n (\ell_i - \bar{\ell}_i)^2 \right] / (n-1)}$$

m ... # of parameters

# Testing Parameter Significance

Reasons for reducing the number of model parameters

- Simplicity, computational efficiency
- Over-parameterization (i.e. high-degree trend models)
  - unrealistic extrema in data voids where control points are missing
- Unnecessary terms may bias other parameters in model
  - hinders capability to assess model performance



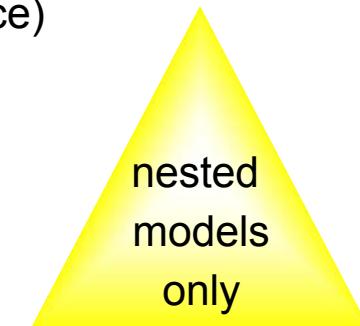
**Parameter Significance**

—————> Need for automated selection process

# Stepwise Procedures

## Backward Elimination Procedure

- Start with highest order model
- Eliminate less-significant terms one-by-one (or several at once)
- Criteria for determining parameter deletion
  - Partial F-test
  - Level of significance,  $\alpha$
  - **Problem:** correlation between parameters



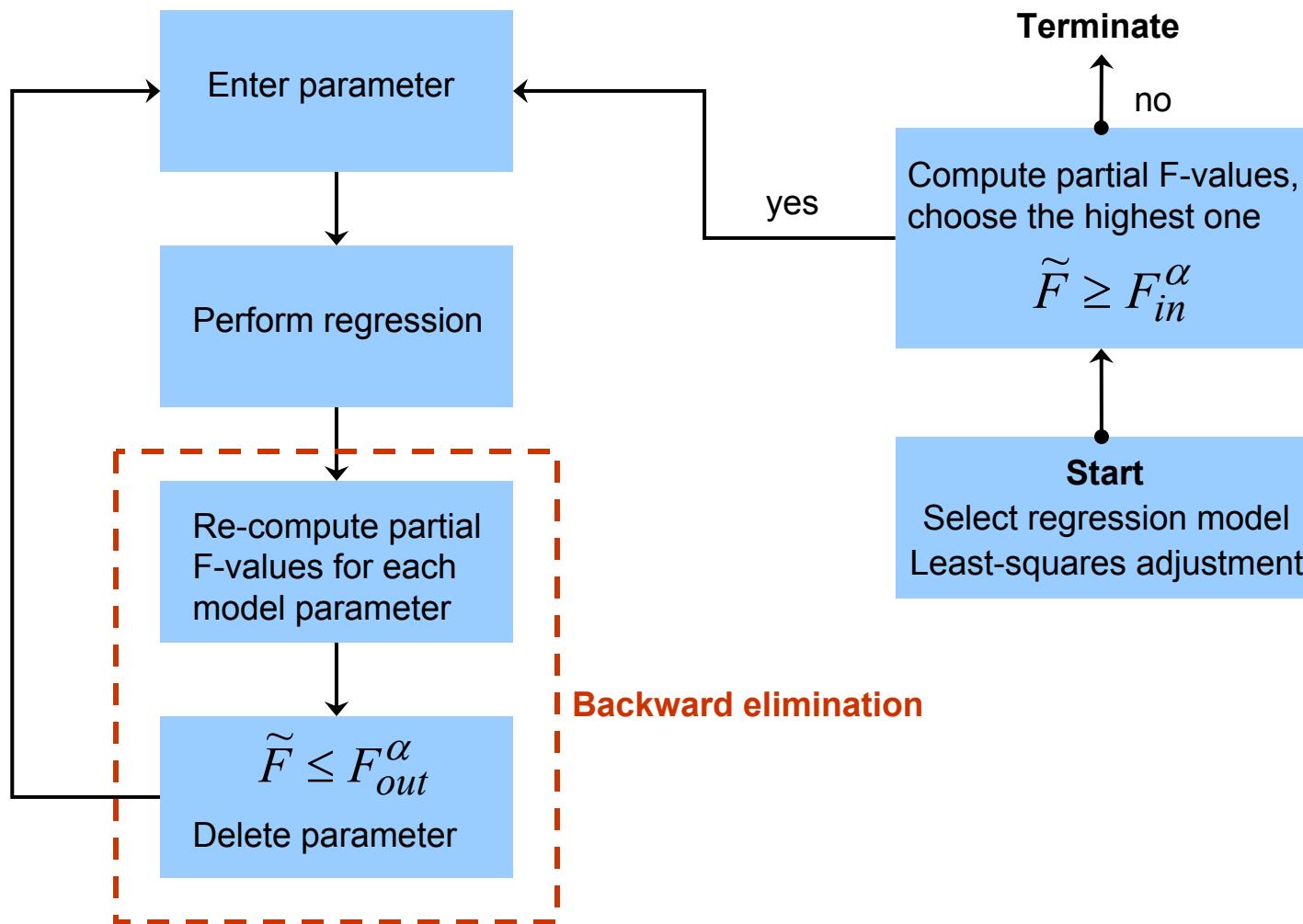
## Forward Selection Procedure

- Start with simple model
- Add parameter with the highest coefficient of determination (or partial F-value)

## Stepwise Procedure

- Combination of backward elimination and forward selection procedures
- Starts with no parameters and selects parameters one-by-one (or several)
- After inclusion, examine every parameter for significance (partial F-test)

# Stepwise Procedure



# Testing Parameter Significance

- Statistical tests are more powerful in pointing out inappropriate models rather than establishing model validity
- Test if a set of parameters in the model is significant or not:

$$x = \begin{bmatrix} x_{(I)} \\ x_I \end{bmatrix} \quad \begin{array}{l} I \dots \text{set of parameters tested} \\ (I) \dots \text{remaining parameters (complement)} \end{array}$$

**hypothesis**  $H_0 : x_I = 0 \quad \text{vs} \quad H_a : x_I \neq 0$

**test statistic**  $\tilde{F} = \frac{\hat{x}_I Q_{\hat{x}_I}^{-1} \hat{x}_I}{k \hat{\sigma}^2} \quad \begin{array}{l} k \dots \text{number of 'tested' terms} \\ Q_{\hat{x}_I} \dots \text{submatrix of } Q = N^{-1} \end{array}$

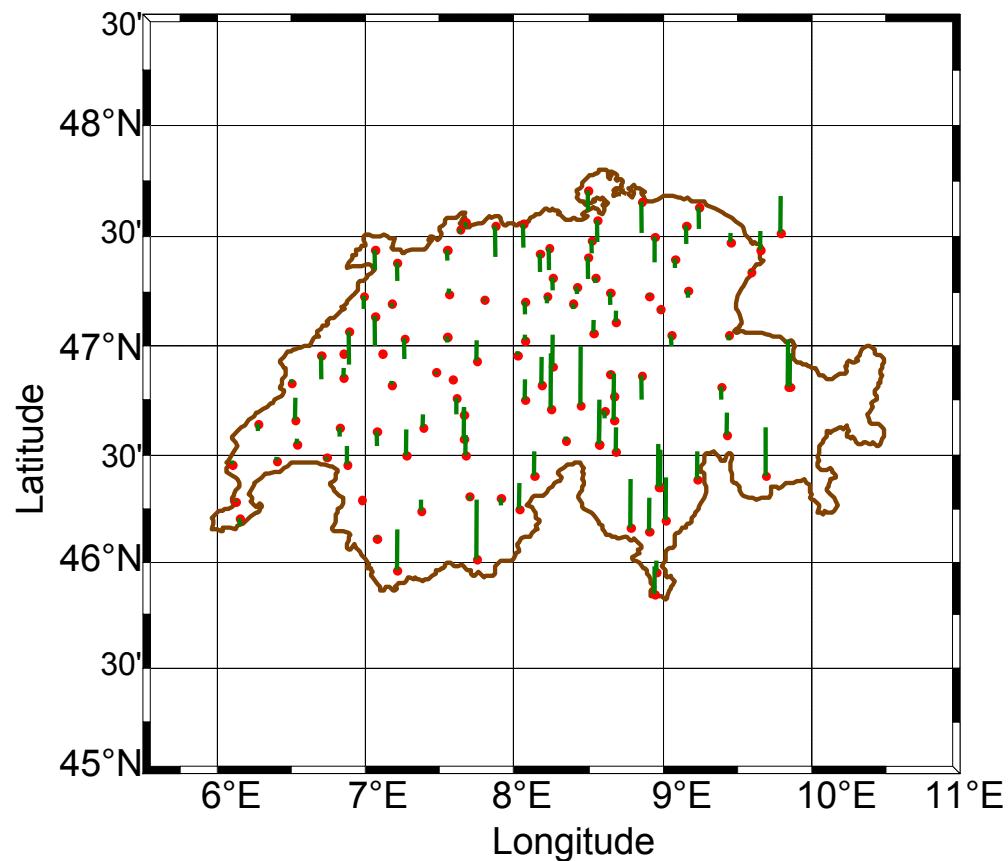
**criteria**  $\tilde{F} \leq F_{k,f}^\alpha \quad H_0 \text{ accepted } \checkmark$

# Examples - Switzerland

- 111 stations in **Switzerland**
- 343 km × 212 km region
- Form ‘residuals’:  
 $\ell_i = h_i - H_i - N_i$

Statistics of residuals before fit

min	-4.9 cm
max	19 cm
mean	1.1 cm
std	3.8 cm
rms	3.9 cm



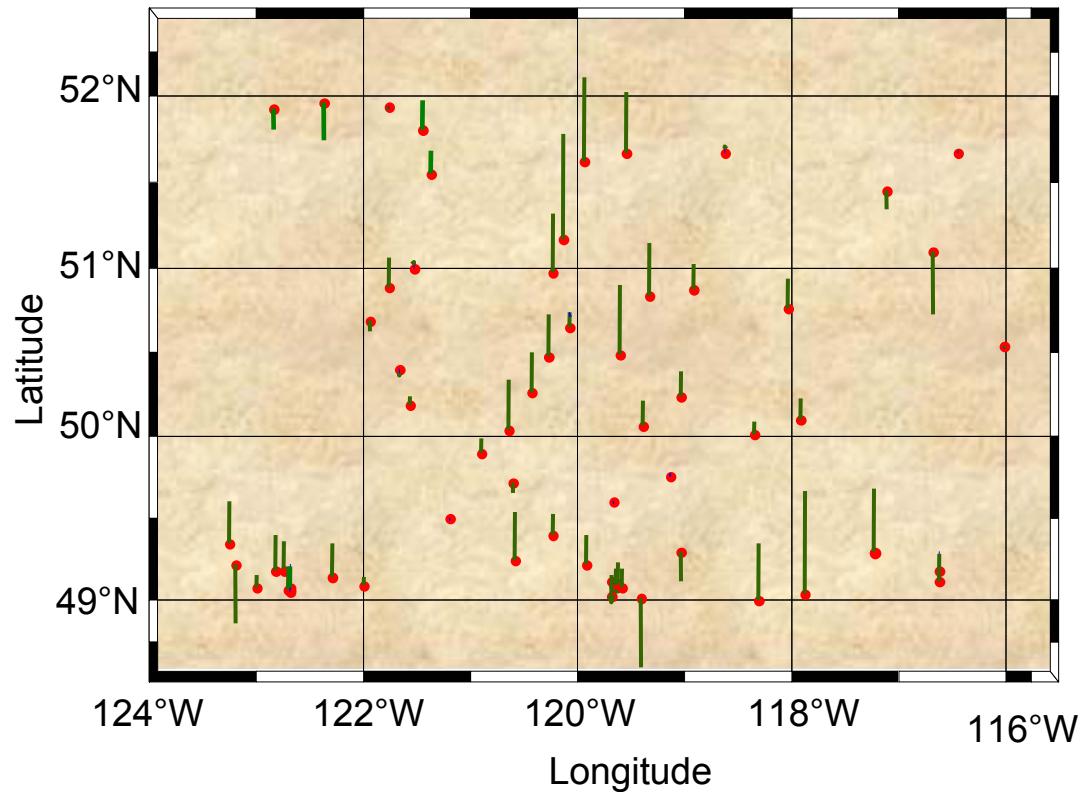
**GPS on Benchmarks (and residuals)**

# Examples - Canada

- 63 stations in **Southern British Columbia & Alberta**
- 495 km × 334 km region
- Form ‘residuals’:  $\ell_i = h_i - H_i - N_i$

Stats of residuals before fit

min	-17.1 cm
max	25.2 cm
mean	4.5 cm
std	8.1 cm
rms	9.3 cm



**GPS on Benchmarks (and residuals)**

# Examples of Analytical Models

## *Nested bilinear polynomial series*

$$1 \ d\varphi \ d\lambda \ d\varphi d\lambda \ d\varphi^2 \ d\lambda^2 \ d\varphi^2 d\lambda \ d\varphi d\lambda^2 \ d\varphi^3 \ d\lambda^3 \ d\varphi^2 d\lambda^2 \ d\varphi^3 d\lambda \ d\varphi d\lambda^3 \ d\varphi^4 \ d\lambda^4$$

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## *Classic trigonometric-based polynomial fits*

$$1 \ \cos\varphi \cos\lambda \ \cos\varphi \sin\lambda \ \sin\varphi$$

$$1 \ \cos\varphi \cos\lambda \ \cos\varphi \sin\lambda \ \sin\varphi \ \sin^2\varphi$$

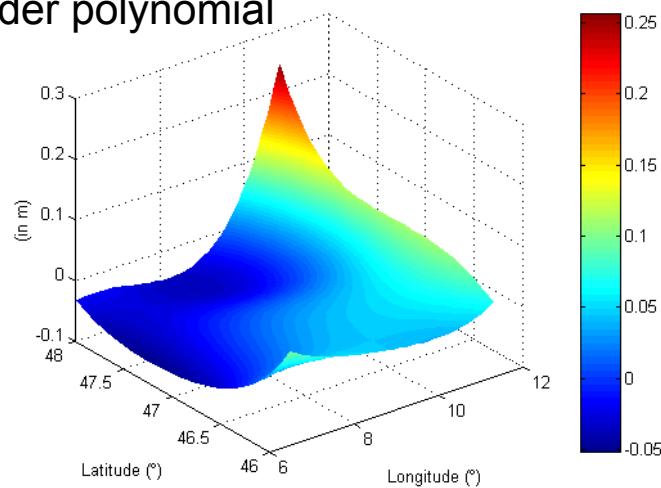
## *Differential similarity transformation*

$$\cos\varphi \cos\lambda \ \cos\varphi \sin\lambda \ \sin\varphi \ \frac{\sin\varphi \cos\varphi \sin\lambda}{W} \ \frac{\sin\varphi \cos\varphi \cos\lambda}{W} \ \frac{1-f^2 \sin^2\varphi}{W} \ \frac{\sin^2\varphi}{W}$$

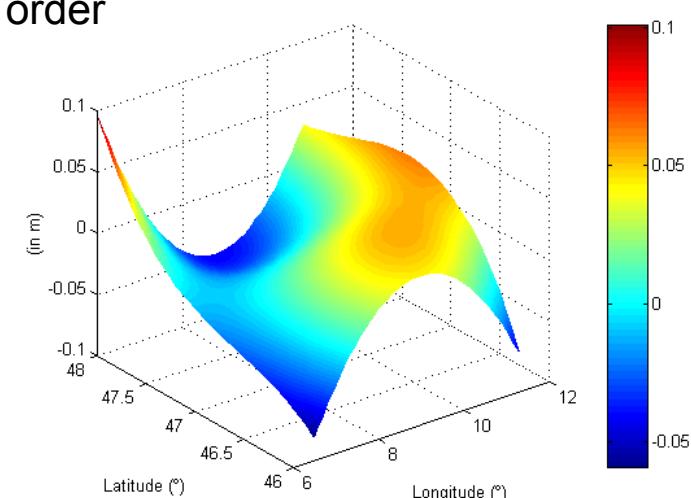
where,  $W = \sqrt{1 - e^2 \sin^2\varphi}$

# Analytical Models

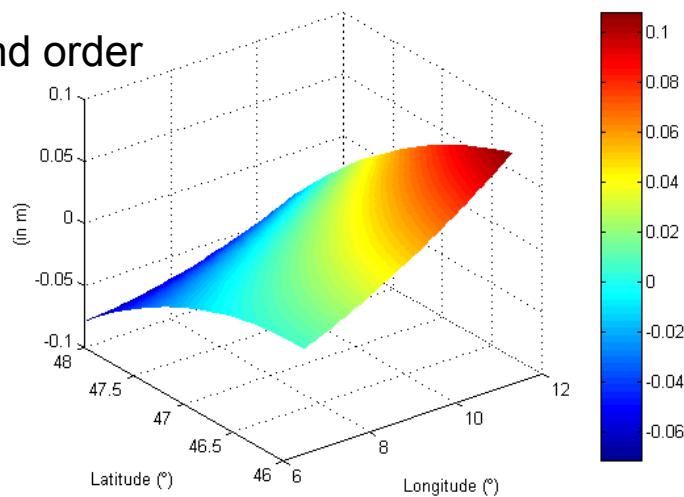
4th order polynomial



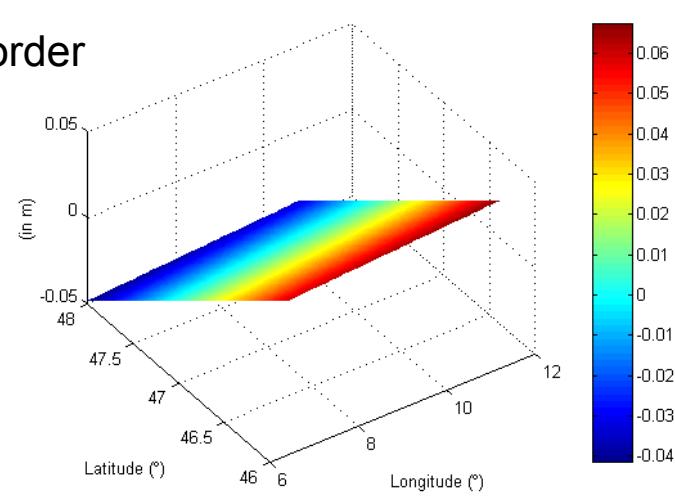
3rd order



2nd order

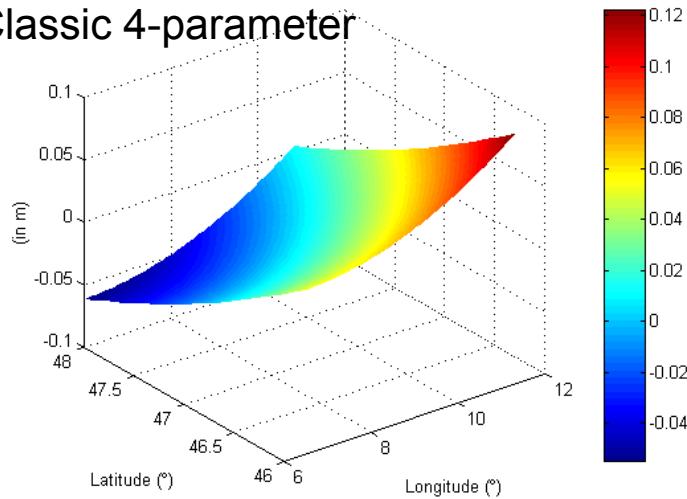


1st order

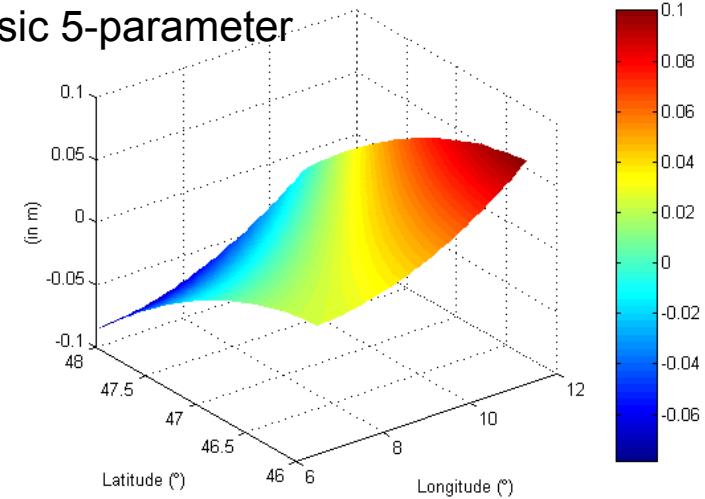


# More Analytical Models

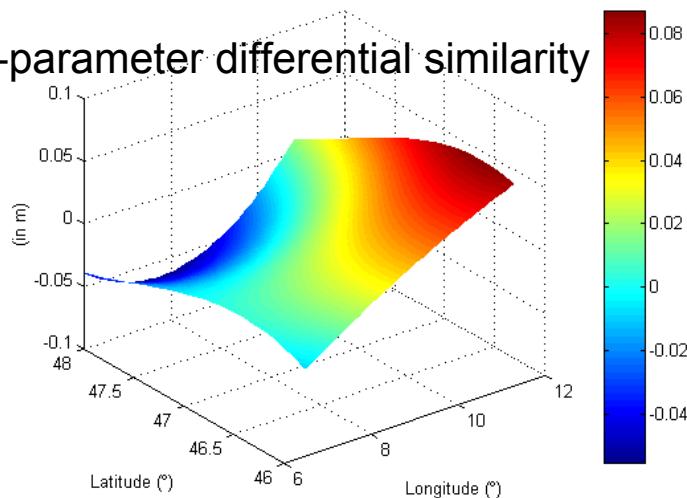
Classic 4-parameter



Classic 5-parameter



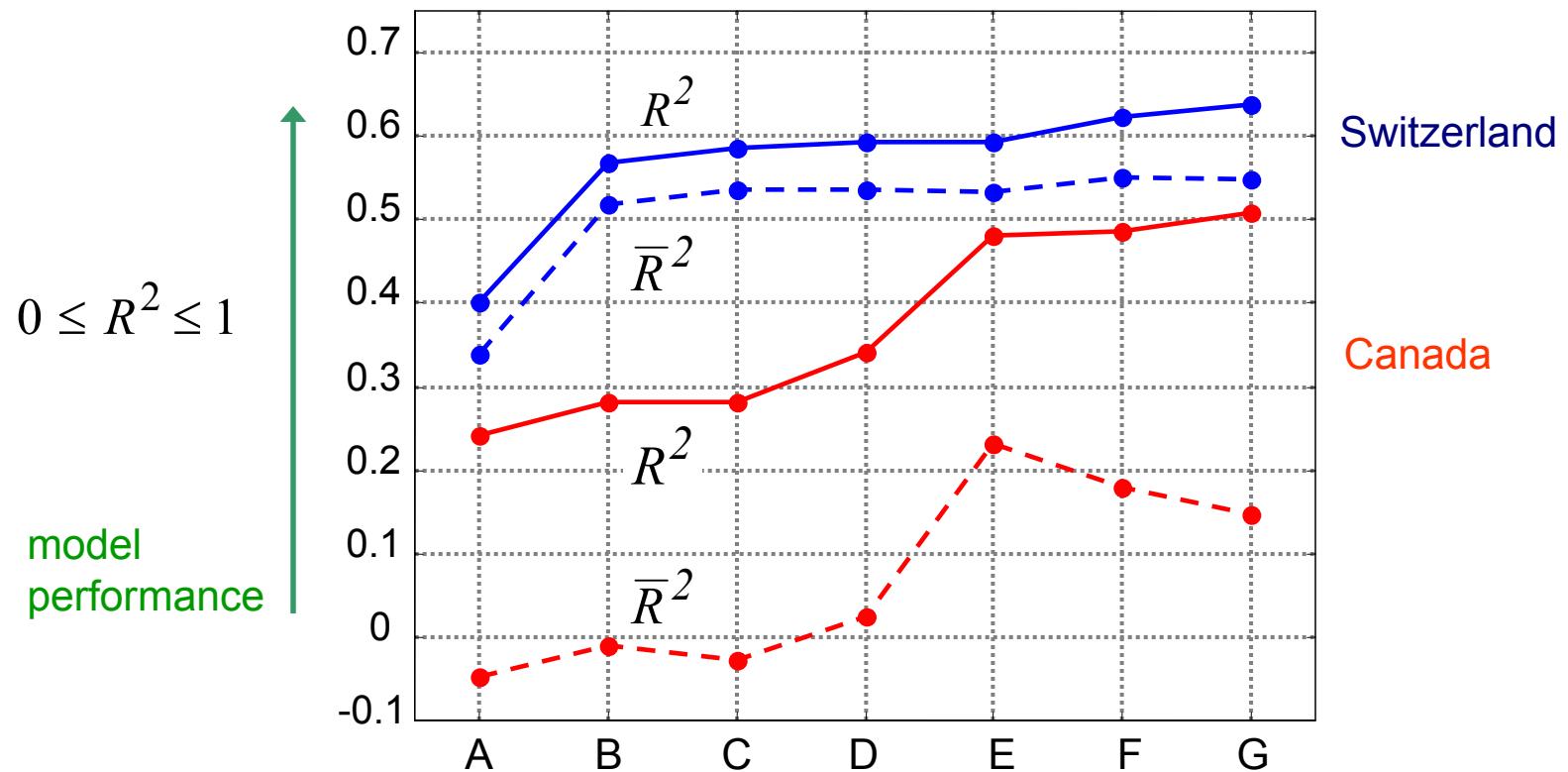
7-parameter differential similarity



## Notes

- all values shown in m
- GPS BMs in Switzerland used
- Full models shown (no parameters omitted)

# Example - Coefficient of Determination



- A** 1<sup>st</sup> order polynomial
- D** 2<sup>nd</sup> order polynomial
- G** 4<sup>th</sup> order polynomial

- B** Classic 4-parameter
- E** Differential Similarity

- C** Classic 5-parameter
- F** 3rd order polynomial

# Empirical Testing (including cross validation)

## Conclusions

Residuals after fit

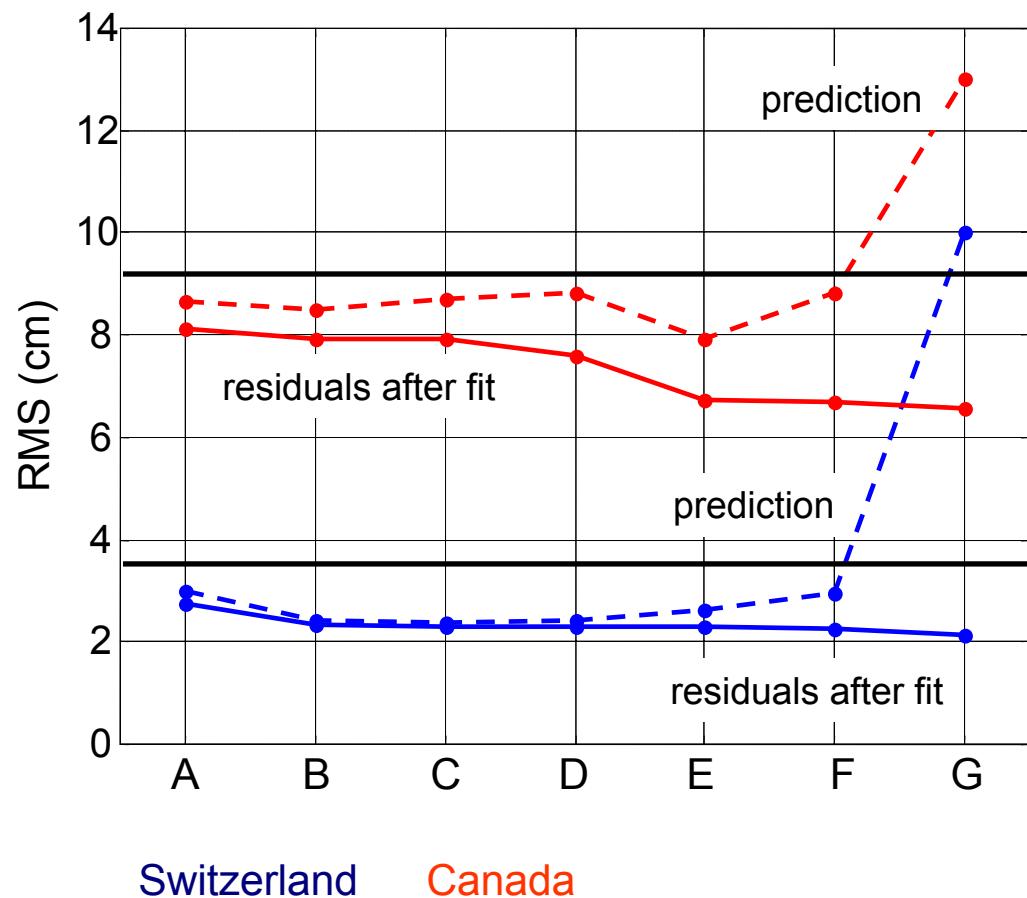
→ 4th order polynomial

Prediction (external test)

→ Any model except 4th order polynomial

Not enough of a difference between models to justify statistical parameter significance testing

→ use lowest order model



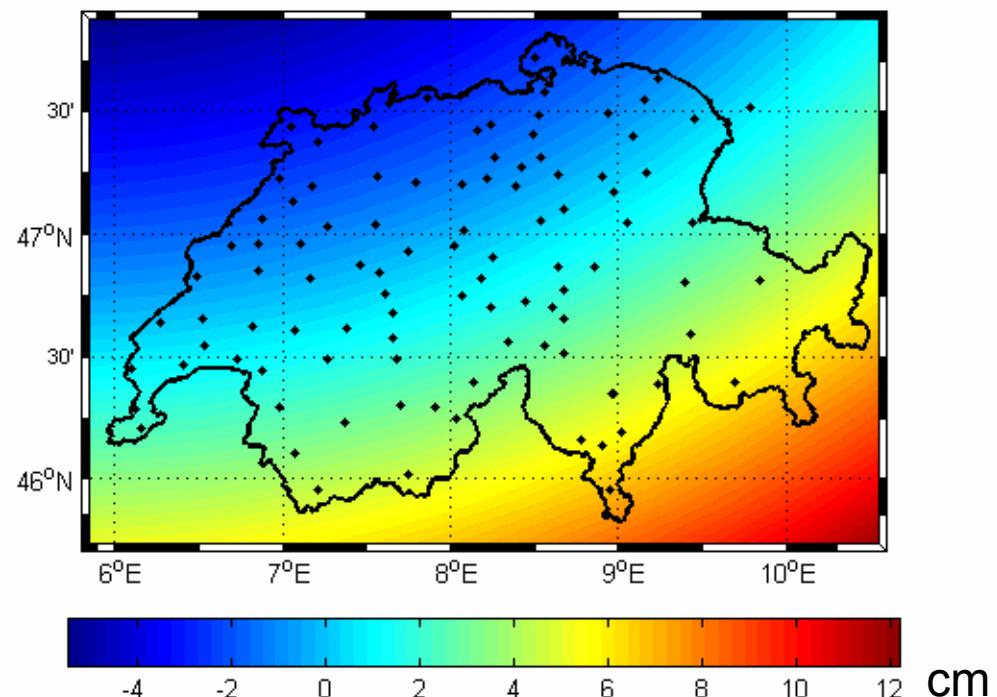
# Results - Switzerland

## Classic 4-parameter fit

$$1 \cos\varphi\cos\lambda \quad \cos\varphi\sin\lambda \quad \sin\varphi$$

## Selection criteria

$R^2$	0.5668
$\bar{R}^2$	0.5181
$\sqrt{\hat{v}^T \hat{v}}$	24.5 cm
condition number	$2.77 \times 10^7$
rms after fit	2.4 cm
rms (prediction)	2.4 cm



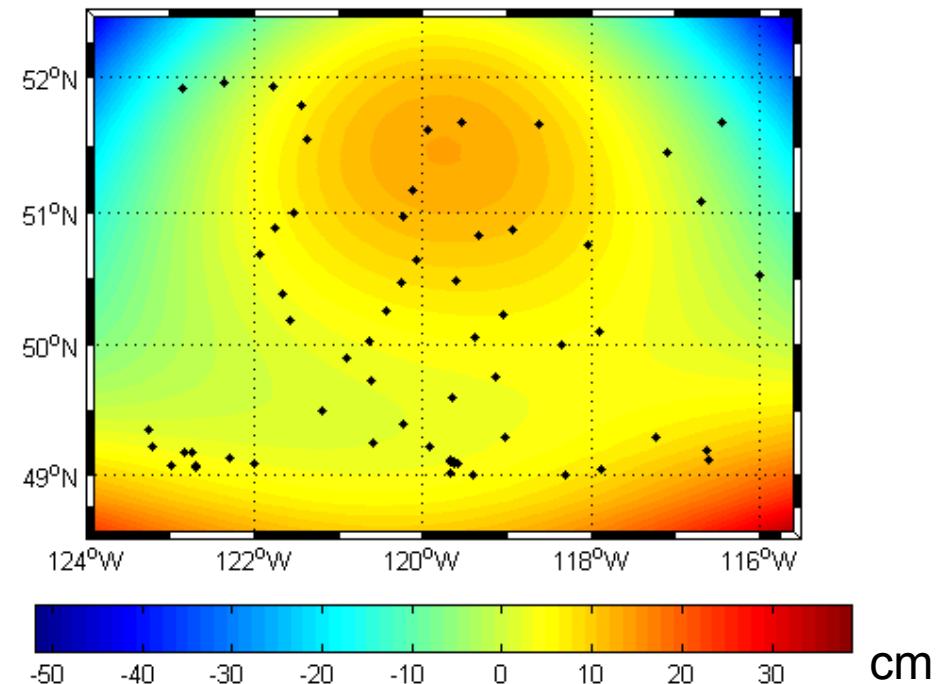
# Results - Canada

## Differential Similarity Fit (7-parameters)

$$\begin{array}{cccccc} \cos\varphi\cos\lambda & \cos\varphi\sin\lambda & \sin\varphi & \frac{\sin\varphi\cos\varphi\sin\lambda}{W} & \frac{\sin\varphi\cos\varphi\cos\lambda}{W} & \frac{1-f^2\sin^2\varphi}{W} & \frac{\sin^2\varphi}{W} \end{array}$$

### Selection criteria

$R^2$	0.4805
$\bar{R}^2$	0.2311
$\sqrt{\hat{v}^T \hat{v}}$	53 cm
condition number	$1.52 \times 10^{12}$
rms after fit	6.7 cm
rms (prediction)	7.9 cm



# Summary

- **Semi-automated procedure** for **comparing parametric surface models** and **assessing model performance** was presented
- ***Semi***
  - no unique straightforward solution
  - some user intervention required
- In most cases, the best test is cross-validation (prediction)
  - independent ‘external’ test
  - depends on quality of data
- When model parameters are highly correlated (as is the case with polynomial regression), statistical testing may not be conclusive
- Use orthogonal polynomials to eliminate problems with high correlation between parameters (i.e. Fourier Series)
- Procedure should include a **combination** of empirical and statistical testing