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INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS

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Matemática Aplicada e Computacional acelerando o desenvolvimento do país - São José dos Campos - SP

Inverse Problems in Space Research
Methods and Applications

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Inverse problems

Methods

- Optimization problem with constrains:
  - Deterministic optimizer: Quasi-Newton
  - Deterministic optimizer: variational approach
- Optimization problem with constrains:
  - Stochastic optimizer: Ant Colony System
  - Stochastic optimizer: Multi-Particle Collision Algorithm
- Optimization problem: hybrid methods
- Artificial neural networks

Inverse problems

Optimization problem with constrains

$$J_\alpha(f) = \left\| A(f) - \theta^\delta \right\|_2^2 + \alpha \Omega[f]$$

$$\Omega[f] = \sum_{k=0}^{p} \mu_k \left\| f^{(k)} \right\|_2^2 \qquad \text{(Tikhonov)}$$

$$\Omega(f) = \sum_{q=1}^{p} s_q \log(s_q) \,, \ \text{with: } s_q = r_q^{(k)} \Big/ \sum_{q=1}^{N} r_q^{(k)} \qquad \text{(Entropy)}$$

$$r_q^{(k)} = \begin{cases} f_q & \text{for } k = 0 \\ f_{q+1} - f_q + (f_{\max} - f_{\min}) + \varsigma & \text{for } k = 1 \\ f_{q+1} - 2f_q + f_{q-1} + 2(f_{\max} - f_{\min}) + \varsigma & \text{for } k = 2 \end{cases}$$

Inverse problems

Deterministic: Quasi-Newton

1. Solve the direct problem for $\boldsymbol{f}^n$ and compute the objective function $M^\alpha(\boldsymbol{f}^n)$.

2. Compute by finite differences the gradient $\nabla M^\alpha(\boldsymbol{f}^n)$.

3. Compute a positive-definite quasi-Newton approximation to the Hessian $\mathbf{H}^n$:

$$\mathbf{H}^n = \mathbf{H}^{n-1} + \frac{\mathbf{b}^n (\mathbf{b}^n)^T}{(\mathbf{b}^n)^T \mathbf{u}^n} - \frac{\mathbf{H}^{n-1} \mathbf{u}^n (\mathbf{u}^n)^T \mathbf{H}^{n-1}}{(\mathbf{u}^n)^T \mathbf{H}^{n-1} \mathbf{u}^n} \quad ,$$

   where: $\mathbf{b}^n = \boldsymbol{f}^n - \boldsymbol{f}^{n-1}$,
   $\mathbf{u}^n = \nabla M^\alpha(\boldsymbol{f}^n) - \nabla M^\alpha(\boldsymbol{f}^{n-1})$.

4. Compute the search direction $\mathbf{d}^n$ as a solution of the following quadratic programming subproblem:

$$\text{Minimize } [\nabla M^\alpha(\boldsymbol{f}^n)^n]^T \mathbf{d}^n + \tfrac{1}{2}(\mathbf{d}^n)^T (\mathbf{H}^n) \mathbf{d}^n \text{ subjected to } l_q - p_q^n \leq d_q \leq u_q - p_q^n \quad .$$

5. Set $\boldsymbol{f}^{n+1} = \boldsymbol{f}^n + \beta^n \mathbf{d}^n$, where the step length β^n minimizes $M^\alpha(\boldsymbol{f}^n + \beta^n \mathbf{d}^n)$.

6. Test the convergence; stop or return to step 1.

Inverse problems

Deterministic: Variational approach

Step 1: Choose an initial guess $\mathbf{K}^0$.

Step 2: Solve the direct problem, Eqs. (1)–(2), to obtain $\mathbf{x}(t)$.

Step 3: Solve the adjoint problem, Eqs. (15)–(16), to obtain the *Lagrange* multiplier vector $\boldsymbol{\lambda}(t)$.

Step 4: Knowing $\boldsymbol{\lambda}(t)$, compute the gradient function vector $\mathbf{J}'[\mathbf{K}]$ from Eq. (19).

Step 5: Compute the conjugate coefficient vector $\boldsymbol{\gamma}^n$ from Eq. (22).

Step 6: Compute the direction of descent vector $\mathbf{P}^n$ from Eq. (21).

Step 7: Set $\Delta\mathbf{K} = \mathbf{P}^n$ [14], and solve the sensitivity problem, Eqs. (10)–(11), to obtain $\Delta\mathbf{x}(t)$.

Step 8: Compute the step size vector $\boldsymbol{\beta}^n$ from Eq. (24).

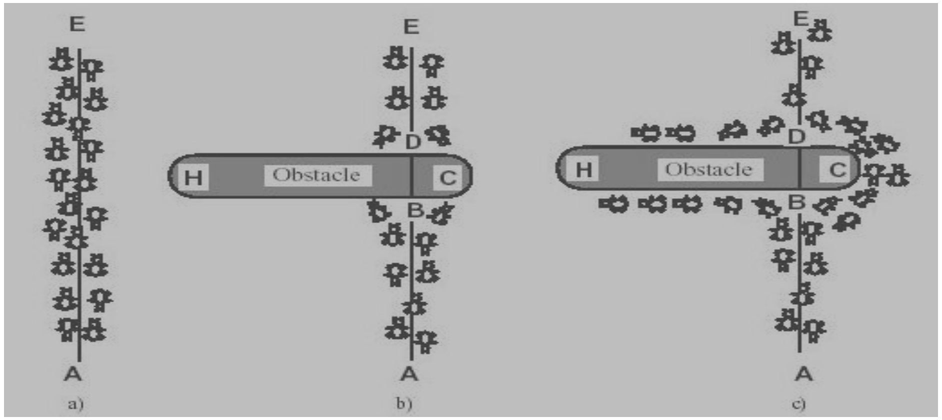
Step 9: Compute $\mathbf{K}^{n+1}$ from Eq. (20).

Step 10: Test if the stopping criteria, Eq. (28), is satisfied. If not, go to step 2.

Inverse problems

ACS (Ant Colony System)

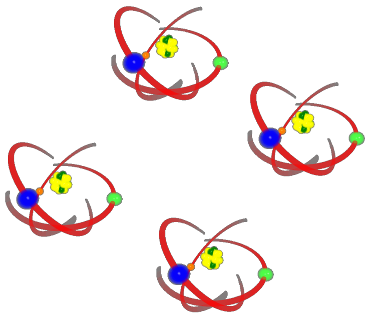
- Ant: a candidate solution
- For each iteration: the best ant is selected
- After iterations, “best of the bests” ant is chosen!
- Modified ACS: only 10% smoothers (2nd-order Tikhonov) of the ant population are selected

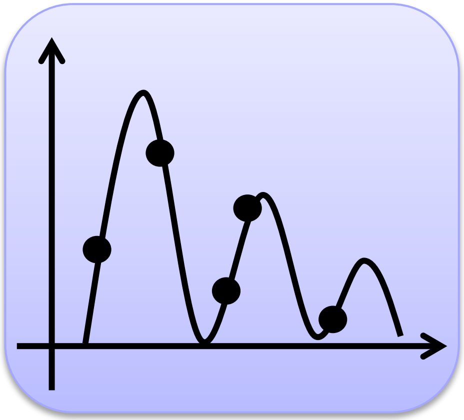


Inverse problems

MPCA (Multi-Particle Colisium Algorithm)

- Particle: a candidate solution
- Neutron traveling inside a nuclear reactor
- Two phenomena: absorption and scattering
- Multi-particle: several particles in cooperation





Inverse problems

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A new multi-particle collision algorithm for optimization in a high performance environment

Eduardo Fávero Pacheco da Luz, José Carlos Becceneri and Haroldo Fraga de Campos Velho

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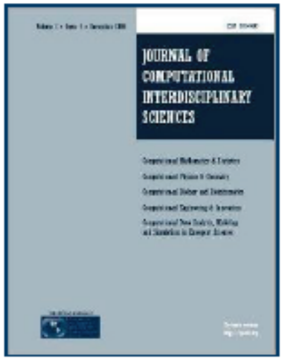
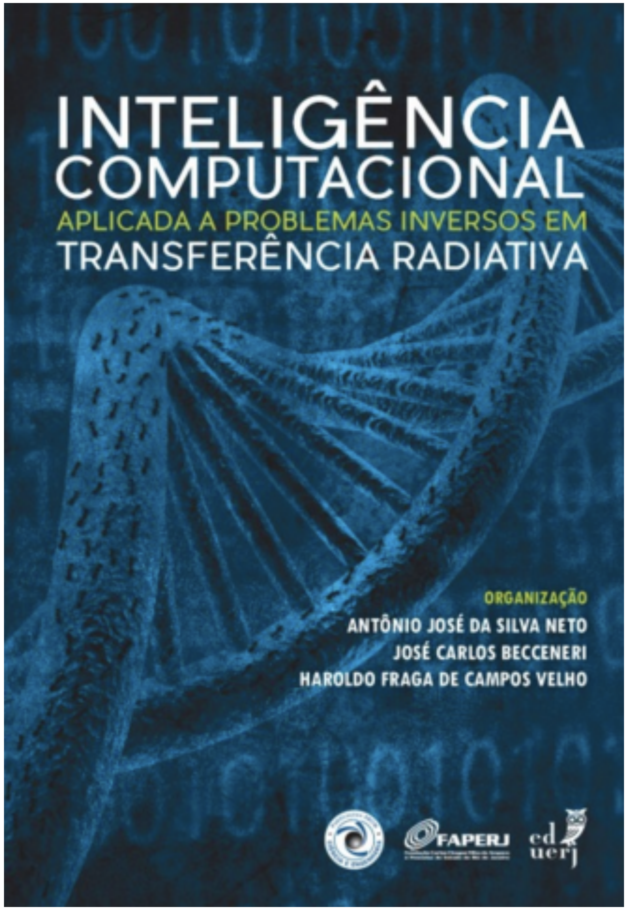


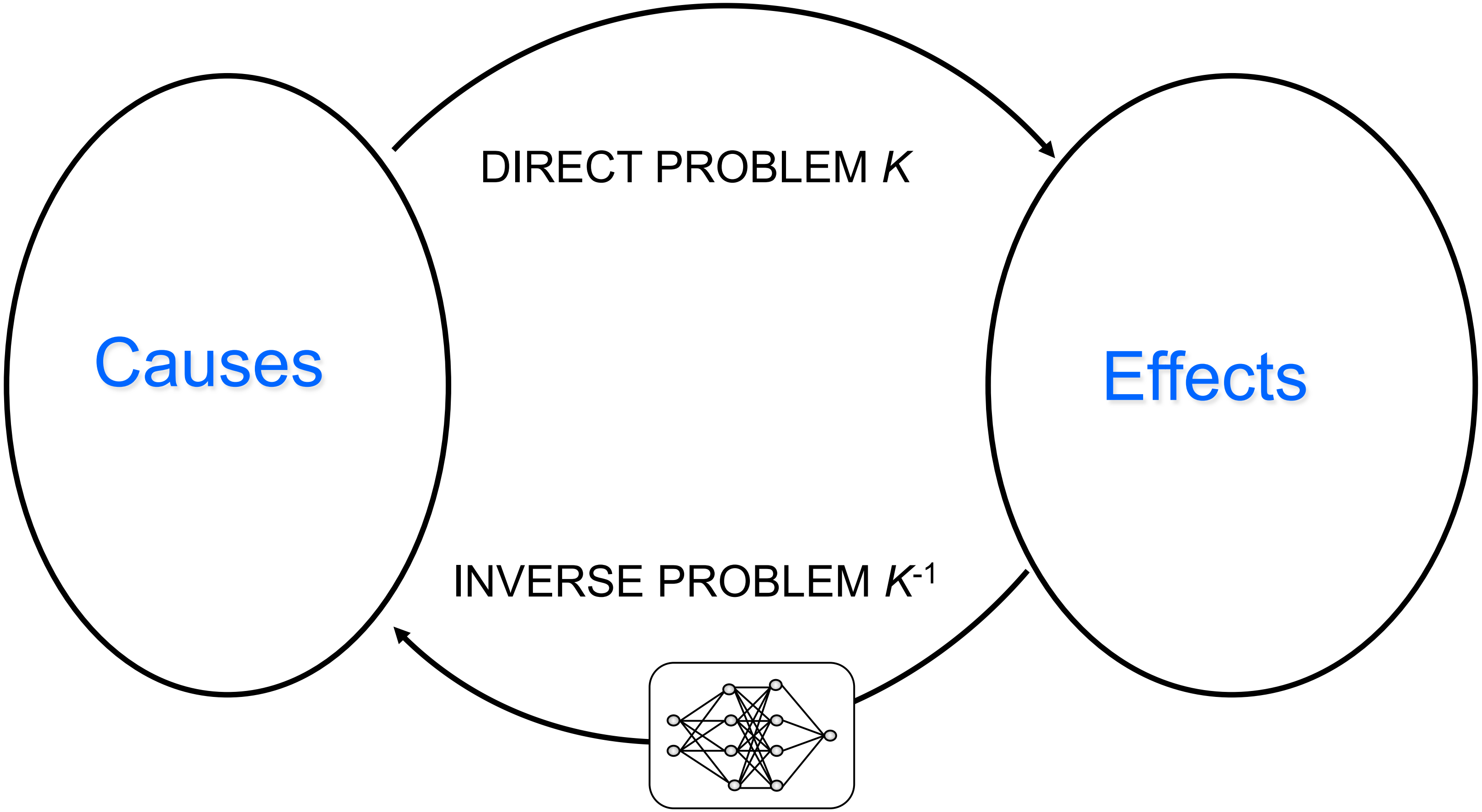
Inverse problems

Meta-heuristics for inverse problems



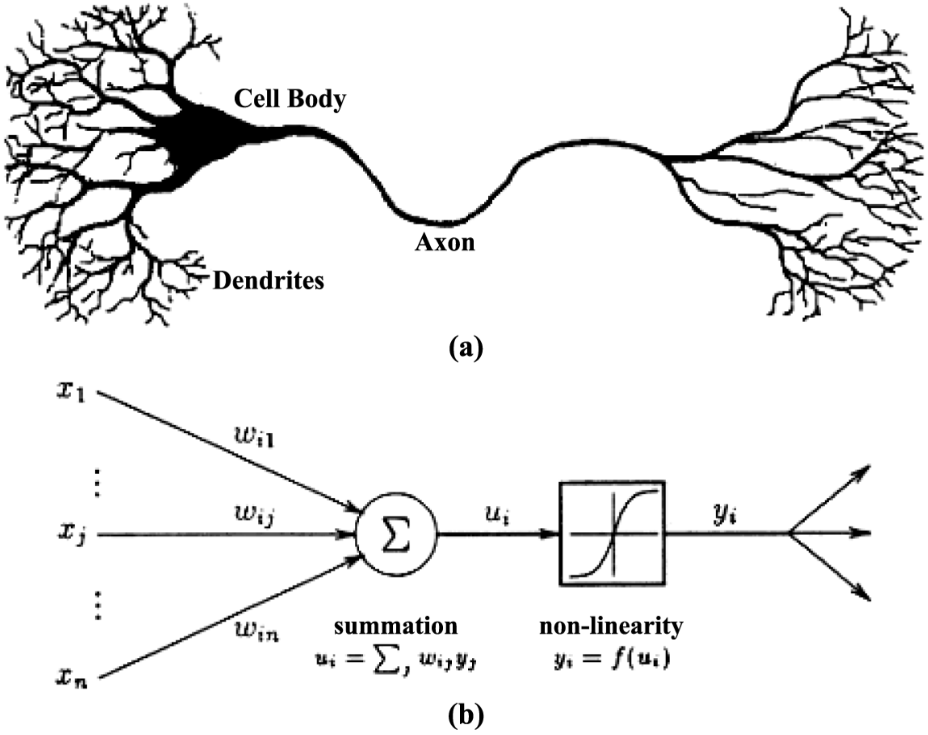
Inverse problems

Neural networks for inverse problems



Inverse problems

Neural networks for inverse problems



Biological neuron

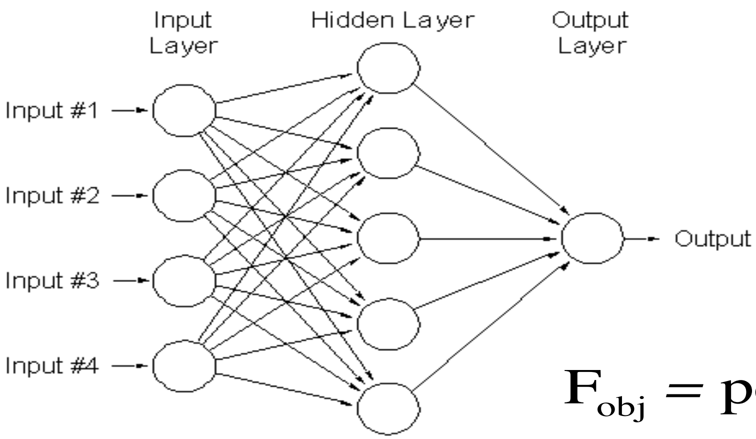
Artificial neuron

$$u_i = f\left(\sum w_{ij} x_j + b_j\right)$$

$$y_i = \varphi\left(u_i\right)$$

Inverse problems

Optimal neural network for IP



$$F_{obj} = \text{penality} * \frac{(\rho_1 * E_{train} + \rho_2 * E_{activ})}{\rho_1 + \rho_2}$$

$$\text{penality} = \underbrace{\left(c_1 * \left(e^{\#\text{neuron}}\right)^2\right)}_{\text{complexity factor-1}} \times \underbrace{\left(c_2 * (\#\text{epoch})\right)}_{\text{complexity factor-2}} + 1$$

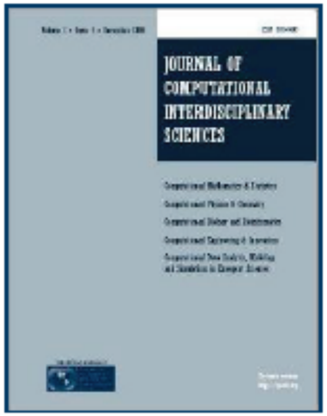
Inverse problems

Optimal neural network for IP

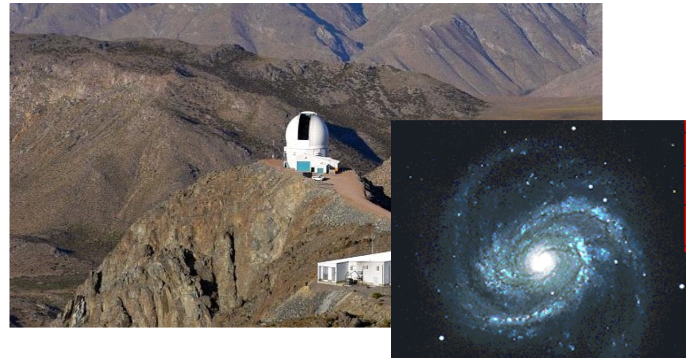
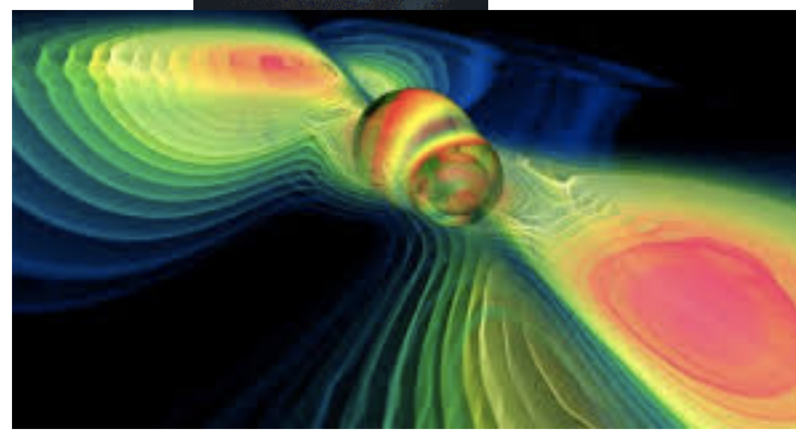
$$F_{obj} = \text{penality} * \frac{(\rho_1 * E_{train} + \rho_2 * E_{activ})}{\rho_1 + \rho_2}$$

Parameters	Value
# hidden layer	|1| |2| |3|
# neurons	|1| ... |32|
Learning rate	|0| ... |1|
Momentum	|0| ... |0.9|
Activation function	|hiperbolic tangente| |Logistic| |Gaussian|

Optimization by MPCA



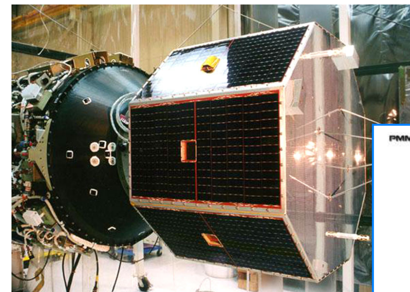
Space Research: Four Pillars

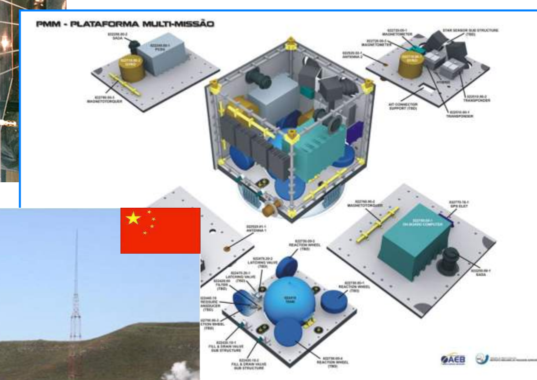



- Space Science
- Space Engineering
- Space Applications
- Space Health/Medicine (*)

Space Research: four pillars

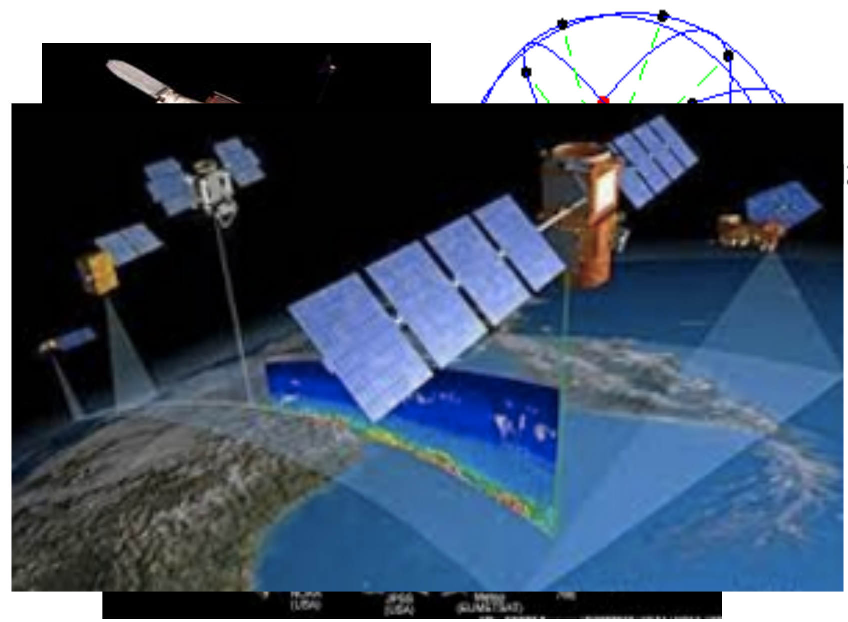
- Space Science
- Space Engineering
- Space Applications
- Space Health/Medicine (*)





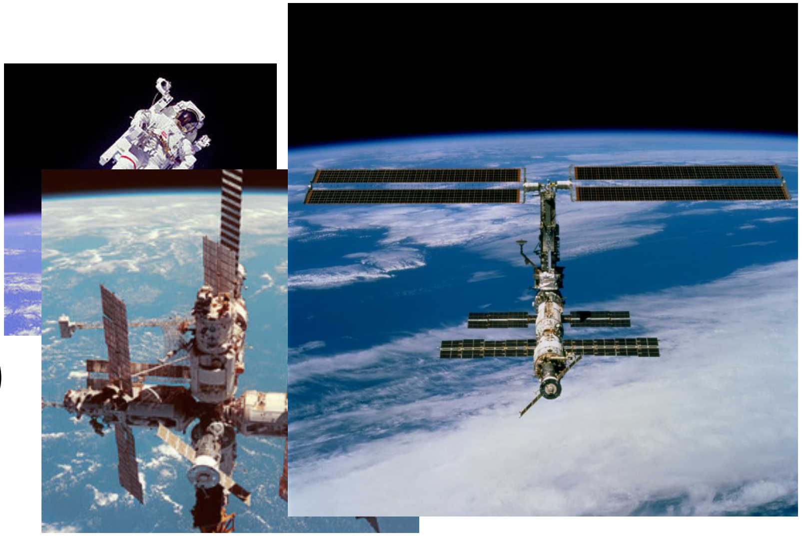
Space Research: four pillars

- Space Science
- Space Engineering
- Space Applications
- Space Health/Medicine



Space Research: four pillars

- Space Science
- Space Engineering
- Space Applications
- Space Health/Medicine (*)



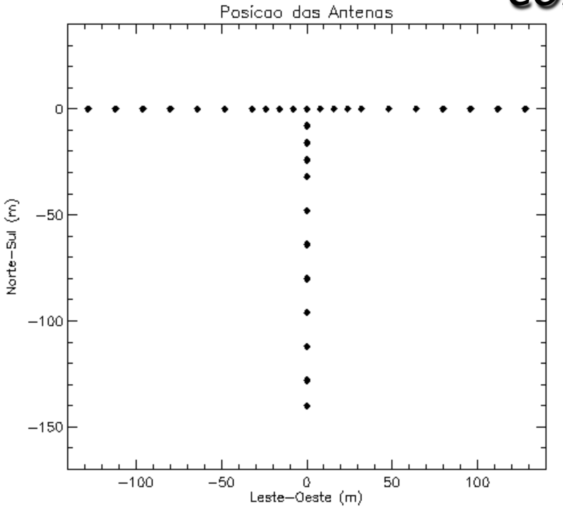
Space Research (Space Science)

B D A

BRAZILIAN
DECIMETRIC
ARRAY

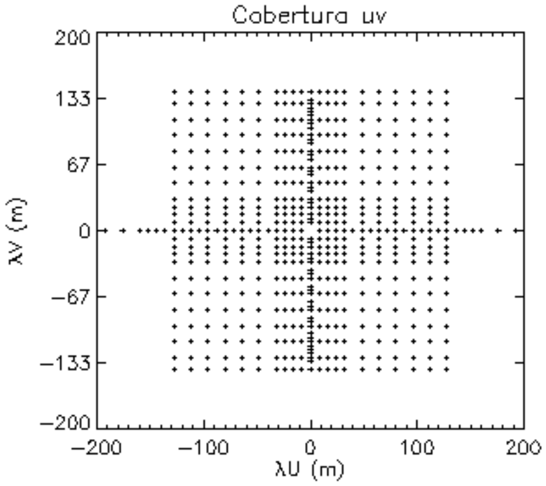
Space Research (Space Science)

configuration



correlation

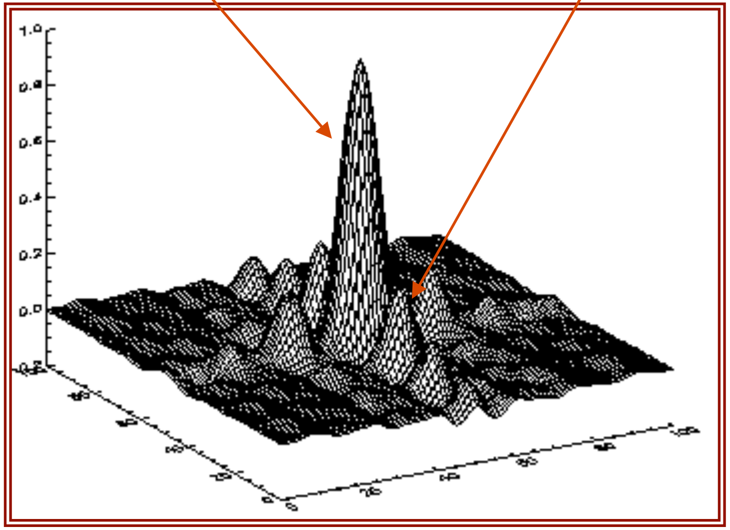
samples



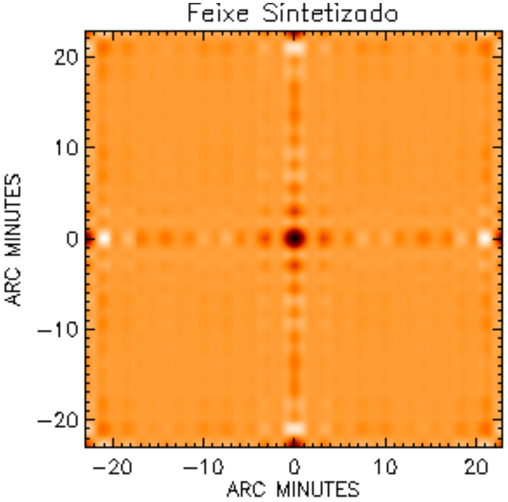
Fourier^{-1}

Central peak

Secundary peaks



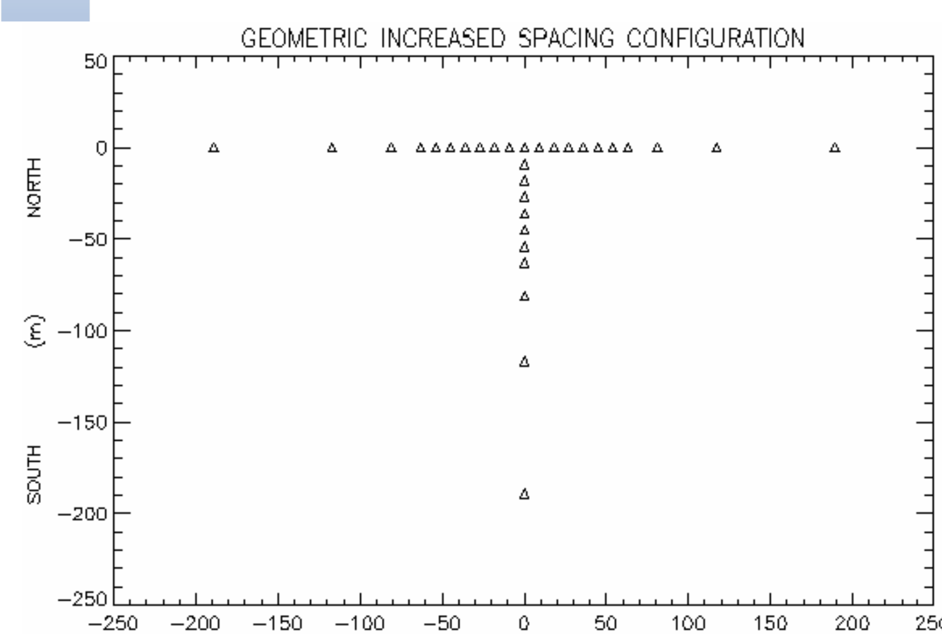
Synthesized beam

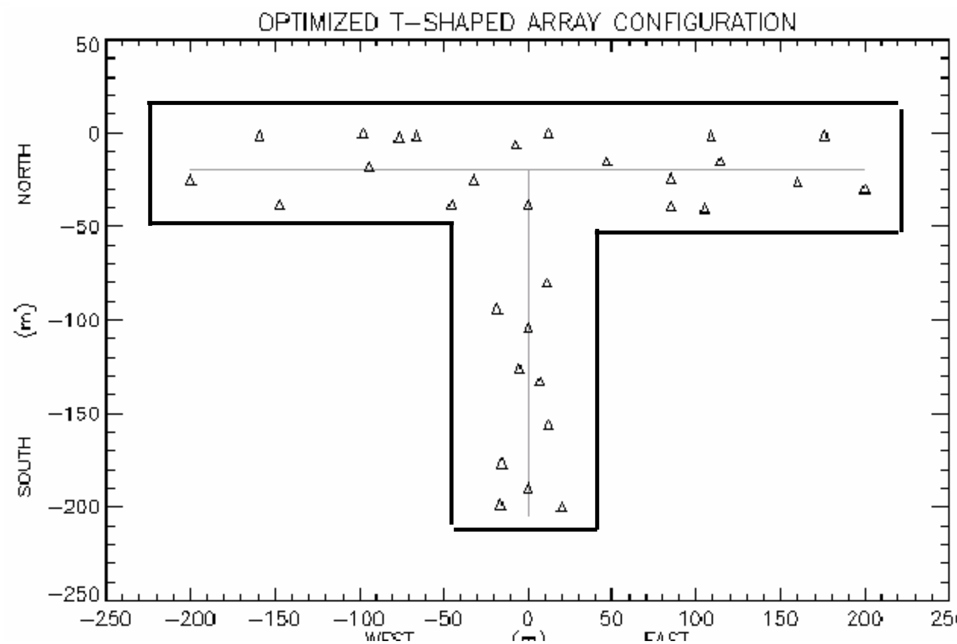


Space Research (Space Science)

Objective function:

$$J(\chi) = \sum_{m}\sum_{n} q_{mn}\log(q_{m}) \quad \text{with} \quad q_{mn} = \frac{B_{mn}}{\sum_{i}\sum_{j} B_{ij}}$$



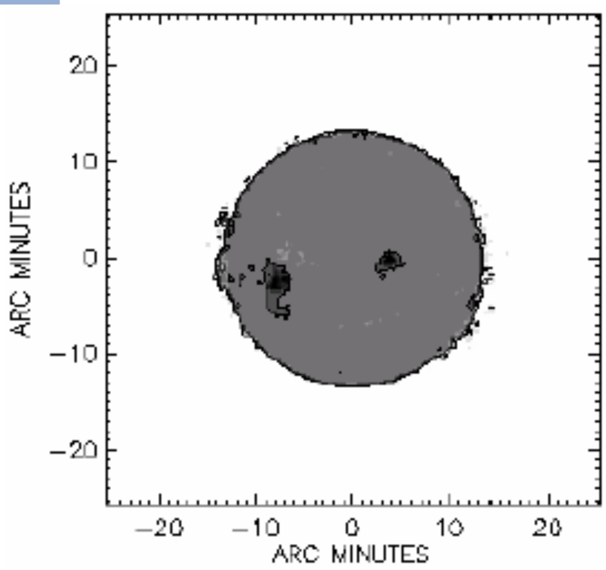


Optimizer: ACO (Ant Colony Optimization)

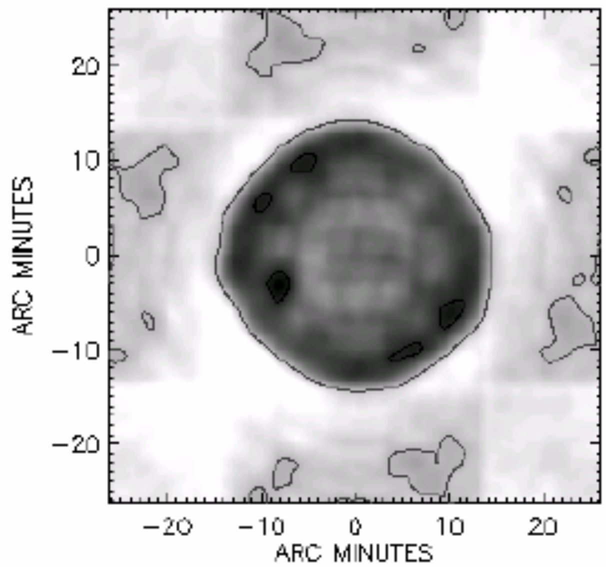
Space Research (Space Science)

Images for radio-interferometric telescope

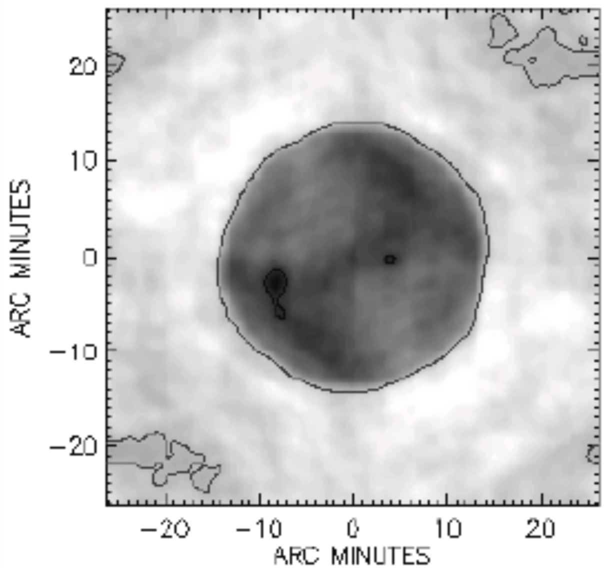
True



T-thin

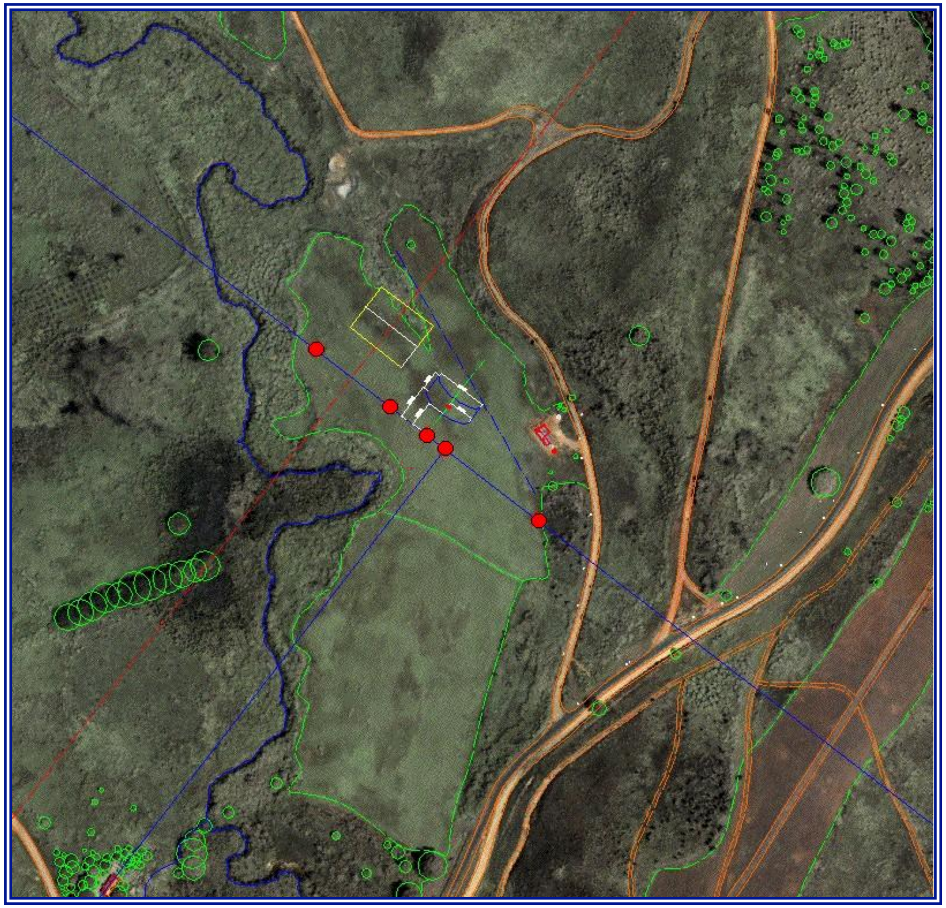


T-fat (optimized)

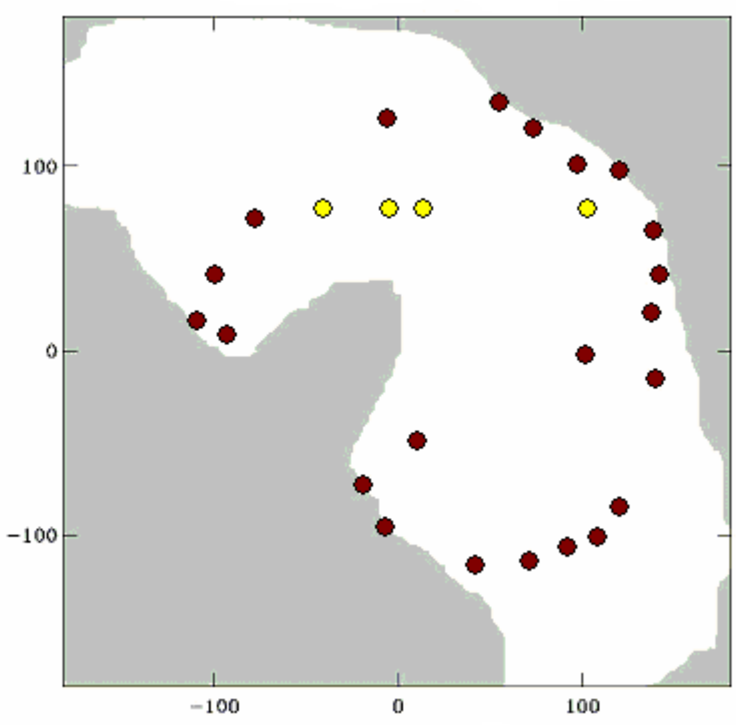


Space Research (Space Science)

Welcome to the real world!



Final optimized configuration



Space Research (Space Science)

Magneto-telluric inversion

Eqs. Maxwell 2D :

$$\vec{\nabla} \times \vec{H} = 4\pi\sigma \vec{E}$$
$$\vec{\nabla} \times \vec{E} = 4\pi\sigma \vec{H}$$

H=H(y,z) magnetic field
E=E(y,z) electric field

$$\begin{cases} \dfrac{\partial H_z}{\partial y} - \dfrac{\partial H_y}{\partial z} = 4\pi\sigma E_x \\ \dfrac{\partial H_x}{\partial z} = 4\pi\sigma E_y \\ -\dfrac{\partial H_x}{\partial y} = 4\pi\sigma E_z \end{cases}$$

$$\begin{cases} \dfrac{\partial E_z}{\partial y} - \dfrac{\partial E_y}{\partial z} = 4\pi\sigma H_x \\ \dfrac{\partial E_x}{\partial z} = -i\omega H_y \\ -\dfrac{\partial E_x}{\partial y} = -i\omega H_z \end{cases}$$

$$\begin{cases} \nabla^2 H_x = \dfrac{\partial^2 H_x}{\partial y^2} + \dfrac{\partial^2 H_x}{\partial z^2} = i\eta^2 H_x \\ -\dfrac{\partial H_x}{\partial y} = 4\pi\sigma E_z \;\; ; \;\; \dfrac{\partial H_x}{\partial z} = 4\pi\sigma E_y \end{cases}$$

$$\begin{cases} \nabla^2 E_x = \dfrac{\partial^2 E_x}{\partial y^2} + \dfrac{\partial^2 E_x}{\partial z^2} = i\eta^2 E_x \\ -\dfrac{\partial E_x}{\partial y} = -i\omega H_z \;\; ; \;\; \dfrac{\partial E_x}{\partial z} = -i\omega H_y \end{cases}$$

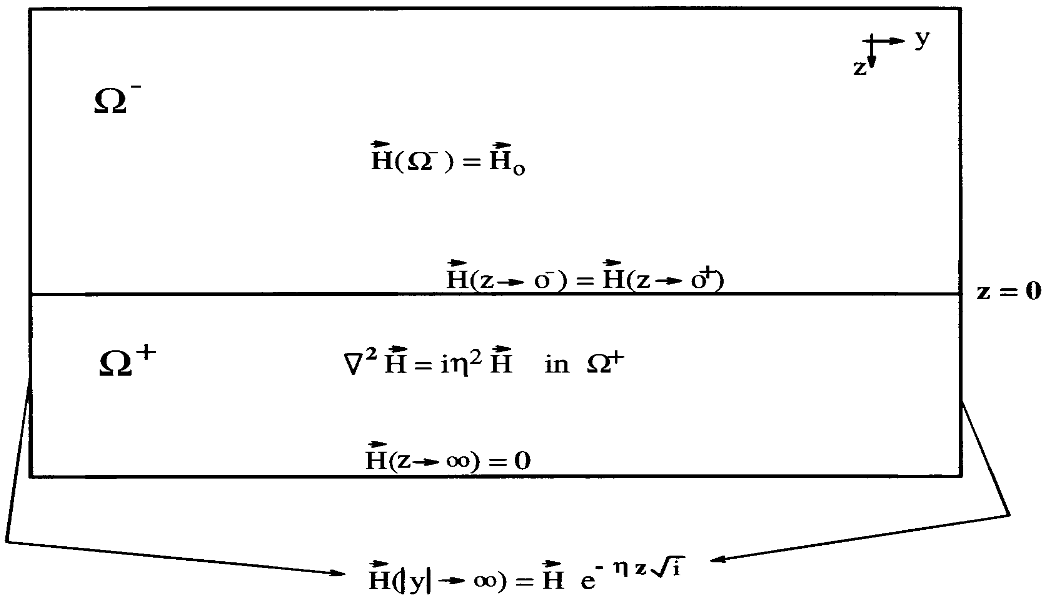
Space Research (Space Science)

Magneto-telluric inversion

$$J(\boldsymbol{p}) = R(\boldsymbol{p}) - \gamma_0 S_0(\boldsymbol{p})/S_{\max} + \gamma_1 S_1(\boldsymbol{p})/S_{\max}$$

$$R(\boldsymbol{p}) = \sum\sum\left[\Phi_{j,m}^{\mathrm{Exp}} - \Phi_{j,k^*,m}^{\mathrm{Mod}}(\boldsymbol{p})\right]$$

Outline of problem physical:
σ - electric conductivity
Ω^+ - conductive region
Ω^- - atmosphere



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Space Research (Space Science)

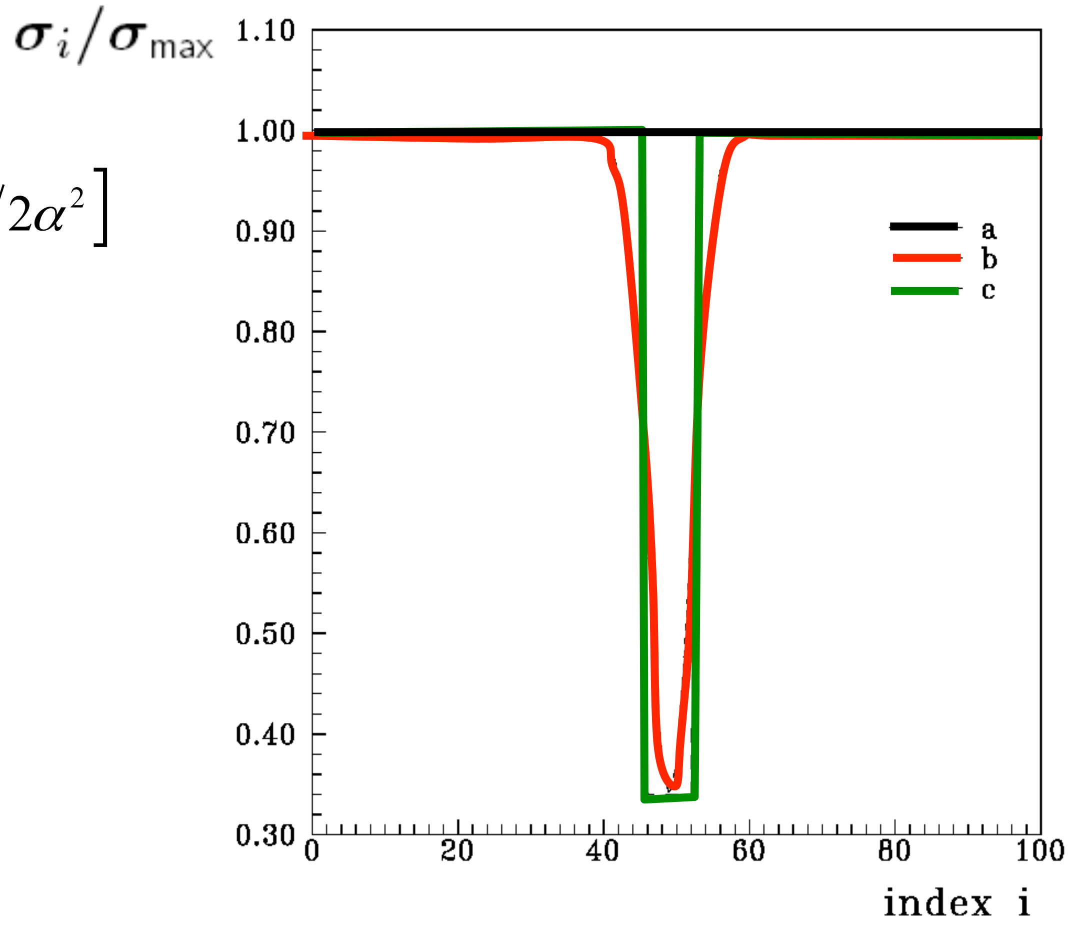
Magneto-telluric inversion

$$\sigma^a = 1 \ \text{(constant)}$$

$$\sigma^b = 1 - \left(1/\alpha\sqrt{2}\right)\exp\left[-(x-x_*)^2/2\alpha^2\right]$$

$$\sigma^c = \begin{cases} 0.35 & x \in [x_* - \varepsilon, x_* - \varepsilon] \\ 0 & x \in [x_* - \varepsilon, x_* - \varepsilon] \end{cases}$$

$$S_0^a = 1$$
$$S_0^b = 0.9969$$
$$S_0^c = 0.9955$$



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Space Research (Space Science)

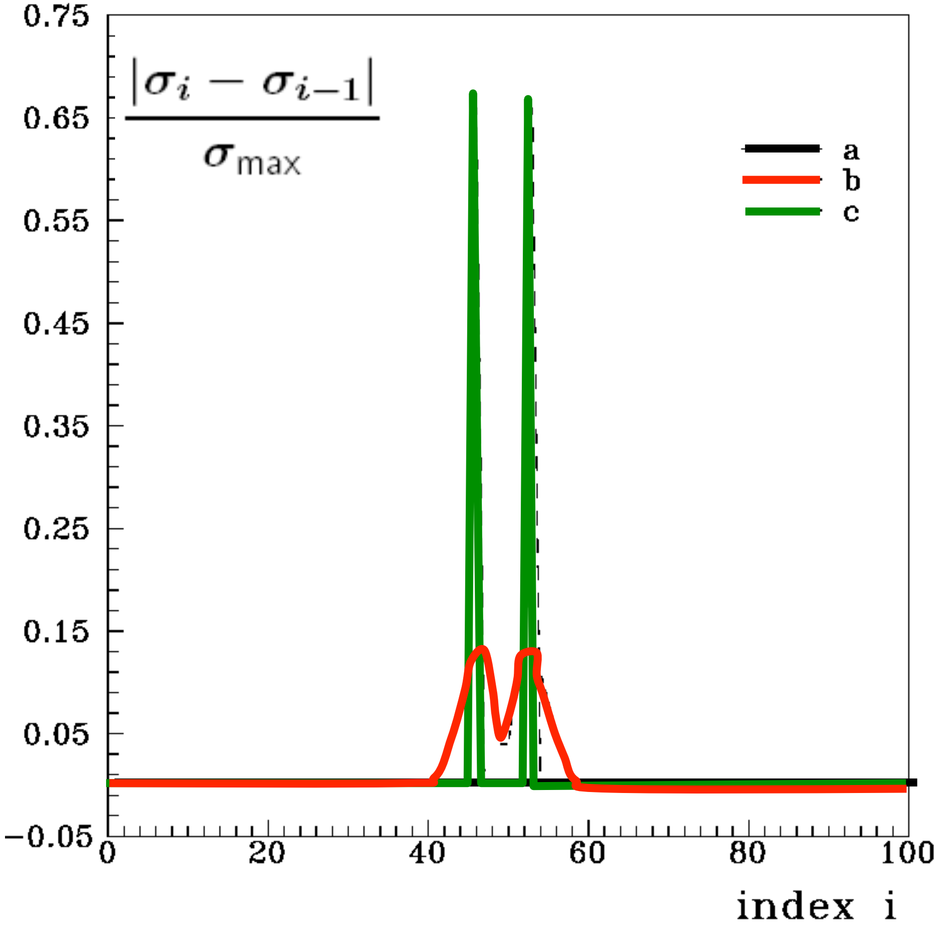
Magneto-telluric inversion

$$\sigma^a = 1 \text{ (constant)}$$

$$\sigma^b = 1 - \left(1/\alpha\sqrt{2}\right)\exp\left[-(x - x_*)^2/2\alpha^2\right]$$

$$\sigma^c = \begin{cases} 0.35 & x \in [x_* - \varepsilon, x_* - \varepsilon] \\ 0 & x \in [x_* - \varepsilon, x_* - \varepsilon] \end{cases}$$

$$S_1^a = 1.00$$
$$S_1^b = 0.60$$
$$S_1^c = 0.15$$



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Space Research (Space Science)

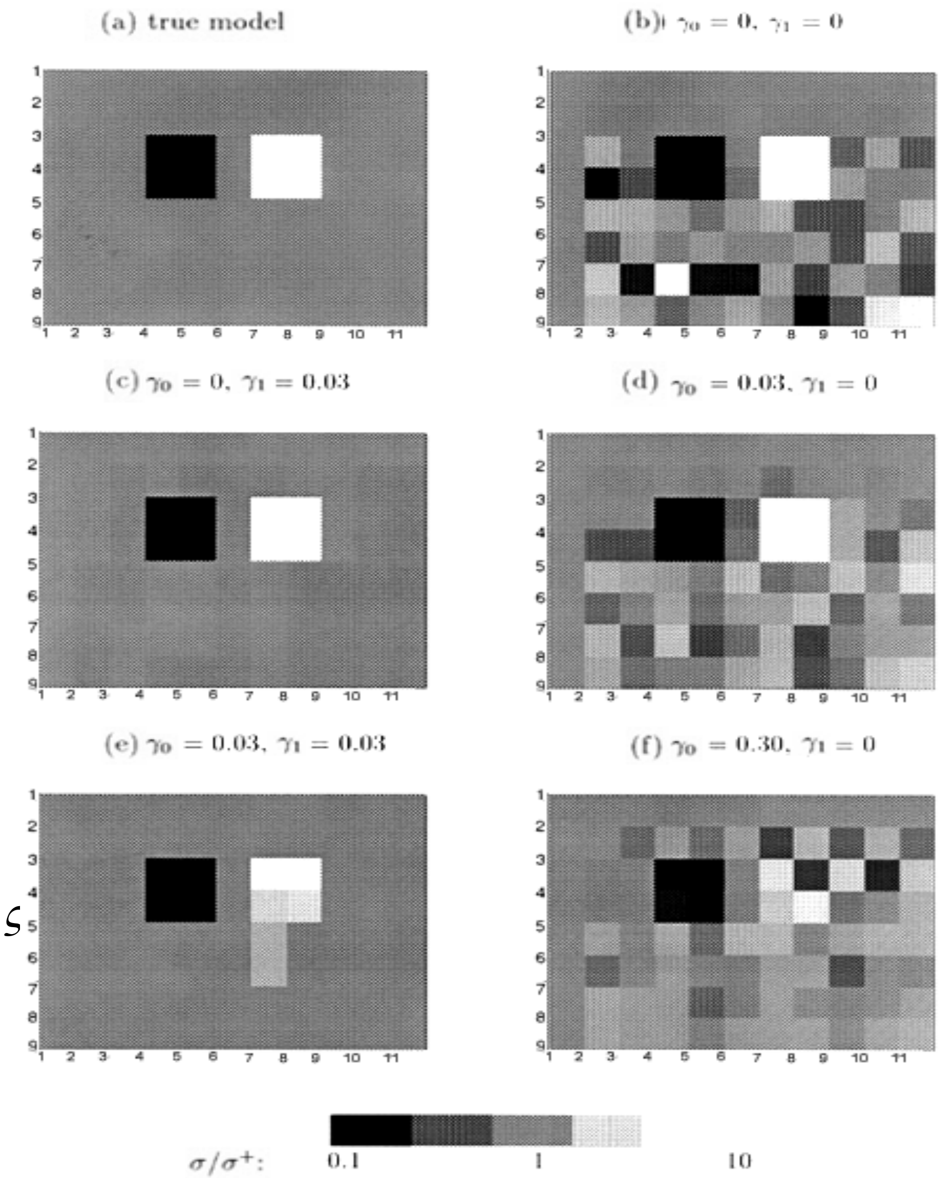
MaxEnt-0: $\gamma_0 \neq 0$, $\gamma_1 = 0$

MinEnt-1: $\gamma_0 = 0$, $\gamma_1 \neq 0$

$$S(u) = \sum_{q=1}^{N} u_q \log(u_q)\,;$$

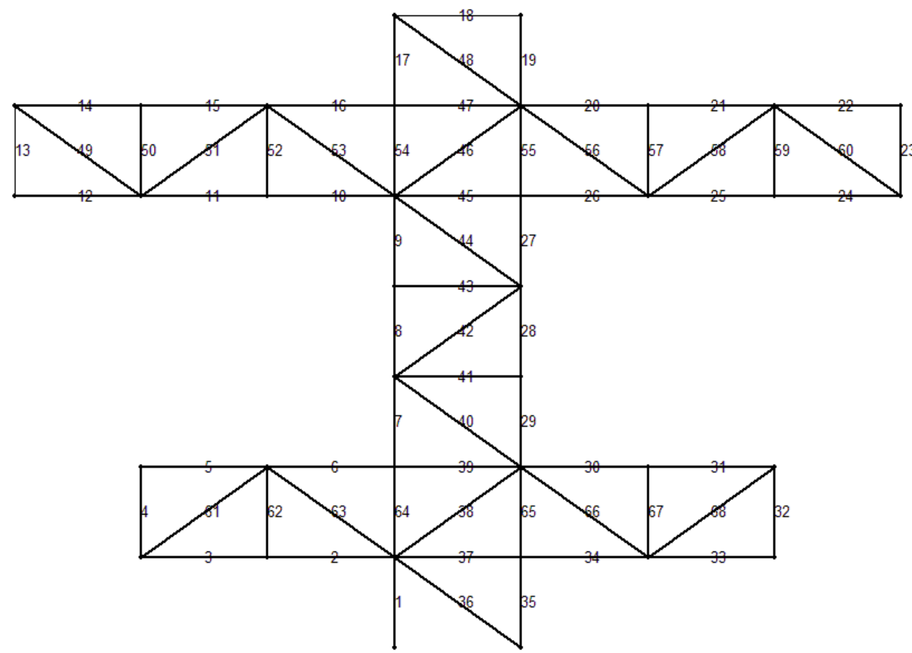
$$u_q = r_q^{(k)} \Big/ \sum_{q=1}^{N} r_q^{(k)}\,;$$

$$r_q^{(k)} = \begin{cases} u_q \\ u_{q+1} - u_q + (u_{\max} - u_{\min}) + \varsigma \\ u_{q+1} - 2u_q + u_{q-1} + 2(u_{\max} - u_{\min}) + \varsigma \end{cases}$$



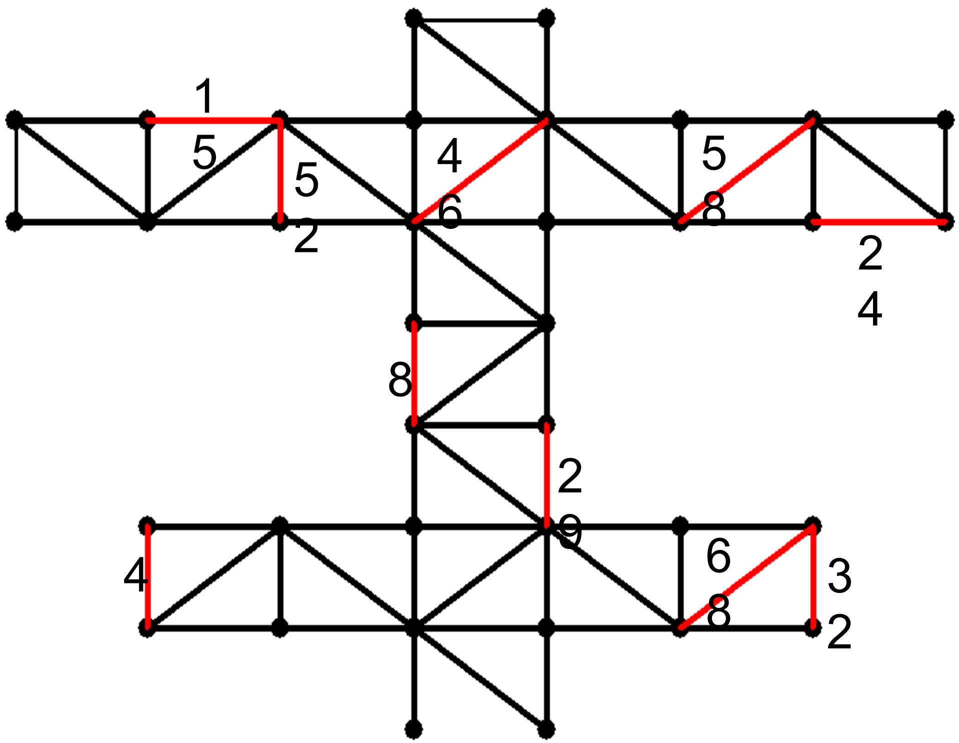
Space Research (Space Engineering)

Damage in aerospace structure



Space Research (Space Engineering)

Damage in aerospace structure



Damage severity:

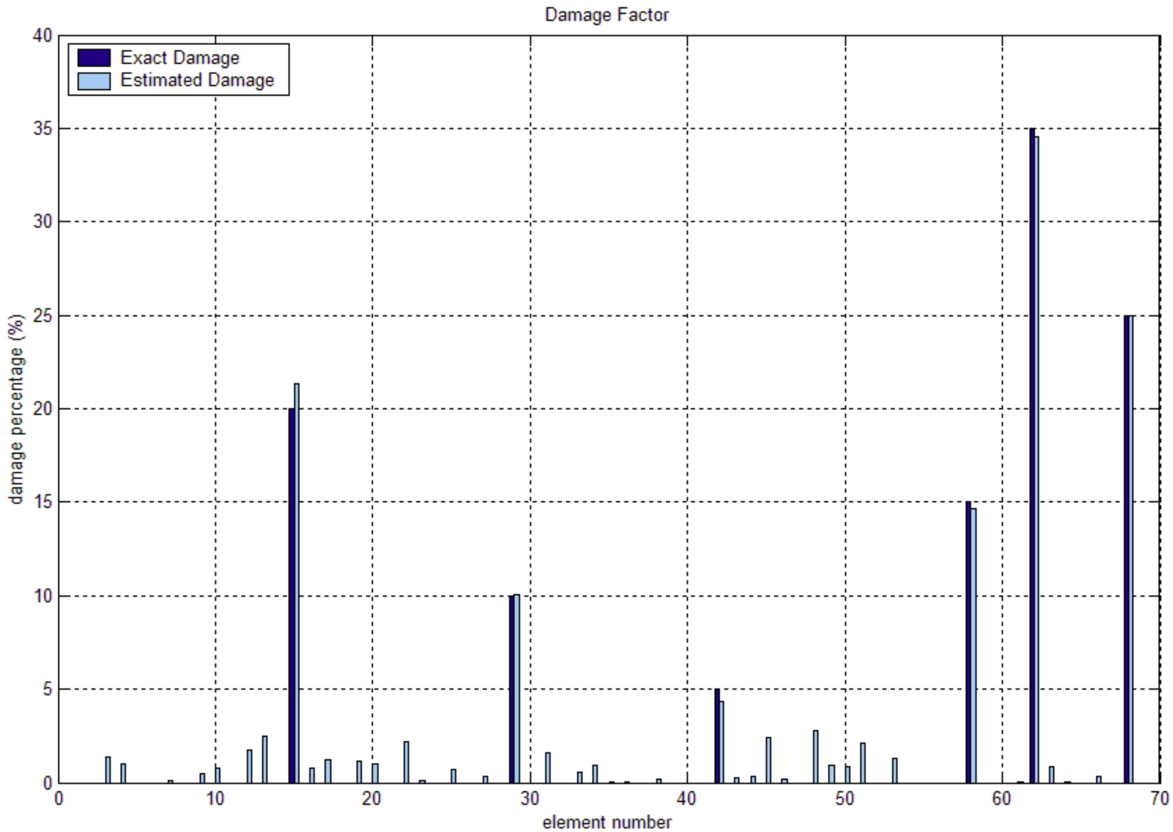
Element	Damage
8, 24, 46, 68	5%
4, 29, 52	10%
15, 32, 58	15%

Space Research (Space Engineering)

Damage in aerospace structure

Noisy experimental data: $\mathbf{x}^{exp}(t) = \mathbf{x}(t)\,(1 + \sigma\,\mathcal{R})$

σ = 1%.



Space Research (Space Engineering)

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Acta Astronautica 62 (2008) 592–604

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Damage assessment of large space structures through the variational approach

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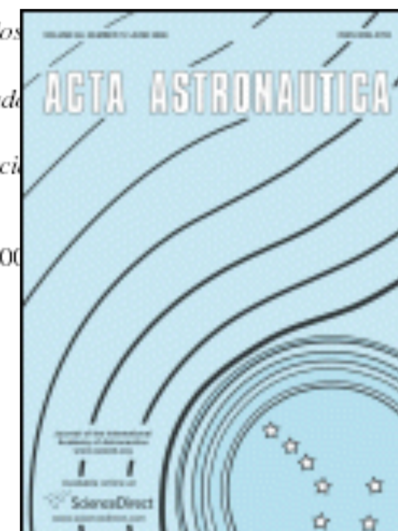
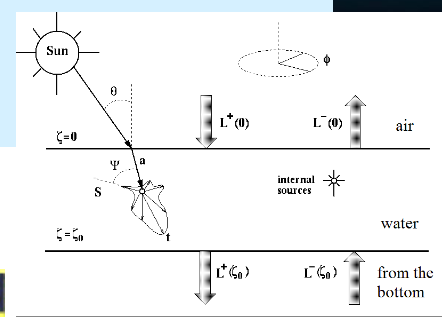


Space Research (oceanography)

Inverse hydrological optics

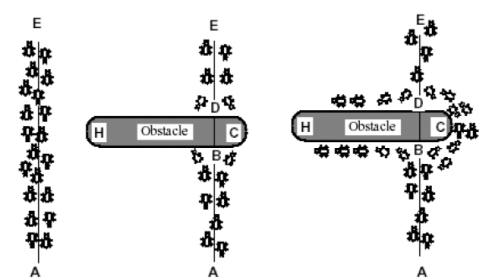
Hydrologic optics

Radiative transfer process



Inverse problem

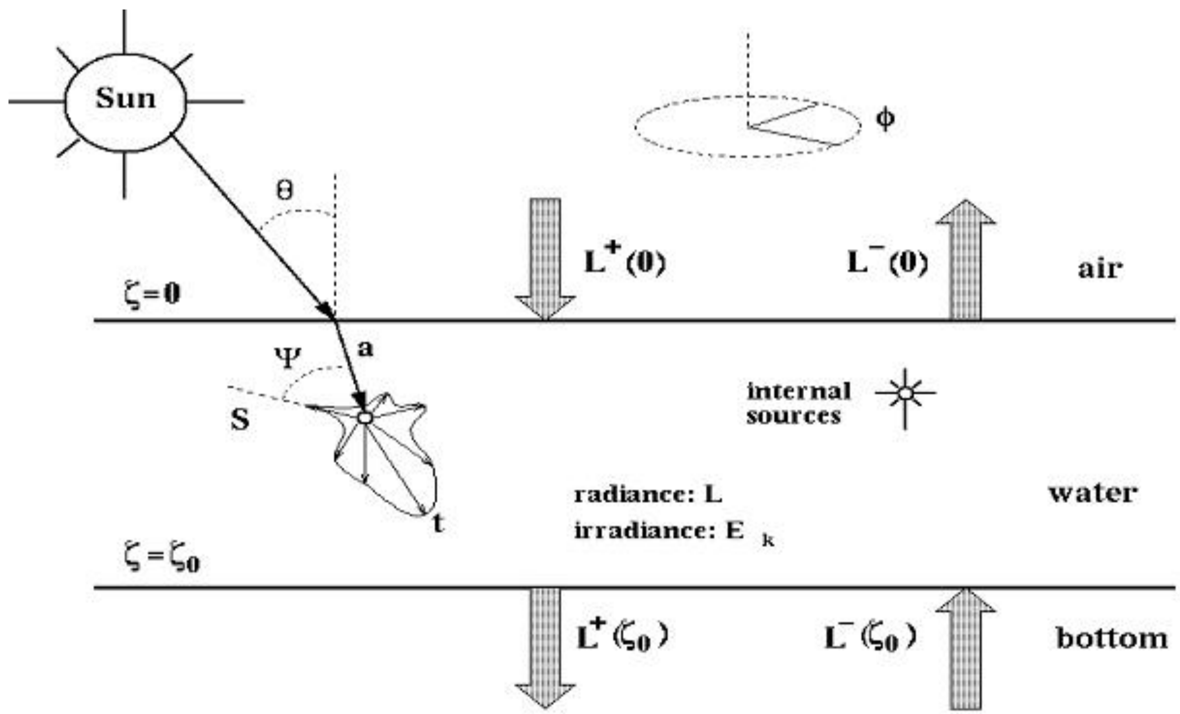
Ant colony optimization



Space Research (oceanography)

Inverse hydrological optics

$$\mu \frac{dL_\lambda(\zeta,\xi)}{d\zeta} + L_\lambda(\zeta,\xi) = \overbrace{\frac{b_\lambda}{a_\lambda + b_\lambda}}^{\varpi_0} \iint_{\Xi,\lambda} \beta(\lambda',\xi' \rightarrow \lambda,\xi)\, d\xi d\lambda + S_\lambda(\zeta,\xi)$$



Space Research (oceanography)

Inverse hydrological optics

Absortion and scattering coefficients:

$$a_{r,g} = \left[a_g^w + 0.06 a_g^c C^{0.65}(z)\right]\left[1 + 0.2 e^{-0.014(\lambda_g - 440)}\right]$$

$$b_{r,g} = \left[550/\lambda_g\right] 0.30\, C^{0.65}(z)$$

Chorophyll concentration: $C(z) = C_0 + \frac{h}{s\sqrt{2\pi}} e^{-1/2\left[(z - z_{max})/s\right]^2}$

Phase function: $p(\cos\Theta) = \frac{1}{4\pi} \frac{1 - f^2}{\left(1 + f^2 - 2f\cos\Theta\right)^{3/2}}$

Space Research (oceanography)

Inverse hydrological optics

$$J(\mathbf{p}) = \sum_{k=1}^{N_\lambda} \sum_{l=1}^{N_\xi} \left[L_{k,l}^{\mathrm{Exp}} - L_{k,l}^{\mathrm{Mod}}(\mathbf{p}) \right]^2 + \alpha \Omega[\mathbf{p}]$$

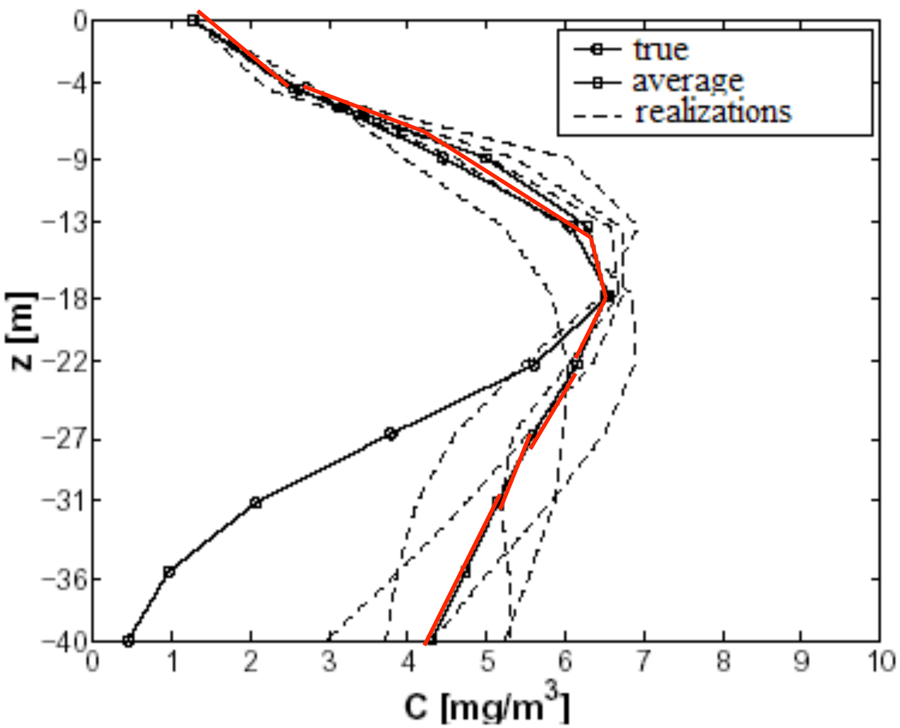
being N_λ the number of sensors (satellite chanels), N_ξ is the number of angle direções and $L_{k,l} = L(\zeta^*, \xi_l, \lambda_k)$, being ζ^* a reference level (water superface).

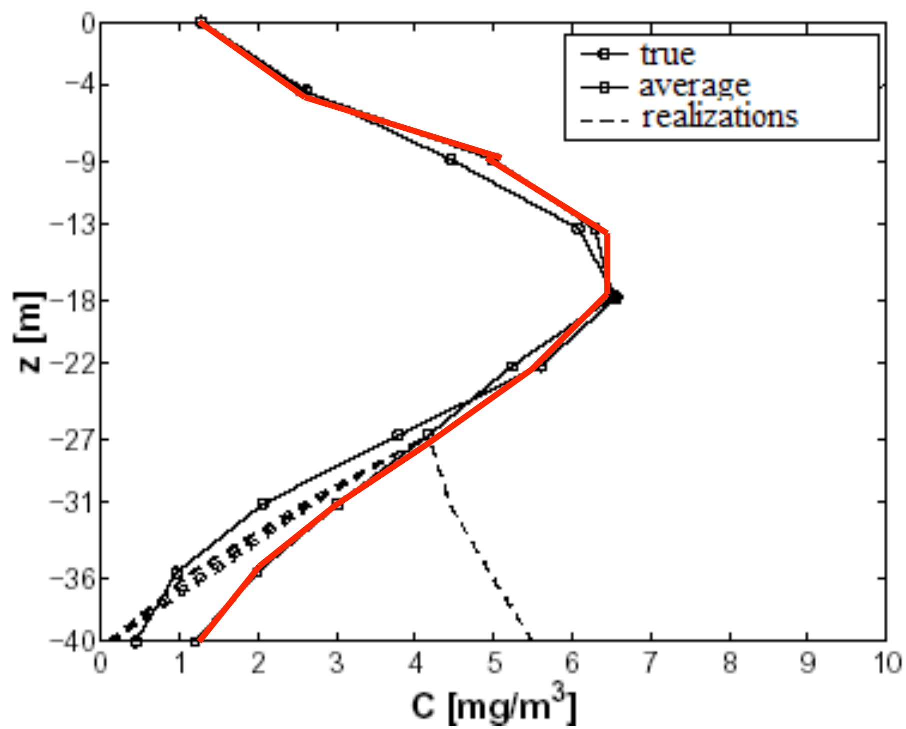
Preliminar results were obtained with estimation of source terms, where the LTS_N method the modified ant colony system is applied.

Space Research (oceanography)

Inverse hydrological optics

seeds	ns	np	na	mit	ρ	q_0
{17,33,55,81,99}	10	3000	90	500	0.03	0.0





Space Research (oceanography)

Inverse hydrological optics

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Applied Numerical Mathematics 47 (2003) 365–376

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Multispectral reconstruction of bioluminescence term in natural waters

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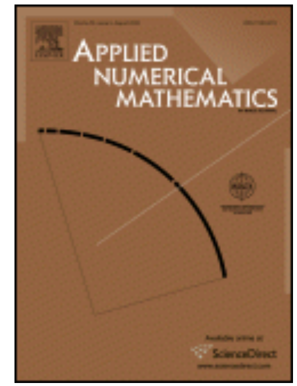
National Institute for Space Research, Laboratory for Computing and Applied Mathematics,
P.O. Box 515, 12245-970 São José dos Campos, SP, Brazil



+ Model
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Mathematics and Computers in Simulation xxx (2006) xxx–xxx

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Reconstruction of vertical profiles of the absorption and scattering coefficients from multispectral radiances

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[a] *Postgraduate Program in Applied Computing (CAP/INPE), INPE—National Institute for Space Research,*
PO Box 515, CEP 12245-970 São José dos Campos, SP, Brazil
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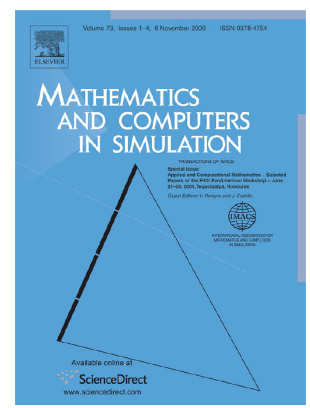
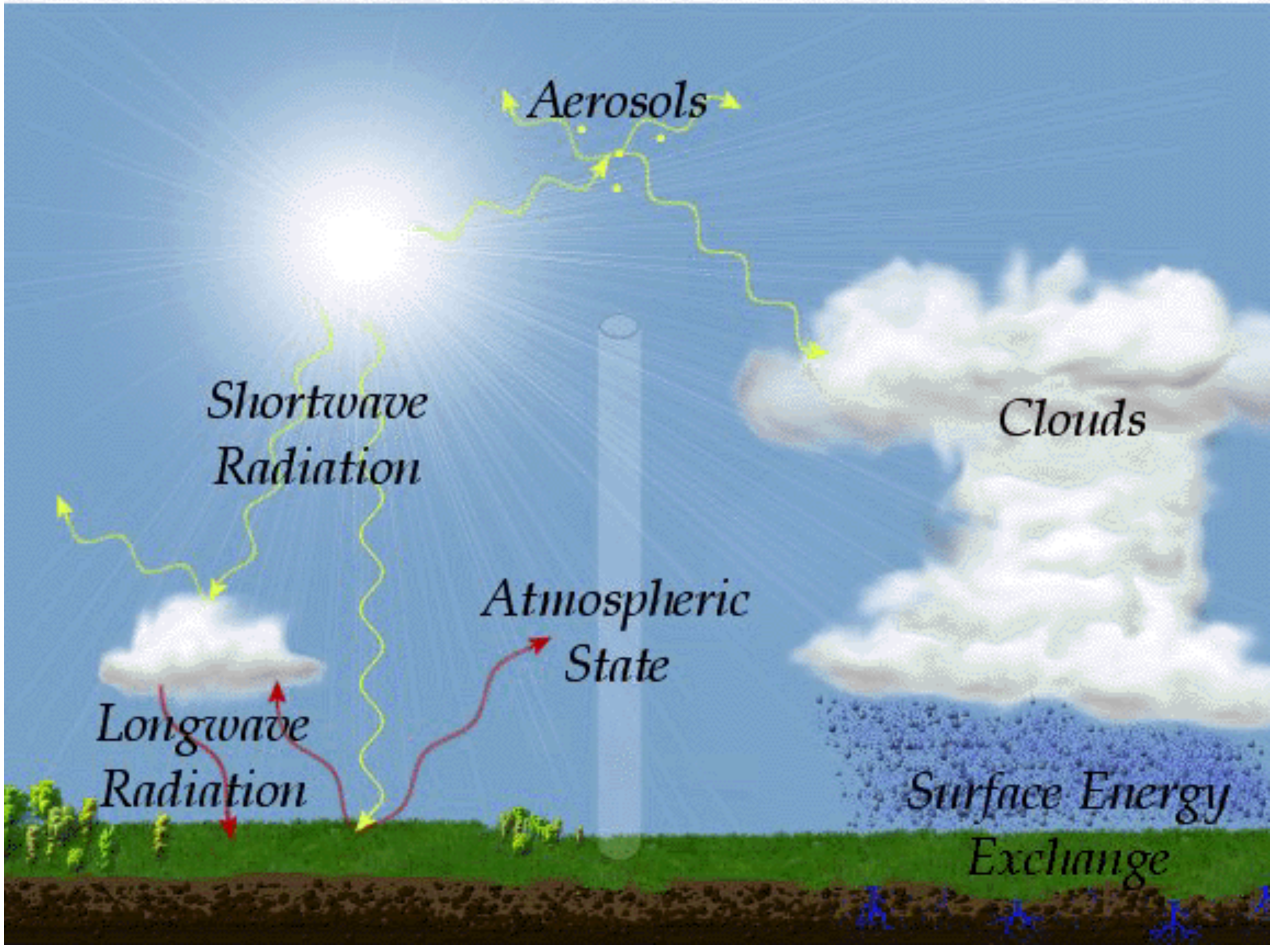
PO Box 515, CEP 12245-970 São José dos Campos, SP, Brazil



Space Research (meteorology)

Atmospheric temperature from satellite data

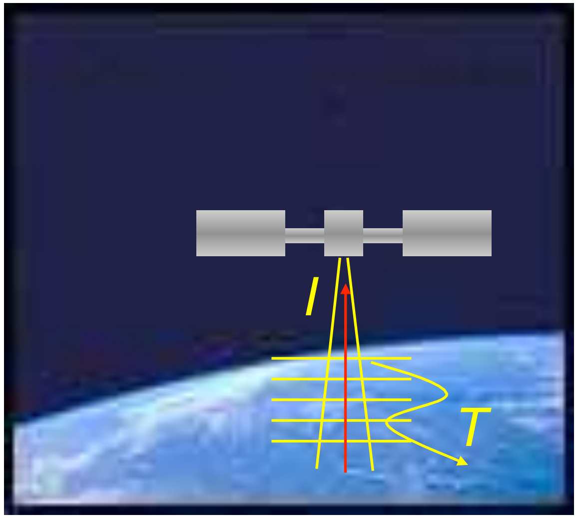


Space Research (meteorology)

Atmospheric temperature from satellite data

$$\widetilde{I}_\lambda(\tau_\lambda) = I_\lambda(\tau_\lambda) - I_\lambda(\tau_\lambda^{(s)}) = -\int_{\tau_\lambda^{(s)}}^{\tau_\lambda} B_\lambda(\tau_\lambda)\,d\tau_\lambda$$

$$B_\lambda(T) = \frac{2h\lambda^3}{c^2\left[e^{h\lambda/(KT)} - 1\right]} \quad \text{(Planck function)}$$



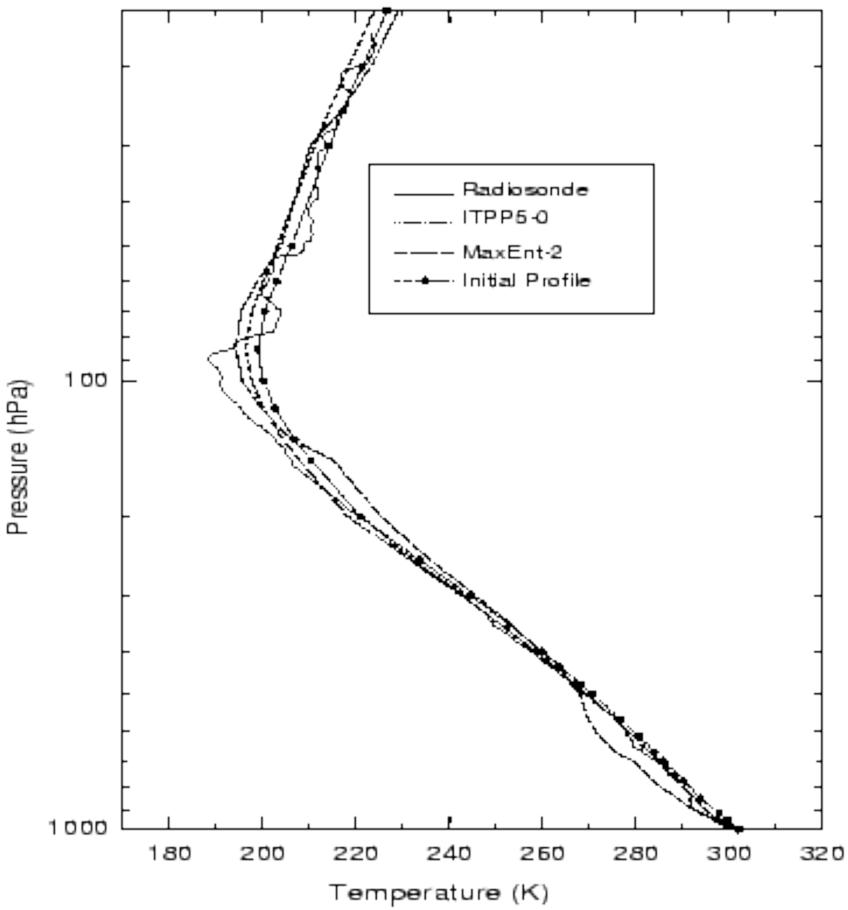
$I_\lambda(\tau_\lambda^{(s)})$: radiation intensity emitted from the earth's surface

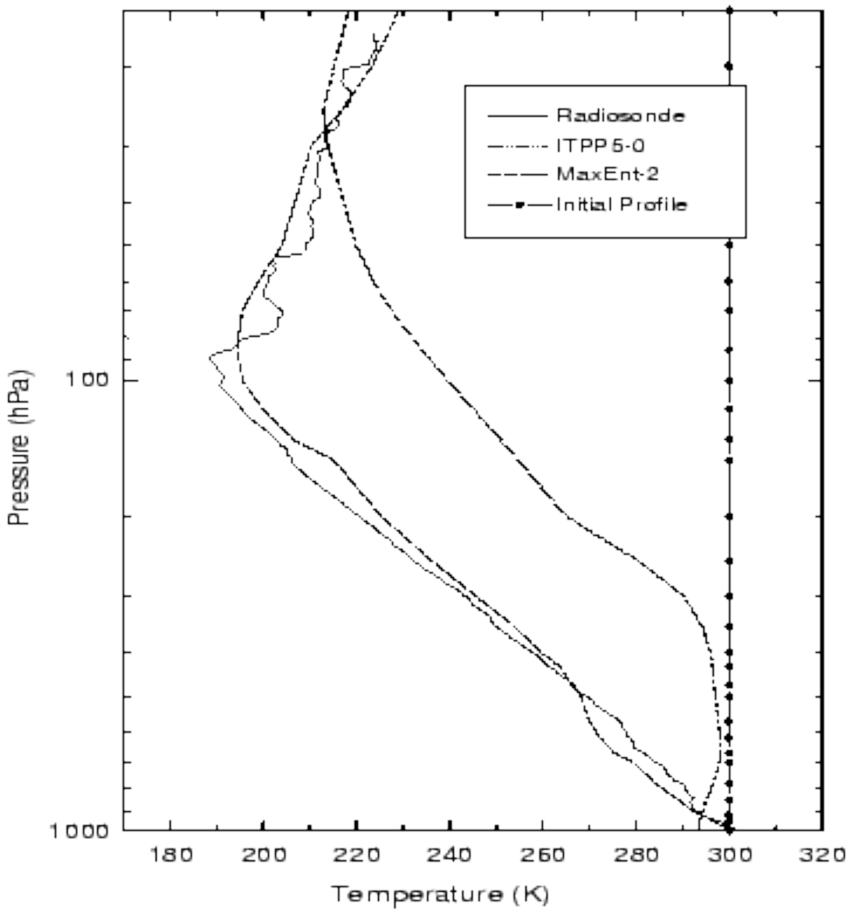
$\tau_\lambda(z)$: vertical transmittance from height z

$T(z)$: vertical temperature profile

Space Research (meteorology)

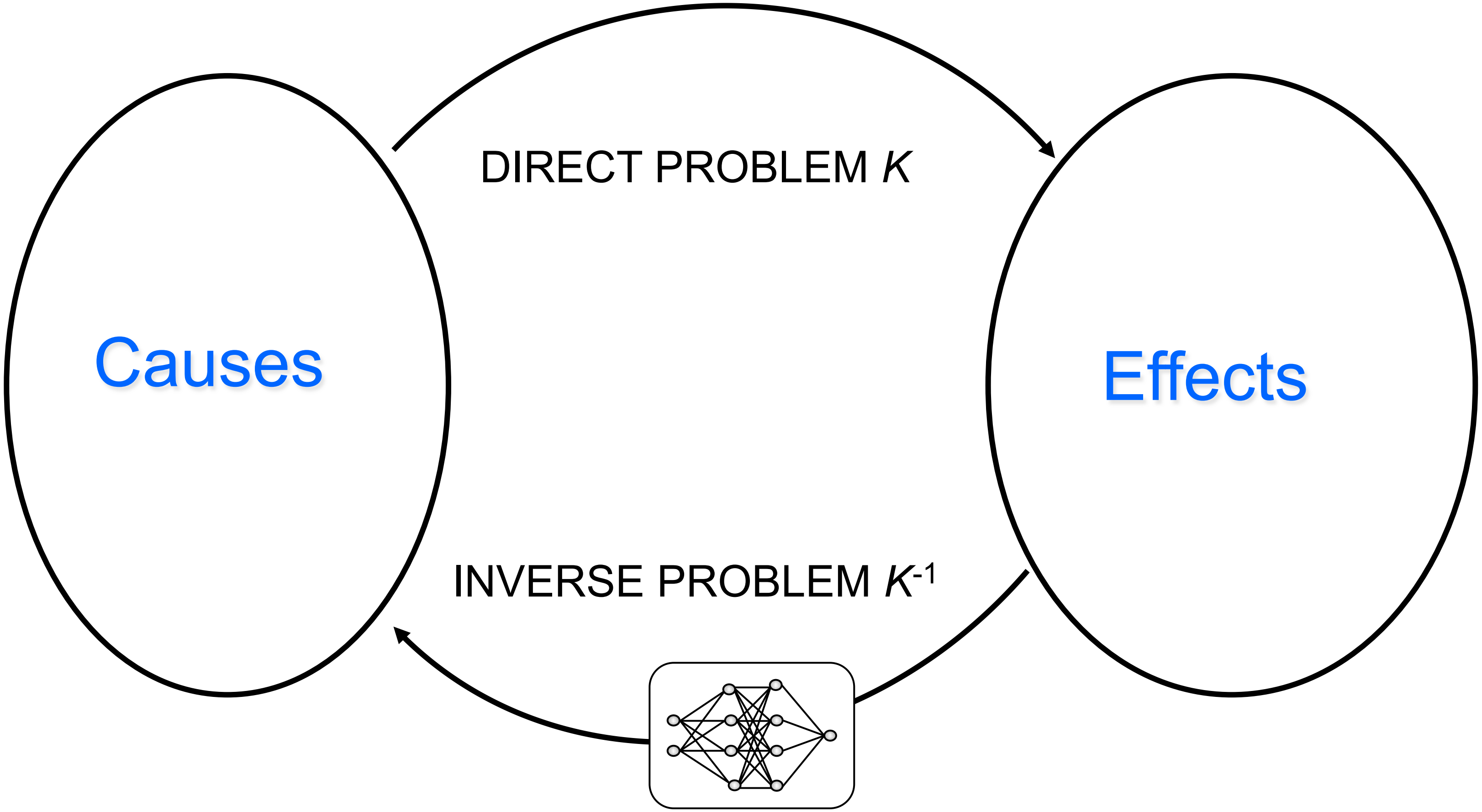
Regularization: 2n order entropy





Inverse problems

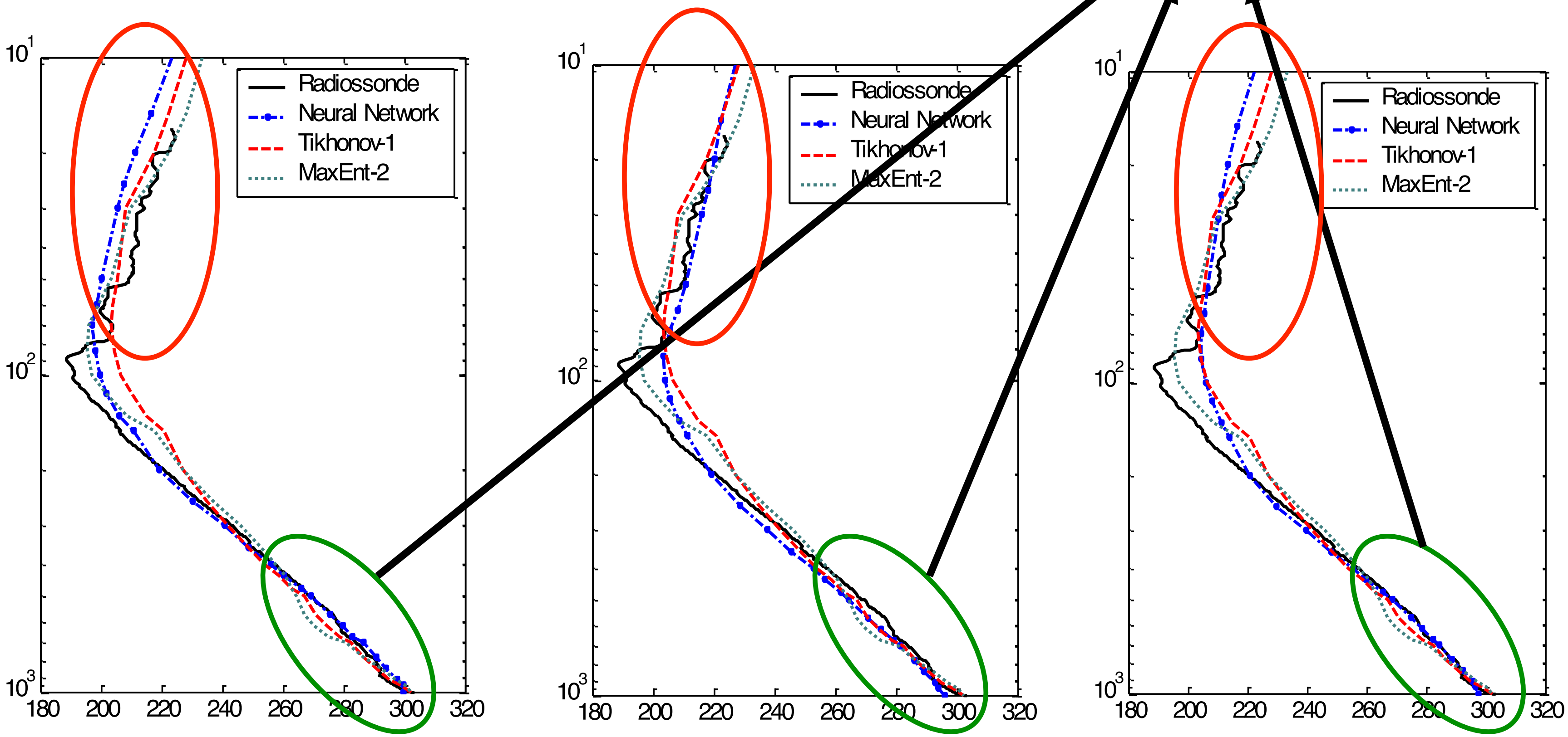
Neural networks for inverse problems



Space Research (meteorology)

Atmospheric temperature

More important for numerical weather prediction



Retrievals using SDB1 for training phase.

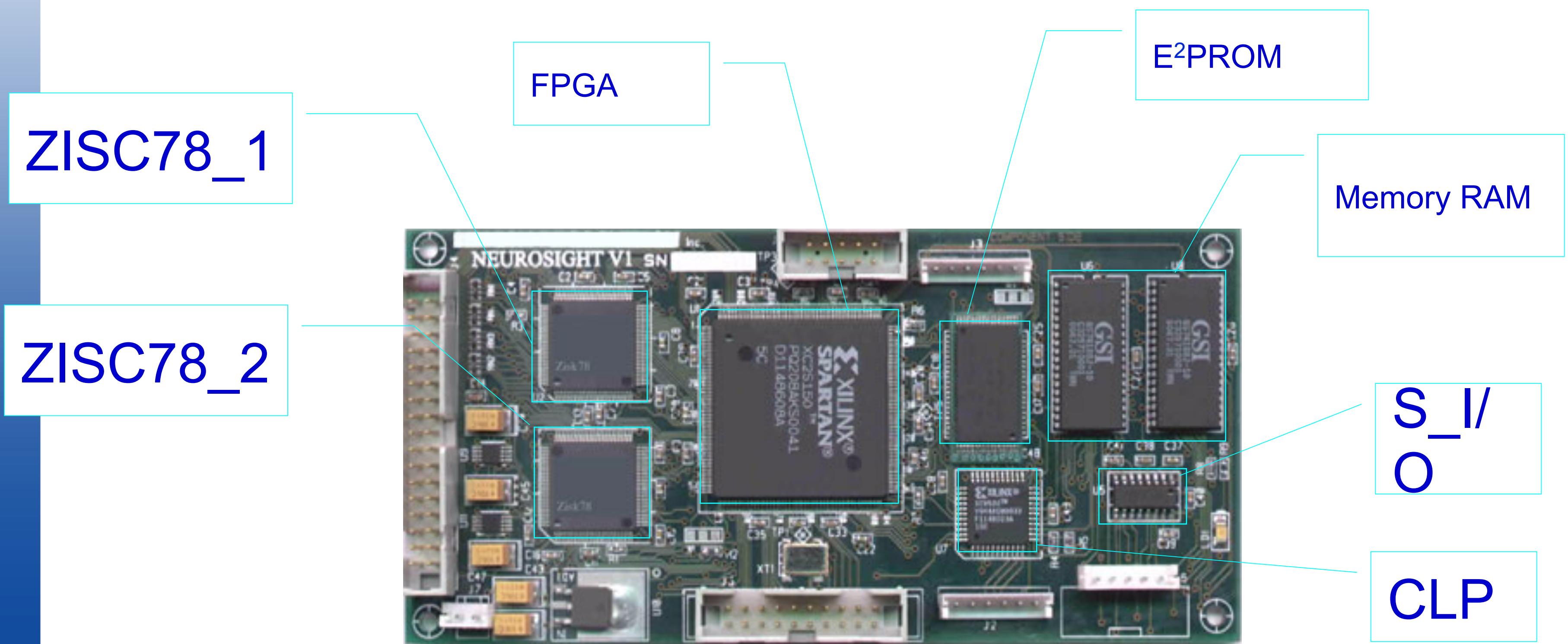
Retrievals using TIGR for training phase.

Retrievals combining SDB1+TIGR.

Space Research (meteorology)

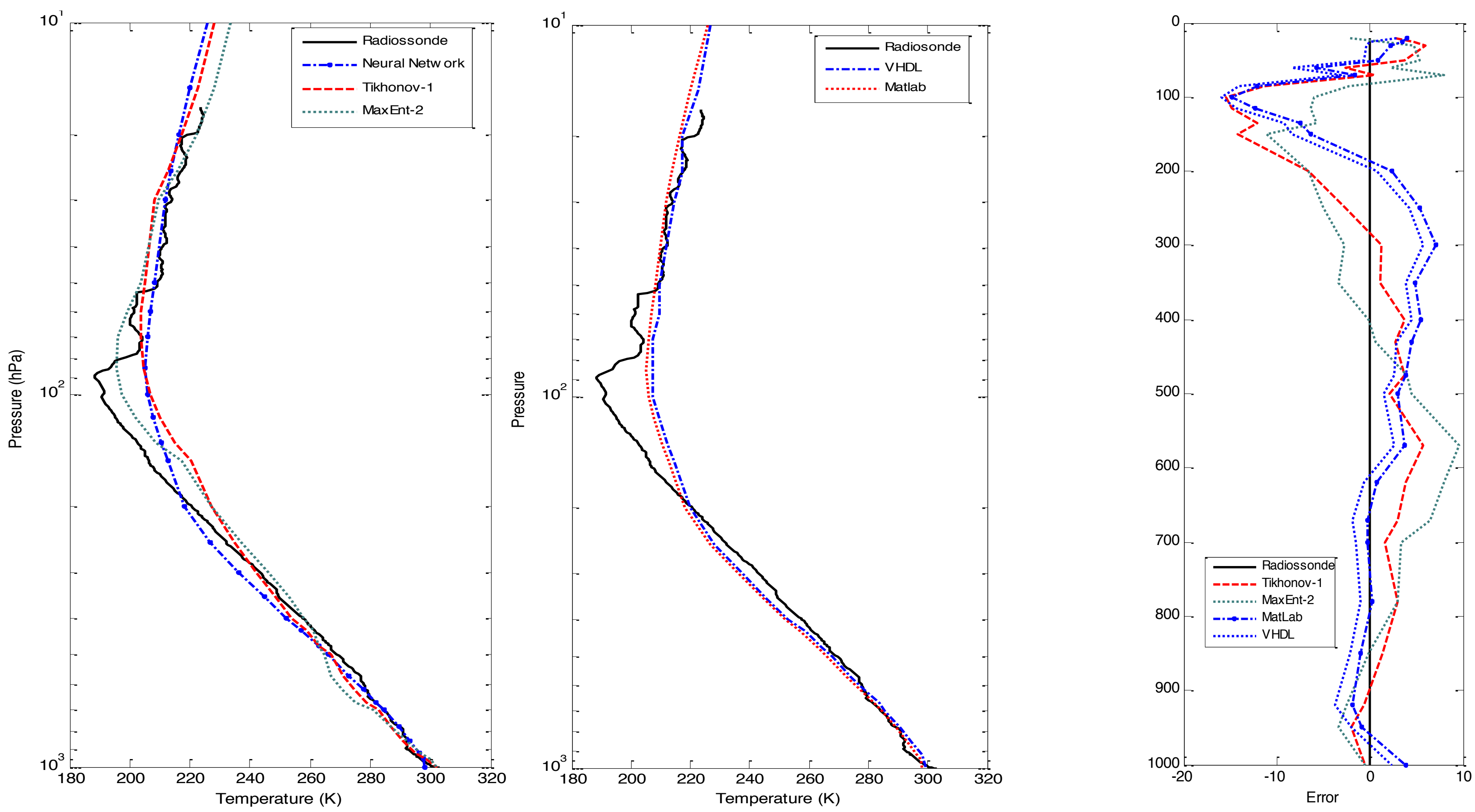
Atmospheric temperature from satellite data

Neurocomputers: implemented by FPGA



Space Research (meteorology)

Atmospheric temperature from satellite data



Atmospheric temperature retrieval using a Radial Basis Function Neural Network

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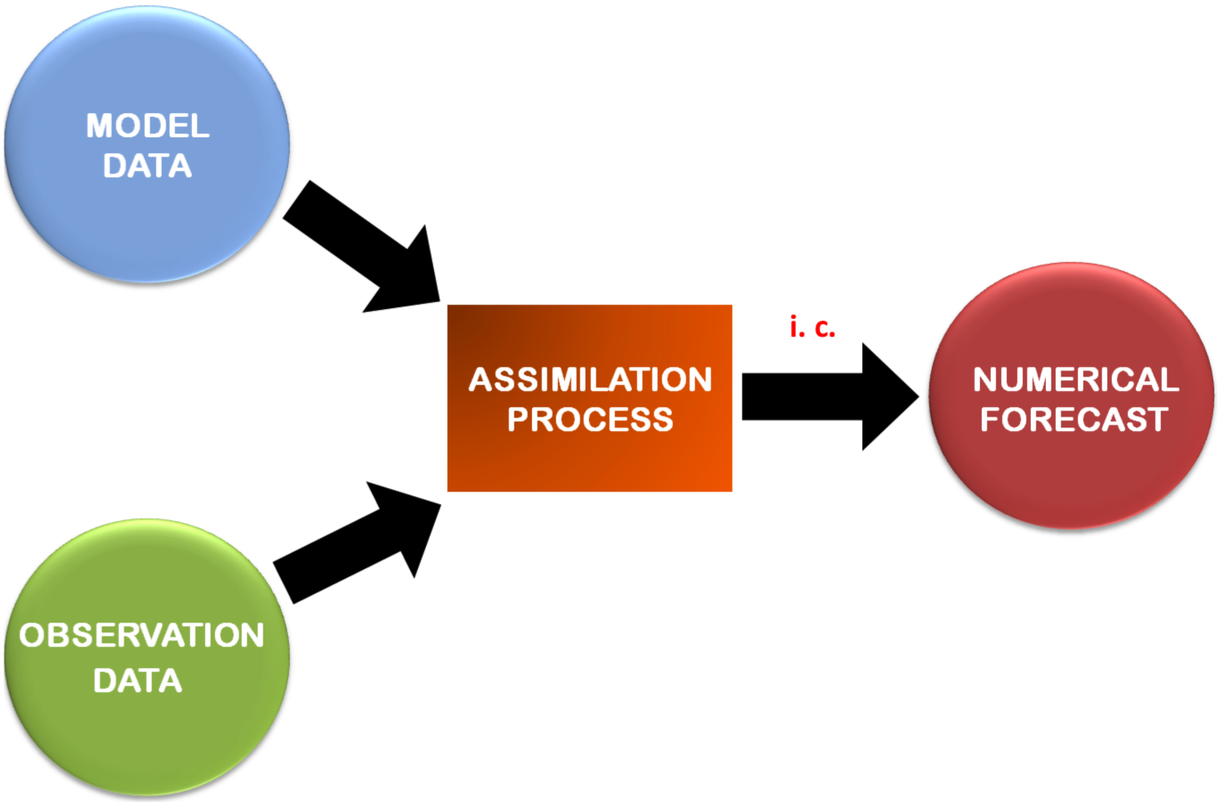
Space Research (meteorology)

Data assimilation: finding initial condition

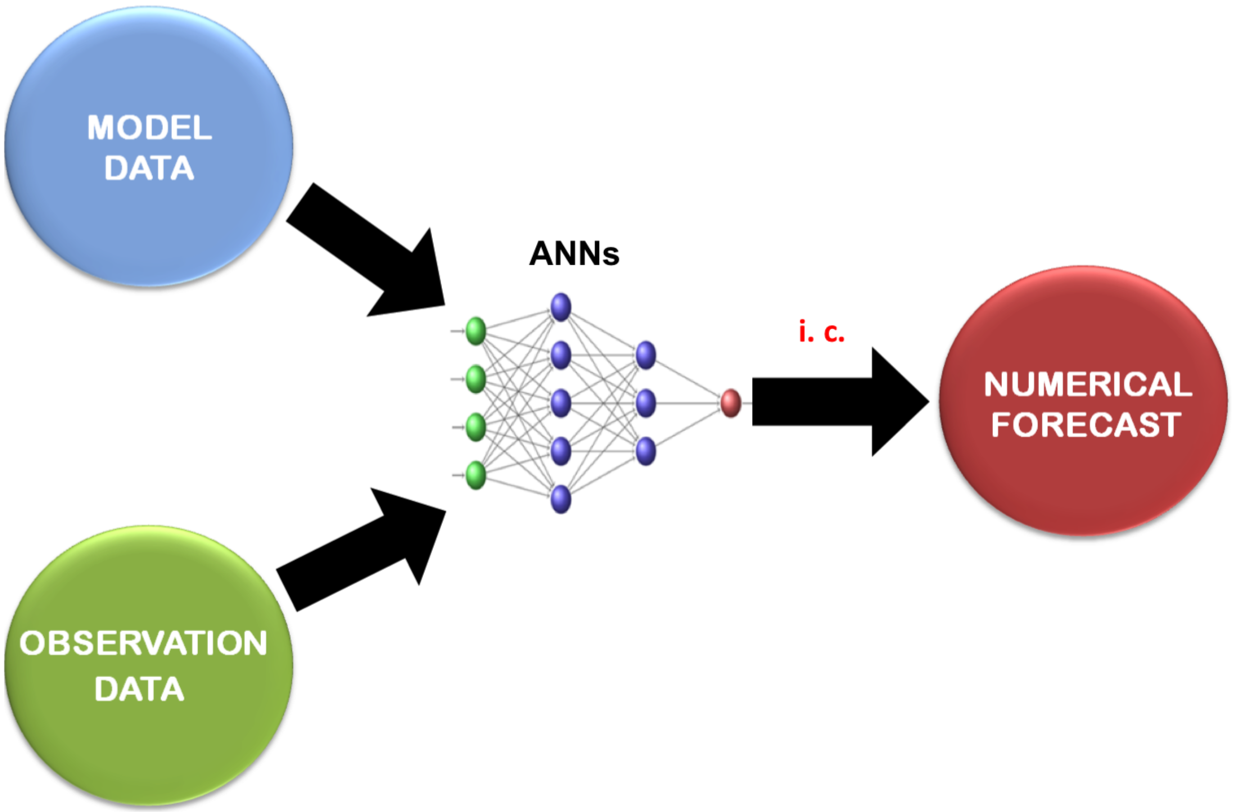
Space Research (meteorology)

Data assimilation: finding initial condition



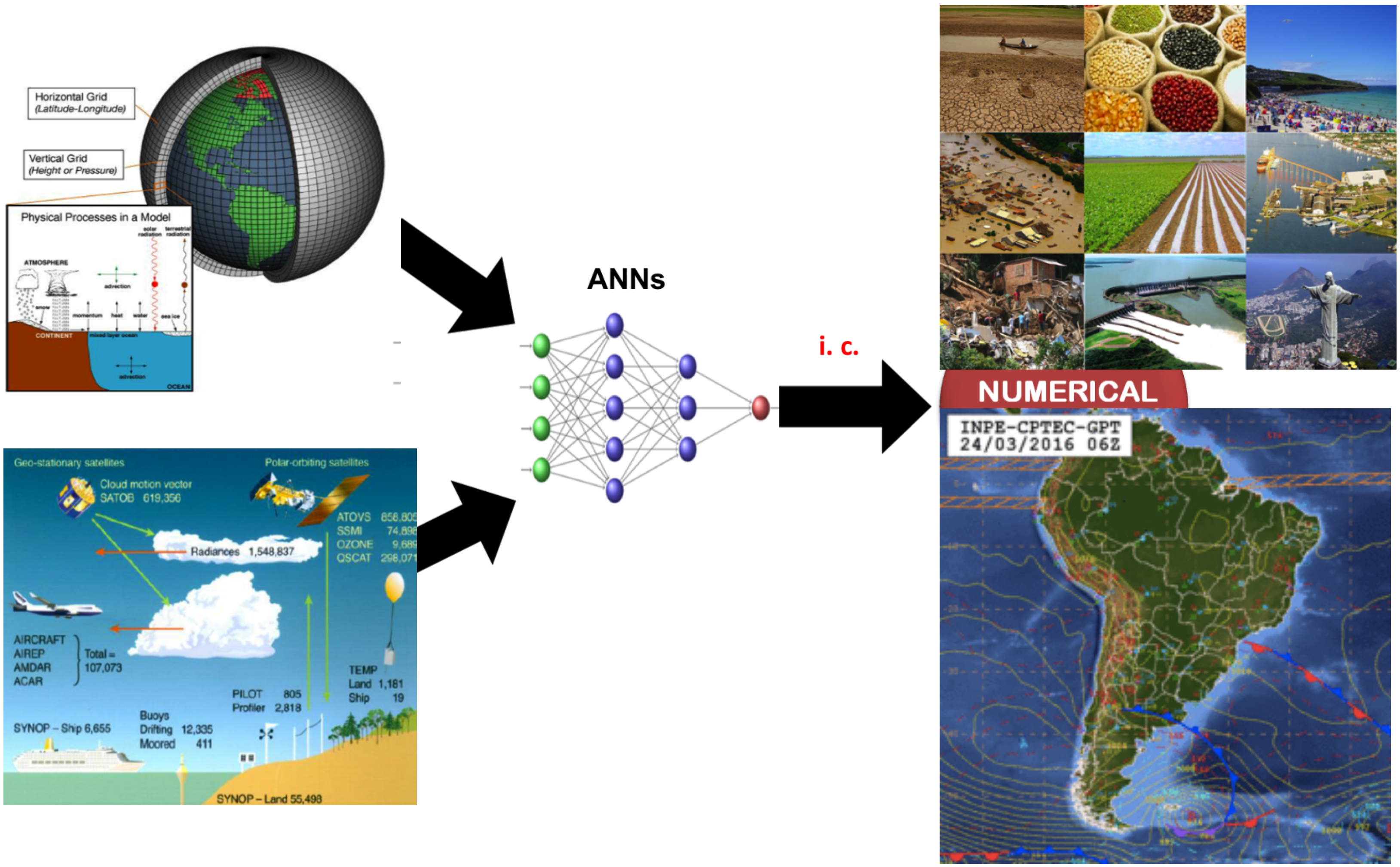
Space Research (meteorology)

Data assimilation: finding initial condition



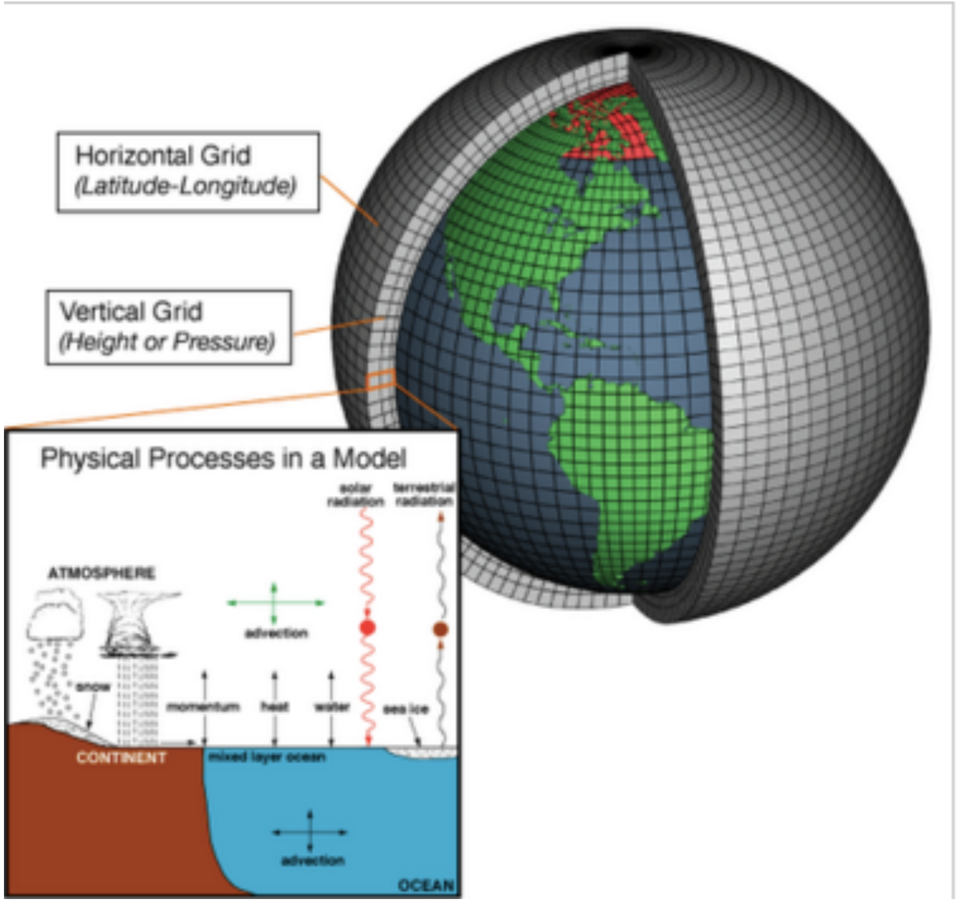
Space Research (meteorology)

Data assimilation: finding initial condition



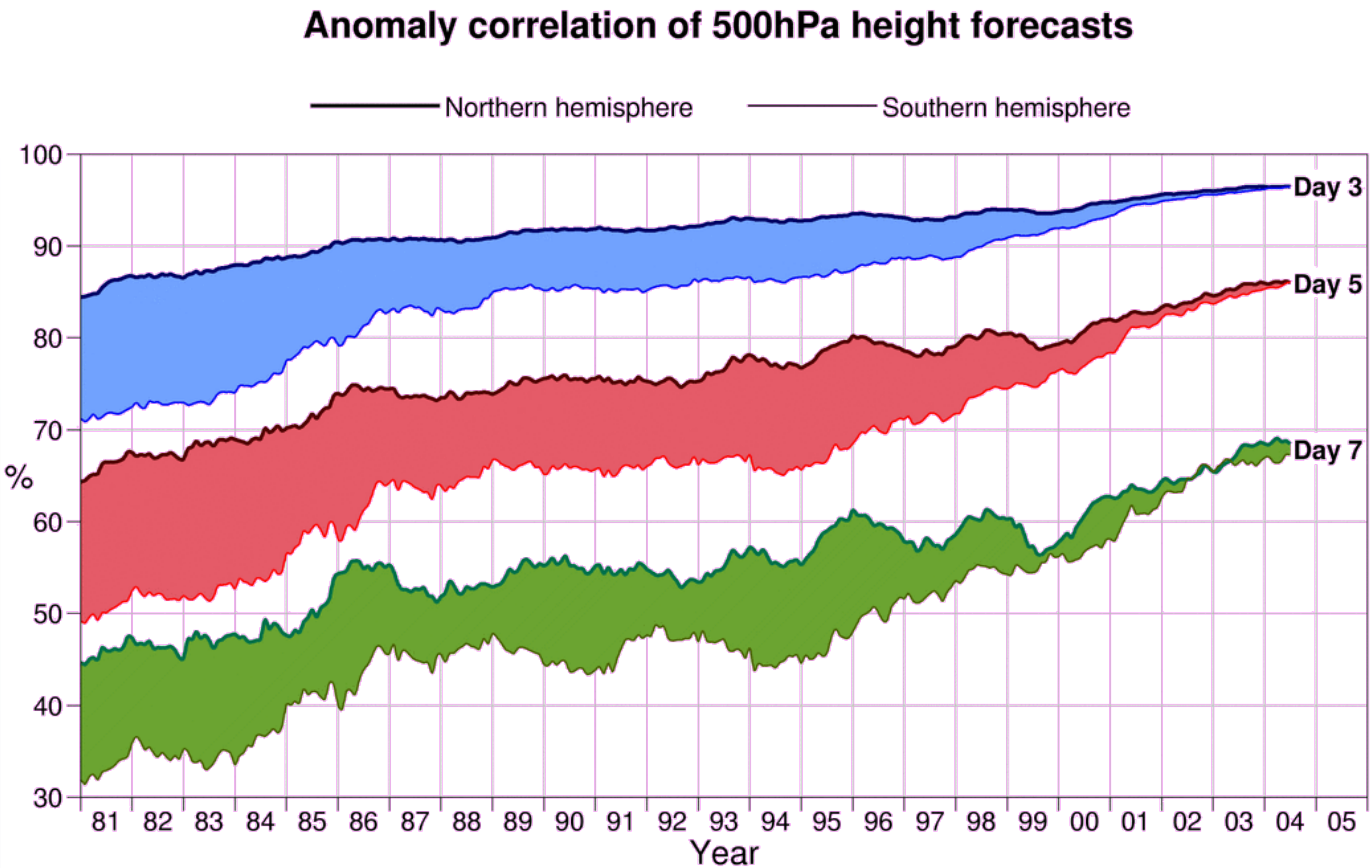
PART 2 – Applications to Space Research

- **Numerical Weather Prediction**
- Relevant and computer intensive simulation



Forecasts Scores

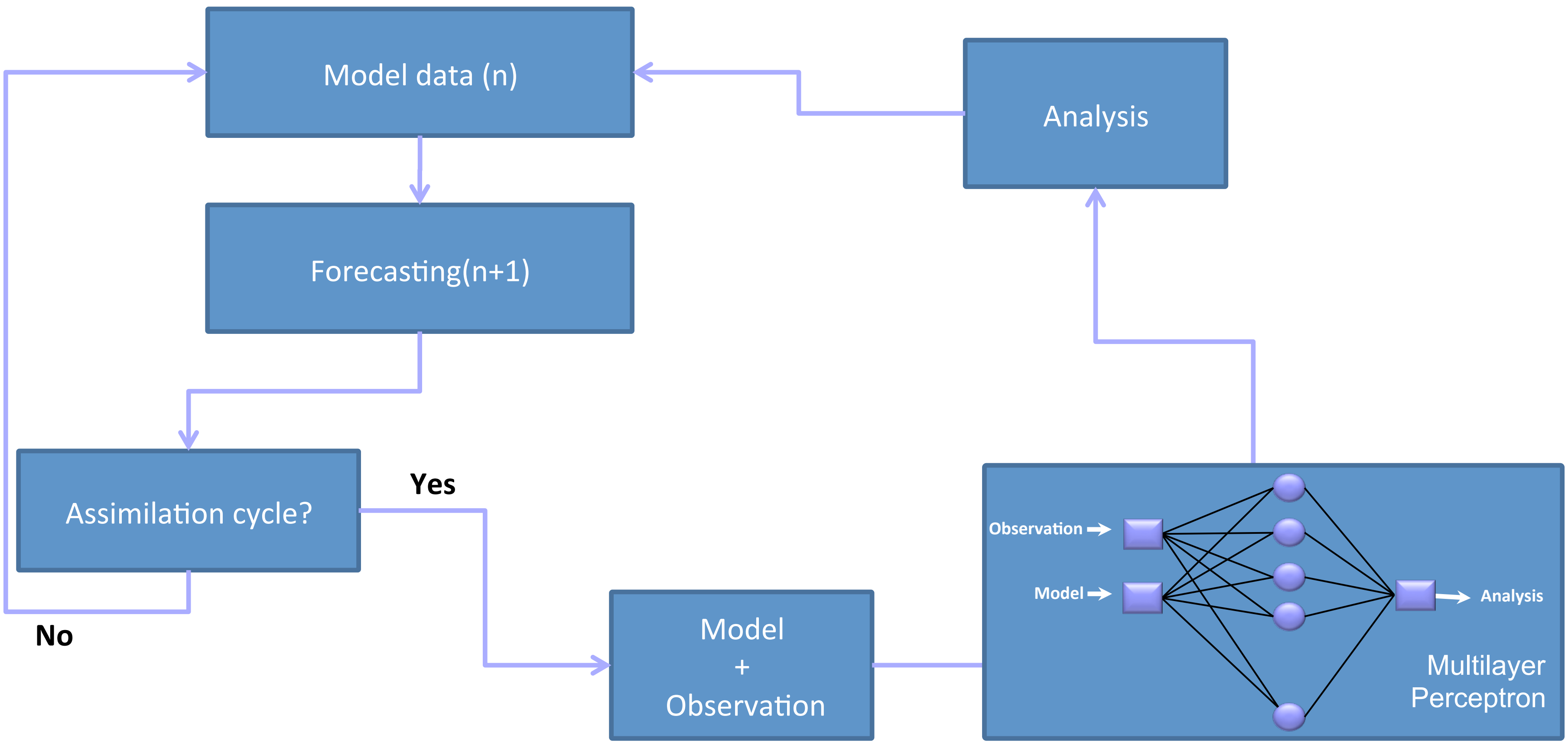
ECMWF



Adrian Simmons

Space Research (meteorology)

Data assimilation: finding initial condition



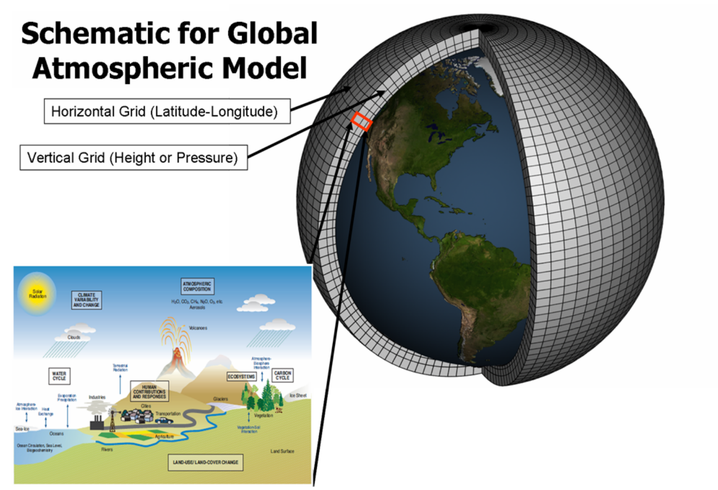
Space Research (meteorology)

Data assimilation: finding initial condition

FSUGSM

(Florida State University global spectral model)

~ regular grid 96 x 192 x 27



Globe divided into 4 horizontal and 6 vertical sub-domains (regions), with different neural network for each meteorological variable:

neural networks: 4 x 6 x 6 = 144 networks.

How can we do that?

Other applications with MPCA

- **Inverse Problem:**

Automatic configuration for neural network applied to atmospheric temperature profile identification.
INTERNATIONAL CONFERENCE ON ENGINEERING OPTIMIZATION, 2012.

- **Inverse Problem:**

MPCA for solving an inverse radiative problem.
IIMSE – INTEGRAL METHODOS IN SCIENCE AND ENGINEERING, 2014

- **Climate Prediction:**

MPCA meta-heuristics for automatic architecture optimization of a supervised artificial neural network.
10th WORLD CONGRESS ON COMPUTATIONAL MECHANICS, 2012.

- **Data Assimilation:**

MPCA meta-heuristics for automatic architecture optimization of a supervised artificial neural network.
2nd CONFERENCE ON UNCERTANTIES, 2014.

PART 2 – Applications to Space Research

- **Numerical Weather Prediction:** equations

Movement Equation ***(momentum)***

$$\frac{du}{dt} - fv + \frac{1}{\rho}\frac{\partial p}{\partial x} = 0 \qquad \frac{dh}{dt} + g + \frac{1}{\rho}\frac{\partial p}{\partial z} = 0 \qquad \frac{dv}{dt} + fu + \frac{1}{\rho}\frac{\partial p}{\partial y} = 0$$

Continuity Equation ***(mass)***

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x}(\rho u) + \frac{\partial}{\partial y}(\rho v) + \frac{\partial}{\partial z}(\rho h) = 0$$

Thermodynamic equation ***(energy)***

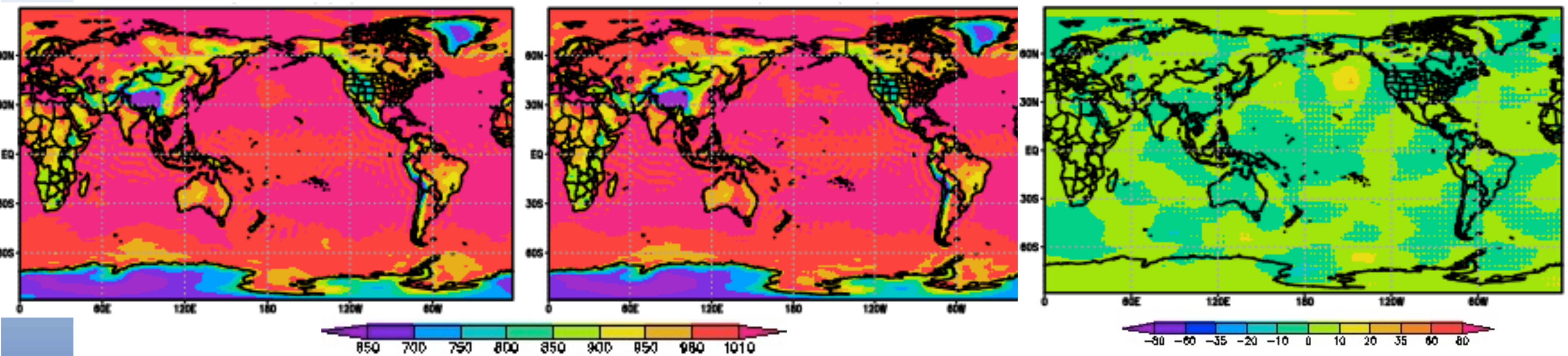
$$p = f(T)\rho \rangle \Rightarrow \frac{f(T)}{T} = \frac{g(\rho)}{\rho} \equiv R(cte) \qquad p = g(\rho)T$$

$$p = \rho RT$$

$$C_v \frac{dT}{dt} + p\frac{d(1/\rho)}{dt} = \frac{dq}{dt}$$

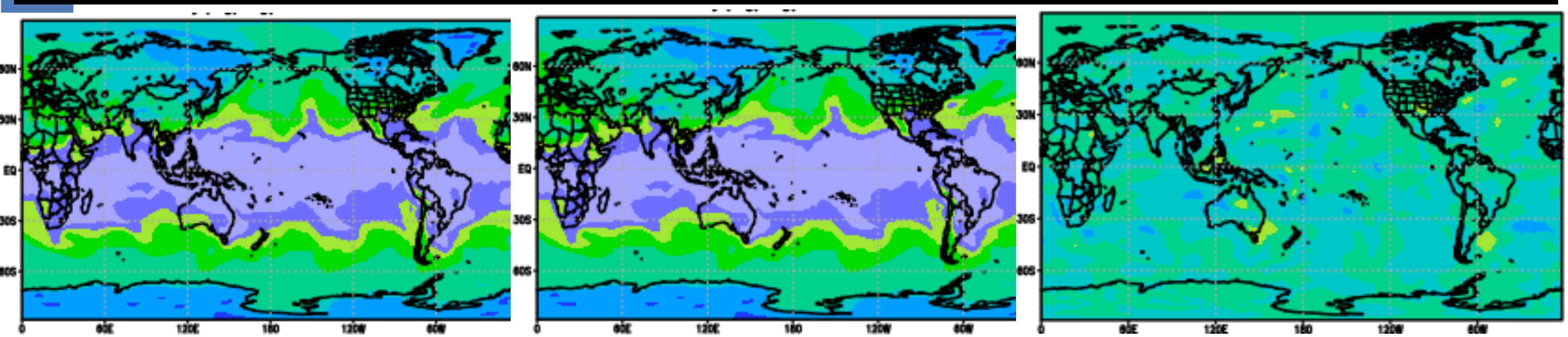
Space Research (meteorology)

Surface Pressure(Kg/Kg) generalization 04/Jan/2005 – 12 UTC



LETKF analysis MLP analysis Differences analysis

Specific Humidity (Kg/Kg) generalization 04/Jan/2005 – 12 UTC



LETKF analysis MLP analysis Differences analysis

Space Research (meteorology)

Data assimilation: finding initial condition

Execution of 124 cycles	MLP-DA (hour:min:sec)	LETKF (hour:min:sec)
Analysis time	00:02:29	11:01:20
Ensemble time	00:00:00	15:50:40
Parallel model time	00:27:20	00:00:00
Total Time	00:29:49	26:52:00

← 266 times faster (Analysis time)

← 55 times faster (Total Time)

Data assimilation: an essential issue

- **Neural networks: Elman and Jordan ANN**

Revista Brasileira de Meteorologia, **v.20**, **n.3**, 411-420, 2005

REDES NEURAIS RECORRENTES TREINADAS COM CORRELAÇÃO CRUZADA APLICADAS A ASSIMILAÇÃO DE DADOS EM DINÂMICA NÃO-LINEAR

FABRÍCIO PEREIRA HÄRTER e HAROLDO FRAGA DE CAMPOS VELHO

Data assimilation: an essential issue

- Neural networks: Shallow water equation (RBF-NN)

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APPLIED MATHEMATICAL MODELLING

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New approach to applying neural network in nonlinear dynamic model

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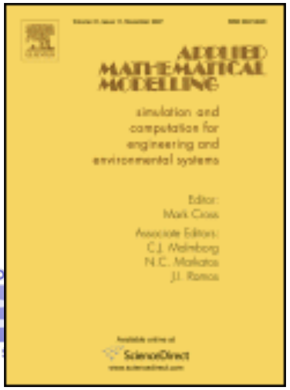
Received 2 January 2007; received in revised form 31 July 2007; accepted 17 September 2007
Available online 30 October 2007



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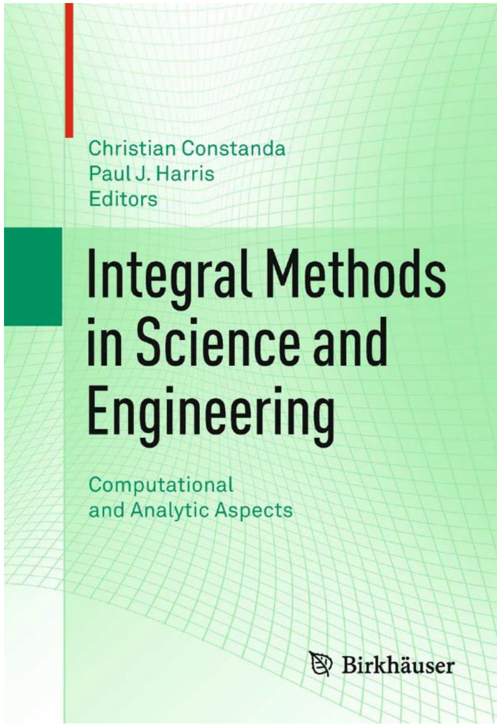
Data assimilation: an essential issue

Adaptive Particle Filter for Stable Distribution

H.F. de Campos Velho and H.C. Morais Furtado



Data assimilation: an essential issue

IOPscience

iopscience.iop.org

6th International Conference on Inverse Problems in Engineering: Theory and Practice IOP Publishing
Journal of Physics: Conference Series **135** (2008) 012073 doi:10.1088/1742-6596/135/1/012073

Data assimilation: particle filter and artificial neural networks

**Helaine Cristina Morais Furtado,
Haroldo Fraga de Campos Velho,
Elbert Einstein Nehrer Macau**

Data assimilation: an essential issue

IOPscience iopscience.iop.org

Dynamic Days South America 2010 IOP Publishing

Journal of Physics: Conference Series **285** (2011) 012036 doi:10.1088/1742-6596/285/1/012036

Neural networks for emulation variational method for data assimilation in nonlinear dynamics

Helaine C. Morais Furtado

Haroldo F. de Campos Velho

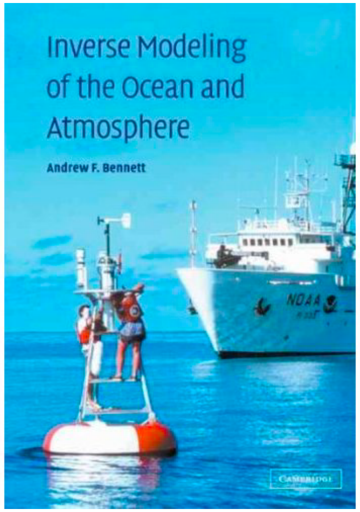
Elbert E. Macau

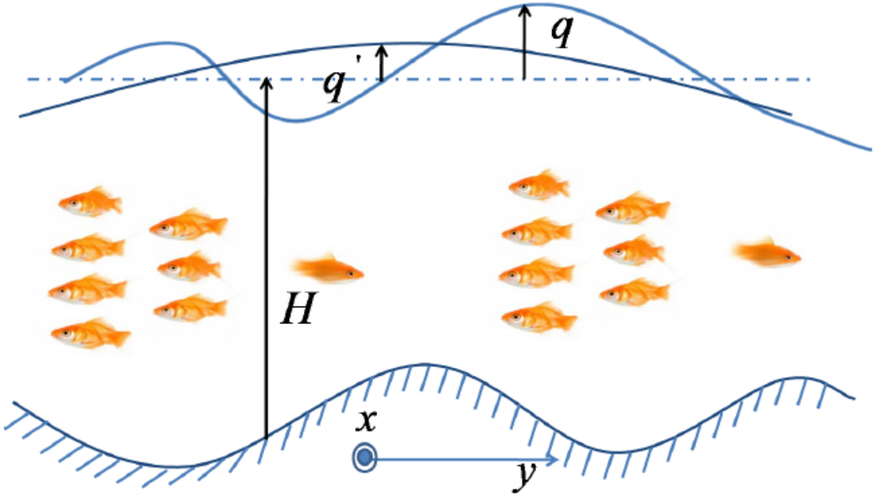
Shallow water 2D for ocean circulation

$$\frac{\partial u}{\partial t} - fv + g\frac{\partial q}{\partial x} + r_u u = F_u$$

$$\frac{\partial v}{\partial t} + fu + g\frac{\partial q}{\partial y} + r_v v = F_v$$

$$\frac{\partial q}{\partial t} + H\left(\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y}\right) + r_q q = 0$$





Obrigado!