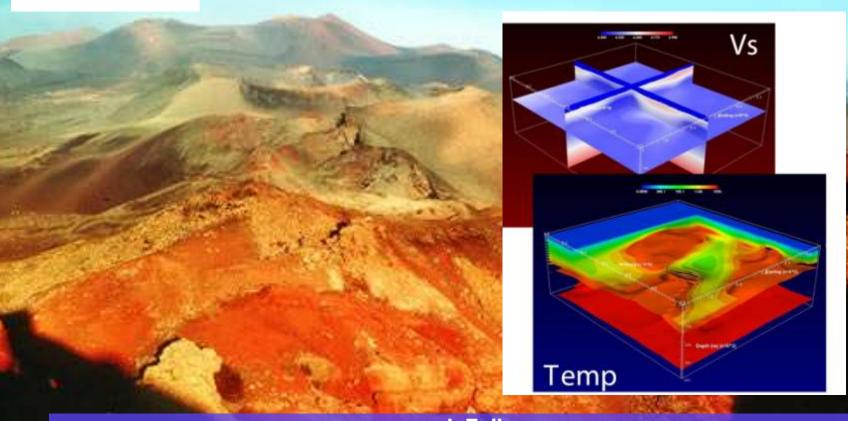


#### **EO** Integrated geophysical and petrological modelling of the uppermost mantle: forward and inversion approaches



J. Fullea Institute of Geosciences (IGEO) CSIC-UCM Madrid, Spain J. C. Afonso, A. G. Jones, S. Lebedev, J. Connolly, Y. Yang, N. Rawlinson, W. Griffin, S. O'Reilly

Outline

# Integrating (self-consistently) geophysical and petrological data to image the lithosphere/uppermost mantle

#### Density (kg/m') Vs (km/s) 36 40 4 2800 3000 3200 3400 4.4 4.8 Geophysical & petrological data -50 Depth (km) -100 Vs ρ -150 -200 Inversion Resistivity (Ohm.m) -150 (g -200 1/σ WMQ ULN Depth 5.0 4.5 4.0 Forward modeling 3.5 3.0 2.5 20 100 200 500 5 10 50 Integrated Forward approach modelling

> Non-linear probabilistic inversion

*Temperature, Pressure, Composition* 

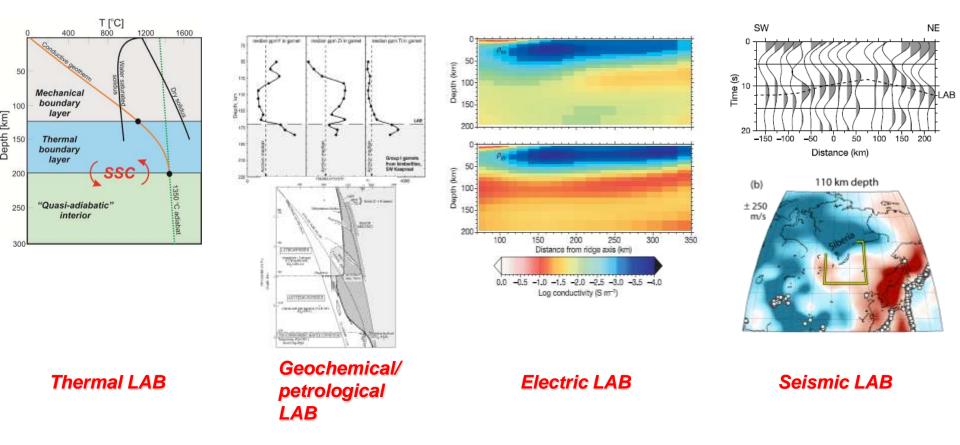
**Geophysical parameters** 



#### Why integrated modelling ...?

A fundamental upper mantle discontinuity for plate tectonics: the lithosphere-asthenosphere boundary (LAB) can be defined as **thermal, mechanical and chemical boundary** 

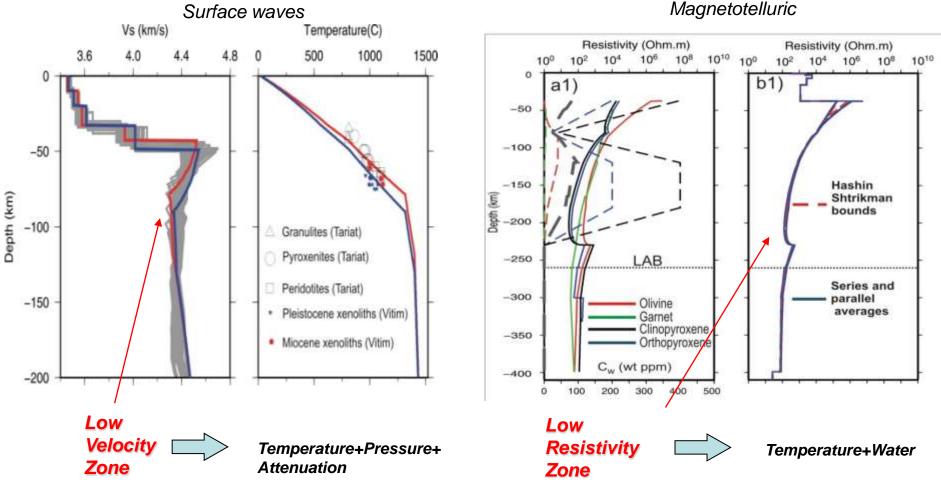
According to the property we focus on (e.g., **temperature, composition, Vs, Vp, anisotropy, electrical conductivity...**) there are many possible "**LABs**" (e.g. Eaton 2009):





#### Why integrated modelling ...?

Ultimately most of the LAB definitions depend upon temperature/pressure and composition



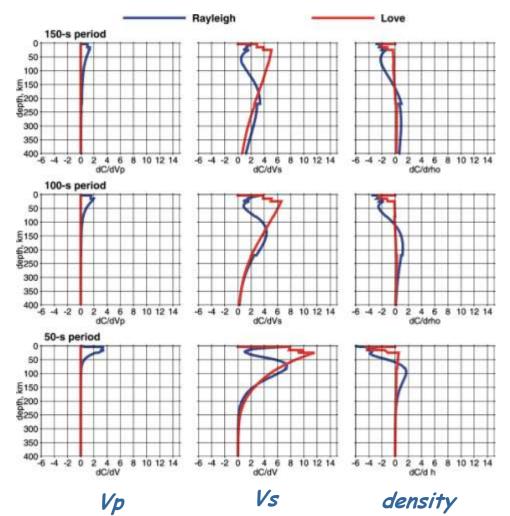
→ Unify LAB's criteria



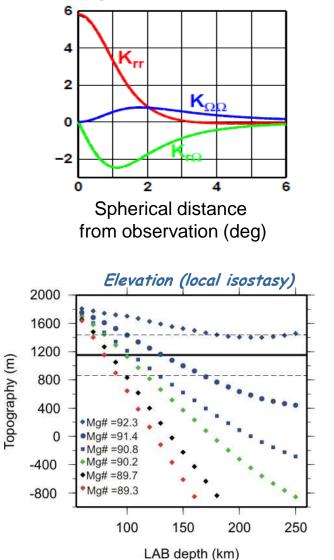
#### Why integrated modelling ...?

**Geophysical observables** have different sensitivities to T, C variations (via seismic velocities, densities, conductivity...)

#### Surface waves sensitivity kernels



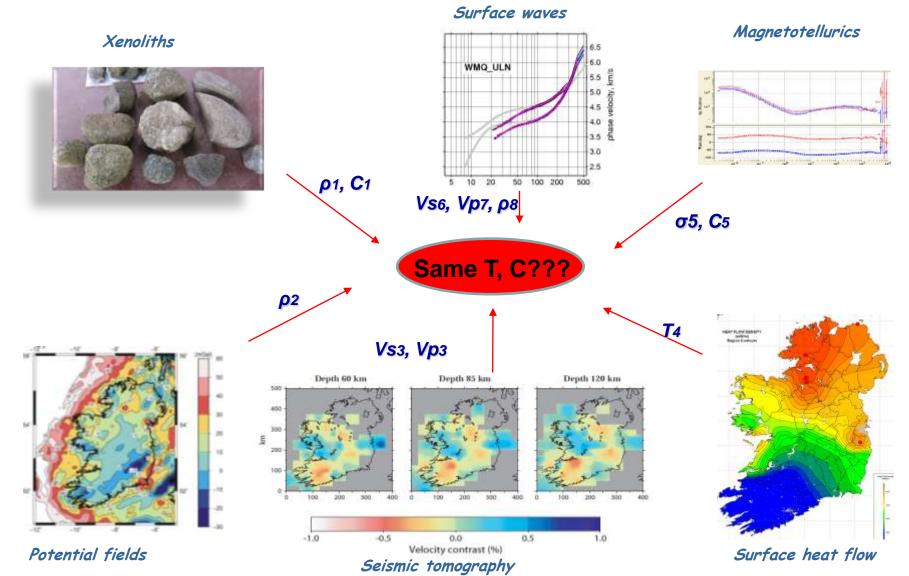
Gravity gradients kernels @ 255 km





#### Why integrated modelling ...?

Modelling all the observables together **avoids** (*some*) inconsistencies given the non-uniqueness of the physical problem at hand





Ultimately most of the LAB definitions depend upon temperature/pressure and composition

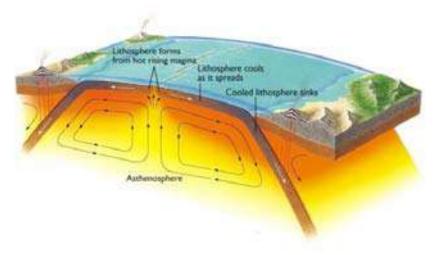
#### Heat transport equation:

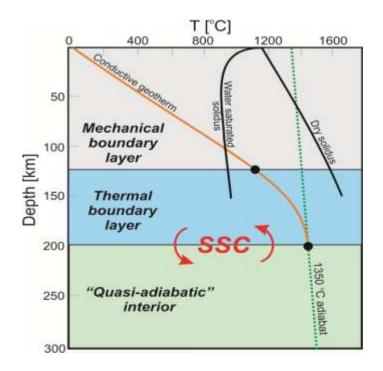
$$\rho c_p \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) + H - \rho c_p \vec{u} \cdot \nabla T$$

#### Lithosphere: conductive mantle

Steady-state conduction equation: dT/dt=0 and  $U=0 \rightarrow Diffusion PDE$ 

$$\nabla \cdot [k(\vec{x}, T, P)\nabla T(\vec{x})] = -H(\vec{x})$$





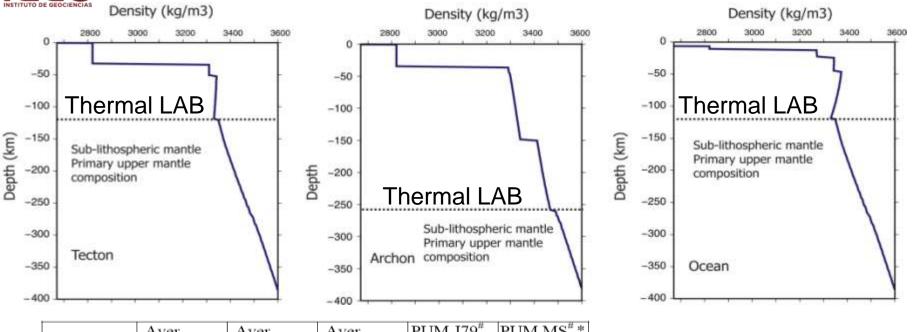
#### Sub-Lithosphere: mantle convection

Convection in the mantle (i.e. no heat interexchange with the surroundings). Fast heat transport mechanism compared to conduction

$$\left(\frac{\partial T}{\partial r}\right)_{S} = \frac{T\alpha g}{c_{P}}$$

Adiabatic gradient: typically 0.45-0.6 K/km in the uppermost mantle





	Aver.	Aver.	Aver.	PUM J $79^{\#}$	$PUM MS^{#} *$
	Archon	Kaapvaal	Tecton		
	Gnt.	Harzburg.	Gnt.		
	SCLM*		SCLM *		
$SiO_2$	45.7	45.9	44.5	45.2	45
TiO <sub>2</sub>	0.04	0.05	0.14	0.22	0.2
$Al_2O_3$	0.99	1.3	3.5	4	4.5
$Cr_2O_3$	0.28	0.34	0.4	0.46	0.38
FeO	6.4	6.0	8.0	7.8	8.1
MnO	0.11	0.1	0.13	0.13	0.14
MgO	45.5	45.5	39.8	38.3	37.8
CaO	0.59	0.5	3.1	3.5	3.6
Na <sub>2</sub> O	0.07	0.07	0.24	0.33	0.36
NiO	0.3	0.28	0.26	0.27	0.25
Mg#	92.7	93.1	89.9	89.7	89.3
Cr/(Cr+Al)	0.16	0.27	0.07	0.07	0.05

In the mantle, stable mineral assemblages can be computed by Gibbs free energy minimization either within the system CaO-FeO-MgO-Al2O3-SiO2 (CFMAS) or Na2O-CaO-FeO-MgO-Al2O3-SiO2 (NCFMAS) [*Connolly*, 2005]. Each mantle body is therefore characterized by a specific **major**element composition (in wt.%), which translates into specific bulkrock properties.

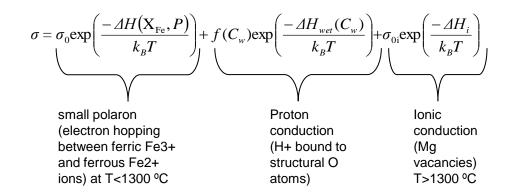


All thermophysical properties (e.g. **density, seismic velocities, electrical conductivity**) depend on **T, P, and Composition** 

$$dG = V dP - S dT + \Sigma_i \mu_i dX_i + Dd\vec{E}$$

*Thermodynamic equilibrium (T>500 C)* 

$$V = \left(\frac{\partial \mathcal{G}}{\partial P}\right)_T \qquad V\alpha = -\left(\frac{\partial \mathcal{S}}{\partial P}\right)_T = \left(\frac{\partial^2 \mathcal{G}}{\partial P \partial T}\right) \qquad C_P = -T\left(\frac{\partial^2 \mathcal{G}}{\partial T^2}\right)_P \qquad c_{ijkl} = \frac{1}{V}\left(\frac{\partial^2 \mathcal{G}}{\partial S_{ij}S_{kl}}\right)_{P,T}$$



→ connect laboratory studies & thermodynamics with geophysics



N

Integrated modelling

#### Why integrated modelling ...?

Representativeness of observed mantle samp (xenoliths, peridotite massifs etc..) on the lithos scale

Carbonate rocks

6

	ntle samples the lithosphe	ric Forv	ward		
harzburgite	т	foliation dip < 40°	deling		and and
Iherzolite with breccias carbonate roc section localiz	websteritic layering - foliation in harzb foliation	foliation dip > 40°			
leted		Depleted +metasomati	ised	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	
) Av. EXO	3) Av. Harz. La	4) Av. HLCO	5) Av. Ocean floor	6) Av. Middle Atlas (wt%) <sup>e</sup>	
nerife /t%) <sup>b</sup>	Palma av. (wt%) <sup>c</sup>	Tenerife (wt%) <sup>b</sup>	peridot. (wt%) <sup>d</sup>		
3.32 ).61	43.07 0.53	42.14 0.73	45.09 2.33	43.48 2.38	

Geophysical data

		O section local	ization in lherz		1		
a. 1 11.	50 m	Depleted		Depleted +metasomat	rised		
	1) Av. Harz.	2) Av. HEXO	3) Av. Harz. La	4) Av. HLCO	5) Av. Ocean floor	6) Av. Middle Atlas (wt%) <sup>e</sup>	
	Lanzarote (wt%) <sup>a</sup>	Tenerife (wt%) <sup>b</sup>	Palma av. (wt%) <sup>c</sup>	Tenerife (wt%) <sup>b</sup>	peridot. (wt%) <sup>d</sup>		
SiO <sub>2</sub>	43.78	43.32	43.07	42.14	45.09	43.48	
$Al_2O_3$	0.7	0.61	0.53	0.73	2.33	2.38	
FeO	7.79	8.04	8.43	8.8	8.4	8	
MgO	46.1	45.31	45.19	44.14	41.23	42.6	
CaO	0.6	0.81	0.68	1.68	1.32	2.83	
Na <sub>2</sub> O	0.1	0.14	0.17	0.18	0.23	0.24	
Mg#	91.34	90.96	90.53	89.94	89.7	90.47	

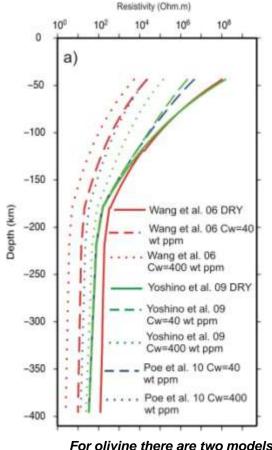
Mantle Depletion (partial melting)

Mantle metasomatism (refertilization)

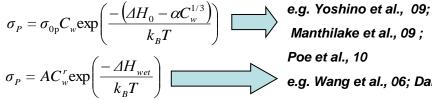


#### Why integrated modelling ...?

olivine



For olivine there are two models for proton conduction based on lab studies:



Manthilake et al., 09 ;

Poe et al., 10

e.g. Wang et al., 06; Dai and Karato 09

#### Jagersfontein: Comparison of H2O models T=740 C, P=3.2 Gpa, Mg#=93.2, Ol=69.5%, Opx=24.17%, Cpx=3.4%, Gt=3.4%, Sp=0.32% а log(conductivity [S/m]) Karato model (Ol only) Yoshino model (Ol only) Pee Av model (Ol only) Karato (Jag whele reck composition) Yoshino (Jag whole rock composition) Pee Av (Jag whele reck composition) agersfentein H2O-Log(sigma) datum Karato revised-Ol model (Jag composition) Suggested Ol-model (Jag composition 80 100 20 40 60 120 140 0 160180 200 Cw (ppm)

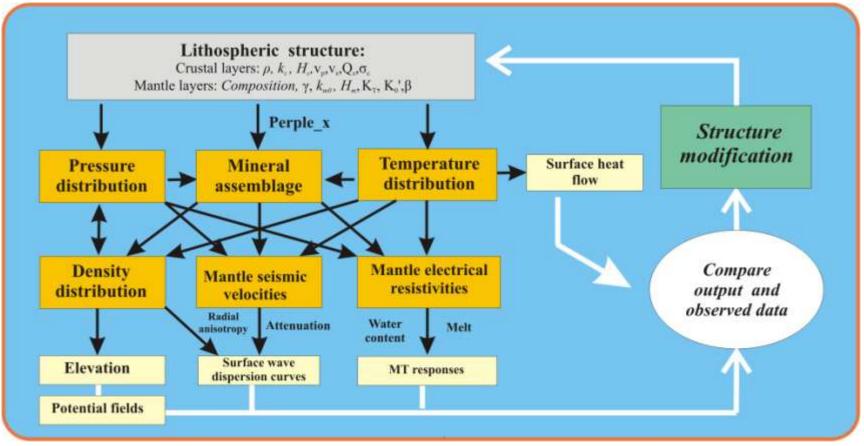
#### → Calibrate lab studies with geophysics

Forward approach



## Forward modelling: trial and error

Lithospheric model→Observables (e.g., topography, potential fields, seismic data, MT...)



All necessary files containing thermodynamic information can be generated with the freely available software **Perple\_X** [www.perplex.ethz.ch, Connolly, 2005]. Forward codes **LitMod** (1D,2D,3D) for integrated modelling available at [http://eps.mq.edu.au/~jafonso/Software1.htm , Afonso et al., 2008; Fullea et al, 2009]. Forward approach



-20

-60

-100

-140

-180

-220

-260

0 -20

-60

-100

-140

-180

-220

-260

0

200

400

600

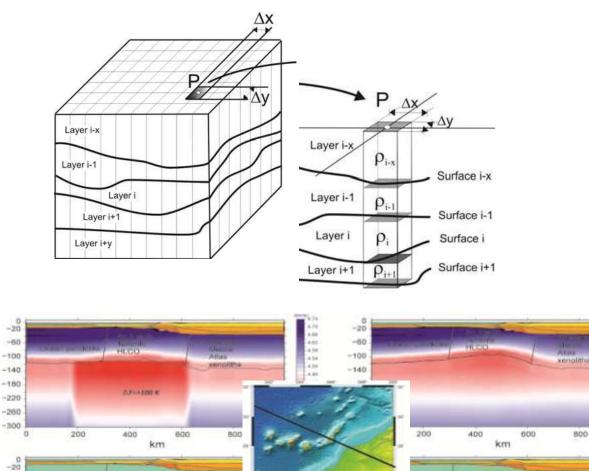
km

800

Depth (km)

Cepth (Mm)

### Forward modelling: advantages



-140

-160

-220

-260

0

200

400

600

km

800

1.000

1040

1010

6180

.....

1,9400

\*High spatial resolution (fine grids) depending on computational power available

\*Exploratory nature, hypothesis testing

1.16

4.54

.....

4.40 4.45

4.36

4.34

4 341

-

1040

-

100

1000

1100

1140

54.00

Forward approach



## Forward modelling: disadvantages

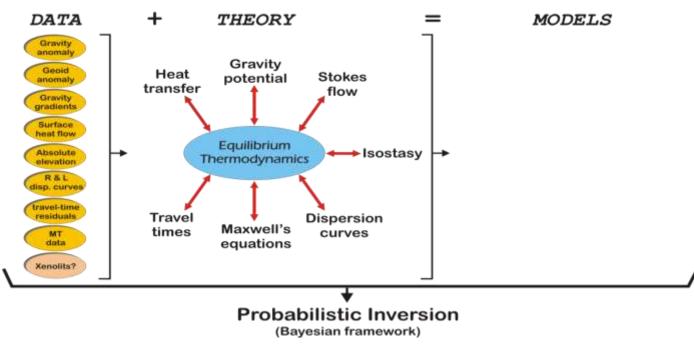
\*Requires a priori/complementary info

\*Huge (potential) parameter space, time demanding task

\*Possible bias from the modeller's prejudices/background

Inversion "version" of LitMod??

LitMod\_4INV



Afonso et al. I and II JGR (2013).



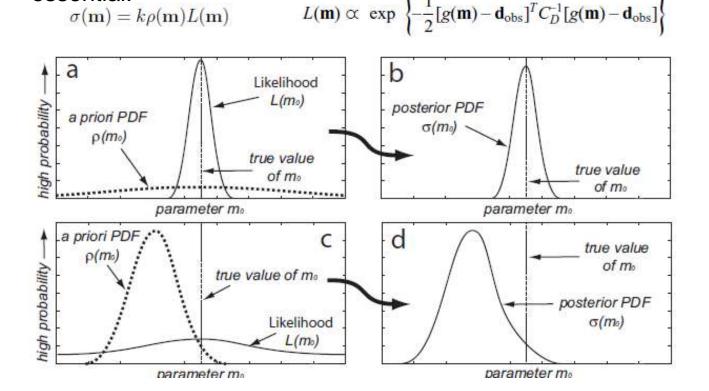
## **Probabilistic non-linear inversion**

\*Looking for T and C (5 oxides+water) at every model node \*Typical forward model: 50x50x200 (5E5) nodes→ 5E5\*7 param/node=3.5 millions of parameters!!

\*Systematic brute-force inversion scheme not affordable

\* The physical problem is highly non-linear

\*A good control on prior PDF  $\rho(\mathbf{m})$  (a priori info) and likelihood  $\mathbf{L}(\mathbf{m})$ (observational and theoretical uncertainties. covariance matrix) is essential.  $\sigma(\mathbf{m}) = k\rho(\mathbf{m})L(\mathbf{m})$   $L(\mathbf{m}) \propto \exp\left\{-\frac{1}{2}[g(\mathbf{m}) - \mathbf{d}_{obs}]^T C_D^{-1}[g(\mathbf{m}) - \mathbf{d}_{obs}]\right\}$ 

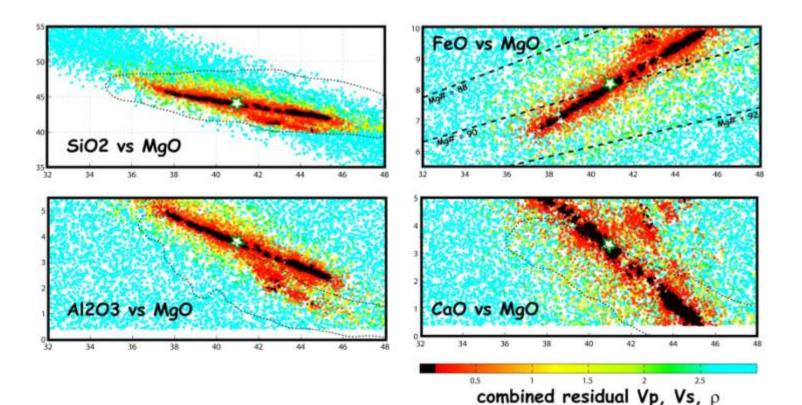




## **Probabilistic non-linear inversion**

- \* Trade-offs between T and C
- \* T has a greater effect than C in most of the observables
- \* Non uniqueness of compositional field (worse in the lithosphere than in the sublithosphere)

$$\sigma(\mathbf{m}) = k\rho(\mathbf{m})L(\mathbf{m}) \qquad \qquad L(\mathbf{m}) \propto \exp\left\{-\frac{1}{2}[g(\mathbf{m}) - \mathbf{d}_{obs}]^T C_D^{-1}[g(\mathbf{m}) - \mathbf{d}_{obs}]\right\}$$





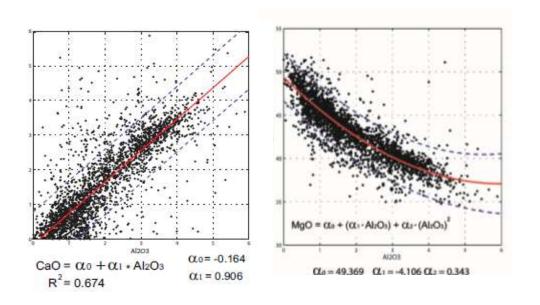
# **Defining prior PDF** $\rho(m)$

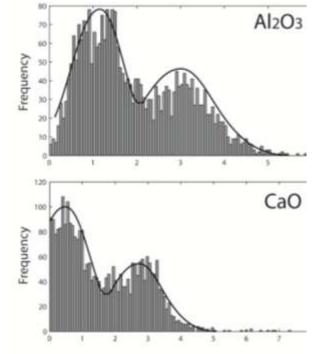
\* A priori petrological data base (>2900 samples from xenoliths, perid. Massifs and ophiolites)

\* Correlation between oxides (Al2O3 and FeO as independent C param.), regardless of tectonic age or facies.

\* Possible bias in database (e.g. double peaks ) due to

\* Wide Al2O3 and FeO ranges (>95% of natural variability) with uniform probability density





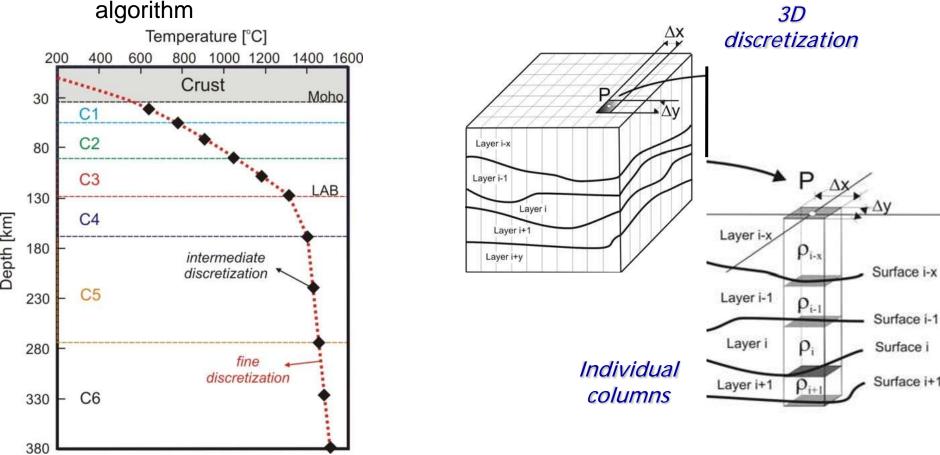


## **Reducing the parameter space**

\* Lower resolution: 6 compositional layers and 12 "thermodynamic nodes" (vs 200 vertical nodes in fwd. models)

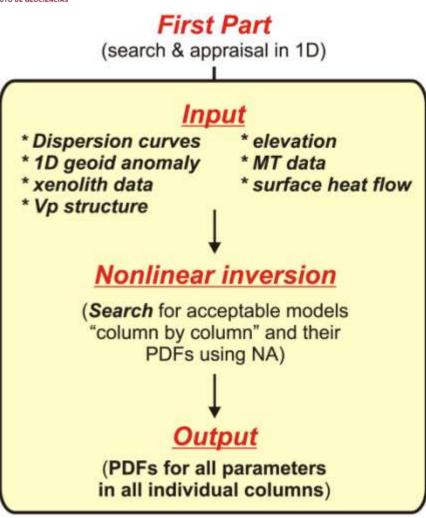
\* Split the 3D problem into 1D columns (for 1D data)  $\rightarrow$  first order PDF's used as priors in the full 3D inversion

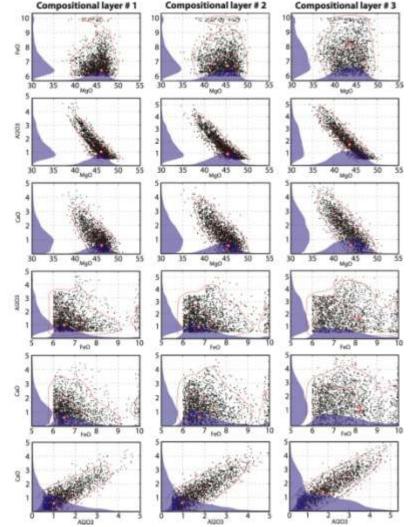
\* PDF's sampled via MCMC simulation using Metropolis-Hastings





Method I



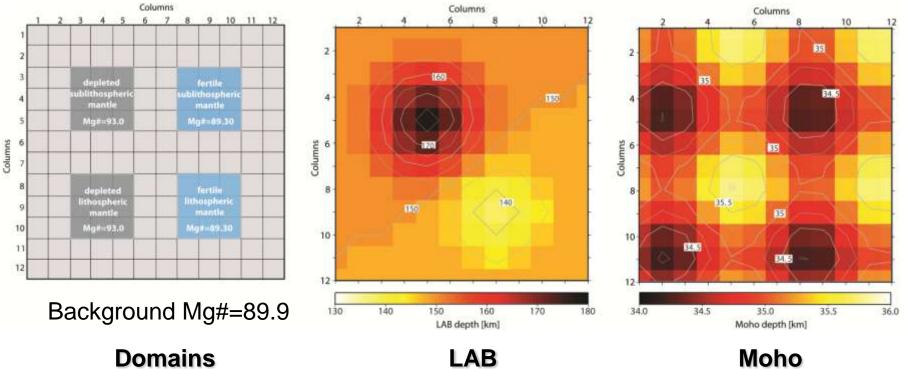


1D Search focused in T: average lithospheric/sub-lithospheric C, dT>200 K 1D search focused on C: 6 compositional layers using LAB posterior PDF



# Synthetic test

\*4 compositional domains + laterally varying LAB and Moho  $\rightarrow$  its forward responses+noise serve as input for the inversion



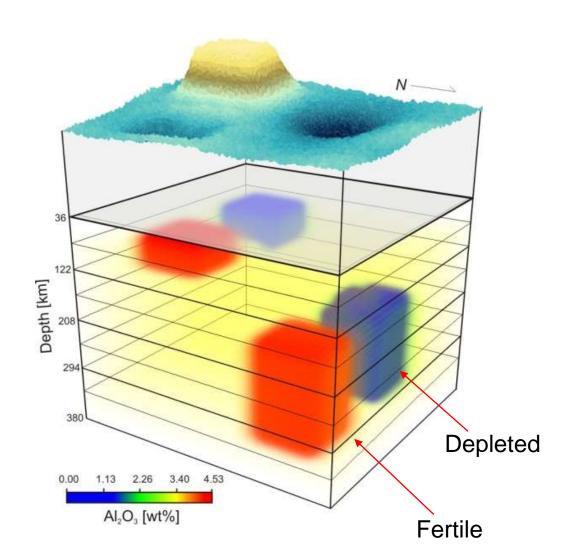
**Domains** 

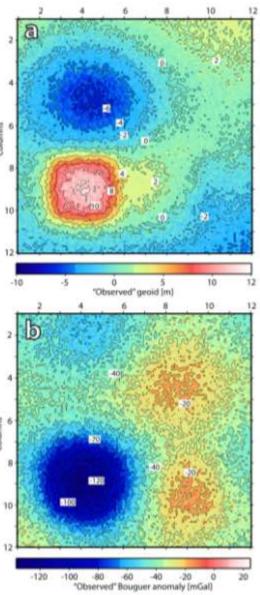




# Synthetic test

Inputs (synthetic fordward+noise) used in the inversion









## Synthetic test

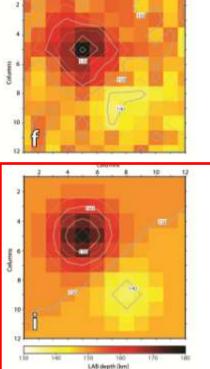
a

Mean models of 8 random ensembles with 500 samples each taken from the total posterior.

Regular and smooth posterior PDF→ averaging is meaningful

#### Columna # Cifuters 10 12 . 10 12 2 Columns Columns Calumes . 10 12 Columna 6 B 10 Columns 12 10 a.

#### **Results for LAB geometry**



10

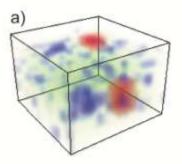
12



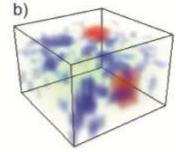
# Synthetic test

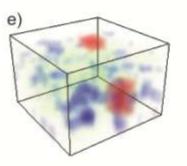
Mean models of 8 random ensembles with 500 samples each taken from the total posterior

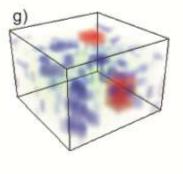
Depleted domains (high Mg#) are recovered, fertile ones (low Mg#) are blurred

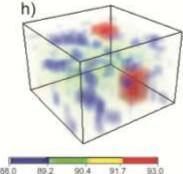


d)

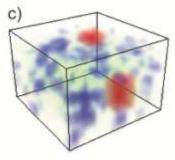


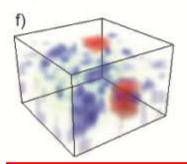


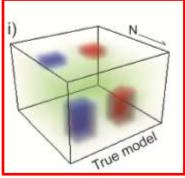












**Results for Mg#** 

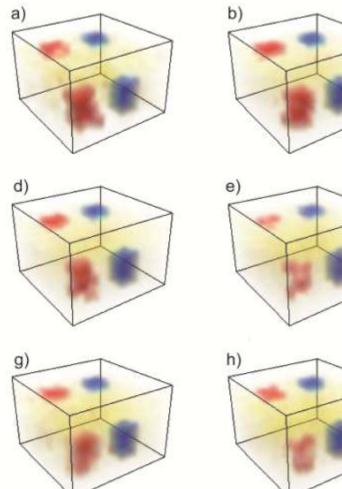


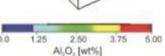
# Synthetic test

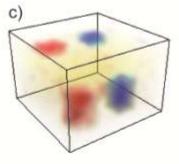
### **Results for bulk Al2O3**

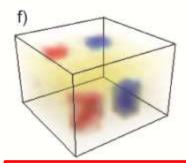
Mean models of 8 random ensembles with 500 samples each taken from the total posterior

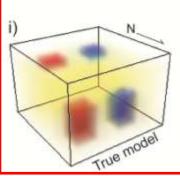
Fertile and depleted domains are recovered → Al2O3 is a sensible indicator for compositional endmembers













# Internally consistent combination of geophysical observables with different sensitivities to T and C

## Integrated modelling: forward vs (and) inversion approaches

#### \*Forward model:

- Requires a priori/complementary info
- Huge (potential) parameter space, time demanding task
- Possible bias from the modeller's prejudices/background
- + Relatively fast (seconds-minutes)
- + High resolution affordable

#### \*Probabilistic Inversion:

+ It does not require a priori/complementary info

- + Parameter space (T, C) effectively explored in hours-days
- + No bias from the modeller's prejudices/background
- Relatively low resolution

## The best of both worlds...



(1) Inversion and (2) detailed forward modelling based on (1) for hypothesis testing

Conclusions



