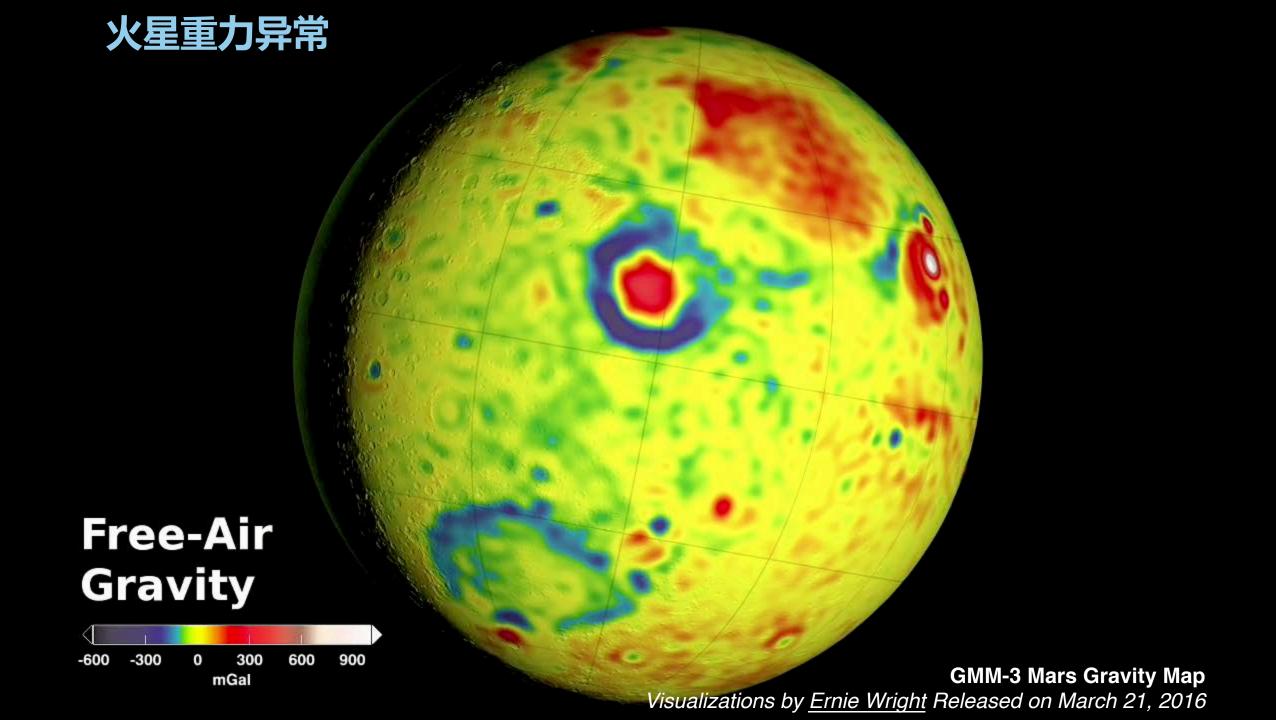
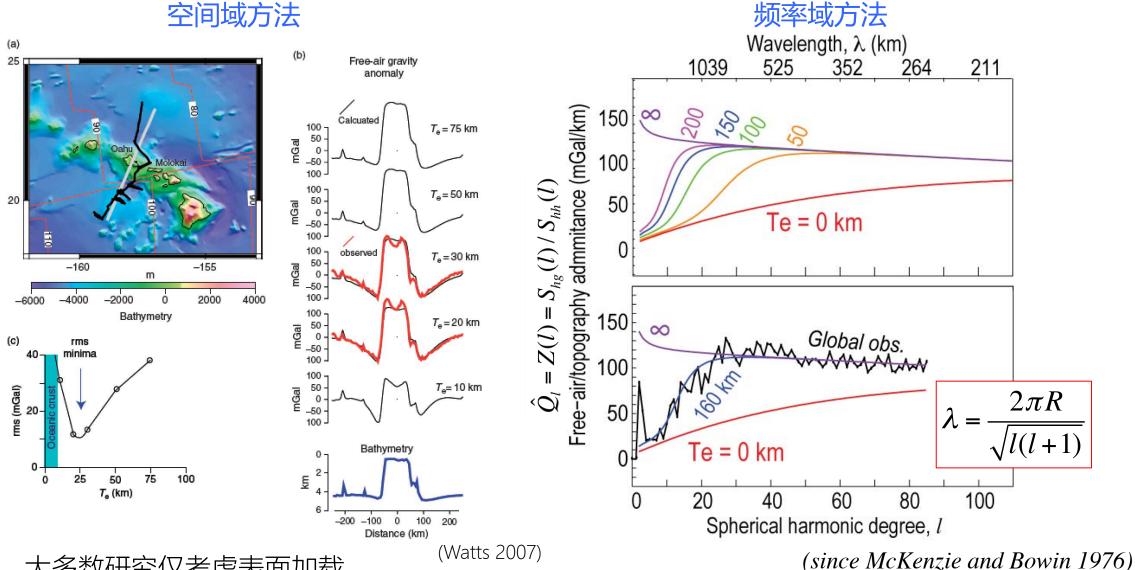
基于火星重力数据的

岩石圈强度反演研究

丁忞 2019 年

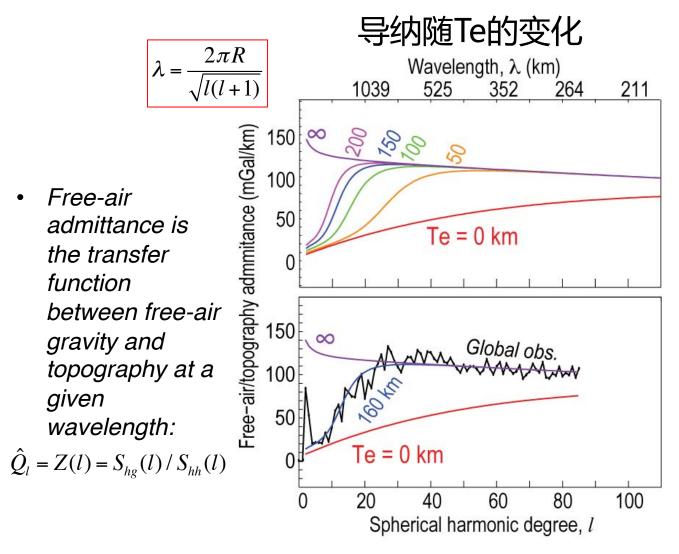


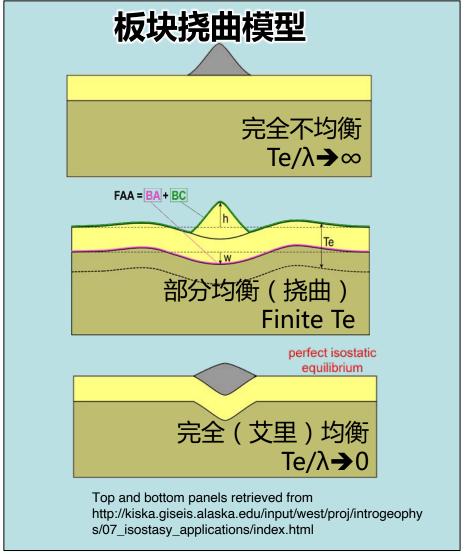
重力数据反演岩石圈有效弹性厚度 (Te) 的方法



- 大多数研究仅考虑表面加载。
- 原则上空间域和频率域方法应该得到相同的结果。

板块挠曲模型下频率域正演计算

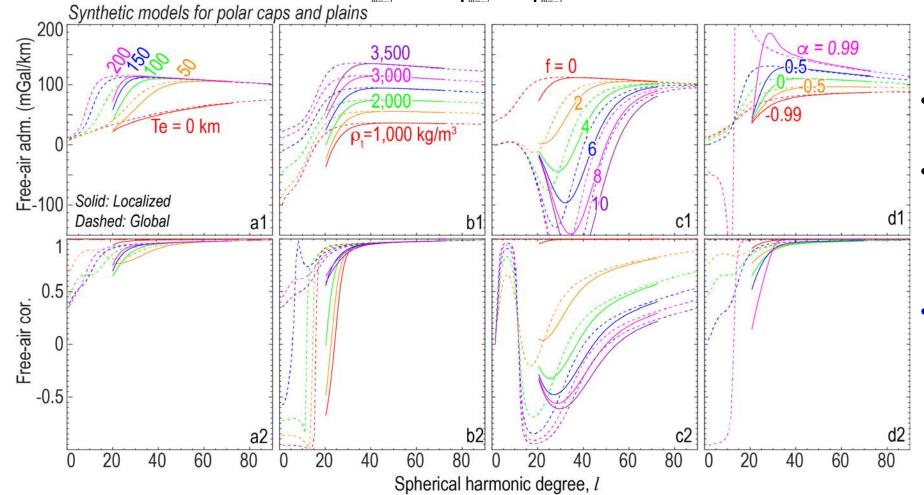




- 假设板块只有地表加载,导纳将与载荷多少无关。
- 可以用重力/地形导纳唯一地反演 Te, 称为"逆谱法"。

- •岩石圈有效弹性厚度: Te
- 地表载荷密度: ρ_t
- 地下载荷相对强度: $f = \Delta \rho_b \sqrt{\sum_{m=-l}^{l} (w_{lm}^i)^2 / \rho_t \sqrt{\sum_{m=-l}^{l} (h_{lm}^i)^2}}$
- 地下/地表载荷相关系数:

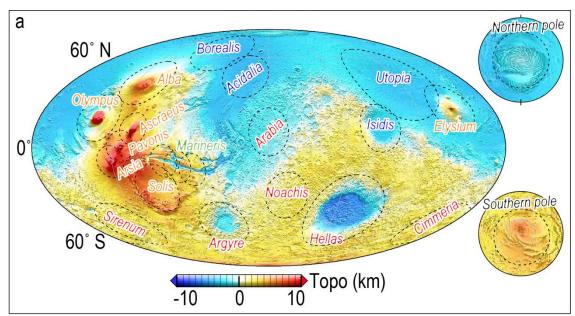
$$\alpha = \left(\sum_{m=-l}^{l} h_{lm}^{i} w_{lm}^{i}\right) / \left[\sqrt{\sum_{m=-l}^{l} (h_{lm}^{i})^{2}} \sqrt{\sum_{m=-l}^{l} (w_{lm}^{i})^{2}} \right]$$

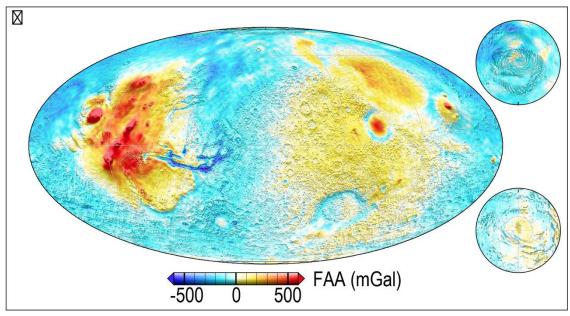


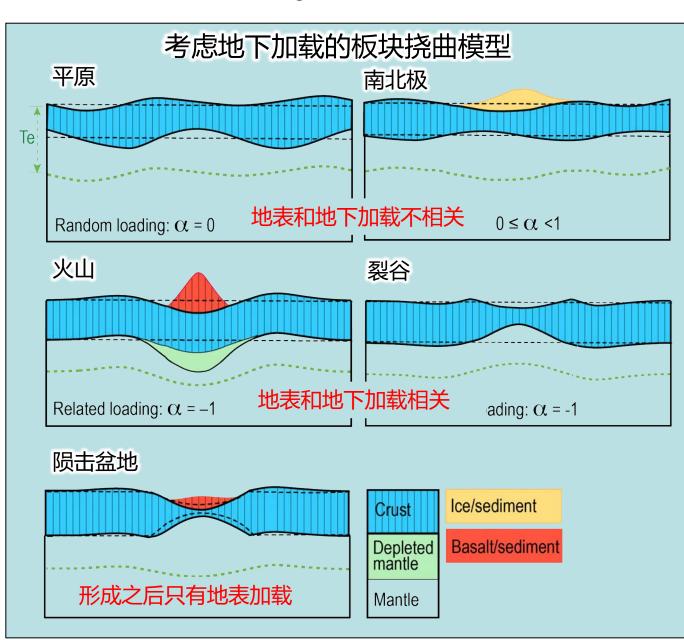
- •除 Te 外,三个加载参数 也影响了导纳。
- 重力和地形的相关性也应 作为反演 Te 的约束 (Forsyth, 1985).
- 逆谱法的重要先验假设是 模型参数和空间尺度(即 波长或球谐度)无关。

Ding+2019

火星上的五种构造类型 Ding+2019

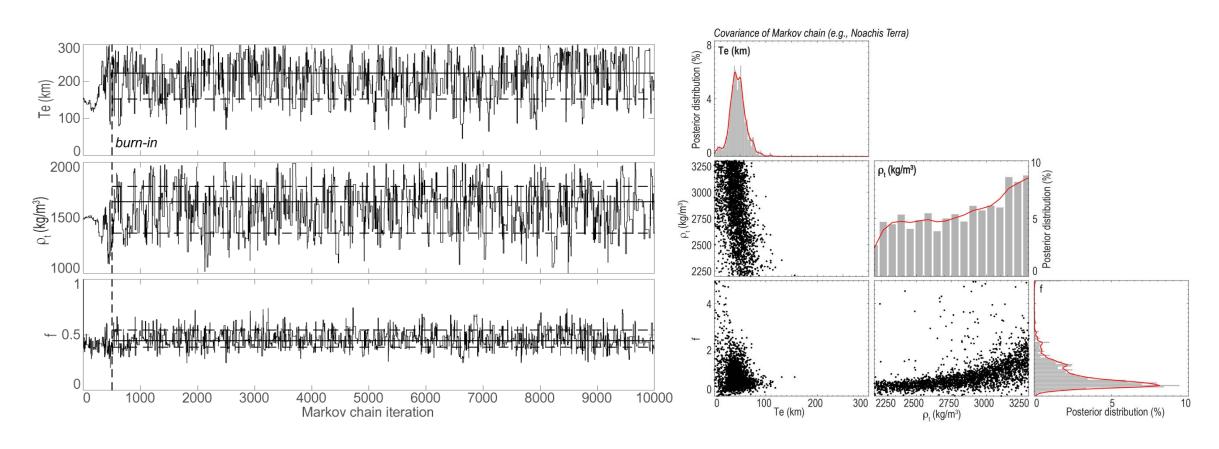






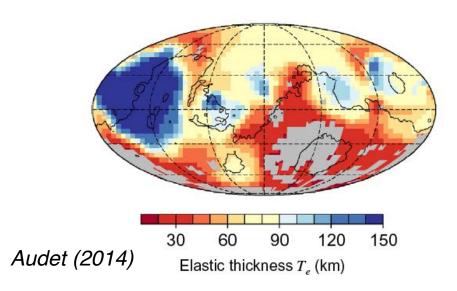
反演方法:马尔可夫链蒙塔卡罗法 MCMC

贝叶斯后验概率: $P(X^i|Z^{obs}(l),\gamma^{obs}(l)) \propto P(X^i)P(Z^{obs}(l),\gamma^{obs}(l)|X^i)$,

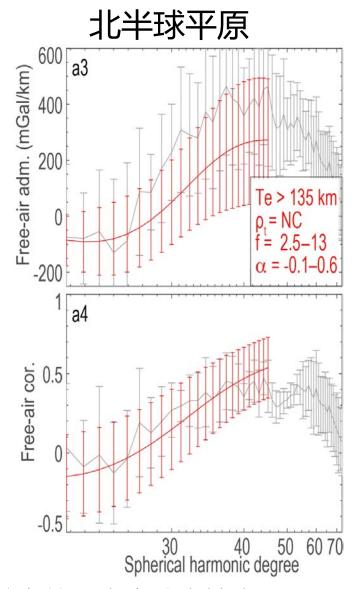


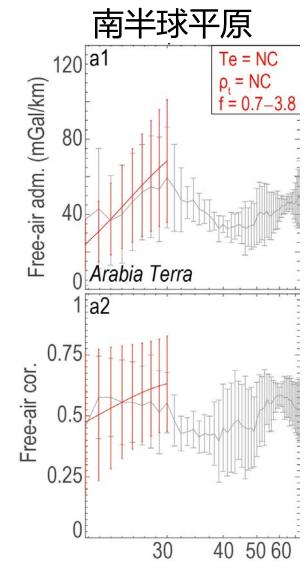
• 更好量化不确定度,更清晰的参数空间可视化。

加载示意图 地表载荷 = 地壳岩石: 沉积/火山岩 (2,200–3,300 kg/m³)



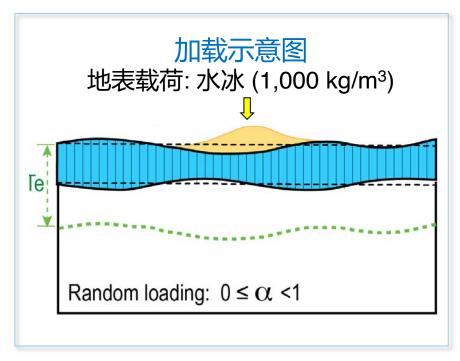
构造类型1:平原

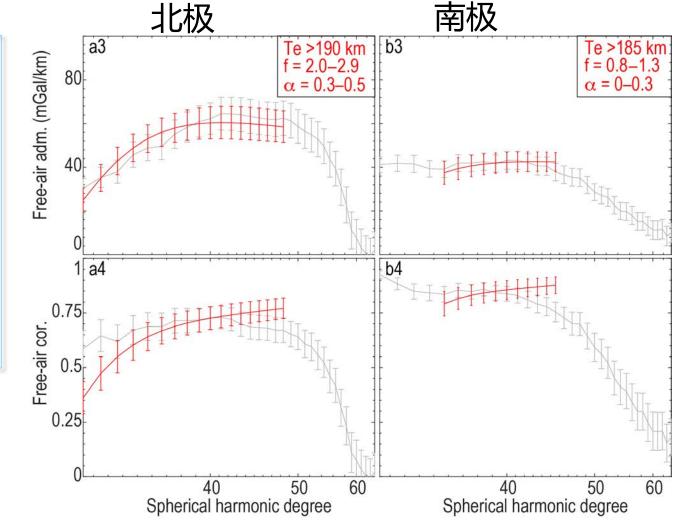




- (较年轻的)北半球低地 Te 比(较老的)南半球高地大。
- 短波长数据难以用相同参数拟合。

构造类型 2: 极地

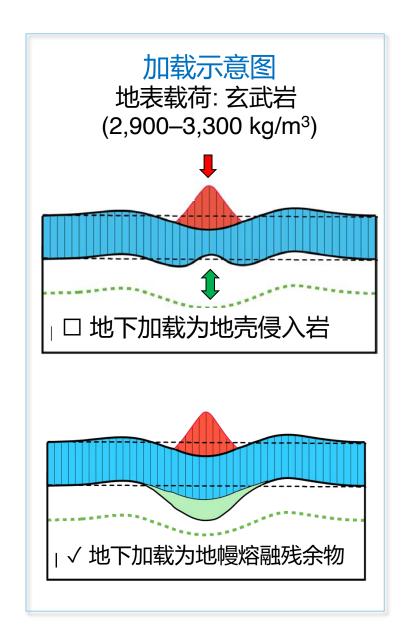


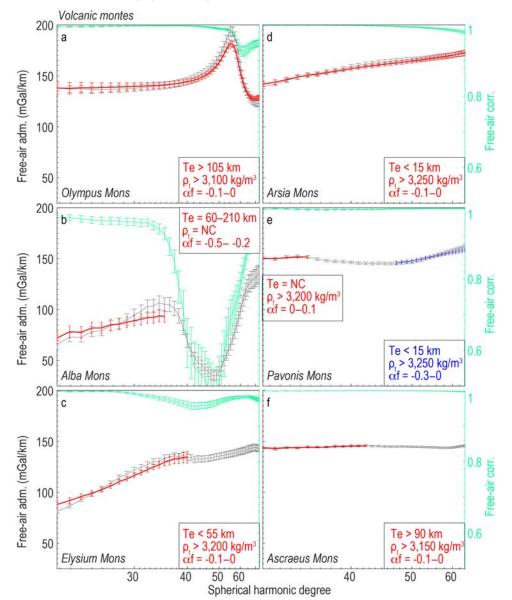


- 反演的 Te 是所有研究区域中最大的.
- 北极的 α 和 f 值比南极大,相应 Moho 面起伏的差异性可能是由早期南北极冰盖不同的分布和融化过程造成的。 Ding+2019

构造类型 3: 火山

数据和反演结果

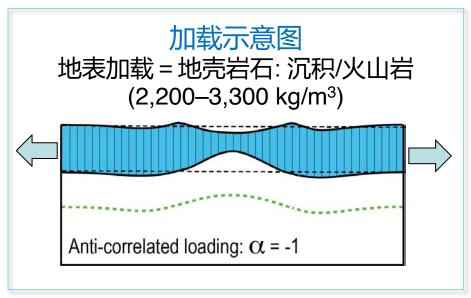


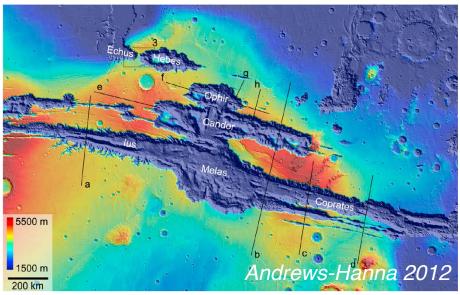


- 为正确计算大坡度 地形对重力信号的 非线性影响,采用 McGovern et al. (2002)的正演方法。
- α = -1: 地下加载为 地幔熔融残余物。
- 火山地区 Te 差异 极大。
- 地表加载密度比较大。

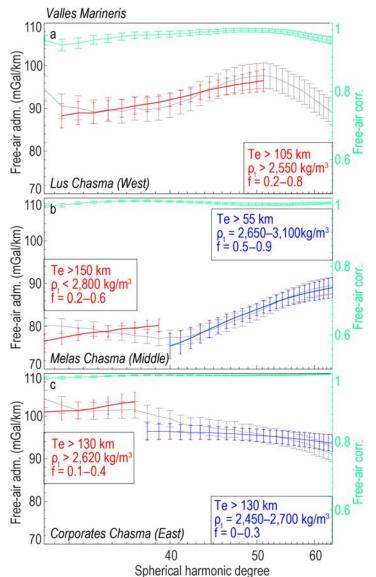
Ding+2019

构造类型 4: 裂谷





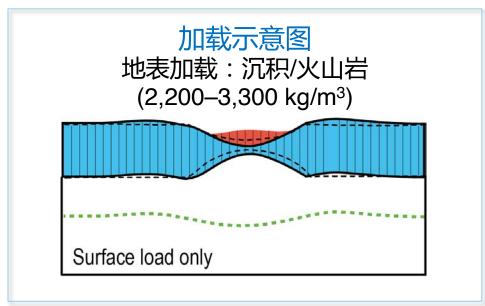
数据和反演结果

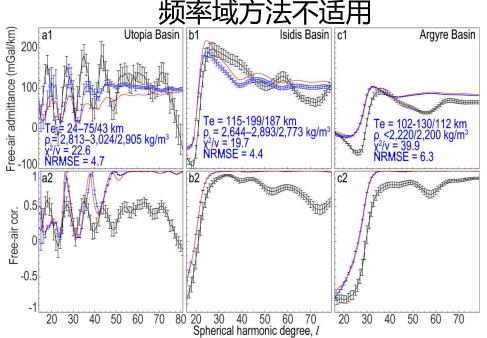


- Te 变化没有规律性。
- 水手谷的演化过程涉及两期过程,可能需采用更复杂的模型 (Beuthe et al., 2012)

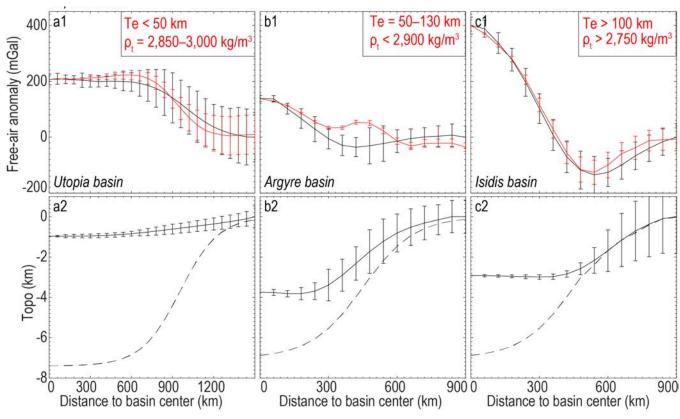
Ding+2019

构造类型 5: 陨击盆地



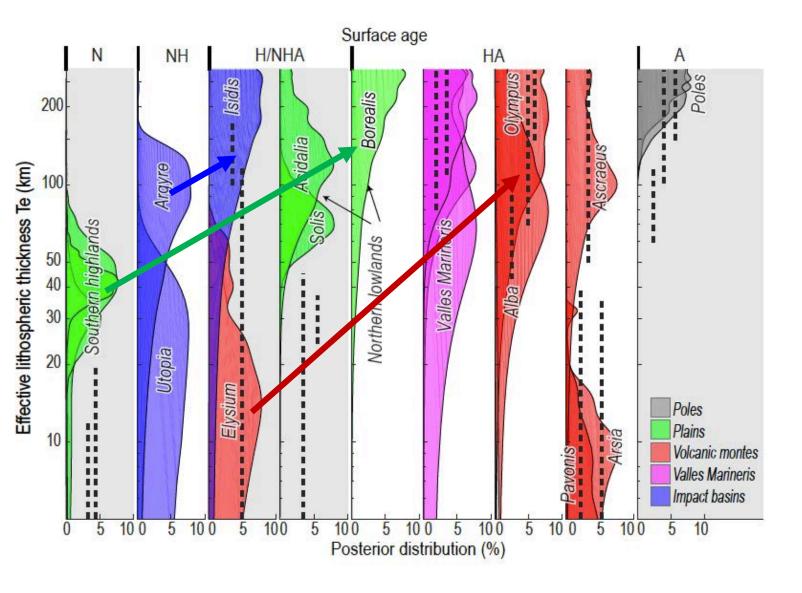


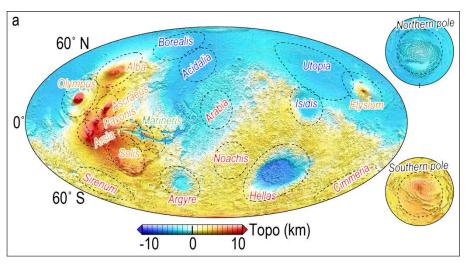
空间域重力异常和反演结果 (Azimuthally averaged profiles)



- 初始结构应当包括包括盆地地形和地幔抬升。
- 伊希地盆地的 Te 和 ρ_t 较大。

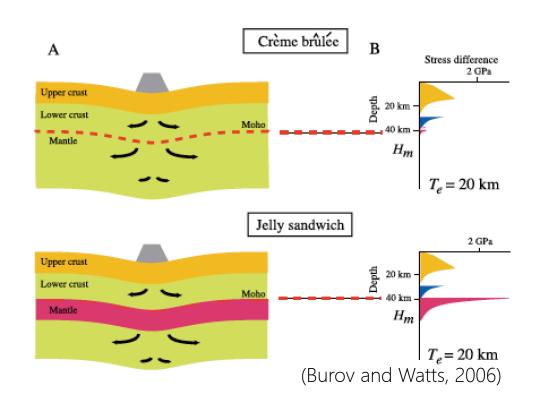
岩石圈有效弹性厚度 Te 反映了加载时的热状态



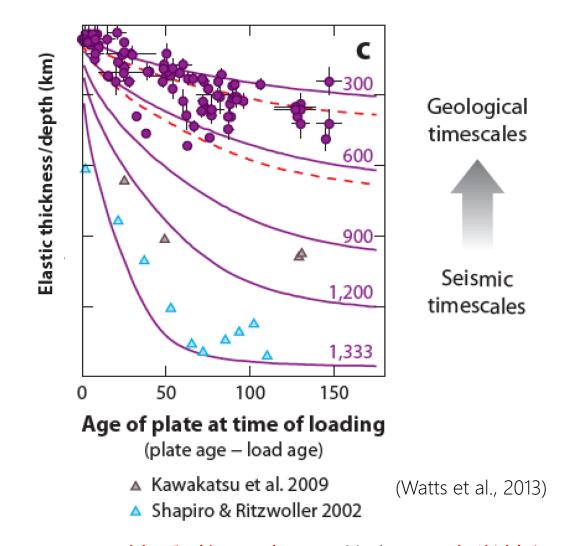


- 加载时间的差异可以解释大多数区域 的 **Te** 变化。
- Arsia & Pavonis 火山: 地壳较厚,可能存在软弱的下地壳使得岩石圈强度变弱.

岩石圈有效弹性厚度 Te 是什么



- Te 是岩石圈**受到加载时**其差应力沿深度 方向的**积分**。
- 控制因素:加载时的温度结构,壳幔的耦合情况,壳幔的完整性,以及加载、应力和岩石圈挠曲 (e.g., McNutt, 1984; Burov and Diament, 1995)。



- Te 是地质时间尺度(Ma)的岩石圈力学特征。
- Te 不是当下可观测的结构。

结论

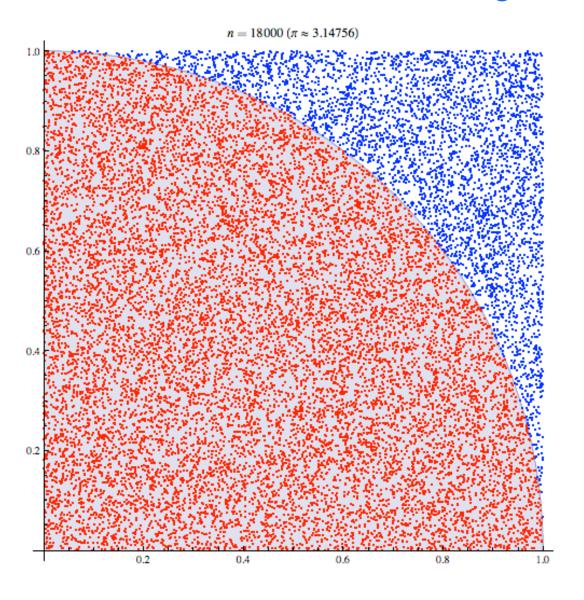
关于模型参数

- •相对值比绝对值可靠。
- Te 随加载时间增加,反映了全球冷却和岩石圈变厚的过程。
- 地表加载的密度差异表明了加载物质的差异。

关于反演方法

- •考察地质背景,建立合理的加载方式模型是正确估计Te的关键。
- 逆谱法的先验假设是模型参数和空间尺度(即波长或球谐度)无关。如果观测与此假设不符,则只能选择有限的频段进行反演。
- 马尔可夫链蒙塔卡罗法可以提高不确定度的估计。

Monte Carlo Method for Integration



Monte Carlo Method for Probability Generation

Example: Estimate the probability distribution of damage caused by tornadoes in the United States over a period of one year.

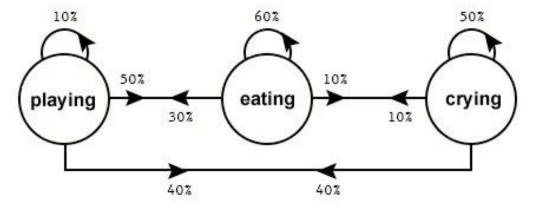
Monte Carlo simulation steps:

- 1. Draw a random number from the distribution of the number of annual events
- If you get n events from the previous step, take n draws from the distribution of the loss for a single event
- 3. Add the values of the n draws of step 2. to obtain a value representing an annual loss caused by n events.

Markov chain

• A Markov chain is a sequence of random variables X={Xi,i∈Z} so that the next realization depends only on the previous realization.

Markov state diagram of a child behaviour



A Recipe of MCMC Approach Based on AM algorithm

Text S4. Markov Chain Monte Carlo Method

The details to construct a Markov chain are as follows. Generalization and proof for this method can be found in Smith (2014). A Markov chain is a sequence of random variables $X=\{X^i,i\in\mathbb{Z}\}$ so that the next realization X^{i+1} depends only on X^i . For each realization we have $X^i=(Te^i,\rho^i_t),(Te^i,\rho^i_t,f^i/\alpha f^i)$ or $(Te^i,\rho^i_t,f^i,\alpha^i)$. The observed admittance and correlation are abbreviated as $F=(Z^{obs}(l),\gamma^{obs}(l))$. The localized admittance and correlation models for X^i are calculated using the methodology in Section 2.3, namely $f(X^i)=(Z^{model}(l,X^i),\gamma^{model}(l,X^i))$. Given X^i , the next realization X^{i+1} is proposed by the adaptive Metropolis (AM) approach (Haario et al., 2001), and is accepted or rejected according to the standard Metropolis-Hastings criterion (Metropolis et al. 1953; Hastings 1970). The detailed procedures are as follows:

1. Propose a candidate Y by a random walk algorithm:

$$Y = X^i + Rz, (S16)$$

where z is a vector of random numbers from Gaussian distribution N(0,1), and R is the Cholesky decomposition of the parameter covariance matrix V^i . This ensures that Y follows a multivariate Gaussian distribution $N(X^i,V^i)$.

2. Calculate the acceptance ratio:

$$\alpha = \min\left\{1, \frac{P_{\beta}(Y|F)}{P_{\beta}(X^{i}|F)}\right\},\tag{S17}$$

where the coarsened posterior for X^i and the proposal Y are calculated using Equation 10.

- 3. Generate a random scalar u within the interval [0 1] for comparison. If $\alpha > u$, accept the proposal and take $X^{i+1} = Y$, otherwise $X^{i+1} = X^i$.
- 4. After every 20 iterations, update the parameter covariance matrix $V^i = s_d \operatorname{cov}(X^0, X^1, ..., X^{i-1})$, where $\operatorname{cov}(X^0, X^1, ..., X^{i-1})$ is the chain covariance matrix, $s_d = 2.4^2/p$ and p is the number of parameters.

Although the initial parameter values X^0 and initial covariance matrix V^0 do not influence the final results, we typically specify X^0 as the set of mean values of the presumed parameter ranges, and V^0 as a diagonal matrix whose element values (i.e., initial parameter deviations) are equal to 10% of the parameter ranges.