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VERS UNE ASSIMILATION DES DONNÉES DE DEFORMATION EN VOLCANOLOGIE

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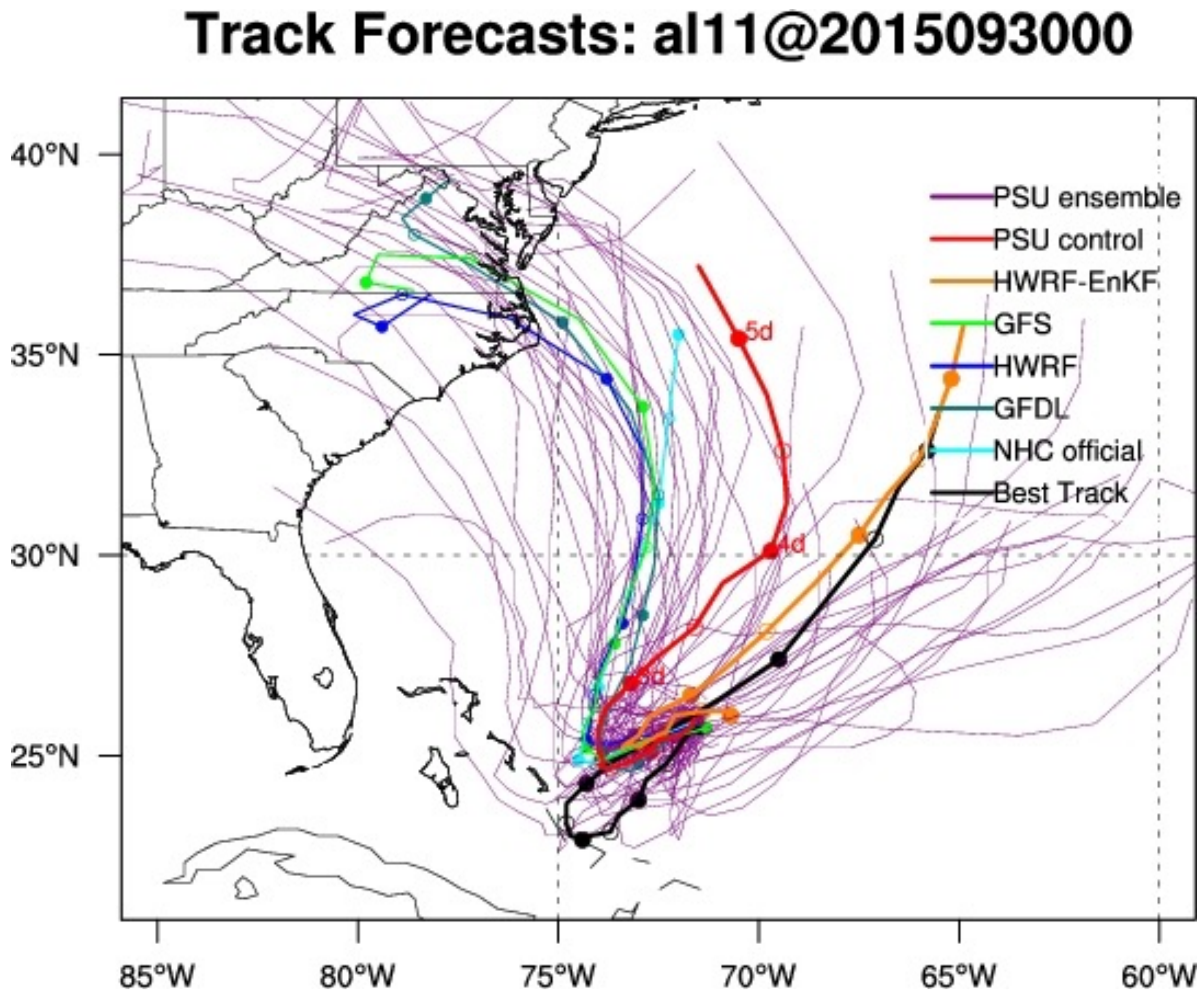
OVERVIEW: WHAT IS DATA ASSIMILATION (DA)?



Example of data assimilation: Forecasting the path of Hurricane Joacquin

Data assimilation is a time-stepping process that combines **models**, **observations** and ***a priori* information** based on error statistics **to predict the state of a dynamical system**

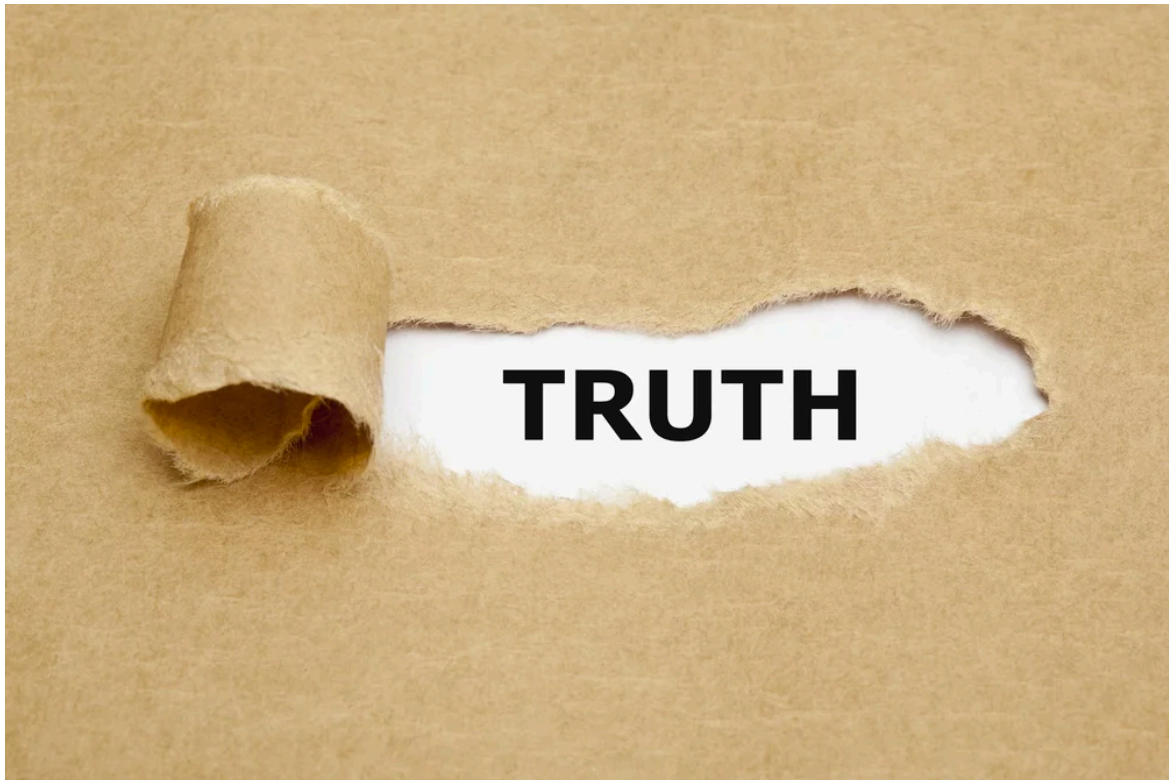
☑ Common approach used in numerical weather prediction (NWP)

☑ Gained popularity in other fields of geosciences:

- vegetation and soil moisture
- natural resource exploration
- geomagnetism

OVERVIEW: BASIC CONCEPT OF DATA ASSIMILATION

Everyone wants the "truth", but the truth is, we can only infer the "truth"



- Models (M) are incorporated with errors (q)

M: Model operator

☑ $$x^f_{t+1} = \mathcal{M}(x^a_t) + q$$

- Observations (D) are not free of noise (ϵ)

H: Observation operator; link between **x** and ***D***

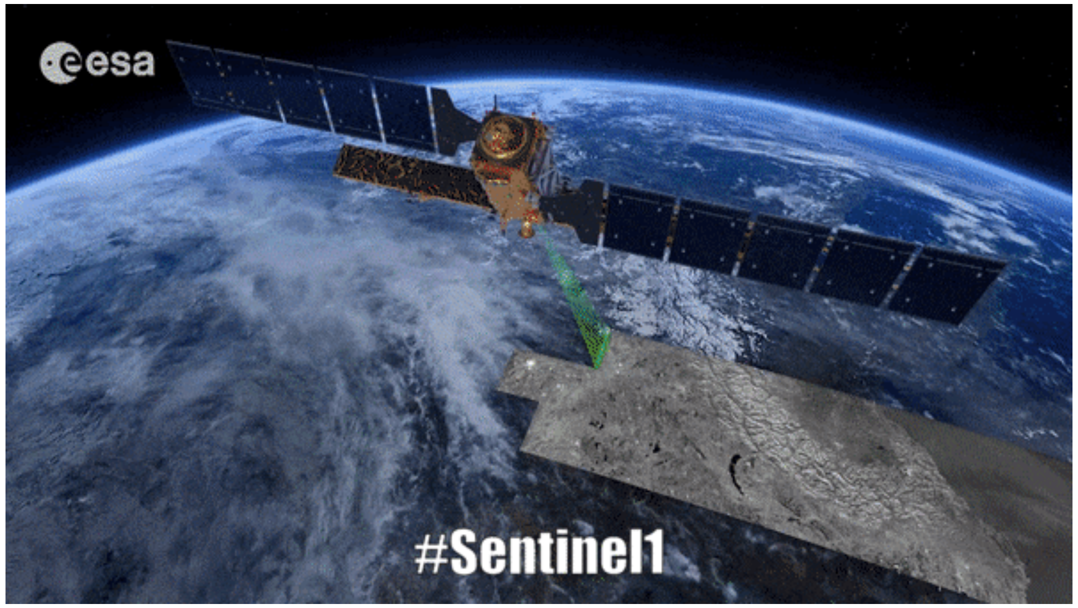
☑ $$D_{t+1} = \mathcal{H}(x^f_{t+1}) + \epsilon$$

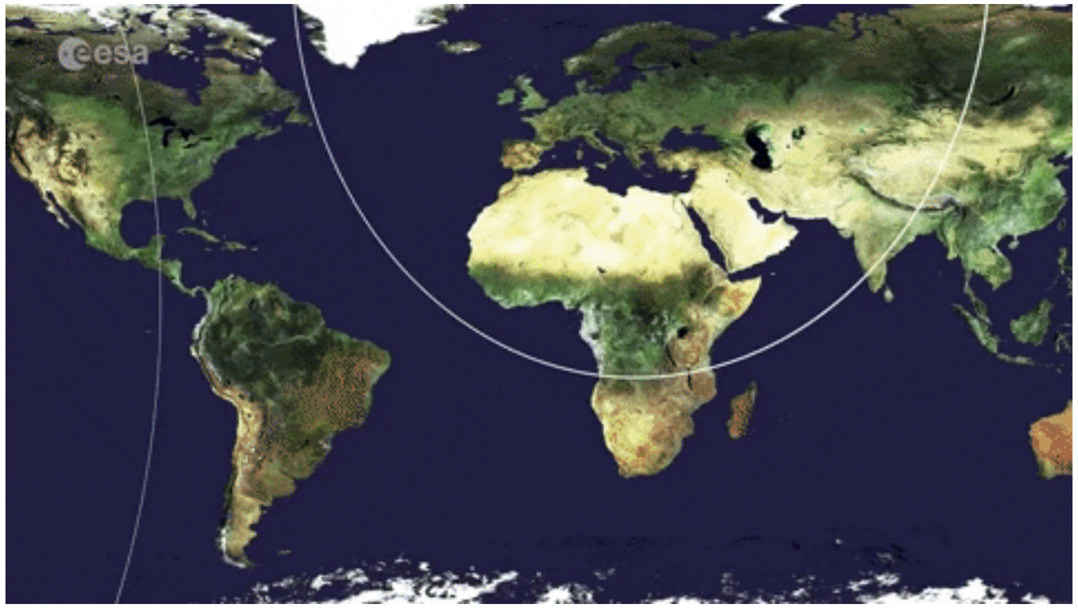
- Efficient model + data technique

**f: forecast*
a: analysis

OVERVIEW: INGREDIENTS OF DATA ASSIMILATION

- Observations / data
  - ☑ Deformation data (e.g. InSAR/GNSS time-series)
- Dynamical model
  - ☑ Two-chamber model (Reverso et. al. 2014)
- *A priori* information (Gaussian PDF)





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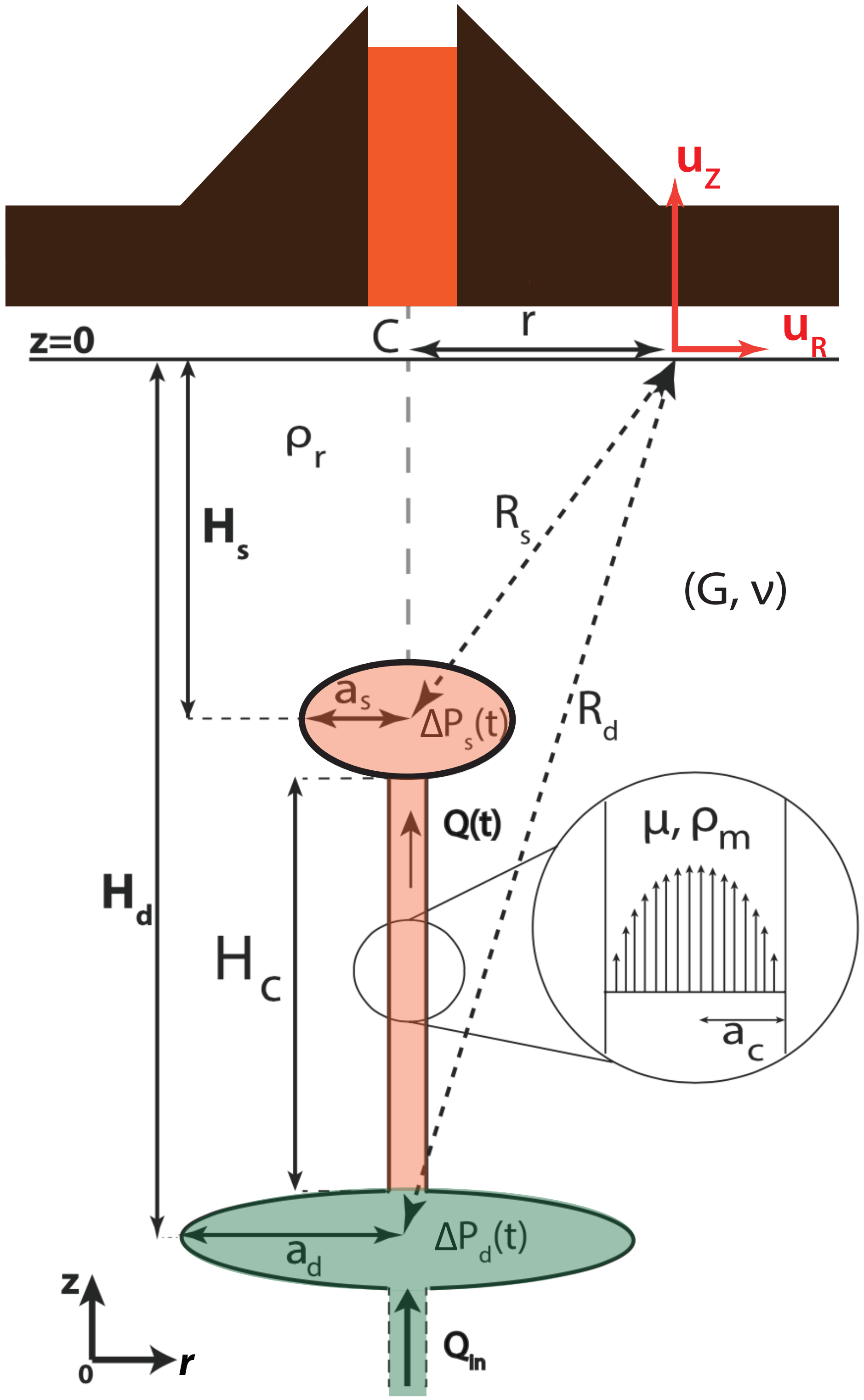


modified after Reverso et. al. 2014

OVERVIEW: INGREDIENTS OF DATA ASSIMILATION

Model description:

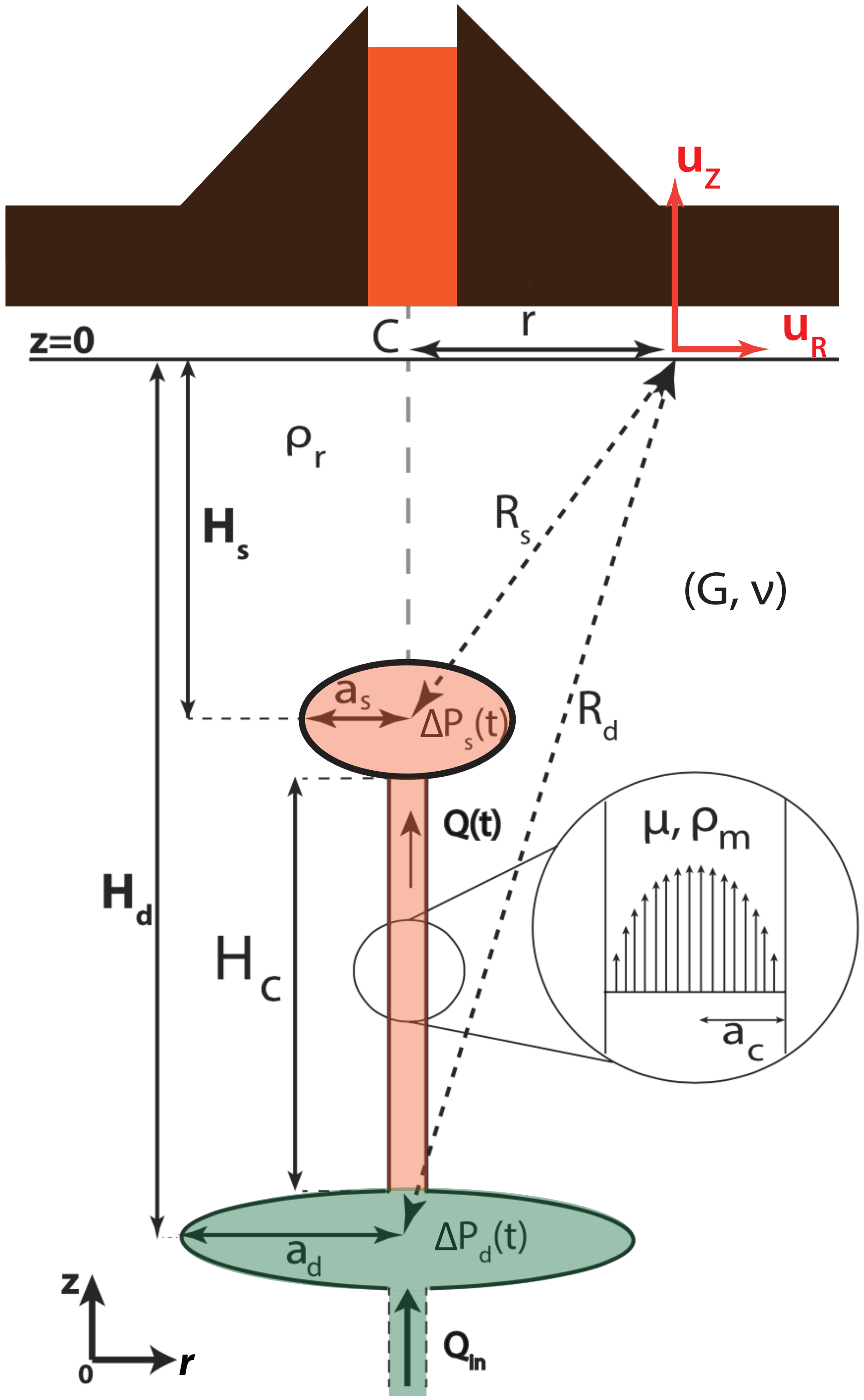
- Homogeneous, isotropic, elastic half-space
- Two reservoirs connected by a hydraulic pipe
- Deeper reservoir is fed by a magma inflow, Q_{in}

Several volcanoes are evidenced to have multiple reservoir systems

Data / observations:

U_z : Vertical displacement

U_R: Radial displacement



modified after Reverso et. al. 2014

OVERVIEW: INGREDIENTS OF DATA ASSIMILATION

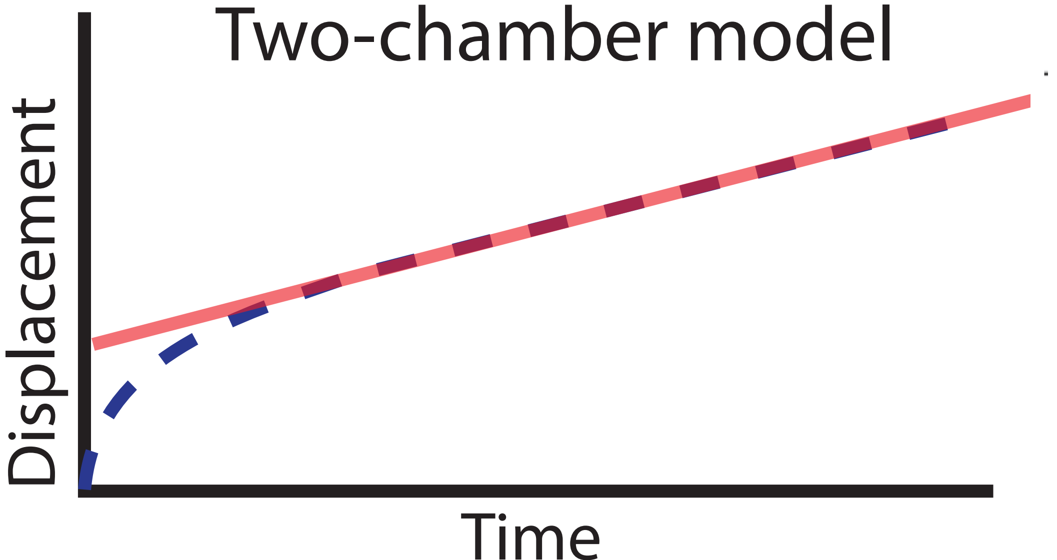
Evolution of overpressures: ***M***

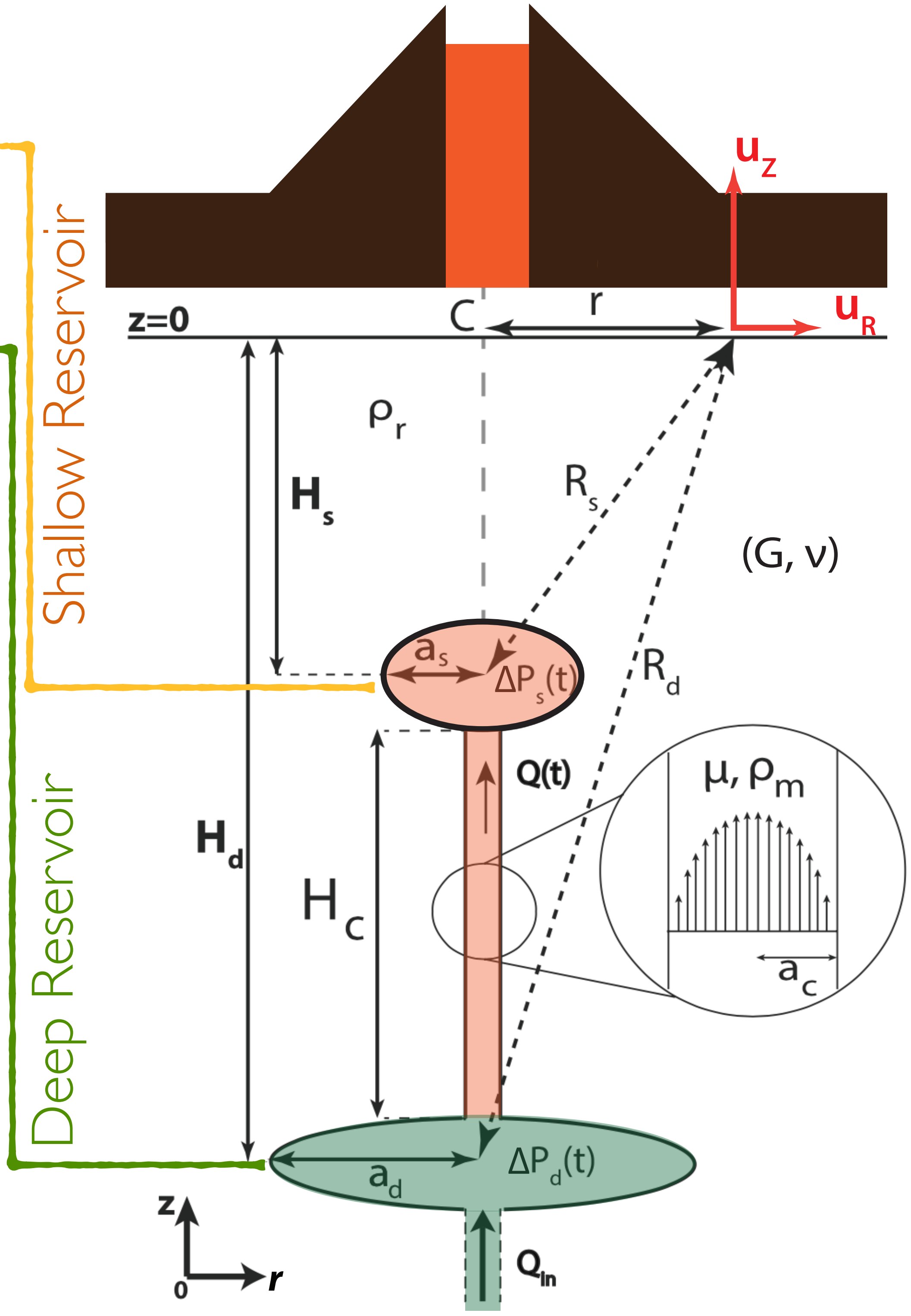
$$\frac{\Delta P_{s_{t_{i+1}}} - \Delta P_{s_{t_i}}}{t_{i+1}-t_i} = \frac{G {a_c}^4}{8\mu\gamma_s H_c {a_s}^3}((\rho_r - \rho_m) g H_c + \Delta P_{d_{t_i}} - \Delta P_{s_{t_i}})$$

$$\frac{\Delta P_{d_{t_{i+1}}} - \Delta P_{d_{t_i}}}{t_{i+1}-t_i} = \frac{G}{\gamma_d \pi {a_d}^3} Q_{in} - \frac{\gamma_s {a_s}^3}{\gamma_d {a_d}^3} \frac{\Delta P_{s_{t_{i+1}}} - \Delta P_{s_{t_i}}}{t_{i+1}-t_i}$$

Overpressure-Displacement Data Relationship: ***H***

$$u_R(r,t_i) = \frac{(1-v)}{G} r \left(\alpha_s \frac{{a_s}^3}{R_s^3} \Delta P s_{t_i} + \alpha_d \frac{{a_d}^3}{R_d^3} \Delta P_{d_{t_i}} \right)$$
$$u_z(r,t_i) = \frac{(1-v)}{G} \left(H_s \alpha_s \frac{{a_s}^3}{R_s^3} \Delta P s_{t_i} + H_d \alpha_d \frac{{a_d}^3}{R_d^3} \Delta P_{d_{t_i}} \right)$$





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OVERVIEW: INGREDIENTS OF DATA ASSIMILATION

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- Dynamical model
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- *A priori* **information (Gaussian PDF)**

Initial Guess ?

https://careercenter.umich.edu/files/cc/field/image/blank_business_card.png

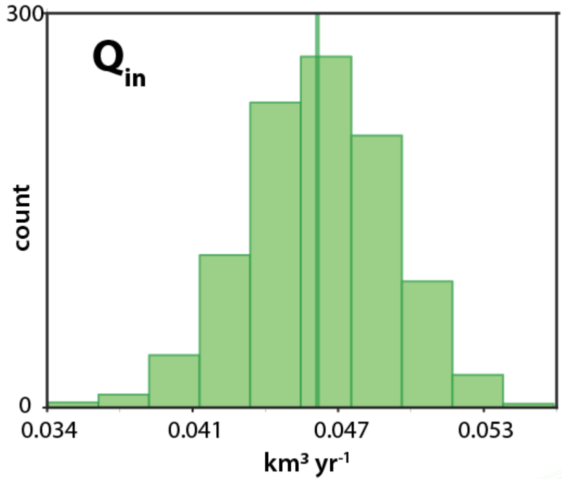
OVERVIEW: SEQUENTIAL DATA ASSIMILATION

$$X = \begin{bmatrix} \Delta P_s \\ \Delta P_d \\ Q_{in} \end{bmatrix}$$

state variables
(have link to data)

uncertain model parameter/s
(no link to data)

A priori information



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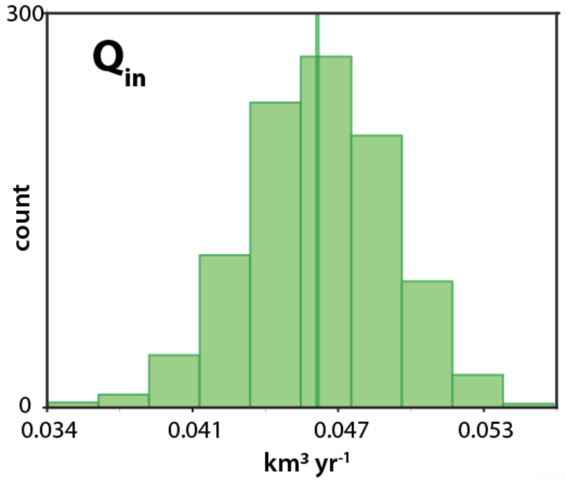

Dynamical model

$$x^f_{t+1} = \mathcal{M} x^a_t + q$$

OVERVIEW: SEQUENTIAL DATA ASSIMILATION

**f: forecast step*

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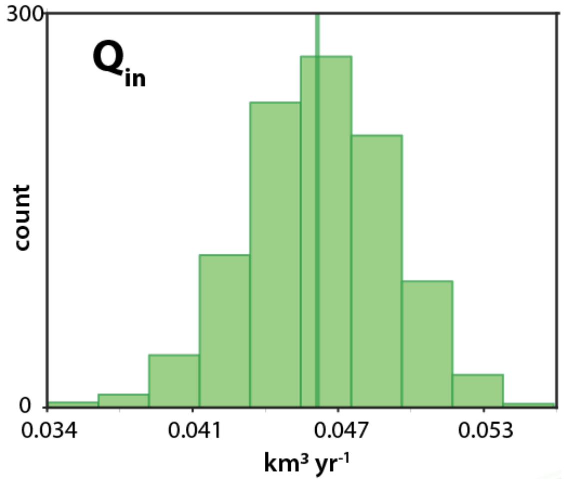
A priori information



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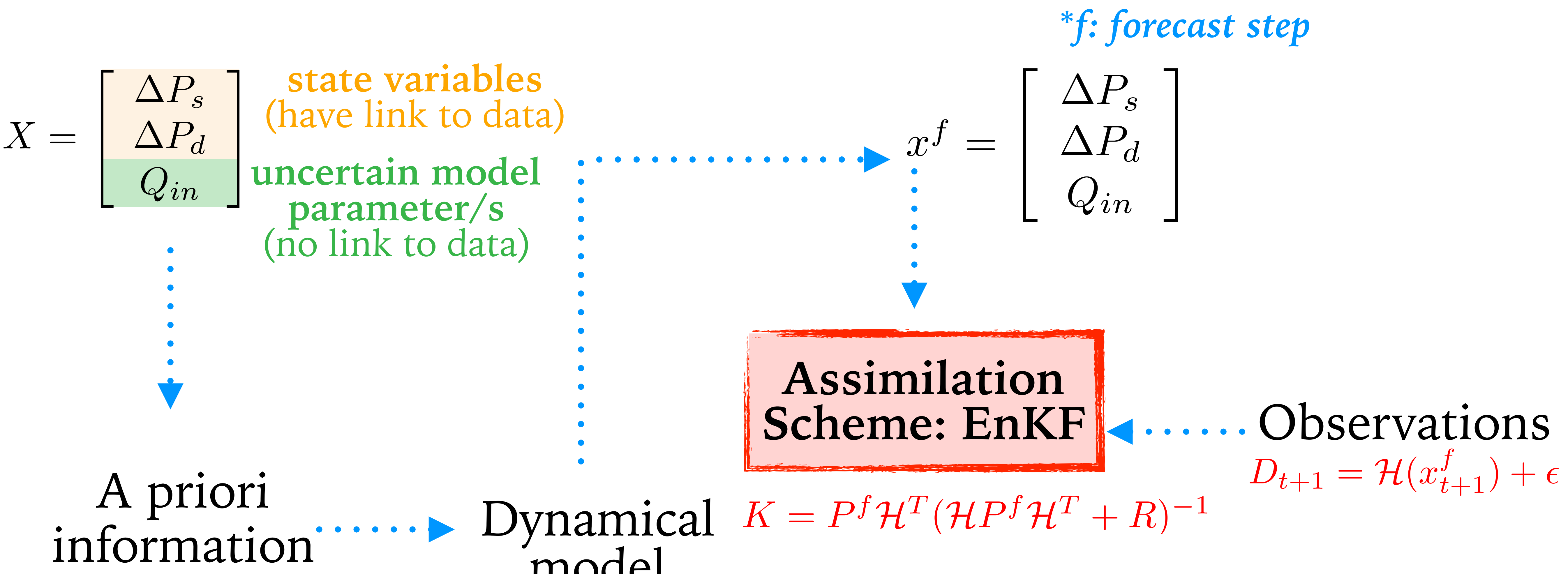

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$$X = \begin{bmatrix} \Delta P_s \\ \Delta P_d \\ Q_{in} \end{bmatrix}$$

state variables
(have link to data)

uncertain model parameter/s
(no link to data)

$$x^f = \begin{bmatrix} \Delta P_s \\ \Delta P_d \\ Q_{in} \end{bmatrix}$$

Assimilation Scheme: EnKF

Observations

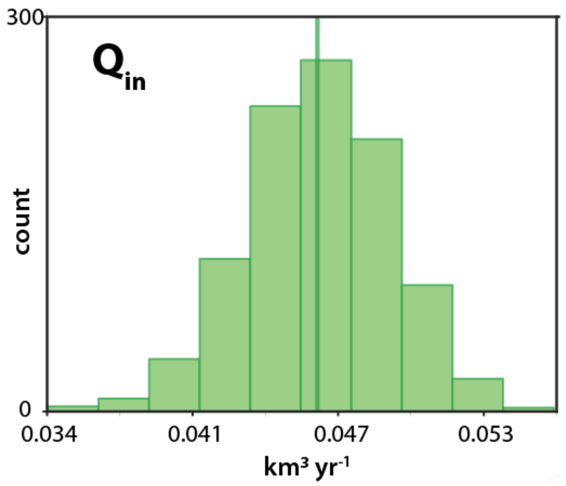
$$D_{t+1} = \mathcal{H}(x^f_{t+1}) + \epsilon$$

A priori information

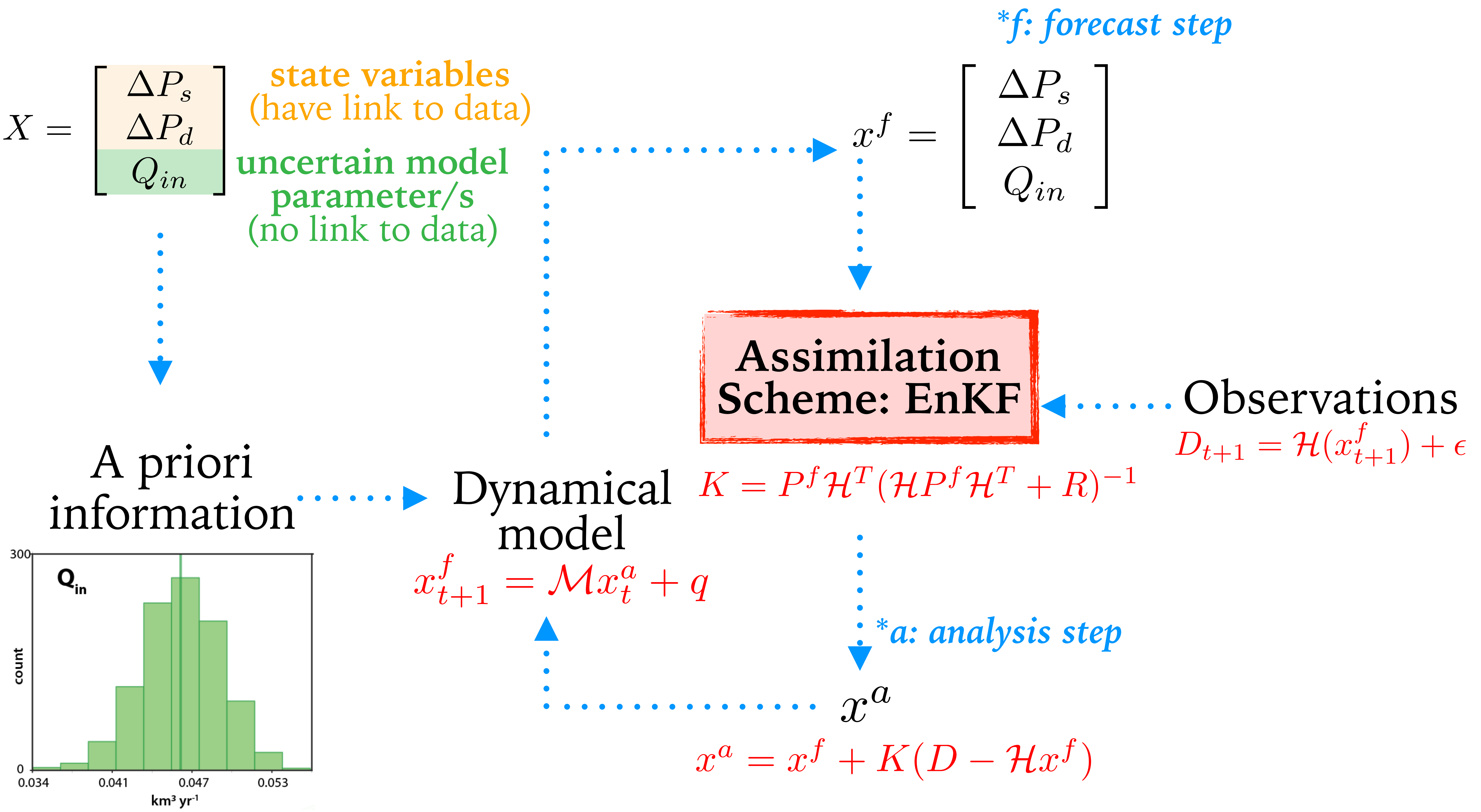
Dynamical model

$$K = P^f \mathcal{H}^T (\mathcal{H} P^f \mathcal{H}^T + R)^{-1}$$

$$x^f_{t+1} = \mathcal{M} x^a_t + q$$



OVERVIEW: SEQUENTIAL DATA ASSIMILATION



$$X = \begin{bmatrix} \Delta P_s \\ \Delta P_d \\ Q_{in} \end{bmatrix}$$

state variables
(have link to data)

uncertain model parameter/s
(no link to data)

f: forecast step

$$x^f = \begin{bmatrix} \Delta P_s \\ \Delta P_d \\ Q_{in} \end{bmatrix}$$

Assimilation Scheme: EnKF

Observations

$$D_{t+1} = \mathcal{H}(x^f_{t+1}) + \epsilon$$

A priori information

Dynamical model

$$x^f_{t+1} = \mathcal{M} x^a_t + q$$

$$K = P^f \mathcal{H}^T (\mathcal{H} P^f \mathcal{H}^T + R)^{-1}$$

a: analysis step

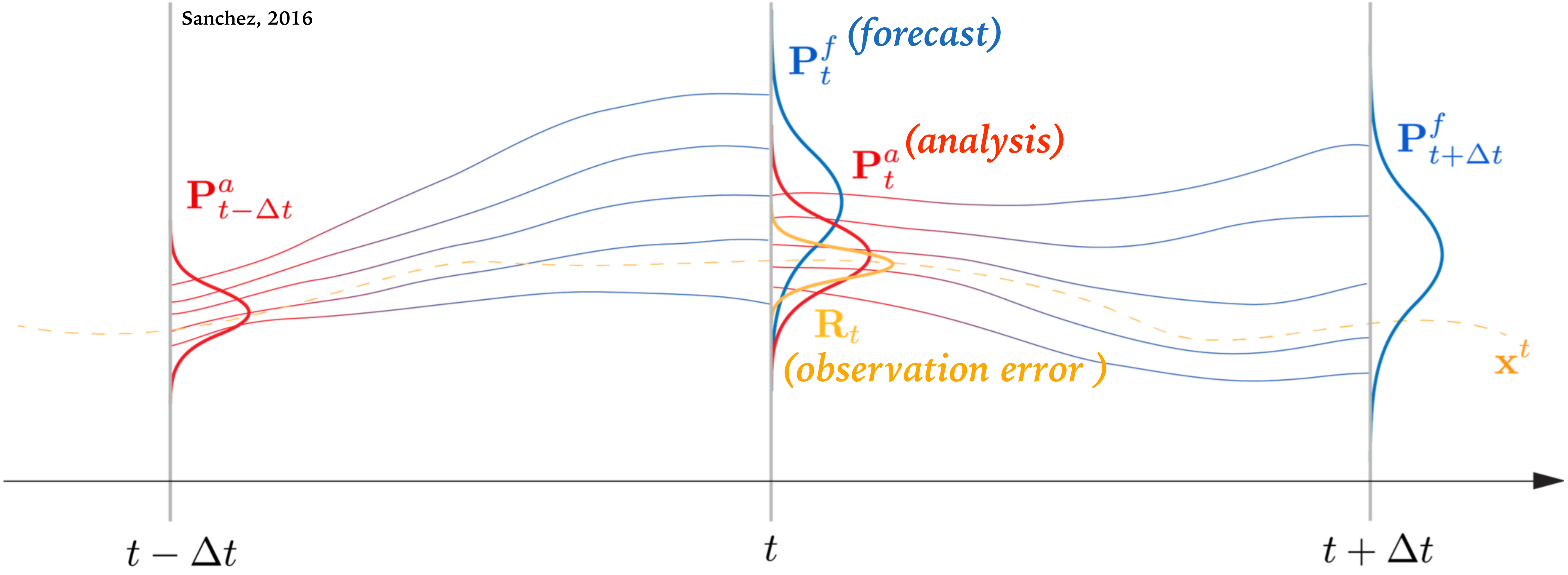
$$x^a$$

$$x^a = x^f + K(D - \mathcal{H} x^f)$$

OVERVIEW: THE ENSEMBLE KALMAN FILTER (EnKF)

Model Error Covariance

$$P^f = \overline{(x^f - \overline{x^f})(x^f - \overline{x^f})^T}$$
$$P^a = \overline{(x^a - \overline{x^a})(x^a - \overline{x^a})^T}$$


Sanchez, 2016

Can we apply data assimilation to volcanology to forecast volcanic unrest?

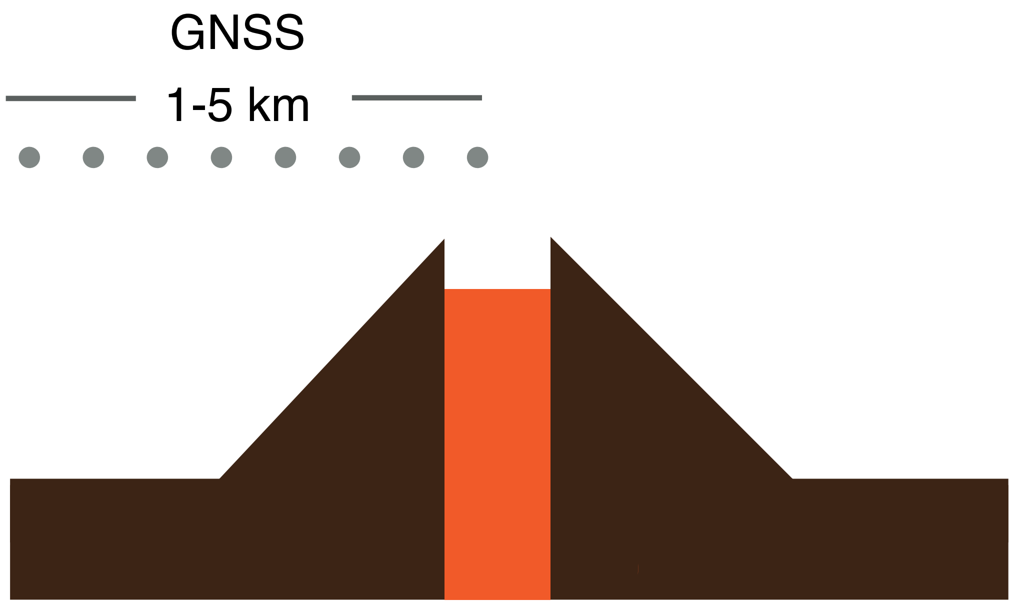
VOLCANIC DATA ASSIMILATION: HOW TO?

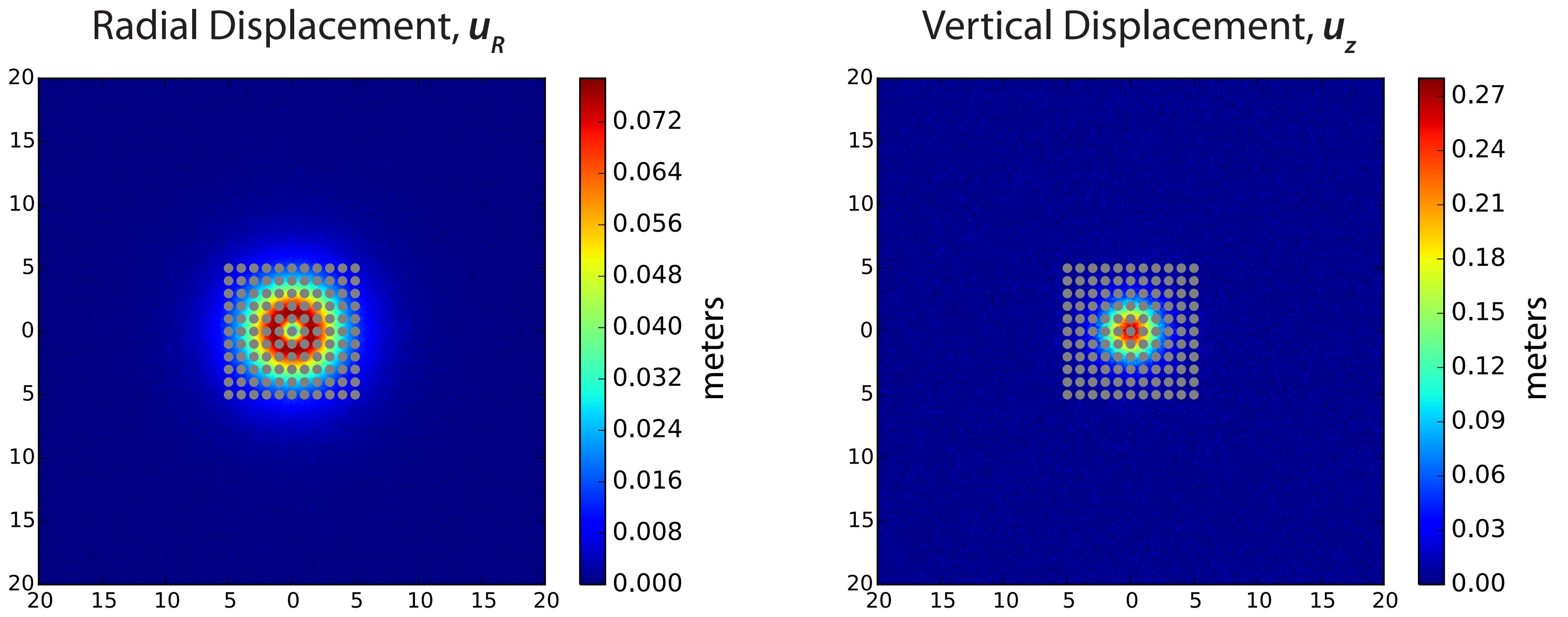
Key parameter: **Overpressure**

The magma chamber can rupture if it surpasses a failure overpressure value.

Objective: Find out when the magma chamber will rupture

JOINT ASSIMILATION OF GNSS AND INSAR: SYNTHETIC CASES





GNSS dataset:

The assimilation interval, $\Delta t = 2 \text{ days}$

The frequency of available observation **every 2 days.**

10 observations are used for the synthetic cases.

- ☑ 5 radial and 5 vertical

InSAR dataset:

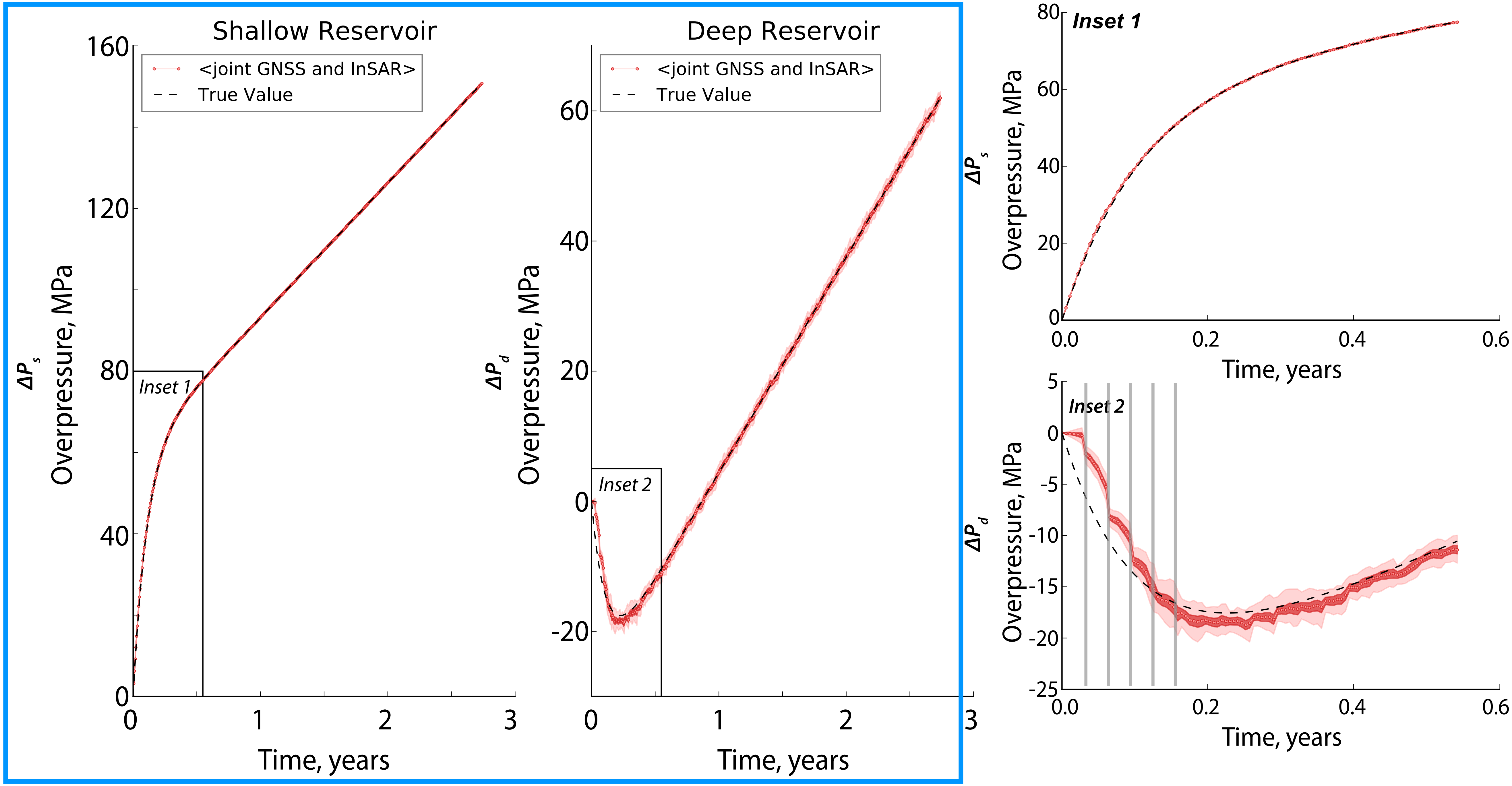
The assimilation interval, $\Delta t = 2 \text{ days}$

The frequency of available observation is **every 12 days.**

242 observations are used for the synthetic cases.

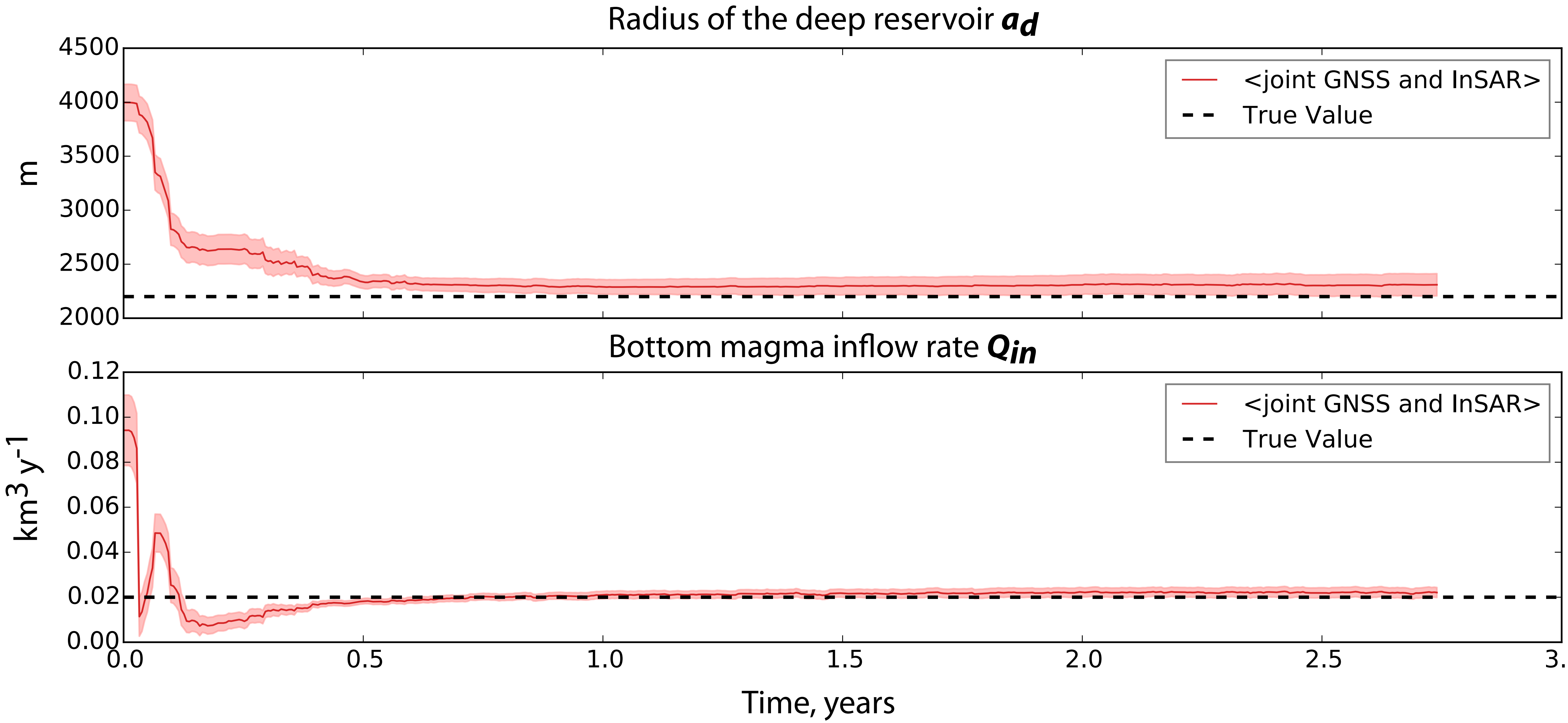
- ☑ 11x11 radial and 11x11 vertical

JOINT ASSIMILATION OF GNSS AND INSAR: SYNTHETIC CASES



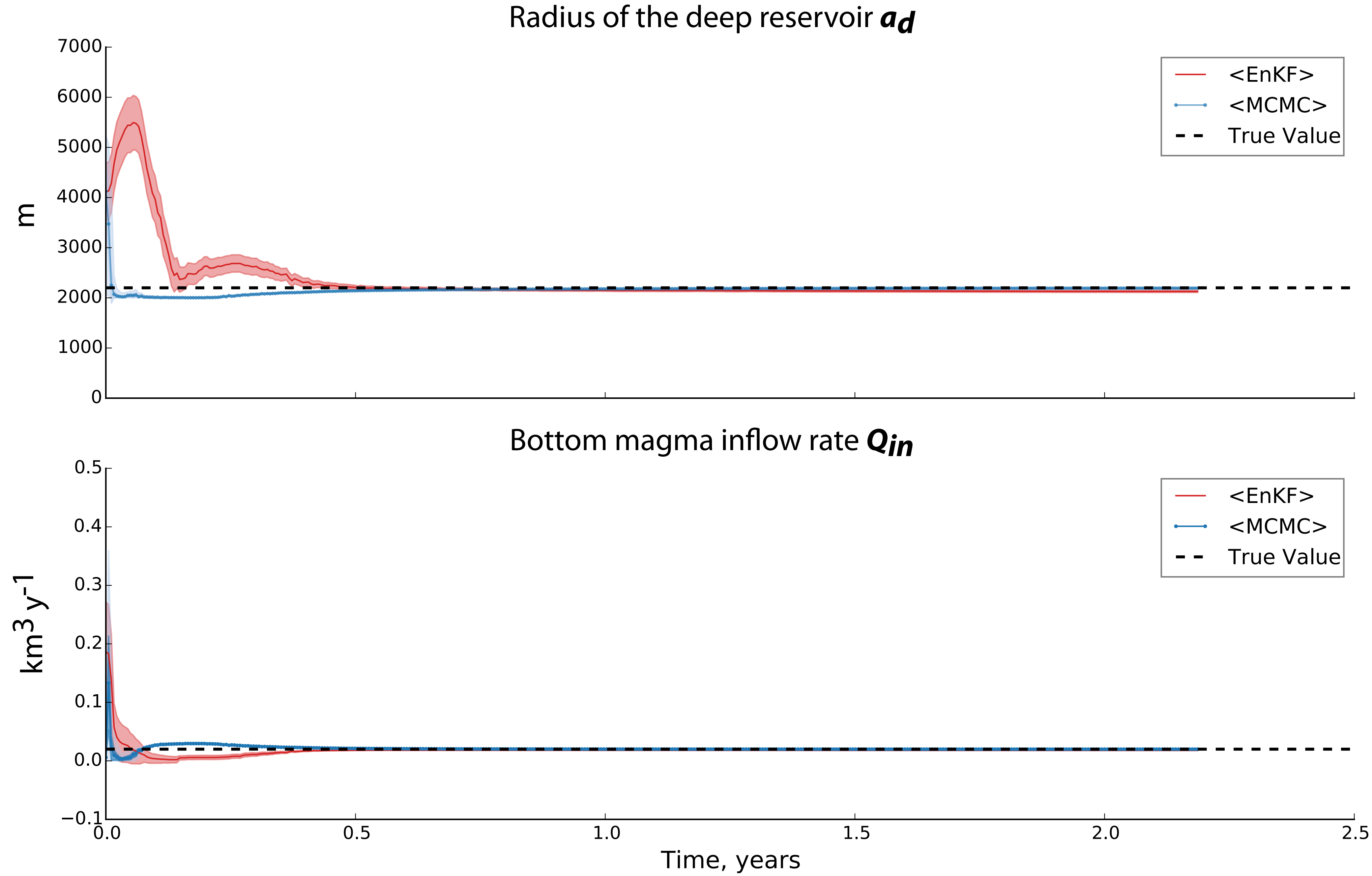
Every time InSAR is introduced, the trajectory of the estimation is forced towards its true behaviour.

JOINT ASSIMILATION OF GNSS AND INSAR: SYNTHETIC CASES



EnKF works as well with parameter estimation using joint assimilation of GNSS and InSAR!

DATA ASSIMILATION VS BAYESIAN INVERSION: SYNTHETIC CASES



MCMC allows faster convergence to true values assuming that the parameters remained constant in time

If inversion (like MCMC) is super awesome, then why do we need data assimilation?

Inversion still has some limitations which include:

1. inefficiency to incorporate data in real time,
2. model errors are often neglected during the process, and
3. difficulty in estimating time-dependent parameters

Inversion still has some limitations which include:

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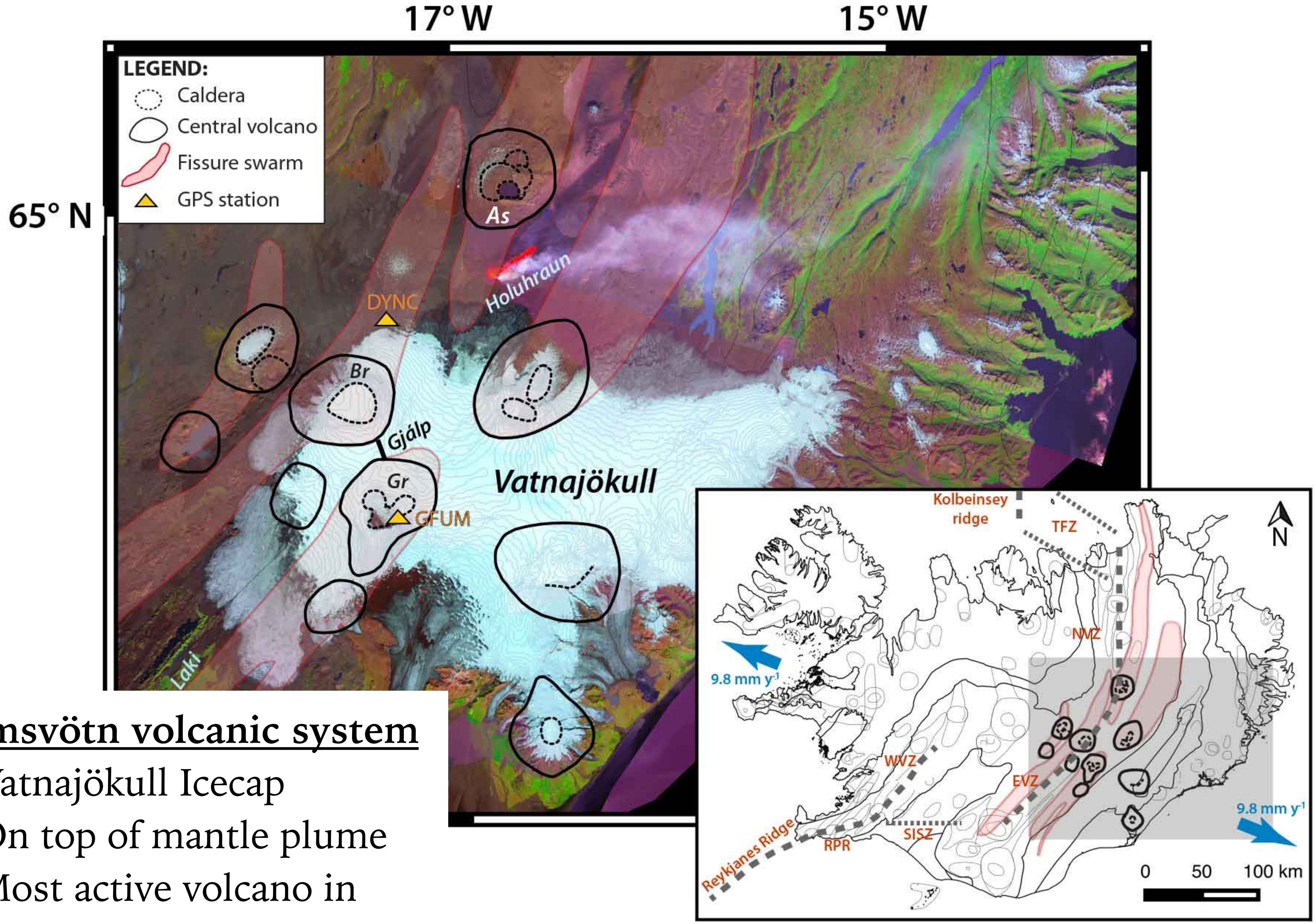
I propose data assimilation as a **complimentary tool** to inversion in order to address these problems

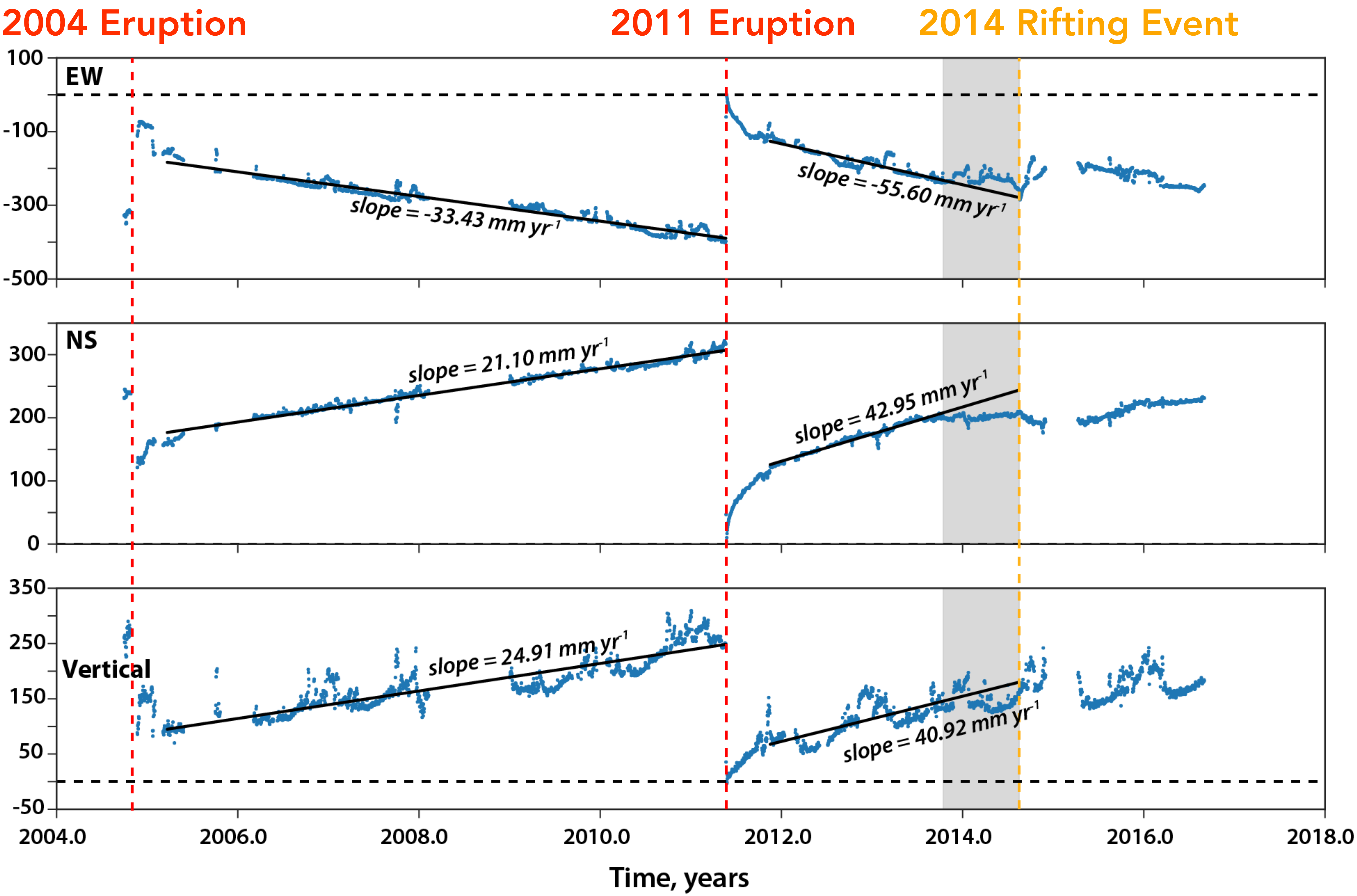
TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING



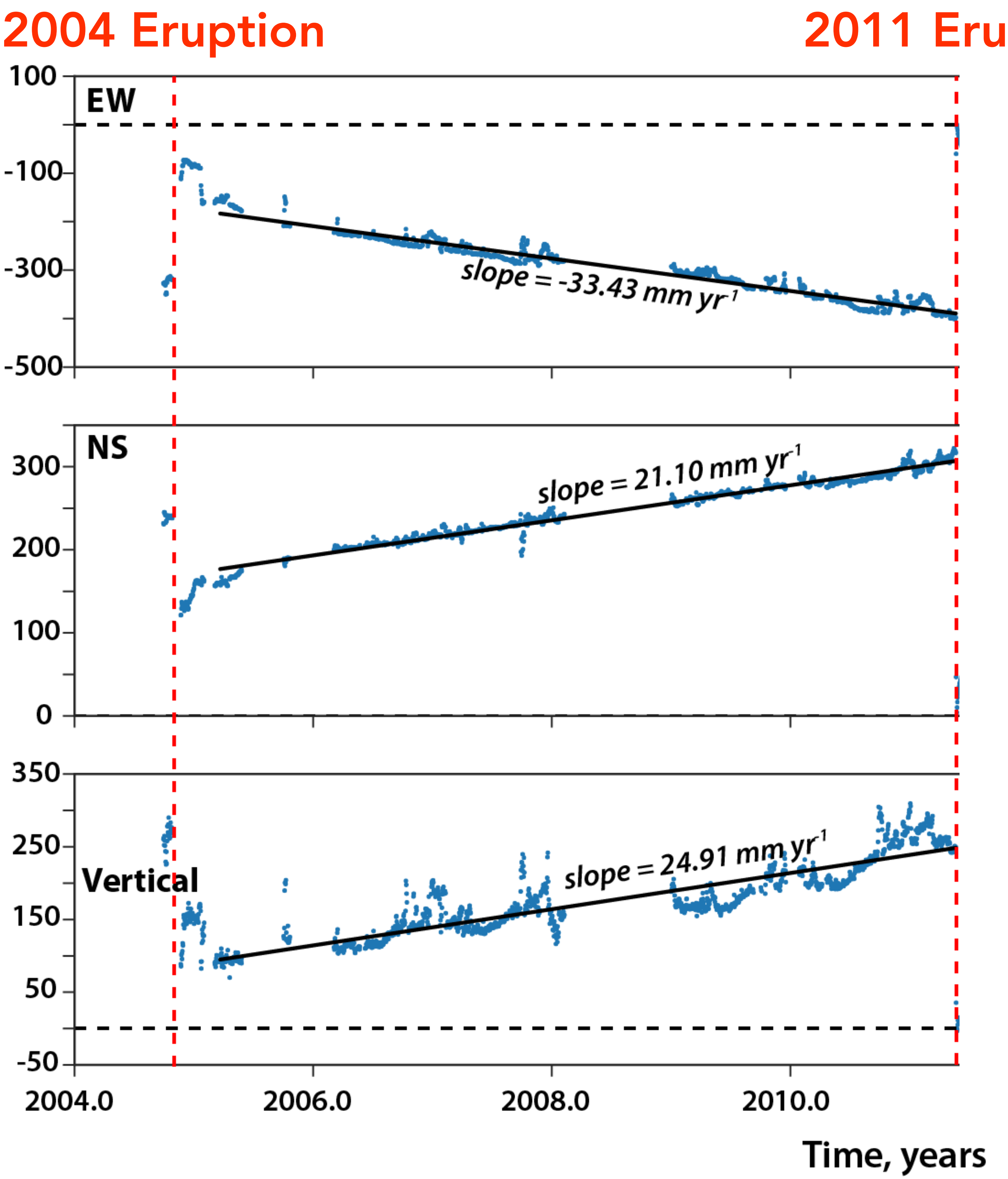
Grímsvötn volcanic system

- ☑ Vatnajökull Icecap
- ☑ On top of mantle plume
- ☑ Most active volcano in Iceland (1998, 2004, 2011)

TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING



LET'S DO SOME "FORECASTING" WITH THE 2004-2011 INTER-ERUPTIVE DATASET



Remember:

$$X = \left[\begin{array}{c} \Delta P_s \\ \Delta P_d \\ Q_{in} \end{array}\right] \begin{array}{l} \left.\vphantom{\begin{array}{c}\Delta P_s\\ \Delta P_d\end{array}}\right\} \text{state variables} \\ \left.\vphantom{Q_{in}}\right\} \text{uncertain parameter/s} \end{array}$$

Daily GNSS data is assimilated into the two-chamber model to get ***X***.

NO data, **NO** update.

TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

When will the [shallow] magma chamber rupture?

Step-1: Define a failure overpressure, P_f

Step-2: Calculate probability of rupture

TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

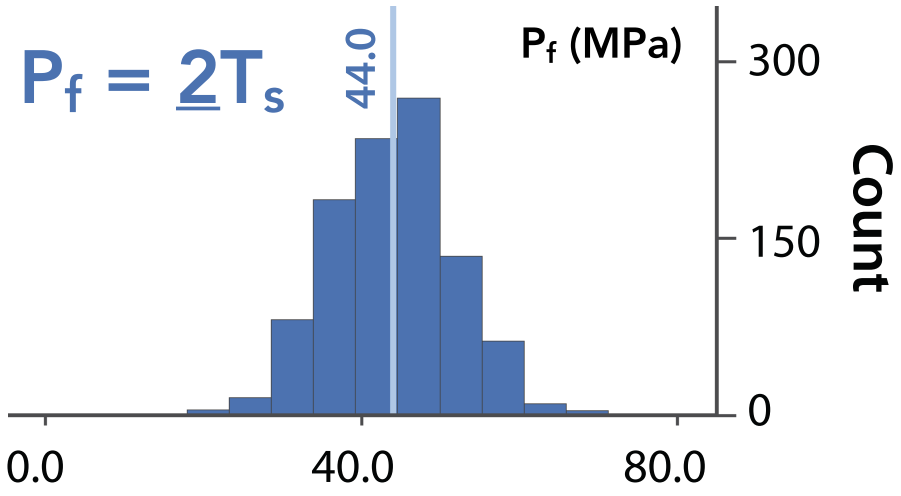
Step-1: Define a failure overpressure, P_f

In forecasting the rupture of a magma chamber, we can define a failure overpressure for the shallow magma chamber.

BUT P_f has a large uncertainty. It can vary depending on:

- ☑ the geometry of the reservoir
- ☑ local stress field

It must be defined carefully per specific volcano.



Failure overpressure

constant

Tensile Strength

$$P_f = k\ T_s$$

at Grímsvötn: T_S = 22 MPa

(Albino et al, 2010)

But *in situ data* are much lower

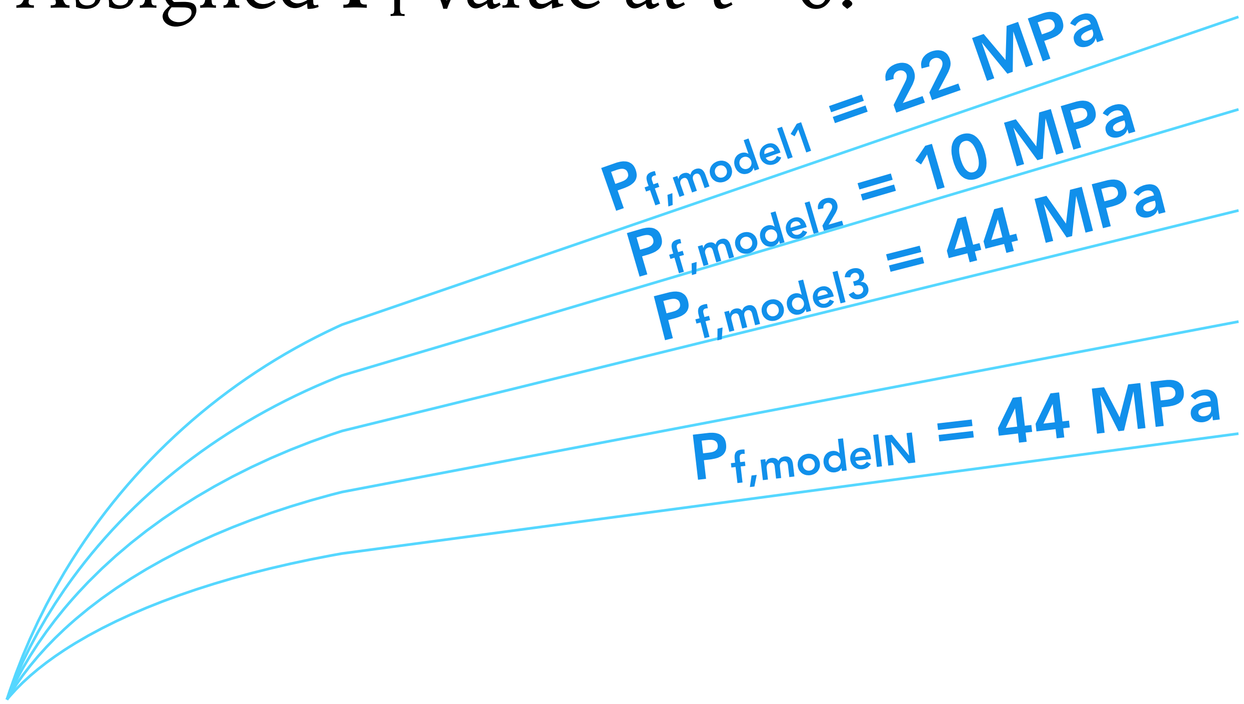
T_S = 1 to 10 MPa

(Haimson and Rummel, 1982)

TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

Step-2: Calculate probability of rupture

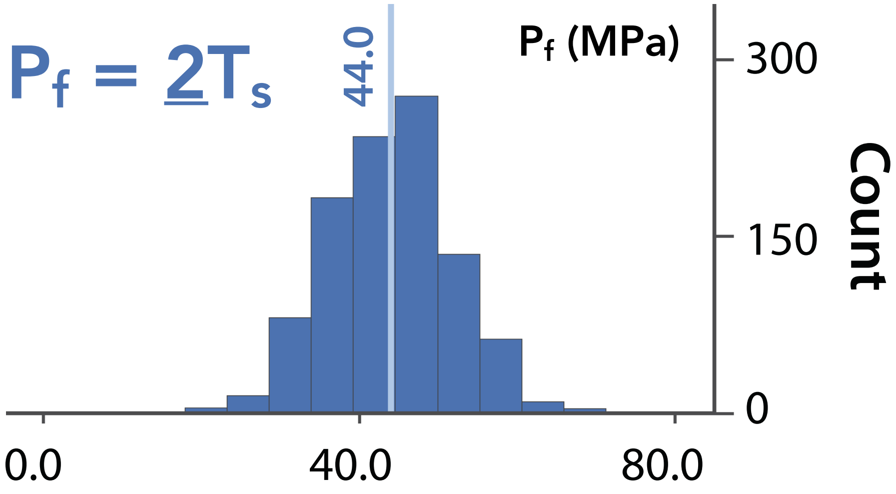
i. Assigned **P_f** value at t=0:



ii. Check at each step how many models exceeded the initially assigned **P_f** value:

iii. Compute for the probability of rupture

$$\text{Probability of rupture} = \frac{\text{\# of models that exceeded } P_f}{\text{Total \# of ensemble}}$$



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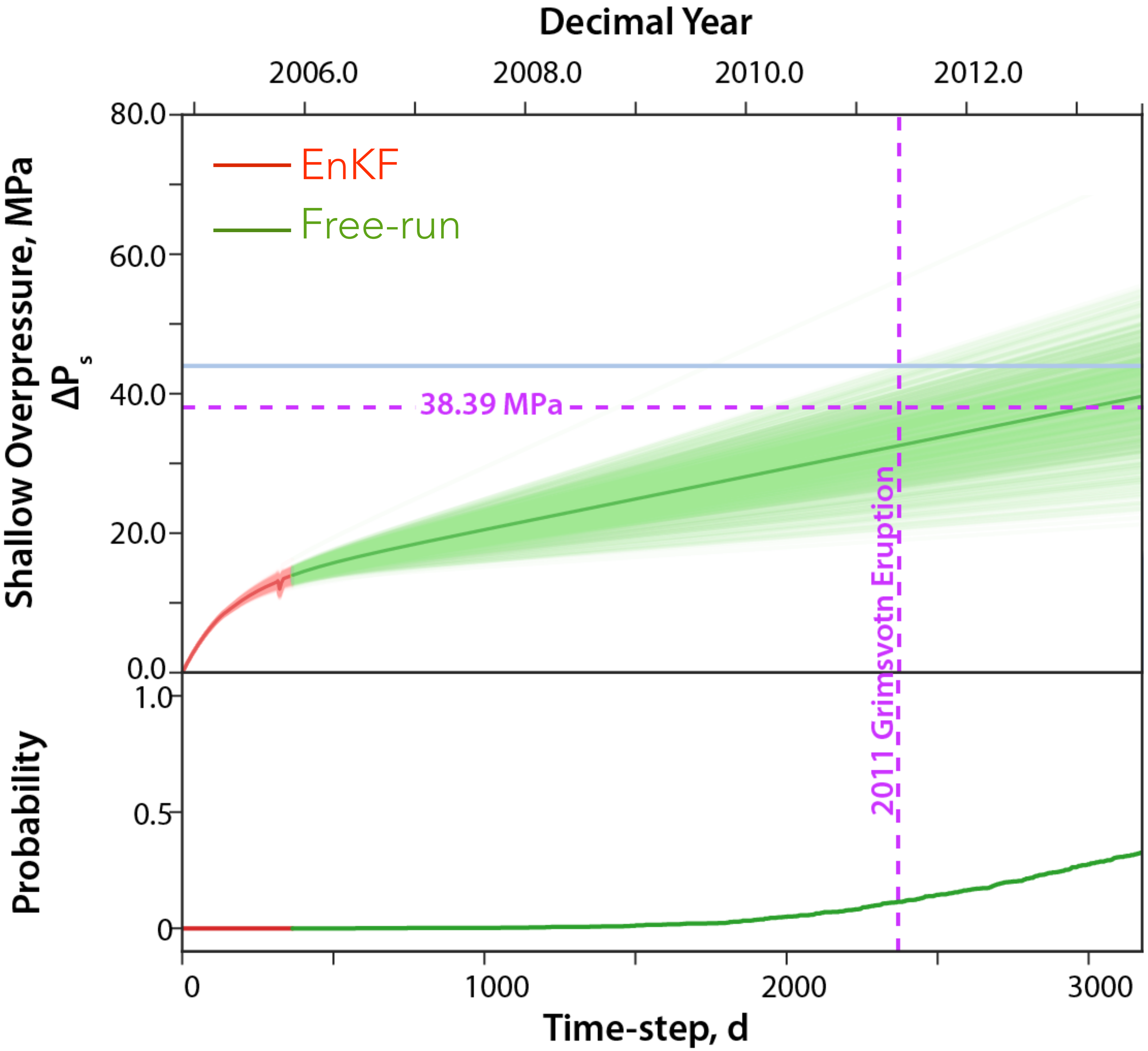
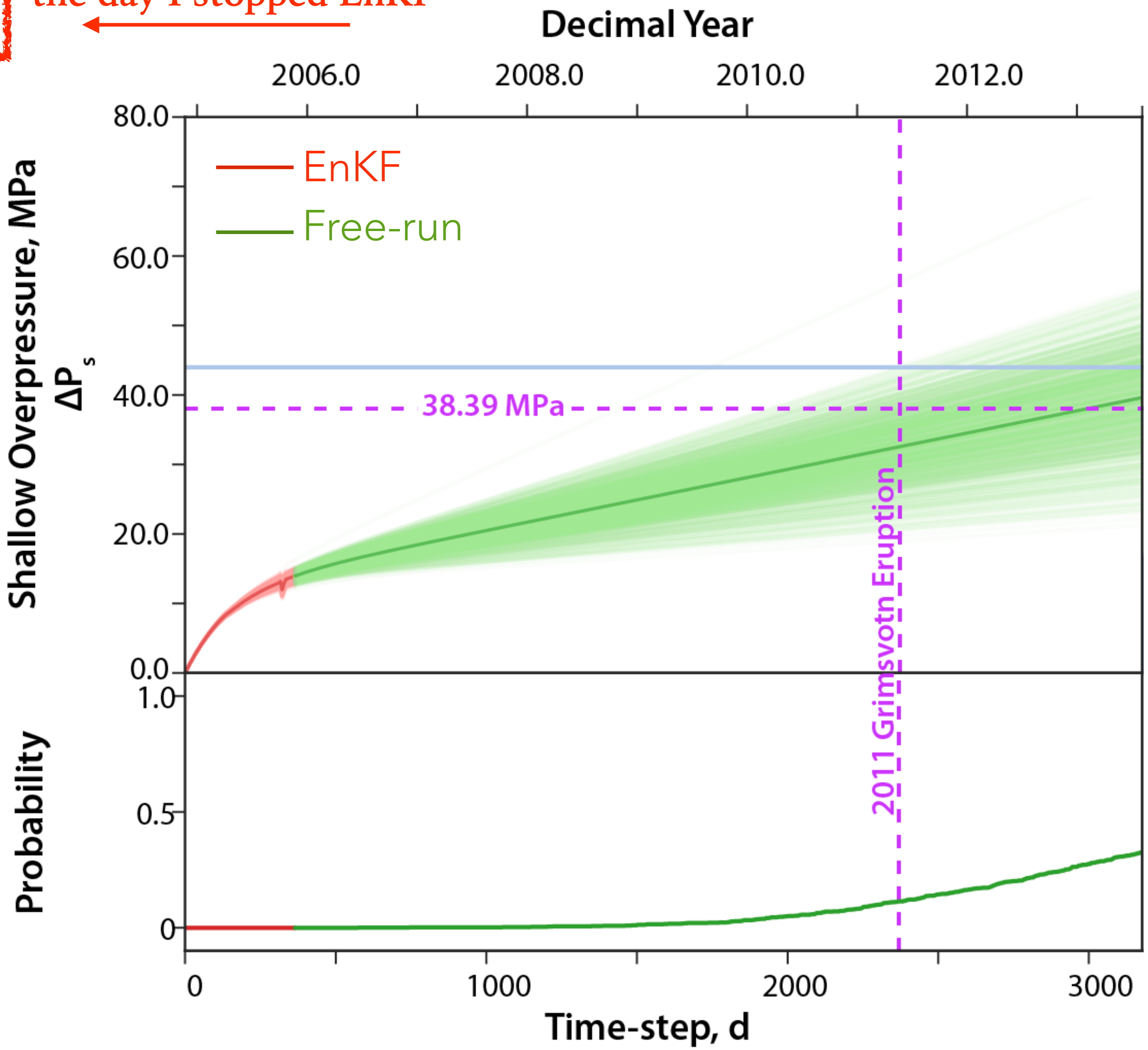


TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

At day = 0365

the day I stopped EnKF



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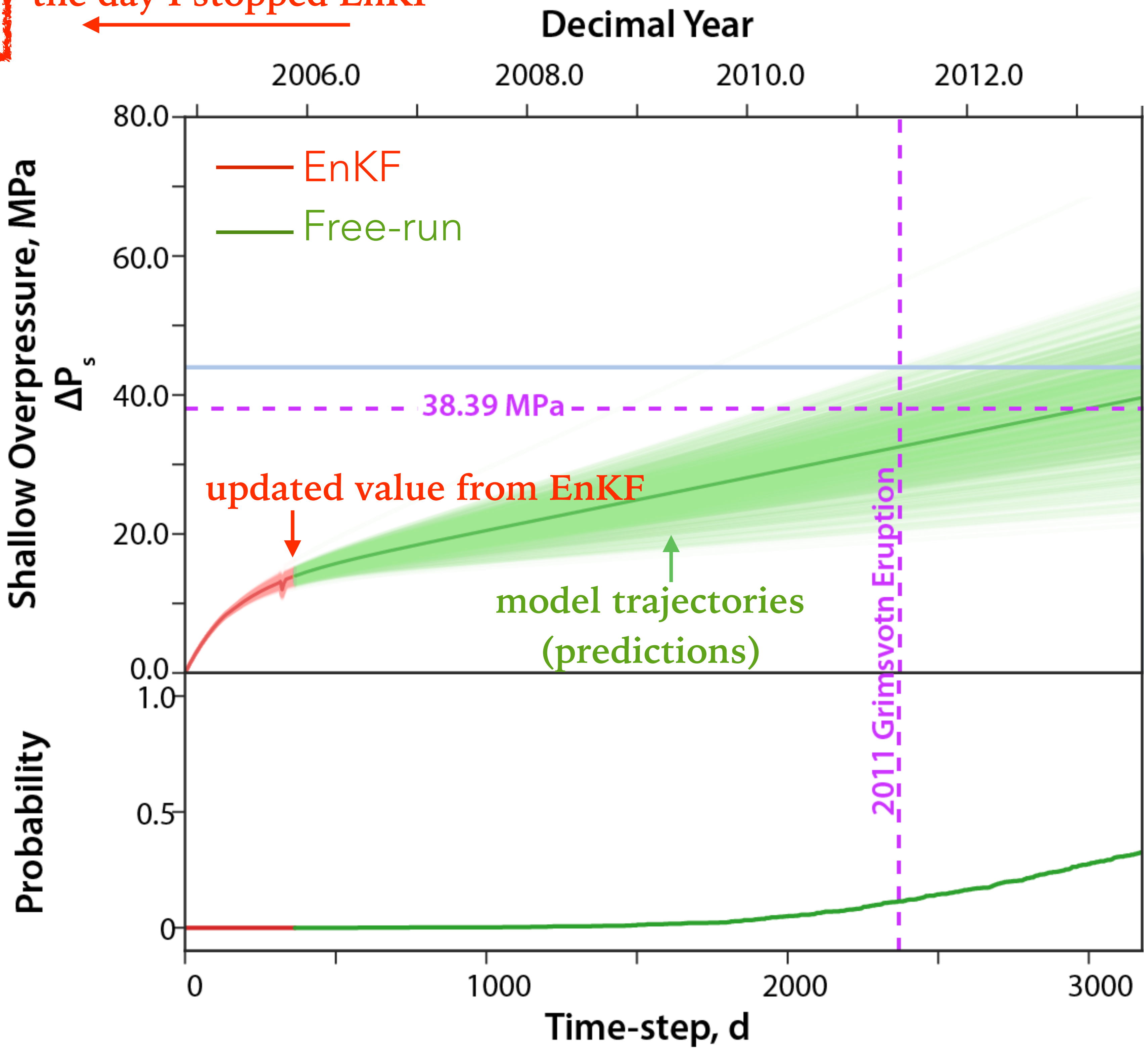


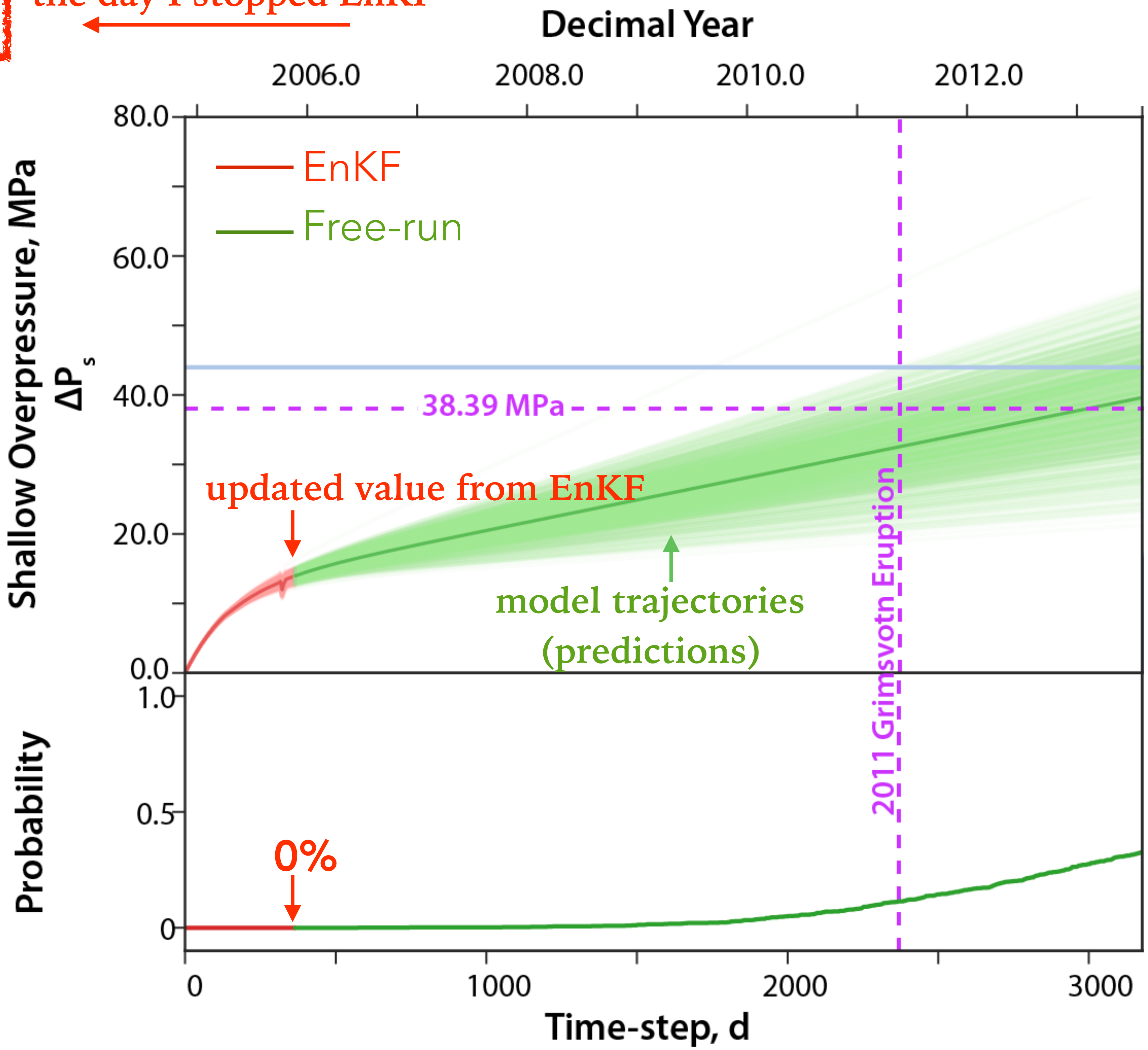
updated value from EnKF

model trajectories (predictions)

TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

At day = 0365

the day I stopped EnKF



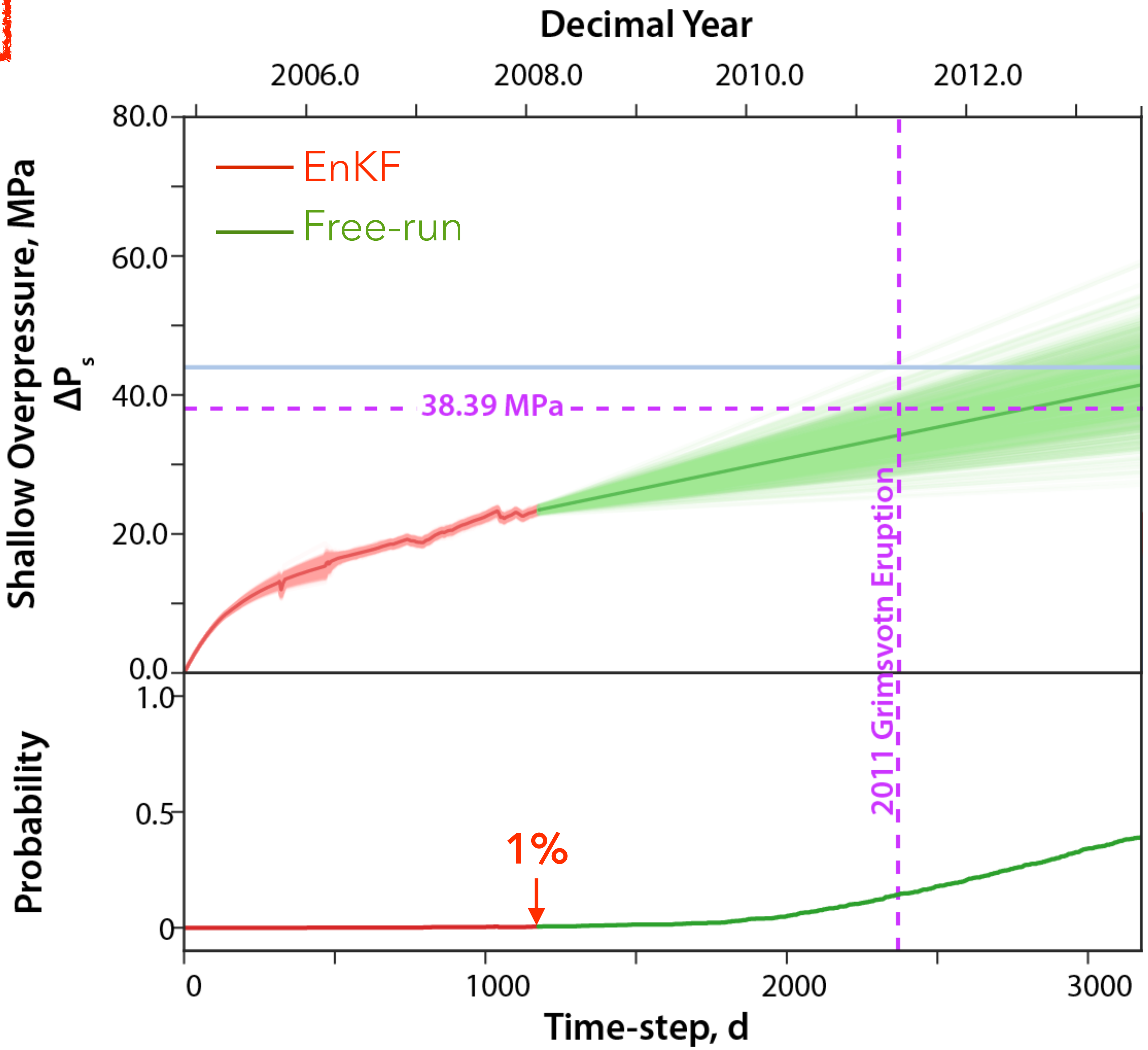
updated value from EnKF

model trajectories (predictions)

0%

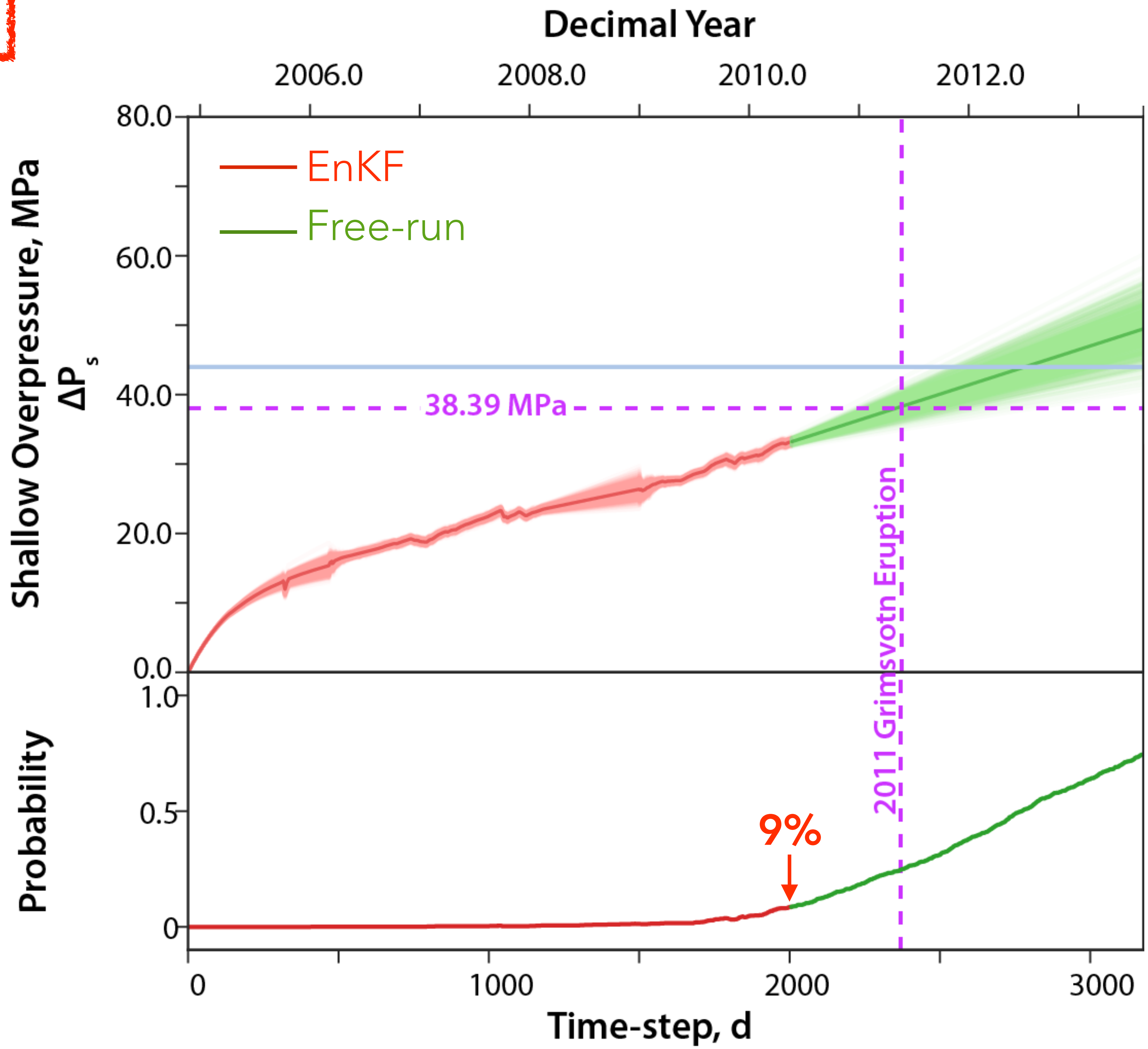
TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

At day = 1176



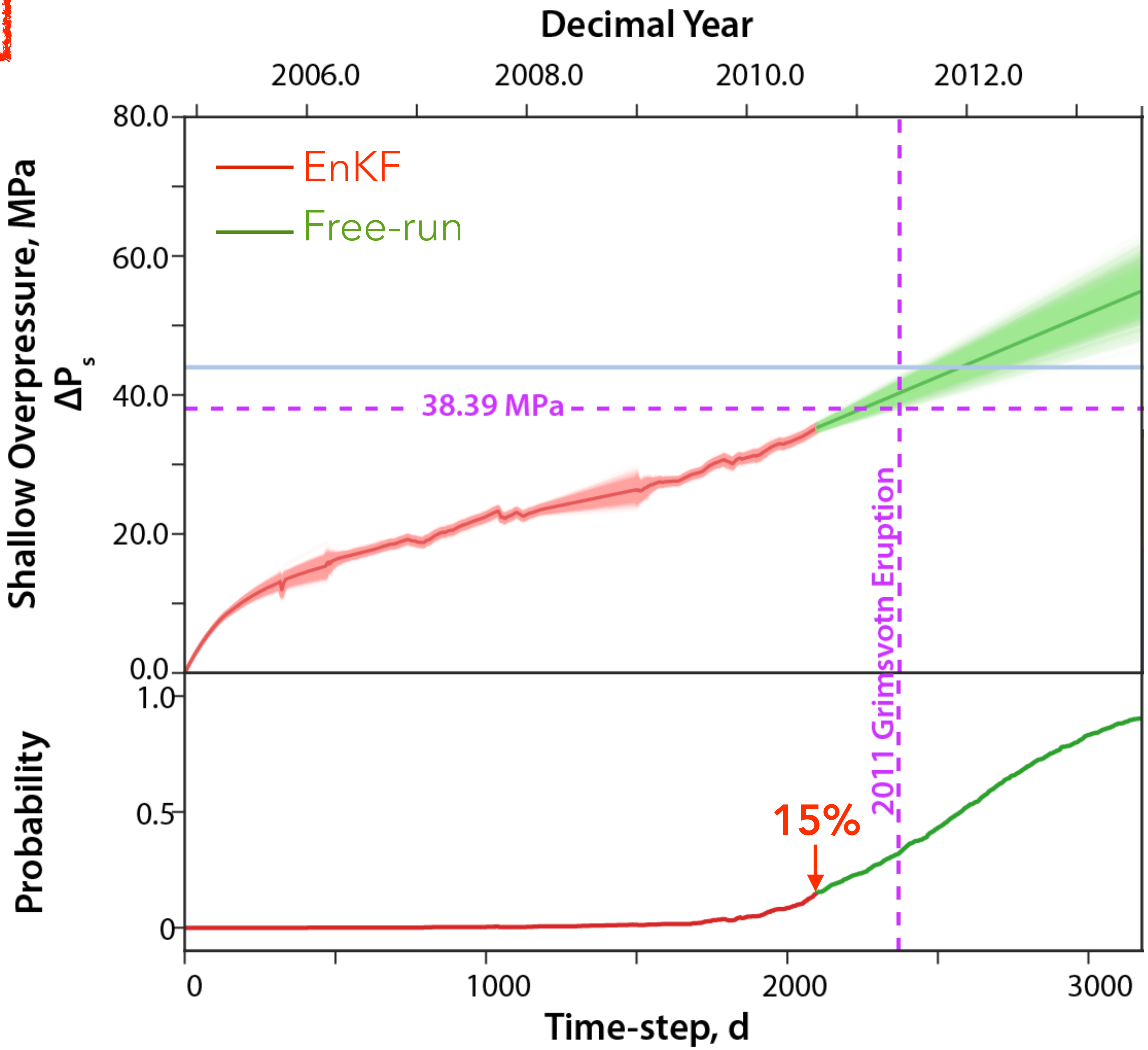
TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

At day = 2006



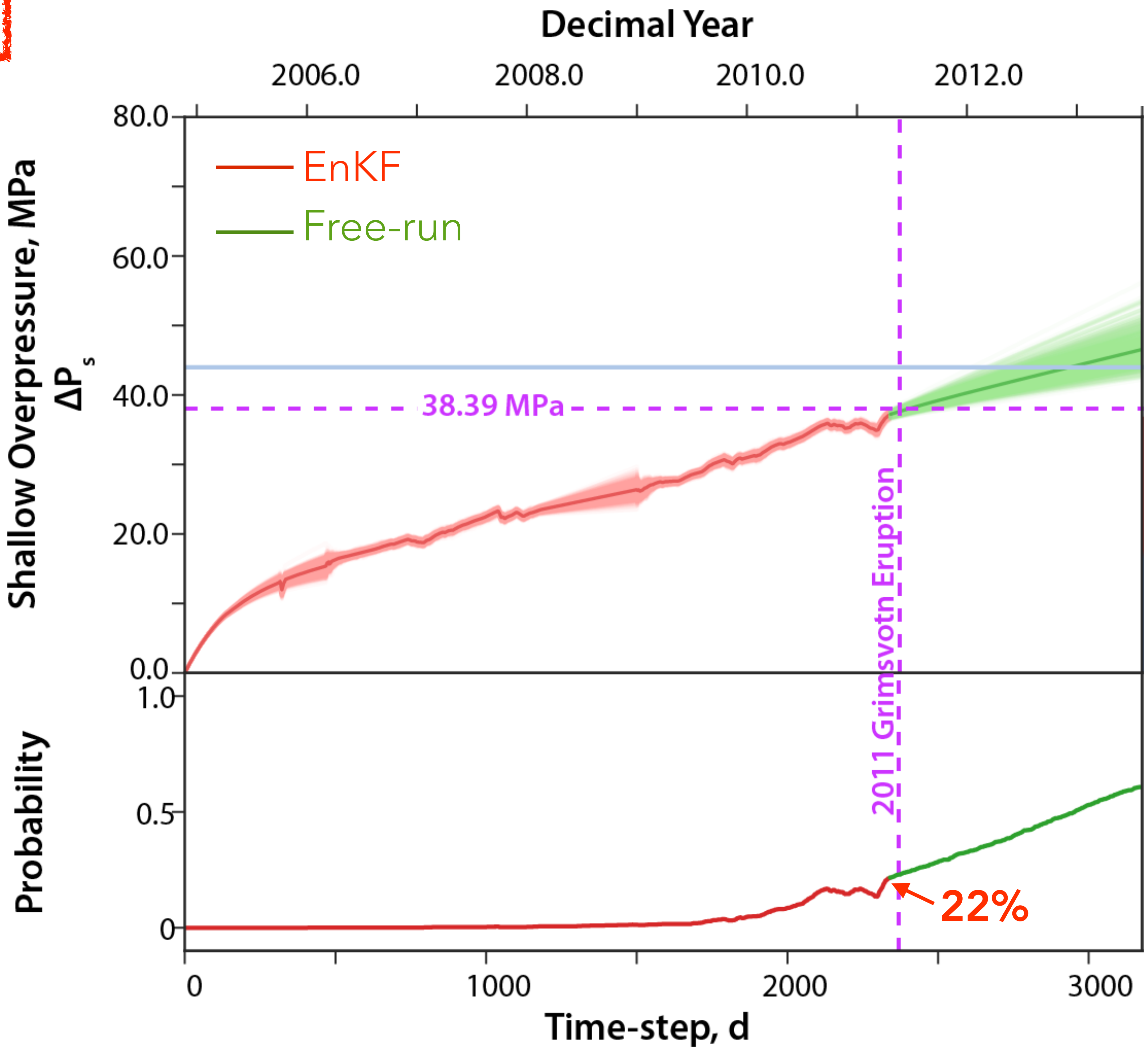
TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

At day = 2100



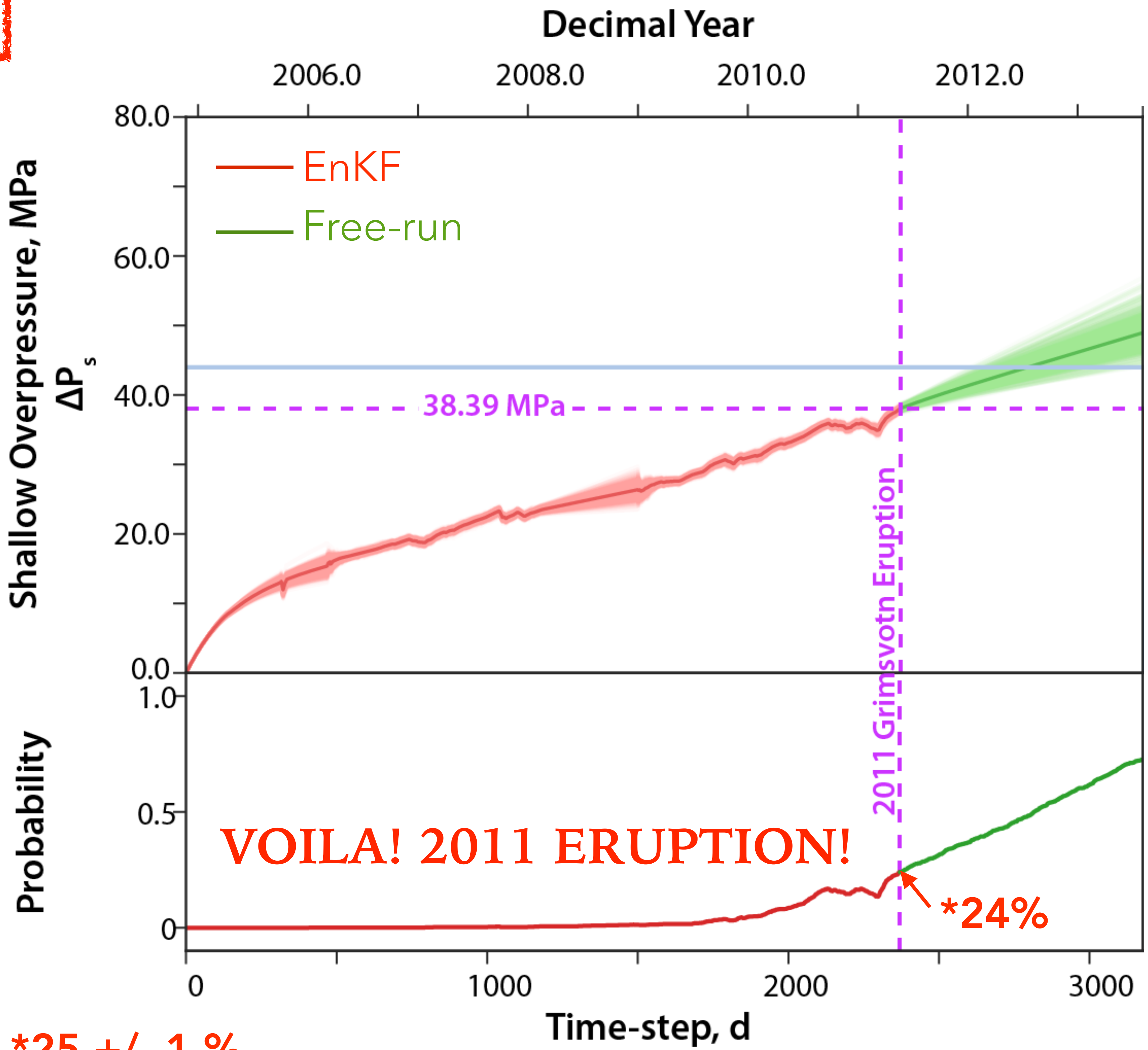
TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

At day = 2341



TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

At day = 2371



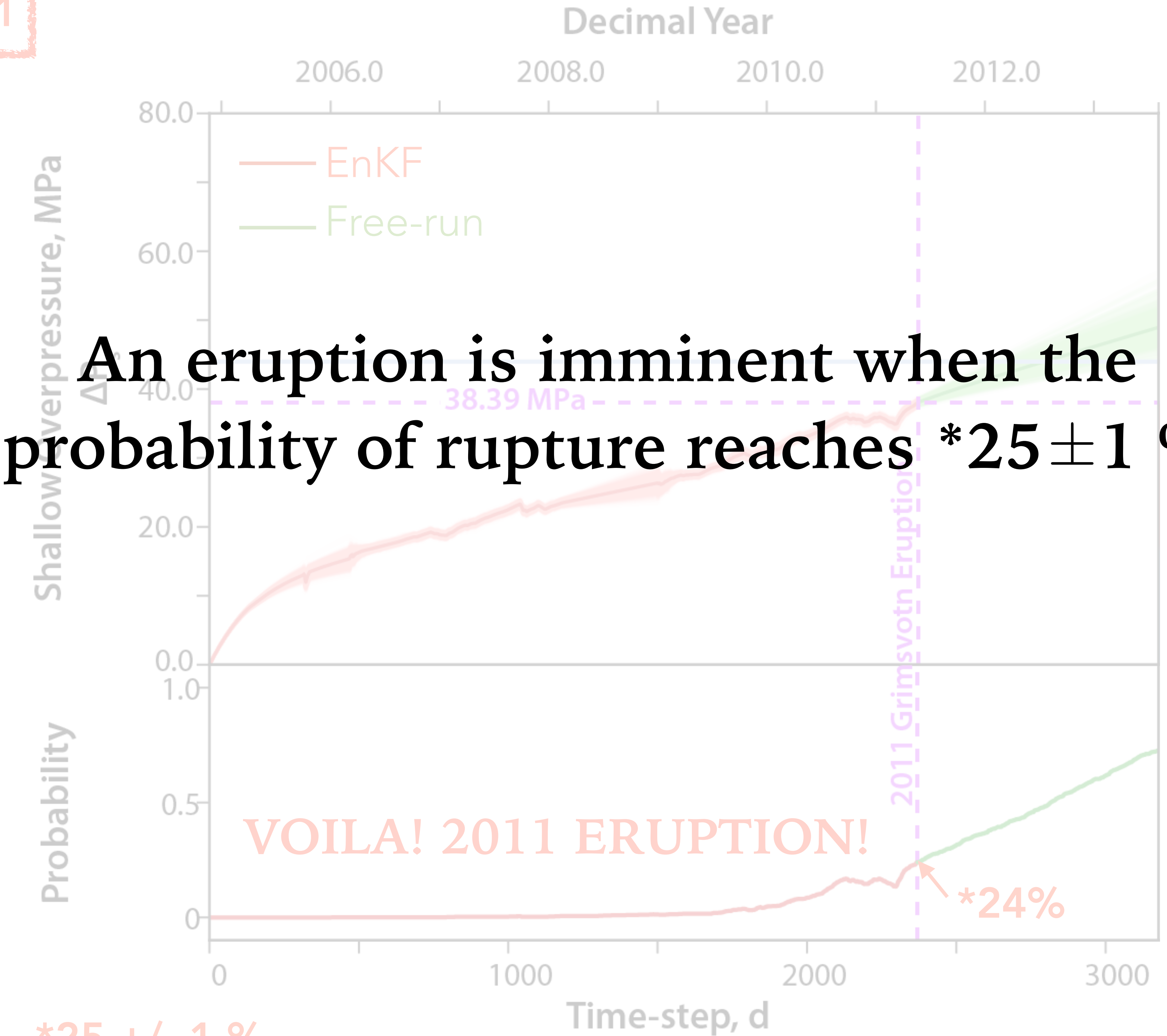
VOILA! 2011 ERUPTION!

*24%

*25 +/- 1 %

TOWARDS [NEAR] REAL-TIME ERUPTION FORECASTING

At day = 2371

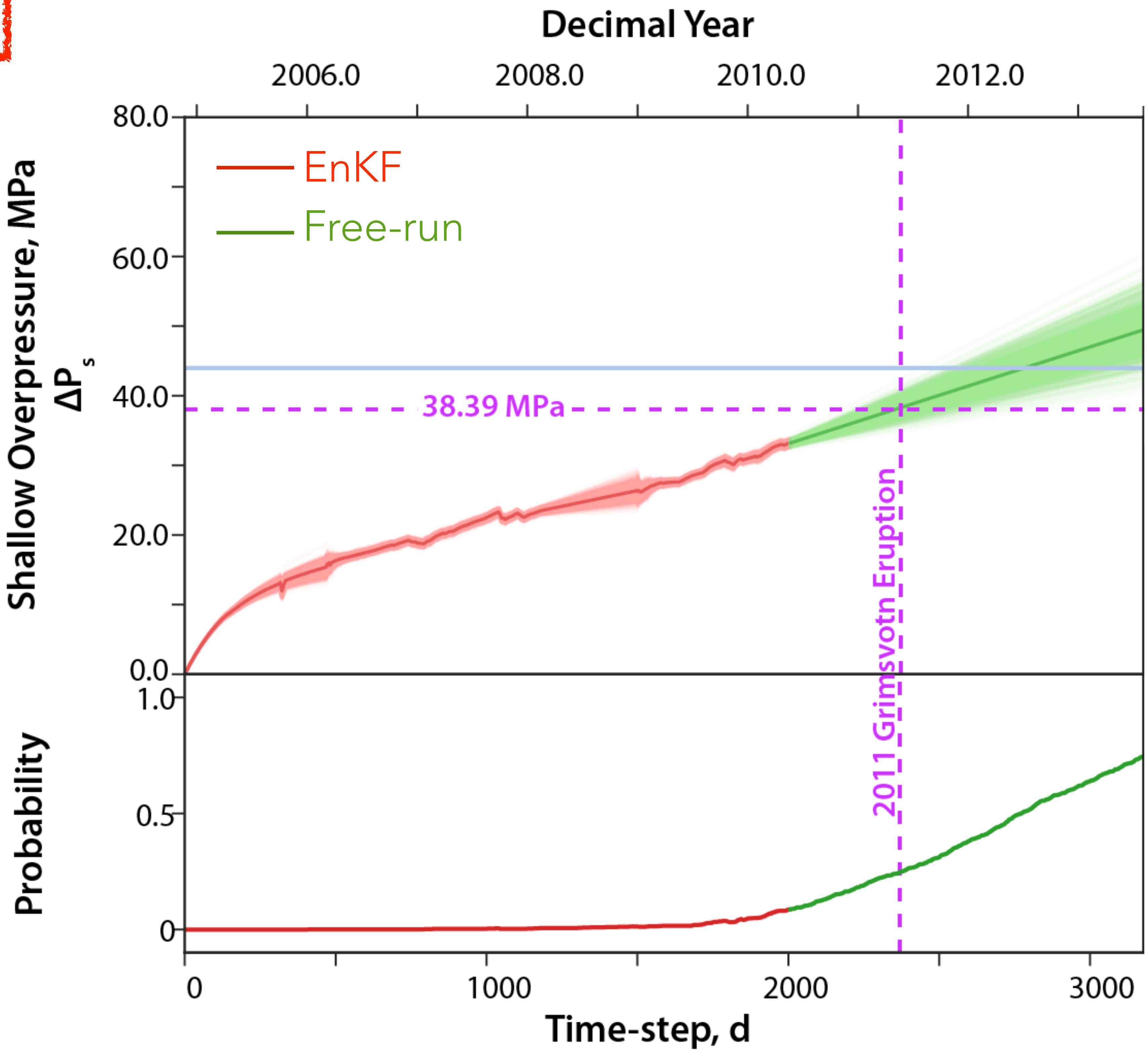


An eruption is imminent when the probability of rupture reaches *25±1 %

*25 +/- 1 %

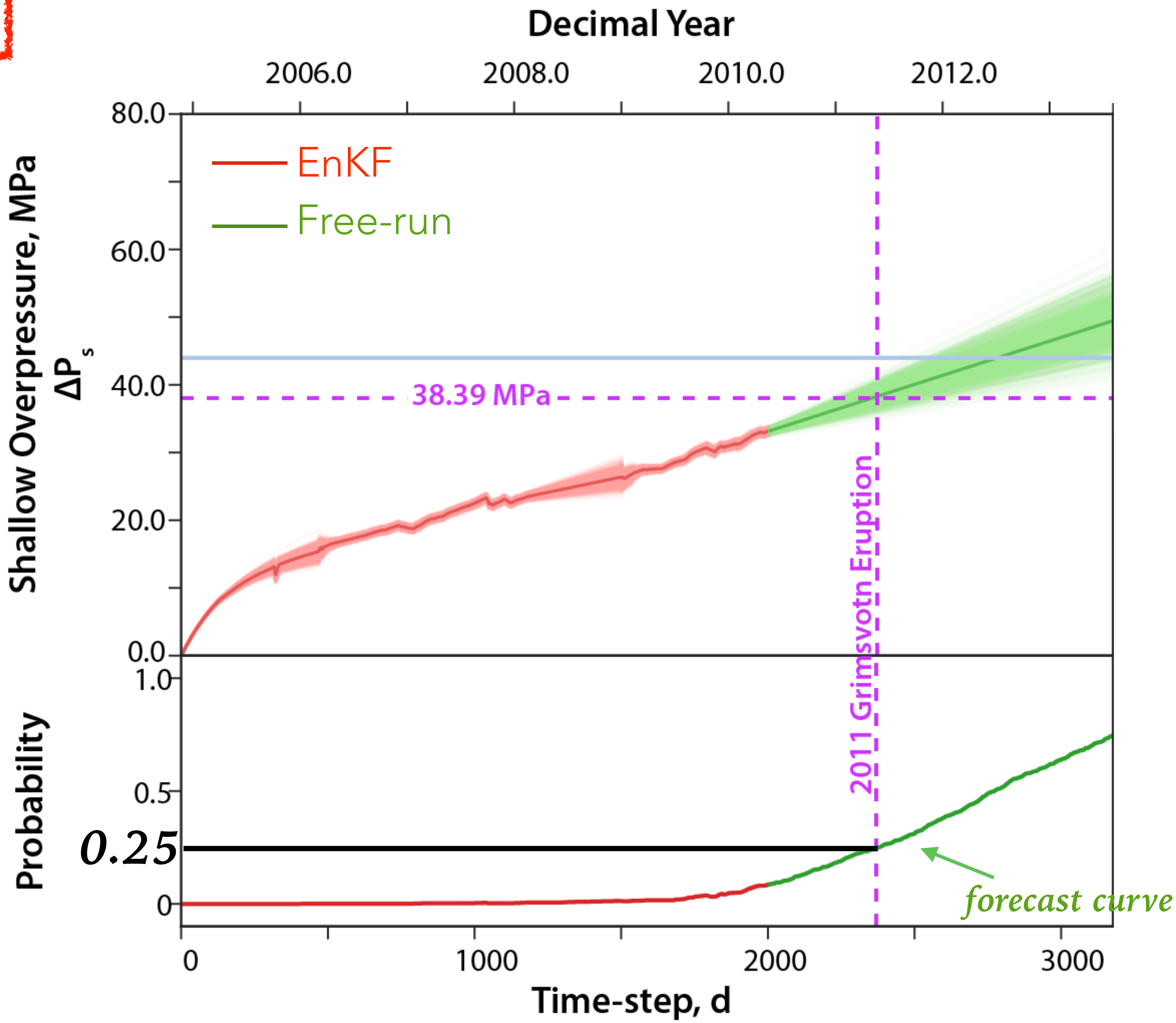
LET'S GO BACK IN TIME AND SEE WHAT HAPPENS…

At day = 2006



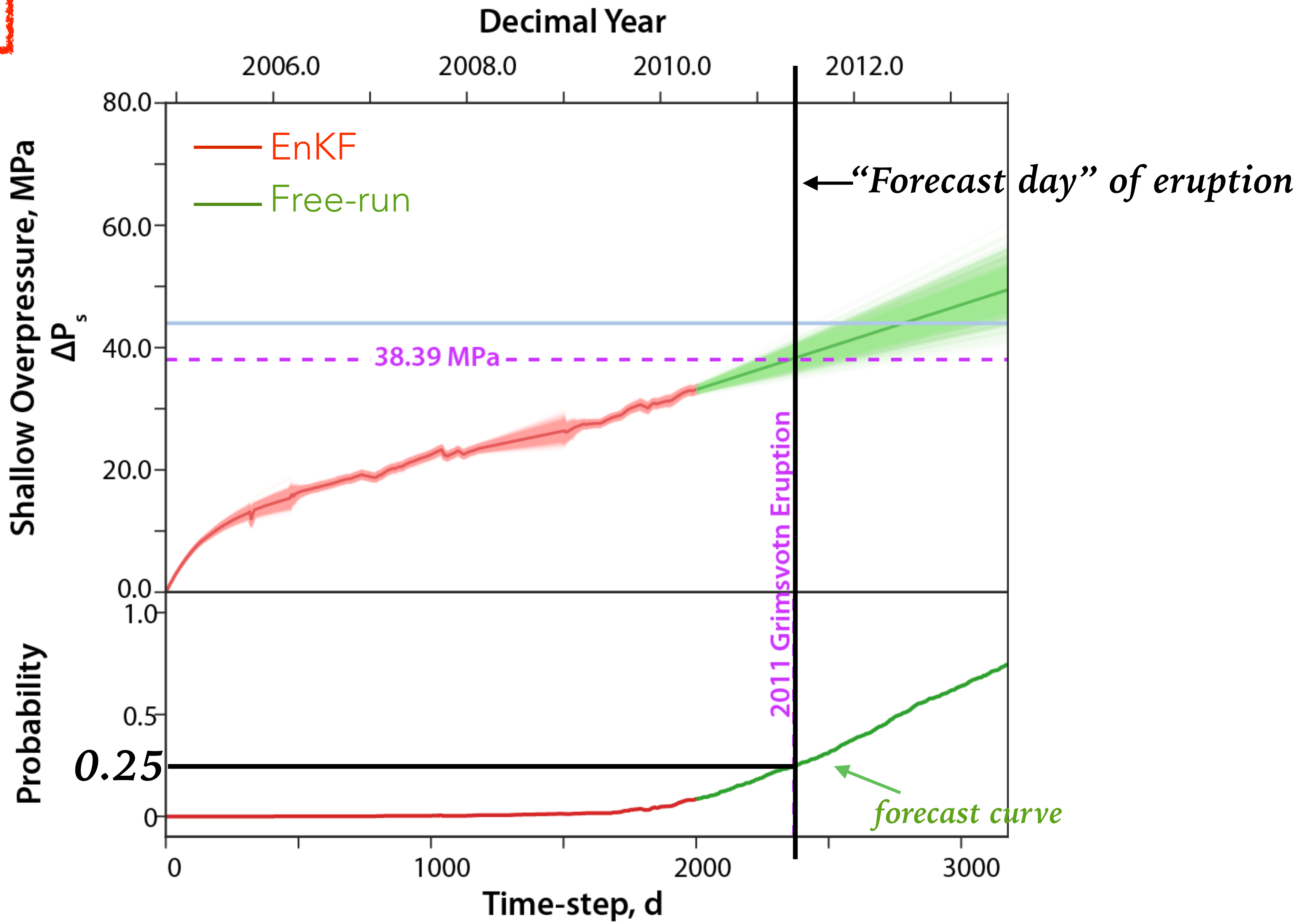
LET'S FIND WHERE THE **0.25 PROBABILITY** FALLS….

At day = 2006

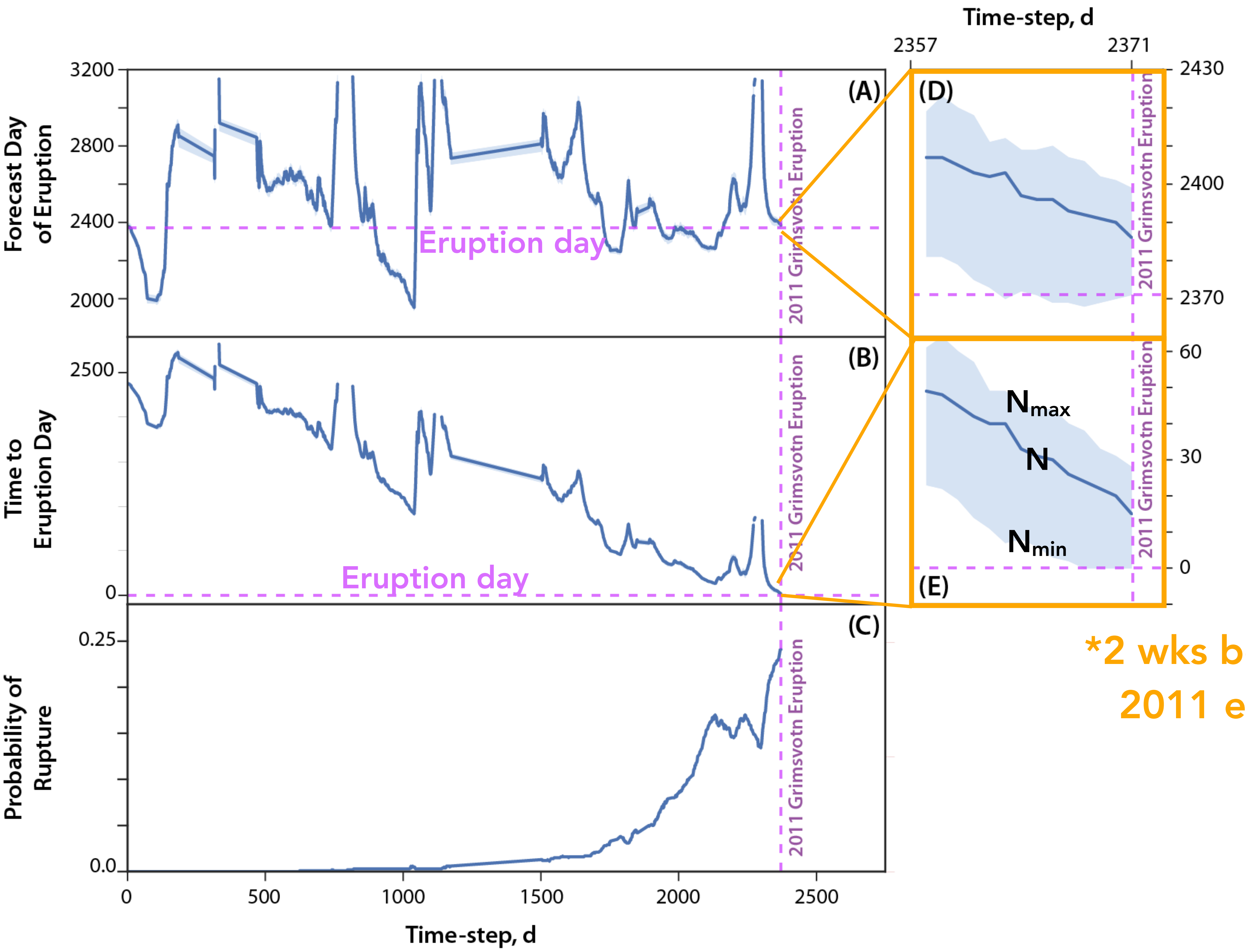


LET'S FIND WHERE THE <u>0.25 PROBABILITY</u> FALLS…. ET VOILA!

At day = 2006



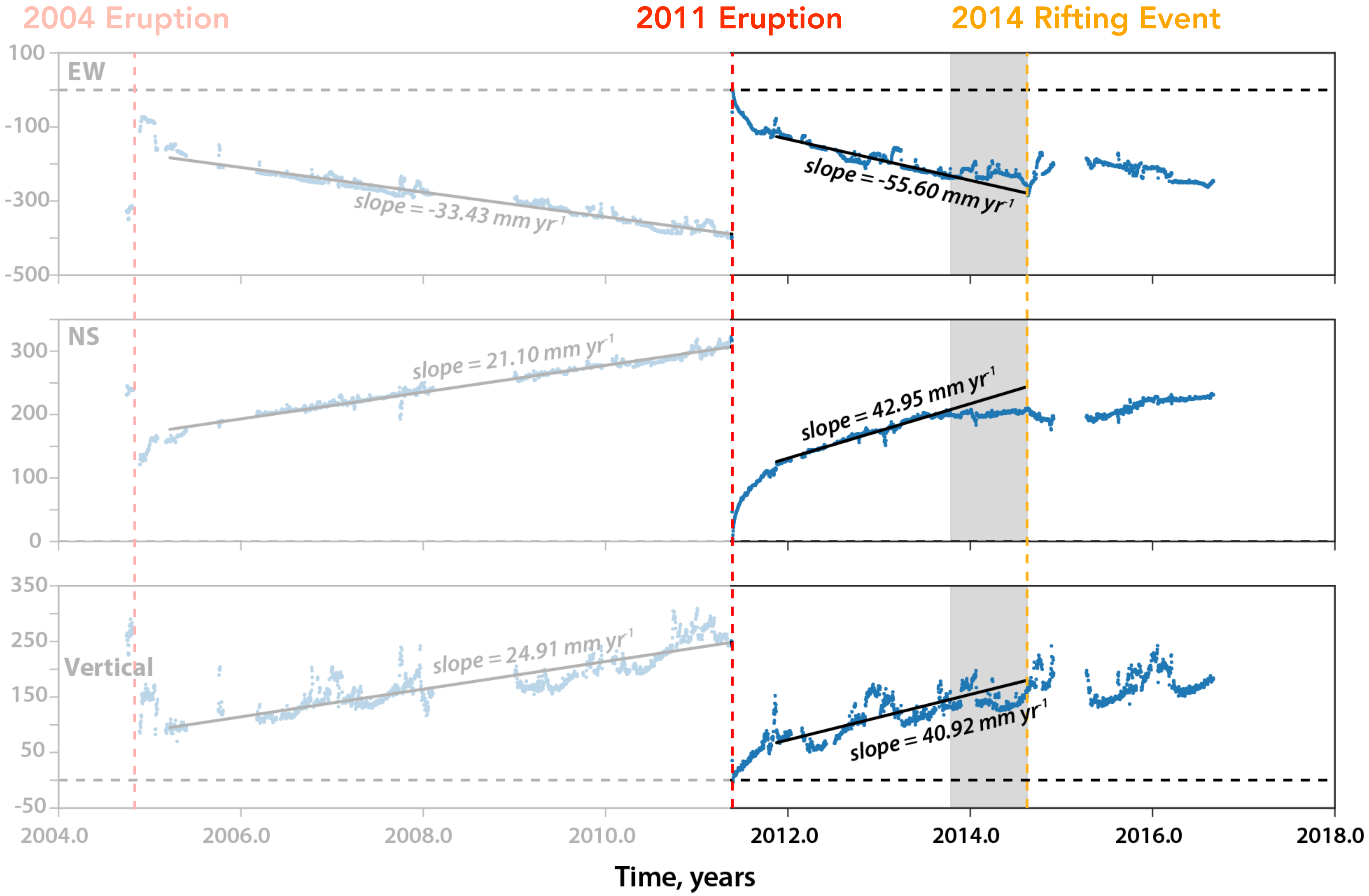
PREDICTED TIMING OF THE ERUPTION AS A FUNCTION OF TIME



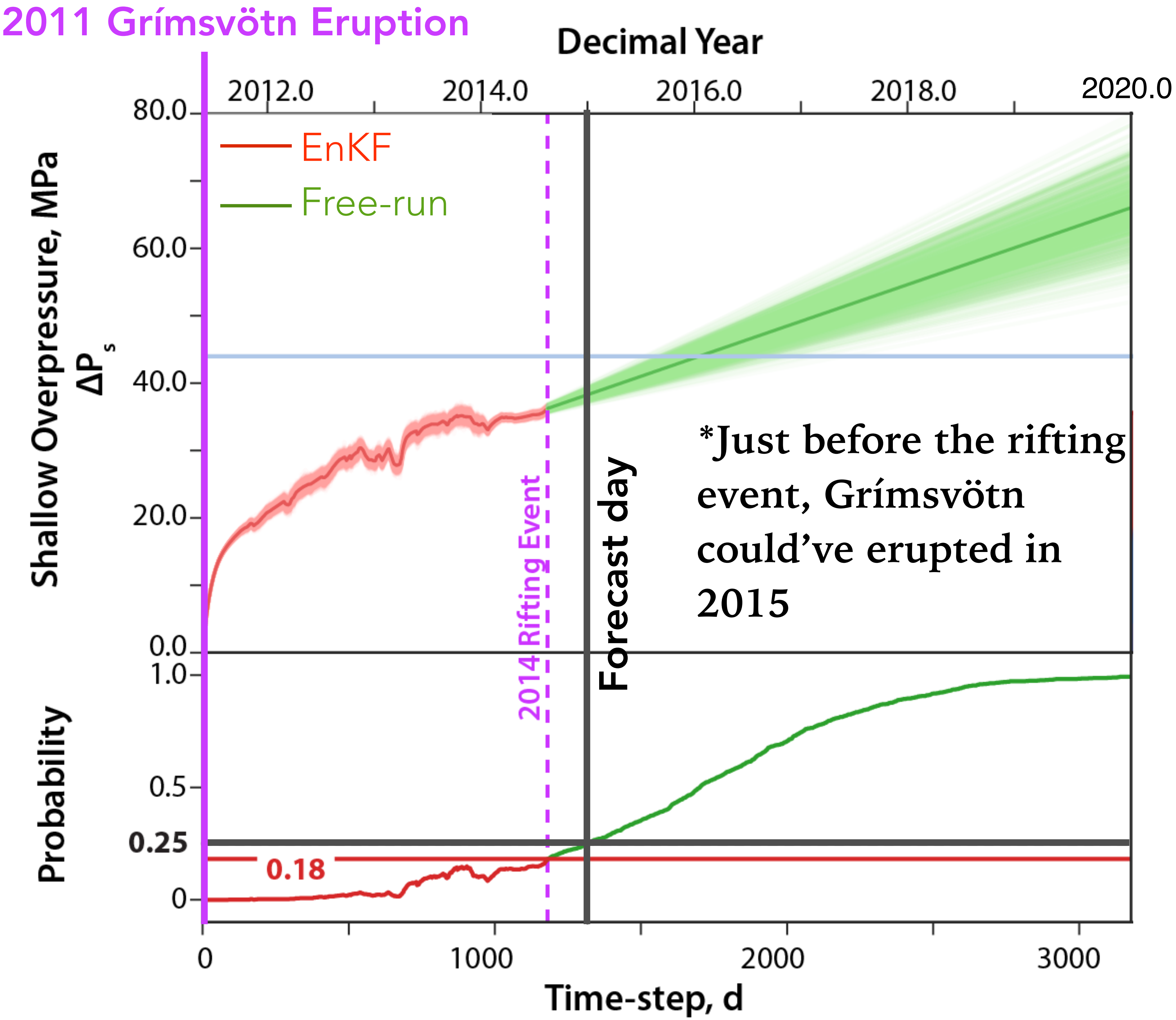
*2 wks before the 2011 eruption

I KNOW WHAT YOU'RE THINKING… IT'S TOO GOOD TO BE TRUE!

"Can the ***25 ±1% criterion*** work for the next eruptive cycle (2011 post-eruptive dataset)?"

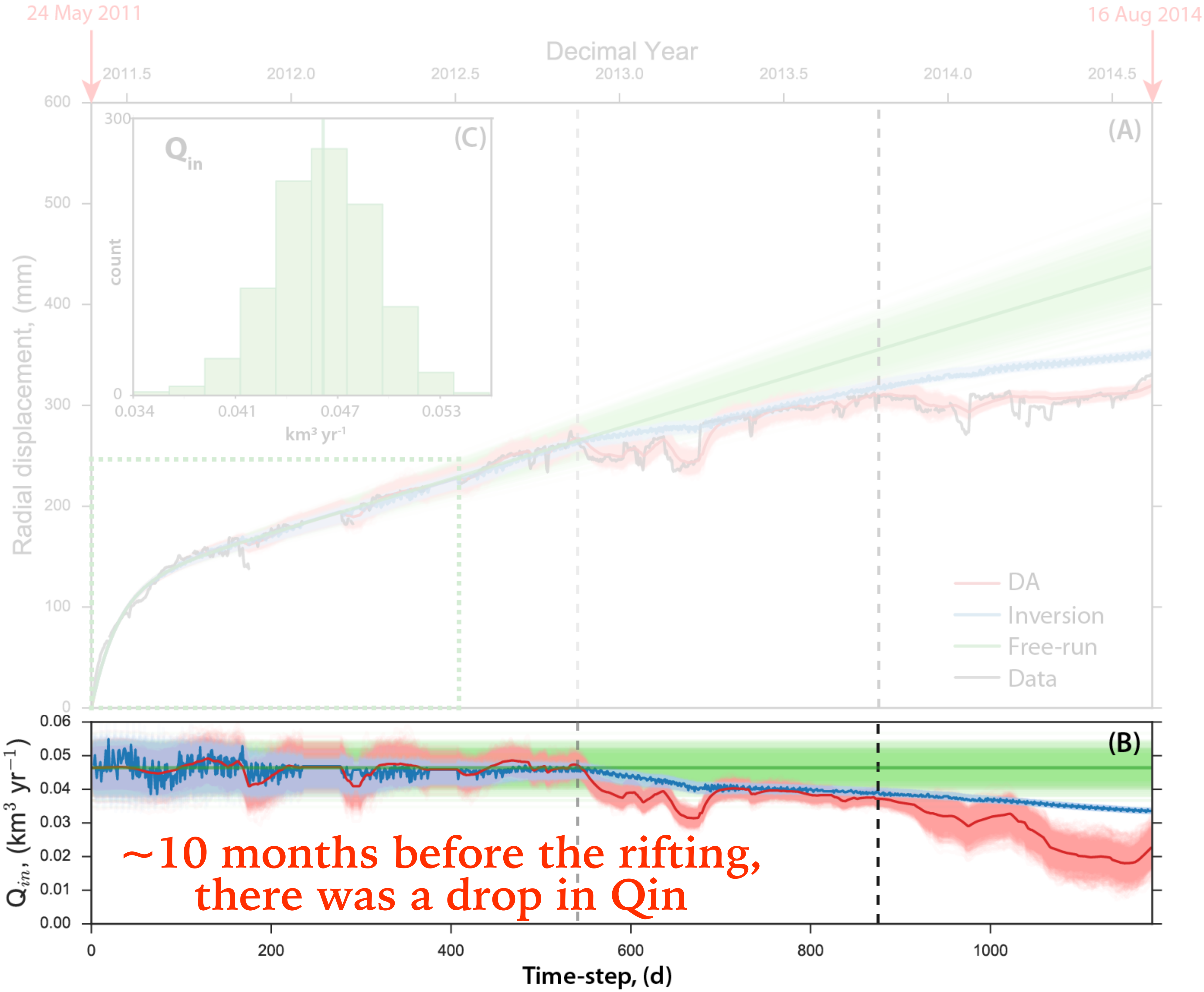


DARN! THE ANSWER IS NO…



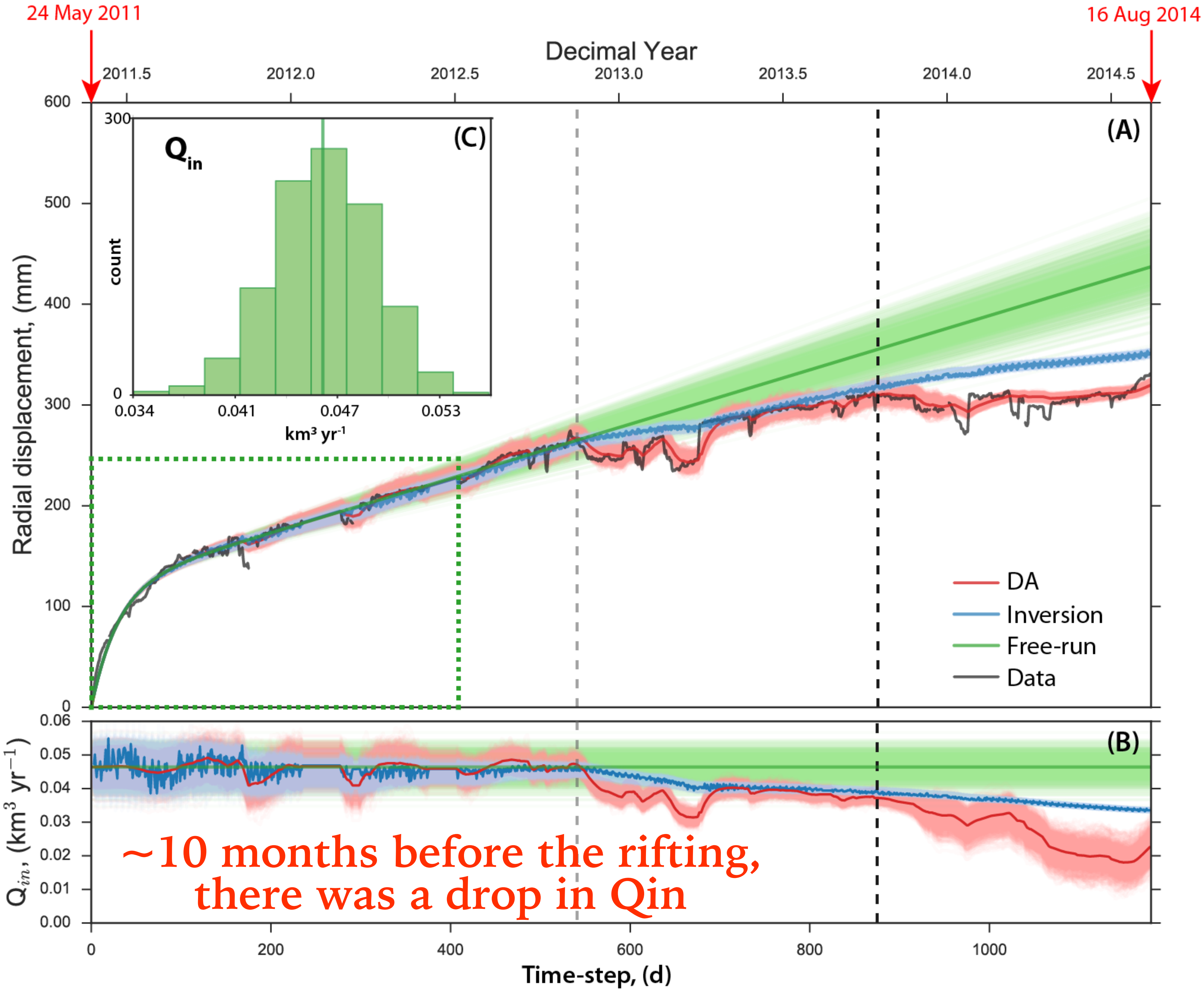
*Just before the rifting event, Grímsvötn could've erupted in 2015

BUT WAIT! DON'T LOSE HOPE! SOMETHING CHANGED…



~10 months before the rifting,
there was a drop in Qin

BUT WAIT! DON'T LOSE HOPE! SOMETHING CHANGED…

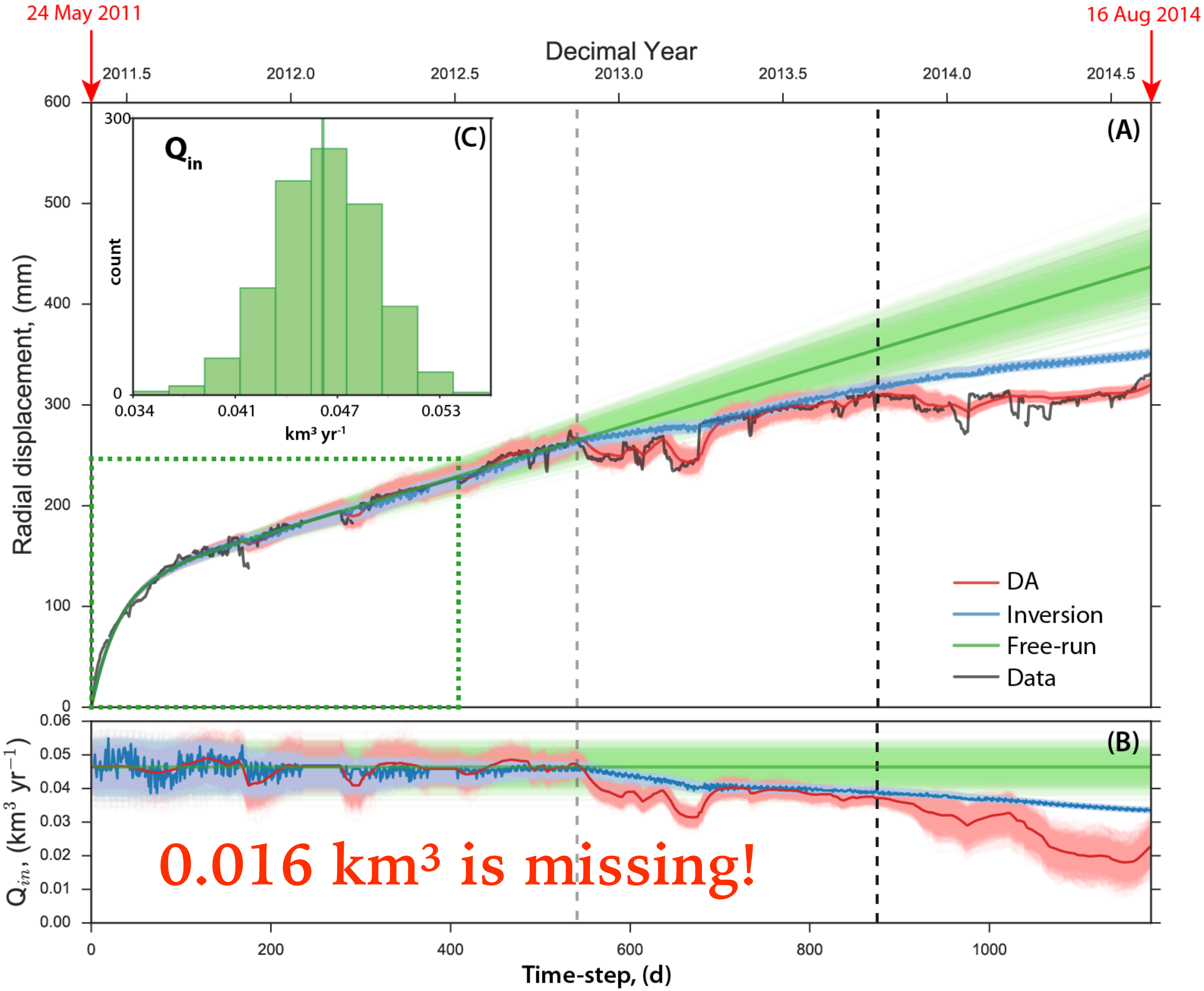


24 May 2011

16 Aug 2014

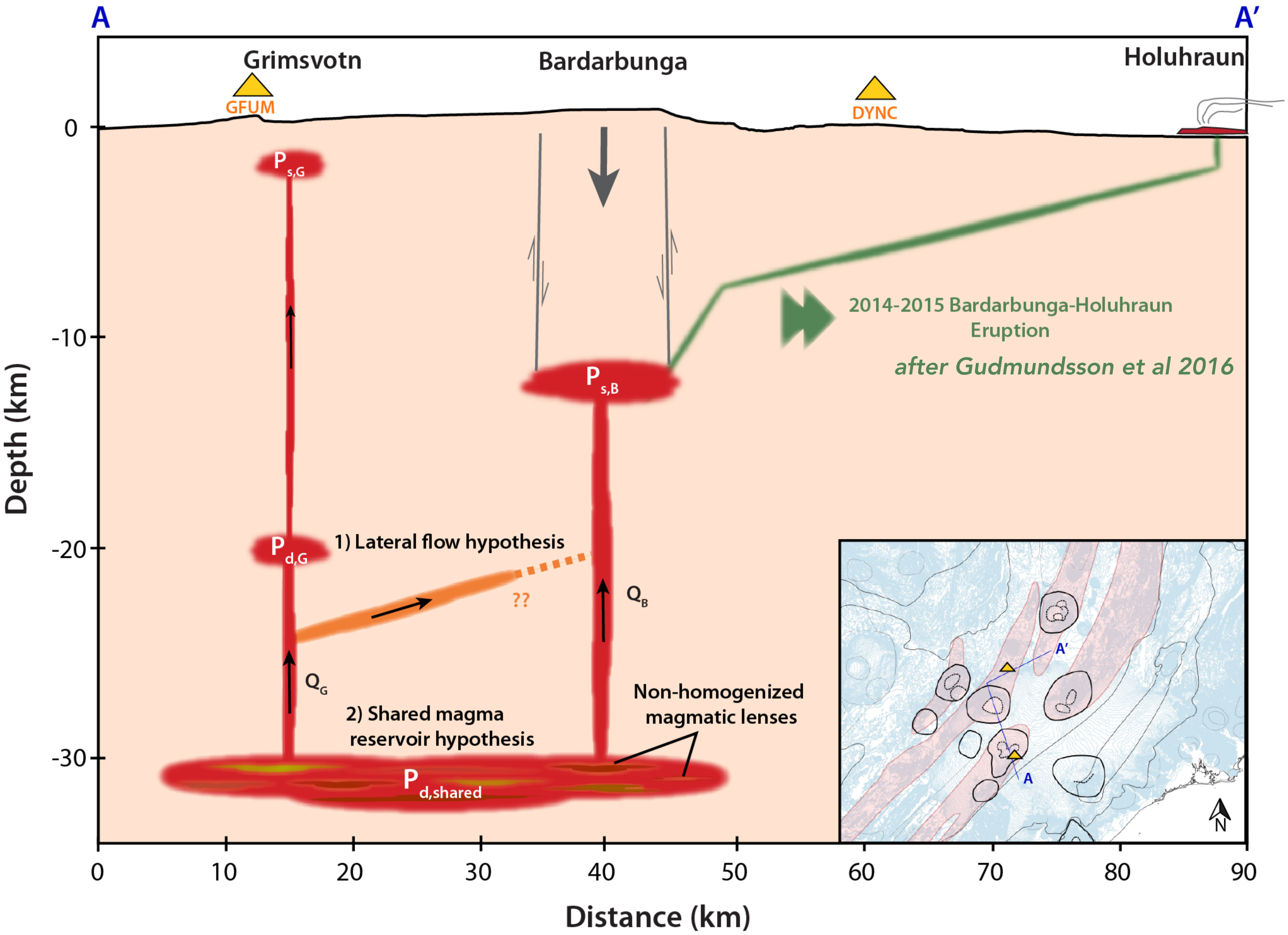
~10 months before the rifting, there was a drop in Qin

BUT WAIT! DON'T LOSE HOPE! SOMETHING CHANGED…



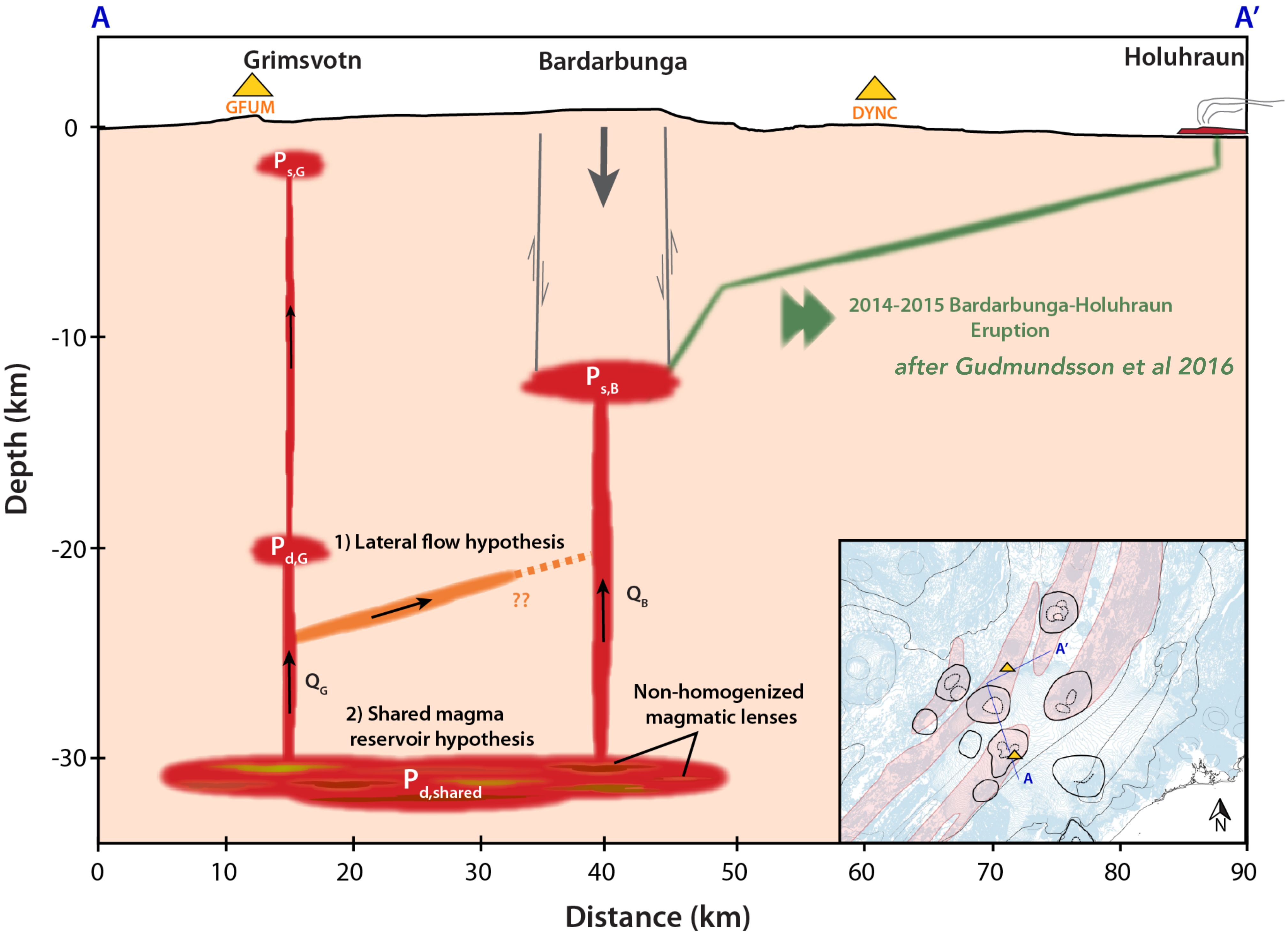
0.016 km³ is missing!

SO WHAT HAPPENED TO THE MISSING MAGMA?



after Gudmundsson et al 2016

SO WHAT HAPPENED TO THE MISSING MAGMA?



Surge in magma supply at Bárdarbunga + rifting event + gradual caldera collapse
= 6-month long eruption

TO SUMMARIZE ALL MY "BLA BLAS"…

- ☑ **Data assimilation shows great promise** in addressing problems in volcanology.
- ☑ We can have a **dynamic information on the volcanic system** (e.g. overpressures, magma inflow rate).
- ☑ We can **predict the timing of eruption** given some assumptions on threshold overpressure.
- ☑ In addition to predicting volcanic eruptions, sequential assimilation of geodetic data has a unique potential to **give insights into volcanic system roots**.
  - ▷ We are able to **track the variation of magma supply rate** and evidence subsurface processes that occur between neighbouring volcanoes—**which have never been done before.**

PERSPECTIVES

Volcanic data assimilation is still in its infancy—there are a lot more things to do!

PERSPECTIVES

Volcanic data assimilation is still in its infancy—there are a lot more things to do!

> *"What is more likely to happen in the next decades is the development of ensemble models, which make volcanic forecasts that take account of both uncertainties and nonlinear dynamics"*
>
> *- Steve Sparks [2003]*

Guatemala volcano alert too late to save lives, officials admit

Sofia Menchu

6 MIN READ

EL RODEO, Guatemala (Reuters) - A communication breakdown between a disaster agency and volcanologists in Guatemala delayed evacuations as gas and ash clouds cascaded down the Fuego volcano last Sunday in its most violent eruption in four decades, authorities have admitted.

https://www.reuters.com/

itv / express.co.uk

Twitter

DETAILS ABOUT OUR WORK:

[*] Bato MG, Pinel V, Yan Y, Jouanne F. *[Near] real-time forecasting of the rupture of a magma chamber using sequential data assimilation.* *in preparation for JGR*.

[1] Bato MG, Pinel V, Yan Y, Jouanne F & Vandemeulebrouck J (2018). *Possible deep connection between volcanic systems evidenced by sequential assimilation of geodetic data.* Nature Scientific Reports, 8(1), 11702. DOI:10.1038/s41598-018-29811-x

[2] Bato MG, Pinel V, Yan Y (2017). *Assimilation of Deformation Data for Eruption Forecasting: Potentiality Assessment Based on Synthetic Cases.* Frontiers Earth Science 5:48. DOI: 10.3389/feart.2017.00048

PRESS MENTIONS:

[1] Volcano Forecast? New Technique Could Better Predict Eruptions, Scientific American
[2] Scientists are trying to use satellites to forecast volcanic eruptions, CNBC
[3] Think weather forecasts are bad? Try forecasting a volcanic eruption, Popular Science
[4] Predicting eruptions using satellites and math, Eurekalert
[5] Scientists predict volcanic eruptions with satellites and GPS, CNN Tech

Merci !