

Volcano Model-Data Fusion

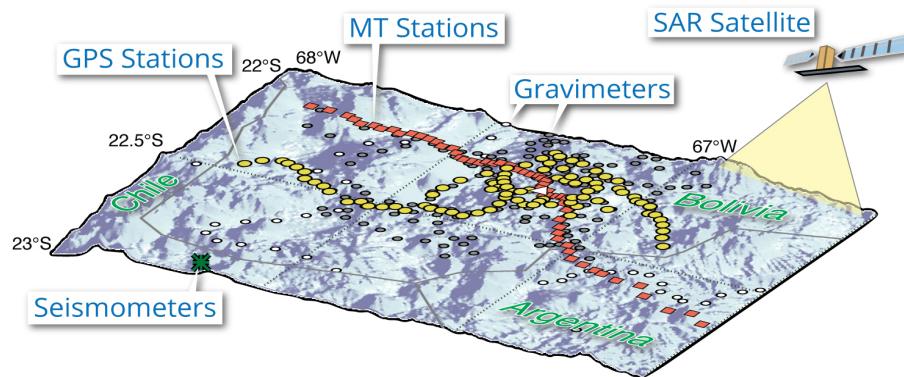
DATA

- + Direct observation, good error estimates
- Gaps, incomplete coverage

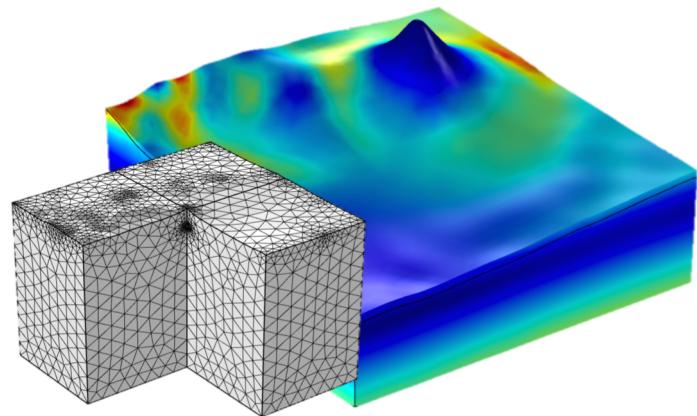
MODELS

- + Knowledge of system evolution
- Poor error estimates

Central Andes | PLUTONS project



Pritchard & Gregg, Elements (2016)



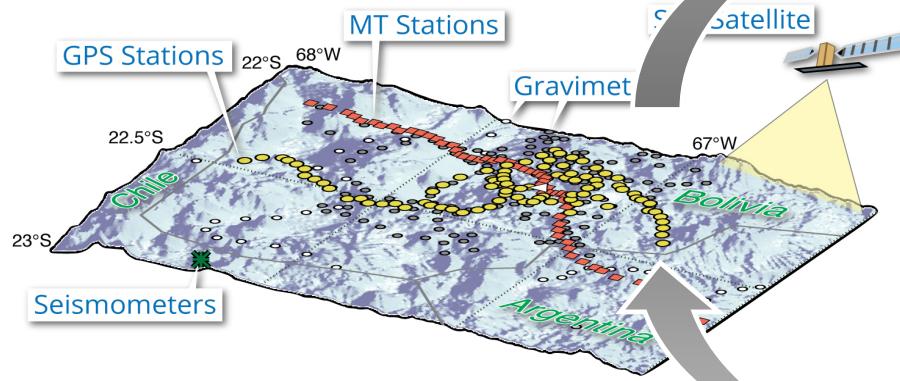
Zhan & Gregg, JVGR (2017)

Volcano Model-Data Fusion

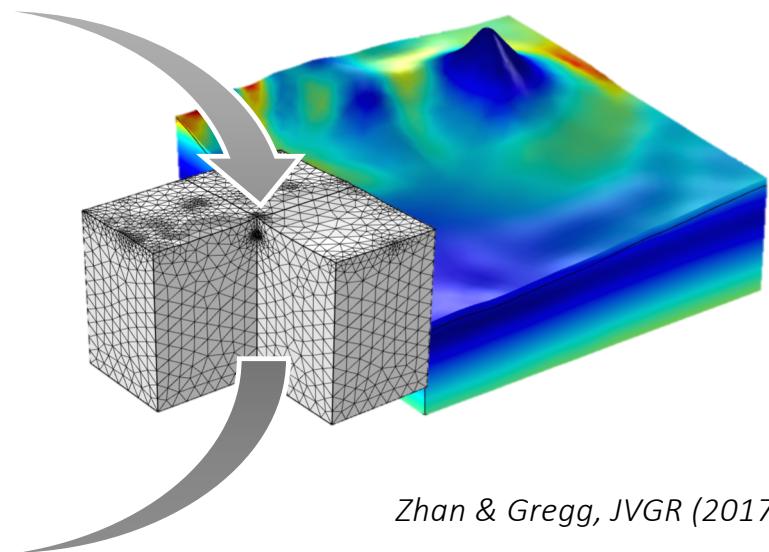
MODEL-DATA FUSION

- The data improves the model's performance by adjusting unknown model parameters or variables and correcting the model's trajectory.
- The model improves data targets by constraining gaps in our observations.

Central Andes | PLUTONS project

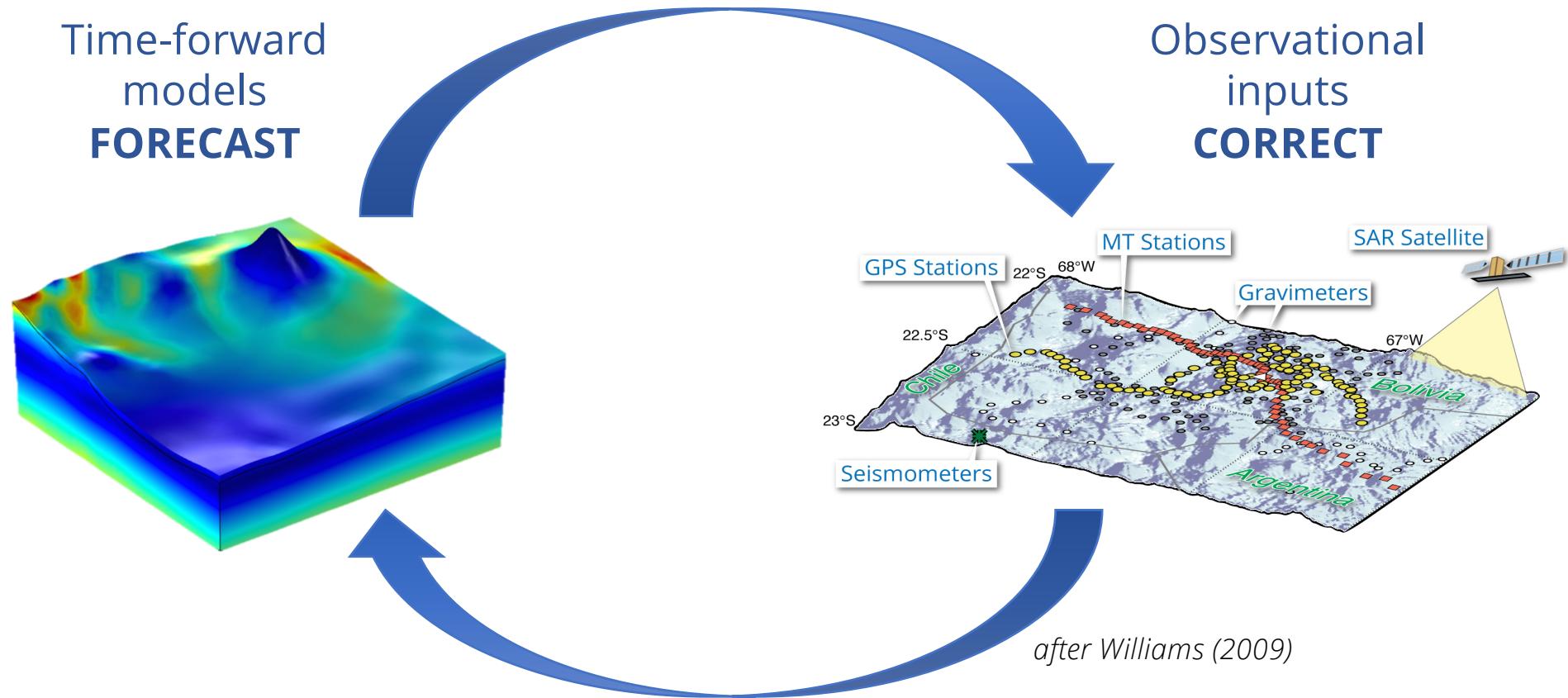


Pritchard & Gregg, Elements (2016)



Zhan & Gregg, JVGR (2017)

The Goal: A forecast-correction method using observations



Sequential Data Assimilation – A brief history leading up to EnKF

Modern Data Assimilation

1700's

Instruments developed to collect meteorological information (T, P, precip)

1854

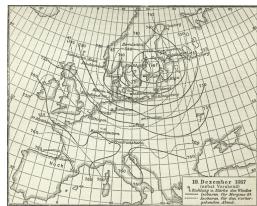
FitzRoy appointed British Chief of Board of Trade and charges ships with collection of weather data at sea

1700



T. Bayes 1701-1761

1800

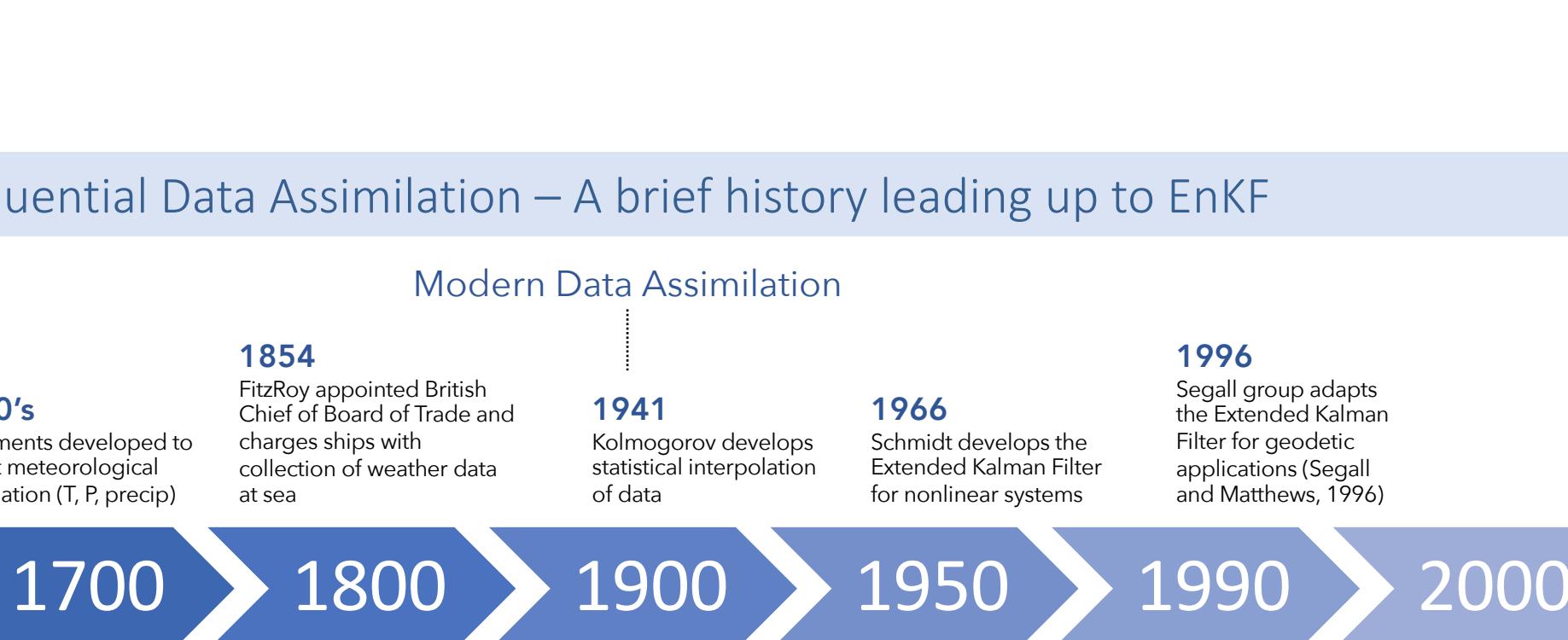


Weather map from 1887

1941

Kolmogorov develops statistical interpolation of data

1900



1835

Electrical telegraph invented allowing the rapid transfer of meteorological data

1922

Richardson publishes first attempt at numerical weather forecasting

1966

Schmidt develops the Extended Kalman Filter for nonlinear systems

1950

1946 – 50s

Monte Carlo method was invented by Stanislaw Ulam and developed with von Neumann

1996

Segall group adapts the Extended Kalman Filter for geodetic applications (Segall and Matthews, 1996)

1990

1994

Evensen develops the Ensemble Kalman Filter (EnKF) using MCMC methods

2000

2016

EnKF adapted for volcanology (Gregg and Pettijohn, 2016)

"Big Data"

Early 2000's

UCAR / NCAR adopts EnKF for Global Climate modeling community

Comparison of Kalman Filtering Approaches

| | Linearity | Computational load | Model independent? |
|---|--|--------------------|--------------------|
| Kalman Filter (KF) <i>Kalman (1960)</i> | Linear | high | NO |
| Extended Kalman Filter (EKF) <i>Schmidt (1966); Kalman and Schmidt (1968)</i> → Segall and Matthews (1996) | Quasi-Linear uses PDEs to linearize the model | >> KF | NO |
| Unscented Kalman Filter (UKF) <i>Julier & Uhlmann (2004)</i> → Fournier, Freymueller, Cervelli (2009) | Non-linear NL transformations for covariance matrix | 2-3 x EKF | NO |
| Ensemble Kalman Filter (EnKF) <i>Evensen (1994)</i> → Gregg and Pettijohn (2016), etc. | Non-linear uses MCMC methods for covariance matrix | << KF | YES |

Why EnKF?

EnKF is the standard / state-of-the-art technique for data assimilation used in **climate and weather forecasting** and has been adopted by NCAR and UCAR.

The screenshot shows the NCAR RAL Research Applications Laboratory website. The header features the NCAR UCAR logo, the RAL Research Applications Laboratory name, and the tagline "science • serving • society". The navigation menu includes links for RAL HOME, WHO WE ARE, WHAT WE DO, SOLUTIONS (which is highlighted in blue), and WORK WITH US. A search bar at the top right includes a "Google Custom Search" field and a "Search" button. Below the header, a breadcrumb trail shows the path: RAL Home » Solutions » Products » Ensemble Kalman Filter System (EnKF). The main content area is titled "ENSEMBLE KALMAN FILTER SYSTEM (ENKF)" and includes a map visualization of atmospheric data. A link "Link to Product" is provided. A detailed description of the EnKF system follows, mentioning it is a Monte-Carlo algorithm for data assimilation using ensemble forecasts. To the right, a sidebar titled "PRODUCTS + TOOLS" lists various application areas: Agriculture + Food, Aviation, High Impact Weather, Human Health, National Security, Renewable Energy, Surface Transportation, Testing + Evaluation, and Water Resources.

science • serving • society

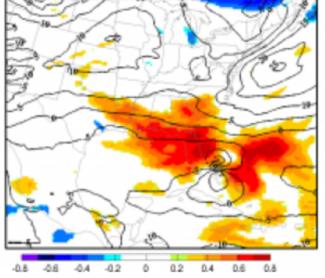
RAL HOME | WHO WE ARE | WHAT WE DO | **SOLUTIONS** | WORK WITH US | Google Custom Search | Search

RAL Home » Solutions » Products » Ensemble Kalman Filter System (EnKF)

ENSEMBLE KALMAN FILTER SYSTEM (ENKF)

[Link to Product](#)

Sensitivity of 1048 minimum SLP longitude to deep-layer u-wind valid 2005/03/27 00



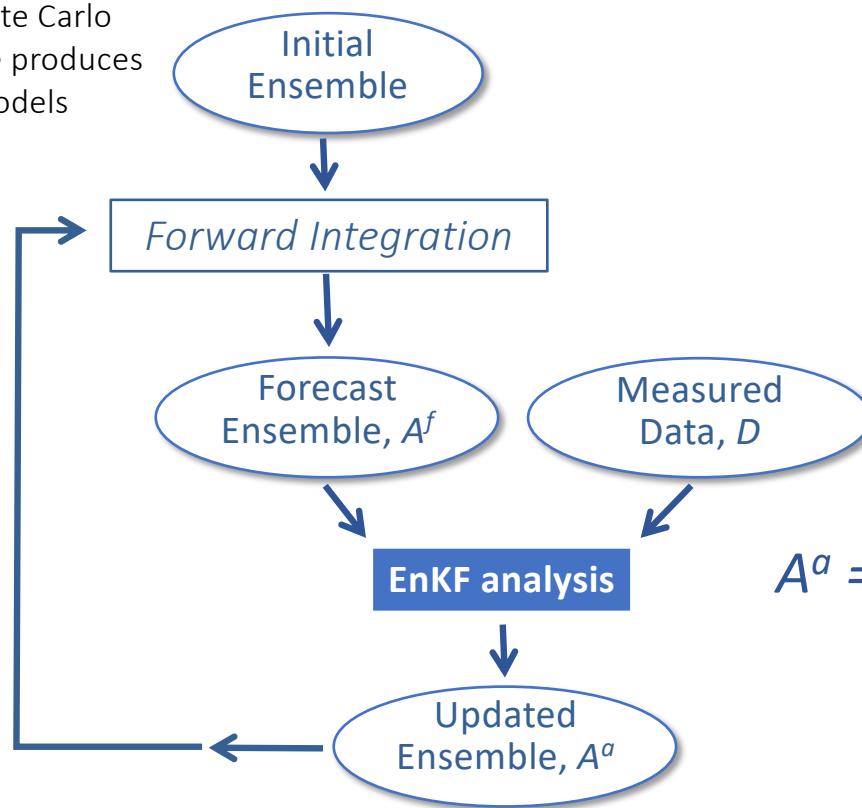
The community EnKF system is a Monte-Carlo algorithm for data assimilation that uses an ensemble of short-term forecasts to estimate the background-error covariance in the Kalman Filter. It is designed to be flexible, state-of-art, and run efficiently on various parallel computing platforms. The EnKF system is in the public domain and is freely available for community use.

PRODUCTS + TOOLS

- > Agriculture + Food
- > Aviation
- > High Impact Weather
- > Human Health
- > National Security
- > Renewable Energy
- > Surface Transportation
- > Testing + Evaluation
- > Water Resources

Ensemble Kalman Filter (EnKF) - Markov Chain Monte Carlo Approach

Monte Carlo
suite produces
 N models



EnKF Workflow

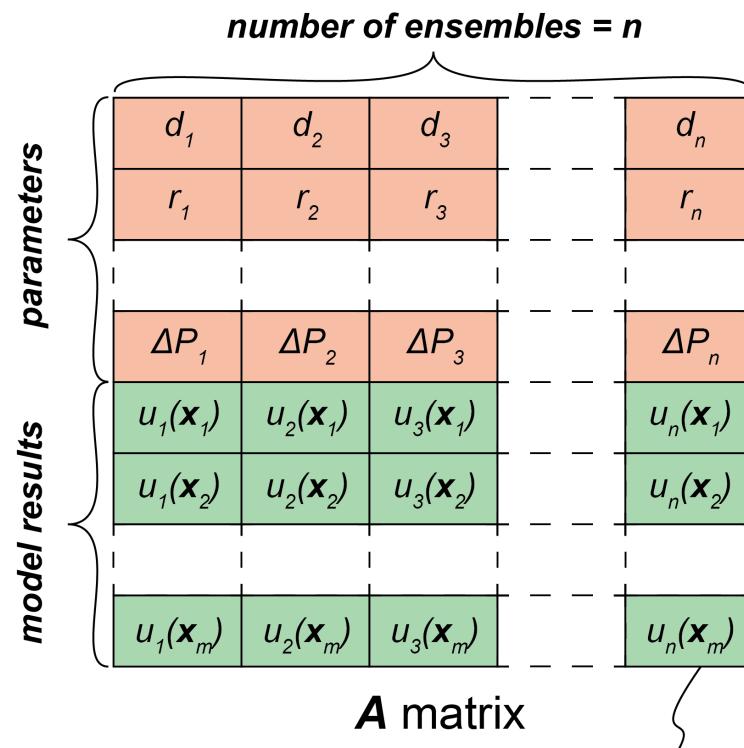
*Gregg and Pettijohn (2016)
based on Evensen (1994)*

$$A^a = A^f + X H^T (H X H^T + C)^{-1} (D - H A^f)$$

A^f model forecast
 A^a updated model
 H model operator matrix
 D data
 C data covariance matrix
 X ensemble covariance matrix

Ensemble Kalman Filter (EnKF) - Markov Chain Monte Carlo Approach

$$\mathbf{A}_a = \mathbf{A} + \underbrace{\mathbf{P}_e \mathbf{H}^T (\mathbf{H} \mathbf{P}_e \mathbf{H}^T + \mathbf{R}_e)^{-1} (\mathbf{D} - \mathbf{H} \mathbf{A})}_{K = \text{"Kalman gain"}}$$



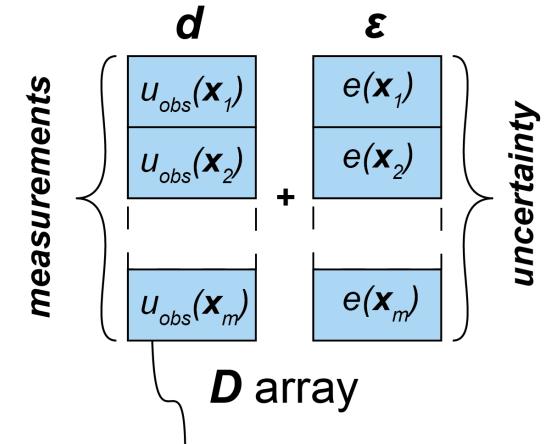
e.g., Mogi: $u(\mathbf{x}) = f(\mathbf{x}, \mathbf{d}, \mathbf{r}, \Delta P)$

\mathbf{P}_e = covariance of \mathbf{A}

\mathbf{R}_e = covariance of $\boldsymbol{\varepsilon}$

$\mathbf{P}_e \sim \text{inf}, K = 1$

$\mathbf{R}_e \sim \text{inf}, K = 0$



e.g., GPS motion at \mathbf{x}