

# Supporting Information

Title: In Situ Monitoring of Groundwater Contamination Using the Kalman Filter

Authors:

Franziska Schmidt<sup>\*</sup>

franziska\_schmidt@berkeley.edu

Department of Nuclear Engineering, University of California Berkeley

Etcheverry Hall, 2521 Hearst Ave, Berkeley, CA 94709

Haruko M. Wainwright

hmwainwright@lbl.gov

Climate and Ecosystem Sciences Division, Lawrence Berkeley National Laboratory

1 Cyclotron Road, MS 74R-316C, Berkeley, CA 94720-8126

Boris Faybishenko

bafaybishenko@lbl.gov

Energy Geosciences Division, Lawrence Berkeley National Laboratory

1 Cyclotron Road, Berkeley, CA 94720-8126

Miles Denham

mdenham@Panoramic.consulting

Panoramic Environmental Consulting, LLC

P.O. Box 906, Aiken, SC 29802

Carol Eddy-Dilek

carol.eddy-dilek@srnl.doe.gov

Savannah River National Laboratory

Savannah River Site, Aiken, SC 29808

6 pages, 1 text, 3 figures

# Text S1

The Kalman filter is a recursive two-step process consisting of a state prediction step and an update step, as graphically shown in Figure S3. A detailed derivation is available in Reid (2011).<sup>1</sup>

The goal is to estimate the state vector  $\mathbf{x}_t$  as  $\hat{\mathbf{x}}_t$  and its error covariance  $\mathbf{P}_t$  at each time step  $t$ .

The prediction step describes the temporal evolution of the state vector  $\mathbf{x}_t$  from the previous step. The state-transition equation (Equation 5) is used to predict the expected value of the state vector as  $\hat{\mathbf{x}}_{t|t-1}$  based on the estimate at the previous time step  $\hat{\mathbf{x}}_{t-1}$ :

$$\hat{\mathbf{x}}_{t|t-1} = \mathbf{F} \hat{\mathbf{x}}_{t-1}$$

Similarly, the error covariance  $\mathbf{P}_t$  is predicted as  $\mathbf{P}_{t|t-1}$  based on the covariance at the previous step  $\mathbf{P}_{t-1}$ :

$$\mathbf{P}_{t|t-1} = \mathbf{F} \mathbf{P}_{t-1} \mathbf{F}^T + \mathbf{Q}$$

The update step improves the estimate of the state vector by including observations  $\mathbf{z}_t$  through the data correlation model. Based on the state-observation equation (Equation 7), the estimate  $\hat{\mathbf{x}}_t$  is determined by:

$$\hat{\mathbf{x}}_t = \hat{\mathbf{x}}_{t|t-1} + \mathbf{K}_t [\mathbf{z}_t - (\mathbf{H} \hat{\mathbf{x}}_{t|t-1} + \mathbf{u})],$$

where the Kalman gain  $\mathbf{K}_t$  is determined by:

$$\mathbf{K}_t = \mathbf{P}_{t|t-1} \mathbf{H}^T [\mathbf{H} \mathbf{P}_{t|t-1} \mathbf{H}^T + \mathbf{R}]^{-1}.$$

The error covariance is updated as:

$$\mathbf{P}_t = (\mathbf{I} - \mathbf{K}_t \mathbf{H}) \mathbf{P}_{t|t-1} (\mathbf{I} - \mathbf{K}_t \mathbf{H})^T + \mathbf{K}_t \mathbf{R} \mathbf{K}_t^T,$$

where  $\mathbf{I}$  is the identity matrix.

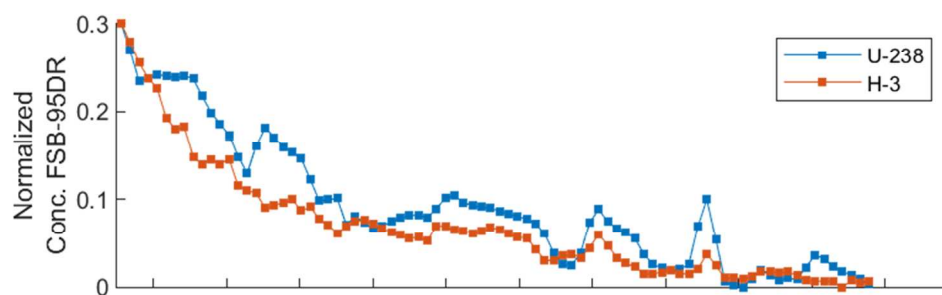
Reference:

(1) Reid, I. Estimation II

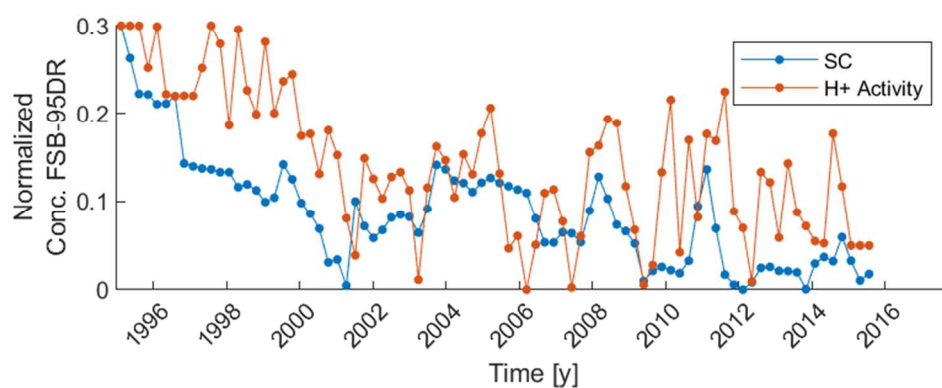
<http://www.robots.ox.ac.uk/~ian/Teaching/Estimation/LectureNotes2.pdf> (accessed Jan 1, 2017).

# Figure S1

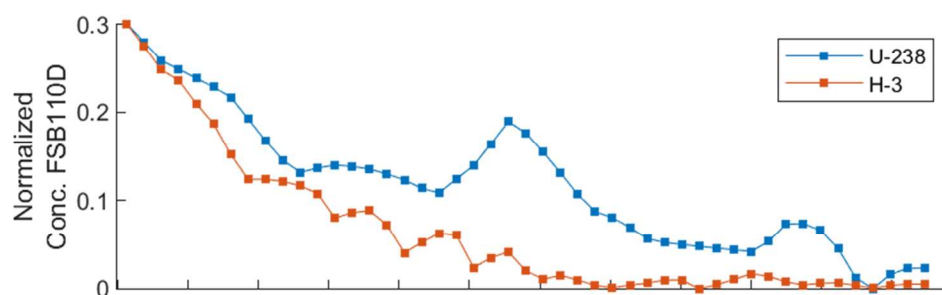
a)



b)



c)



d)

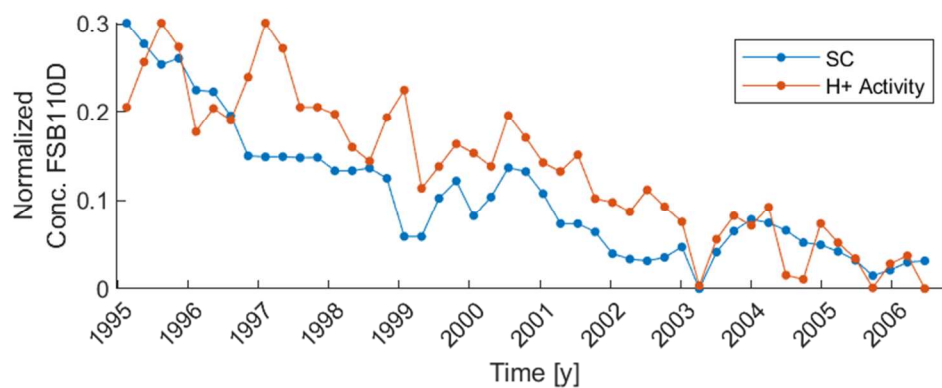


Figure S1

*Figure S 1 – a) Interpolated log-normalized (see Methodology) time series of the contaminants U-238 and H-3, as well as b) the groundwater quality variables SC and  $H^+$  for samples taken between 1995 and 2016 at well FSB-95DR. c), d) The same variables for samples taken between 1995 and 2007 at well FSB-110D.*

## Figure S2

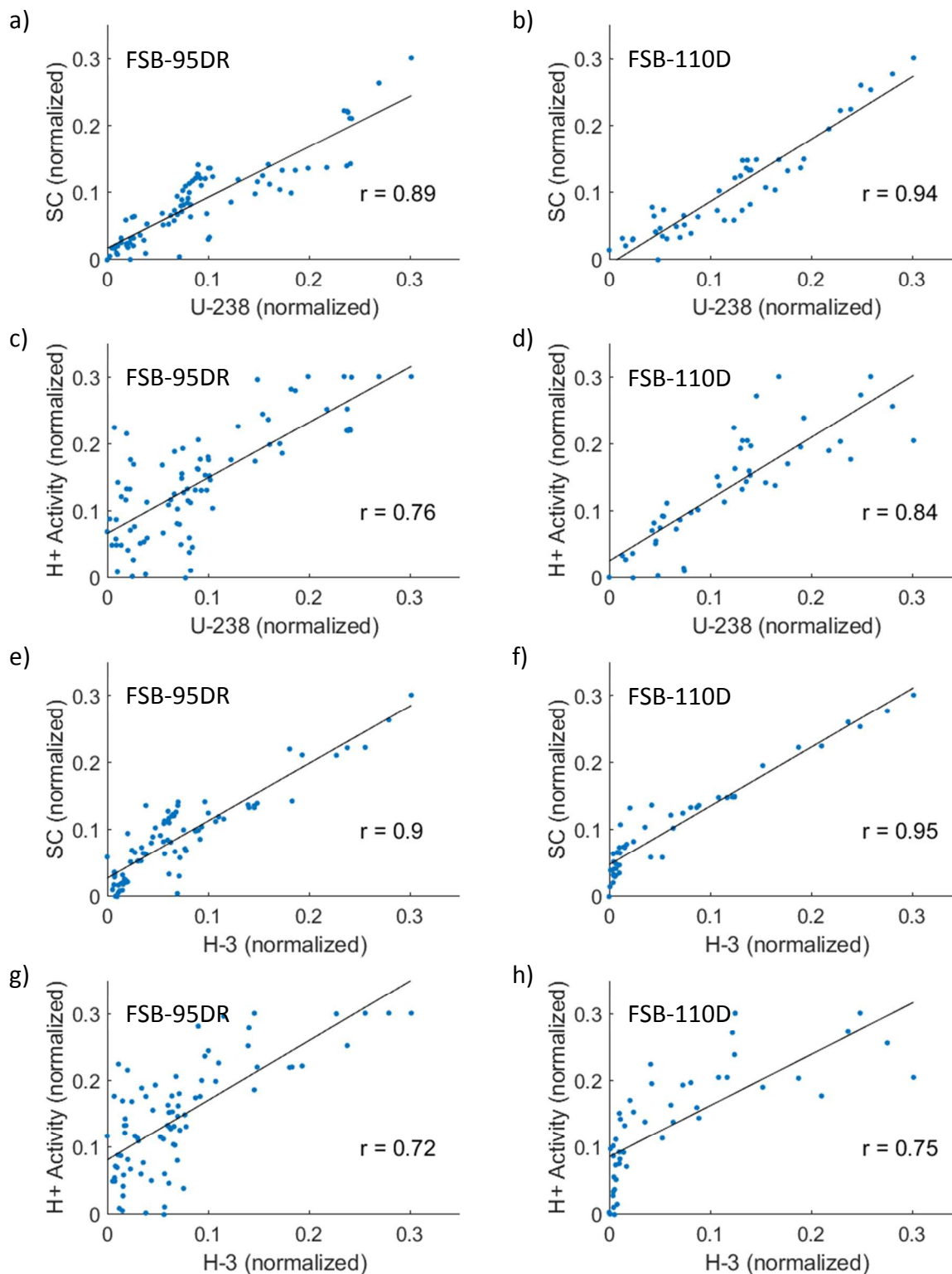


Figure S2 – a) Scatterplots for the entire time series with first order fitted trend lines and Pearson's  $r$  for a) the SC and c)  $H^+$  vs. U-238 at well FSB-95DR and well FSB-110D (b) and d), respectively). e) – h) The same plots with H-3 as the contaminant.

Figure S2

Figure S3

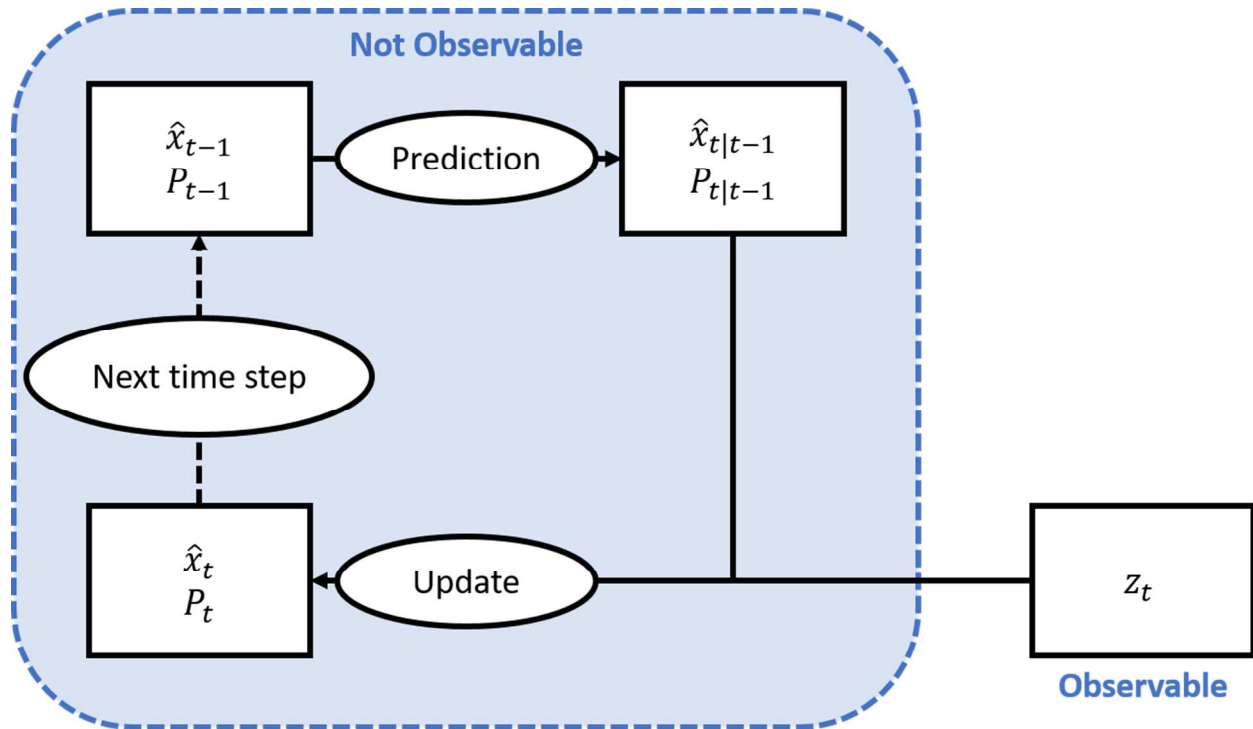


Figure S 3 – Kalman filter overview. The filter is recursive and repeats two steps: the prediction and the update step. It predicts the system state  $\hat{x}_{t|t-1}$  based on the previous time step at  $t - 1$  and via the temporal evolution model. The predicted value is then updated based on external observations  $z_t$ . The resulting estimate is used as the basis for the next prediction.