Application of the Ensemble Kalman Filter for Improved Mineral Resource Recovery (PPT)

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Application of the Ensemble Kalman Filter for Improved Mineral Resource Recovery

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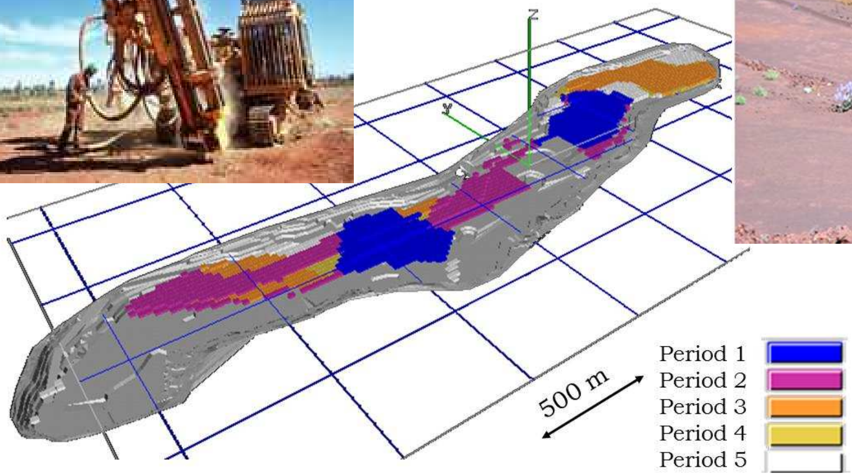
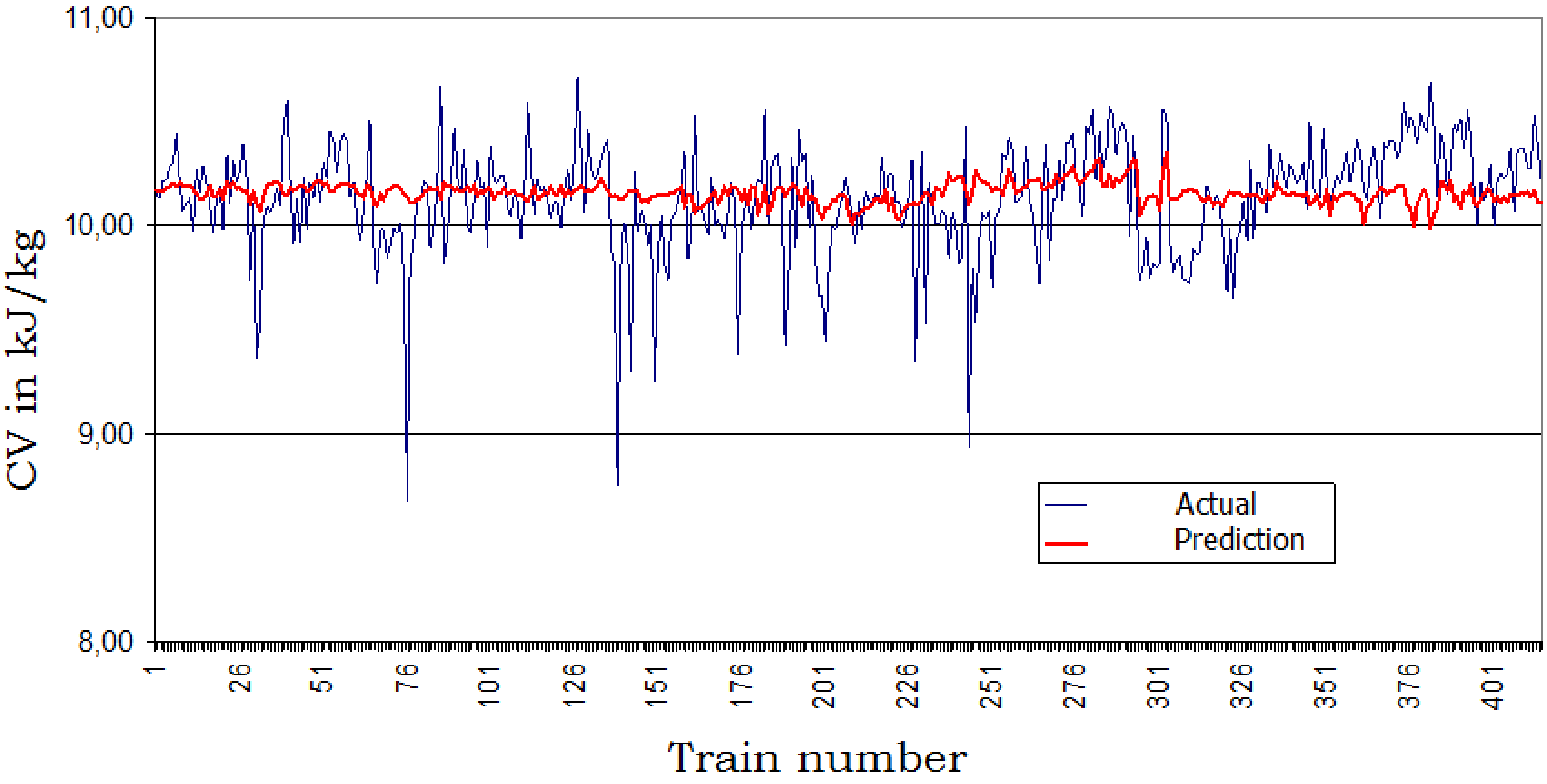
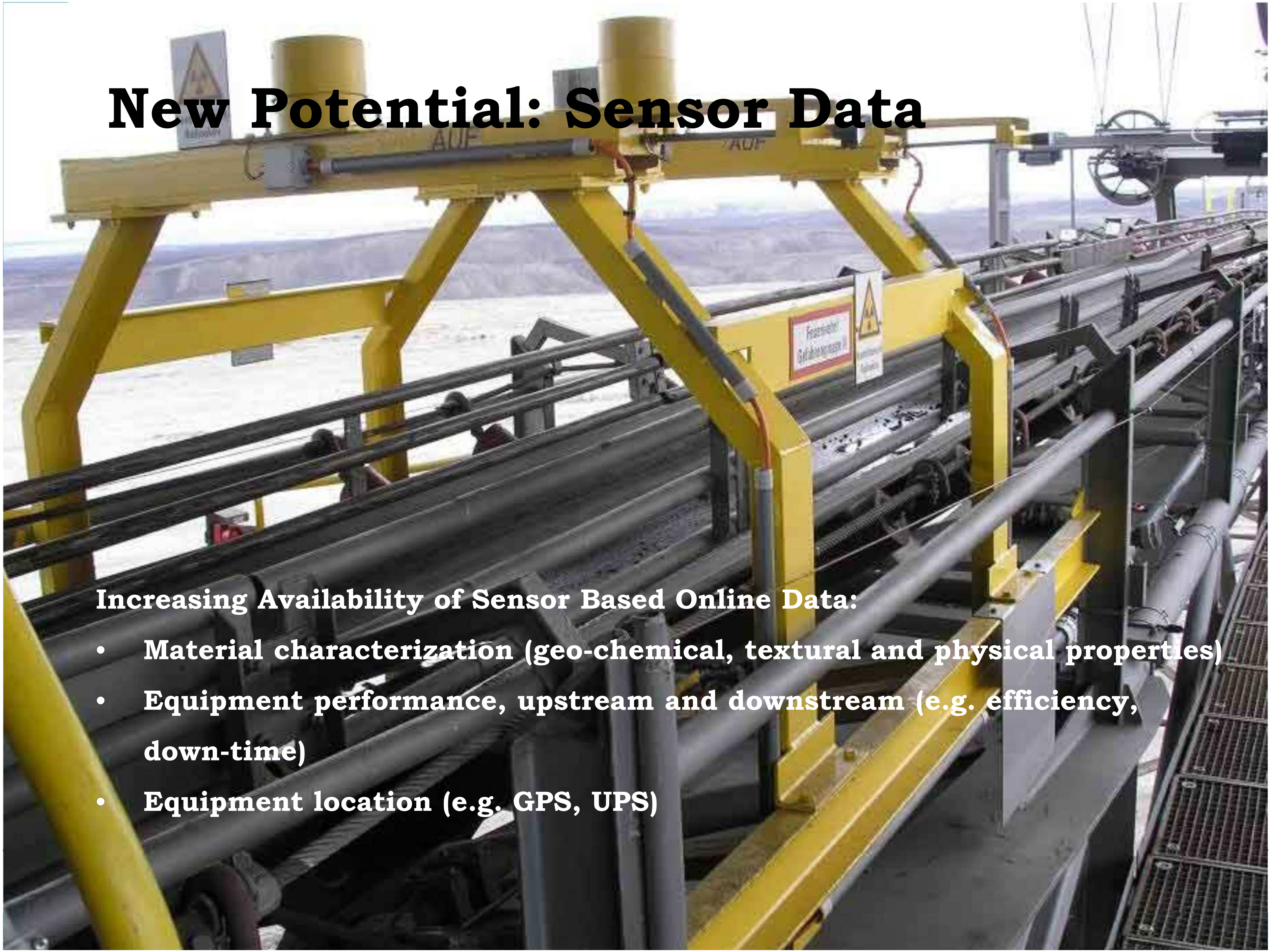
The Flow of Information

- Exploration and Data Collection
- Resource Modelling
- Mine Design Equipment Selection Reserve Estimation
- Production Scheduling and Operation
- Processing and Sale



Uncertainty in Model-based Prediction





New Potential: Sensor Data

Increasing Availability of Sensor Based Online Data:

- **Material characterization (geo-chemical, textural and physical properties)**
- **Equipment performance, upstream and downstream (e.g. efficiency, down-time)**
- **Equipment location (e.g. GPS, UPS)**

Content

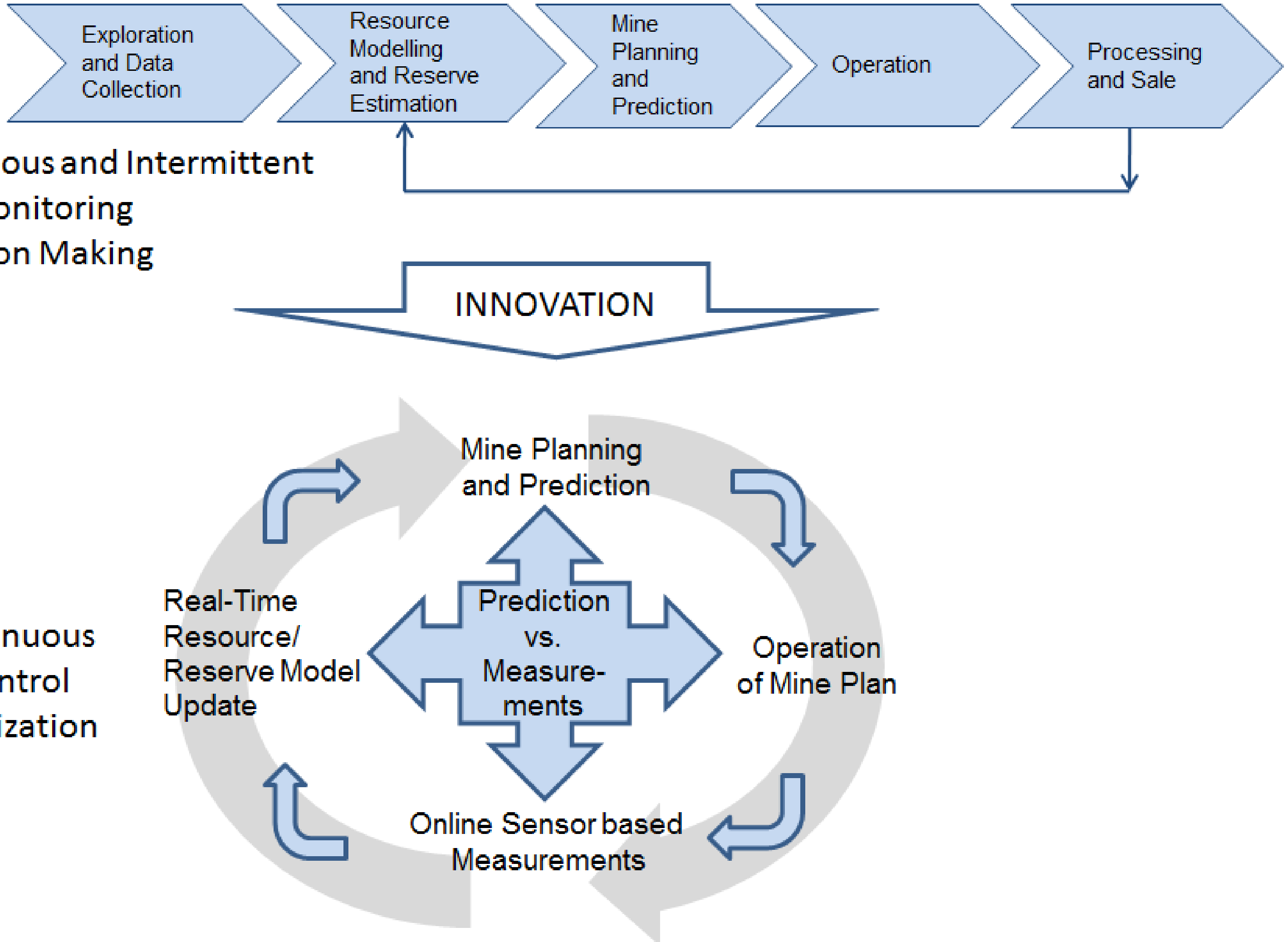
How can we make best use of the available data?

- Closing the Loop: A feed-back framework for Real-Time Resource Model Updating
  - A Kalman Filter Approach
- Using Online Data for Improved Production Control
- Illustrative Case Study: Coal

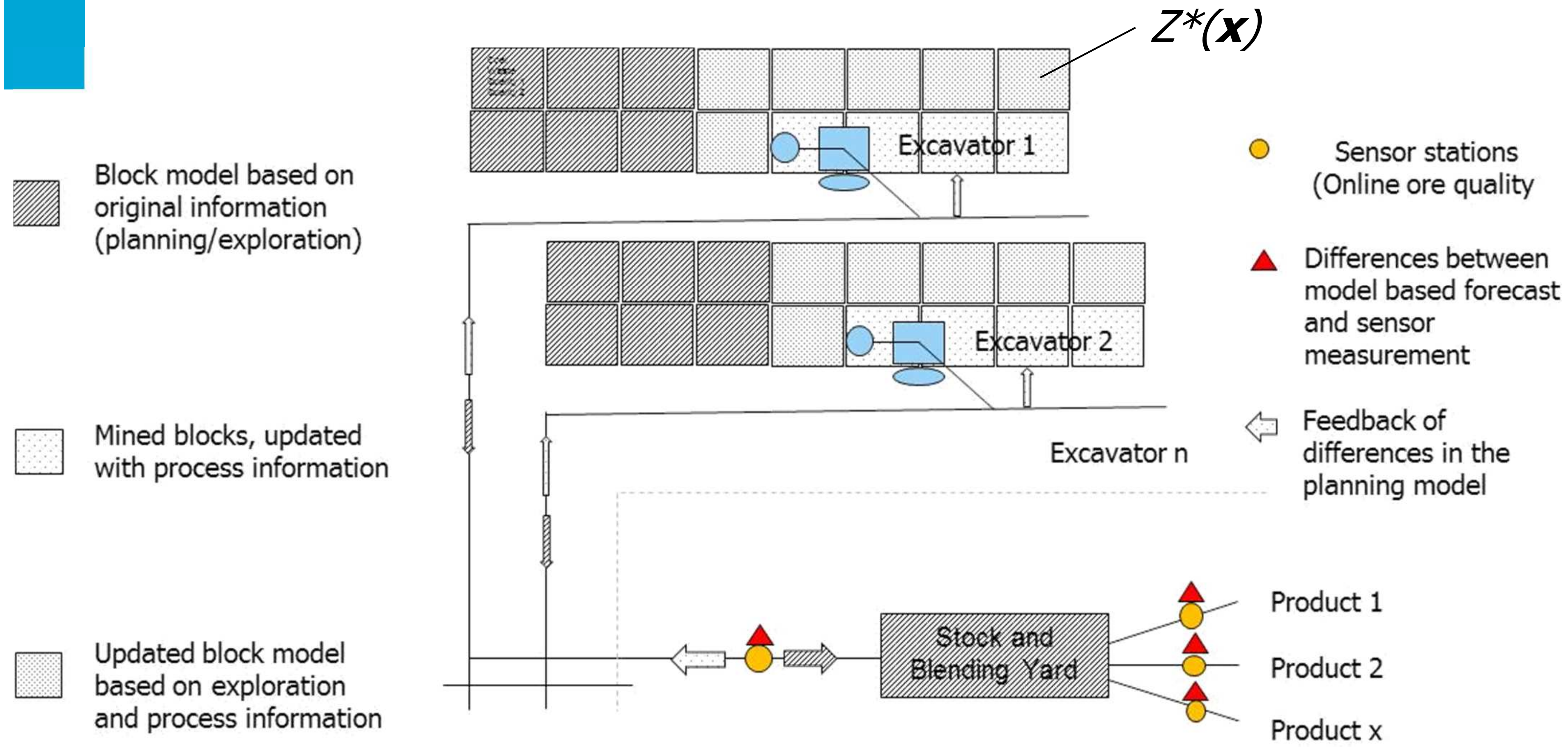
Towards Closed-Loop Management

Discontinuous and Intermittent
Process Monitoring
and Decision Making

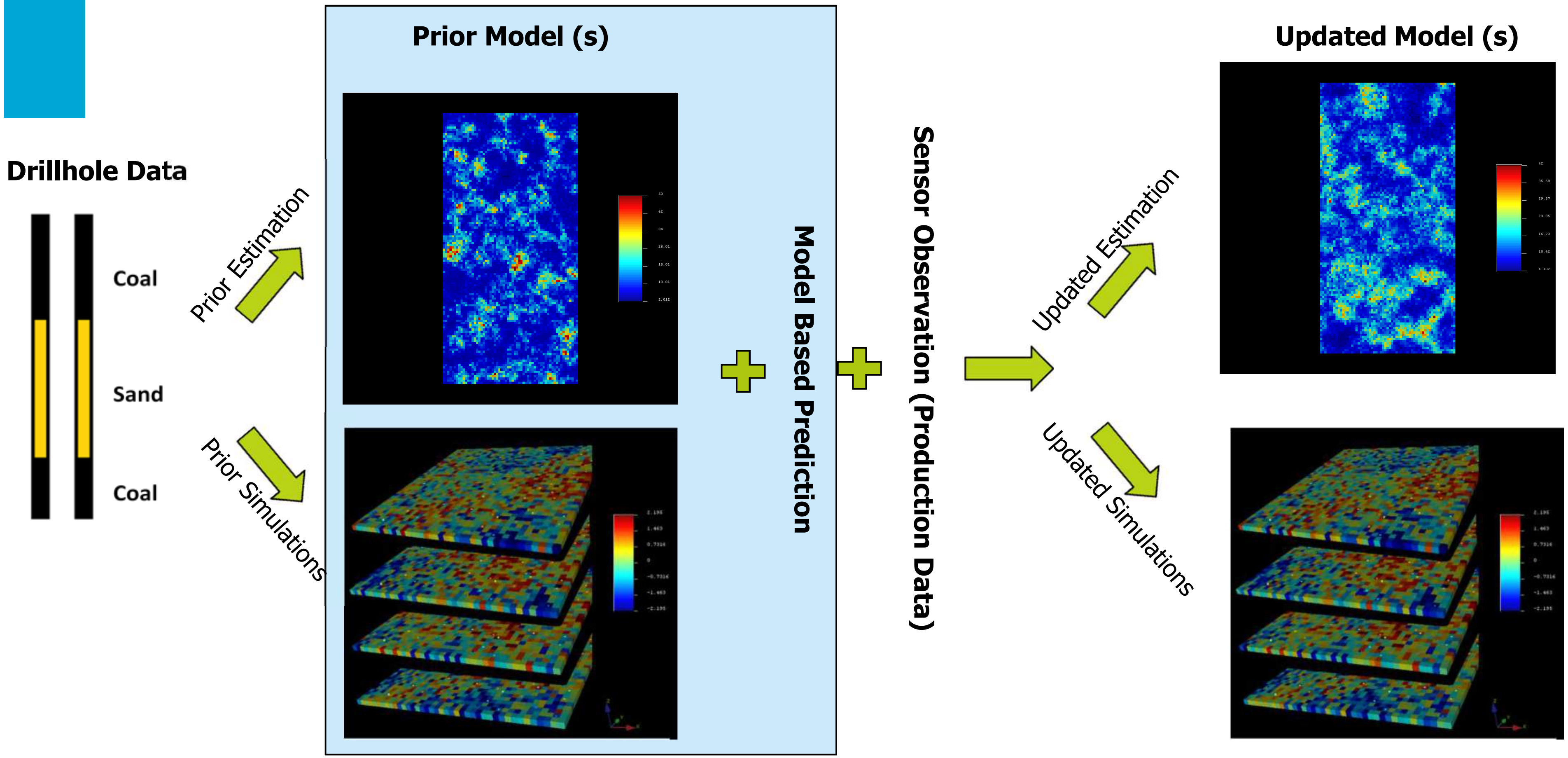
Near-Continuous
Process Control
and Optimization



Towards Closed-Loop Management



Towards Closed-Loop Management



Resource Model

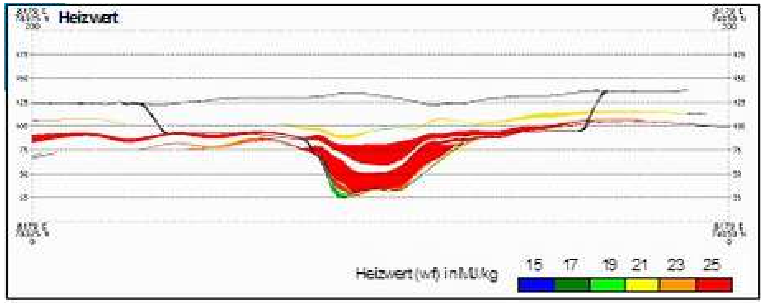
Generation of Prior Models

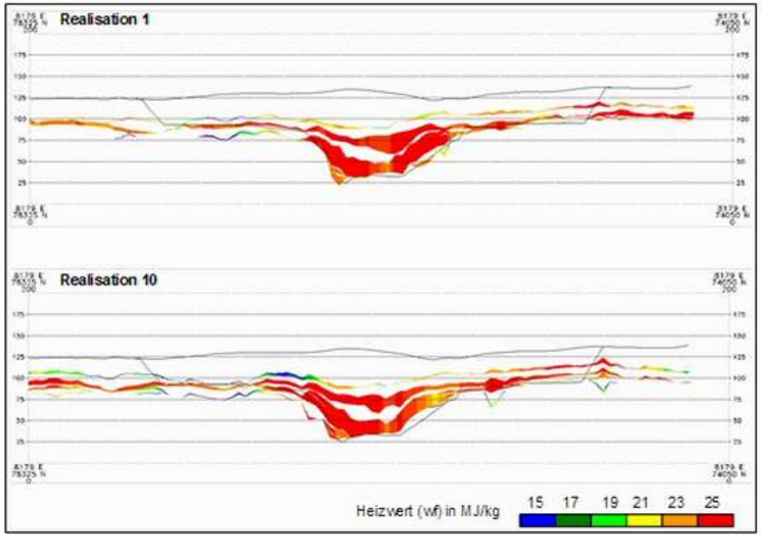
Interpolation (Kriging)

- Best local estimation,
- Minimization of error-variance estimate.

Simulation Realisation 1&10 (Conditional Simulation)

- Represent possible scenarios about the deposit,
- Represent structural behavior of data (in-situ variability),
- Modelled by many different realizations,
- Differences between realizations capture uncertainty

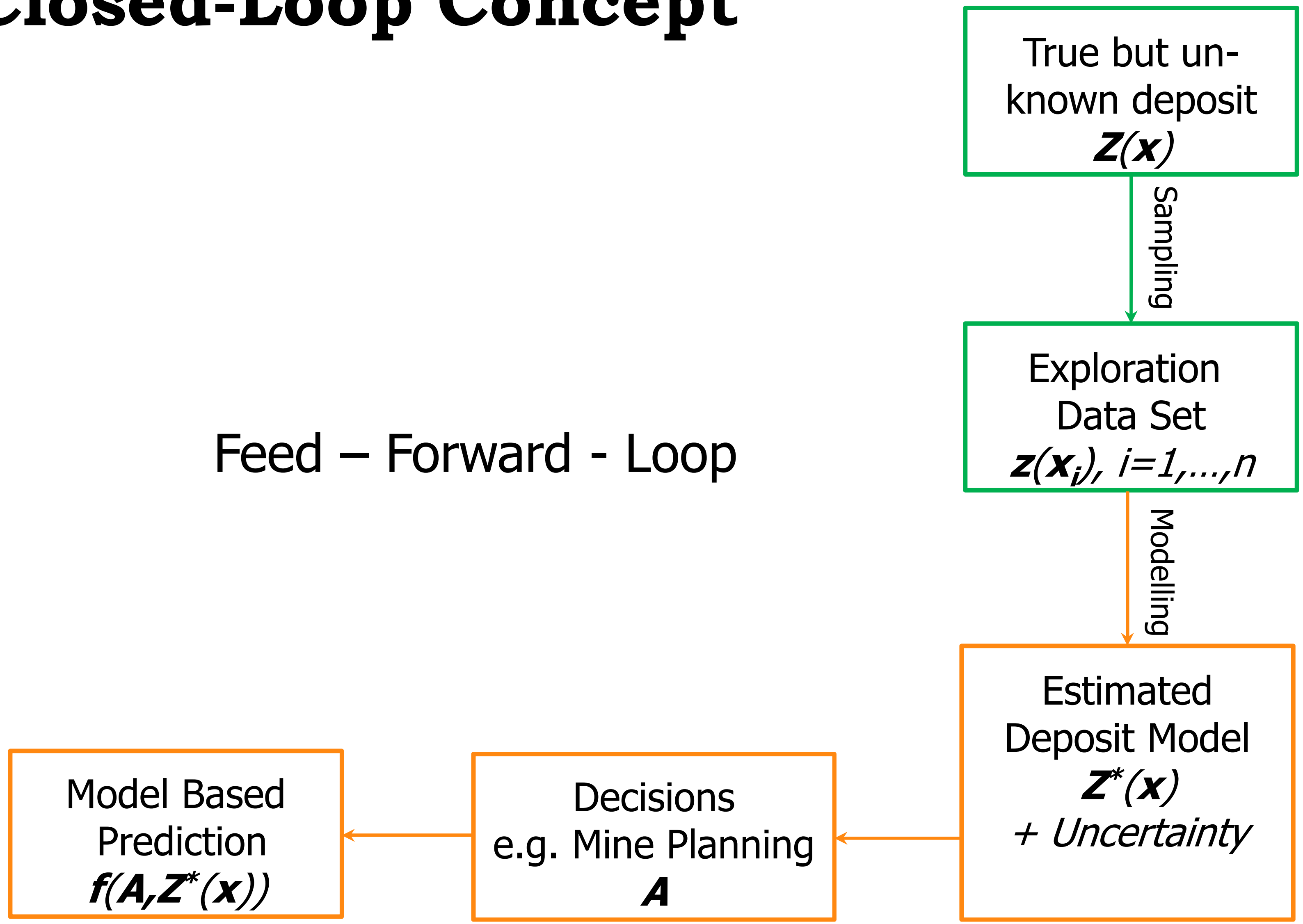




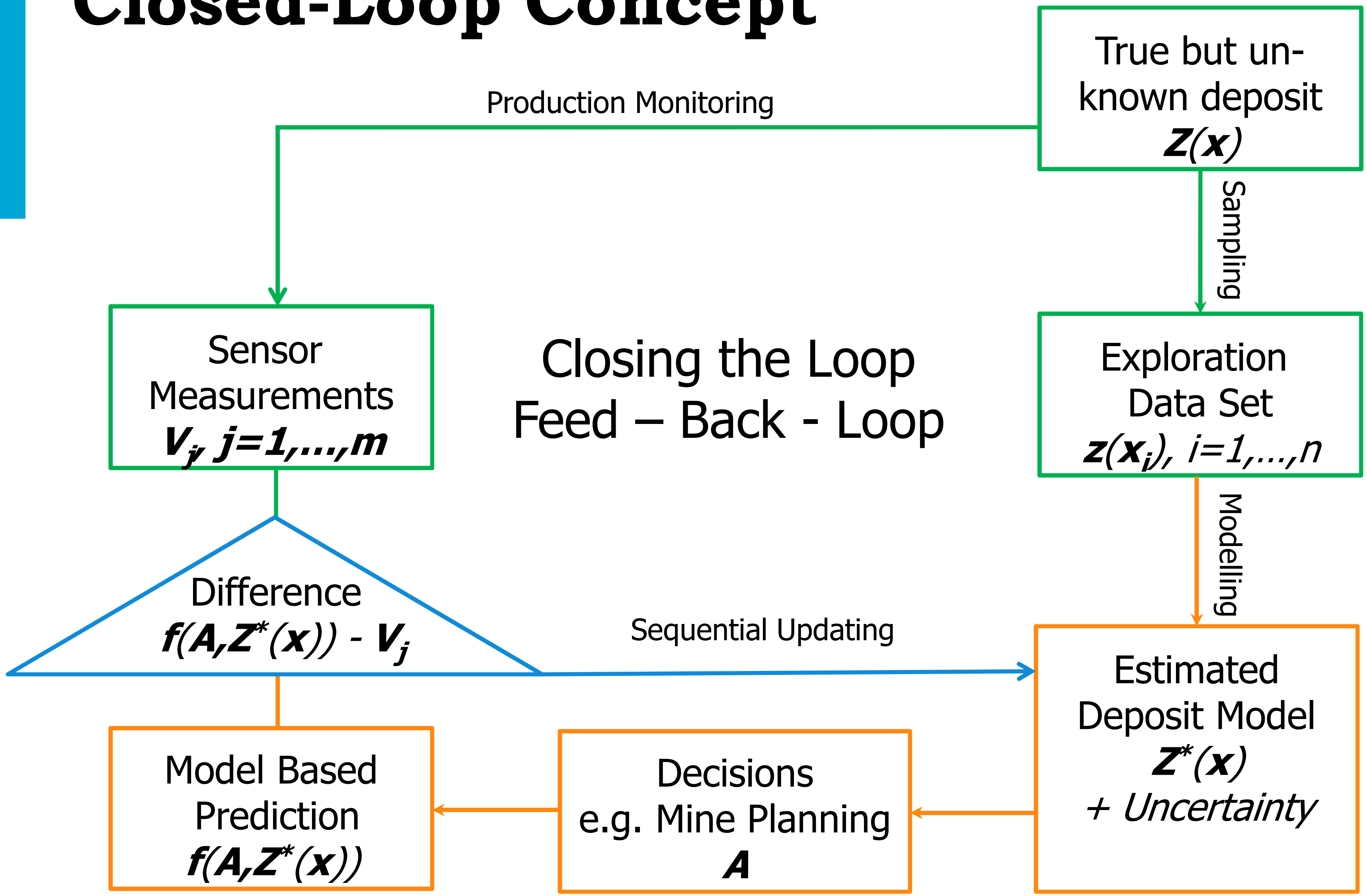
Seam Geometry and CV

(Benndorf 2013)

Closed-Loop Concept

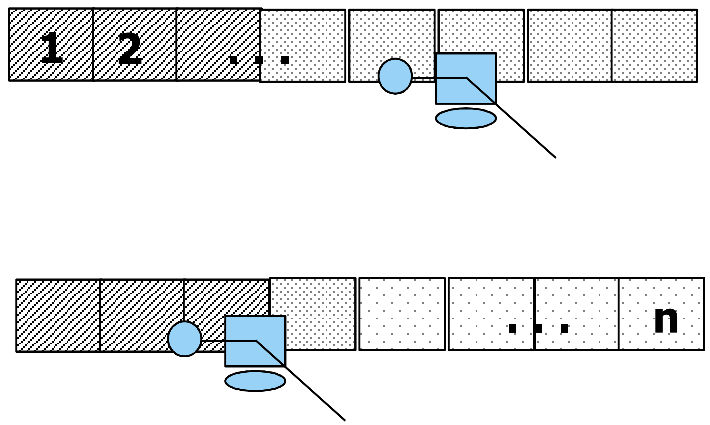


Closed-Loop Concept



Linking Model and Observation

- n mining blocks
- each of the blocks contributes to a blend, which is observed at a sensor station at time t_i
- m measurements are taken
- $a_{i,j}$ proportion block i contributes to the material blend, observed at time j by measurement l_i



Production sequence – Matrix ***A***

$$\begin{array}{cc} & \textit{Mining Blocks} \\ \textit{Observations} & \begin{bmatrix} a_{1,1} & \cdots & a_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,m} \end{bmatrix} \end{array}$$

Resource Model Updating

Sequential Model Updating - A Kalman Filter Approach

$$\boldsymbol{Z}^*(\boldsymbol{x}) = \boldsymbol{Z}^*{}_0(\boldsymbol{x}) + \boldsymbol{K}\,(\boldsymbol{v} - \boldsymbol{A}\boldsymbol{Z}^*{}_0(\boldsymbol{x}))$$

$\boldsymbol{Z}^*(\boldsymbol{x})$ … updated short-term block model (a posteriori)

$\boldsymbol{Z}^*{}_{\boldsymbol{0}}(\boldsymbol{x})$ … prior block model based (without online sensor data)

v … vector of observations (sensor signal at different points in time t)

$\boldsymbol{A}$ … design matrix representing the contribution of each block per time interval to the production observed at sensor station

K … updating factor (Kalman-Gain)

Resource Model Updating

Sequential Model Updating – A “BLUE”

Estimation error:

$$\boldsymbol{e}(\boldsymbol{x})_{t+1} = \boldsymbol{z}(\boldsymbol{x})_{t+1} - \boldsymbol{z}^*(\boldsymbol{x})_{t+1}$$

Estimation variance to be minimized:

$$\boldsymbol{C}_{t+1,t+1} = E\left[\ \boldsymbol{e}(\boldsymbol{x})_{t+1}\boldsymbol{e}(\boldsymbol{x})_{t+1}{}^{T}\right]$$

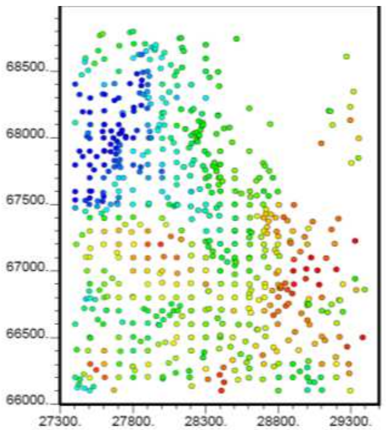
Updating factor:

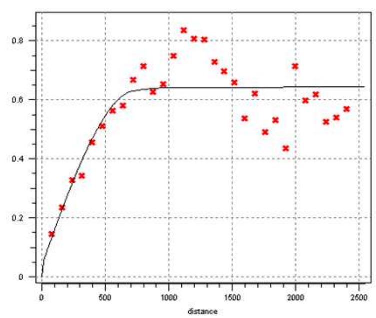
$$\boxed{\boldsymbol{K} = \boldsymbol{C}_{t,t}\boldsymbol{A}^{\boldsymbol{T}}(\boldsymbol{A}\boldsymbol{C}_{t,t}\boldsymbol{A}^{\boldsymbol{T}} + \boldsymbol{C}_{v,v})^{-\boldsymbol{1}}}$$

Resource Model Updating

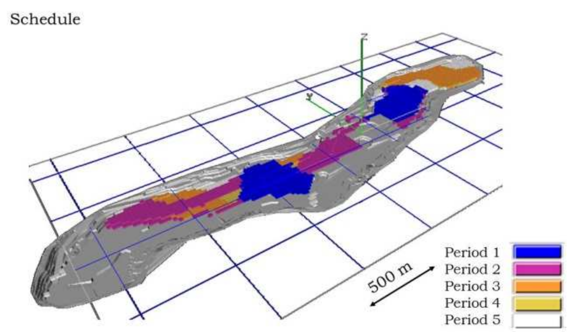
Sequential Model Updating – The Integrative Character

$$\boldsymbol{K} = \boldsymbol{C}_{t,t}\boldsymbol{A}^{T}\left(\boldsymbol{A}\boldsymbol{C}_{t,t}\boldsymbol{A}^{T} + \boldsymbol{C}_{v,v}\right)^{-1}$$





Model Uncertainty



Extraction Sequence

Sensor Precision

Resource Model Updating

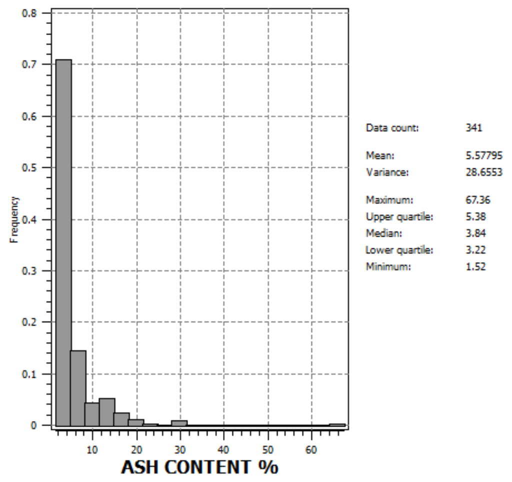
Sequential Model Updating

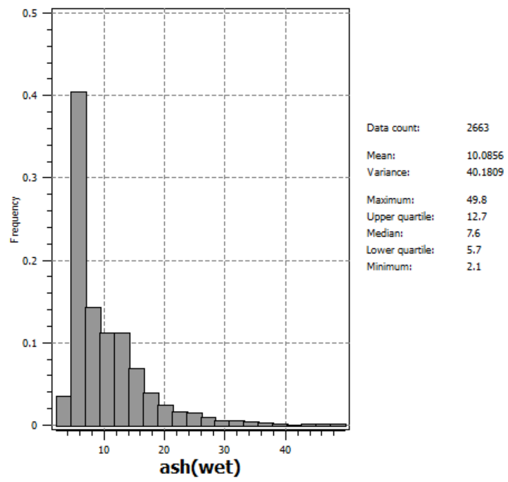
Main challenges:

- Large grids
  - Industrial Case: 4,441,608 blocks

- Non-linear relationships between model and observation

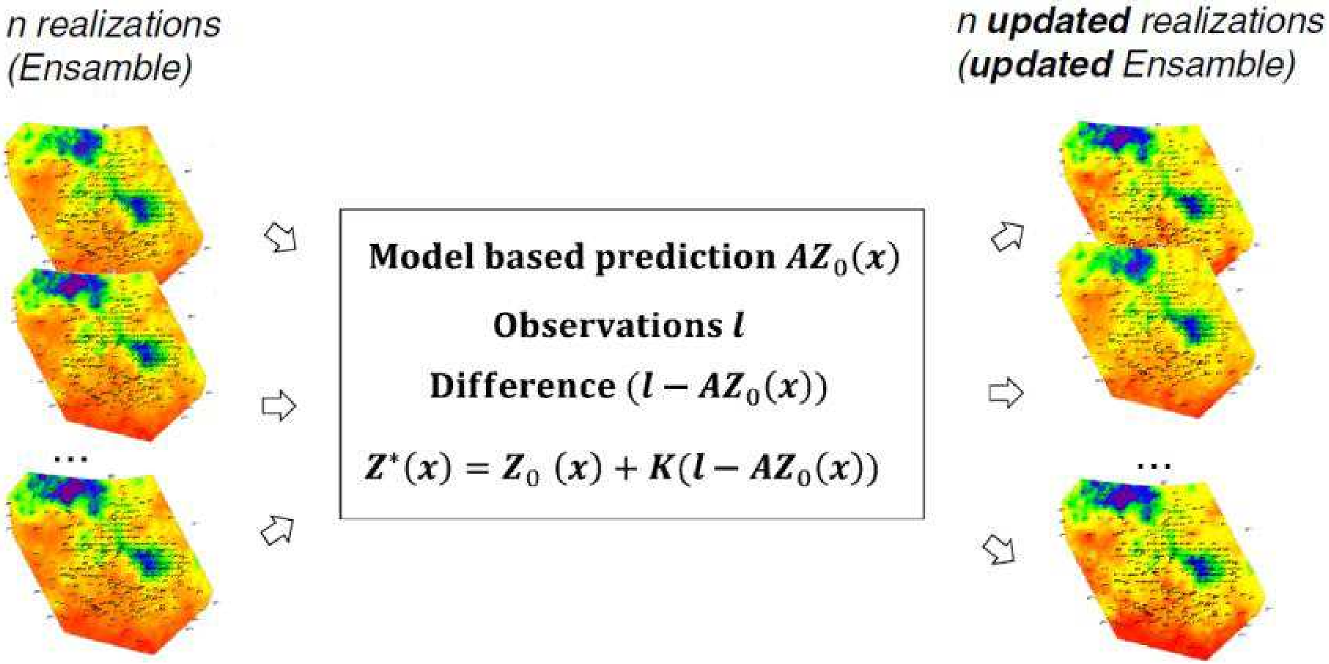
- Non-Gaussian data





Resource Model Updating

Sequential Model Updating
A Non-Linear Version – The Ensemble Kalman Filter

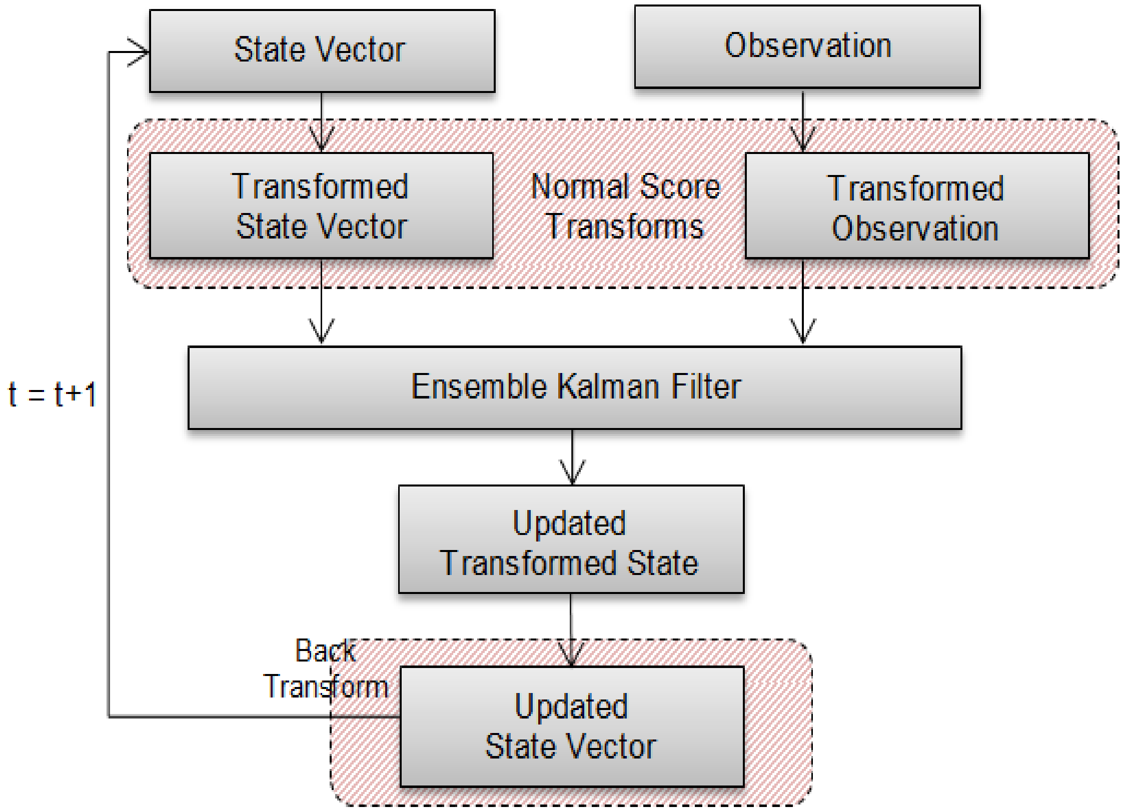


(Reproduced after Geir Evensen 1993)

Resource Model Updating

Sequential Model Updating

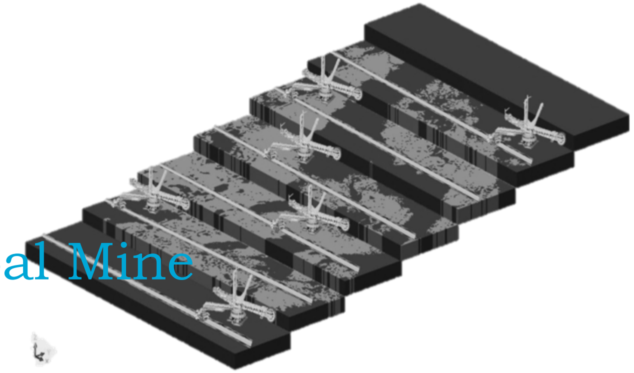
To handle Non-Gaussian Data… N-Score-Ensemble Kalman Filter*



*Z Haiyan, J J Gomez-Hernandez, H H Franssen, L Li. 2011. An approach to handling non-Gaussianity of parameters and state variables. *Advances in Water Resources*, 844-864.

Illustrative Case Study

Updating the Calorific Value in a Large Coal Mine

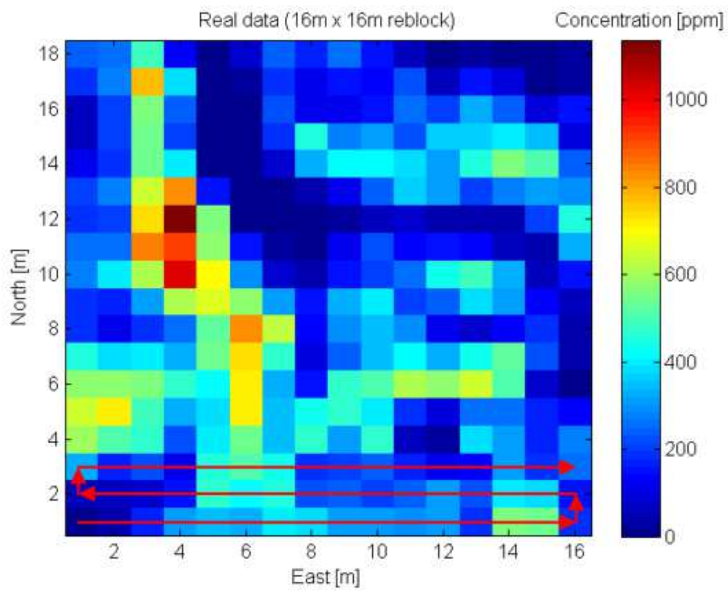


Case Study: Walker Lake Data Set

(Exhaustive “true” data are available)

Model based prediction:

- Estimated block model (5200t/block)
- Capacity Excavator 1: 500 t/h
- Capacity Excavator 2: 1.000 t/h

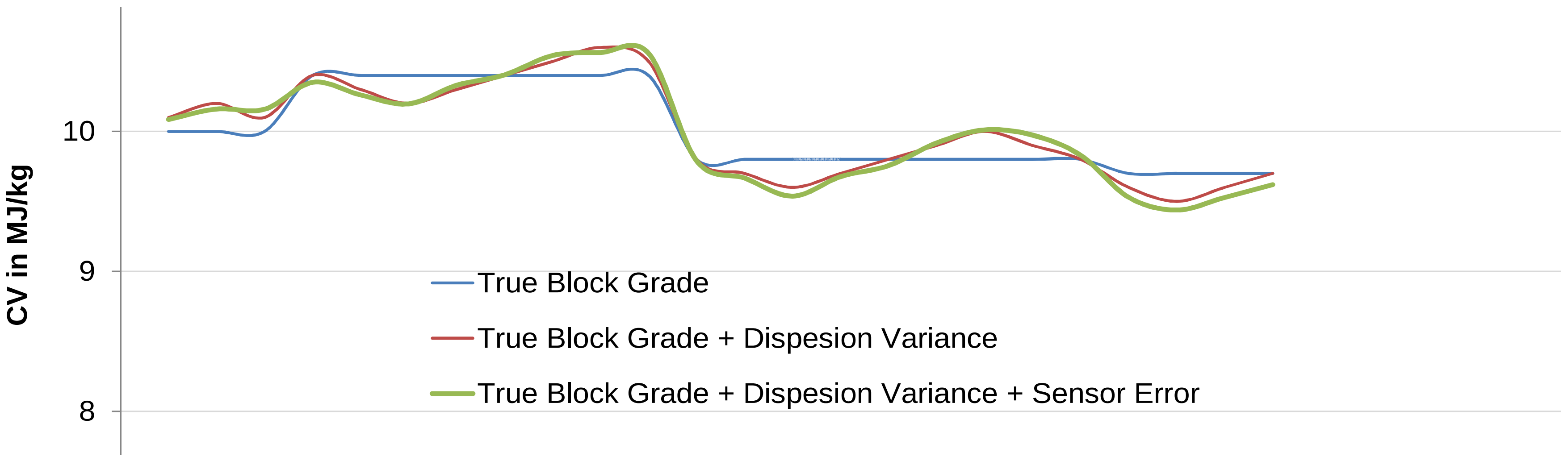


Illustrative Case Study

Updating the Calorific Value in a Large Coal Mine

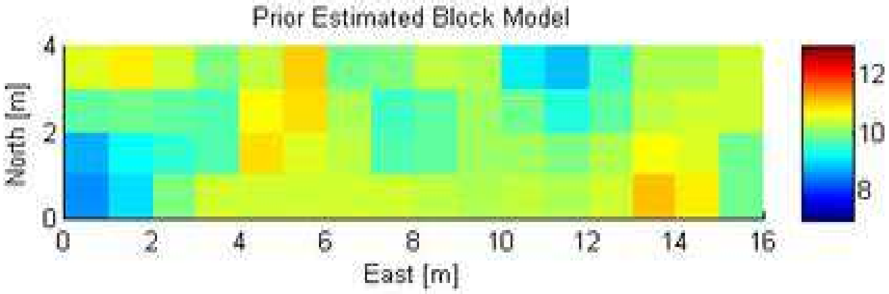
Sensor Observations:

- Artificial sensor data for a 10 minute average (representing 250 t)
- Relative sensor error is varied between 1%, 5% and 10%
- Sensor data obtained:
  - Model based prediction + dispersion variance + sensor error

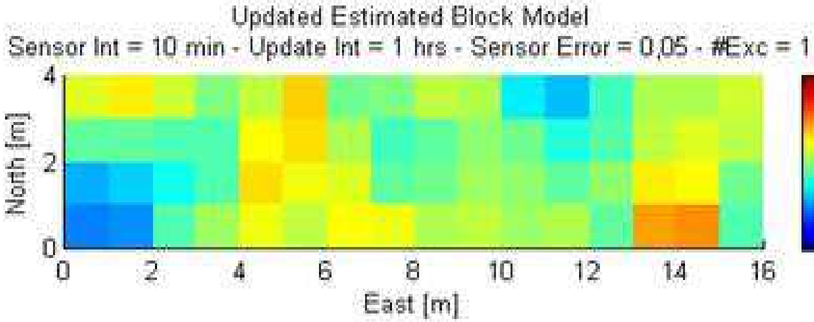


Illustrative Case Study

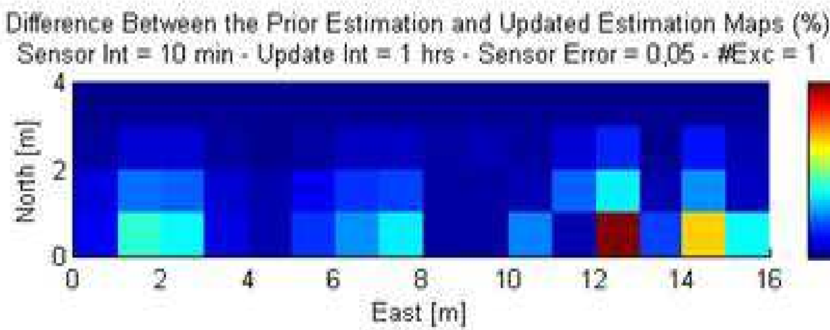
Prior Block Model
based on Exploration Data



Updated Block Model
Integrating Sensor Data

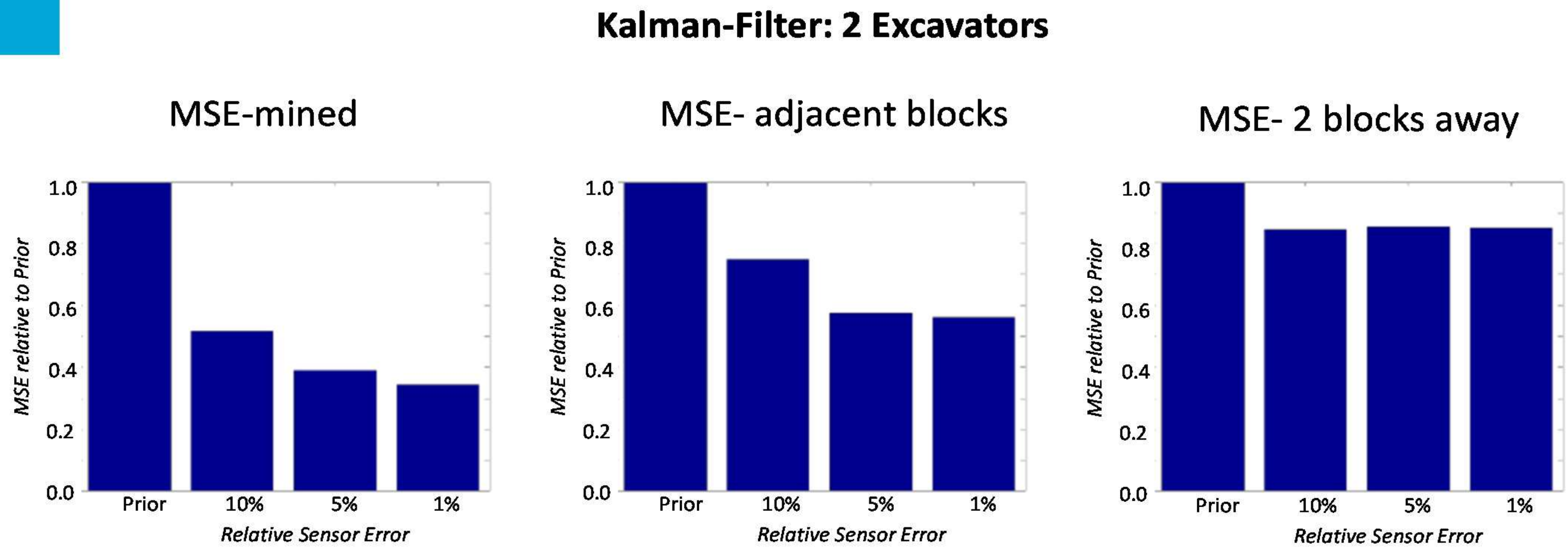


Differences



Illustrative Case Study

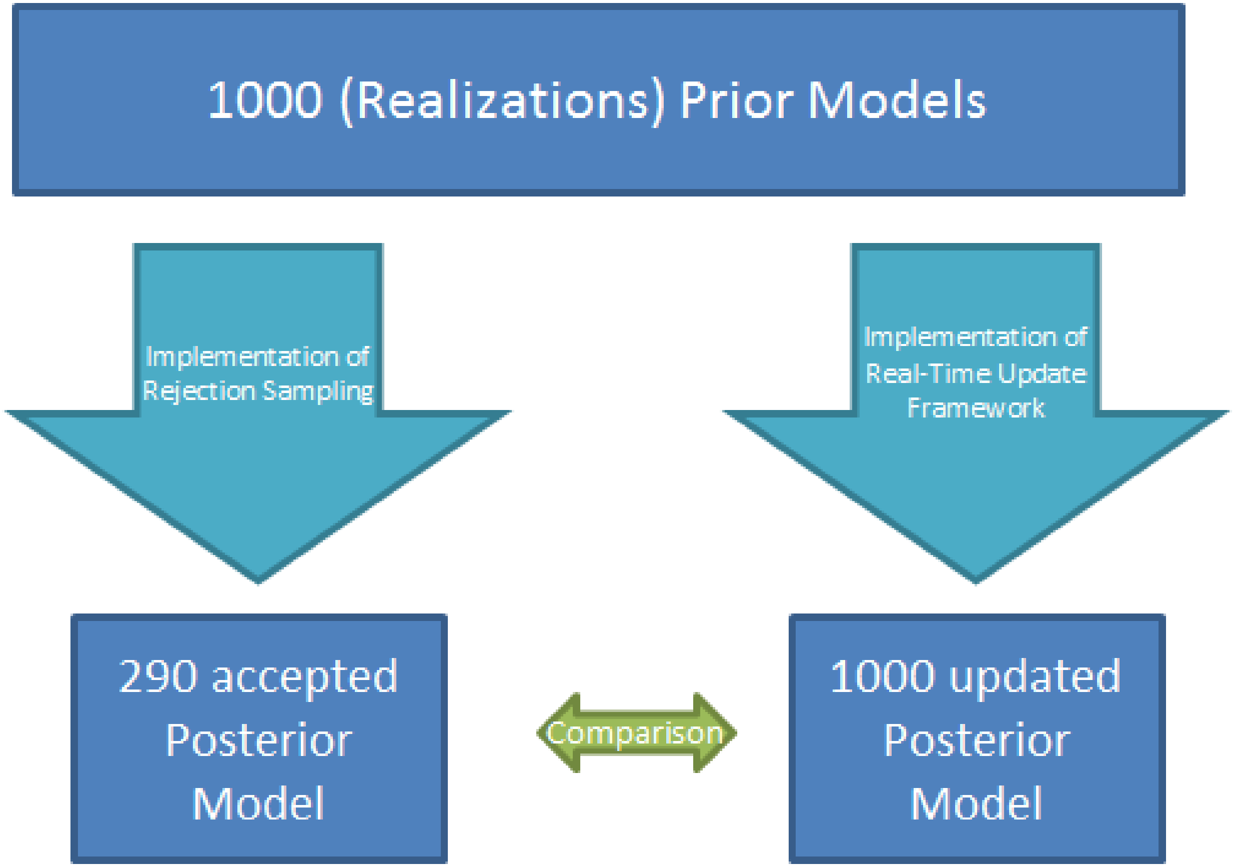
Comparison to Reality



$$\mathrm{MSE} = \frac{1}{N} \sum_{i=1}^{N} (z^*(\mathbf{x}_i) - z(\mathbf{x}_i))^2$$

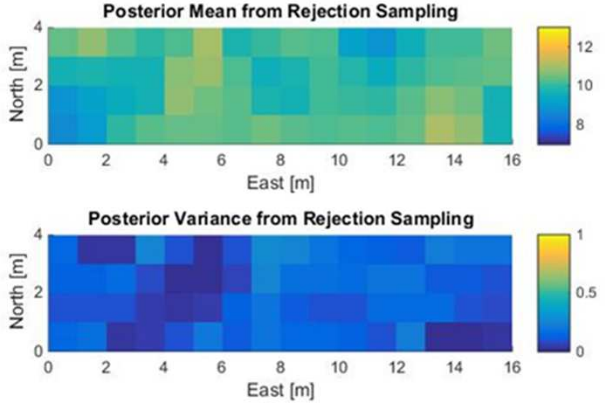
Illustrative Case Study

Rejection Sampling

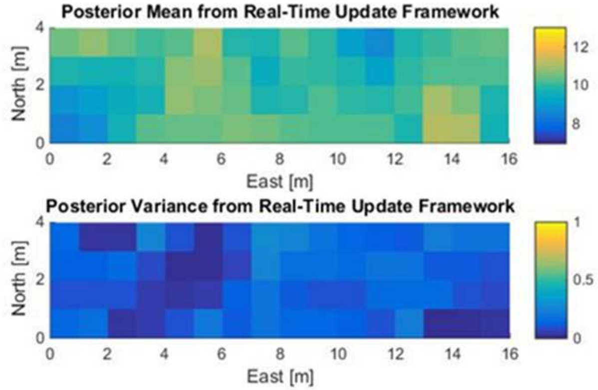


Illustrative Case Study

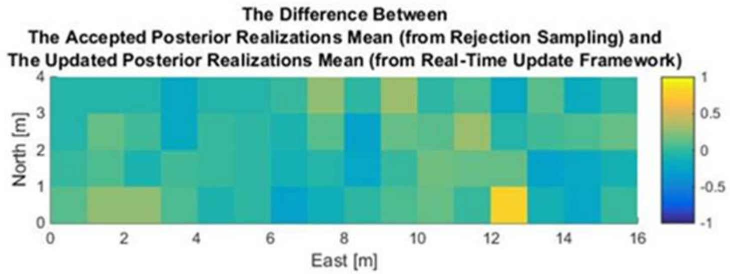
Rejection Sampling



Average mean and variance maps of 290 posterior realizations accepted according to rejection sampling method



Average mean & variance maps of 1000 posterior realizations updated with EnKF framework



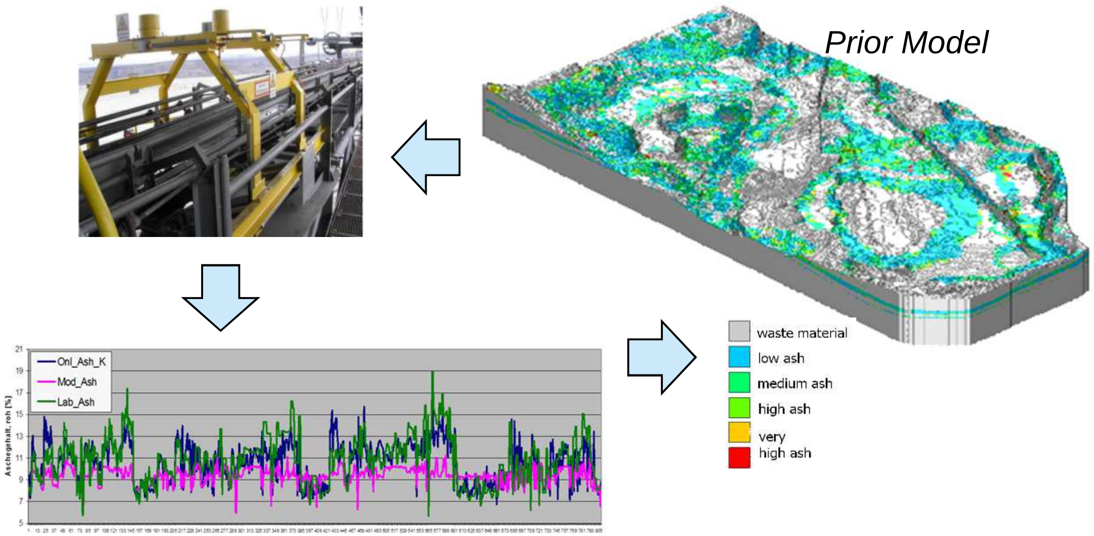
Difference map between the accepted posterior realizations from rejection sampling and updated posterior realizations from real-time update framework

Illustrative Case Study - Results

- Significant improvement in prediction
- Increased confidence in dispatch decisions
    - Less miss-classified blocks (ore/waste)
    - Less shipped train loads out of spec
- Increased customer satisfaction and revenue
- Magnitude of improvement depends on level of exploration, variability and sensor error

Current Work

- **EU - RFCS funded project RTRO-Coal**



with partners:

Conclusions

- Modern ICT provides online data, which can be the basis for (near-) continuous process monitoring at different stages of the mining value chain

- Utilizing these data for (near-) real-time decision making offers huge potential for more sustainable extraction of mineral resource

- Closed Loop Concepts offer:

  - Integration of prediction and process models with data gathering

  - Interdisciplinary and transparent project communication (breaking the silos)

  - More complex use of data for increased resource efficiency


Thank You for Your Attention
Contact: Cansın Yüksel
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Source: RWE