CIM public lecture:

Geometallurgical workflows to optimize mining decisions

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Geometallurgy

- A definition:

  Geometallurgy combines geological, mining and metallurgical information to create **spatially-based predictive models for mining, mineral processing and metallurgy** that can be used **to optimize the decisions**, given all other key project constraints such as environmental restrictions, water availability and energy efficiency.

- There have been many efforts to provide an integrated view of processes in the mining value chain (geology-throughput, mine to mill, clays-flotation, etc.)



Motivation

- **Geometallurgy** has an impact in all stages of the mining business, from early scoping phase, project feasibility study, project development, operational optimization, to mine closure.

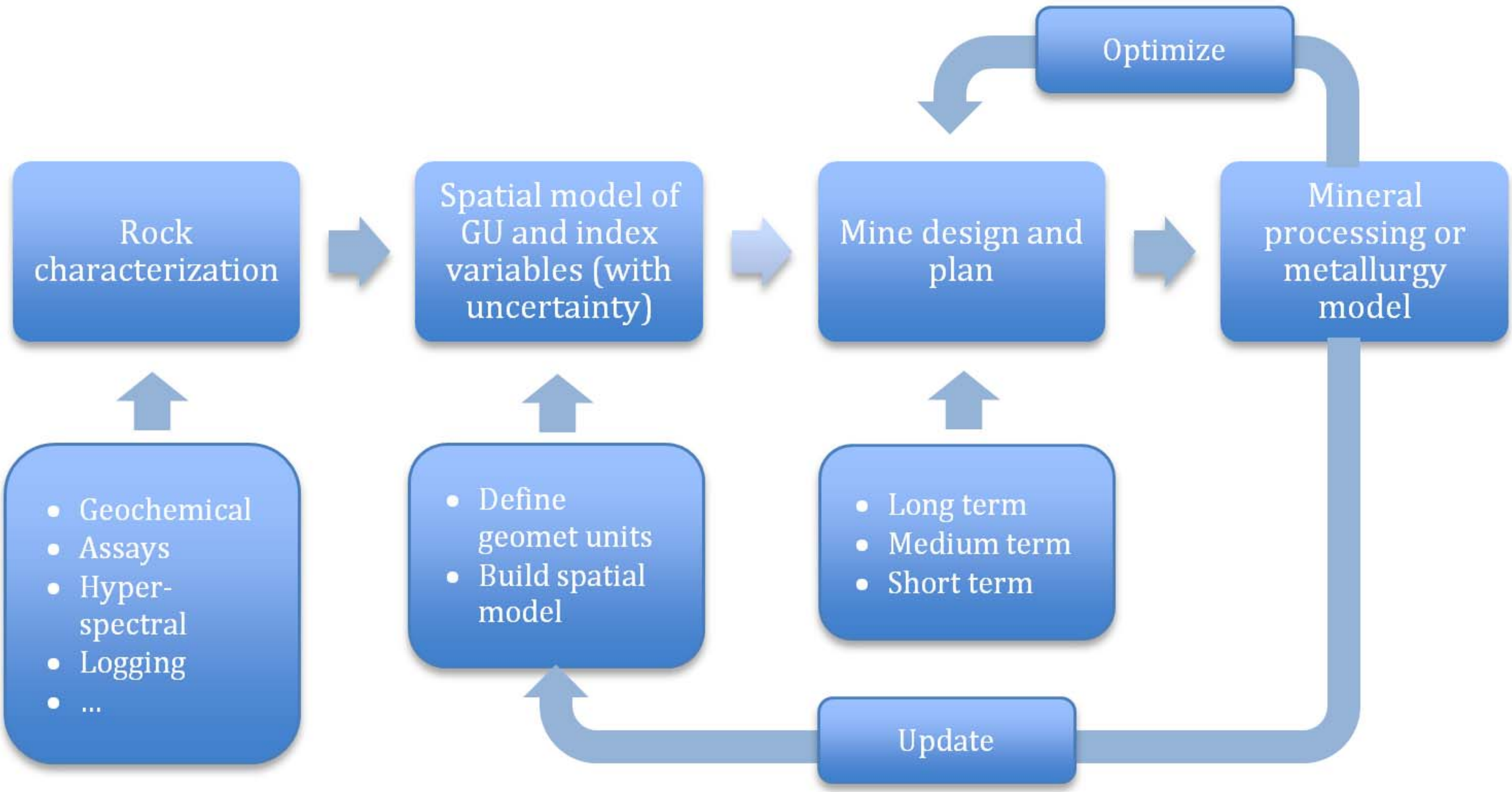
- Steps in geometallurgical modeling can be seen as **building blocks of a workflow**.

- Example:
  1. Acquire geochemical **data**, geological logging, chemical analysis of elements of interest and hyperspectral data.
  2. Perform **metallurgical tests** over representative samples taken in different domains to understand the performance to a given process.
  3. Characterize **geometallurgical units** related to a given process by clustering samples with similar performance into units.
  4. Build a **spatial model** of the geometallurgical units and of the attributes of interest using conventional geostatistical tools.
  5. Infer the **process behavior** based on the local characteristics of each block of material.

- Application is not linear: needs iterations and many “not so easy” steps

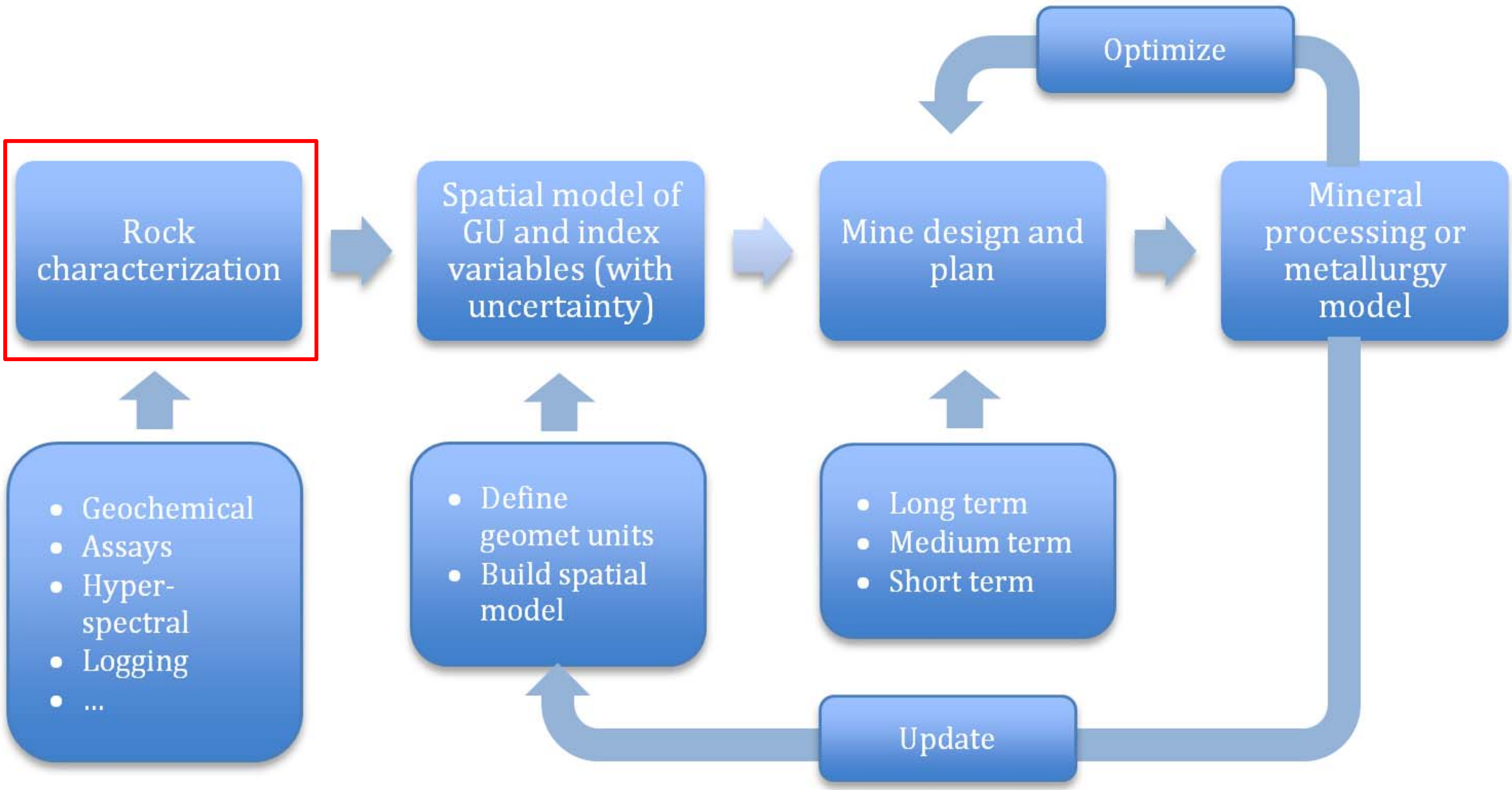
Motivation

General workflow



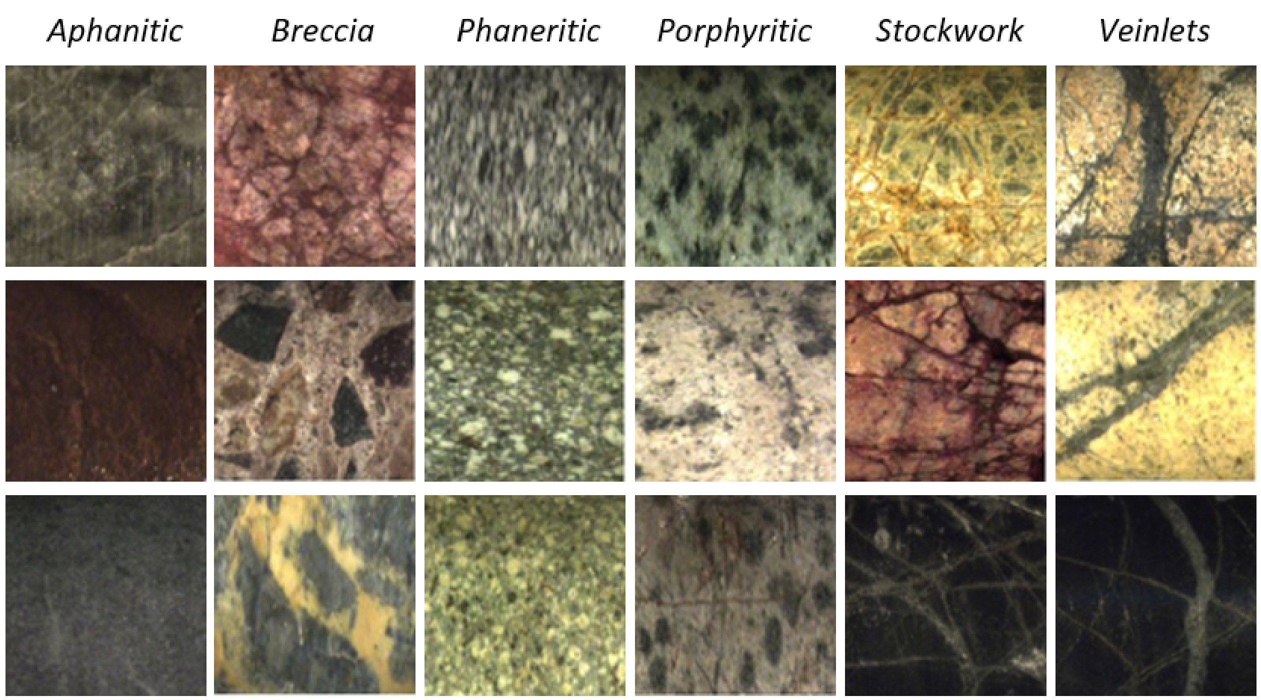
Motivation

General workflow



Application 1: textures characterization and classification

- Link between textures and mineral processing performance
- Make use of drillhole photographic records to automate the texture logging
- Three stages:
  - Proof of concept of texture classification
  - Further development of algorithms and applications
  - Pilot testing with real images

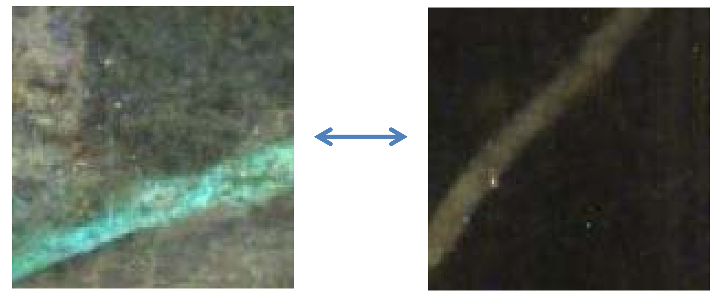


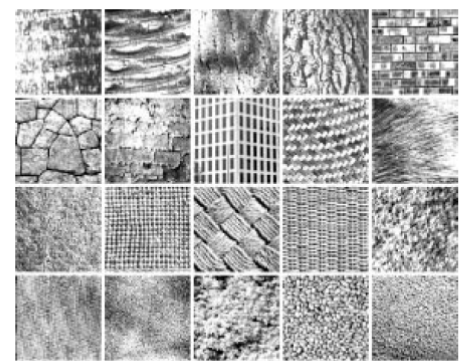
Databases

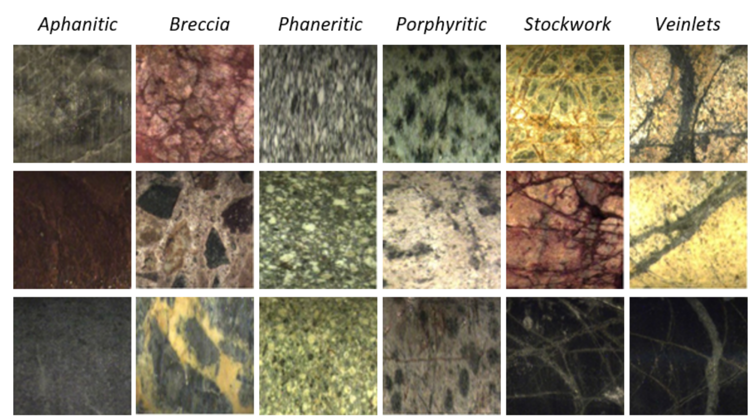
- 16 x 6 photos of clean textures for proof of concept (all labelled)
- Sampling images of bubbles distribution in froth flotation cells to discriminate reagents
- Scanned high resolution drillcore images of 1200m at a porphyry copper deposit

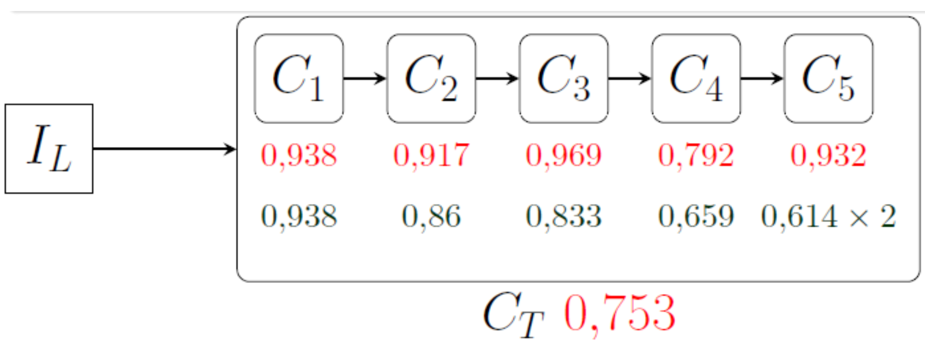
Application 1: textures characterization and classification

- Three stages:
  - Proof of concept of texture classification
    - A hierarchical classifier with 5 binary steps
      - Need to separate “texture” from “structure”
      - Features easy to discriminate were identified for each binary classifier
        - Wavelet and shearlet transforms, total variations, filters
      - Similarity: MSE, SSIM, Kullback-Leibler distance
    - Tested in natural rock textures data base and image analysis textures data base





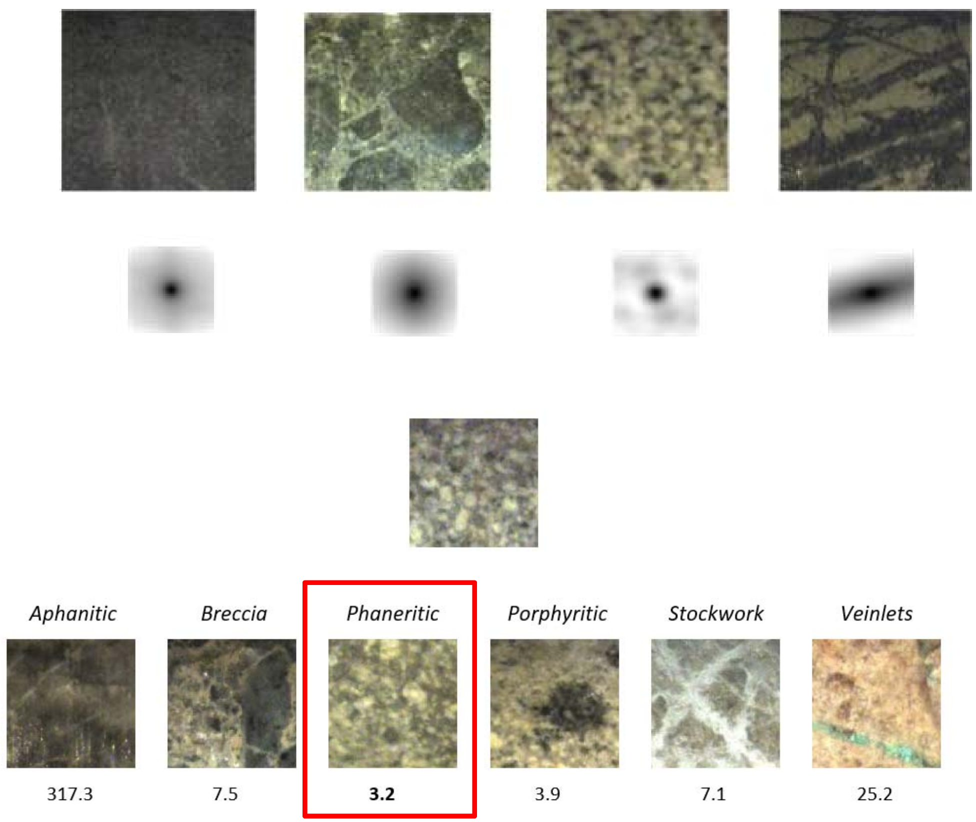


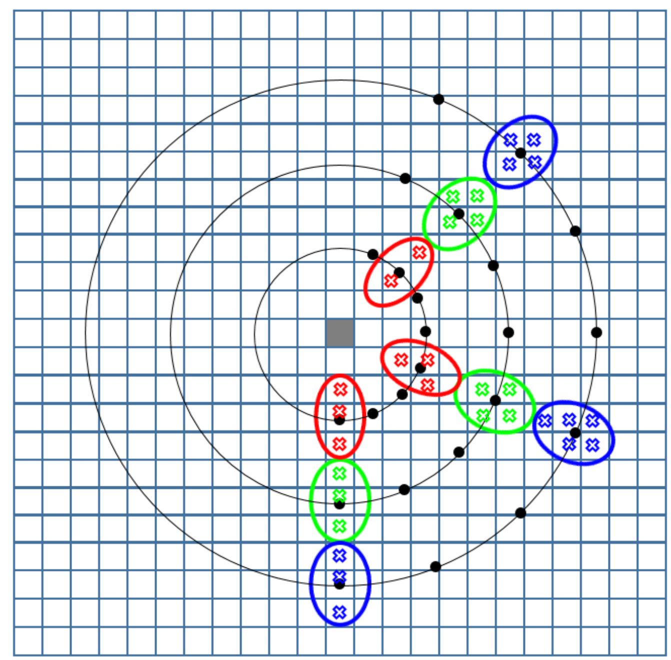


Application 1: textures characterization and classification

- Three stages:
  - Further development of algorithms and applications
    - Use of variogram map
    - Use of compact variogram

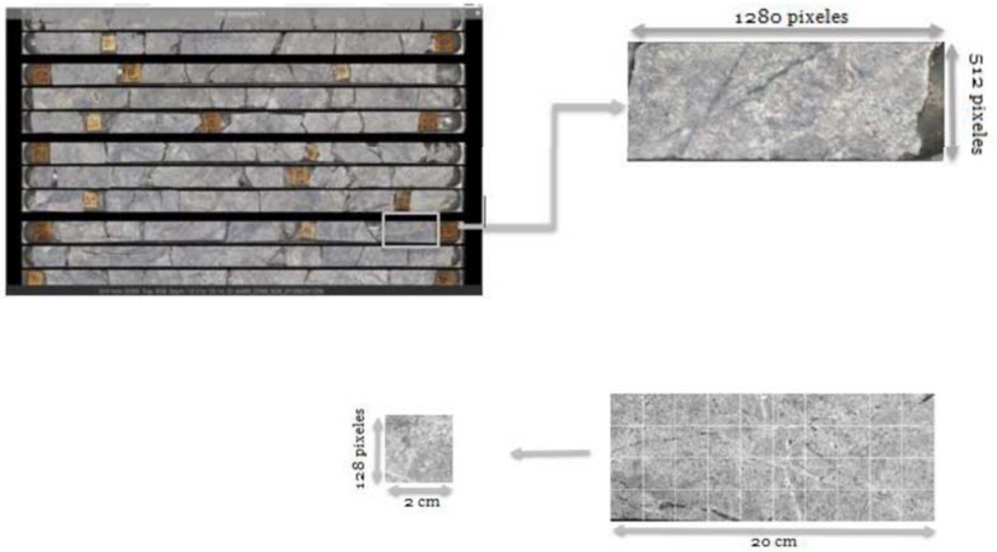
$$\gamma(h) = \frac{1}{2N(h)} \sum_{k=1}^{N(h)} \left(Z(x_k) - Z(x_k + h) \right)^2$$





Application 1: textures characterization and classification

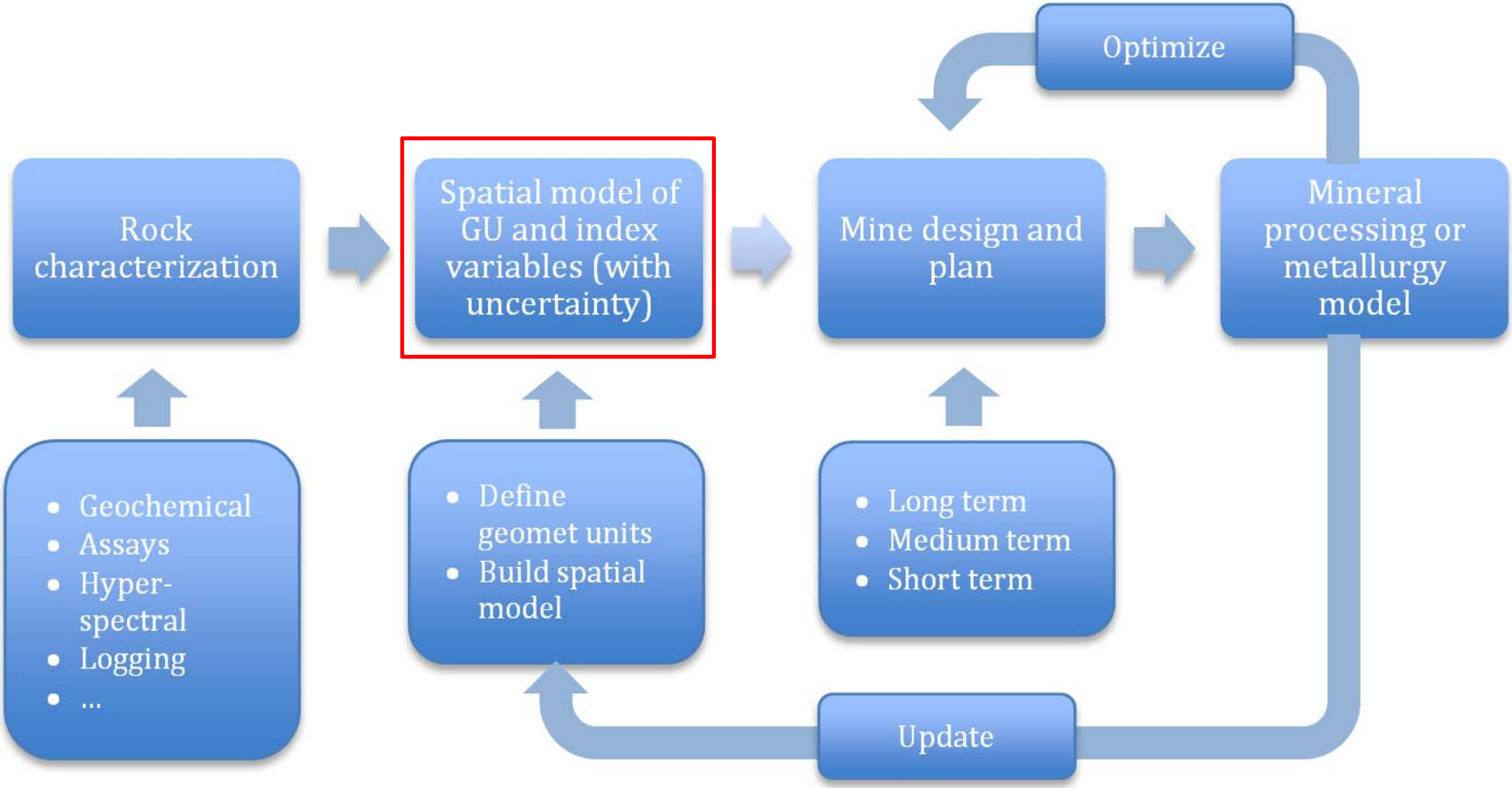
- Three stages:
  - Pilot testing with real images
  - 14000 images
  - 326 samples logged by two geologists
  - Procedure
    - Automated process (64.0% match)
    - Review of misclassification cases
    - Preprocessing (filtering and normalization)
    - Reprocessing (84.8% match)



In conclusion:
- Using the photographs of drillcores is possible.
- We could populate the database with texture classes (up to a % of error), based on a very low number of logged textures done by a geologist, and achieve an ~85% accuracy.
- Textures could be used for domaining, and their relationship with mineral processing performance, could be tested.

Motivation

General workflow



Application 2: modeling of alterations as a proxy for flotation behavior

- Link between alteration types and flotation performance in porphyry copper deposits
- Alterations are logged by geologists → label
- Quantitative characterization of each alteration type allows for better prediction of flotation performance. Geochemical concentrations are used along with the logged alteration types to automate the alteration labelling to get more consistent prediction

Hydrothermal alterations

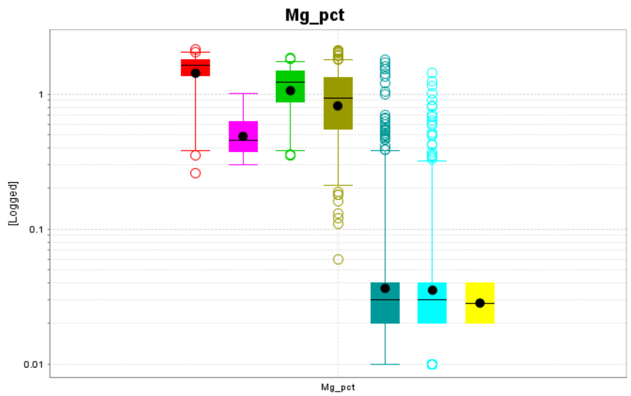
30	K1	Potasic Biotitic
31	K2	Potasic Feldespatic
40	SCC1	Chl-Ser-Clay
41	SCC2	Chl-Ser-Qz
51	S1	Ser-Qz
52	S2	Ser-Qz-Clay
61	AA	Argillic Supergene

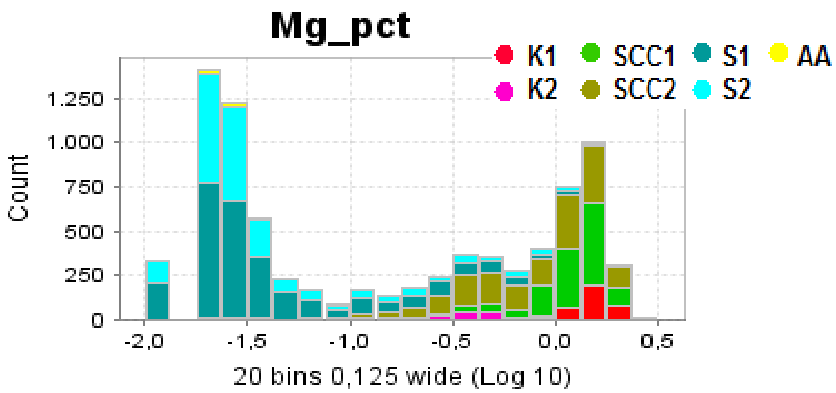
Database
- Represents about 10 years of sampling
- Digestion method: Aqua Regia
- Total database: ~ 32.000 samples
  - 9 major elements [wt%]
    - Al, Mg, K, Ca, Na, S, Cu, Fe and Ti
  - 33 trace elements [ppm]

Variable selection and aggregation → Classification to define geomet units (GU) → Spatial model of GU and index variables → Predictive model of metallurgical behavior

Application 2: modeling of alterations as a proxy for flotation behavior

1. Variable selection and aggregation, based on correlation with response





- Several approaches to define **most discriminant variables** for each alteration type
  - Univariate analysis
  - Forward selection model

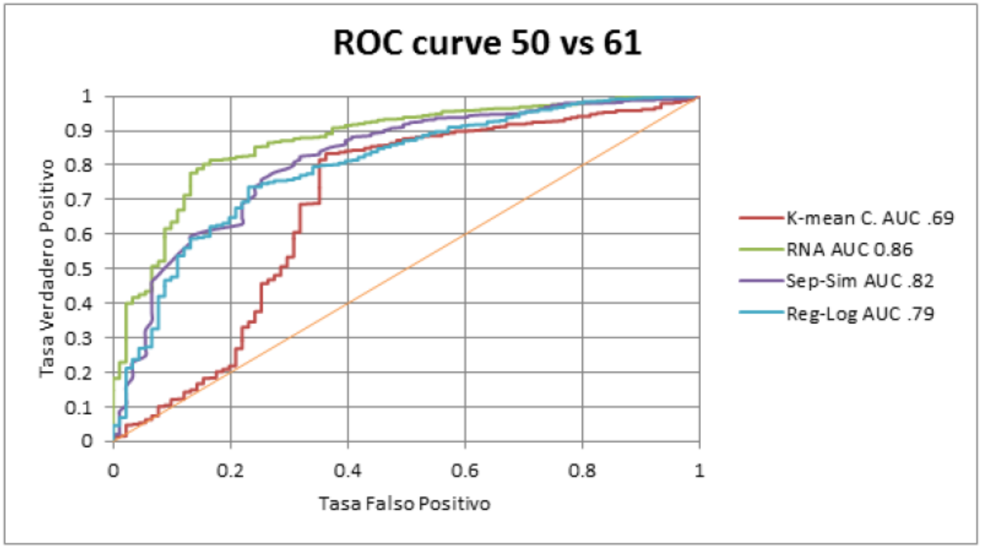
- Synthetic variables are used to highlight features of each alteration
  - K*Al highlight sericite/muscovite in phyllic alteration
  - Al/Mg highlight Al-rich clays in argillic alteration over the Mg-rich clays dominant in other alteration types
  - K/(Ca+Na) highlight the exchange of K cations over Ca and Na in potassic alteration

Application 2: modeling of alterations as a proxy for flotation behavior

2. Classification to define geometallurgical units

- Selected geochemical variables are used to classify alterations
  → maximize matching with logged labels
  → Identify zones where logging may require revision

- Classification methods
  - Max discrim based on single variables
  - K-means clustering
  - Logistic regression
  - Artificial neural networks



- Construct classification tree to label each sample

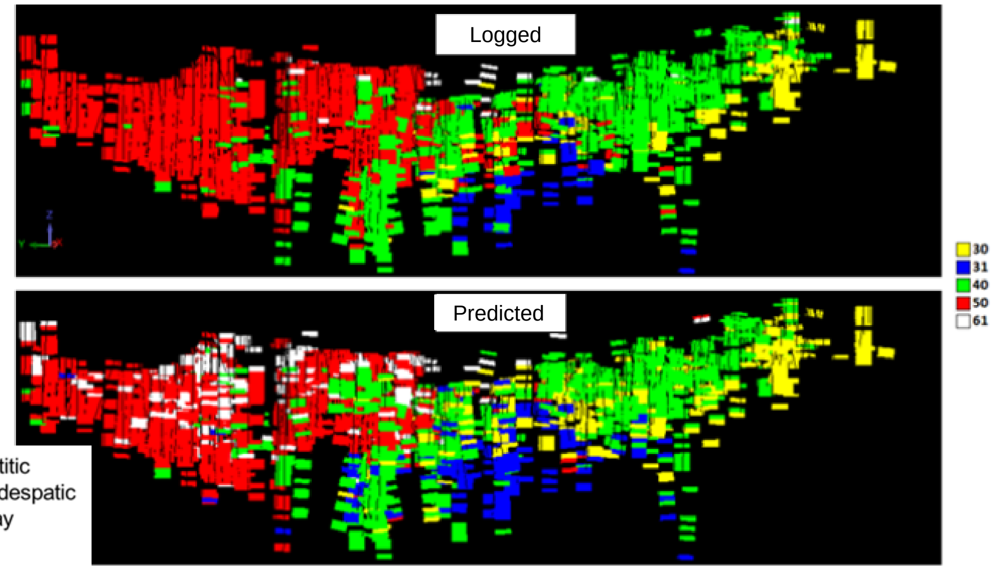
- ROC graphs are used to select best method.

- Analysis can be completed by using membership functions to describe the uncertainty related to the labelling of the alteration type

Application 2: modeling of alterations as a proxy for flotation behavior

3. Spatial model of geometallurgical units

- Once individual samples have been labelled, they are used to construct a spatial model of geometallurgical units
- Done by conventional 3D modeling techniques or by means of geostatistical methods



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61	AA	Argillic Supergene

Comments:

- Analyzing some sections, we can identify areas where mapping was difficult. These drill cores could be re-logged to check the alteration logged, hence improving the result
- Alternatively, if matching is high, alteration type could be “predicted” from geochemistry only

Application 2: modeling of alterations as a proxy for flotation behavior

4. Spatial model of index variables

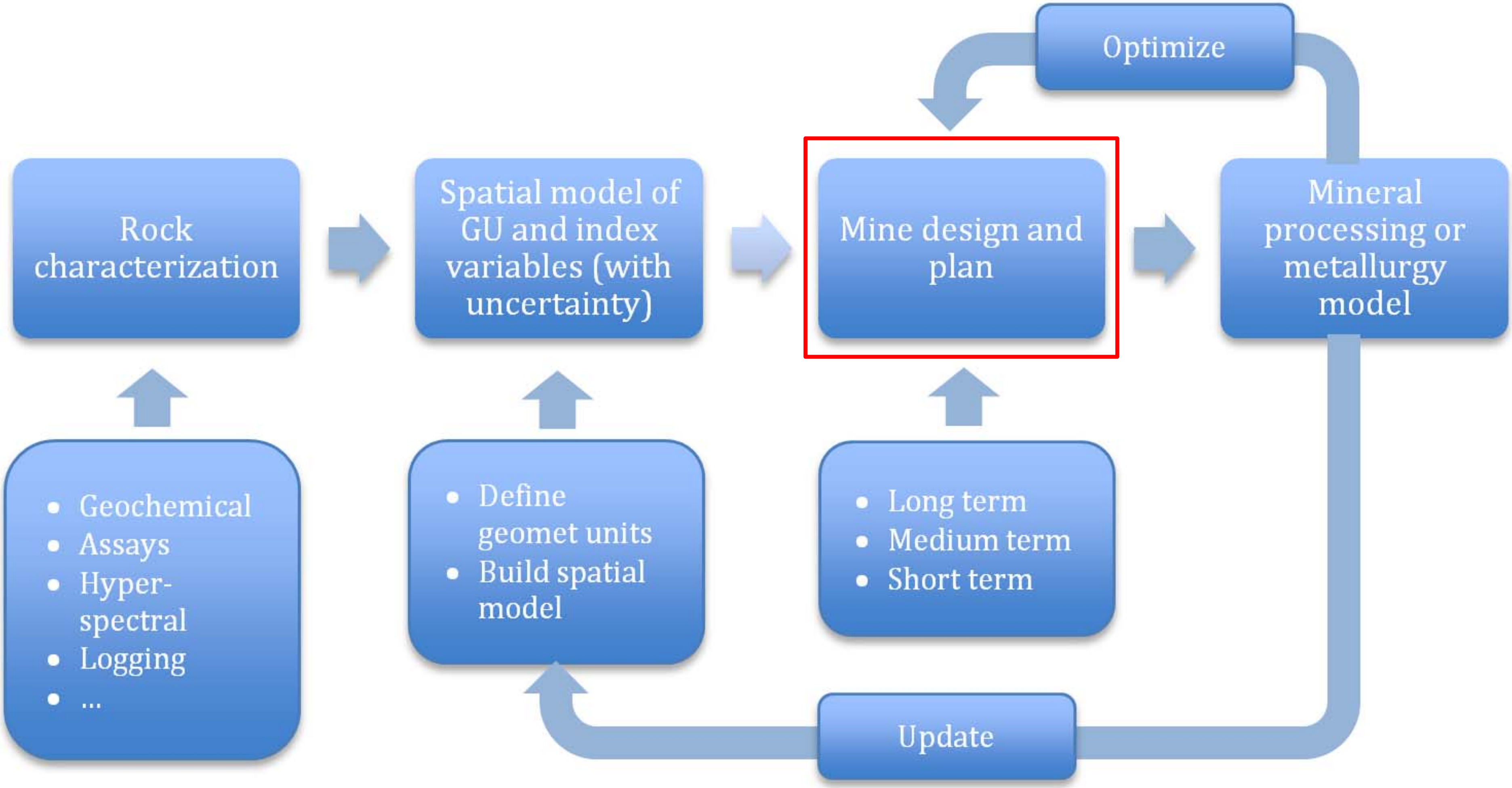
- Index variables (variables deemed more relevant to predict the response) are modeled in space
  - Geostatistical cosimulation → captures the cross relationship and quantifies uncertainty
- Scaling is required to go from the lab assay support to the support that relates to the processing rate

5. Predict metallurgical behavior in space

- Relate index variables with geometallurgical response of interest using conventional multivariate statistics

Motivation

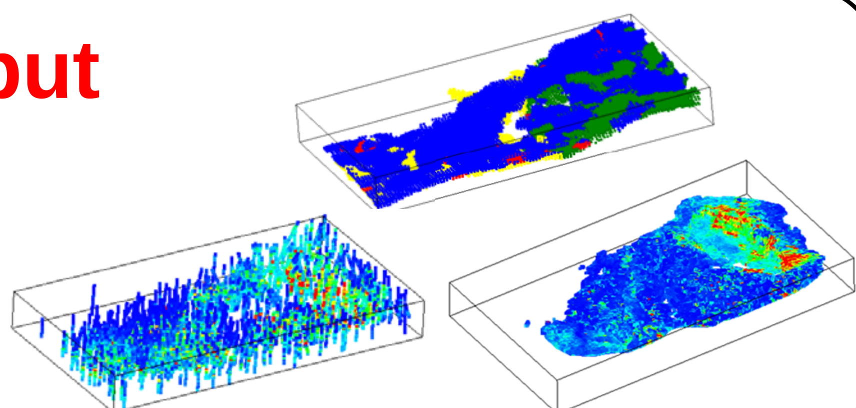
General workflow



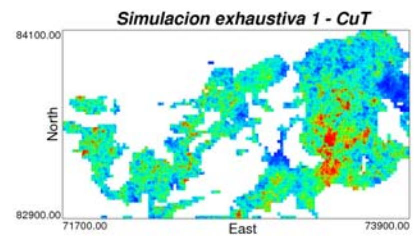
Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning

- Blast hole sampling errors may have a significant economic impact in **short term planning**.
- In this application, the impact of changing the sampling methodology (from conventional BH sampling to advanced RC drilling with automatic sampling) is assessed in an open pit mine.
- Several aspects are studied and their economic impact quantified:
  - **Information quality**: effect of sampling error (precision), systematic bias, geological interpretation
  - **Information quantity**: effect of advanced RC drilling spacing as compared to BH sampling at the blasting spacing.
  - **Estimation method**: effect of implementing kriging Instead of IDW, and estimation parameters

Input



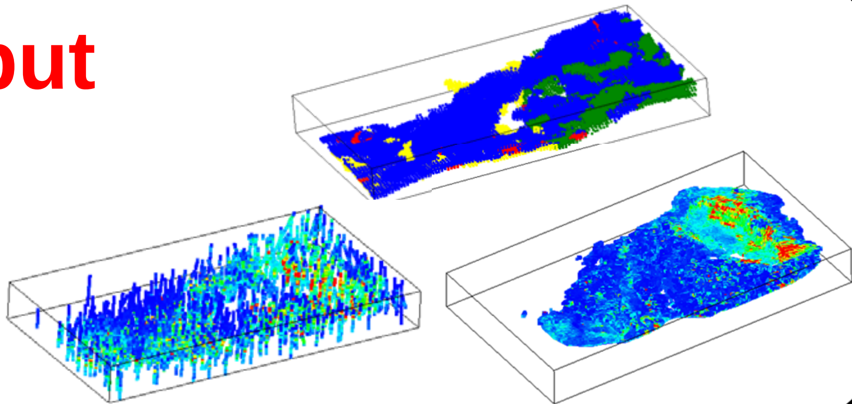
Output

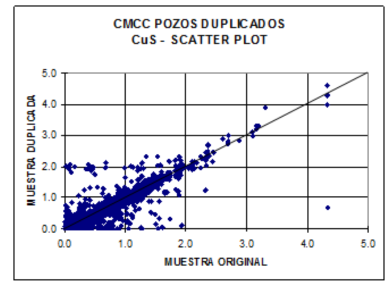


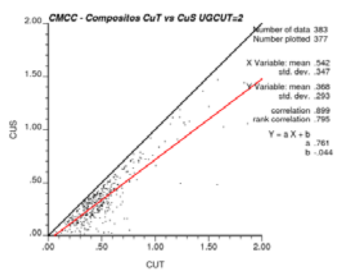
x 10

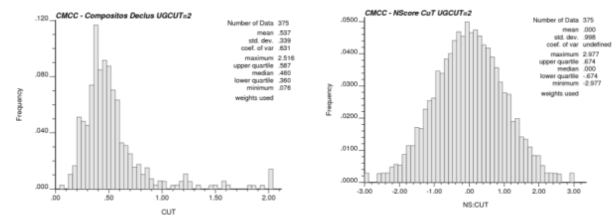
Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning

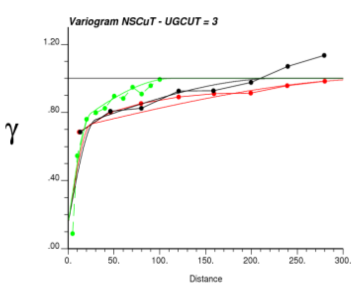
Input

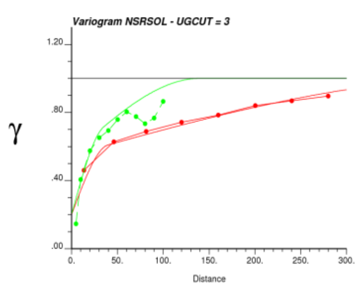












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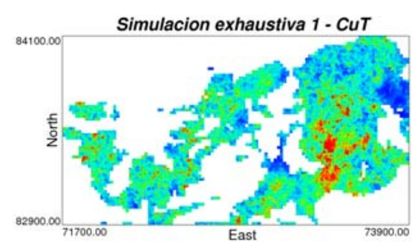
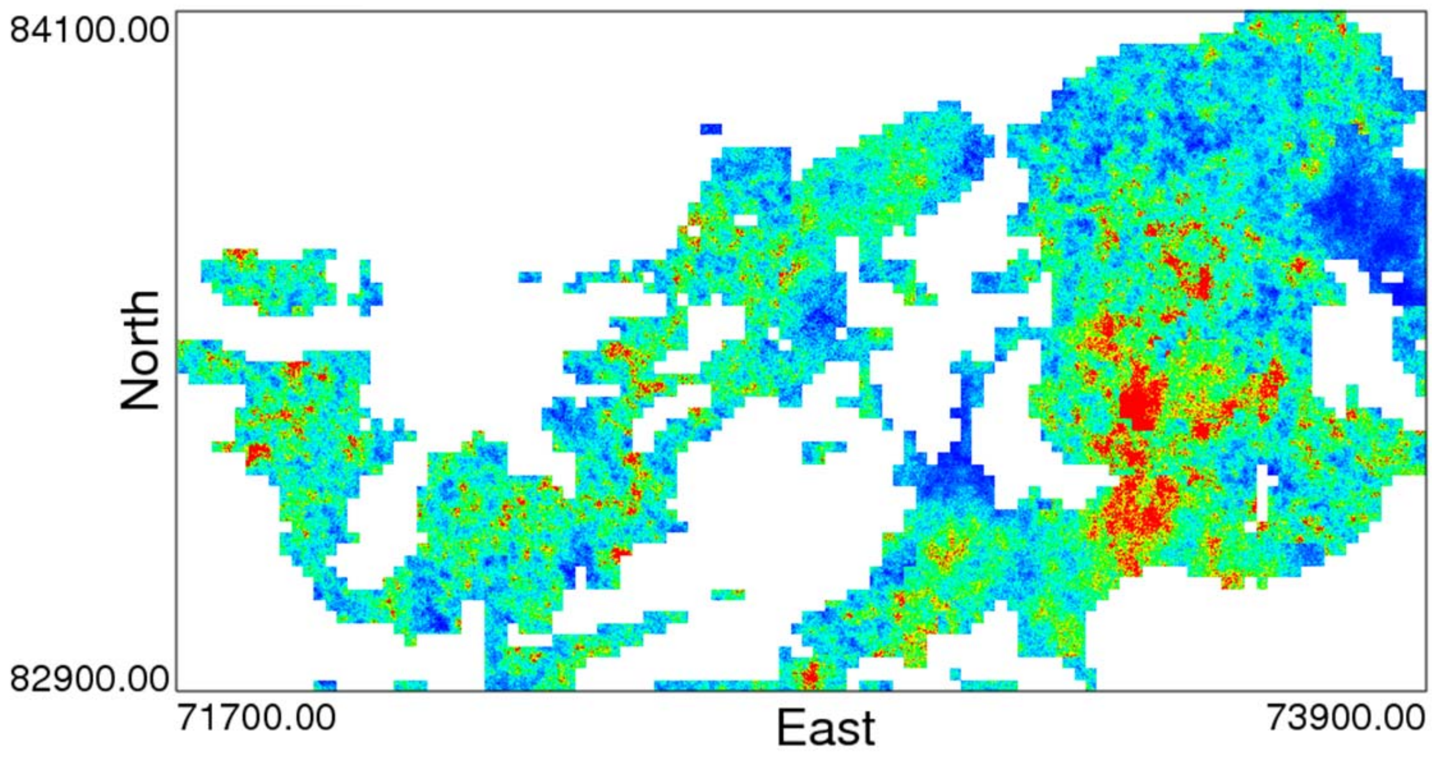


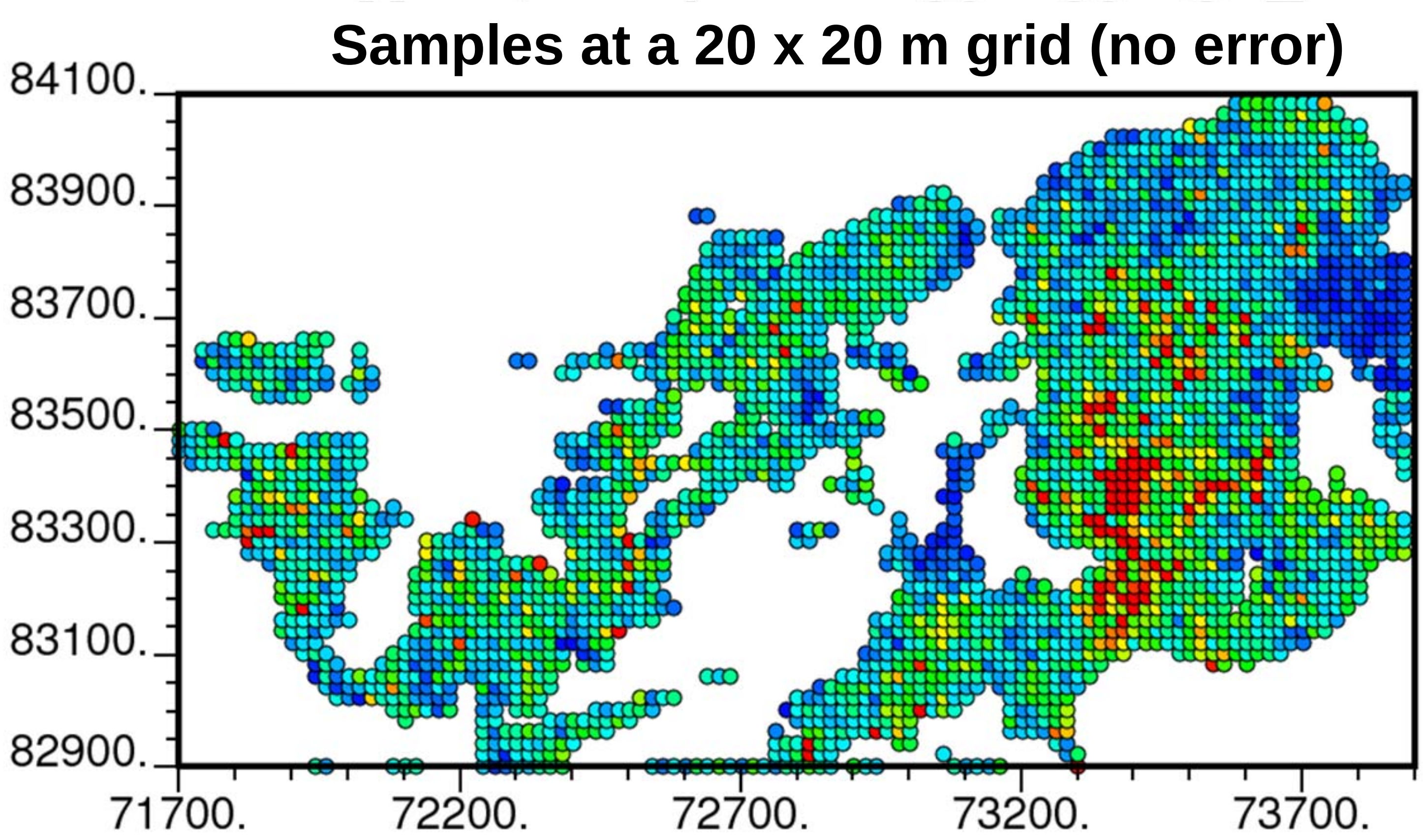
x 10

Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning

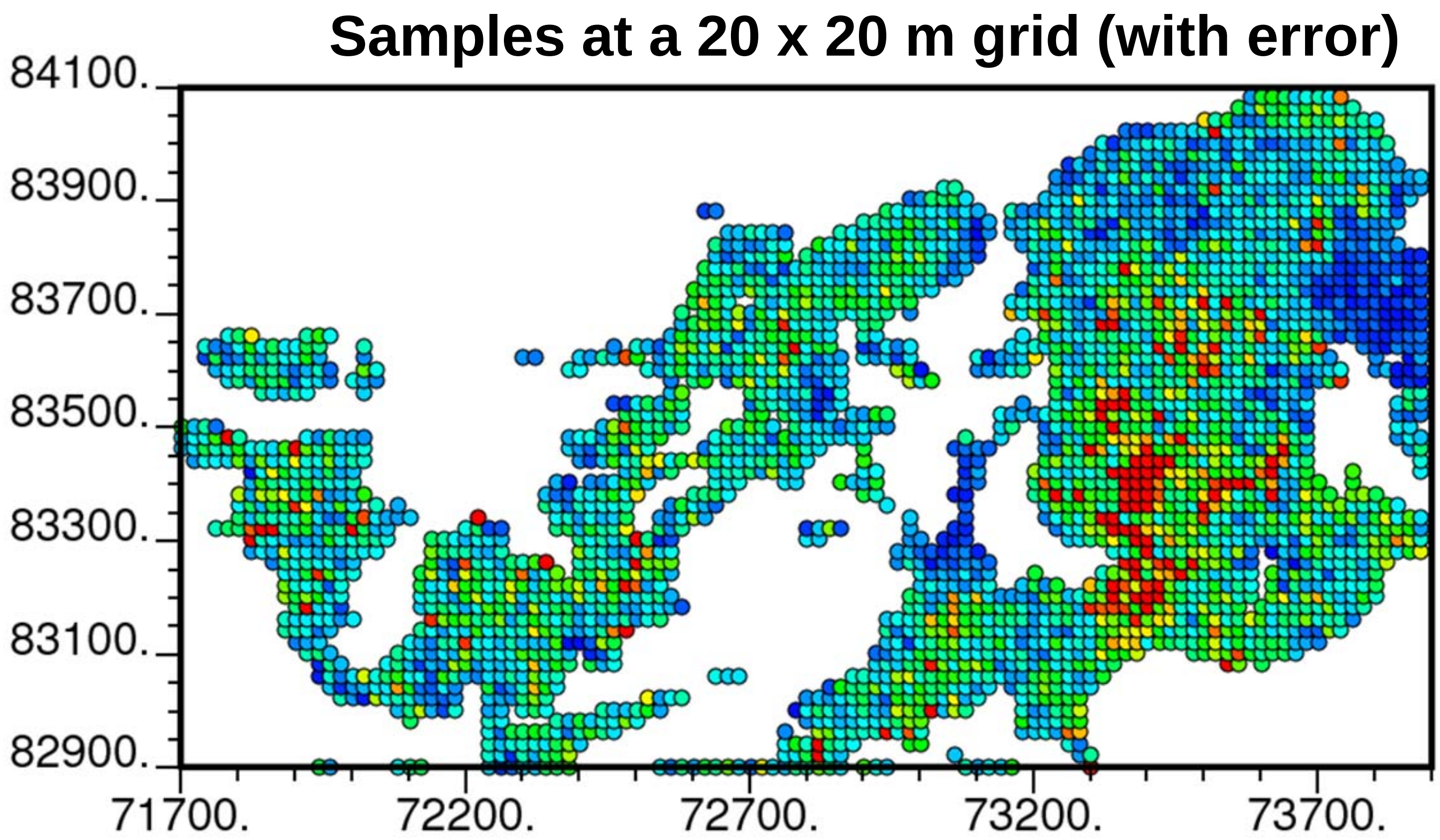
One exhaustive dense simulation



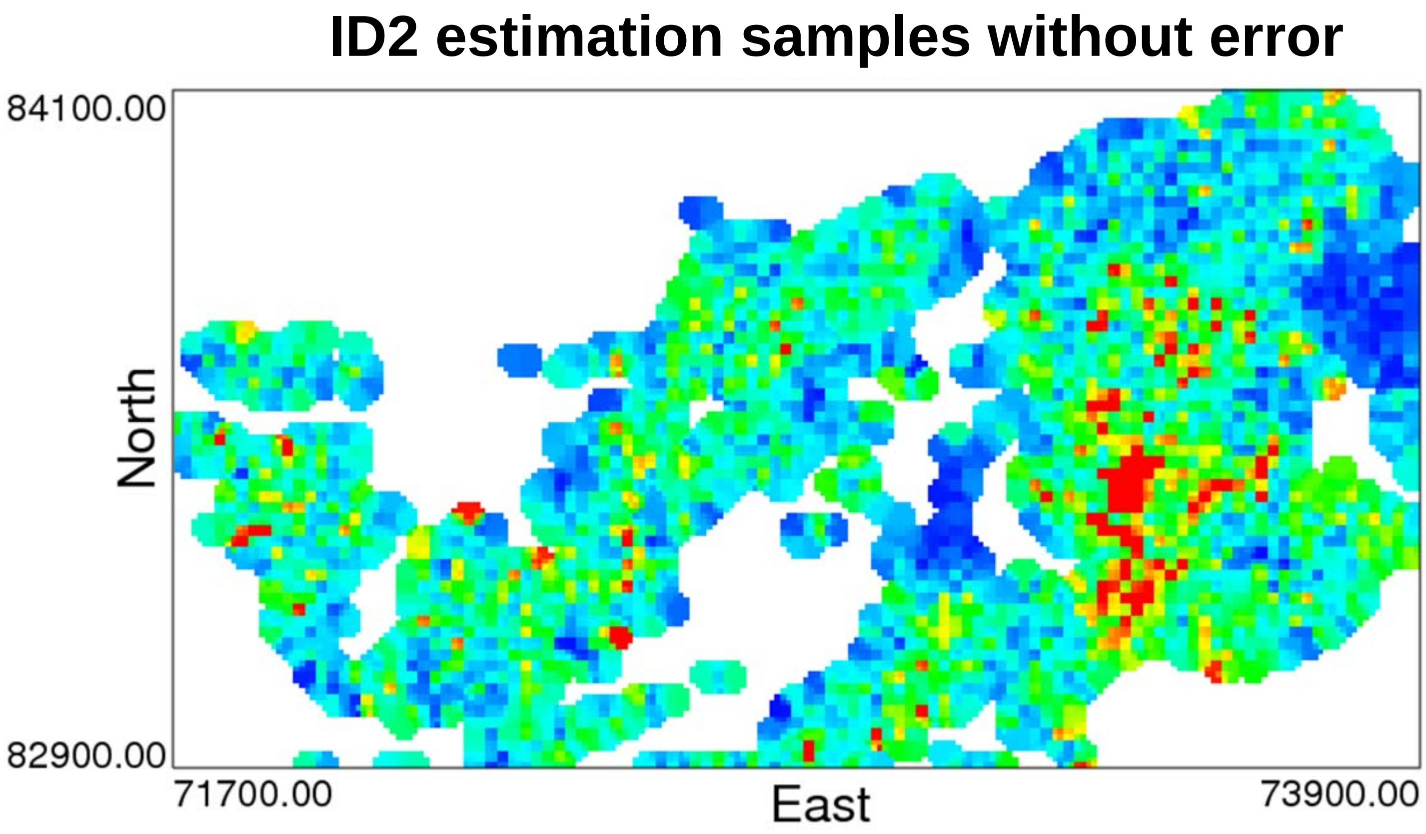
Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning



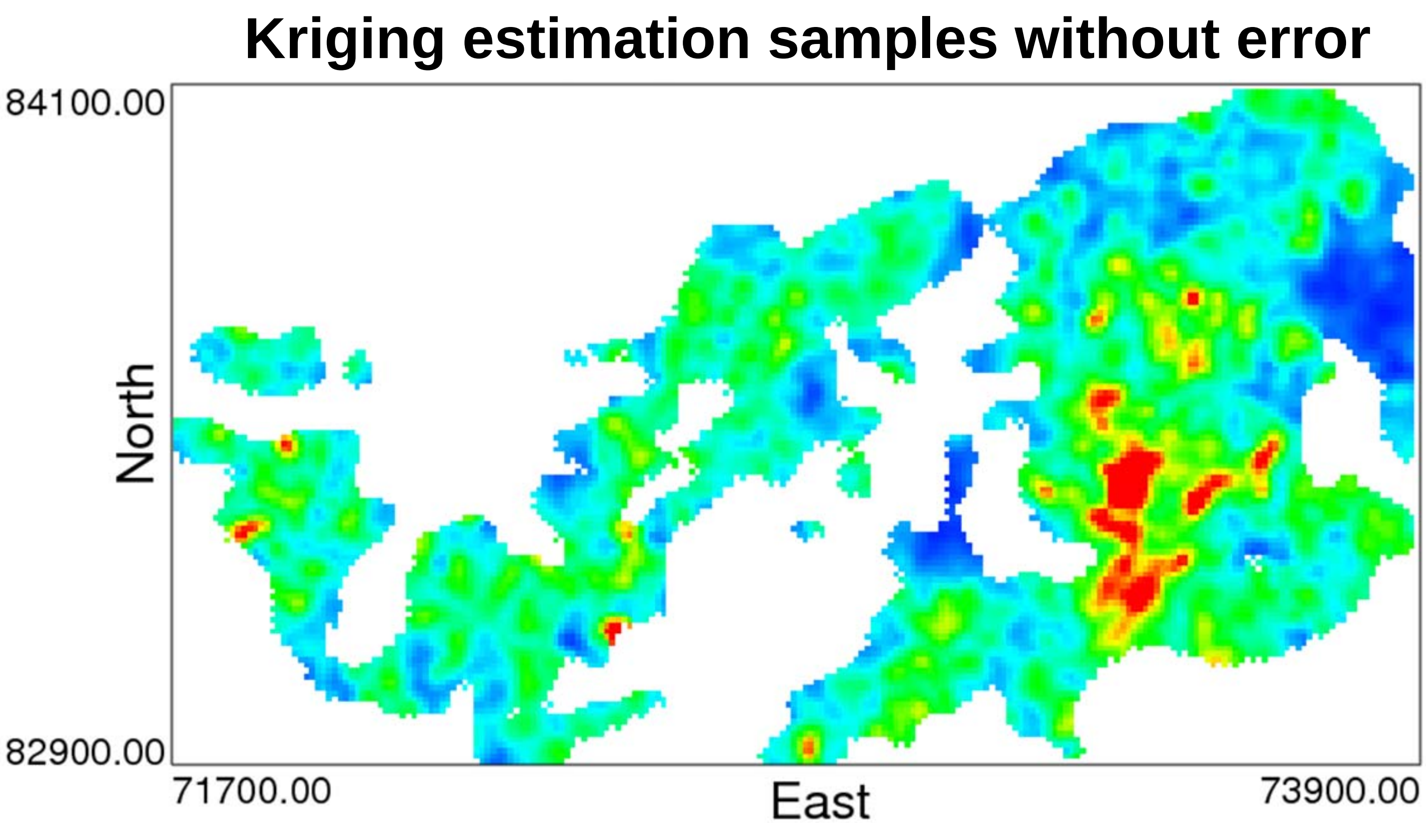
Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning



Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning

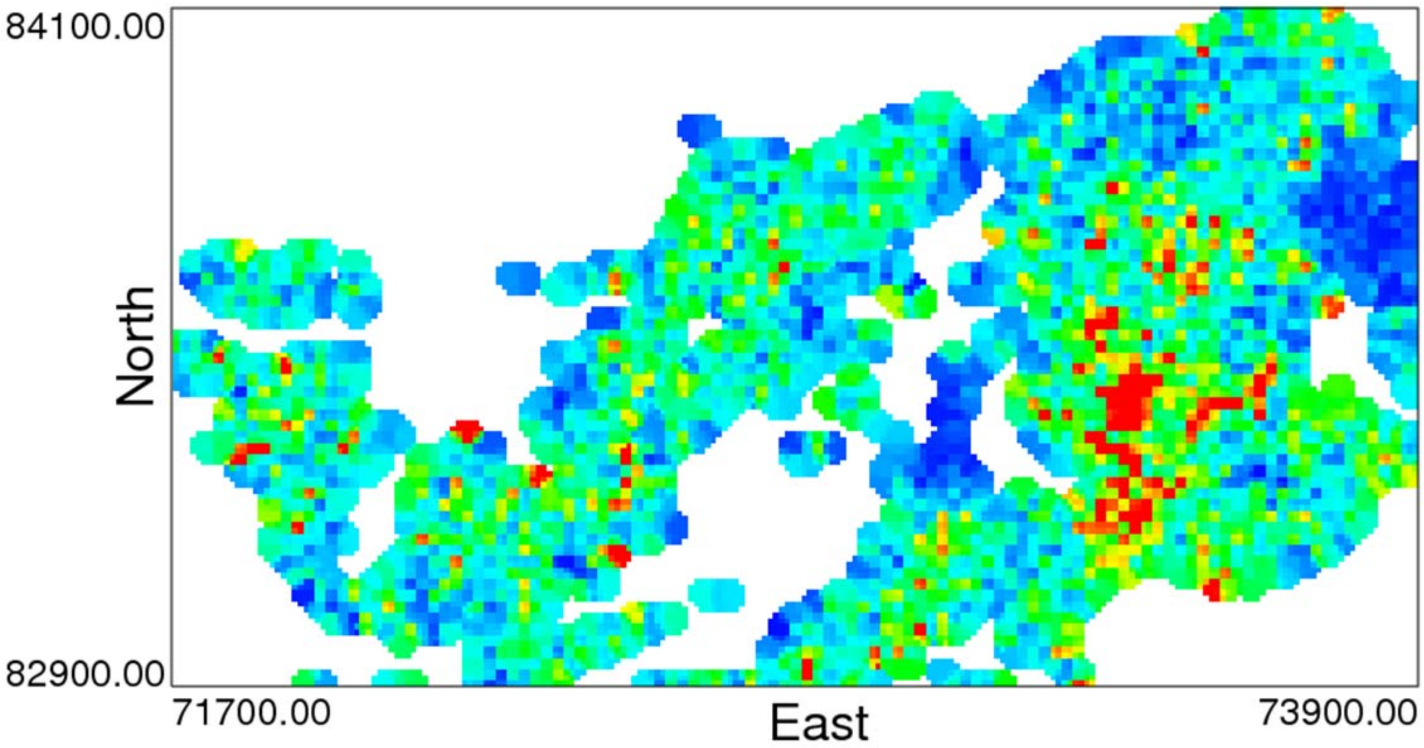


Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning



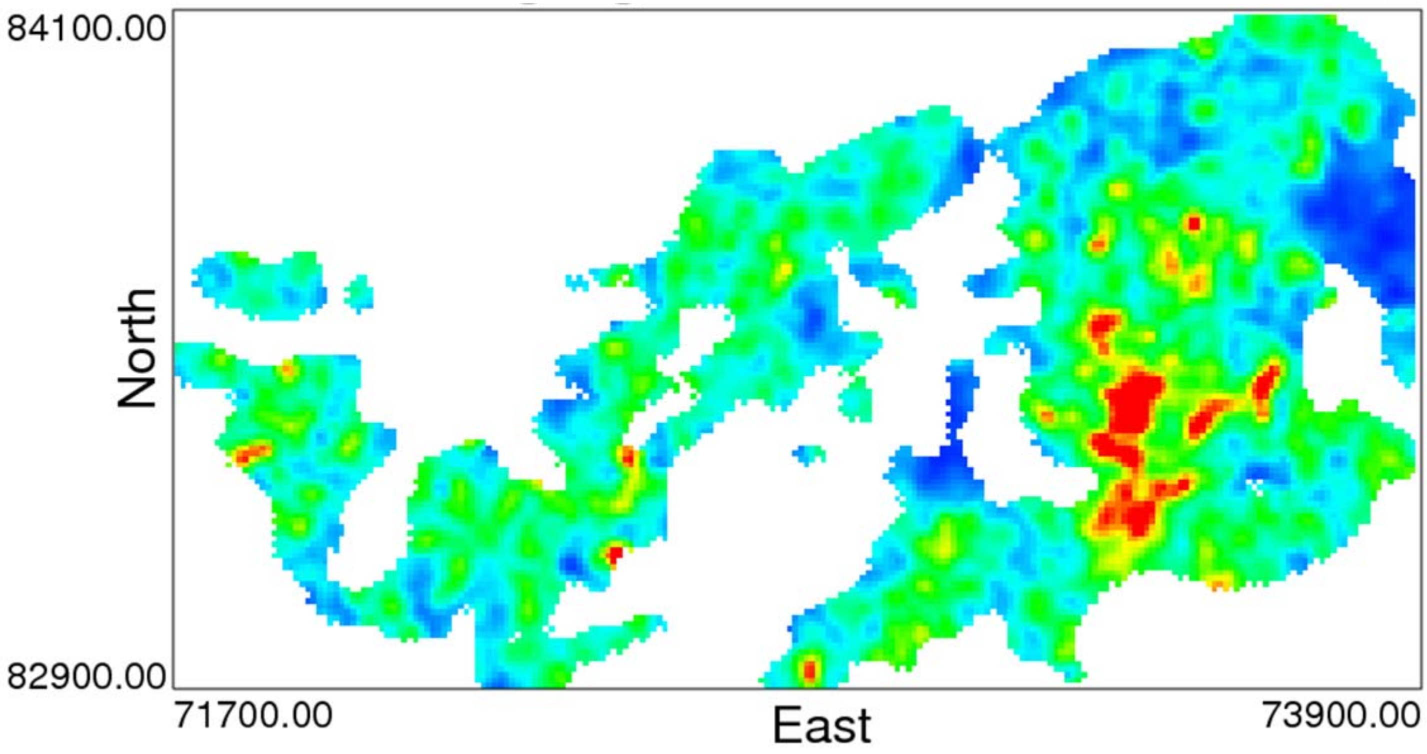
Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning

ID2 estimation samples with error



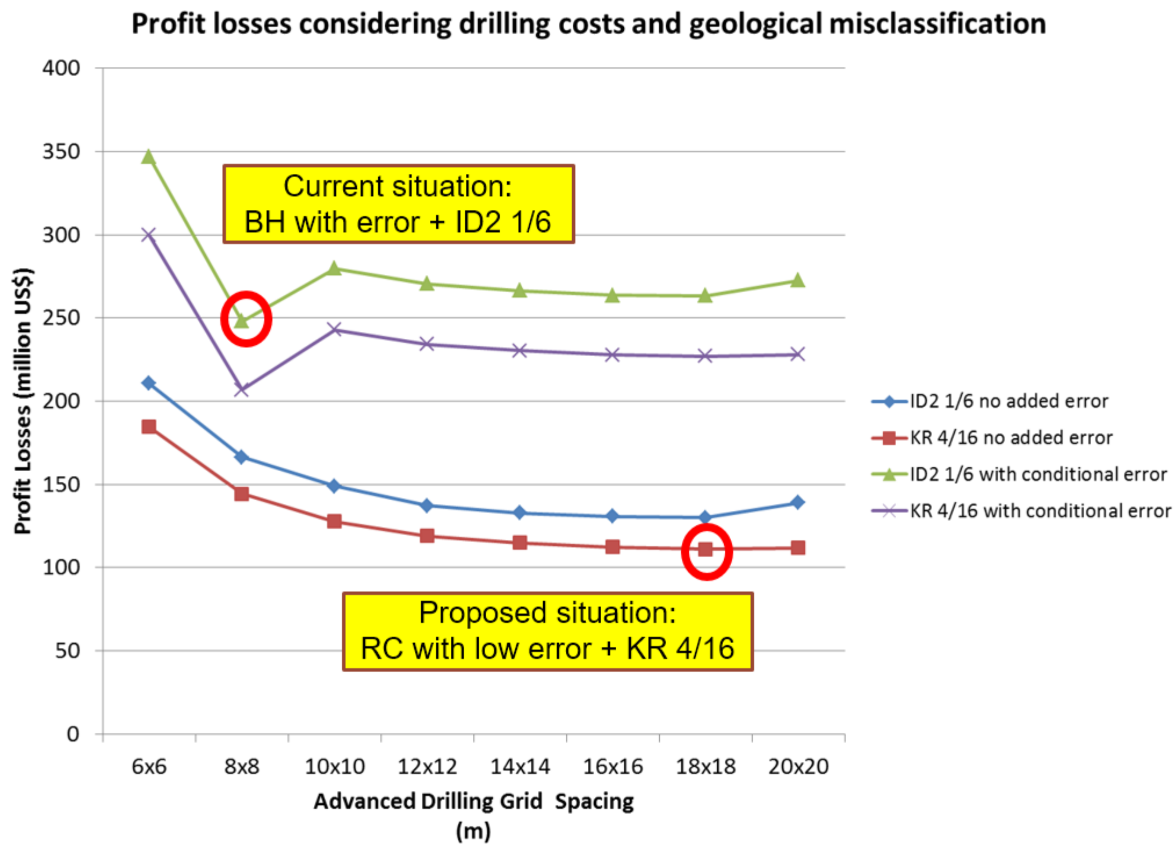
Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning

Kriging estimation samples with error



Application 3: accounting for sampling errors and grade uncertainty to optimize short term planning

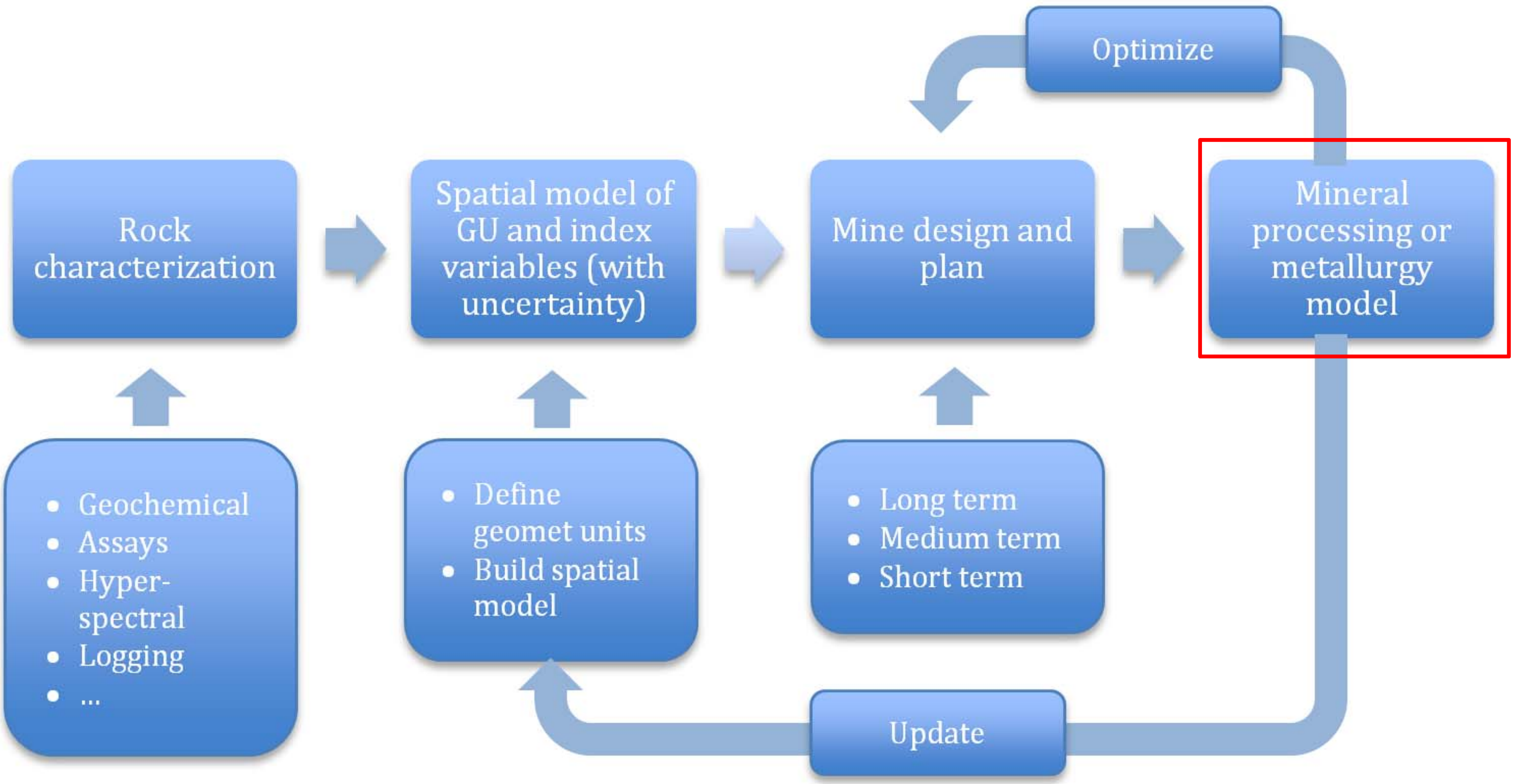
- Building blocks:
  1. Analyze sampling errors
  2. Build 10 simulations of TCu, SCu and solubility at block support
  3. Simulate sampling grids and errors in realizations to emulate short term planning information
  4. Estimate block grades using samples and compare with short term plan considering exhaustive knowledge (from the dense simulations)



  5. Perform economic evaluation
     - Estimate recovery (depends on geological unit, clay types)
     - Estimate acid consumption (depends on recovery and SCu)
     - Assign blocks to plant or waste dump
- Result: **Reduced losses amount to 130 million USD over 5 years**

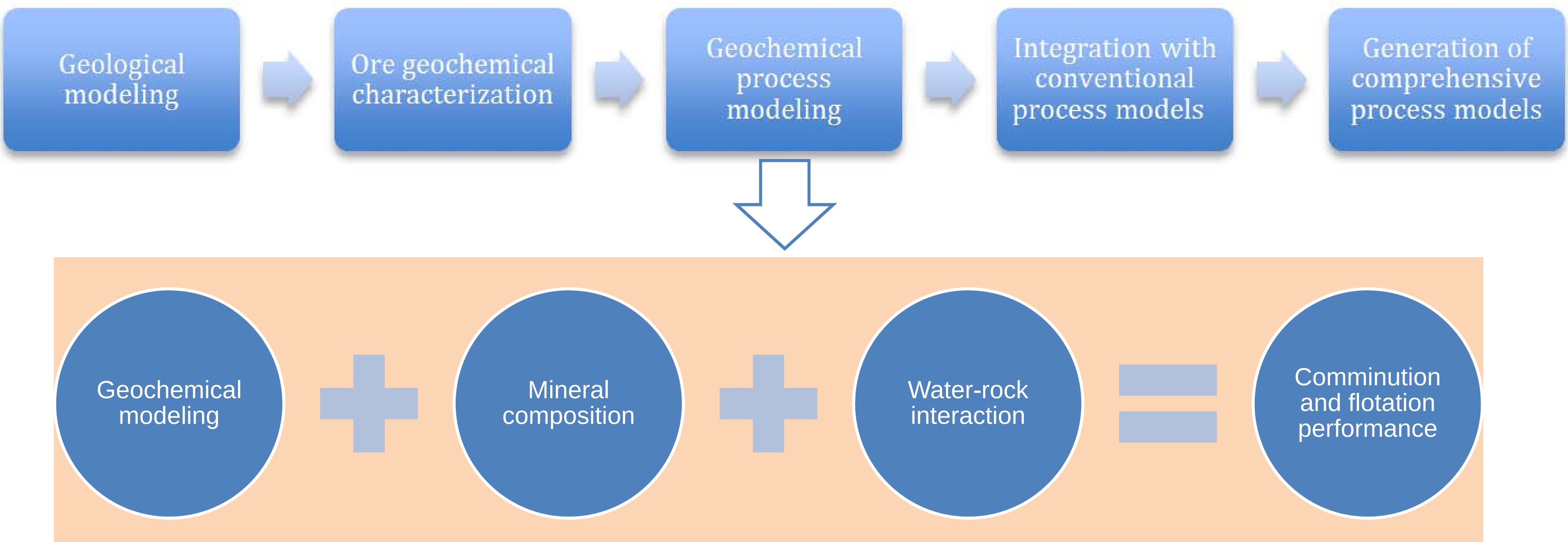
Motivation

General workflow



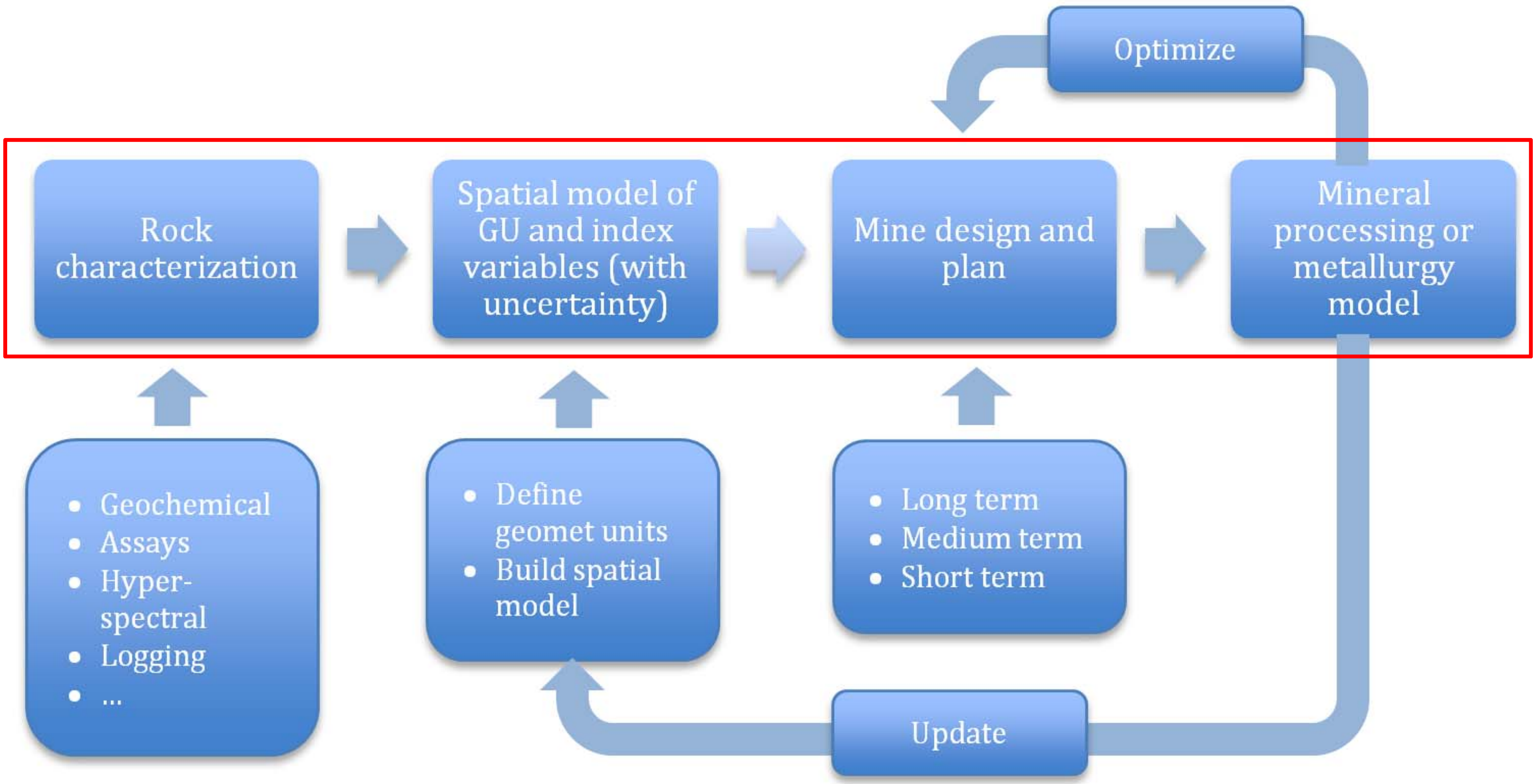
Application 4: prediction of the effect of water-rock interaction in mineral processing

- Hydrothermal mineral associations, when in contact with water, tend to equilibrium, generating physicochemical buffering conditions, in particular pH, Eh, and chemical composition.
- This behavior is not restricted to the mineral deposit; it also occurs when the minerals are being processed; e.g. grinding
- Model using a geometallurgical approach



Motivation

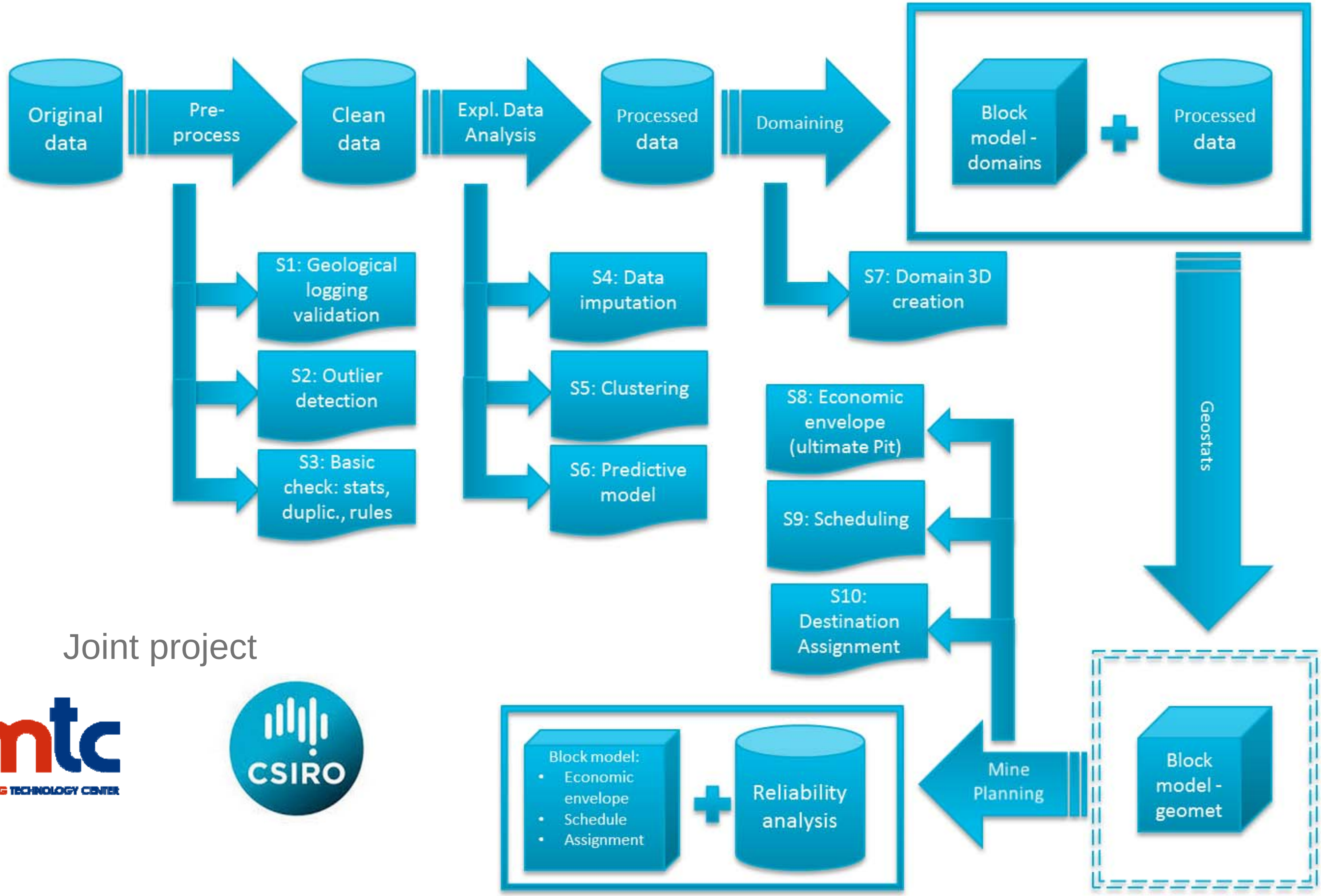
General workflow



Challenges

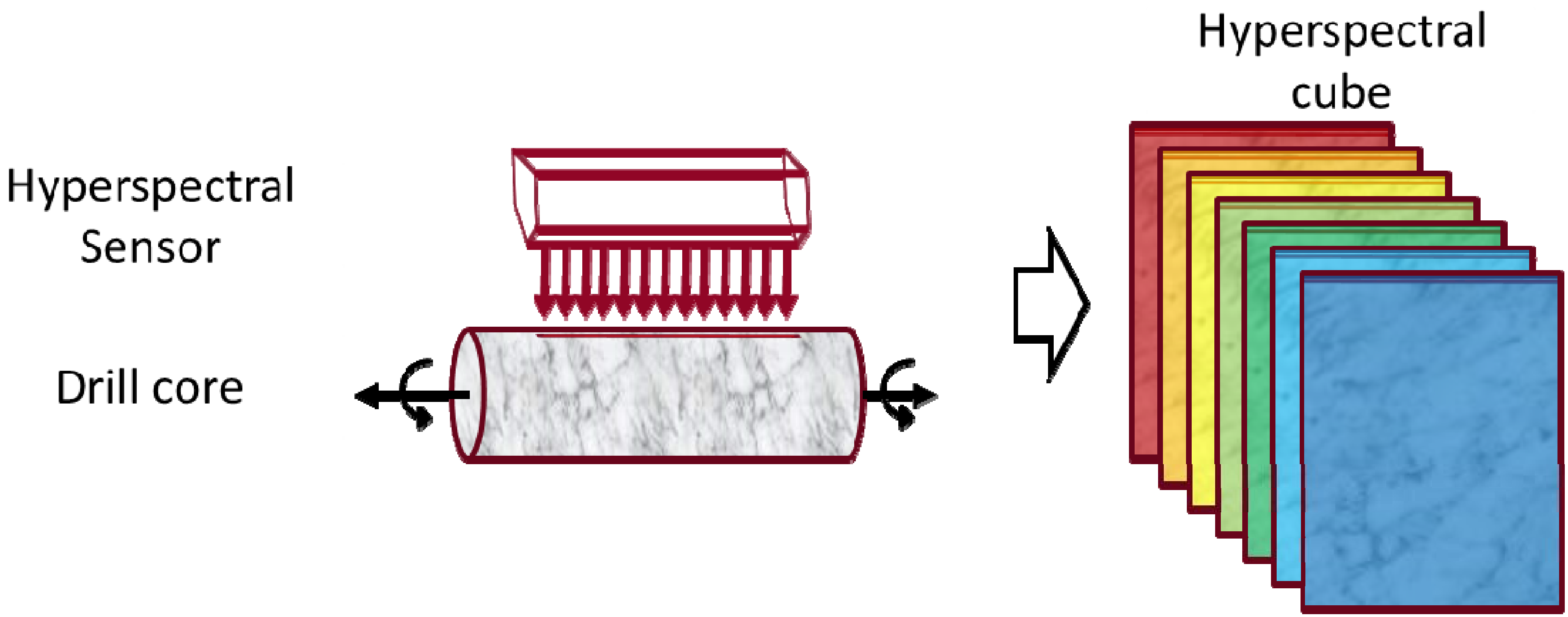
- Data acquisition, and quality assurance and control in geometallurgical data
  - Need for systematic acquisition of relevant data related to elements, minerals, and mineral association, grain size, geotechnical parameters, etc.
  - Must be integrated in the current workflows to capture the information value.
  - Richer data (hyperspectral, quantitative mineralogy, quantitative textural models) may prove extremely important to understand rock behavior.
  - Need for QA-QC protocols in data acquisition and testing.
- Insufficient number of data
  - Need for proxy assays and measures, to lower the cost of geometallurgical data.
- Insufficient tools to discover relationships by statistical means.
  - Efforts should move towards phenomenological models, with integration of geology into the comprehension of mineral processing and metallurgical processes.
- Poor metallurgical models.
  - Incomplete understanding of physical and chemical processes that occur within each one of the mineral processing and metallurgical stages.
  - Experimental studies as well as theoretical ones, are required to improve the knowledge in this area, and scaling is required.

Framework

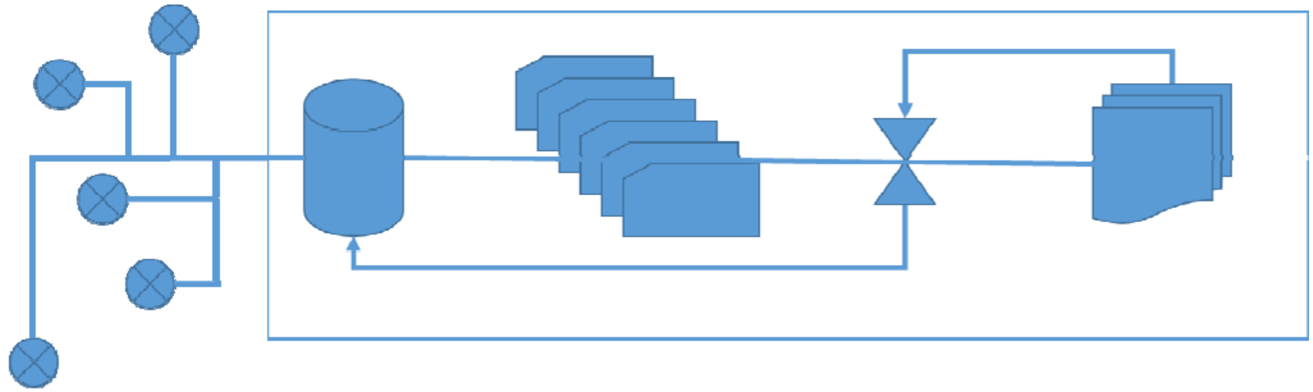


Joint project

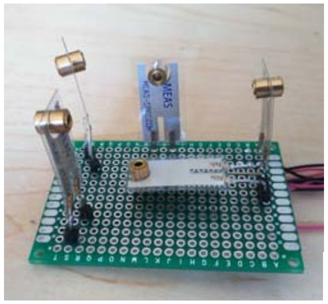
Outlook



Outlook

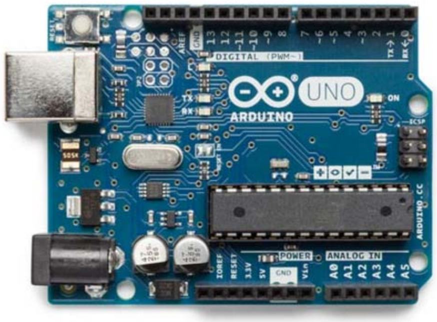


Sensors | Data base | Data analytic tools | Decision making procedures | Reports



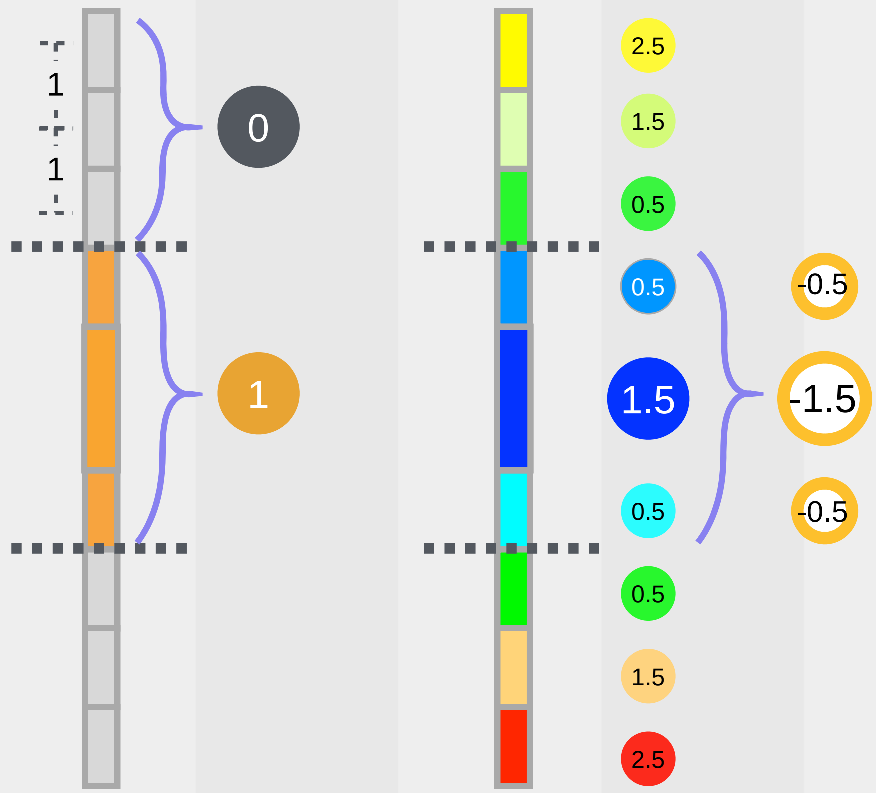
Accelerometer

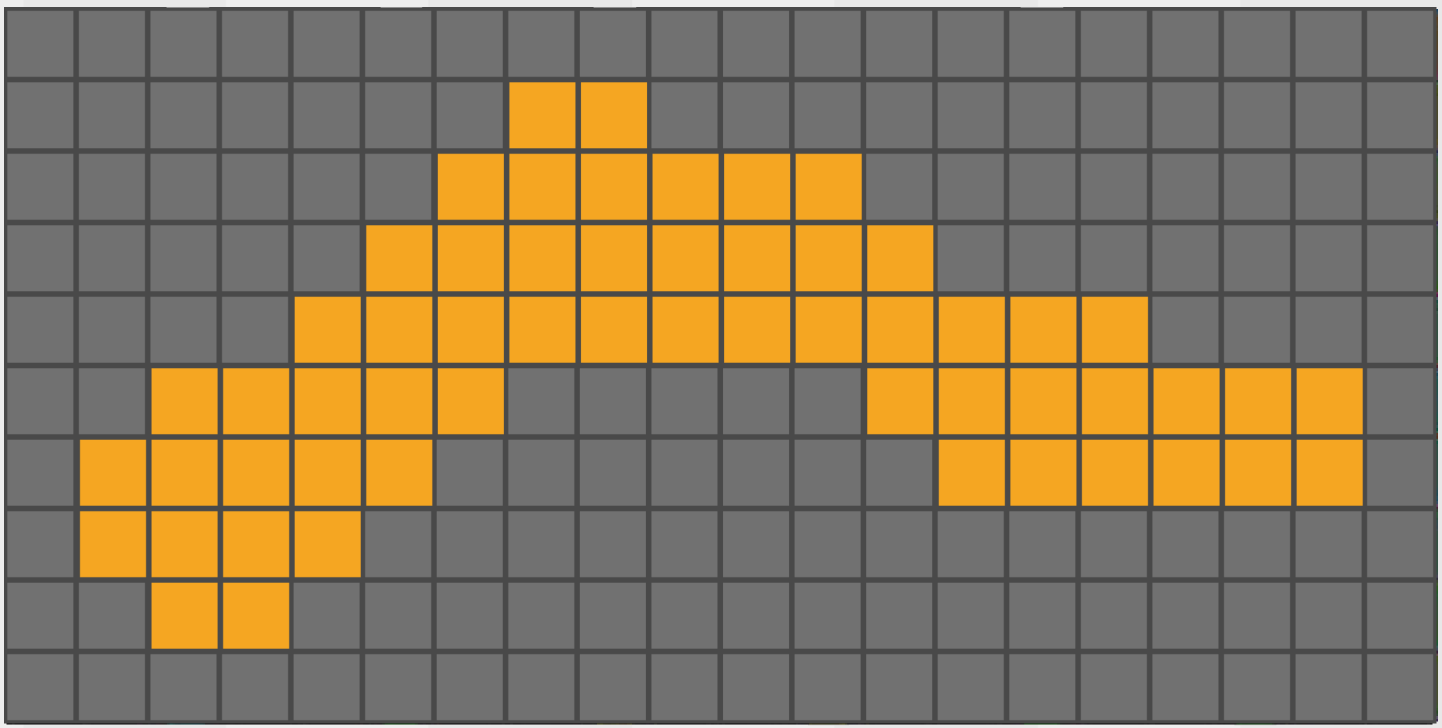
Arduino

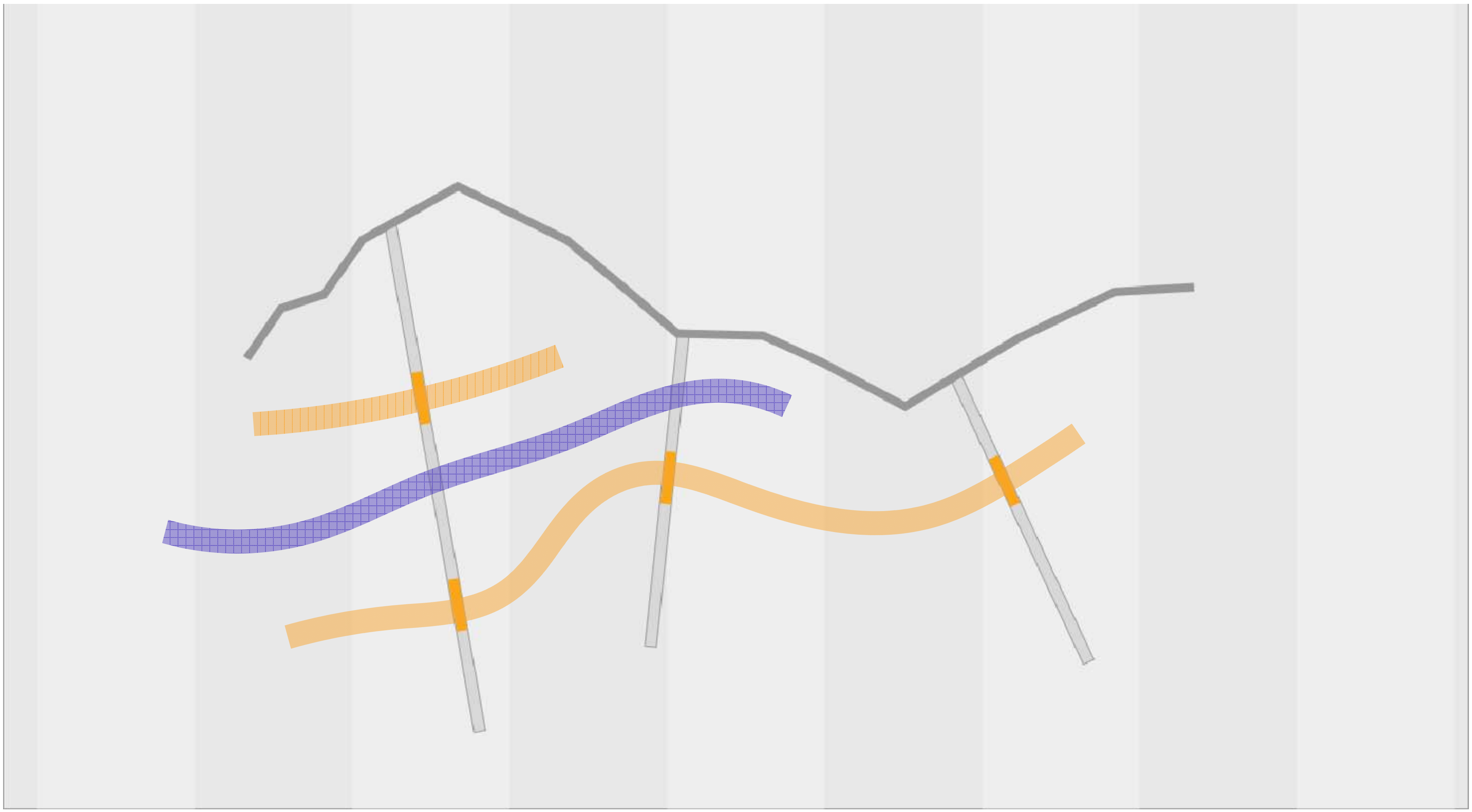


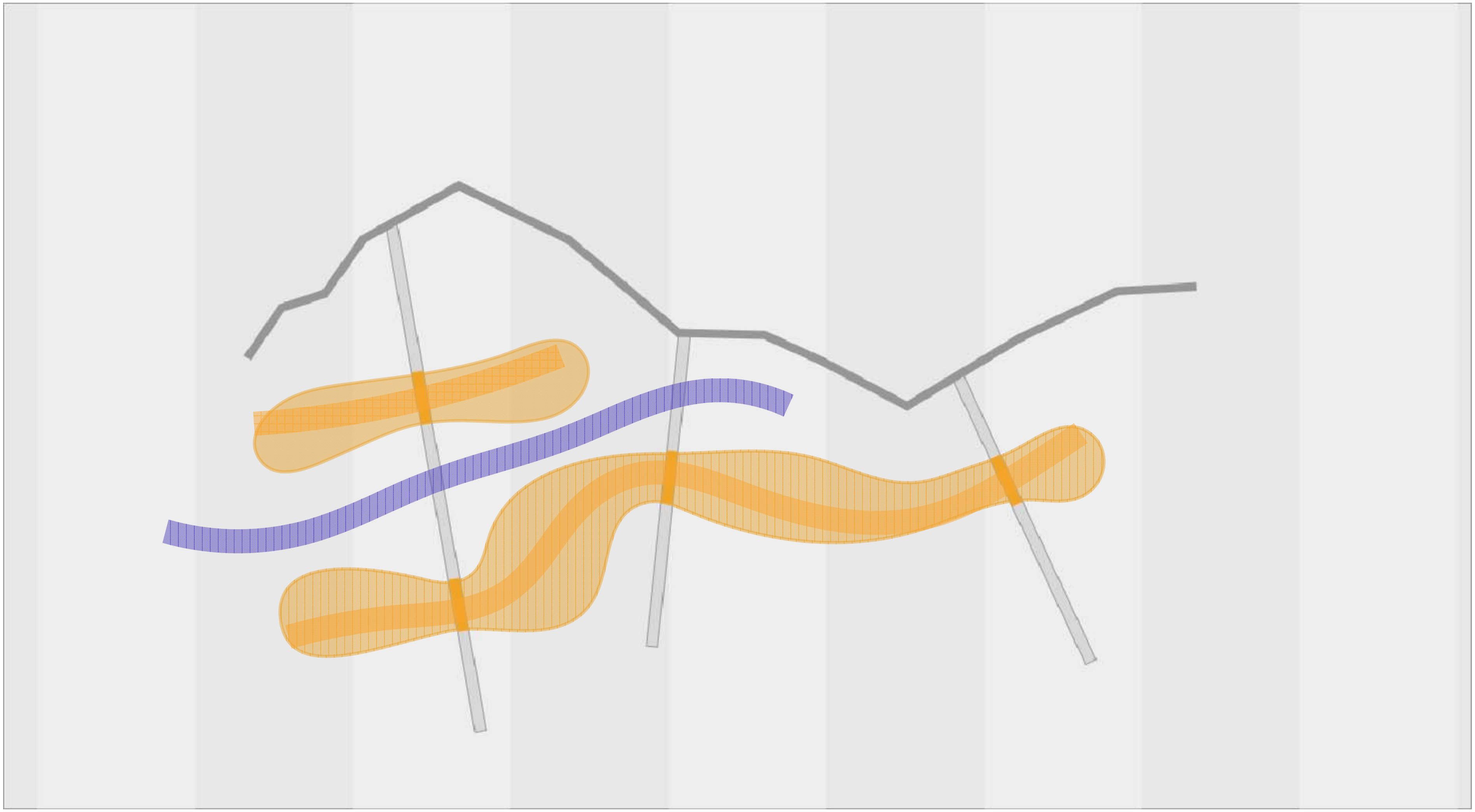
Wireless Tire
Pressure Sensor

Outlook









Conclusions

- Geometallurgy requires integrating geological knowledge into modeling of mining, mineral processing and metallurgical processes

- Linked workflows are helpful to understand what variables and data are relevant to improve the predictive model, and reduces the problem to a manageable parcel

- Modeling the full process is useful even when different levels of sophistication are used in each step (e.g. complex stochastic spatial model of attributes combined with simple predictive model)

- Extensions to rock breakage, environmental modeling of acid drainage, water and energy consumption, etc.

This is mostly an integration step, therefore most of the tools already exist, but the expertise to put them together and interpret the results with a combined geological, mining and metallurgical understanding remains as the most difficult challenge to overcome

Acknowledgments

Many students, researchers, and developers have contributed to this work. Thanks are due to all of them.