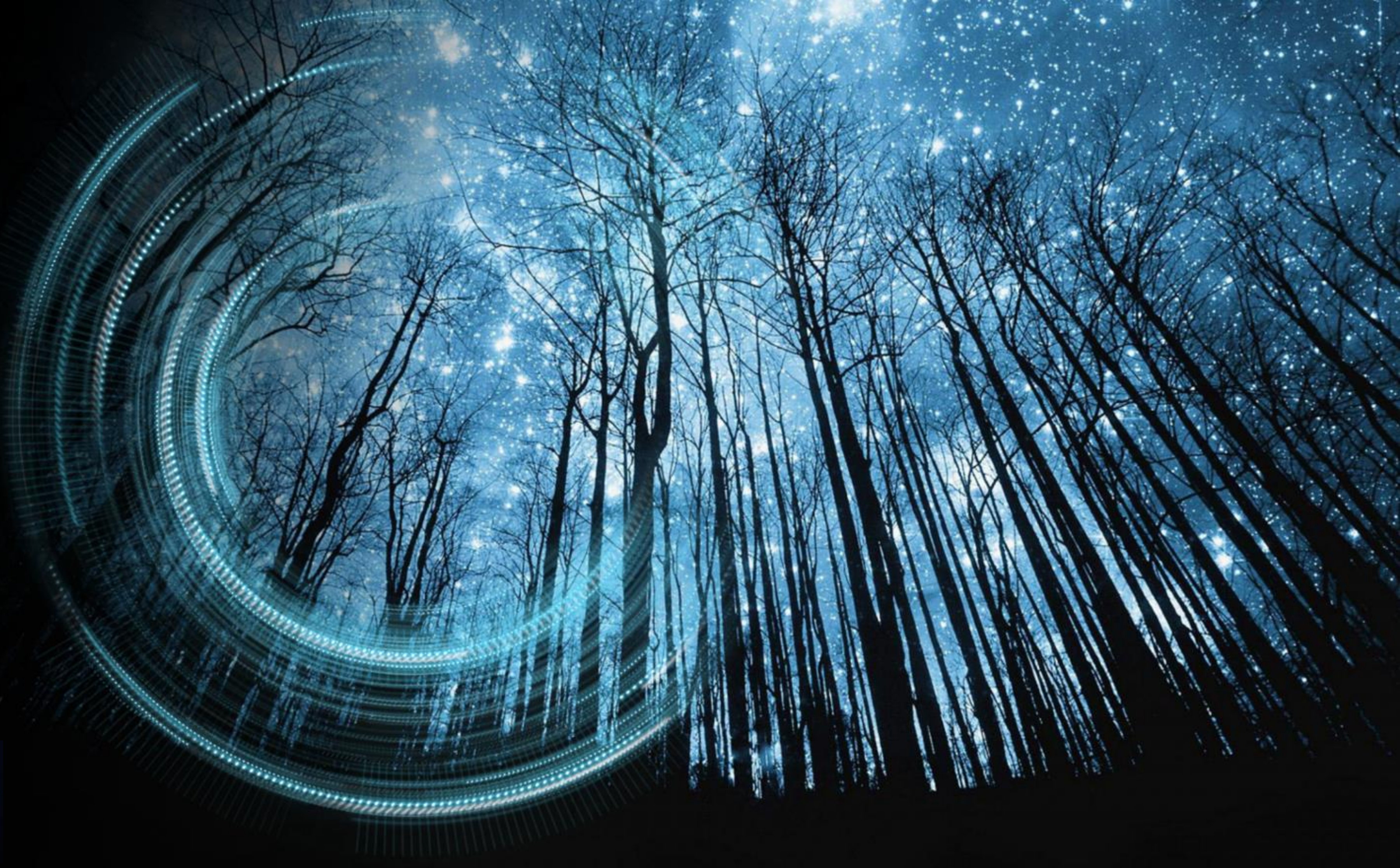
Implementation of OMV Machine-Learning augmented workflows to support scenario evaluations under uncertainty in DELFI



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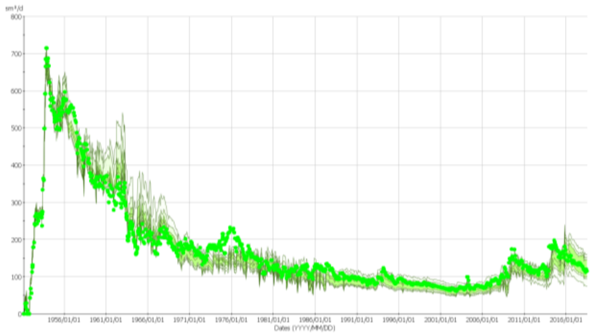
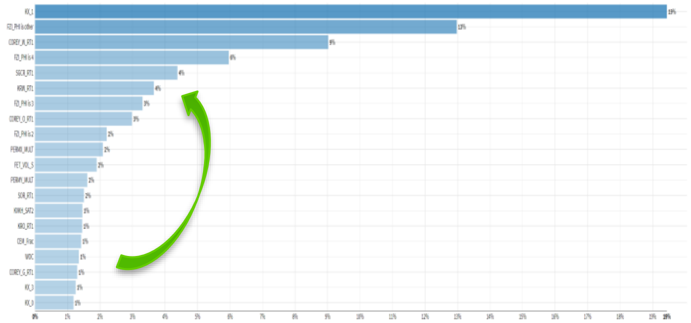
Lucerne, September 2022

The energy for a better life. OMV

The challenge: scenario evaluations under uncertainty



Numerical models can be conditioned to many different types of measured data, this is an ill-posed problem, a multitude of different parameter combinations can lead to acceptable agreement with the observed data.



The final model ensemble conditioned to all observed data can be used to forecast under uncertainty where changing production conditions might change non-sensitive parameters in the history to sensitive parameters in the forecast.

Optimizing field re-developments leads to increasing value ranging from 5 to 50M EUR per field. The risk of failure can be reduced from 40% to 10% by using probabilistic workflows.

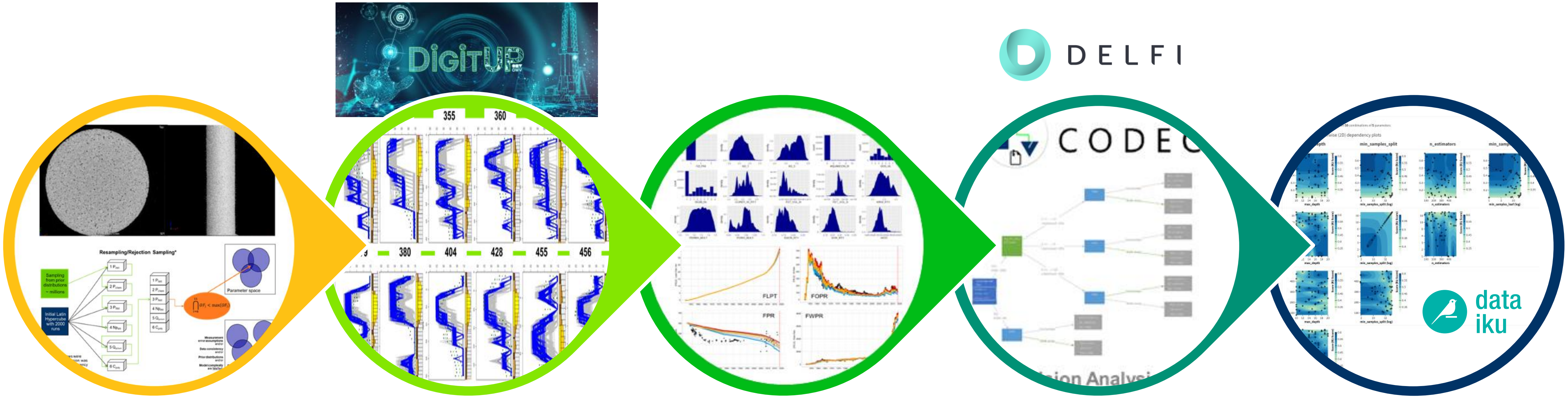
OMV Machine-Learning augmented workflows

Instead of finding the best parameter combination by minimizing the mismatch, prior distributions are used for the different uncertain parameters which are then conditioned to the various observed data obeying Bayes' updating rule.

The Random Forest Machine Learning algorithm is used to generate a large variety of parameter combinations in an acceptable agreement with the various sources of observed data, addressing also parameter interactions.

Machine Learning Workflow 2020

OMV Machine-Learning Workflows Digital Journey



2019: Concept from coreflood simulation study

SPE-200578-MS

2020 Q1: Method applied for water saturation initialization

SPE-203384-PA

2020 Q2-Q4: First workflow application for field studies

SPE-205188-PA & SPE-208194-MS

2021: First Co-Development of Stochastic Modelling in Delfi: Clustering & CODEC ®

2022: Co-Development of Stochastic Modelling in Delfi: **ML Workflows**

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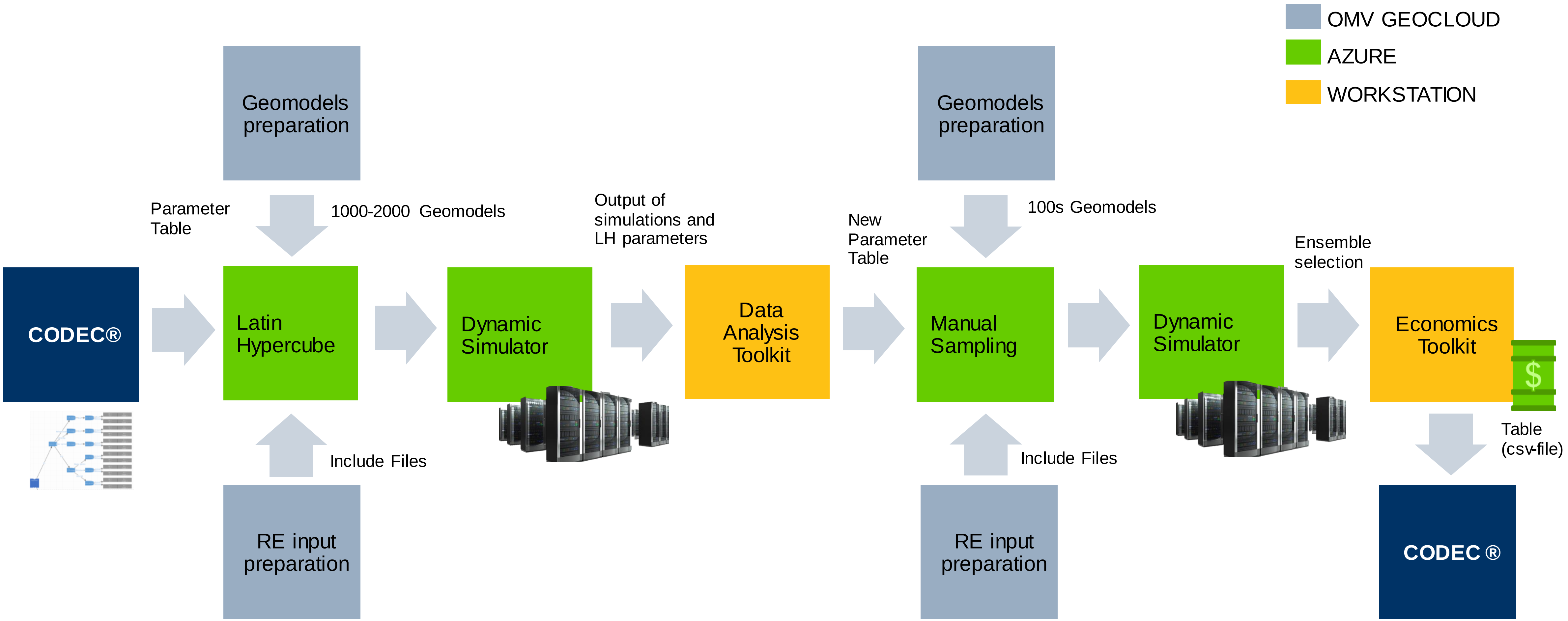
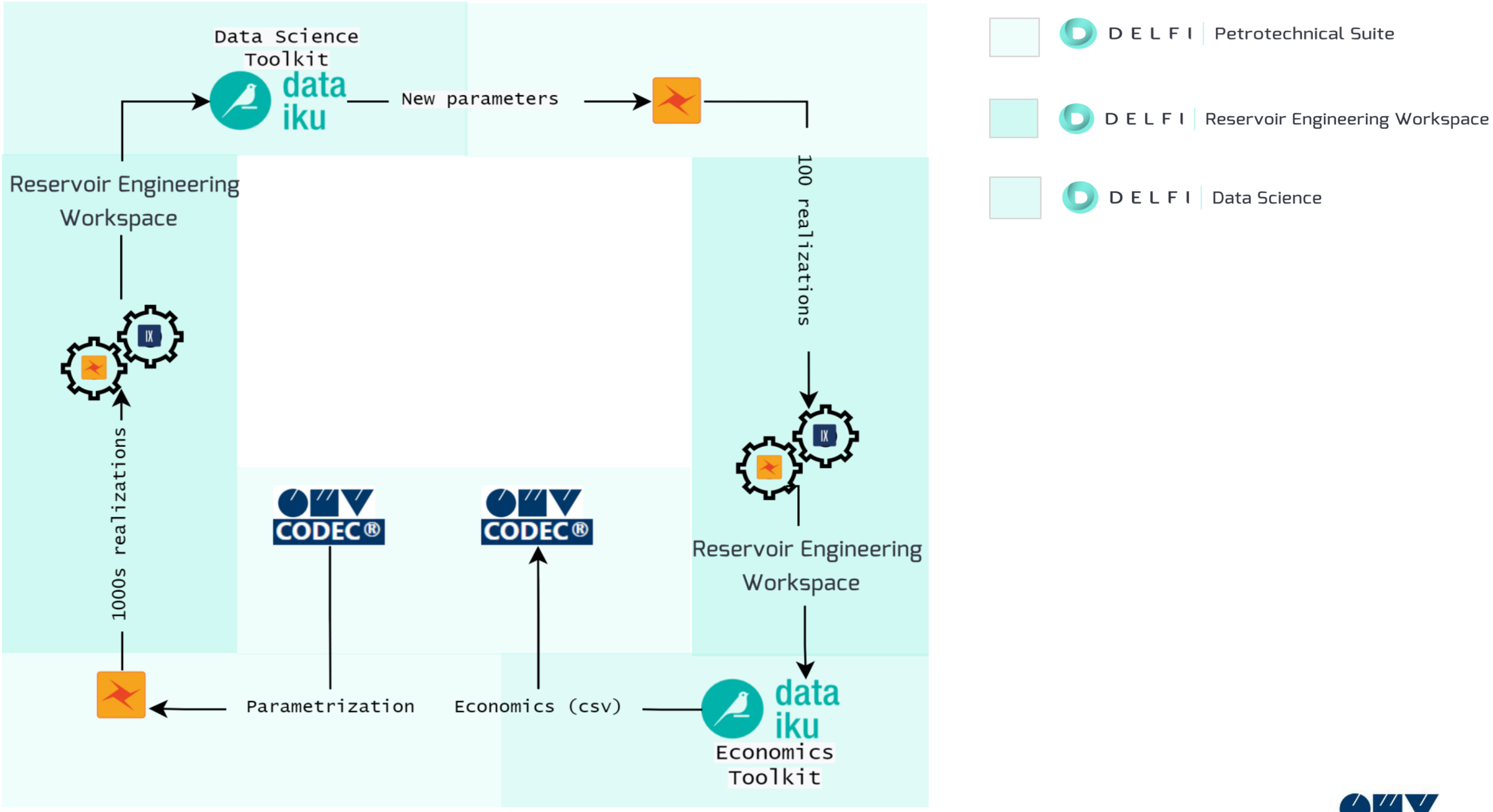
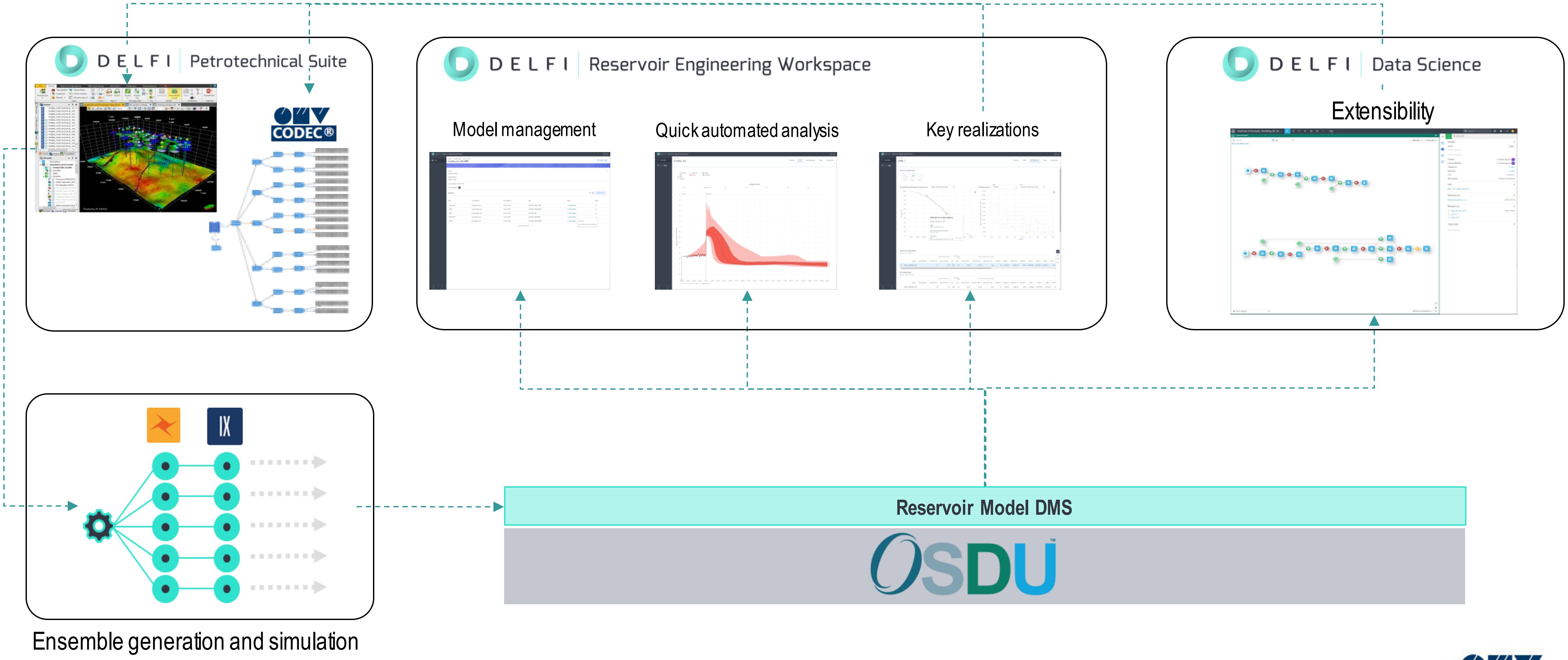
Original workflow



Simplified workflow



Stochastic Modelling Architecture



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OMV ML Model Conditioning Approach

1. Statement of model complexity and parameterization
2. Latin hypercube sampling
3. Falsification of prior uncertainties
4. ML based generation of statistical models to determine discrepancy based on input parameters
5. Utilization of these statistical models to define posterior parameter combinations
6. Simulation using the posterior parameter combinations in order to validate the results

dataiku

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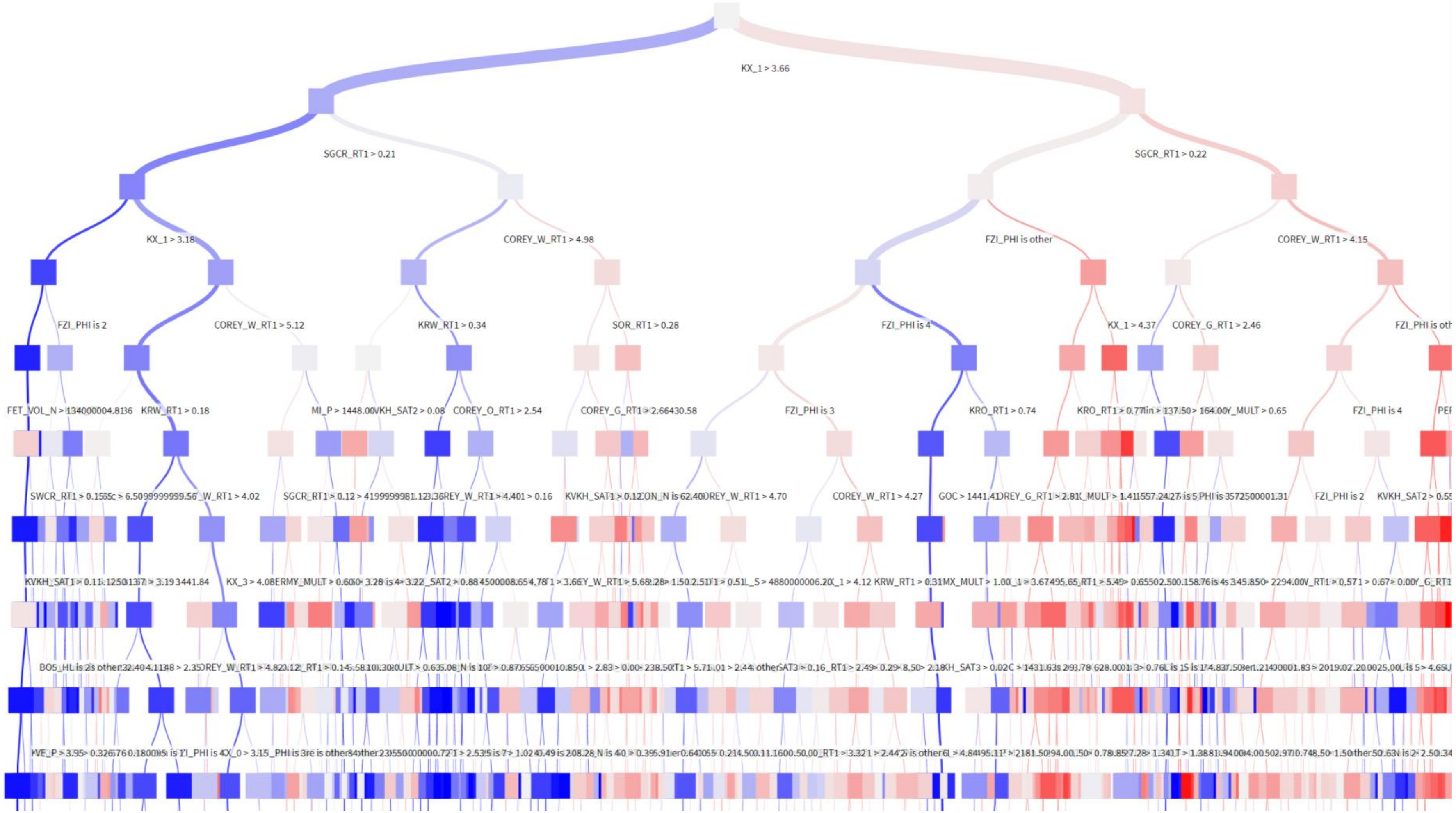
Statistical models: Random Forest

The methodology allows

- Categorical, continuous geological and dynamic model parameters
- Calibration to multiple data at well and reservoir level
- Decision trees created for each observed data type (objective functions) based on the importance of variables in the regression.



Statistical models: Exploring alternative algorithms

DELFI Data Science

- Easy access and testing capabilities to various ML algorithms
- Compare different regression models, evaluate impact, and adapt the workflows

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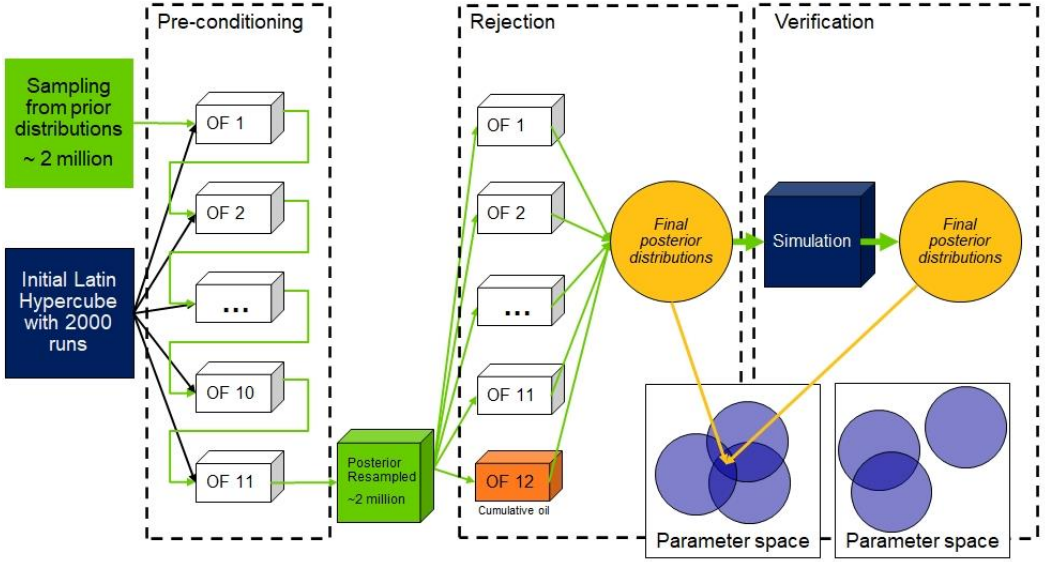
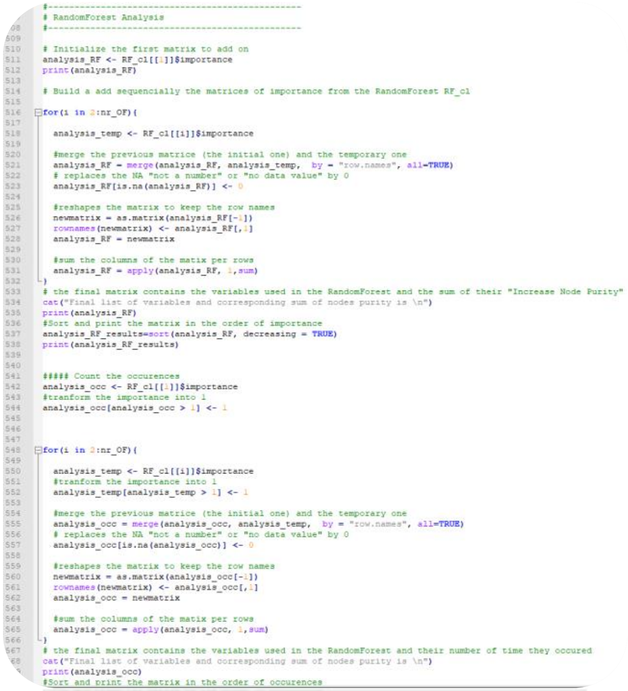
Utilization of statistical models: from concept to scripts

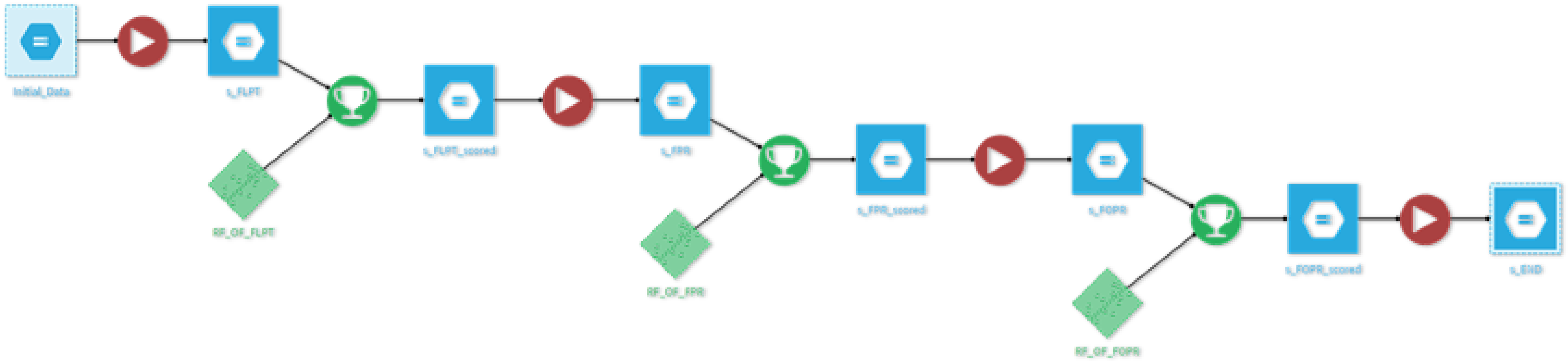


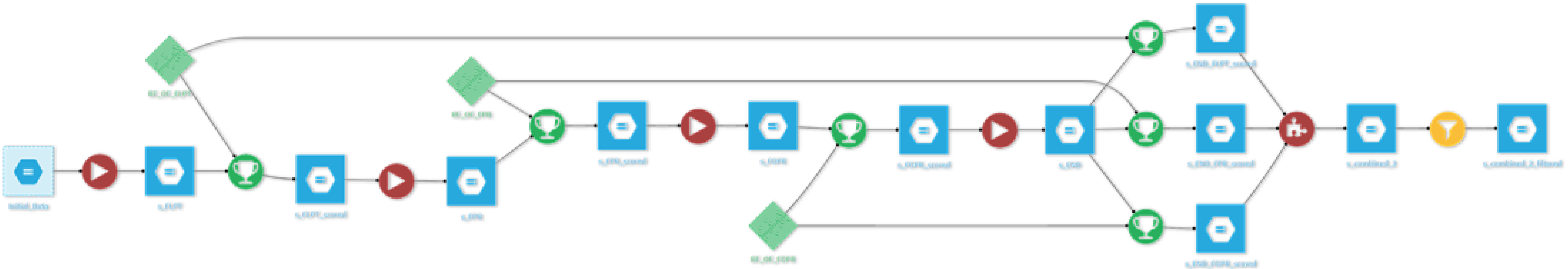
SPE-205188-PA • Conditioning Model Ensembles to Various Observed Data (Field and Regional Level) by Applying Machine Learning Augmented Workflows



```
#-----------------------------------------------
# RandomForest Analysis
#-----------------------------------------------

# Initialize the first matrix to add on
analysis_RF <- RF_cl[[1]]$importance
print(analysis_RF)

# Build a add sequencially the matrices of importance from the RandomForest RF_cl

for(i in 2:nr_OF){

  analysis_temp <- RF_cl[[i]]$importance

  #merge the previous matrice (the initial one) and the temporary one
  analysis_RF = merge(analysis_RF, analysis_temp,  by = "row.names", all=TRUE)
  # replaces the NA "not a number" or "no data value" by 0
  analysis_RF[is.na(analysis_RF)] <- 0

  #reshapes the matrix to keep the row names
  newmatrix = as.matrix(analysis_RF[-1])
  rownames(newmatrix) <- analysis_RF[,1]
  analysis_RF = newmatrix

  #sum the columns of the matix per rows
  analysis_RF = apply(analysis_RF, 1,sum)
}
# the final matrix contains the variables used in the RandomForest and the sum of their "Increase Node Purity"
cat("Final list of variables and corresponding sum of nodes purity is \n")
print(analysis_RF)
#Sort and print the matrix in the order of importance
analysis_RF_results=sort(analysis_RF, decreasing = TRUE)
print(analysis_RF_results)


##### Count the occurences
analysis_occ <- RF_cl[[1]]$importance
#tranform the importance into 1
analysis_occ[analysis_occ > 1] <- 1



for(i in 2:nr_OF){

  analysis_temp <- RF_cl[[i]]$importance
  #tranform the importance into 1
  analysis_temp[analysis_temp > 1] <- 1

  #merge the previous matrice (the initial one) and the temporary one
  analysis_occ = merge(analysis_occ, analysis_temp,  by = "row.names", all=TRUE)
  # replaces the NA "not a number" or "no data value" by 0
  analysis_occ[is.na(analysis_occ)] <- 0

  #reshapes the matrix to keep the row names
  newmatrix = as.matrix(analysis_occ[-1])
  rownames(newmatrix) <- analysis_occ[,1]
  analysis_occ = newmatrix

  #sum the columns of the matix per rows
  analysis_occ = apply(analysis_occ, 1,sum)
}
# the final matrix contains the variables used in the RandomForest and their number of time they occured
cat("Final list of variables and corresponding sum of nodes purity is \n")
print(analysis_occ)
#Sort and print the matrix in the order of occurences
```

Utilization of statistical models: to code-free dynamic workflows

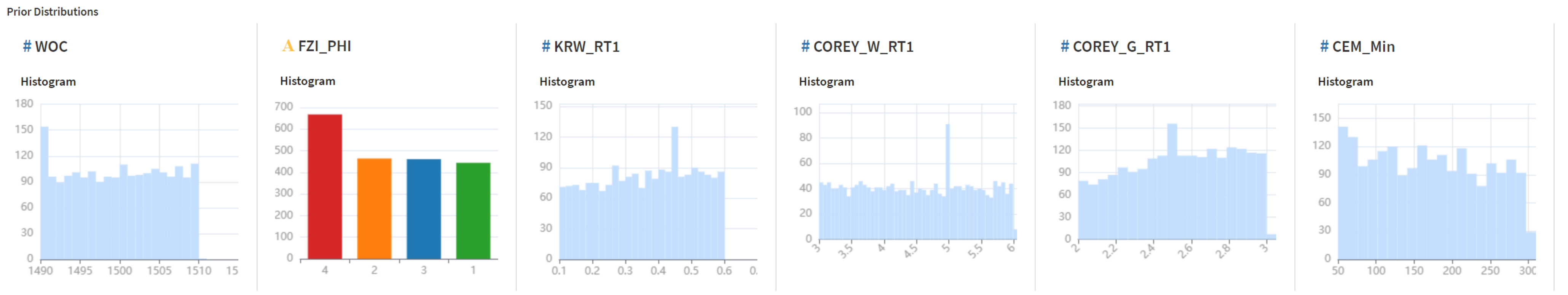


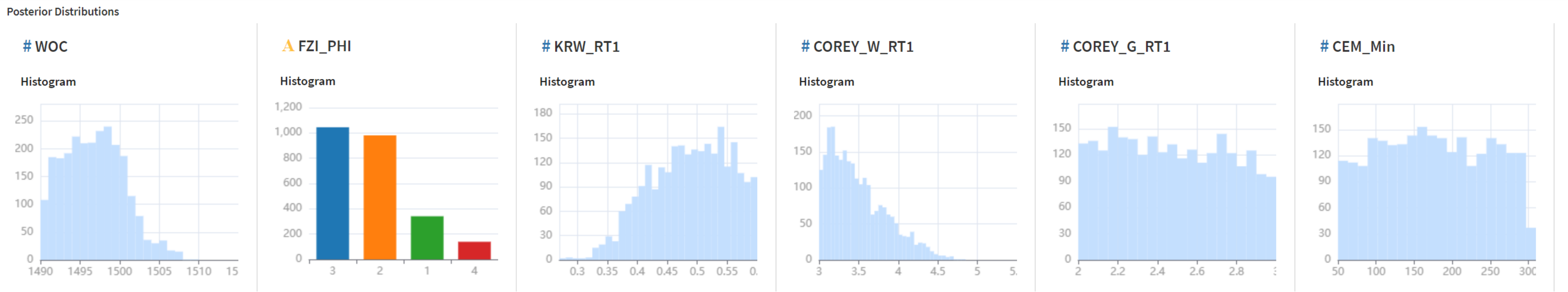


Output and Validation

The use of statistical ML models ensures that non-sensitive parameter ranges are kept aligned to the prior distributions

Fast feed-back on parameter distribution and validity of ensembles





Co-development set up

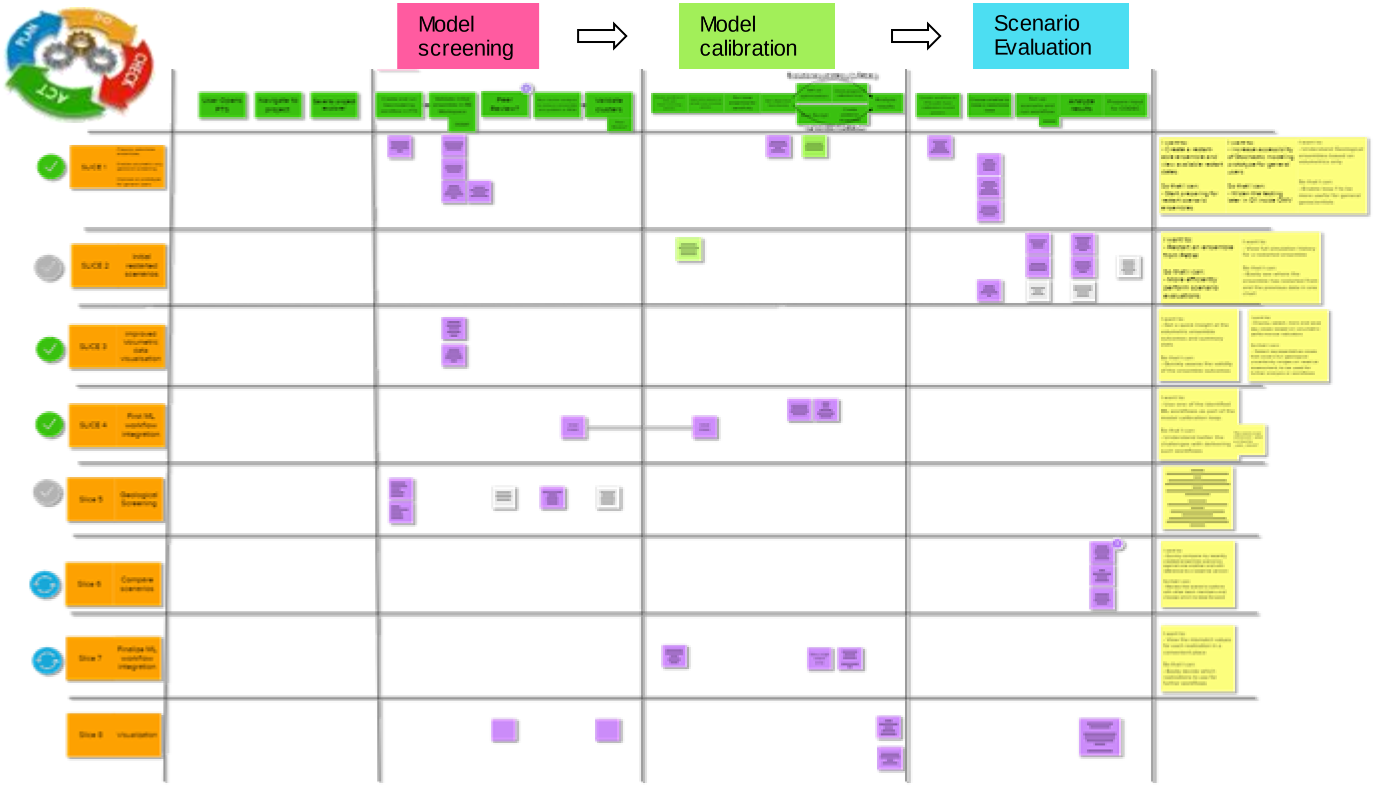
Steering committee, governance team and project team are conformed by OMV and Schlumberger representatives

Bi-weekly sprint review meetings, every 6-month governance meetings and regular updates to the steering committee

Story map captures feedback and direction of development

Testing program based on OMV use cases

Constant dialogue with the development team



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The main benefits to OMV

OMV needs a stochastic modelling workflow to condition model ensembles to multiple data at well and reservoir level for ***systematic and auditable*** probabilistic production forecast profiles.

With the implementation of the Machine-Learning workflow in DELFI we have achieved:

- Reduction of working environments
- Simplification of data transferring
- Full integration of disciplines
- Parallelization of geomodelling and simulation
- Improved user experience from code to interactive interface
- Access to powerful visualization tools for data science
- Easier testing and implementation of alternative algorithms
- Flexible loop back mechanisms (optimization)
- Easier deployment to field business units

Thank you!

OMV Exploration & Production

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The energy for a better life. OMV