Re-thinking the Goliat reservoir models:

History matching and identifying infill targets using an ensemble based method

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Method

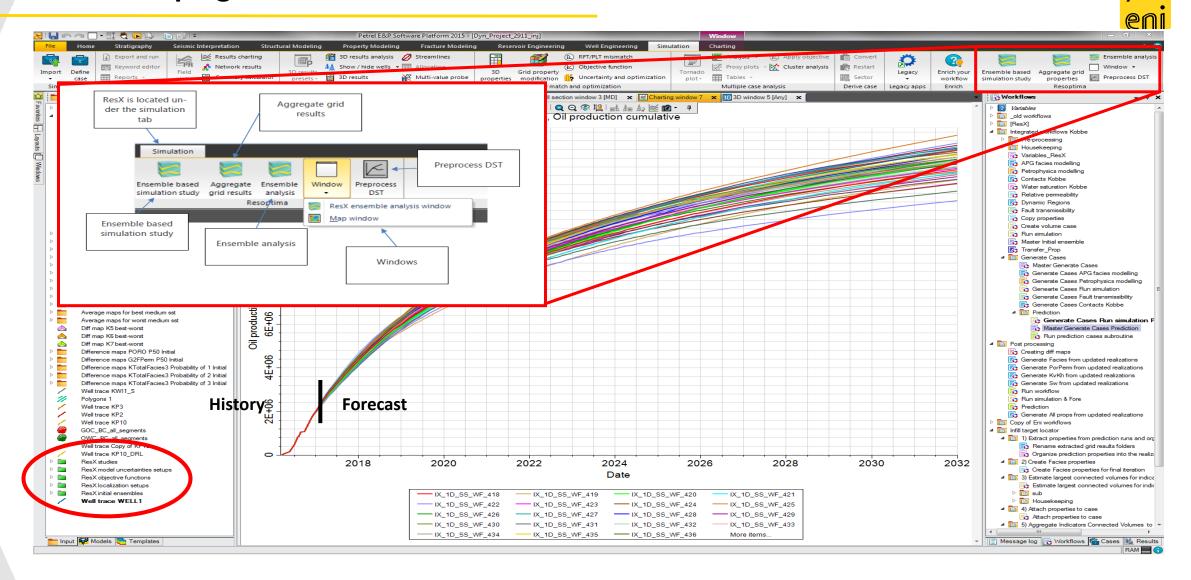
- History matching and forecasting results
- Identification of infill targets
- Conclusion and way forward





METHOD

ResX as a plugin to Petrel

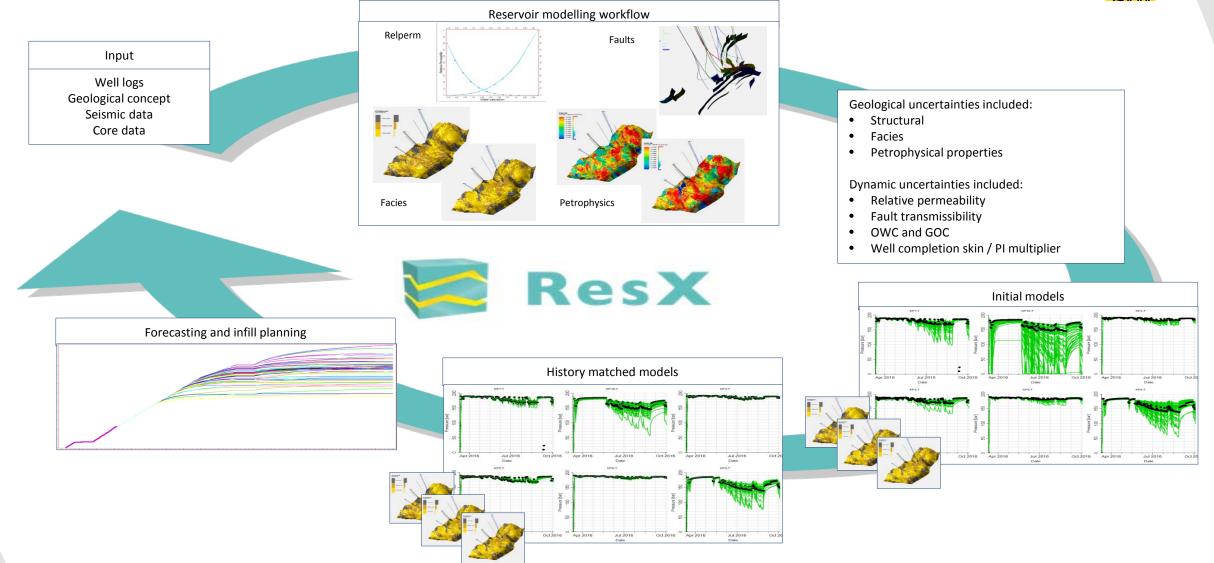




- ResX consistently conditions reservoir models to both static and dynamic data
- The ResX History Matching workflow includes updating of geological properties as well as dynamic parameters on cell by cell level
- Matching a full range of geological uncertainties, not just a base case
- Taking into account the effect of the subsurface uncertainties and generates P10, P50 and P90 statistical results

Ensemble-based reservoir modelling

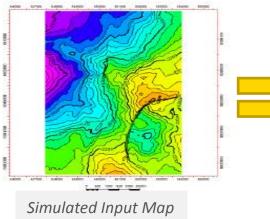


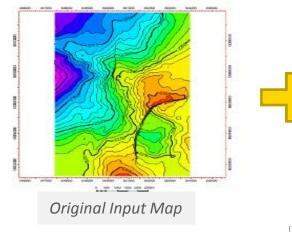


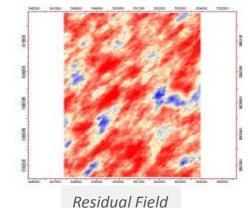
Structural uncertainty



TOP and BOTTOM maps are added a Gaussian random field *horizon/isochore = original + residual*

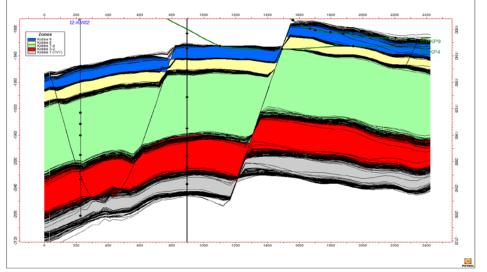






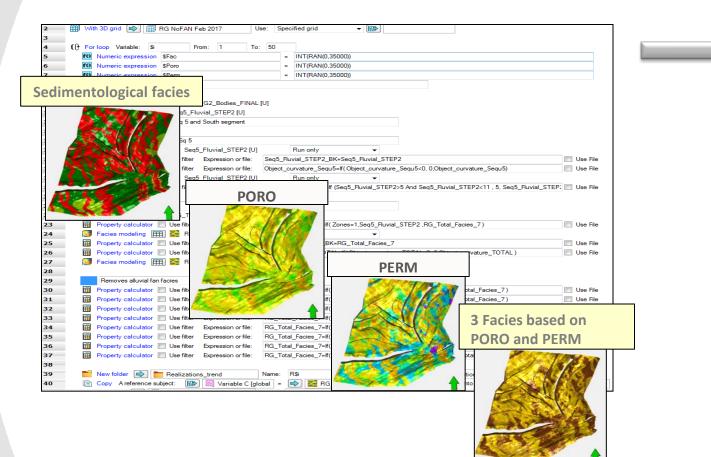
	Distribution	Mean	Std	Min	Max
\$MeanRes	Truncated Normal	0	8	-15	15
\$StdRes	Truncated Normal	3	2	0.5	8
\$MajorRes	Truncated Normal	2000	1000	1000	4000
\$Scalar	Truncated Normal	0.75	0.25	0.5	1
\$AzimuthRes	Truncated Normal	-50	20	-90	-10
\$MinorRes	\$Major x Scalar				

- *MEAN Residual accounts for the velocity model uncertainty*
- STD residual accounts for the mapping uncertainty
- Distance from wells: 300 m



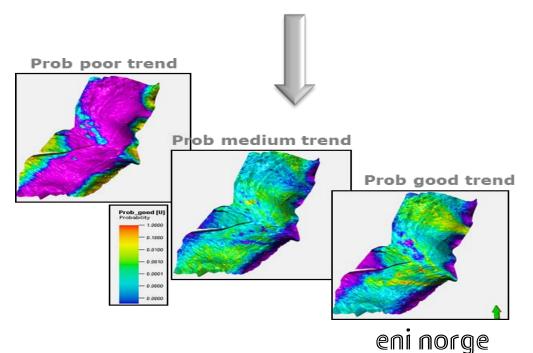
Facies uncertainty (1/2)

Step 1: Creating facies trend maps from the geological conceptual model





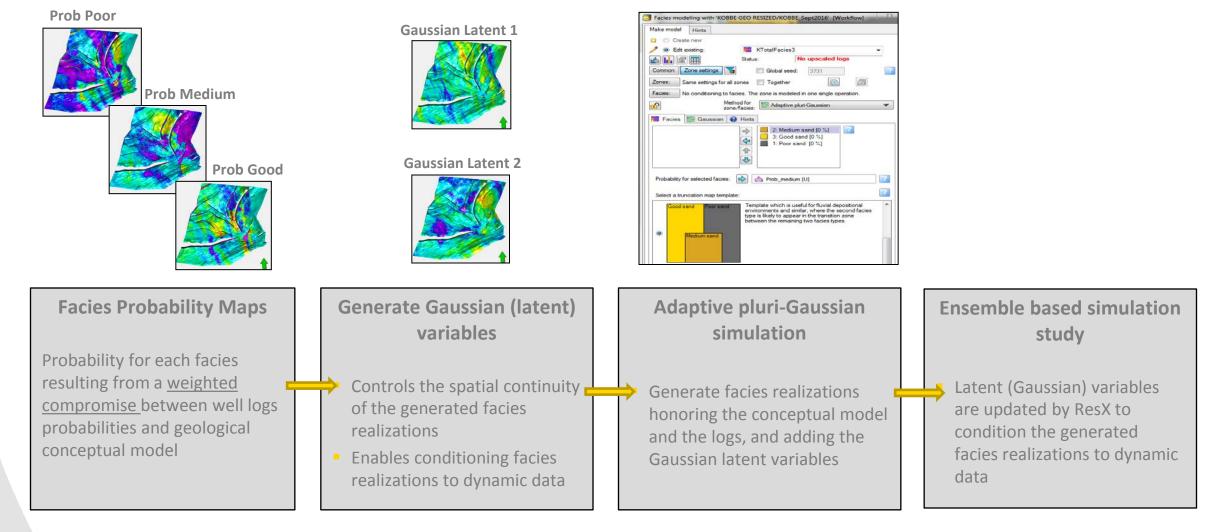
- **1**. Running 50 realizations on original workflow (including sedimentological facies, porosity and permeability)
- 2. Aggregate the **three facies types based on rock quality index** into probability maps for each facies (poor, medium and good)



Facies uncertainty (2/2)

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Step 2: Three facies types distributed using an ADAPTIVE PLURI-GAUSSIAN TECHNIQUE



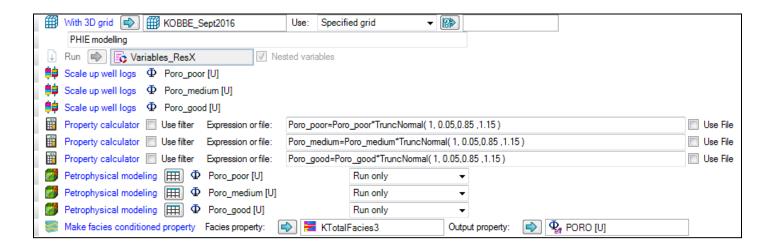
Adaptive Pluri-Gaussian Technique Reference:

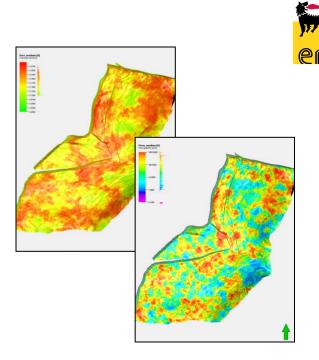
Sebacher, et al. (2013). A probabilistic parametrization for geological uncertainty estimation using the ensemble Kalman filter (EnKF), Computational Geosciences



Petrophysical uncertainty

- Porosity and permeability as a random pick of the log values for each facies plus truncated Gaussian multipliers
- Vertical permeability based on shale volume content or field analogues plus by truncated Gaussian multipliers
- Water Saturation based on J-functions and risked by variability ranges of the coefficients for each facies.

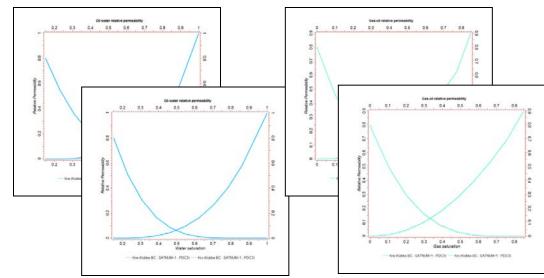


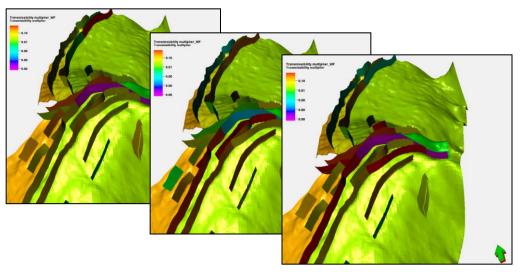


Dynamic uncertainty



- Relative Permeability
 - End point and Corey exponent uncertainty for both water/oil and gas/oil
- Fault Transmissibility
 - Transmissibility multipliers across faults
- OWC and GOC
- Completion skin / PI multiplier

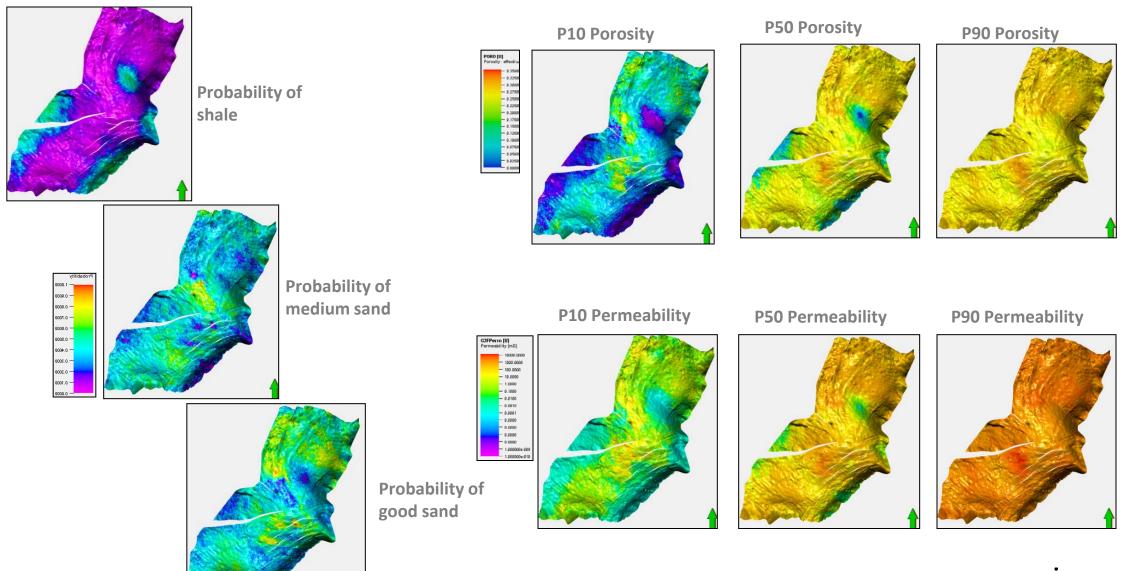






Aggregated properties – initial ensemble





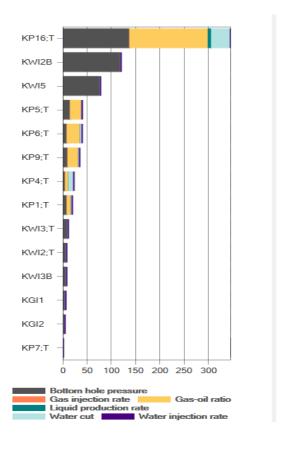
Initial ensemble coverage/variability check

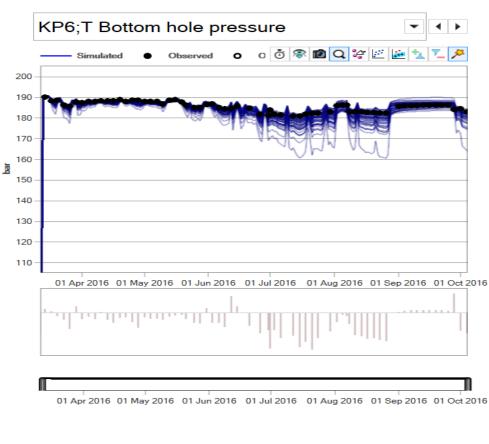


Definition of the objective function



- Selection of production data to be part of the objective
 - Liquid production rate
 - Bottom hole pressure
 - GOR
 - WCT
- Specification of the tolerance
 - 10 bar for pressure
 - 10% for others
- *Ensemble analysis process*
 - Screening tool to analyze the initial ensemble





Model uncertainties and localization

- Specify the history matching variables and boundaries
 - facies probability
 - porosity & permeability
 - shale volume
 - *fault transmissibility*
 - relative permeability
 - well connection multipliers

- Constrain the area of influence
 - radius around the wells
 - zones
 - segments

	field	I here to group by th	at field						
1	Tra	insfer property	Name	Passthrough	Minimum	Maximum	Unit	Transform	Comment
1		GaussianLatent1	GaussianLatent1		-3	2.99999		Linear	•
1		daussianLatent2	GaussianLatent2		-3	3		Linear	•
1	\Rightarrow	k ^h Perm_good	Perm_good		0	19682.6	mD	Logarithmic	-
1		k [↑] Perm_medium	Perm_medium		0	1926.86	mD	Logarithmic	•
1		k ^h Perm_poor	Perm_poor		0	3.0219	mD	Logarithmic	-
1			Poro_good		0	0.404307	m3/m3	Linear	-
1	\Rightarrow	Poro_medium	Poro_medium		0	0.309357	m3/m3	Linear	-
1			Poro_poor		0	0.113912	m3/m3	Linear	-
1	\Rightarrow	A Prob_good	Prob_good		0	1		Probability	-
1	⇒	🔥 Prob_medium	Prob_medium		0	1		Probability	-
1	\Rightarrow	A Prob_poor	Prob_poor		0	1		Probability	-
1		V _{SH} Vsh_good	Vsh_good		1.71866e-05	50	%	Linear	-
1	\Rightarrow	V _{SH} Vsh_medium	Vsh_medium		1.5783e-05	90	%	Linear	•
1		V _{SH} Vsh_poor	Vsh_poor		6.43546e-05	100	%	Linear	-

Drag a fi	ield here to group by that field					2	Values: Impact near well
Identifier	Property	Туре	GaussianLatent1	GaussianLatent2	Perm_good	Perm_me -	Radius: 2,000 m
KP16;T	Liquid production rate	Production data	r=2000 m 😽	r=2000 m 📲	r=2000 m 🚽	r=2000 r	
KP1;T	Liquid production rate	Production data	r=2000 m 🚽	r=2000 m <u></u>	r=2000 m 🛃	r=2000 r	Near perforations only
KP4;T	Liquid production rate	Production data	r=2000 m 🚽	r=2000 m 📲	r=2000 m 🚽	r=2000 r	Impact all cells
KP5;T	Liquid production rate	Production data	r=2000 m 🚽	r=2000 m 🚽	r=2000 m 🚽	r=2000 r [≡]	No impact
KP6;T	Liquid production rate	Production data	r=2000 m 😽	r=2000 m 式	r=2000 m 🚜	r=2000 r	Custom localization property
KP9;T	Liquid production rate	Production data	r=2000 m 😽	r=2000 m 🚽	r=2000 m 😽	r=2000 r	→
KP16;T	Gas-oil ratio	Production data	r=2000 m 🚽	r=2000 m 📲	r=2000 m 🚽	r=2000 r	Filter property
KP1;T	Gas-oil ratio	Production data	r=2000 m 🚽	r=2000 m 🚽	r=2000 m 🚽	r=2000 r	A Zones Regions
KP4;T	Gas-oil ratio	Production data	r=2000 m 🚽	r=2000 m 🚽	r=2000 m 🚽	r=2000 r	🔽 🕂 0: Kobbe 9
KP5;T	Gas-oil ratio	Production data	r=2000 m 😽	r=2000 m 式	r=2000 m 🚜	r=2000 r	🔽 🕂 1: Kobbe 8
KP6;T	Gas-oil ratio	Production data	r=2000 m 🚽	r=2000 m 🚽	r=2000 m 🚽	r=2000 r	🔲 🕂 2: Kobbe 7
KP9;T	Gas-oil ratio	Production data	r=2000 m 🚽	r=2000 m 📲	r=2000 m 🚽	r=2000 r	3: Kobbe 6
KGI1	Bottom hole pressure	Production data	r=2000 m 🚽	r=2000 m 🚽	r=2000 m 🚽	r=2000 r	4: Kobbe 5
KGI2	Bottom hole pressure	Production data	r=2000 m 😽	r=2000 m 🚽	r=2000 m 🚽	r=2000 r	5: Kobbe 4
KP16;T	Bottom hole pressure	Production data	r=2000 m 😽	r=2000 m 🚽	r=2000 m 😽	r=2000 r	
KP1;T	Bottom hole pressure	Production data	r=2000 m 🚜	r=2000 m 🚜	r=2000 m 🚜	r=2000 r	6: Kobbe 3
KP4;T	Bottom hole pressure	Production data	r=2000 m 🚜	r=2000 m 🚜	r=2000 m 🚜	r=2000 r 🍝	7: Kobbe 2
•						Þ	8: Kobbe 1
KP4:1		Production data	r=2000 m 📩	r=2000 m 🔩	r=2000 m 📩	•	Apply V OK



Data assimilation for history matching



Ensemble based simulation stu	dy						23
Initial ensemble 🚺 Define o	bjective function	Define model uncertainties	Define localization setup	History matching	Forecasting 🔒 Settings	Hints	
Study name:	RG_HM_62_2	22122016		_			
Input:							
Ensemble:	🧱 init_62_2	1122016	• ?				
Objective function:	Sective Objective	function NoFan Grid	•				
Model uncertainties:	Se Model un	certainties NoFan grid	•				
Localization:	See Localizat	ion_noKRELinSouth_NoFAN_grid	•				
Generate cases workflow:	🔿 🔂 Maste	er Generate Cases					
Study options:							
Iterations (count / resume from):	4	4 🗘 🔲 🔳 1 🗘	?				
Data inflation scheme:	Slope	• 1.5 🛟	?				
Data inflation coefficients:	13.4, 8.7, 4.7,	, 1.7					
Max simulation time:	7	0 🗘 minutes	?				
Cancel study on variable collapse:			?				
Load results:	Grid prope	arties (Simulation) n data	?				
Store model grid properties:	© Off ⊚ A	All iterations					
		Run test Ru	n Cancel run				
					Apply	ок 🛛 🔀 с	ancel



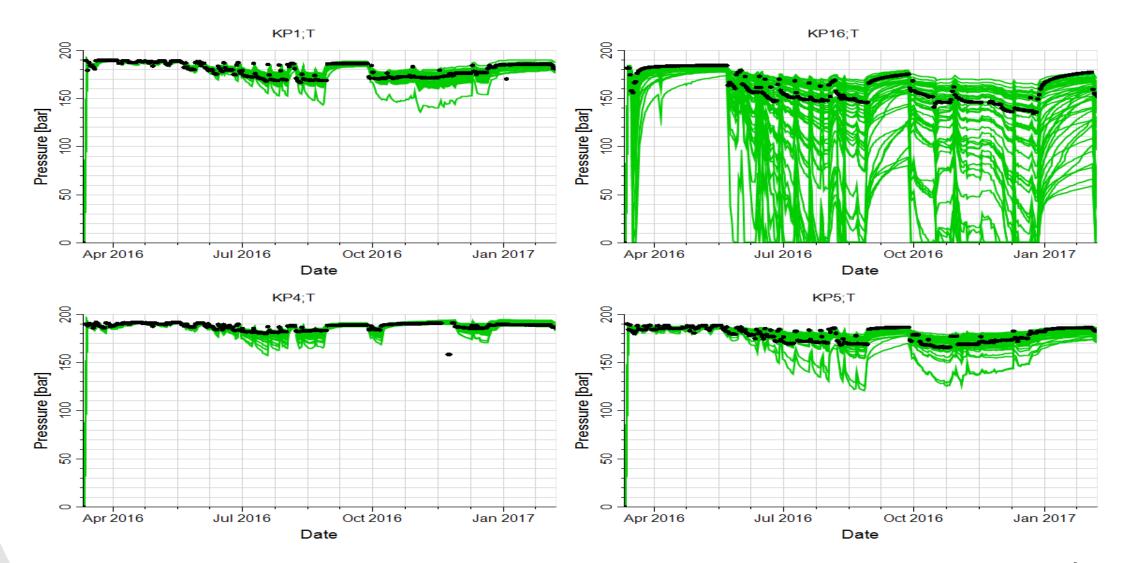


HISTORY MATCHING AND FORECASTING RESULTS



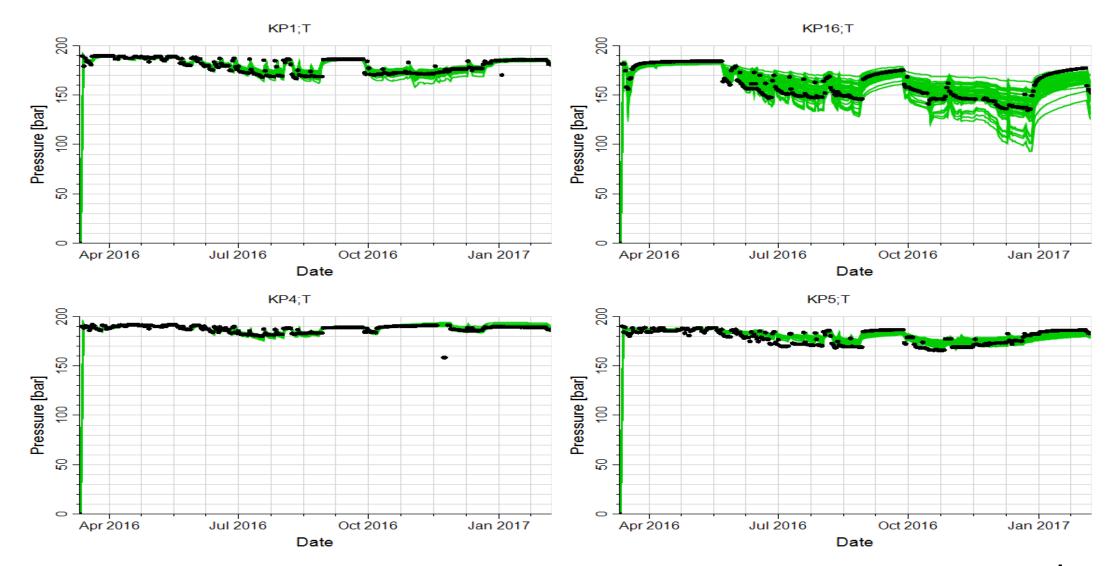
Initial ensemble - BHP





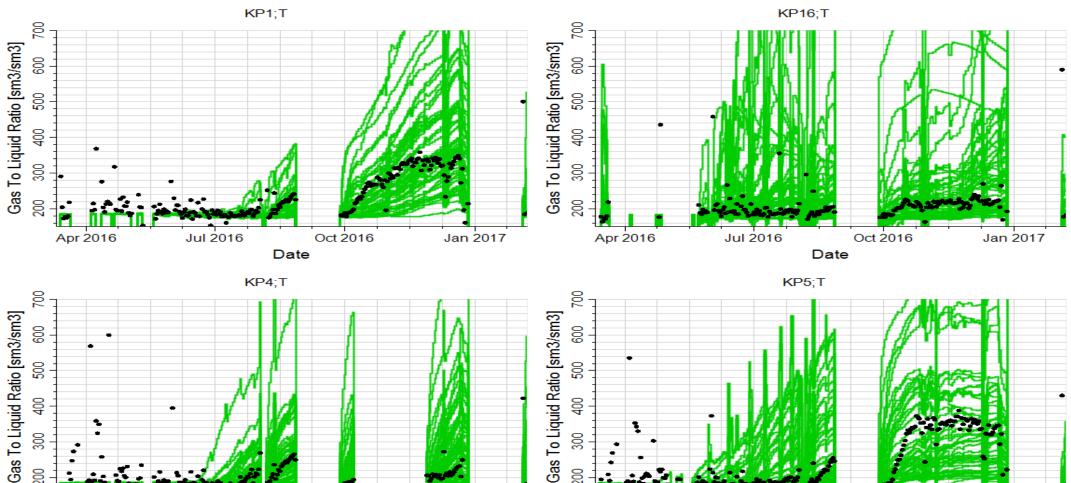
After history match - BHP

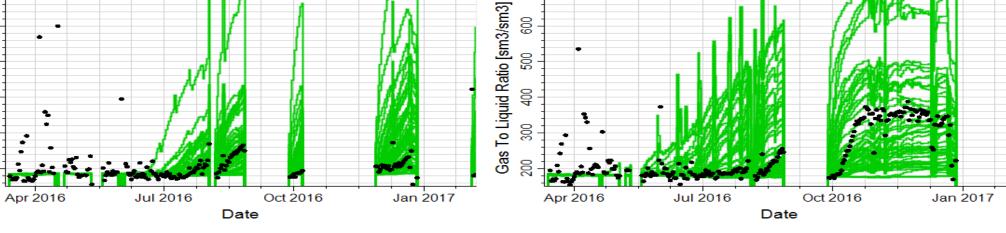




Initial ensemble - GOR







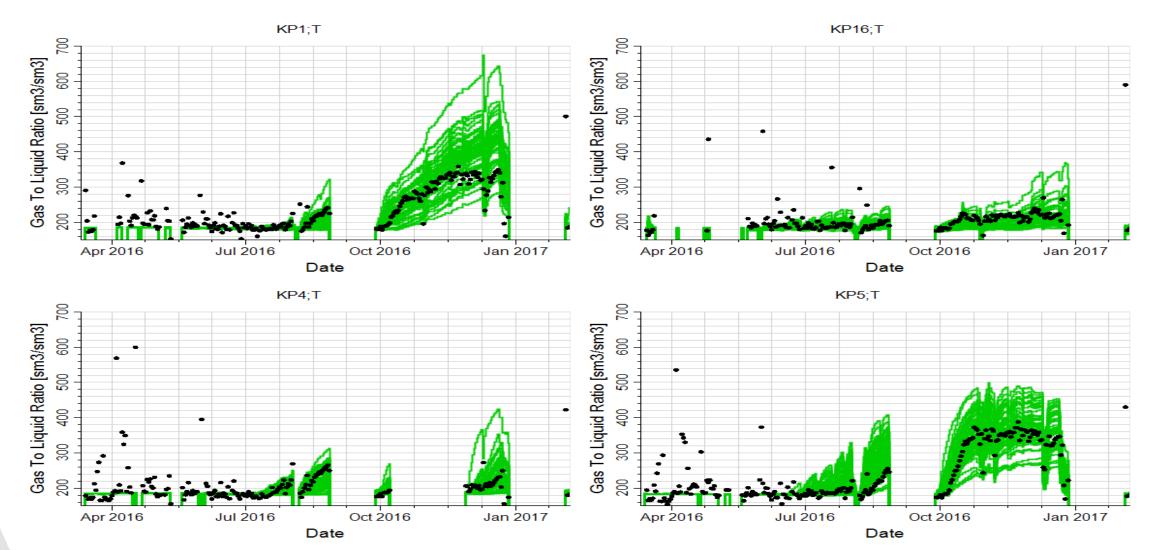
400

30

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After history match - GOR





Forecasting set-up

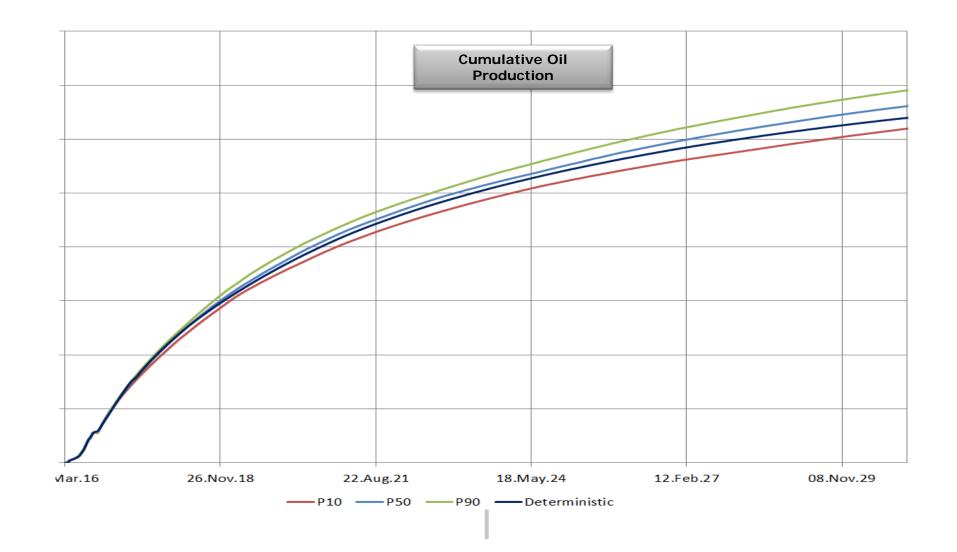


Initial ensemble	Define objective function	Define model uncertainties	Define localization	setup	History matching	Forecasting	ettings _🔞 Hints	
orecast name:	RG_INFILL_RM	P6_RMWI7_INCREASED_BHP			<u> </u>			
nput:								
Study:	🧱 RG_HM_62	2_22122016	•					
Cases:	Initial ens		A.	Gri	d properties Scal	ars		
	⊿ V Iteration 4				Transfer property	Name		
	▼ RG_1 ▼ RG_1							
	▼ RG_1	1345			GaussianLatent	1 GaussianLatent1		
	RG_1	1346		\checkmark	GaussianLatent	2 GaussianLatent2		
			=	\checkmark	🔿 📥 KvKh_good	KvKh_good		
	▼ RG_1 ▼ RG_1			-	🔿 🏙 KvKh_medium	KvKh_medium		
	RG_1			-	KvKh_poor	KvKh poor		
	▼ RG_1				→ k [↑] Perm_good	Perm_good		
	🔽 RG_1	1352			⇒ k [↑] Perm_medium	Perm_medium		
						_		
	▼ RG_1 ▼ RG_1				k Perm_poor	Perm_poor		
	▼ RG_1			V		Poro_good		
	RG_1	1357		\checkmark		Poro_medium		
		1358		\checkmark		Poro_poor		
	▼ RG_1 ▼ RG_1			-	A Prob_good	Prob_good		
	RG_1			-	A Prob_medium	Prob_medium		
	▼ RG_1				A Prob_poor	Prob_poor		
		1363				pool		
	RG_1							
	▼ RG_1 ▼ RG_1		+					
Workflow:		Generate Cases Prediction						
Max simulation time:		minutes						
max simulation time.	800	▼ minutes						
		Ru	n Cancel run					



Ensemble forecast







IDENTIFICATION OF INFILL TARGETS



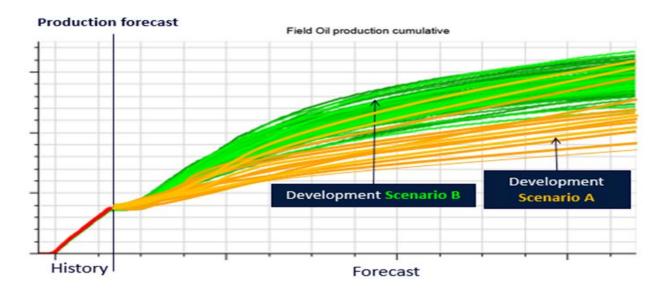
Approach

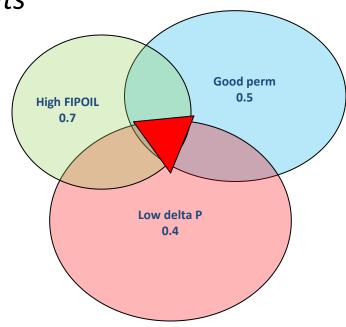


Analyze the ensemble of models to identify robust infill targets

- Identify connected volumes combining:
 - High probability of good perm sand
 - High probability of high in-place volumes
 - High probability of small pressure depletion

Evaluate the different development scenarios





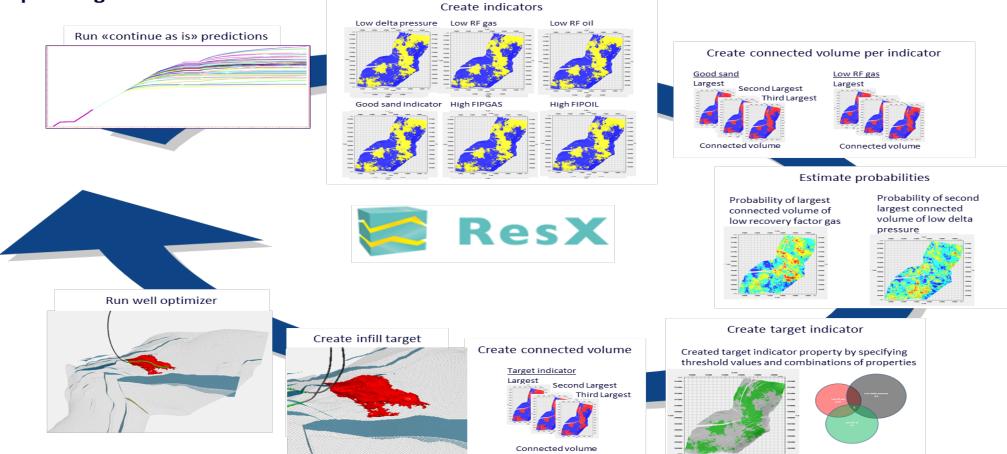


Infill planning workflow



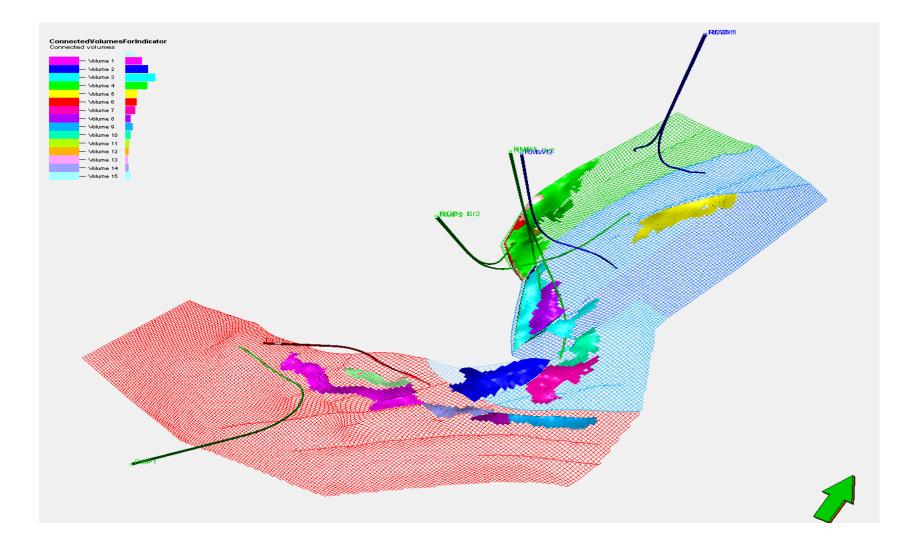
History matching and robust infill drilling

Robust infill planning workflow



Connected volumes – Reservoir 1

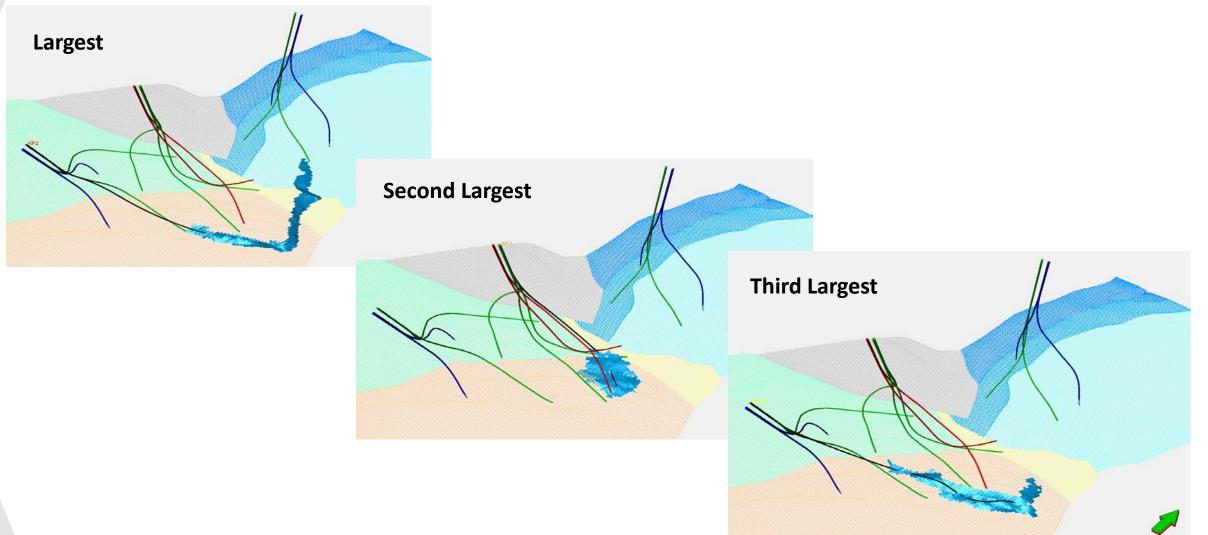






Connected volumes - Reservoir 2







CONCLUSION



Conclusion and way forward



PROS

- Close cooperation between the geologist and the engineer
- Less constrained geological concept more adaptable to the observed dynamic data
- The workflows are easily updated with the historical data
- A better understanding of the residual uncertainty after history matching
- Infill targets can be identified based on the prediction from the entire history matched ensemble

CONS

- The workflows create large models occupying a lot of disk space, and a lot of computing power is needed
- Analysis of the data is time consuming
- Software/computing infrastructure issues
- Way forward
 - Apply ResX for production optimisation

THANK YOU!

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• PL229 Licensees – Statoil Petroleum AS

CHO

- ResOptima
- Goliat Reservoir team, EniNorge