



Technical Session Agenda 2016 SPEE Annual Meeting

Tuesday, June 7, 2016 2016 SPEE Technical Session 2

Salon I/II

8:40 AM

**Utilizing Advanced Data Analytic Methods for
Secondary Recovery Methods**

Chad Kronkosky

BIOGRAPHY

Chad E. Kronkosky – CEK Engineering LLC

As President of CEK Engineering LLC (CEK), formed in 2012; Mr. Kronkosky is solely responsible for coordinating and supervising technical personnel of the company in ongoing reservoir evaluation studies conducted by CEK. Prior to forming CEK, Mr. Kronkosky served in various engineering positions with A.C.T. Operating Company and Bold Operating LLC.

Mr. Kronkosky earned a Bachelors and Masters of Science degrees in Petroleum Engineering from Texas Tech University in 2006 and 2009 respectively. He is currently pursuing a Ph.D. in Petroleum Engineering part-time at Texas Tech University with anticipated candidacy in the Fall of 2016. His doctoral dissertation work involves the Application of Data Science to Advance Petroleum Engineering Topics.

Mr. Kronkosky is a Licensed Professional Engineer in the State of Texas, a member of the Society of Petroleum Engineers (SPE), and is an Associate Member of the Society of Petroleum Evaluation Engineers (SPEE) and American Association of Petroleum Geologist (AAPG).



Utilizing Advanced Data Analytic Methods for Secondary Recovery Estimates

Chad E. Kronkosky, P.E.

Doctoral Aspirant
Bob L. Herd Department of Petroleum Engineering

April 29, 2016



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Presenter Bio

Education

B.S. Petroleum Engineering (TTU 2006)

M.S. Petroleum Engineering (TTU 2009)

PhD. Petroleum Engineering (TTU - Anticipated Spring 2017)

Industry Experience

CEK Engineering LLC, President (2012 - Present)

Professional Engineering Consulting Firm servicing Large Private Equity Management Teams to Small Independent Oil and Gas Operators. Project experience in Texas, Louisiana, New Mexico, Kansas, Colorado Montana, and North Dakota, but our primary focus is the Permian Basin of West Texas.

www.cekengineering.com

Bold Operating LLC, Reservoir Engineer (2010 - 2012)

Small Private Equity Management Team (EnCap) solely focused in the Permian Basin; Grow By The Bit Company. Gained valuable financial experience; worked with lending institutions, private equity analysts/managers. Prepared the reserve/geological study (complex carbonate) that was instrumental in selling most of the companies assets.

A.C.T. Operating Company, Graduate Petroleum Engineer (2006 - 2010)

Worked under Marshal Watson, Ph.D, P.E., Past SPEE President and Current Chair of the Bob L. Herd

Department of Petroleum Engineering. Experience encompassed: Secondary Recovery Project, CBM, Corporate Management, Prospect Development, etc. (almost anything you could imagine, especially for a two man company).

Marshall, thank you for your guidance throughout my career. . .

and for letting me make boneheaded mistakes; on yours and Don's dime! They've been committed to memory!

Outline

- 1 Introduction
- 2 Data-Driven Predictive Analytics
- 3 Application of Data Analytics to Historical Secondary Recovery within the State of Texas
- 4 Example
- 5 Project Status\Software Development



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What is Petroleum Engineering?

Petroleum Engineering is:

- Drilling Engineering
- Completion Engineering
- Production Engineering
- Reservoir Engineering
- Formation Evaluation



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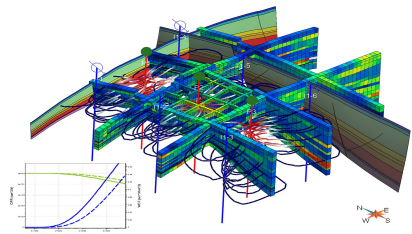


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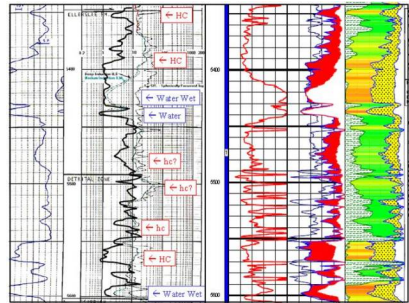


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Data Science is:

- Mathematics & Statistics
- Information Theory
- Computer Science
- Visualization
- Data Mining

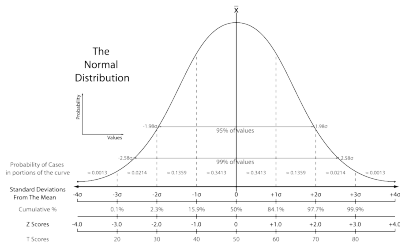


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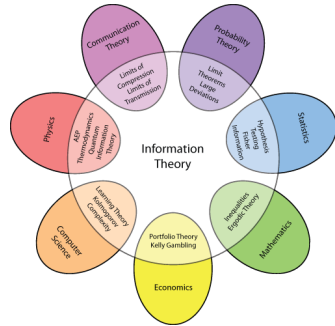


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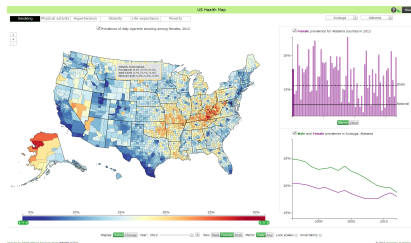
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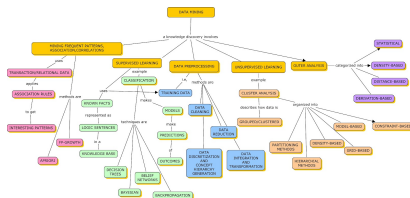


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Application of Data Science in Petroleum Engineering

Petroleum Professionals apply Data Science techniques everyday in the following:

- Petrophysical Well Log interpretation (e.g. rock-type classification; K-means cluster analysis)
- Completion Designs (frac stage count optimization; multivariate Linear Regression)
- Casing Point Selection (pore pressure estimation; multivariate Linear Regression)
- Type Curve Analysis (sub-population determinations; classical statistical analysis/distributions)



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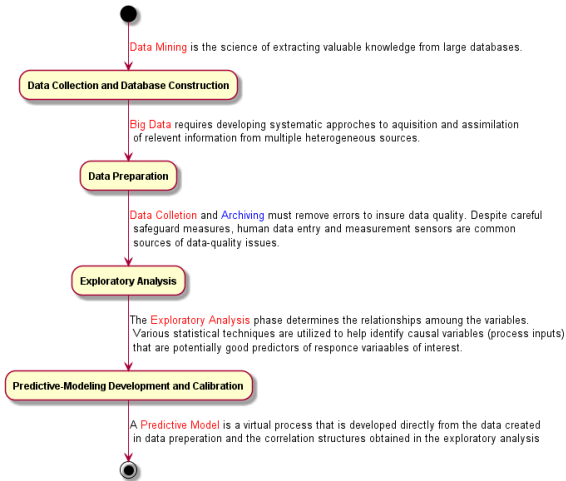
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Data-Driven Predictive Analytic approach (DDPA)

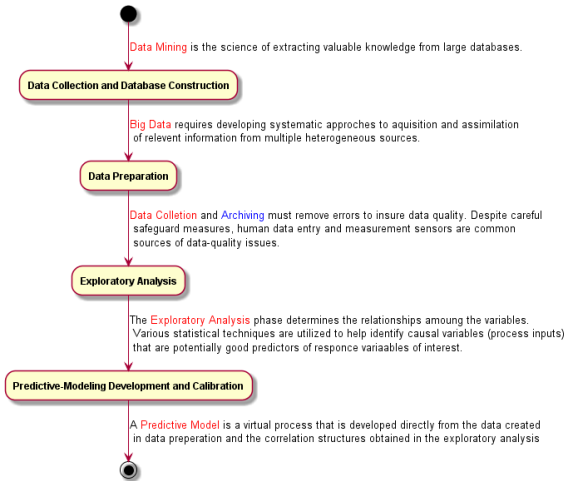
Data-Driven Predictive-Analytic Approach



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Data-Driven Predictive Analytic approach (DDPA)

Data-Driven Predictive-Analytic Approach



We abstract the DDPA approach (as outlined) and apply it to three research topics involving underground injection within the State of Texas.



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Historical Underground Injection within the State of Texas

What makes this an important topic for the industry?

- Estimation and classification of reserves is predicated on data quality and quantity. Because many aspects of reserve evaluation are based on limited or indirect information, it is important that evaluators compare all reserve parameters from analogous reservoirs.
- Public data vendors provide extremely limited injectivity data sets for the State of Texas.
- EOR dates back to the early 1930's in Texas ... there is a significant gap in digital injection information available.
- Injection information from this gap (50 years) is vital to developing appropriate analogy models (S:P).



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What data sets are available (Digital\Hard Copy)?

To the best of our knowledge there are two datasets which provide an accurate underground injection history for the State of Texas.

RRC UIC Database & RRC "Bulletin 82".

- RRC UIC Database – (Digital Cobol Hierarchical File)
IHS is the only major public data vendor which provides injection information. This data set is the backbone of IHS's injection information for the State of Texas.
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 - Monthly Injection Data (1983 to Present)
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 - MIT Tests
 - Regulatory Enforcement Actions
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 - Project\Field Summary Information
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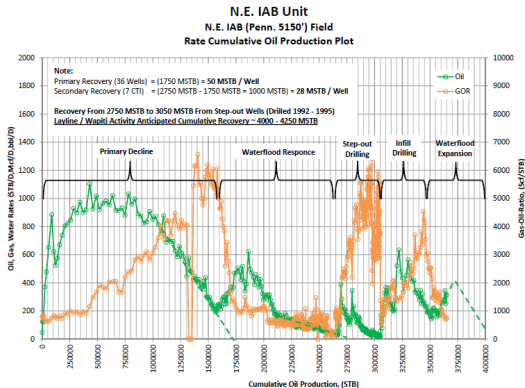
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Gary S. Swindell provided us a limited dataset of this information. This informations contains cumulative volumes instead of annual volumes.
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What are Secondary to Primary Ratios (S:P)? How are they applied?

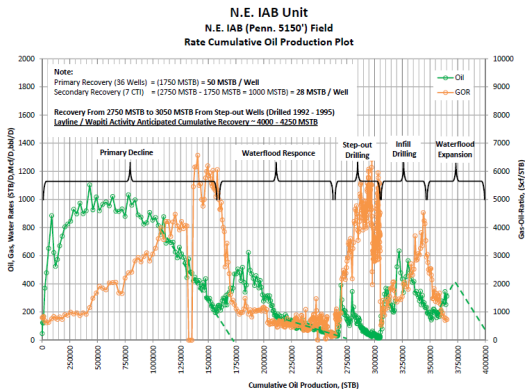


S:P is the ratio of secondary oil production to primary oil production.



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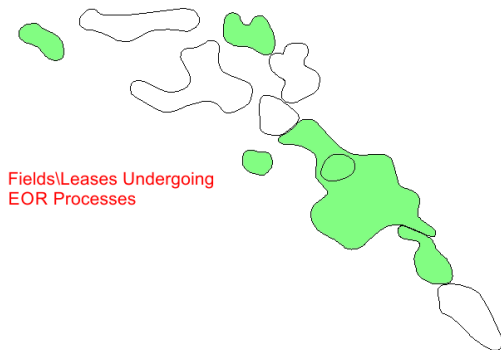
For this particular project:

$$\frac{2750 - 1750}{1750} = 0.57$$



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What are Secondary to Primary Ratios (S:P)? How are they applied?



For Fields\Leases which have not undergone an EOR process we can utilize offset analogous S:P ratios to estimate EOR reserves.



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How can Data Science principles be applied to this topic?

Presently, S:P ratio are typically estimated for a few nearby analogous projects and then averaged.

Incorporating geospatial\multivariate statistics; we believe better estimates of S:P ratio can be made to estimate EOR reserves.

Additionally, data science principles support automation techniques which can be applied to petroleum engineering workflows.



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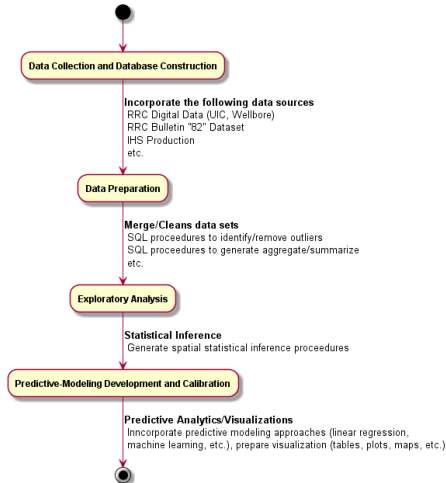
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Conceptual Framework

Data-Driven Predictive-Analytic Approach Investigation of Historical Underground Injection within the State of Texas



We apply the abstracted DDPA approach to study this particular problem.



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Methodology\Workflow

- Construct MDM (PPDM 3.9) and ETL SQL procedures for the following data sets:
 - RRC UIC Database
 - RRC Wellbore Database
 - RRC "Bulletin 82" Gary S. Swindell data
 - IHS production data
- Construct various summary\spatial queries
 - Cum injection\production by leases\units
 - Generate spatial polygons for leases\units
 - Generate a spatial filtering queries
- Construct various statistical analyses\inference on summary queries
 - Generate spatial statistical inference procedures
 - Incorporate a predictive model, machine learning algo, to estimate S:P



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 - RRC Wellbore Database
 - RRC "Bulletin 82" Gary S. Swindell data
 - IHS production data
- **Construct various summary\spatial queries**
 - Cum injection\production by leases\units
 - Generate spatial polygons for leases\units
 - Generate a spatial filtering queries
- Construct various statistical analyses\inference on summary queries
 - Generate spatial statistical inference procedures
 - Incorporate a predictive model, machine learning algo, to estimate S:P



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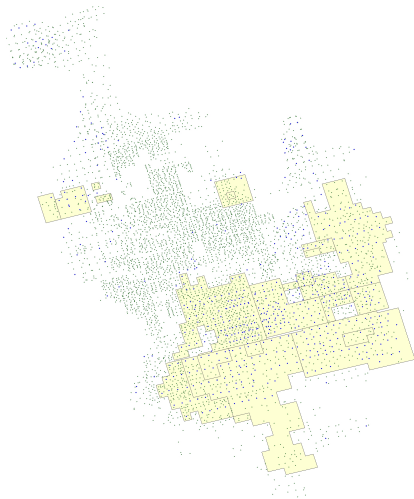
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Example Project Workflow – Spatial Analysis



Carbonate Field in the Permian Basin

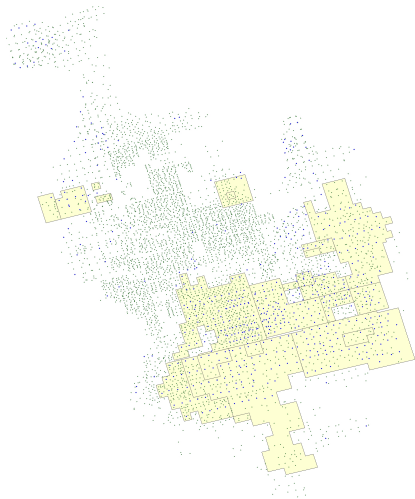
14 Units\Leases in Field with EOR
Projects within the Field

Approximately 50 Analogous Units\Leases
within 20 miles of the Field (Same/Similar
Reservoir and Depositional Environment)



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Example Project Workflow – Spatial Analysis



Incorporate GIS to delineate Units\Leases (not a requirement but helps visualize project bounds).

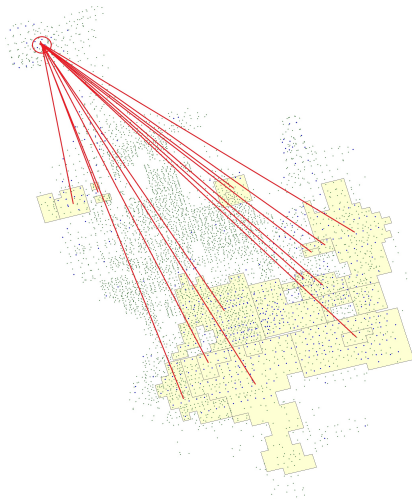
Data Vendors (IHS, DI, Tobin, etc.) may/may not have this information digitally; can typically be found in scanned regulatory filings with minimal effort.

Spatial distances can be incorporated into the statistical model (i.e. spatial distance weight parameter).



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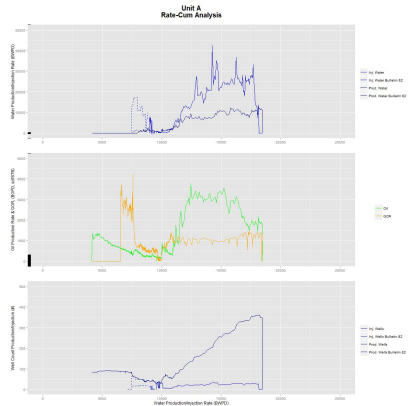
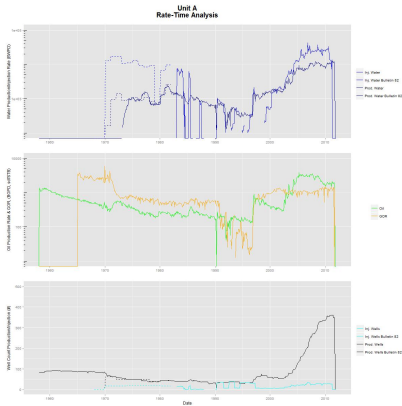
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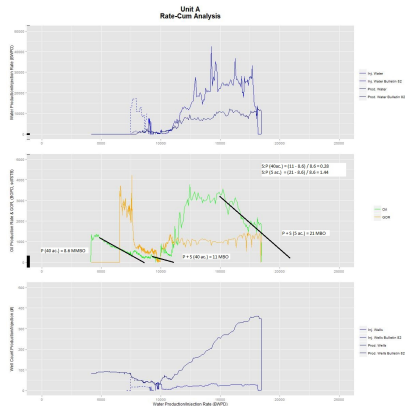
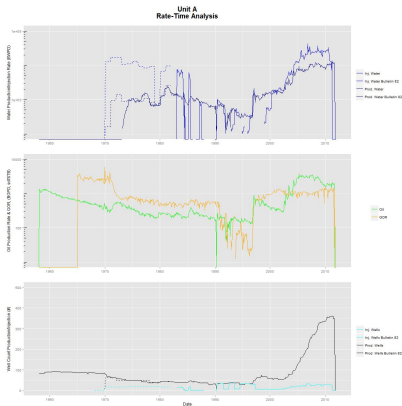


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Example Project Workflow – DCA

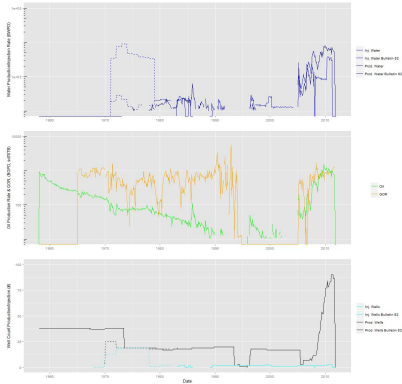


Example Project Workflow – DCA

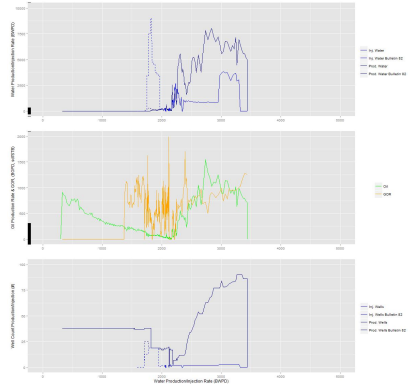


Example Project Workflow – DCA

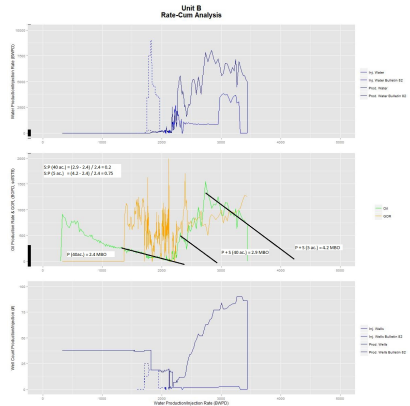
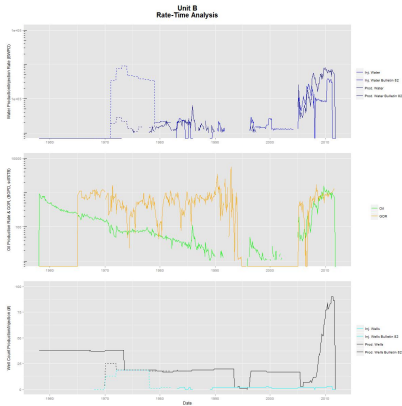
Unit B
Rate-Time Analysis



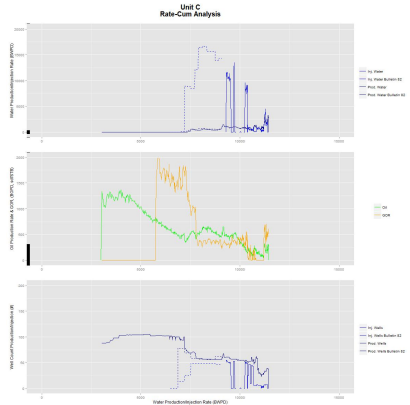
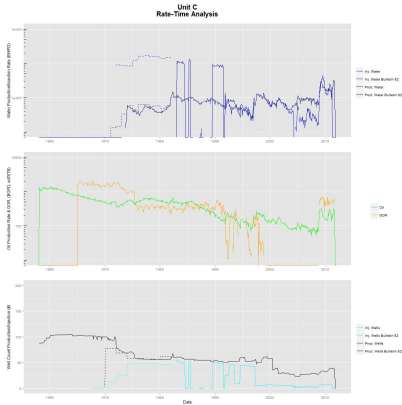
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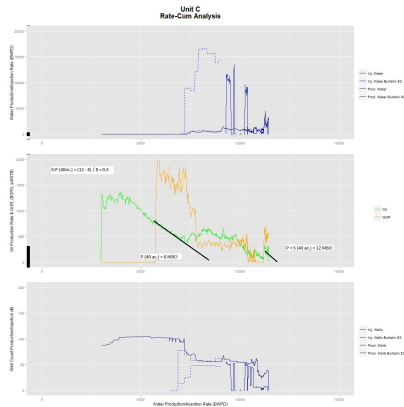
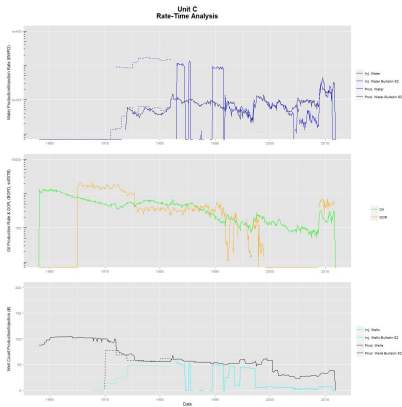
Example Project Workflow – DCA



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Example Project Workflow – DCA



Example Project Workflow – Statistical Analysis

A Multivariate Statistical Analysis is performed, based on Spatial\DCA\RRC Bulletin 82 Parameters, to generate S:P confidence intervals (P90, P50, P10).

Unit\Lease ID	S:P Ratio	Spacing	Pattern	Prod./Inj. Ratio	“	“
Unit A	0.28	40 ac. Pri by 40 ac. Sec CTI	I9	2.2	“	“
Unit B	0.20	40 ac. Pri by 40 ac. Sec CTI	I9	1.0	“	“
Unit C	0.5	40 ac. Pri by 40 ac. Sec CTI	5S	1.2	“	“
Unit A	1.44	40 ac. Pri by 5 ac. Sec CTI/Infill	I9	9.2	“	“
Unit B	0.75	40 ac. Pri by 5 ac. Sec CTI/Infill	I9	18	“	“
“	“	“	“	“	“	“
“	“	“	“	“	“	“

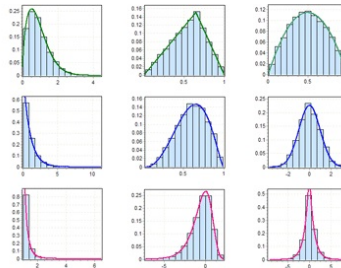
Additional RRC Bulletin 82 Parameters: Avg. Porosity, Avg. Horz. Perm., Avg. Net Pay, Oil Grav., Orig. Res. Pres., Beg. Inj. Pres., Inj. Fluid Type, Project Effectiveness, Inj. Sur. Pres., Prod. Water, Est. Primary Rec., Est. Sec. Rec. Remarks, problems, Inj. Source



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- Web based software platform could allow for industry wide collaboration/work share (i.e. authorized engineers would review/estimate parameters). . . otherwise I'll never have a life.



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Questions?

I appreciate everyones time this morning; and special thanks to Mr. Floyd Siegle for allowing me the opportunity to speak with you.

