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ENERGY CHALLENGE
Today and Tomorrow



Subsurface Temperature Measurement Using Electromagnetic Waves and Machine Learning for Enhanced Oil Recovery

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Outline

- Background and motivation
- EM and borehole field measurements
- Machine learning approach
- Results
- Discussion

Background and motivation

Enhanced Oil Recovery (EOR)

- Allows more (~60%) oil to be extracted from reservoir
 - Viscosity
 - Mobility ratio
- Various methods in use
 - Gas injection
 - Thermal methods ← this application
- Steam injection
 - Need to monitor subsurface temperature profile
 - Use temperature observation wells (TOW)
 - Measure 3-4 times a year, expensive
 - Cost of drilling
 - \$5000,- typical cost per well for measurement
 - No production during measurement

Virtual TOW wish list

- No drilling
- Using surface data
- Measure without well downtime
- Faster acquisition
- More frequent monitoring
- Low cost per measurement
- Easy data processing

EM and borehole field measurements

EM data/TOW data

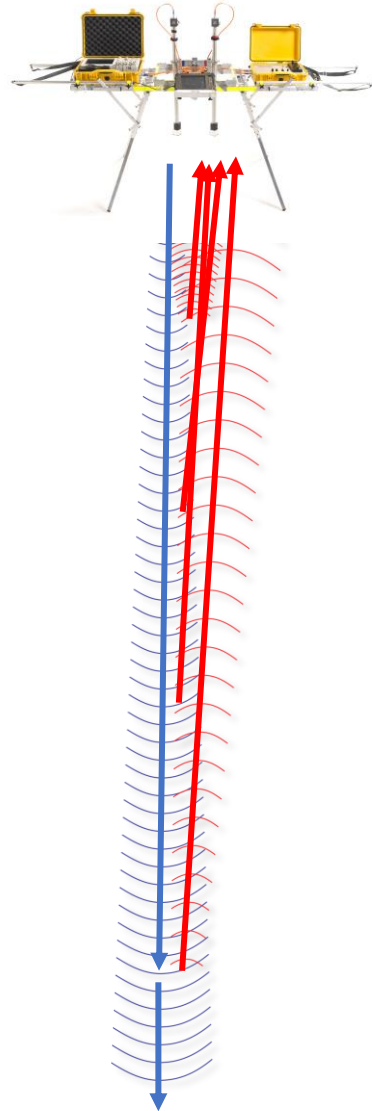
- Pulsed radar subsurface imaging
 - Low frequency (1-3MHz) for deeper penetration
 - Bistatic data acquisition
 - Stacking 100,000 shots
 - Measurement takes a few minutes per well
- Data acquired on 2 large producing oil fields
 - 21 and 40 wells measured from two relatively homogeneous field
 - 3 wells measured from a third oil field
 - TOW data used as ground truth
 - TOW data down to 1400ft

Machine learning

EM data → temperature using ML

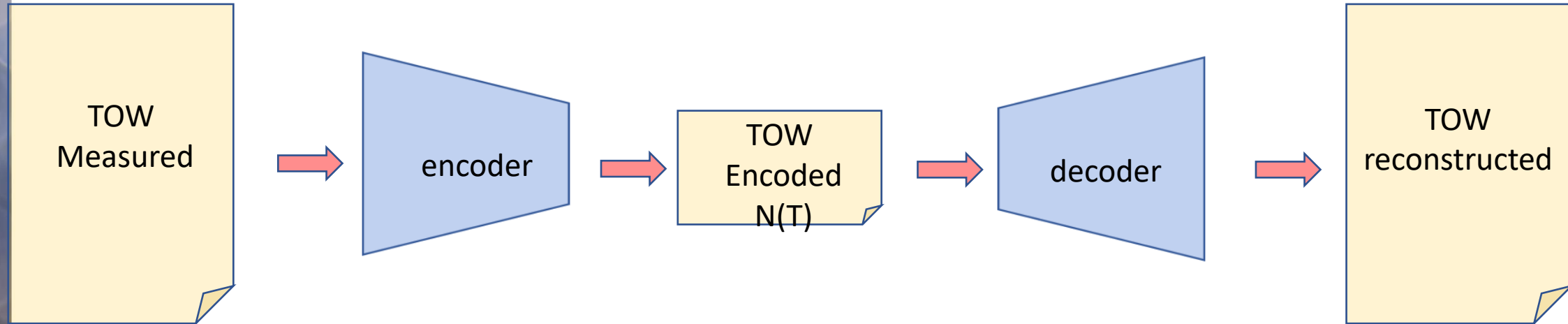
- Both data are “time series”
- Using ML to predict temperature (T) from EM data (M)
- Exclude 1 well from data set and train on rest (blind tests)
- Autoencoder and 5 layer feedforward neural network used
 - Encode T data (not M!) into neural representation $N(T)$
 - Train feedforward network on $M, N(T)$ pairs
 - Then predict well not trained on: $M \rightarrow N(T) \rightarrow (\text{decode}) \rightarrow T$
- 3 sites from third field not used in training
 - Used to evaluate effect of ground conditions

EM data from backscatter



- Transmits broadband pulses of radio waves between **1 to 100 MHz** into the ground.
- Detects the modulated reflections returned from the subsurface.
- Backscatter due to variations in dielectric permittivity and conductivity of material. Time \sim depth.
- Analyses spectral content of the returns to help classify materials (energy, frequency, phase).

Autoencoder



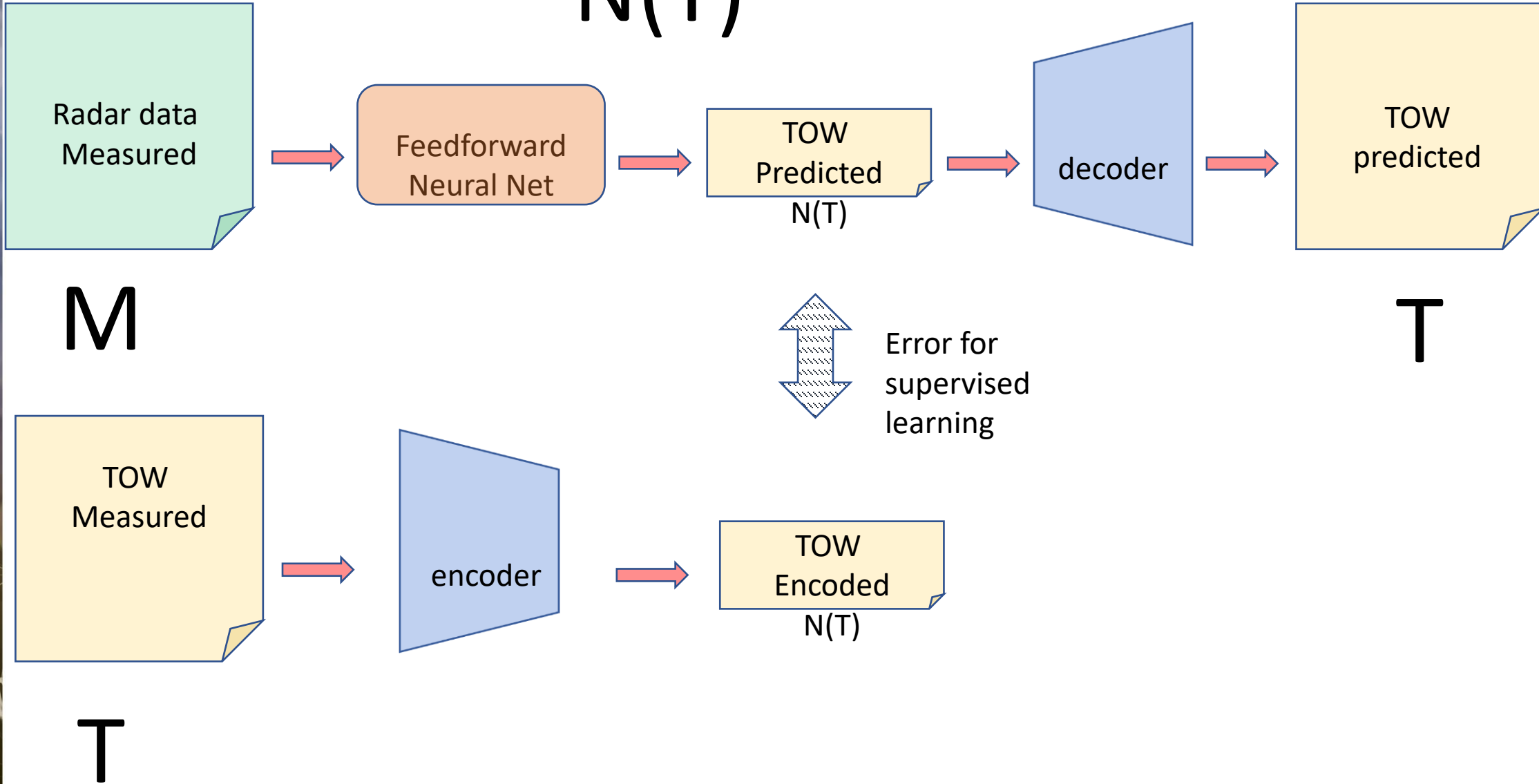
T

$N(T)$

$T_r \sim T$

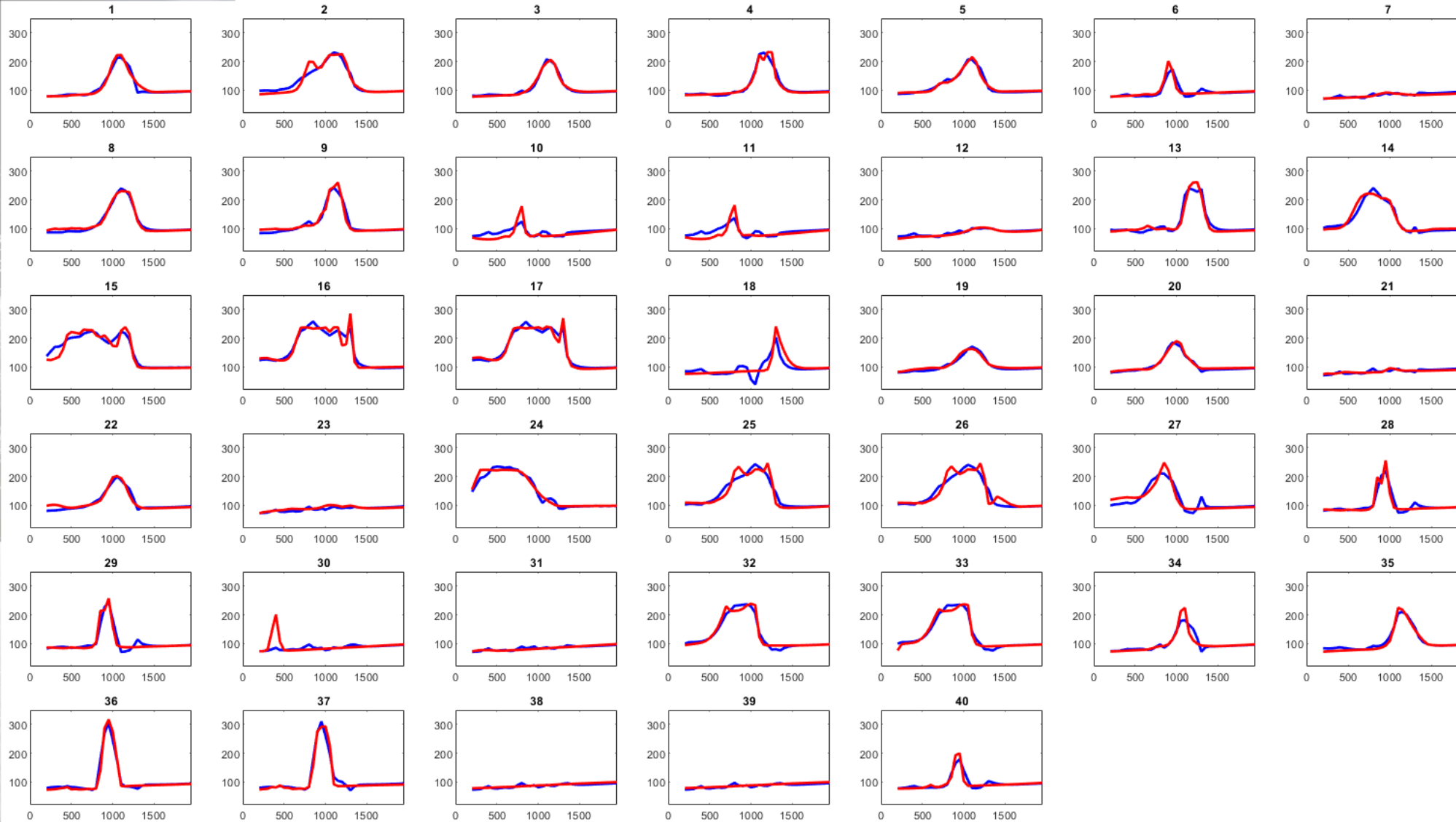
Feedforward neural net

$N(T)$



Results

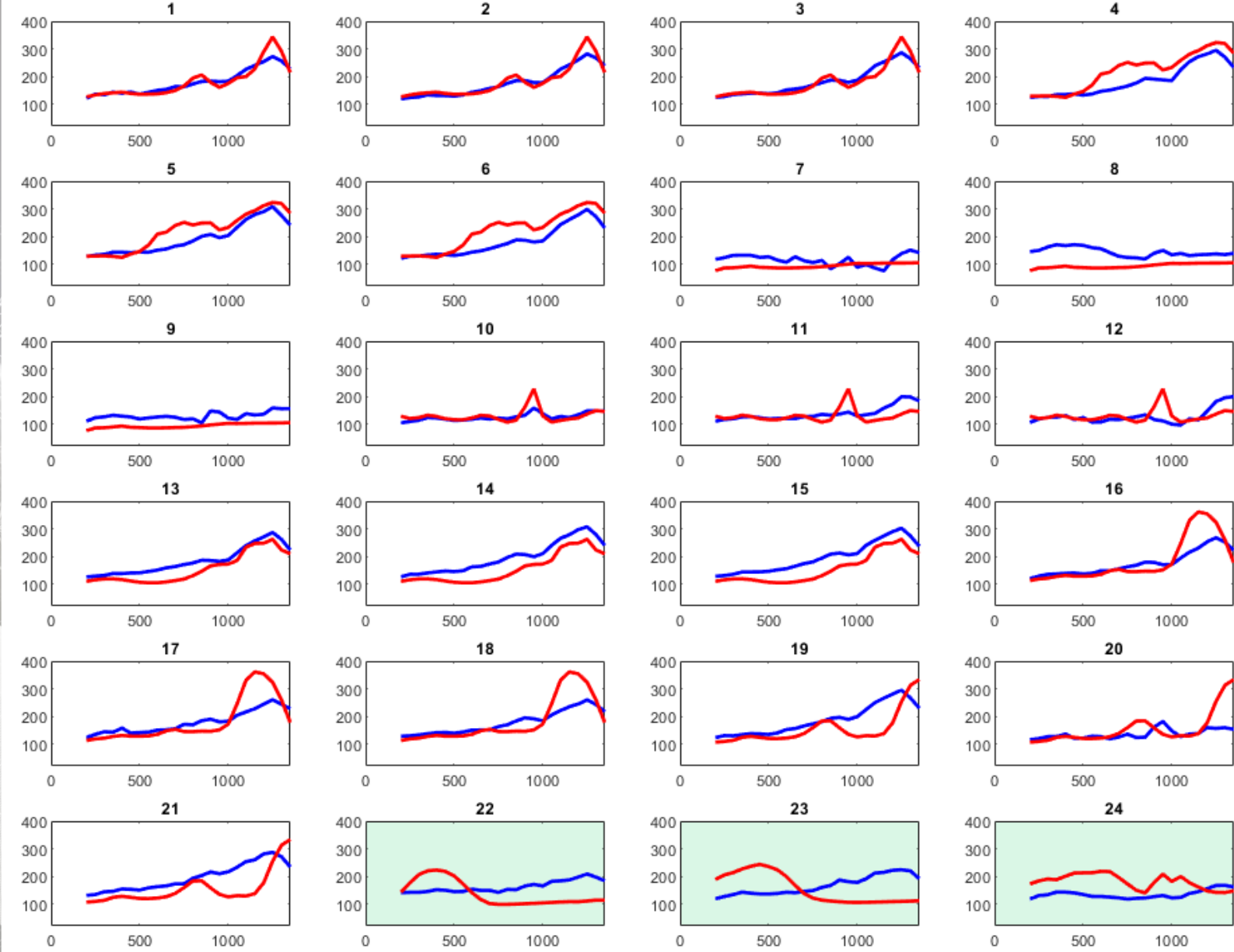
Autoencode T data to 5 activations



40 TOW profiles (red) encoded to 5 activations using an autoencoder network (Blue).

Units:
Fahrenheit + feet.

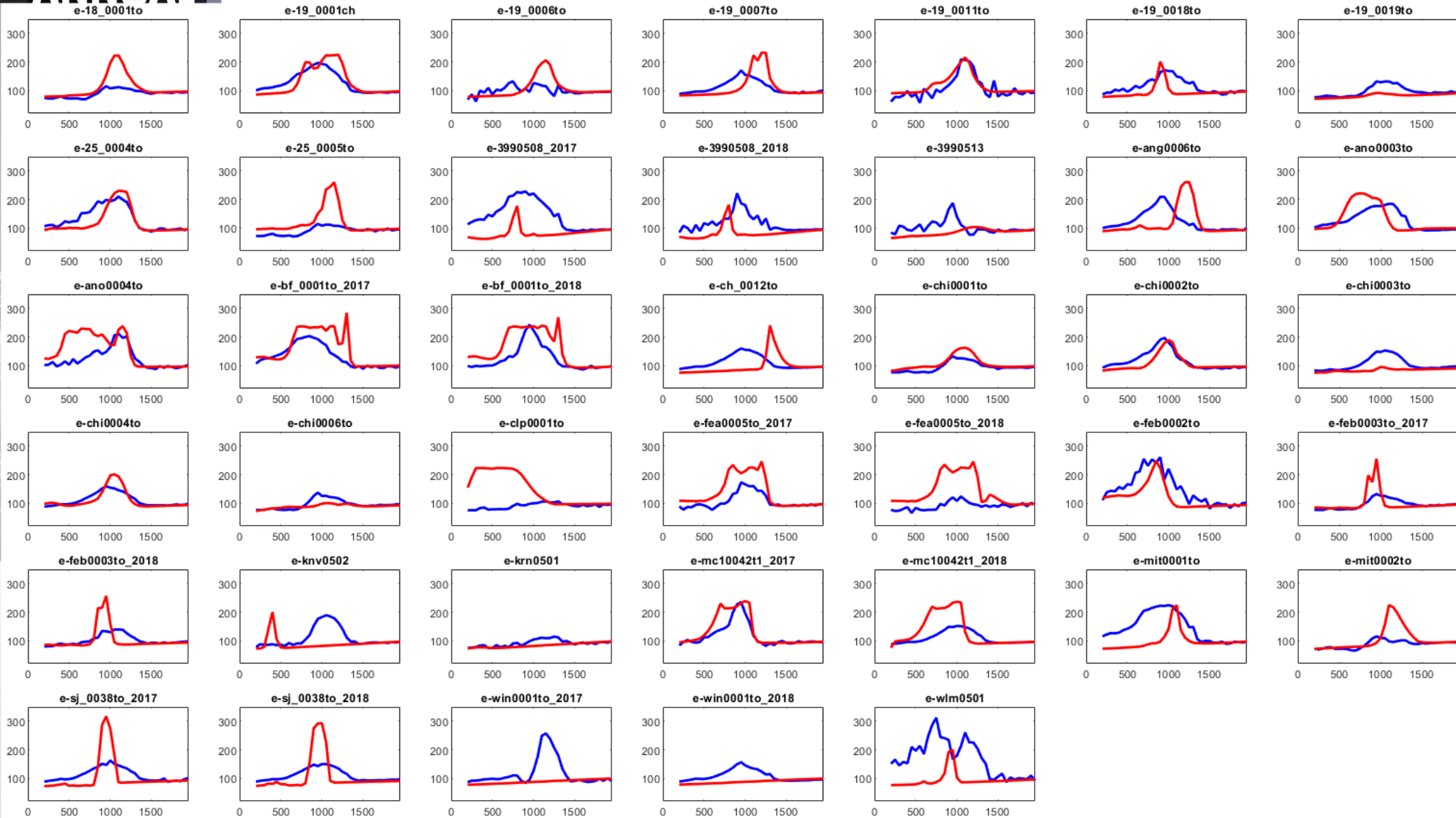
Blind test results: Site 1



Red = TOW data (Fahrenheit)
Blue = EM prediction
Depth in feet

Last 3 are from a different field (not used in training)

Blind test results: Site 2



Discussion

Discussion

- Results are encouraging
- 3 “foreign” wells failed
 - Training site specific
 - Local variations in ground conditions “spoil” results
- How can we improve accuracy/reliability?
 - Assumed ground conditions homogeneous
 - Use also geological data for training to address this
- Why does it work?
 - EM waves penetrate sufficiently deep
 - Similar to apparent seabed imaging using conventional radar

Thank you for your attention!

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