Distributed wireless sensing for methane leak detection technology

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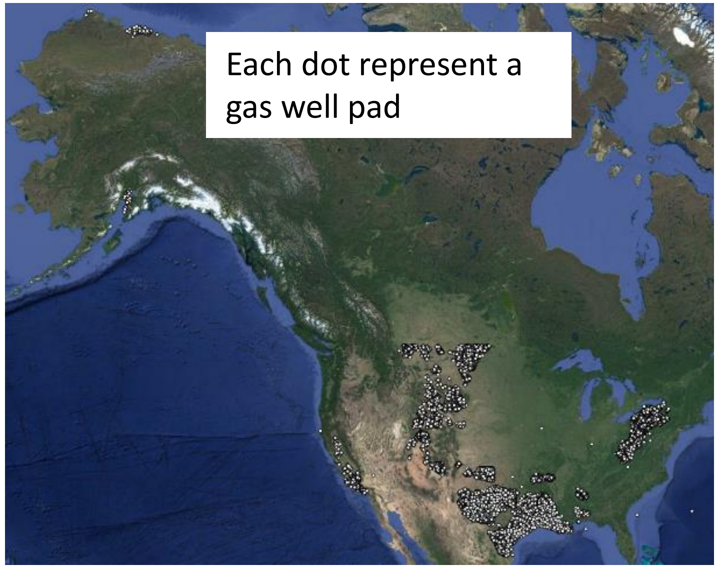
Technology developed in partnership with: arpa·e awardee

Fugitive Methane Emissions in Natural Gas Processing

Methane (CH_4) is the second largest contributor to global warming after CO_2

- Greenhouse warming potential of CH_4 is 37 × greater than CO_2*

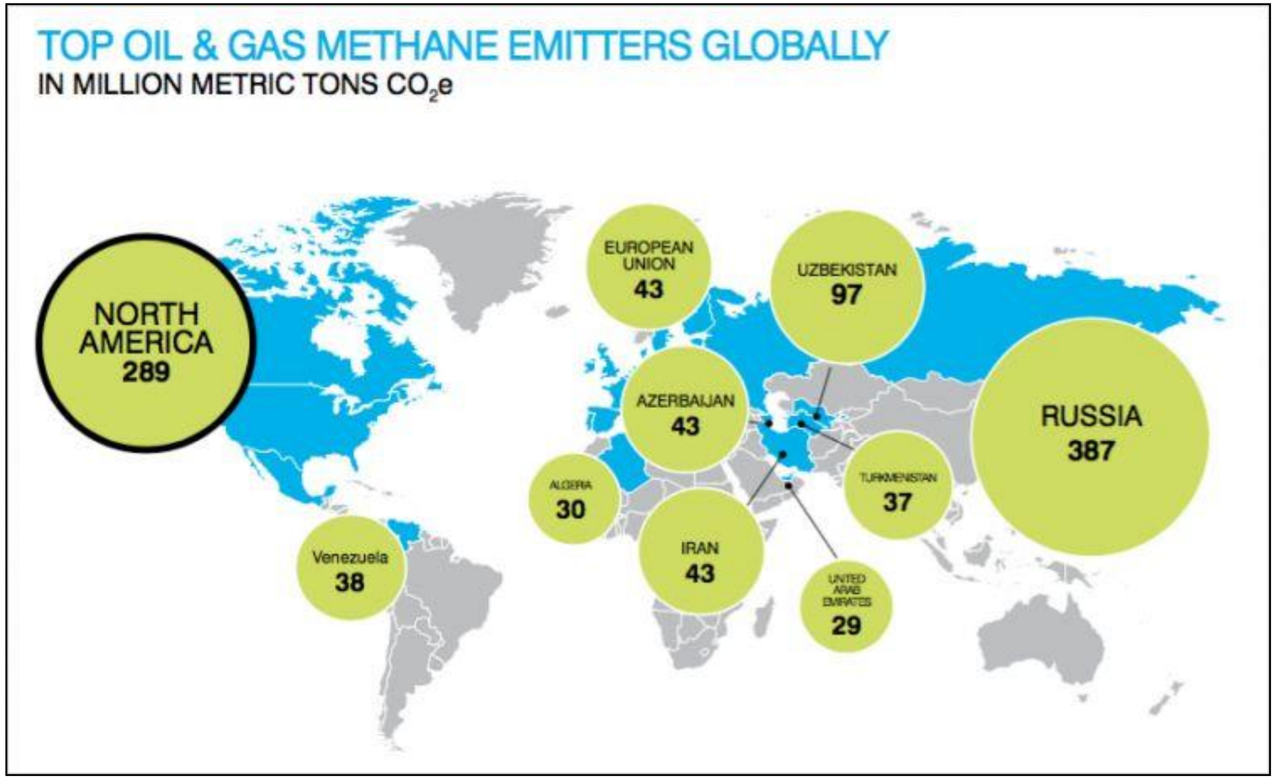


> 0.5 Million active oil and gas wells in the U.S.:

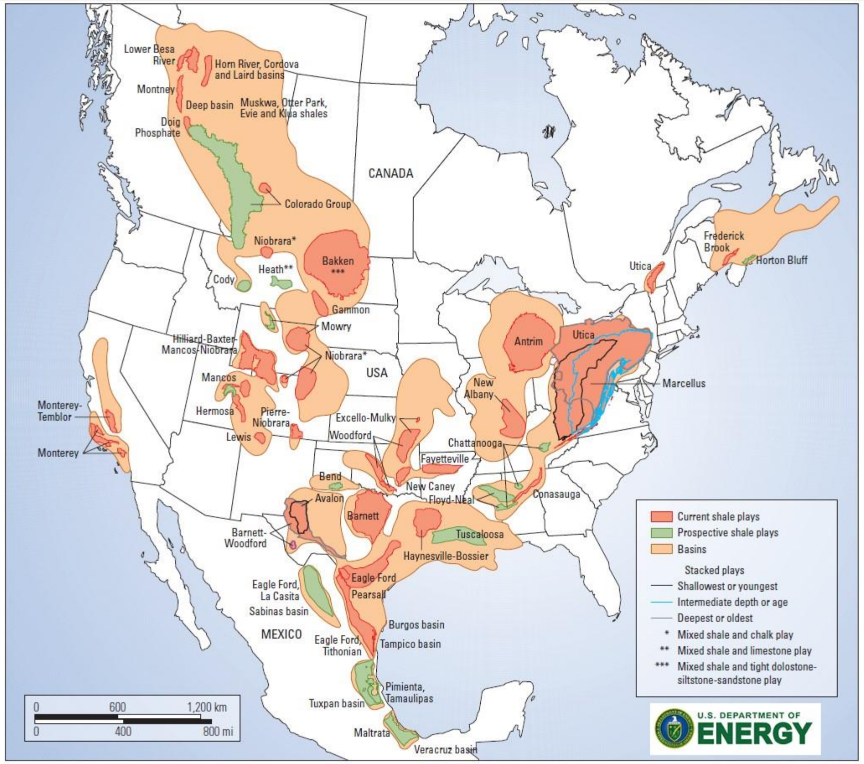
- ~30% of U.S. anthropogenic methane emissions
- ***Estimates: Leakage rate is 2-10% of total production!***

*Alvarez et. al., Proc. Nat. Acad. Sci., 109 (17), pp. 6435-6440, (2012)

Global methane emission



Pembina institute



US DOE

- Methane emission is a global problem
- North America emission is 25% of the global methane emission from oil and gas
- Current national oil/gas emission inventories reported to the UNFCCC are 1.7 Tg a^{-1} for Canada (Environment Canada, 2015), and 3.6 Tg a^{-1} for Mexico (SEMARNAT, 2012), as compared to 9.2 Tg a^{-1} for the US (EPA, 2016) and 67 Tg a^{-1} globally (Rhodium Group, 2015)

Technology specifications

Methane sensing

-1 ppm methane detection sensitivity

-sensing and analytics optimized for 5 scfh to 1000 scfh leak detection

Communications

-sensors are networked to cover from small to large area

-cellular link to transmit data from sensors to cloud

Intelligent sensors

-sensor reading correction for temperature and relative humidity variations

-dynamic data sampling driven by methane leak events

-monitoring system extendable to other gases, e.g. H_2S

Silicon Photonic Optical Trace Gas Sensor: Key Technical Innovations

Solution for deployment of economical, low-power, continuously monitoring sensor networks

IBM technology value proposition:

- **Selectivity to molecule of choice**
- **Orders of magnitude lower cost**
  - < $250/sensor (in volume)
- **Low power consumption**
  - < 1 Watt
- **Leverages volume manufacturing**
  - Same infrastructure used to print billions of transistors on a single microprocessor

Integrated tunable laser and detector:

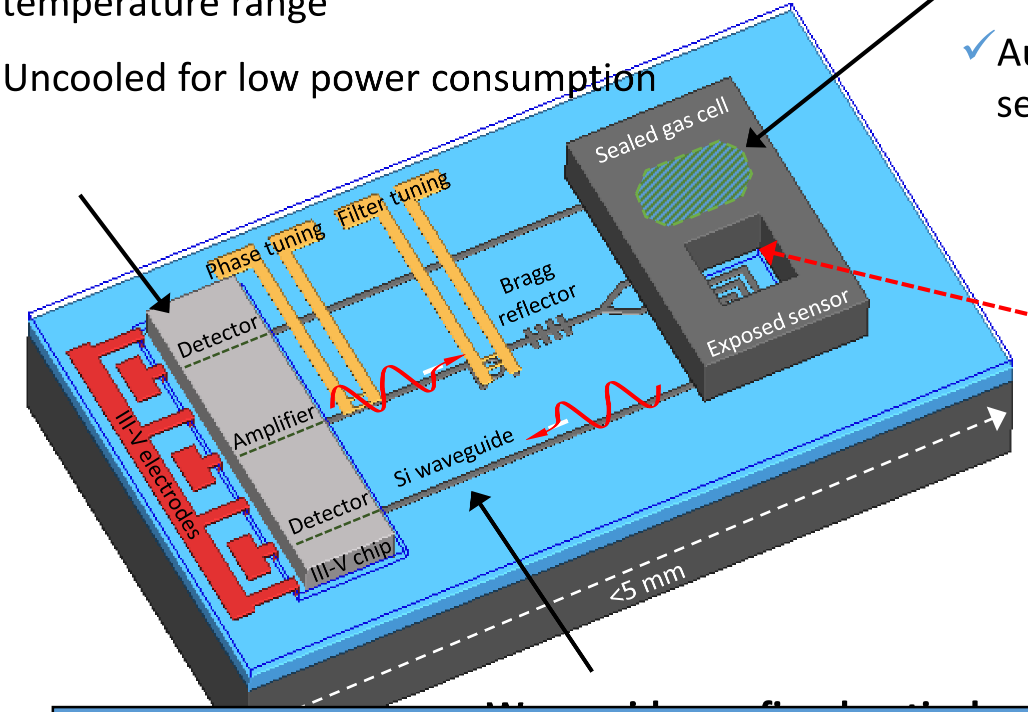
✓ Operation across wide ambient temperature range

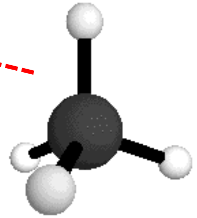
✓ Uncooled for low power consumption

On-chip gas reference cell:

✓ Built-in self-calibration

✓ Autonomous long-term sensor accuracy



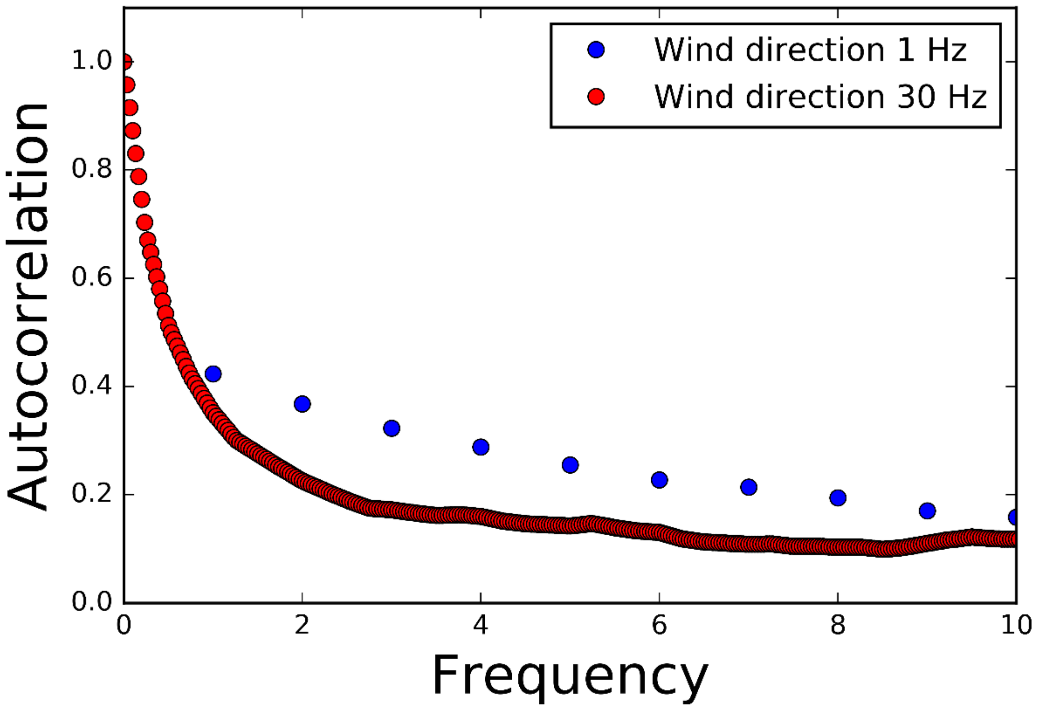


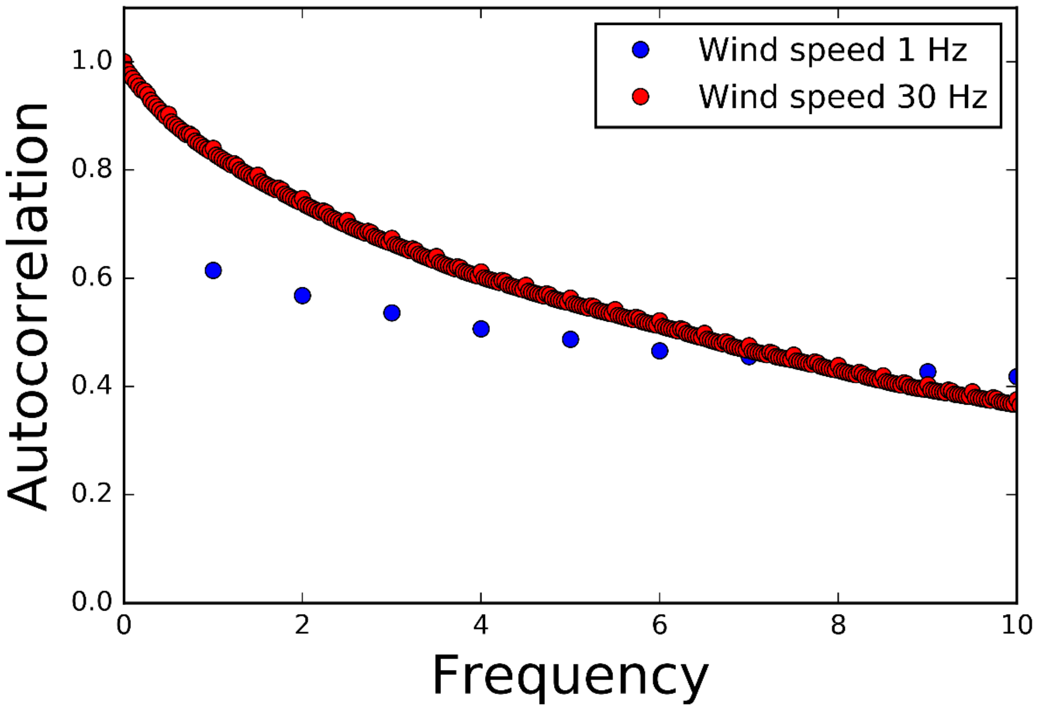
Methane molecule

Sensor sensitivity target: ~5-10 ppmv CH_4

Data acquisition rates

Data acquisition rate is dependent on the stability of the wind and local turbulance.

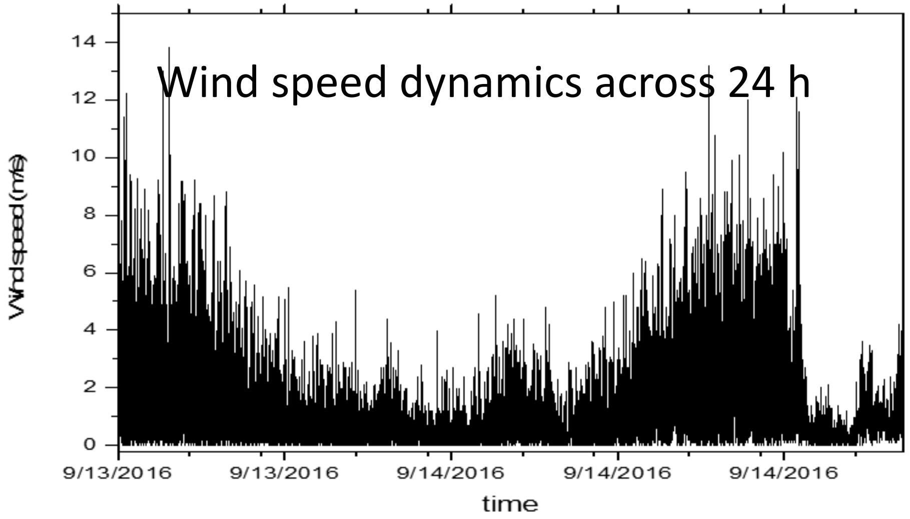




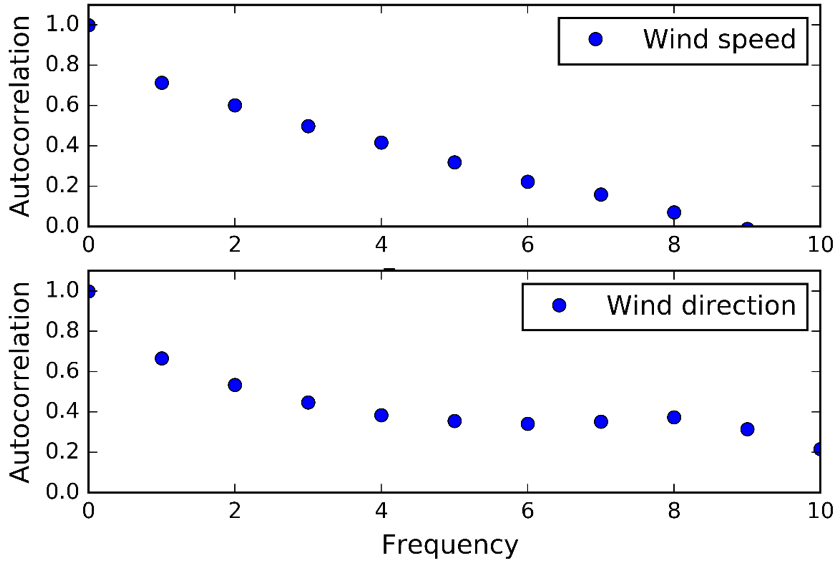
- Data sampling rate driven by autocorrelation of the wind speed/direction.
- Wind speed more stable than wind direction
- Depending on the data sampling rate-autocorrelation can be slightly different.

Spatial-temporal analytics

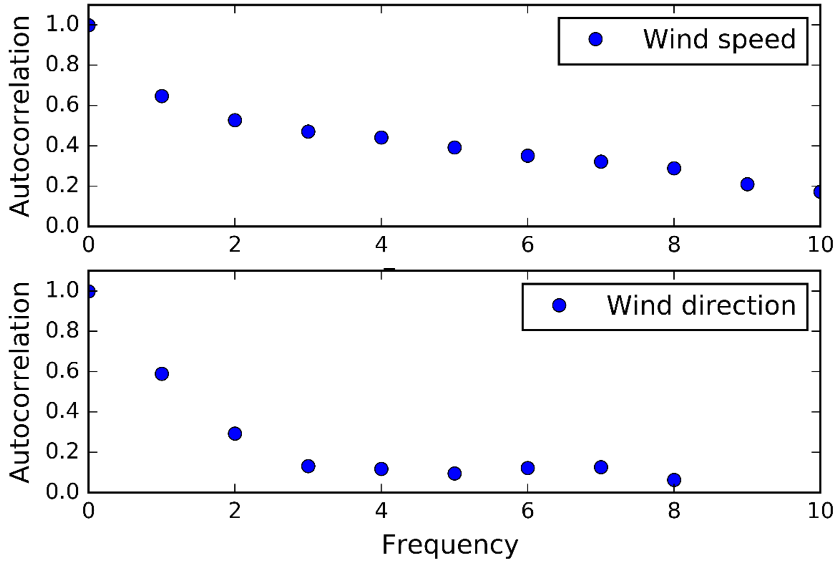
- Wind data has a strong geospatial component
  - -geographical location dependence
  - -daily and seasonal dependence
- Gas leaks may have temporal dependence
- Analytics needs to be adaptable to accommodate dynamic behavior
- The data sampling rate will need to be “cognitive”, recognize the environment and adjust the sampling rate



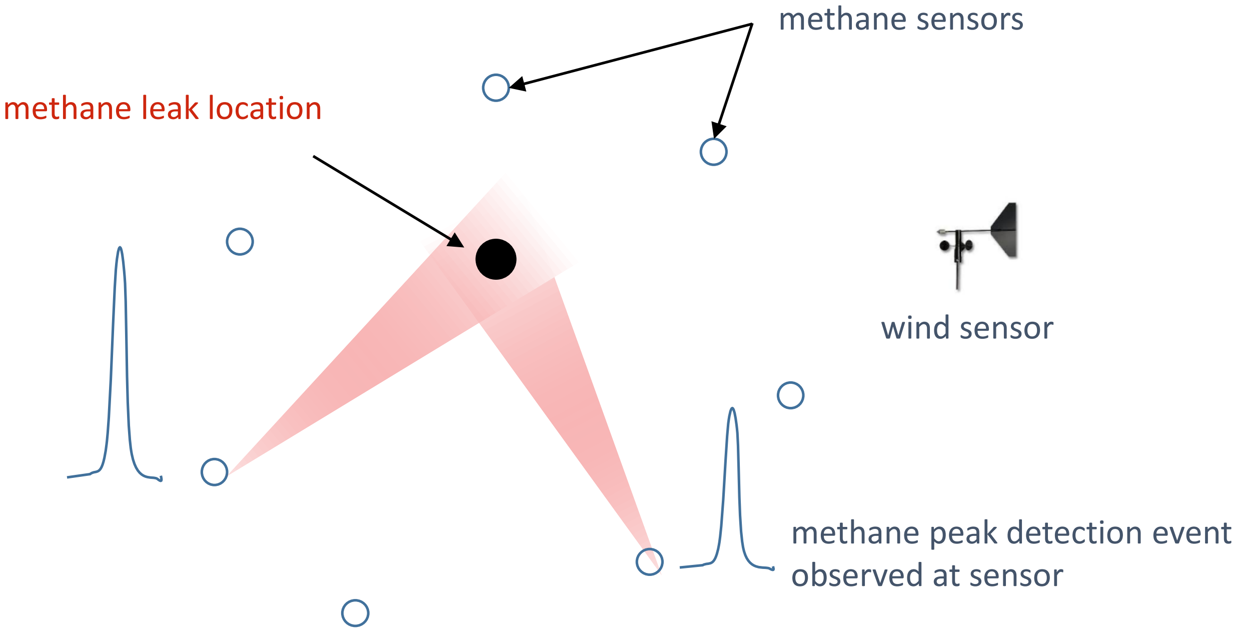
Yorktown Heights, NY July 2017



Dallas, TX July 2017



Methane Leak Location Estimation



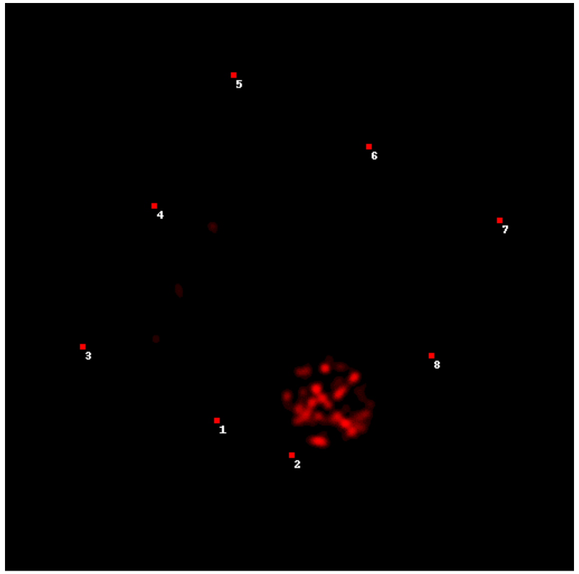
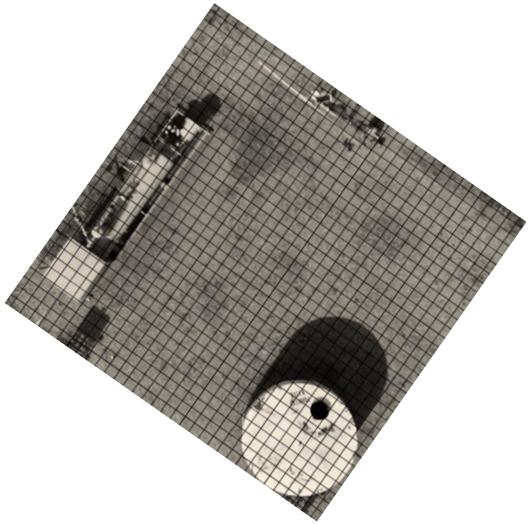


Illustration of point cloud resulting from point leak at tank center



- Peaks observed at methane sensors are used with wind data to estimate the likely direction the plume took to arrive at the sensor
- Intersection points are generated for all peaks vs all other peaks creating a point cloud
- Centroid estimation using many such points allows the estimation of the leak position.
- Cluster analysis and spatial filtering further improves this estimate.
- Typical accuracy of location estimates ~ +/- 1 meter

Source Magnitude Estimate

Assumptions:

largest estimates of source magnitude for a give peak are most likely to correspond to gas having made a full traversal of the plume across the sensor and arrived by the most direct path.

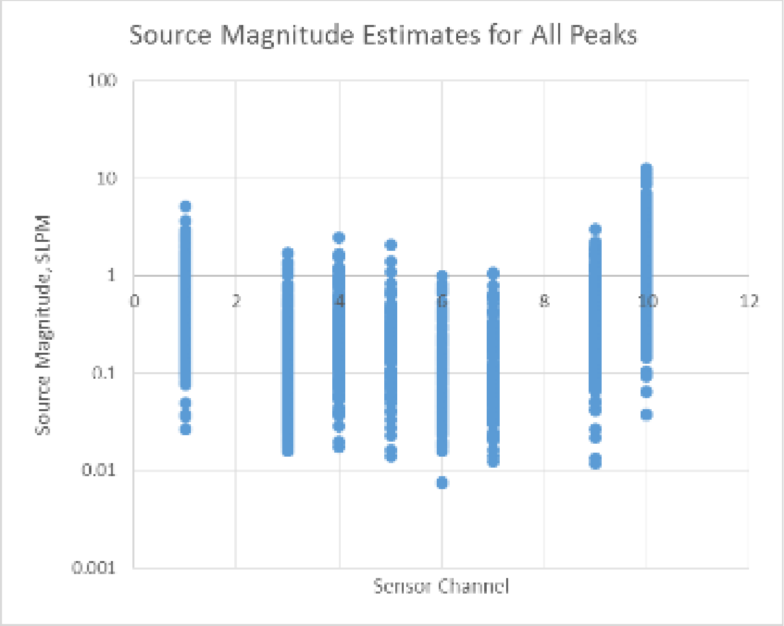
Method:

Use short range plume equations estimate source magnitude at each peak:

$$S_{ij} = \pi\sigma^2 U c_j \qquad \sigma = d\sigma_w/U$$

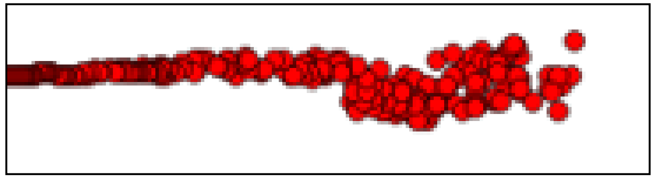
where:

S_{ij} = source magnitude estimate based on sensor j peak i, gms/sec
c_{ij} = peak concentration at sensor j peak I, gms/meter^3
d = distance to source, meters
σ_w = variation of wind velocity over methane peak interval, meters/sec
U = average wind velocity over methane peak interval, meters/sec



Methane plume dispersion

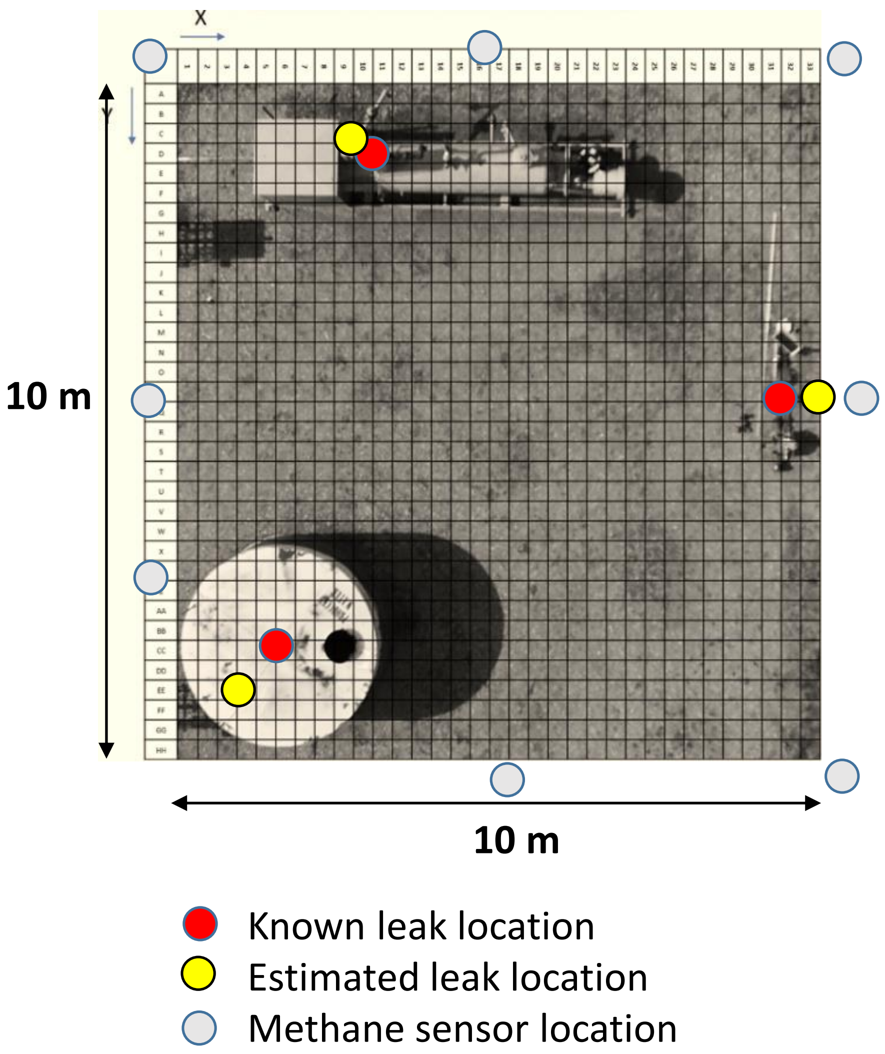
Release point



Average maximum S_{ij} for each sensor to get source magnitude estimate

- typical accuracy for small leaks ~ 25% at sensor level
  (note: put sensor on top of structure for elevated equipment e.g. tanks)

Field Test System Validation



Location of source

Site	Known leak position (m)		Estimated leak position (m)		Error (m)
	X	Y	X	Y	
Tank hatch	1.1	-3.8	1.25	-4.25	**0.48**
GPU	-3.5	0.25	-3.6	0.42	**0.22**
Wellhead	1.5	3.0	1.95	3.76	**0.88**

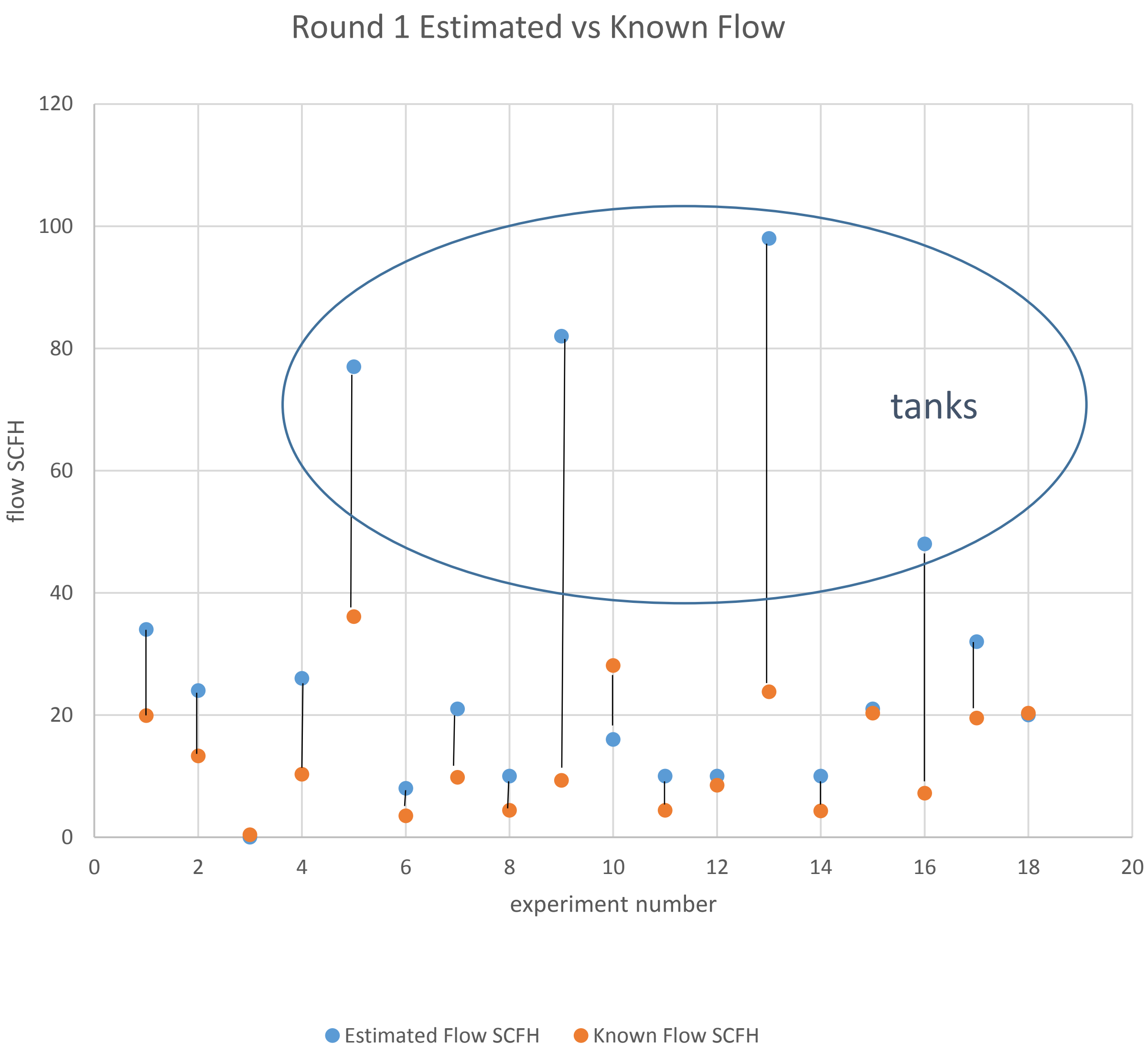
Magnitude of source

Site	Known flow rate (SCFH)	Estimated flow rate (SCFH)	Error (SCFH)	Error (%)
Tank hatch	32	34	2	**7%**
GPU	32	29	-3	**8%**
Wellhead	32	33	1	**4%**

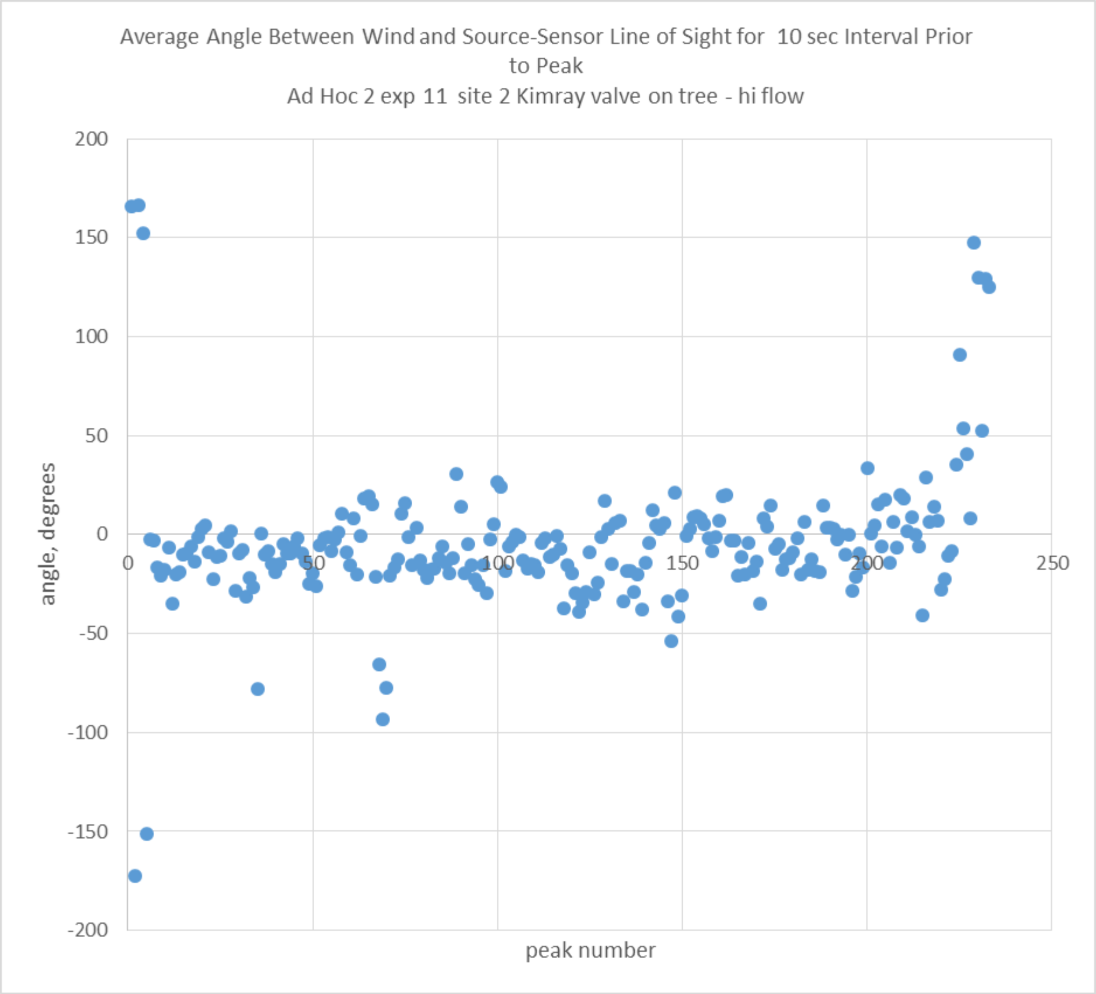
- Good performance with single sources
- Approaches to handle multiple simultaneous sources are under development

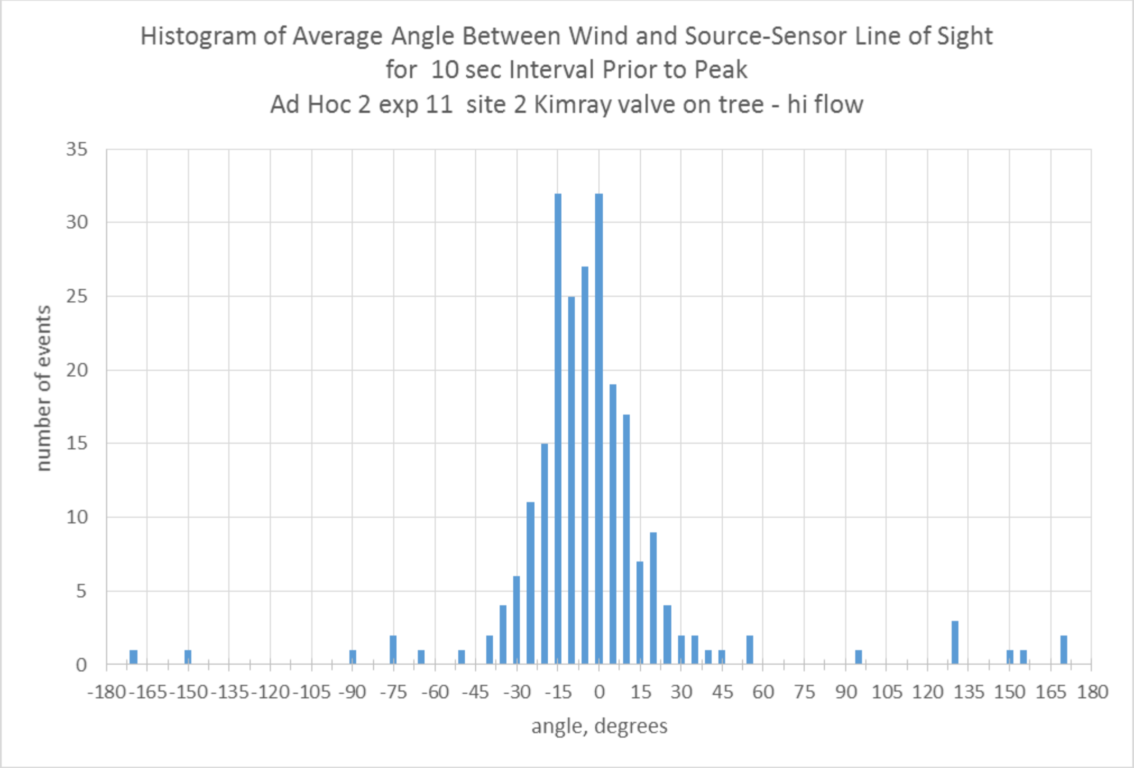
Round 1 Source Magnitude Estimates:

Round 1 Flow Estimat Results		
experiment	Estimated Flow SCFH	Known Flow SCFH
1	34	19.9
2	24	13.3
3	0	0.4
4	26	10.3
5	77	36.1
6	8	3.5
7	21	9.8
8	10	4.4
9	82	9.3
10	16	28.1
11	10	4.4
12	10	8.5
13	98	23.8
14	10	4.3
15	21	20.3
16	48	7.2
17	32	19.5
18	20	20.3



Angle Between Source Line of Site and Wind Direction Prior and During Peak Events:

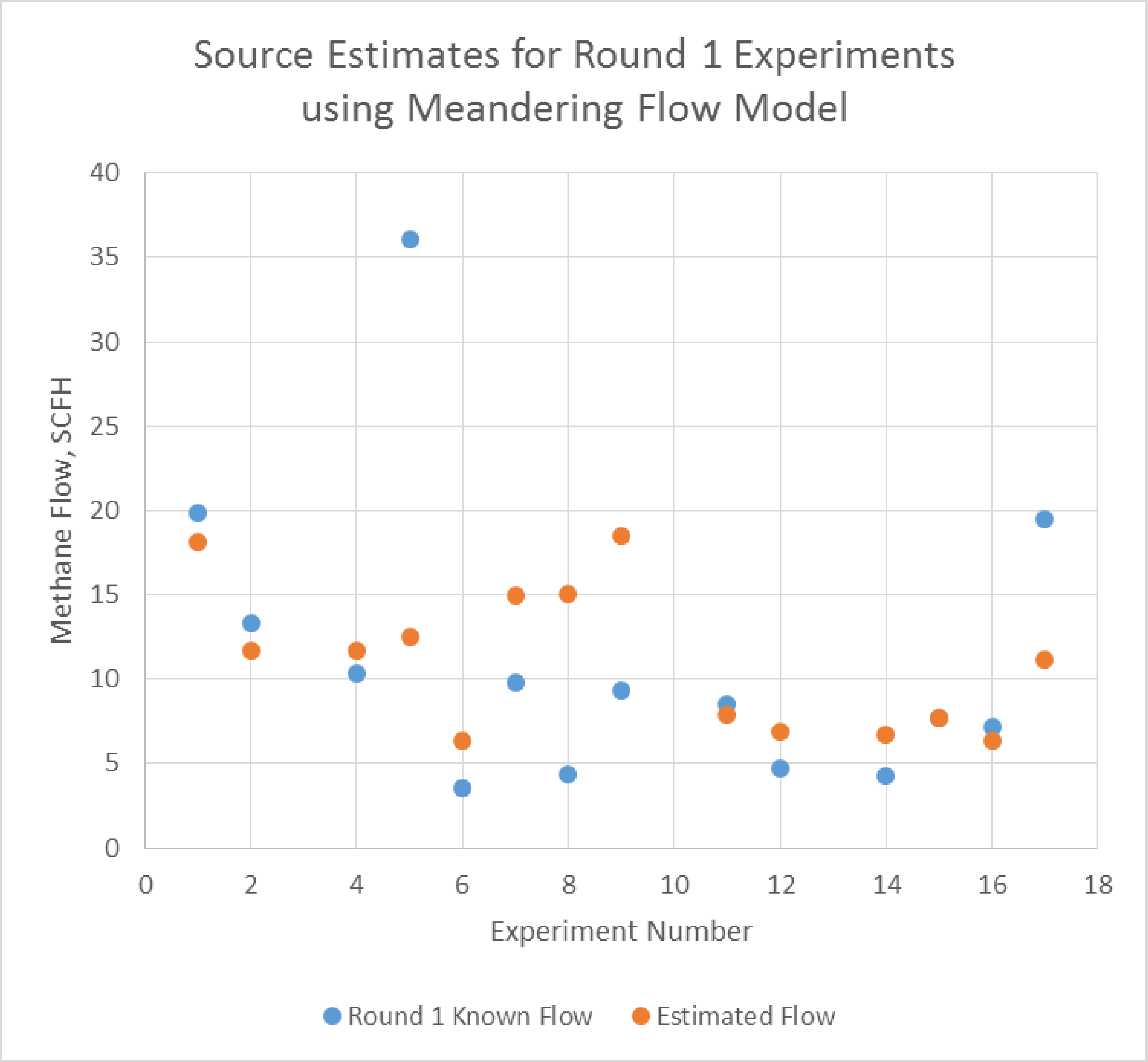




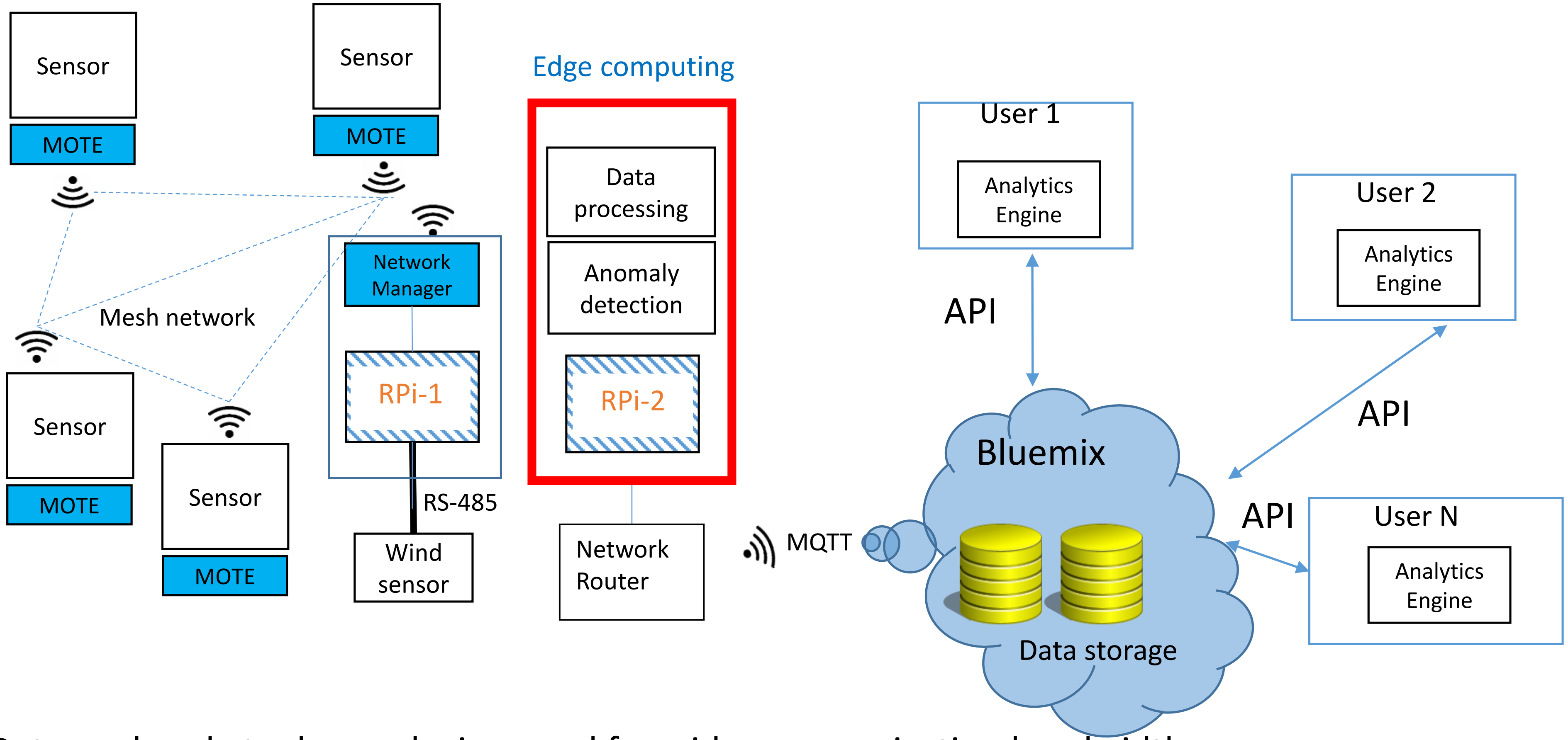
Restricting data to narrow angle range enforces assumption that gas traveled nearly straight line from leak to detector

Machine Learned based methane leak estimates -Round 1 Metec testing

- Leak detection utilize statistical, physical models and machine learning technique to improve accuracy of analytics
- Localization analytics is robust and working 100%.
- *System performed very well during the first round testing.*

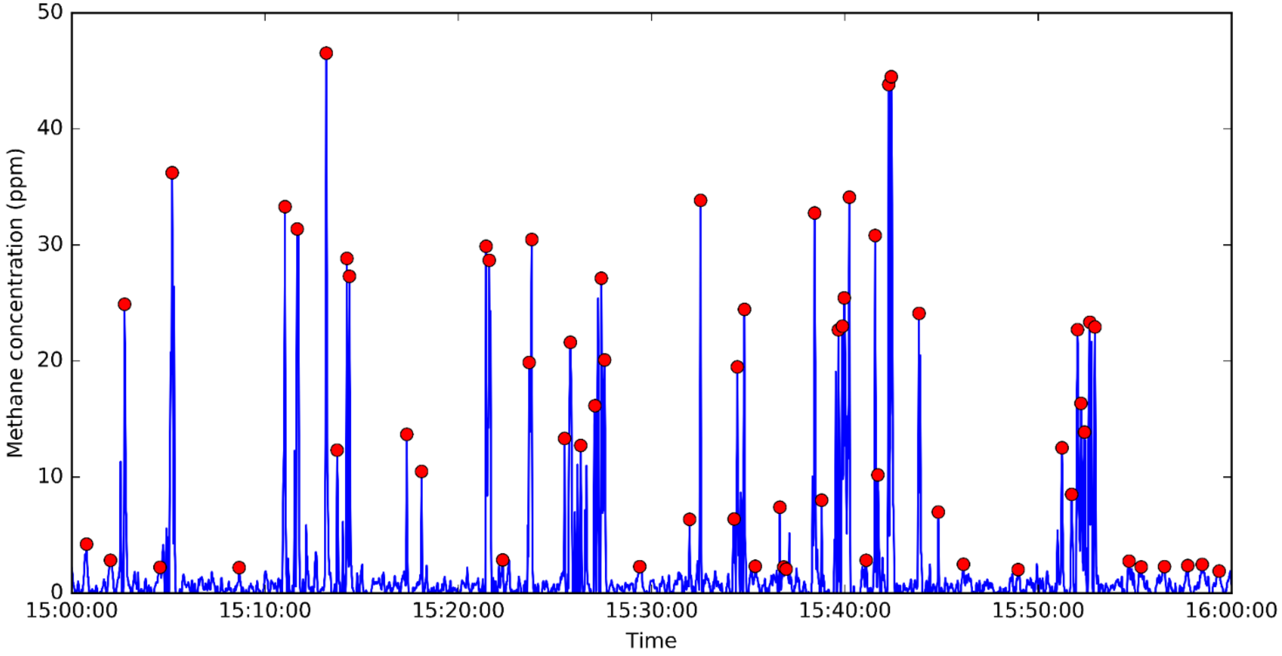


Edge computing



Data analyzed at edge- reducing need for wide communication bandwidth
Uniform data analysis and interpretation
Less storage required

Peak detection algorithm



The information in chemical plume detection is carried by

1. peak height,
2. peak width and
3. timestamp

Additional information:

1. background methane level

Peak detection algorithm:

-wavelet convolution

-derivatives crossing zero

-maxima preceded by a delta

<u>Computationally efficient</u>

<u>Perform well with a given signal</u>

Implemented in Python

Run on a buffered dataset with 10 min of data acquired at 1 Hz frequency

Reduce data size by 99% compared to all data acquired

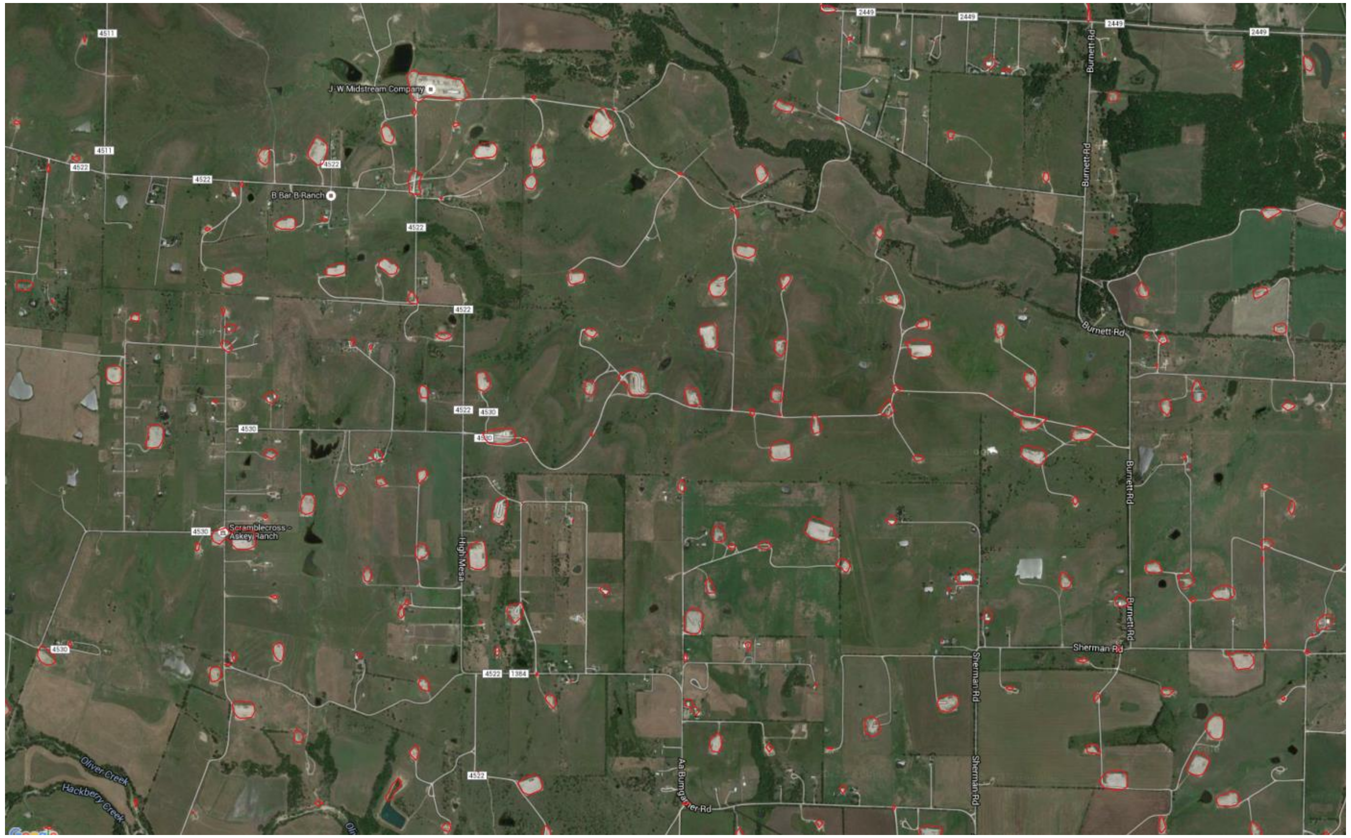
Classification using Multi-Mode Feature Recognition

Conventional:
- Single set of satellite images
- Empirical feature engineering.

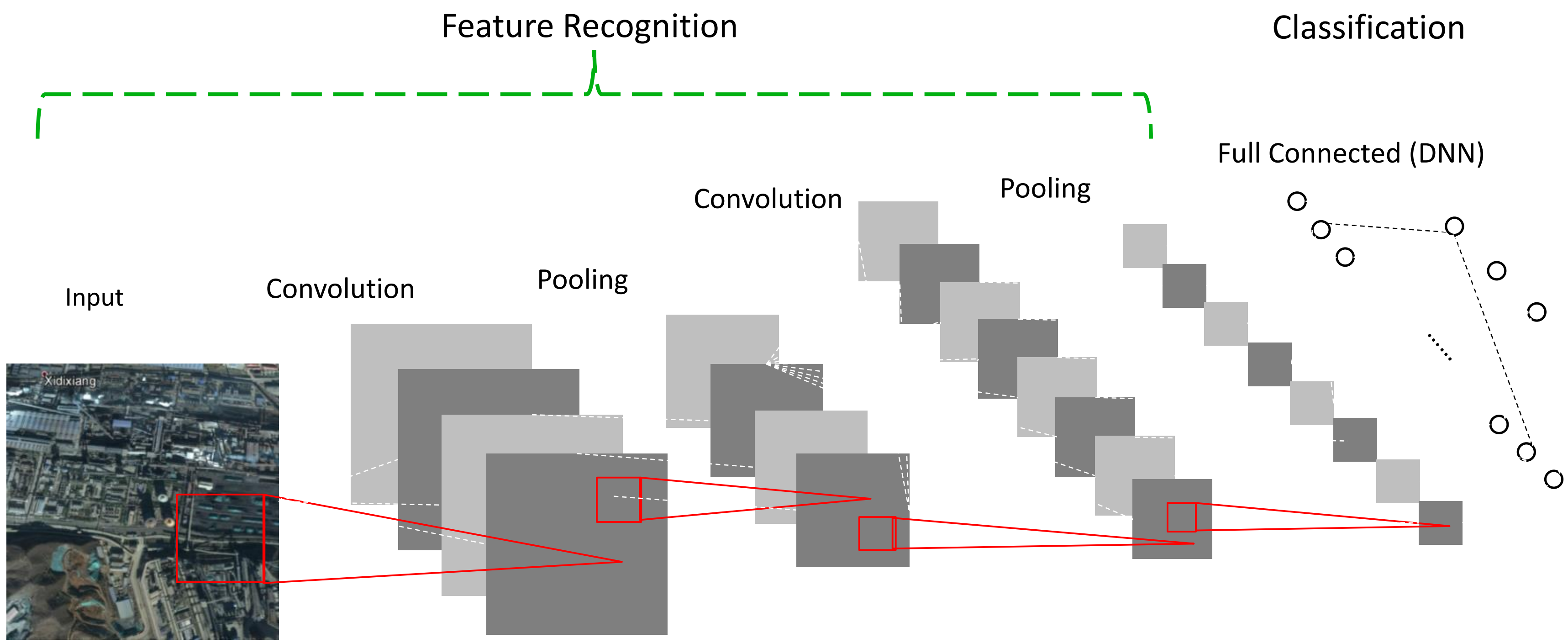
• Multi-Mode Feature Cognition
  - Methane abs@ 1.65 µm, 2.3 µm
  - Shape, Heat, Road Connectivity …

• Deep Learning to extract high-order hierarchical features

Shale gas sites found in Texas

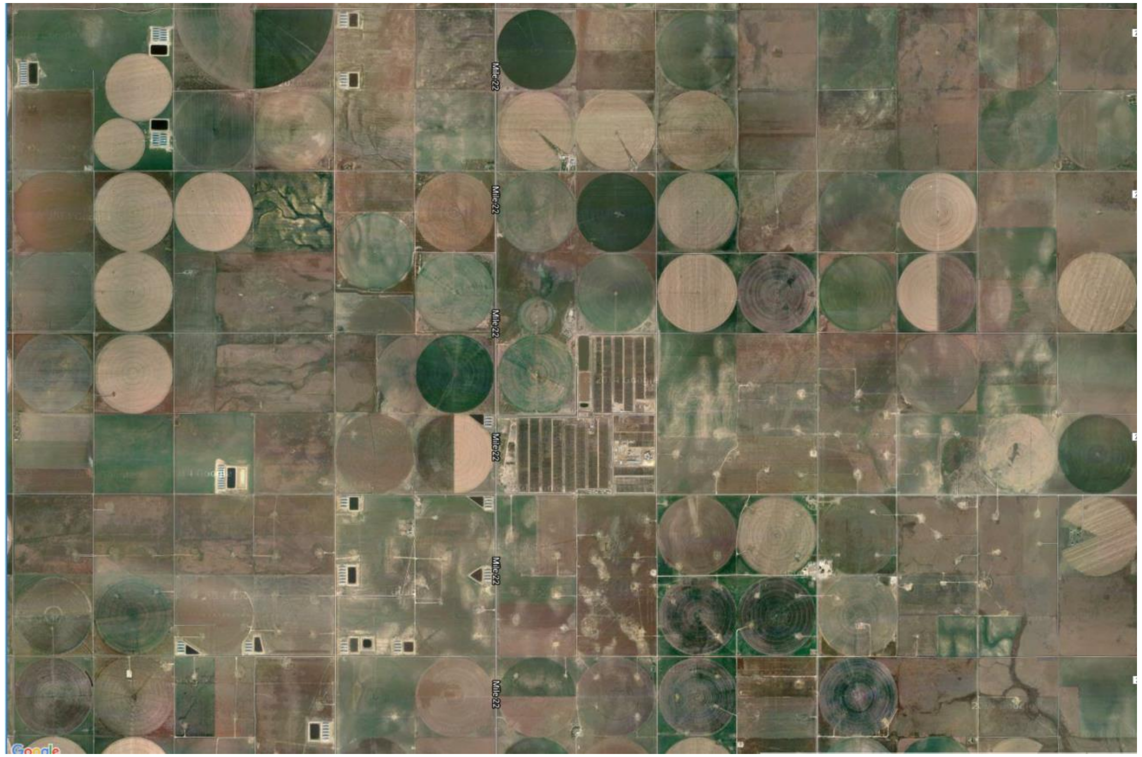


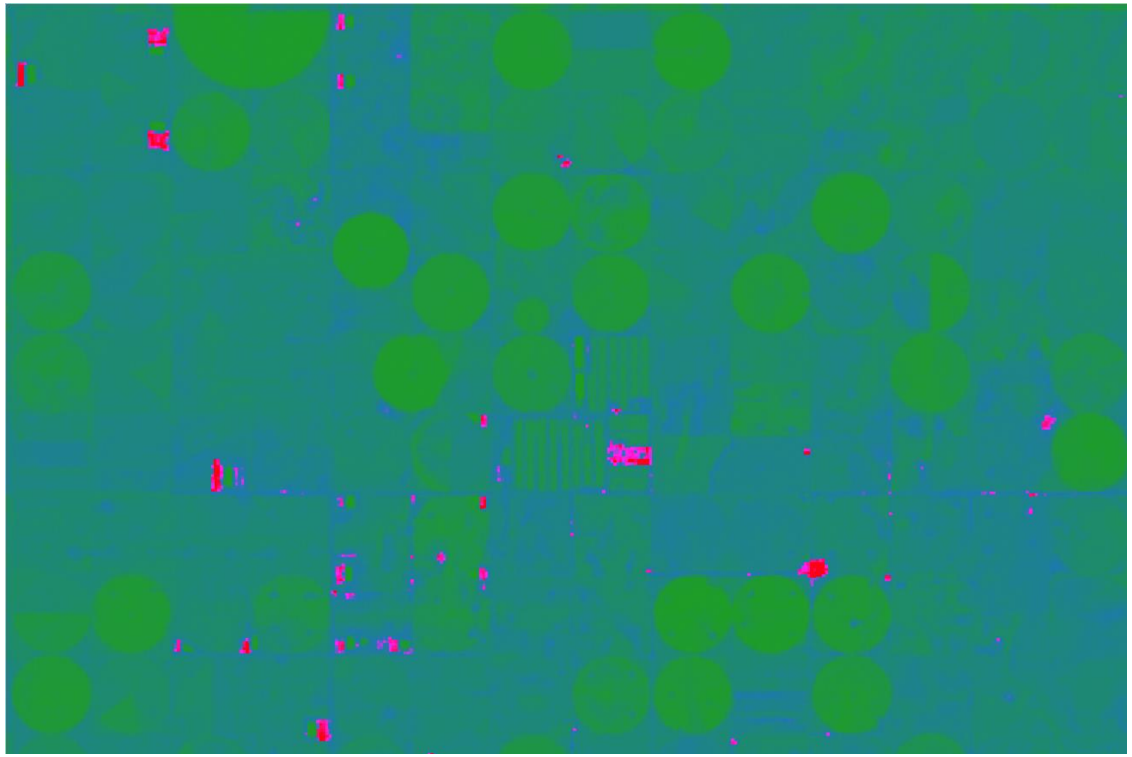
Deep Learning – Extraction of Hierarchical Features



Classification using Multi-Mode Feature Recognition

Kansas, Identification of Livestocks





Conclusions

- Data strategy is driven by industrial applications where signal integrity determines the analytics output.

- Edge computing can reduce data size by orders of magnitude making IoT solution more amenable for remote applications where data bandwidth and connectivity is an issue.

- Contextual data can enable automation of Internet of Things applications