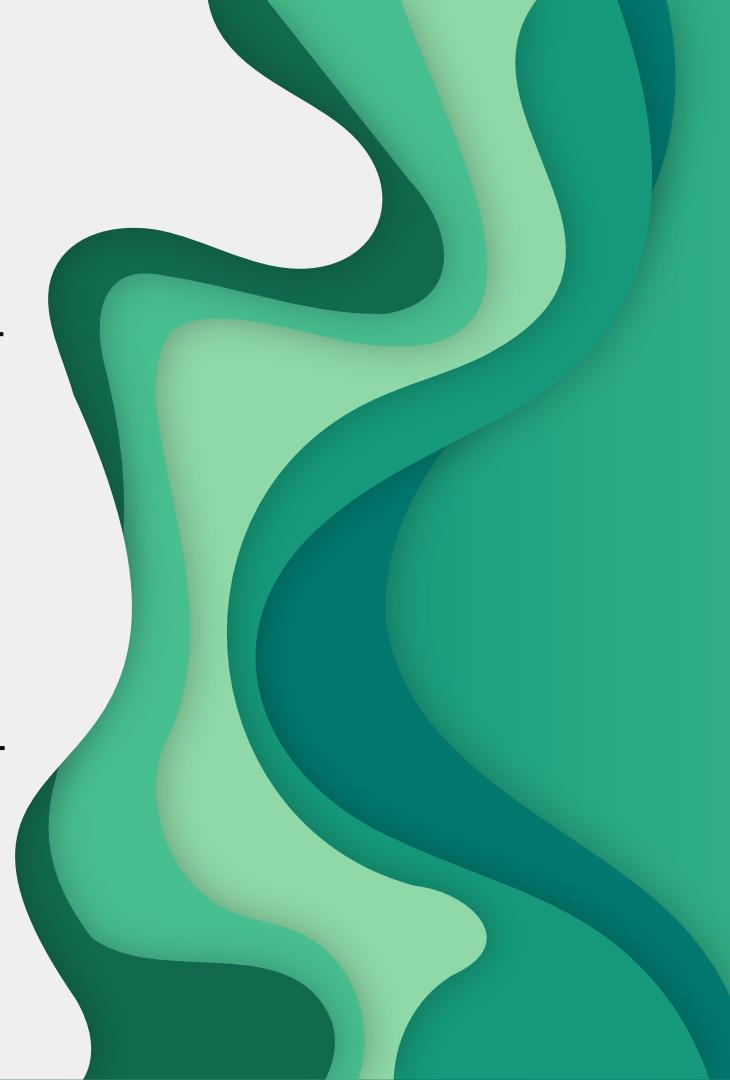




methane anomaly detector

"We're MAD about methane"



The Team



Alyssa Augsburger
Senior Member of
Technical Staff



Jaclyn Andrews
Director



John Lee
Mechanical
Engineer



Karthik Rameshbabu
Senior Software
Engineer



Sanjay Saravanan
Software
Development
Engineer

“

The Environmental Protection Agency estimates that

methane causes about

25x

**more damage than carbon
dioxide**

to the atmosphere over a 100 year period.



NOVEMBER 10, 2021

Methane's short lifespan presents golden opportunity to quickly address climate change

by Christina Procopiou, Lawrence Berkeley National Laboratory



11-29-21 | 1:30 PM | WORLD CHANGING IDEAS

Stemming methane leaks could be key to slowing global warming quickly



Biden joins global push to cut climate-warming methane emissions

Updated November 2, 2021 · 2:36 PM ET ⓘ

The Problem

- Detecting methane leaks is not easy and not cheap
- No simple available resource for monitoring methane
- Methane-emitting facility owners need our help to detect methane leak warning signs



The Solution

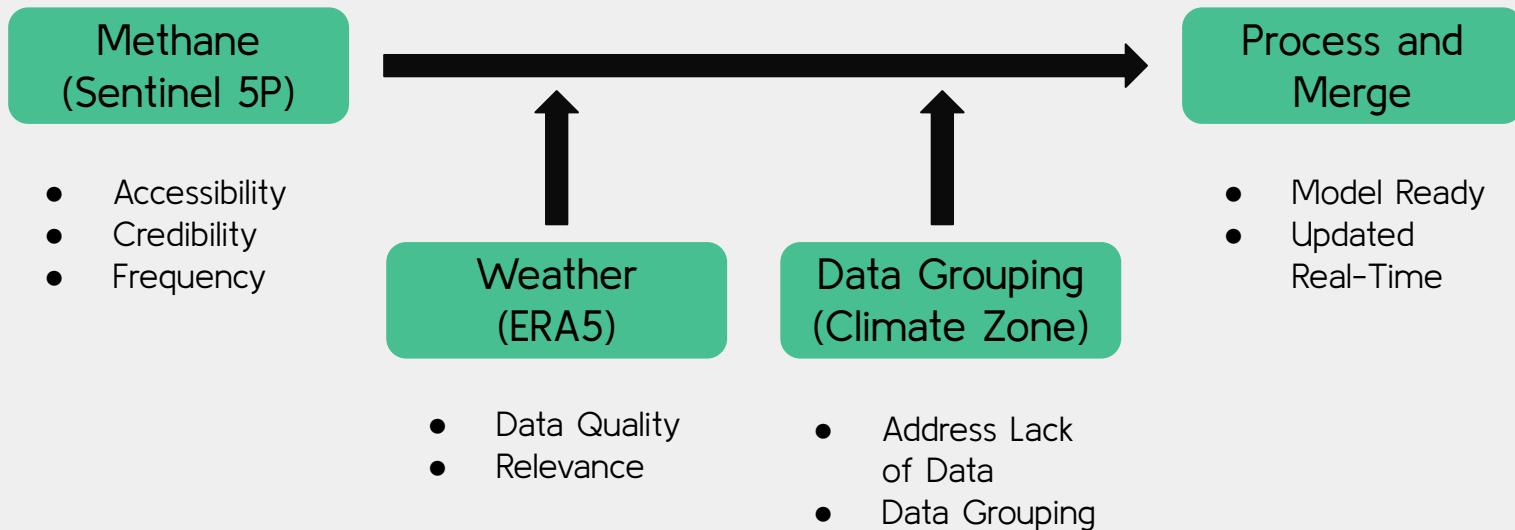
- Machine learning anomaly detection
 - Growing data set
 - Capacity for other signals
- Data as a Product
 - Clean data access





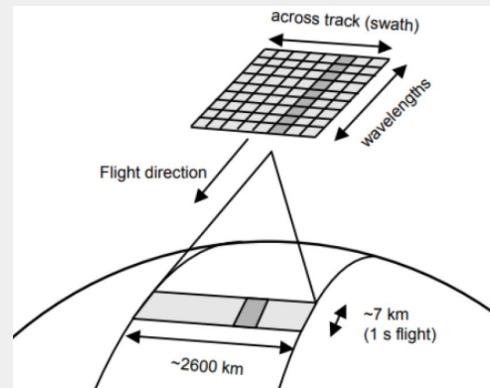
Data

Data Pipeline



Methane

- **Sentinel 5P:**
 - European Space Agency satellite that monitors atmospheric conditions
 - **Credible**
 - Publicly **Accessible**
 - Daily **Frequency**
- **Data:**
 - Methane concentrations (ppb)
 - 7km x 5.5km resolution
 - 90GB raw -> 34mb extracted



Methane Data



Weather Data



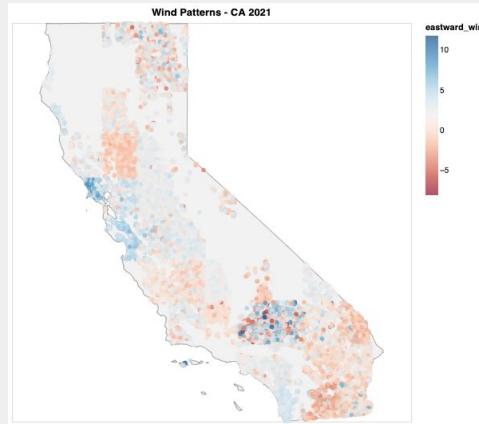
Data Grouping



Process and Merge

Weather

- Why ERA5:
 - Methane **data quality** influenced by weather
 - Methane concentrations can be **correlated** to weather
- ERA5 Data:
 - European Centre for Medium-Range Weather Forecasts
 - Hourly Frequency
 - 250GB raw → 1.3GB extracted



Methane Data



Weather Data

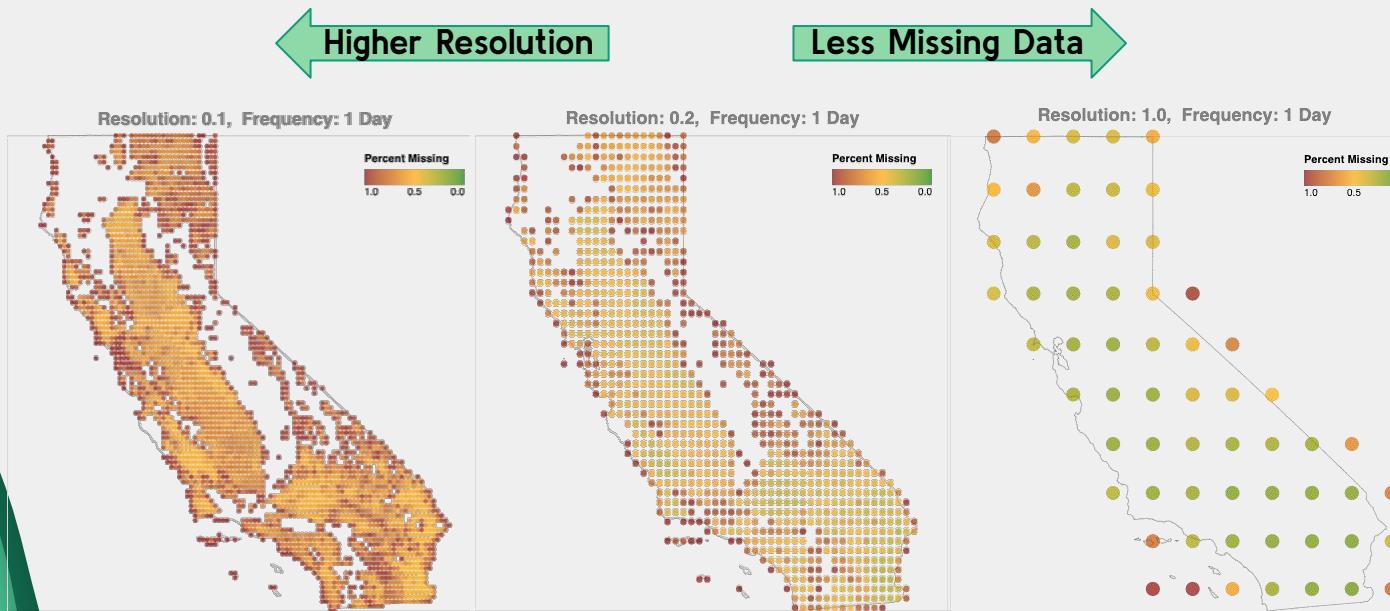


Data Grouping



Process and Merge

Data Grouping



Variations: Rounded lat/lon of 0.1, 0.2, 1.0

Methane Data



Weather Data



Data Grouping



Process and
Merge

Data Grouping

- **Why Zones:**
 - Aggregated data **reduces data sparsity**
 - A method of **grouping**
- **California Climate Zones:**
 - 16 zones adopted by California
 - Varies by climate conditions (e.g. temperature, wind speed, solar radiation)



Methane Data



Weather Data



Data Grouping



Process and
Merge

Process and Merge

Currently: 1,251,651 rows & 31 columns

time	methane	lat	lon	rn_lat_5	rn_lon_5	...	zone
2018-11-28	1879.700317	32.822247	-114.522209	33	-114.5	...	15
2018-11-28	1883.997314	32.726692	-114.938751	32.5	-115.0	...	15
...
2021-10-21	1896.328003	34.465900	-116.691612	34.5	-117.0	...	14
2021-10-21	1892.318359	34.465900	-116.691612	34.5	-116.5	...	14

Methane Data



Weather Data



Data Grouping



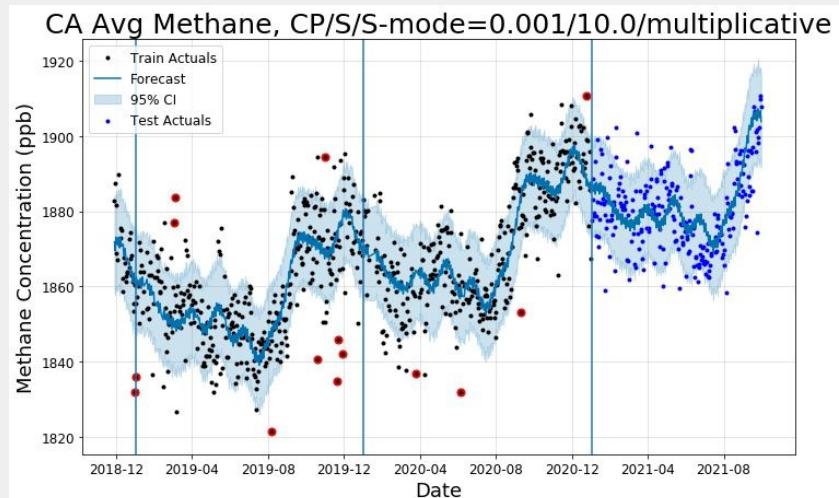
Process and
Merge



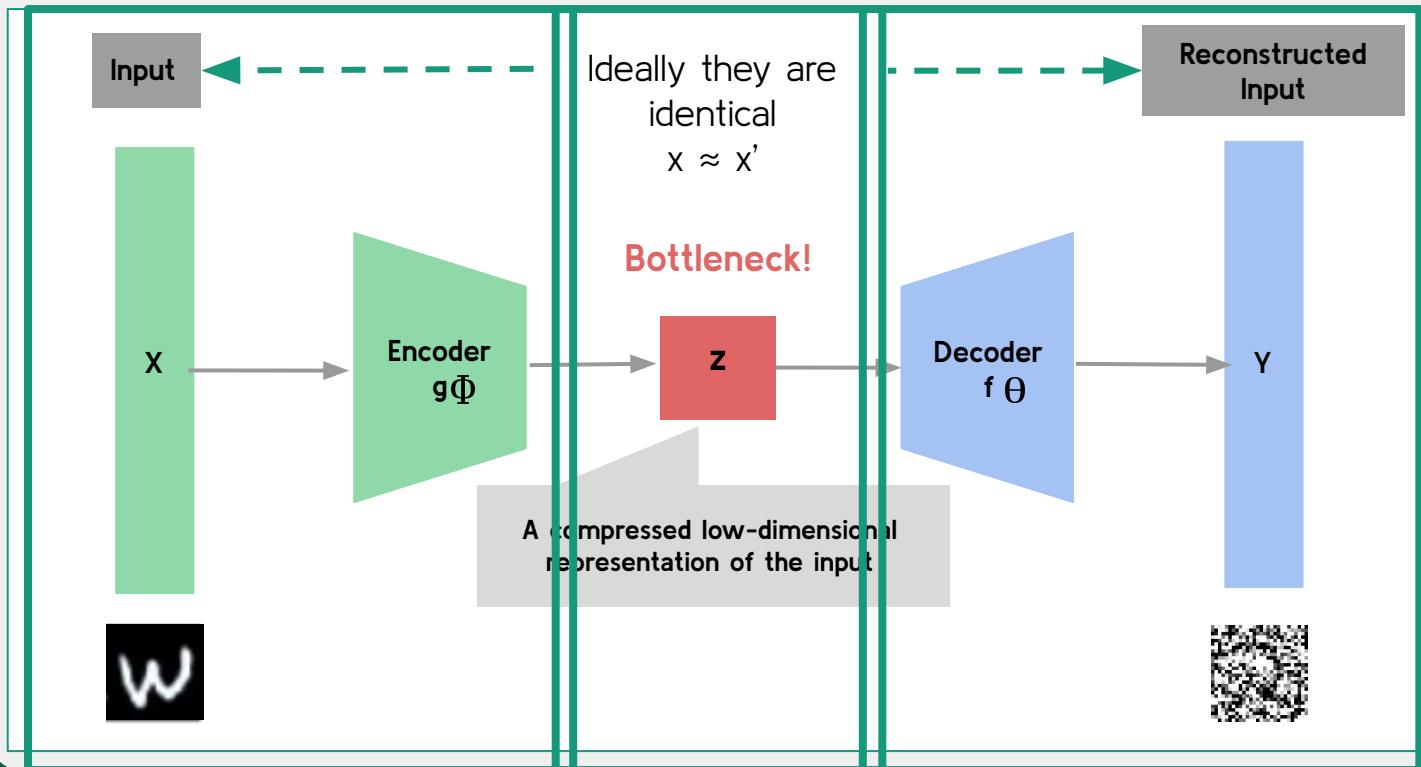
Models

Statistical Modeling

- Facebook Prophet 
- Created baseline time series model using methane readings averaged across CA
- Only captures temporal aspect of the data
- **Limitation**
 - Could not incorporate additional regressors more effectively



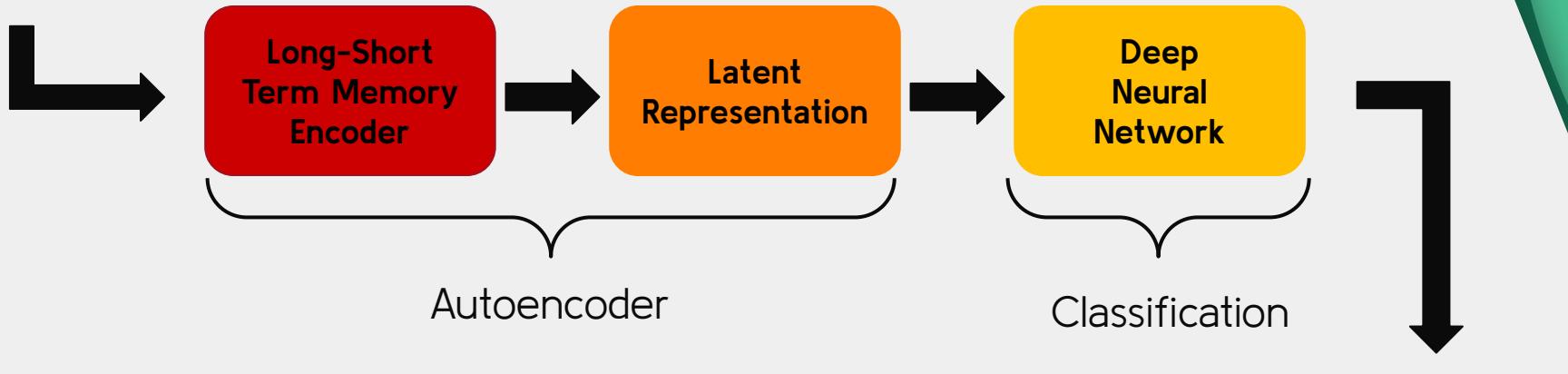
Autoencoder Deep Learning



Autoencoder + Deep Neural Network

(Approach #1)

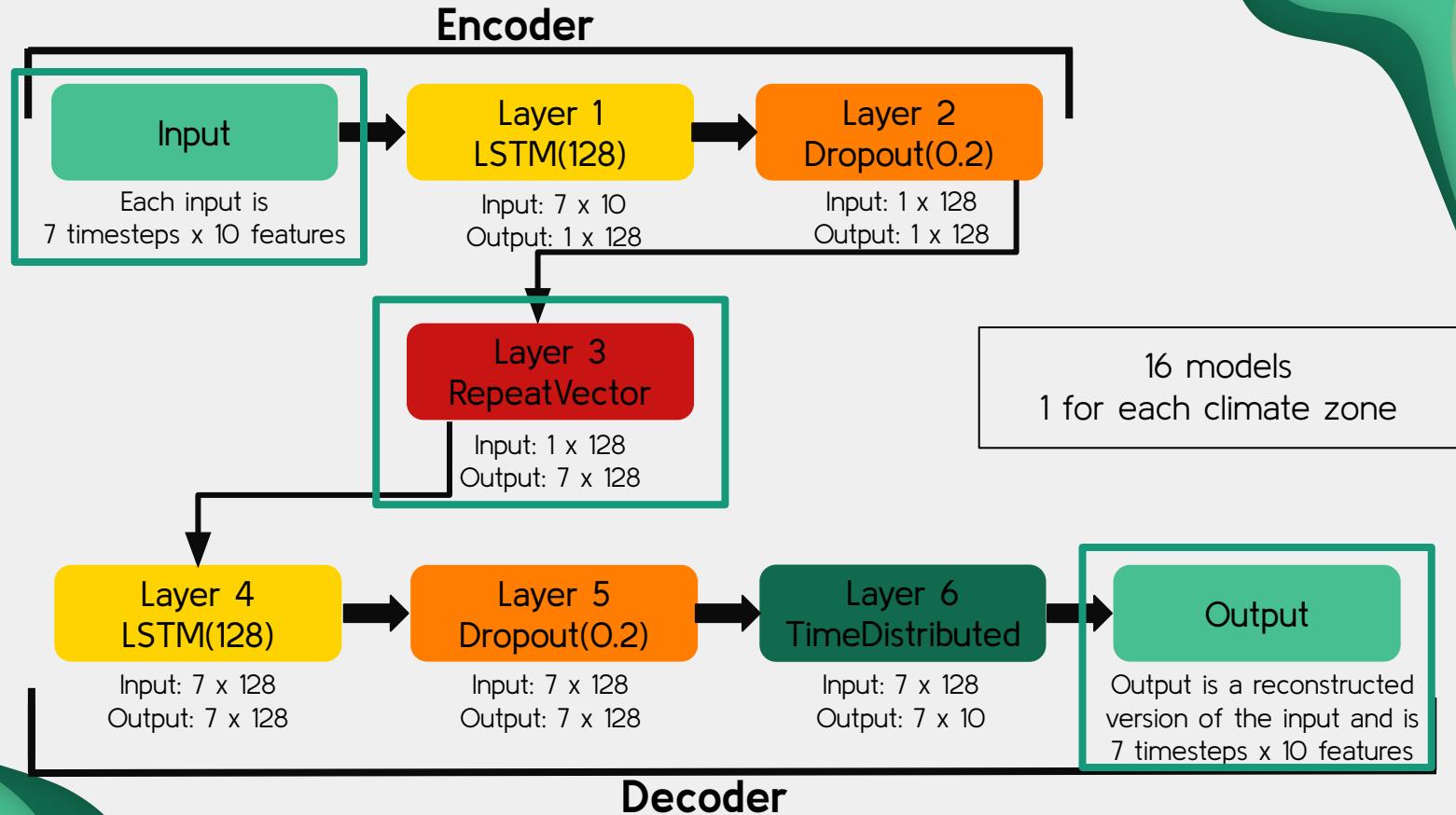
Input Sequence



Accuracy: ~25%
Predicted: ~75% anomalies

Long Short Term Memory (LSTM)

(Final Autoencoder Framework)

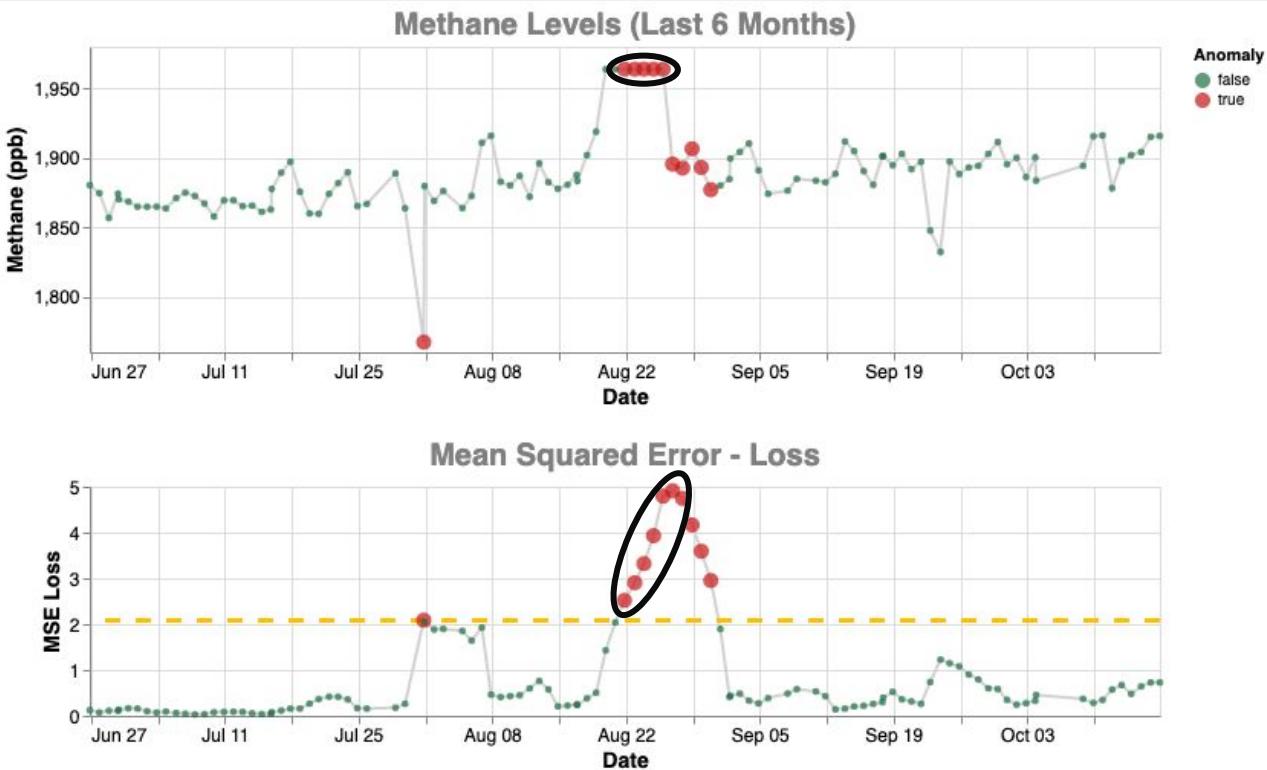


Model Tuning

- Hyperparameter tuning
 - Number of nodes
 - Dropout rates
 - Optimizers
 - Time window size
 - Epochs
- Data tuning
 - Resolution
 - Frequency

Climate Zone 1 Results		
Data	Nodes	Root Mean Square Error (RMSE)
Train	64	0.7119
Train	128	0.6862
Validation	64	0.8206
Validation	128	0.7833

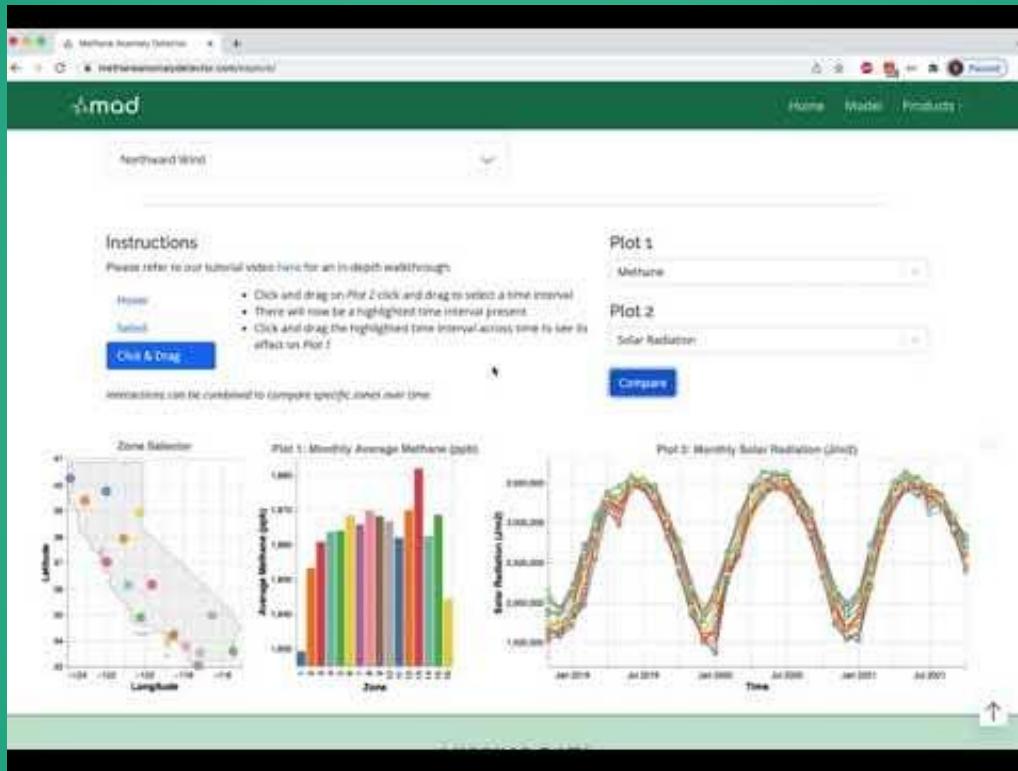
Synthetic Data Analysis



Single
Synthetic
Data Point



Product Demo



Next Steps



Scale globally



Expand to
different
satellites



Retrain models
with growing
data

Thank You

- **Blair Jones**, Methane Enthusiast
- **Sam Schabacker**, Renewable Energy Manager, UC President's Office
- **Bill Collins**, Director of the Climate & Ecosystem Science Division at Lawrence Berkeley National Laboratory & Lead and Collaborating Author of the Fourth IPCC Assessment, for which the IPCC was awarded the 2007 Nobel Peace Prize.
- **Iman Gohari**, Weather Forecasting Expert
- **Ed Dlugokencky**, NOAA Research Chemist
- **Jeff Zimmerman**, Environmental Engineering Manager, AECOM
- **Rick Malmstrom**, Executive Director-Sustainability Operations, Alexandria Real Estate
- **Cheryl Laskowski, Ryan Schauland, Jorn Herner**, California Air Resources Board (CARB)
- **Alberto Todeschini, Fred Nugen, Colorado Reed**, Faculty
- **Fellow classmates**



Thanks!

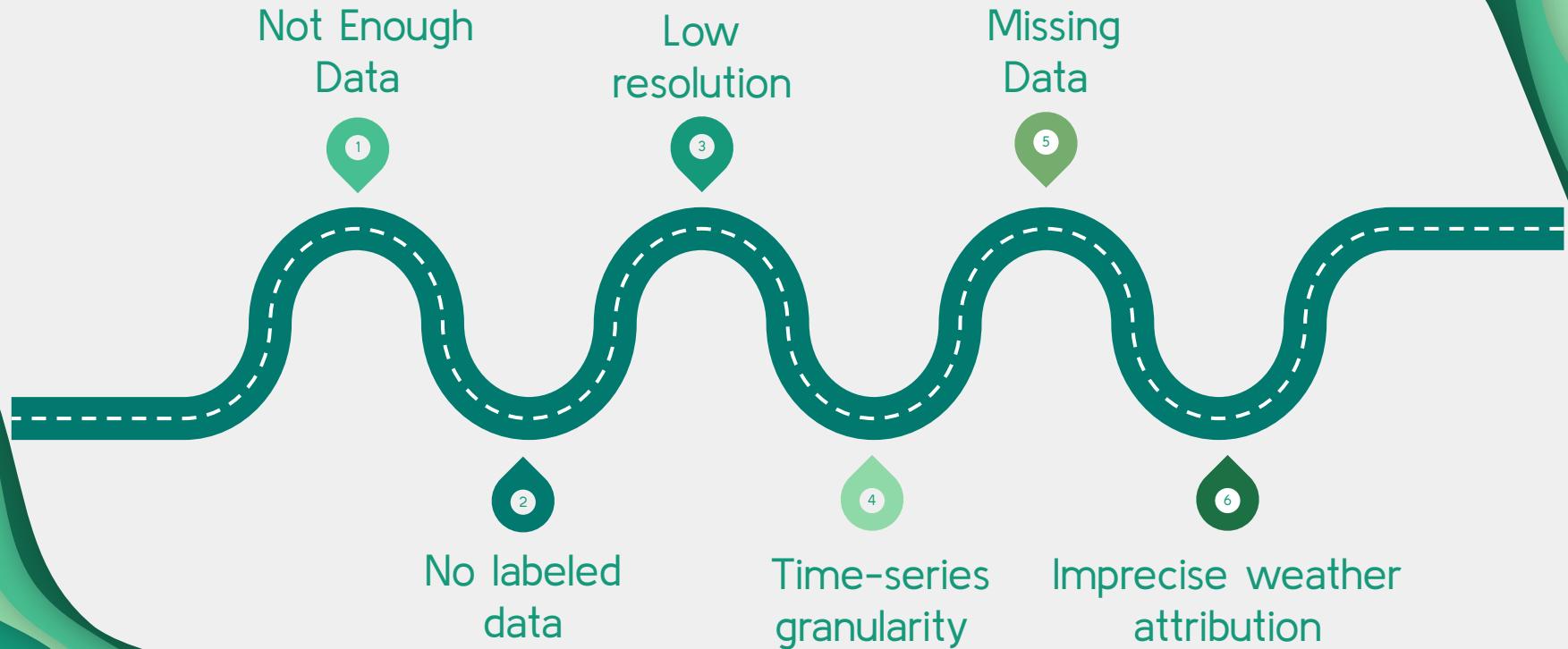
Any questions?

You can find us at:

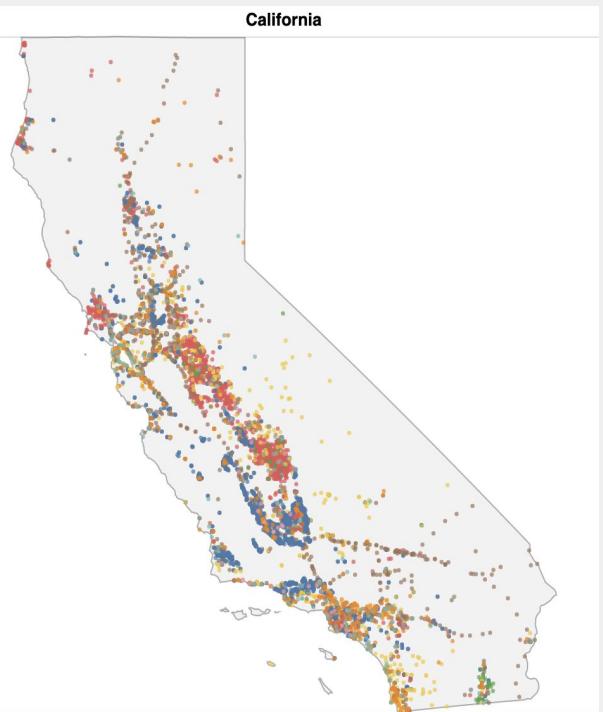
<https://methaneanomalydetector.com/>

Appendix

Appendix – Data Challenges



Appendix - Data - Vista-CA

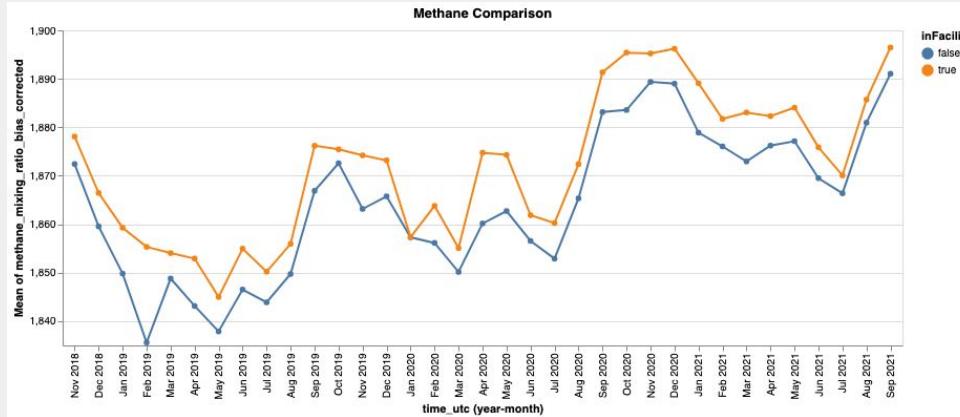
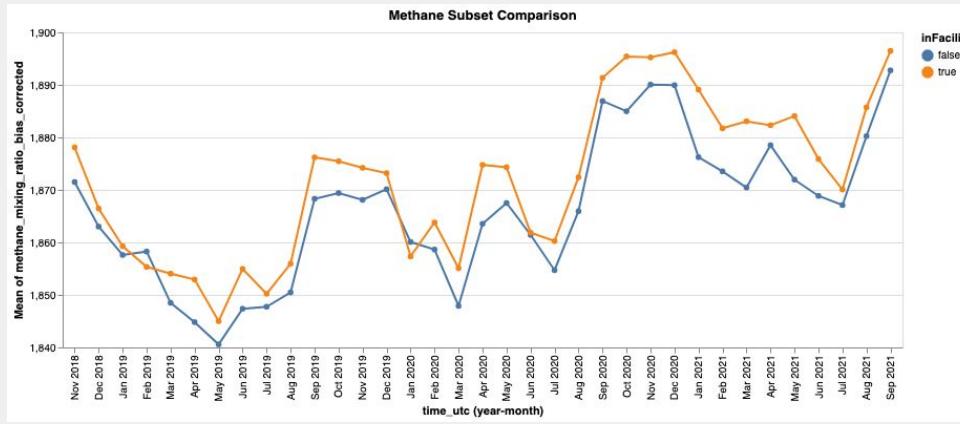


vistatype

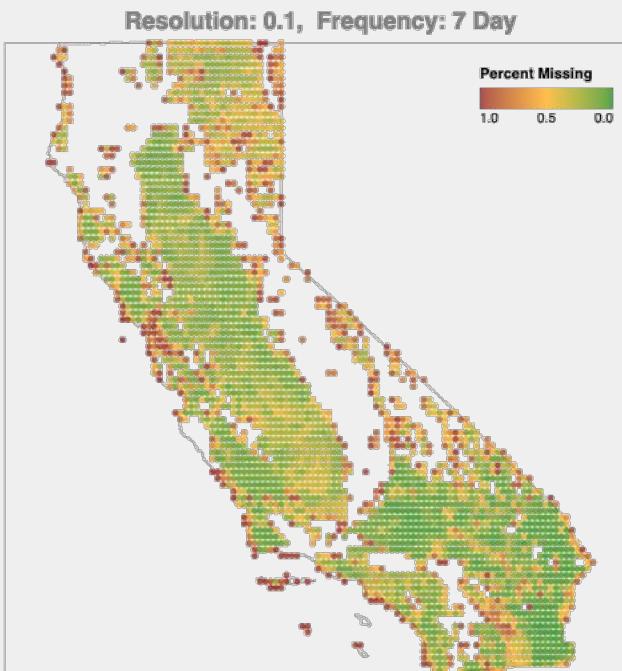
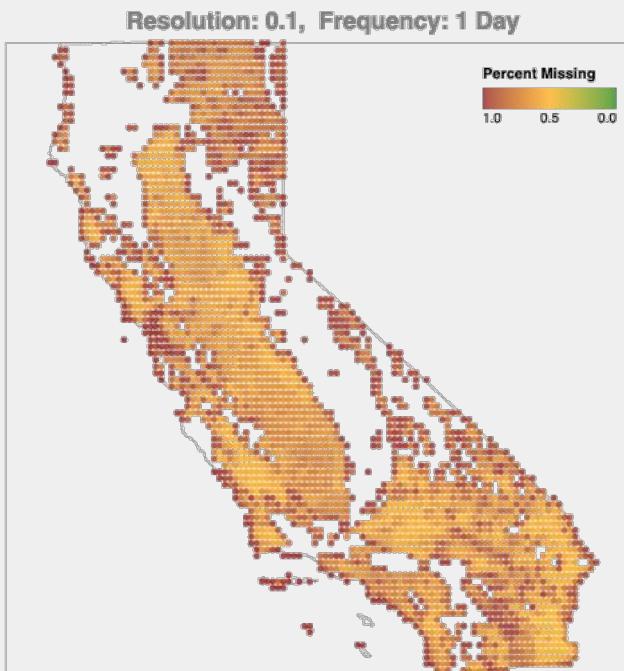
- Composting Sites
- Compressed Natural Gas Fueling...
- Dairy
- Digester
- Feed Lot
- Landfill
- Liquefied Natural Gas Fueling St...
- Natural Gas Processing Plants
- Natural Gas Station
- Natural Gas Storage Field
- Oil and Gas Facility Boundary
- Power Plant
- Refinery
- Wastewater Treatment Plant

	area	vistatype	mean	count
		vistatype		
		Composting Sites	0.001520	860
		Compressed Natural Gas Fueling Station	0.000887	162
		Dairy	0.000000	1715
		Digester	0.020325	33
		Feed Lot	0.000000	72
		Landfill	1.374963	714
		Liquefied Natural Gas Fueling Station	0.000467	46
		Natural Gas Processing Plants	0.356001	26
		Natural Gas Station	0.000000	1120
		Natural Gas Storage Field	25.234850	12
		Oil and Gas Facility Boundary	0.007556	3356
		Oil and Gas Well	0.000000	225766
		Power Plant	0.064109	433
		Refinery	2.182393	26
		Wastewater Treatment Plant	0.670160	149
inFacility				
False			1215953	
True			3381	

Appendix - Data - Vista-CA



Appendix - Data Grouping



Variation: Utilize Frequencies of 1D, 3D, 5D, 7D, 10D

Methane Data



Weather Data



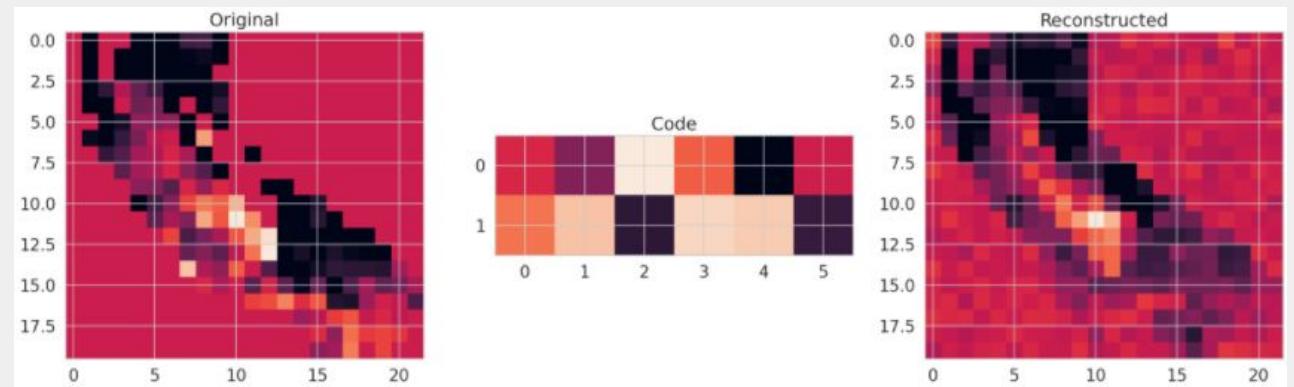
Data Grouping



Process and
Merge

Appendix - Image Representation

- Represented methane readings as an image to capture spatial aspect. Each pixel represents methane reading at a location.
- Used a convolutional neural network (CNN) autoencoder to reconstruct images and measure loss
- Infeasible due to lack of data and lack of precision
- $MSE = 0.1245$



Appendix

Autoencoder Time Series Training

```
print(train[['mmrbc_i']].shape)
train[['mmrbc_i']].head(10)

(760, 1)

      mmrbc_i
      time_utc
2018-12-03  0.388968
2018-12-04  0.332599
2018-12-05  0.276231
2018-12-06  0.219866
2018-12-07  0.163498
2018-12-08  0.107129
2018-12-09  0.050760
2018-12-10 -0.005604
2018-12-11 -0.061973
2018-12-12 -0.118341
```

```
trainX.shape: (753, 7, 1) trainY.shape: (753,)
testX.shape: (266, 7, 1) testY.shape: (266,)
```

Sequence
Windowing

Window #0

```
print("X")
print(trainX[0])
print()
print("Y")
print(trainY[0])
```

```
X
[[0.38896778]
 [0.3325992 ]
 [0.27623063]
 [0.2198662 ]
 [0.16349763]
 [0.10712906]
 [0.05076048]]
```

```
Y
-0.0056039393
```

Window #1

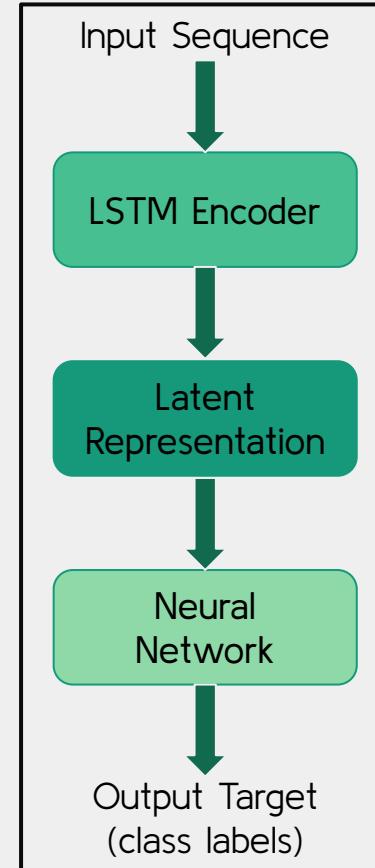
```
print("X")
print(trainX[1])
print()
print("Y")
print(trainY[1])
```

```
X
[[ 0.3325992 ]
 [ 0.27623063]
 [ 0.2198662 ]
 [ 0.16349763]
 [ 0.10712906]
 [ 0.05076048]
 [-0.00560394]]
```

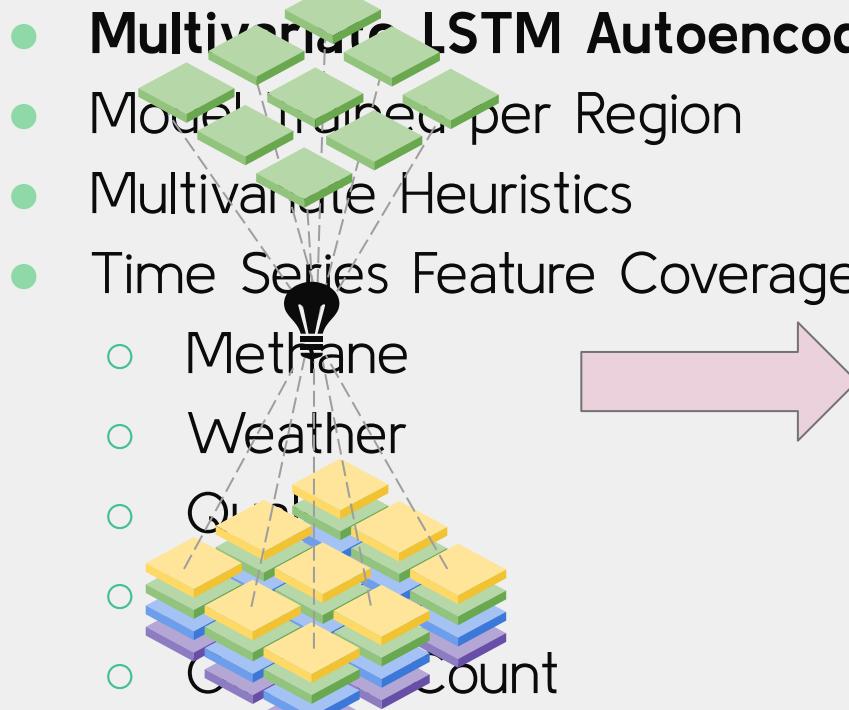
```
Y
-0.061972514
```

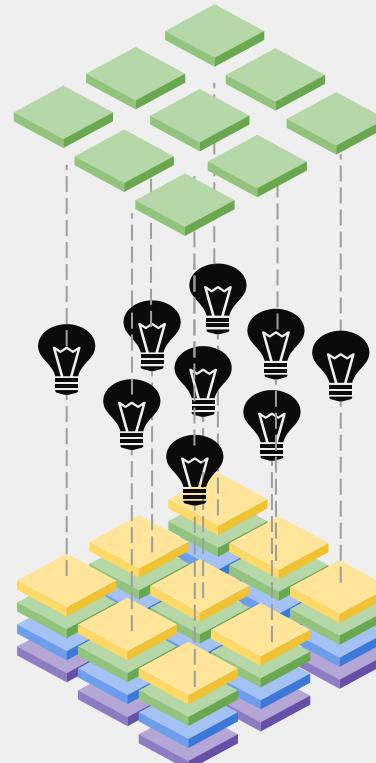
Appendix – LSTM-DNN

- Long Short Term Memory (LSTM) = capture temporal aspect
- Deep Neural Network (DNN) = capture spatial aspect
- Created a multiclass classification problem
- Achieved 25% accuracy
- Infeasible due to lack of data



Appendix – Final Approach

- **Multivariate LSTM Autoencoder**
 - Model Trained per Region
 - Multivariate Heuristics
 - Time Series Feature Coverage
 - Methane
 - Weather
 - Quality
 - Count
- 



Appendix - Feature Importance Example

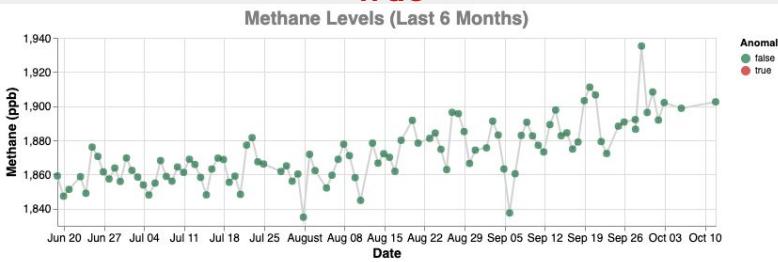
Model Name	All Features	Reading Count	QA Val Mean	QA Val Mode	Air Pressure at Mean Sea Level Mean	Air Temperature at 2 Meters Hour Maximum Mean	Air Temperature at 2 Meters 1 Hour Minimum Mean	Air Temperature at 2 Meters 1 Hour Mean	Dew Point Temperature at 2 Meters Mean	Eastward Wind at 100 Meters Mean	Eastward Wind at 10 Meters Mean	Integral WRT Time of Surface Direct Downwelling Shortwave Flux in Air 1 Hour Accumulation Mean	LWE Thickness of Surface Snow Amount Mean	Northward Wind at 100 Meters Mean	Northward Wind at 10 Meters Mean	Precipitation Amount 1 Hour Accumulation Mean	Snow Density Mean	Surface Air Pressure Mean	Minimum RMSE
TRAIN RMSE																			
Zone 1	0.7061	0.6391	0.6987	0.7580	0.6698	0.6348	0.6219	0.6206	0.6781	0.7119	0.7210	0.5776	0.7529	0.6908	0.6908	0.7533	0.6554	0.7159	0.5776
VALIDATION RMSE																			
Zone 1	0.9118	0.5903	0.7219	0.7713	0.6474	0.5619	0.5589	0.5602	0.5683	0.6795	0.6721	0.5451	0.5334	0.6808	0.6933	1.0720	0.9360	0.6373	0.5334
METHANE RMSE ONLY WITH ONLY FEATURES ADDED PER COLUMN																			
Zone 1	0.7094	0.3207	0.3839	0.4851	0.4982	0.4952	0.4970	0.5027	0.5194	0.5194	0.5006	0.5452	0.5472	0.4184	0.4511	0.5326	0.5908	0.3717	0.3207

Appendix – RMSE Results

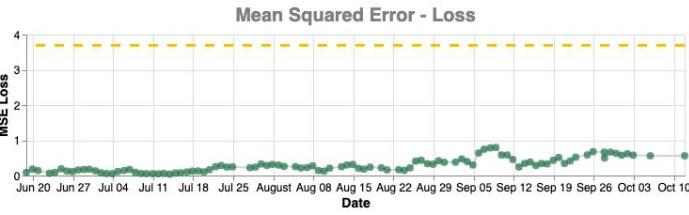
Zone	Train RMSE	Validation RMSE
1	0.7148	0.6035
2	0.6778	0.6195
3	0.6695	0.5930
4	0.6549	0.5816
5	0.6172	0.6612
6	0.6317	1.9263
7	0.6519	0.6765
8	0.6850	0.6332
9	0.6976	0.5981
10	0.6367	0.6937
11	0.6973	0.5853
12	0.6644	0.5887
13	0.7172	0.6370
14	0.6717	0.6095
15	0.6607	0.6729
16	0.7005	0.6226

Appendix - Santa Maria - Synthetic Test - Single Anomaly

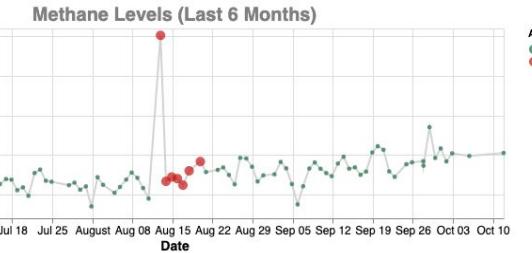
True



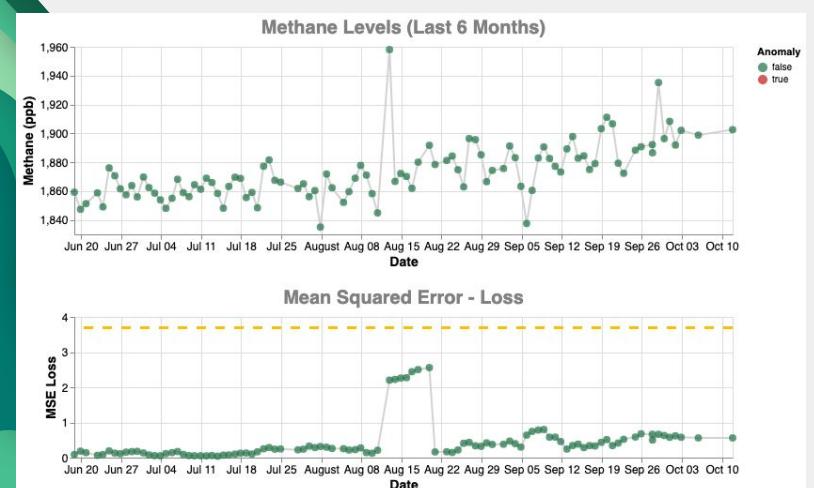
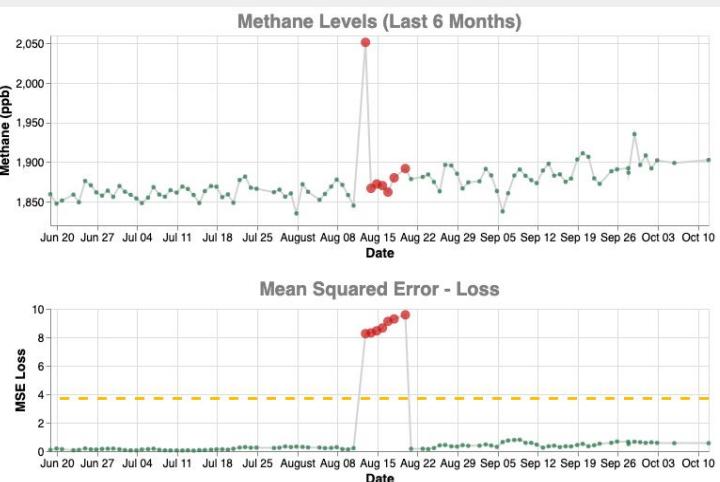
5% + mean



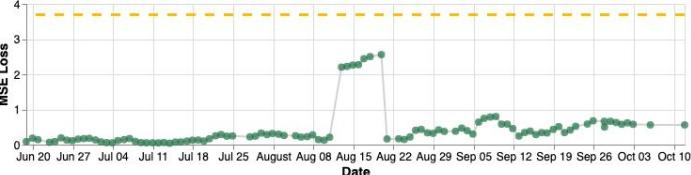
10% + mean



Mean Squared Error - Loss

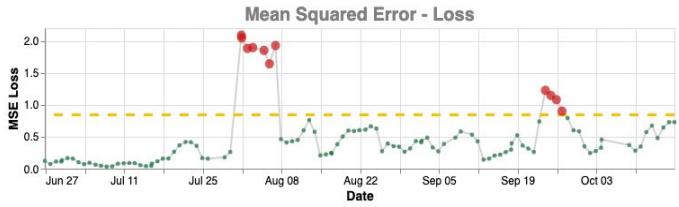
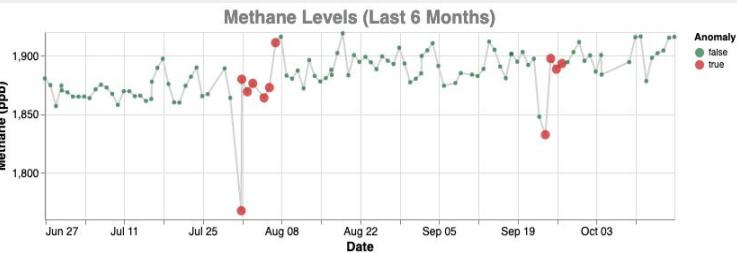


Mean Squared Error - Loss

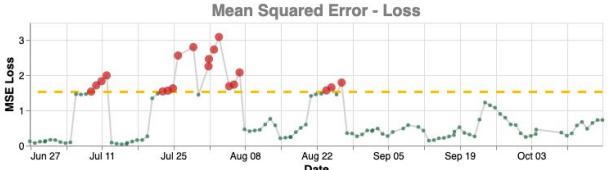
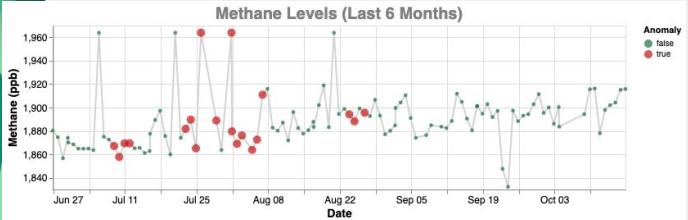


Appendix - Neal Road - Synthetic Test - Random Sequence Anomalies

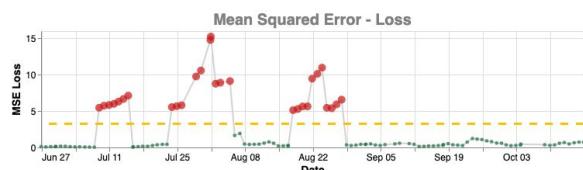
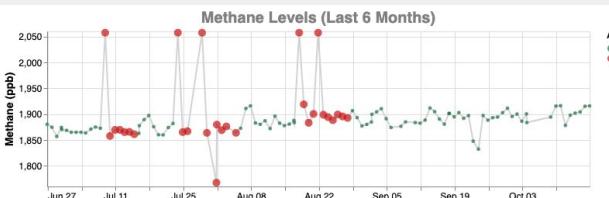
True



5% + mean

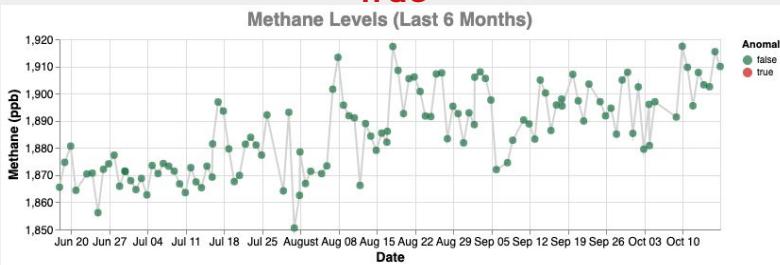


10% + mean

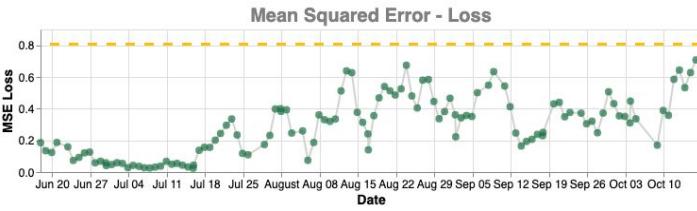


Appendix - Chico - Synthetic Test - Single Anomaly

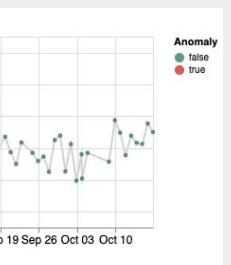
True



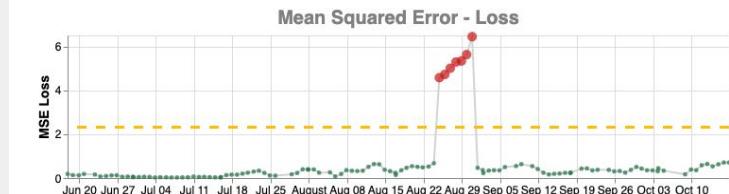
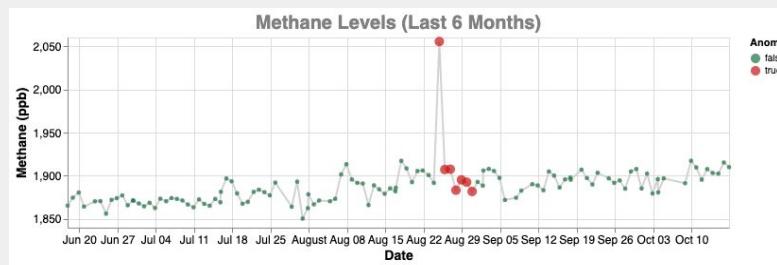
5% + mean



10% + mean



10% + mean



Appendix – Abbreviations

EPA – Environmental Protection Agency

IPCC – Intergovernmental Panel on Climate Change

Appendix – Product Architecture

