Chicago Beaches Water Quality Prediction

Open Source Civic Tech Collaborative Data Science Project

Rebecca Jones

Overview

- Context of project : ChiHackNight collaboration
- Description of problem : E. Coli prediction, both important and difficult
- Modeling approach : Ensemble of GBM and Random Forest models
- Results : Performance comparisons
- Reflections : Pros and cons of collaborative data science work

CHI HACKNIGHT

- Chicago's weekly event to build, share & learn about civic tech.
- Every Tuesday 6-9pm at Merchandise Mart 8th floor, Braintree offices.
- Brings together people with technical skills and people with knowledge of aspects of civic life that can be improved by better use of data and technology.
- https://chihacknight.org/

City of Chicago

- Tom Schenk, Chief Data Officer.
- https://data.cityofchicago.org/

Escherichia coli :
monitored as indicator of microbial contamination

Pathways for bacterial contamination

- Local
  - Geese and other birds. Animal waste.
  - Runoff from streets and waterways. Washout of bacterial load buildup on beachfront.
  - Non functioning storm drains. Illicit discharges. Sewer overflows.

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- Local
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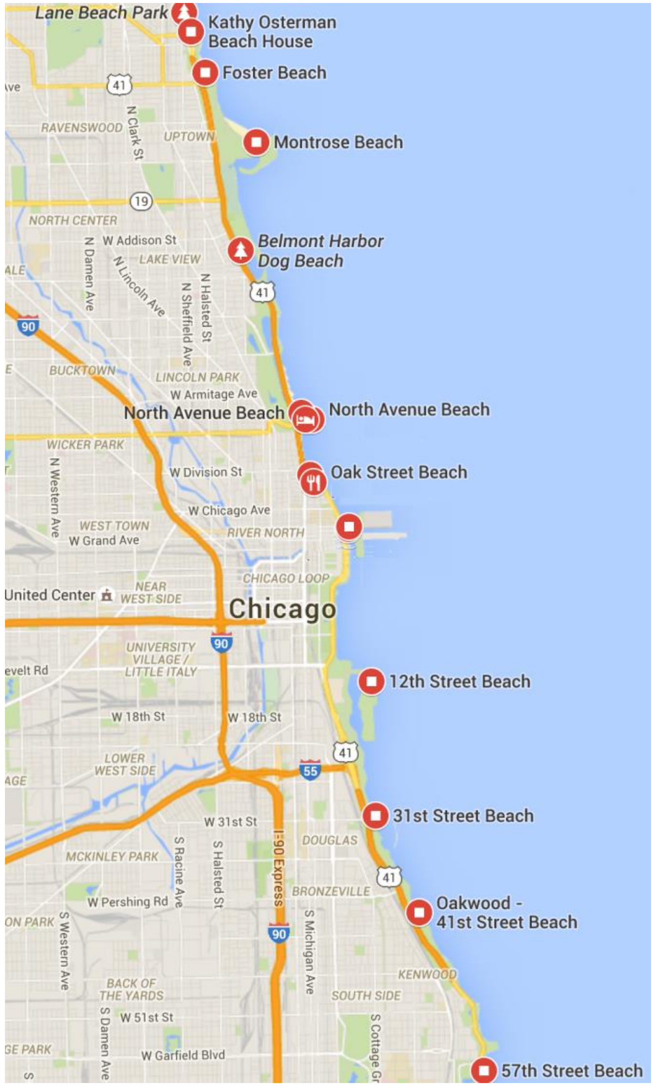
  - Non functioning storm drains. Illicit discharges. Sewer overflows.
- Regional
  - Storm surges. Sediment resuspension.
  - Turbidity currents. Flows from rivers.

Chicago Beach Monitoring:



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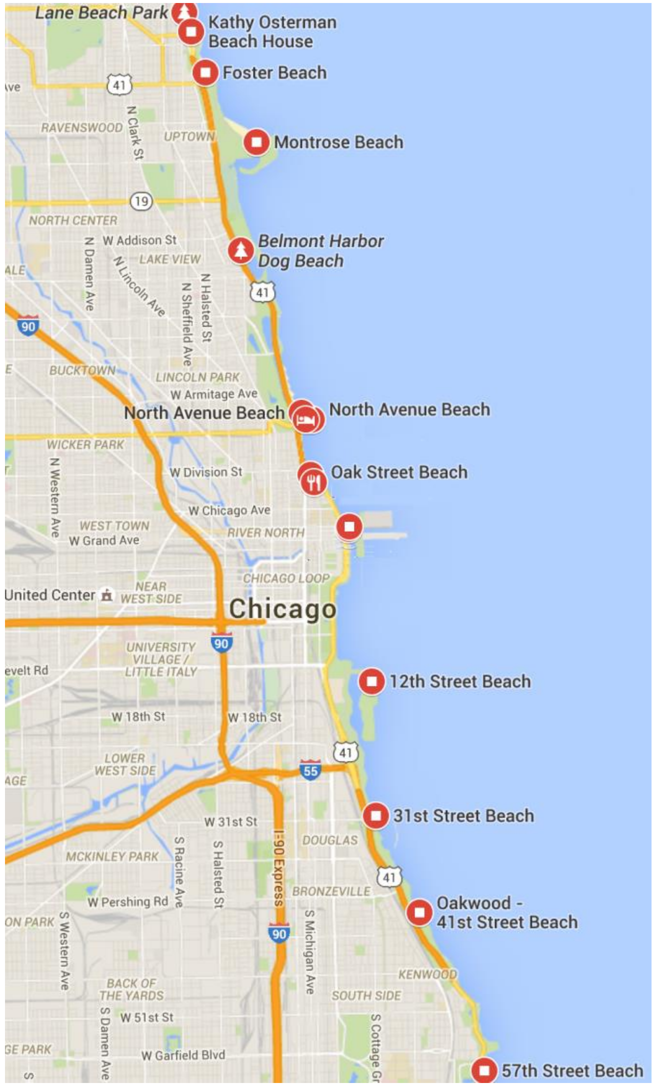

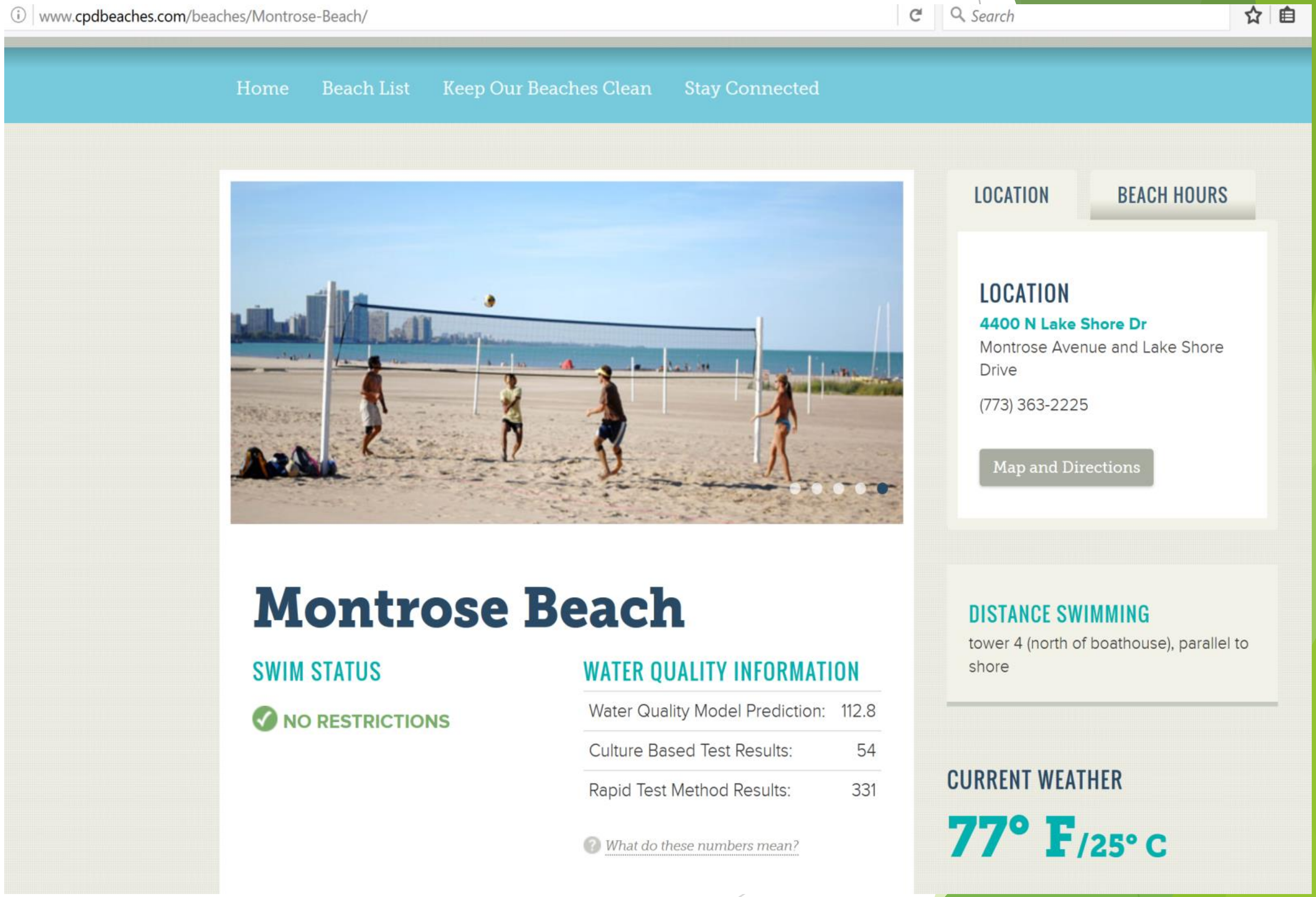

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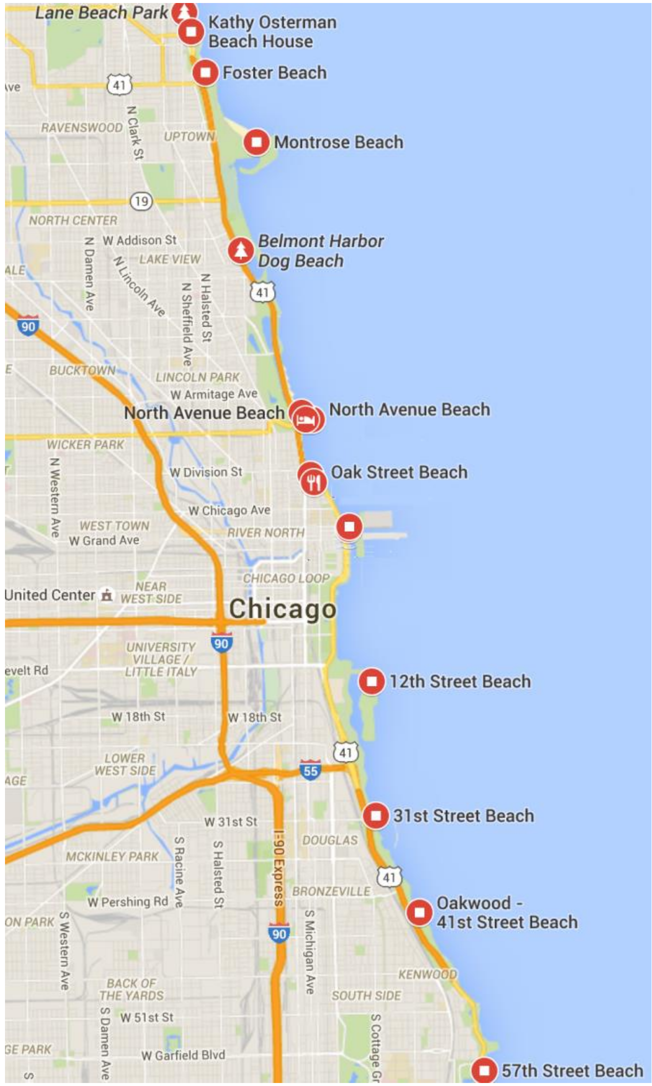

2015 results from current USGS predictive model

BEACH	incorrect_warning	correct_warning	missed_warning
Juneway	0	0	5
Rogers	0	0	7
Howard	0	0	7
Jarvis	0	0	2
Leone	0	0	4
Albion	0	0	6
Osterman	0	0	14
Foster	1	0	9
Montrose	1	5	26
North Avenue	0	0	5
Oak Street	0	0	1
Ohio	1	0	13
12th	0	0	11
31st	2	1	12
Oakwood	2	0	6
57th	2	1	4
63rd	2	1	11
South Shore	2	1	13
Rainbow	3	4	17
Calumet	0	0	30

Warnings are issued when model predicts bacteria counts to be higher than 235 colony forming units per 100 milliliters of water.

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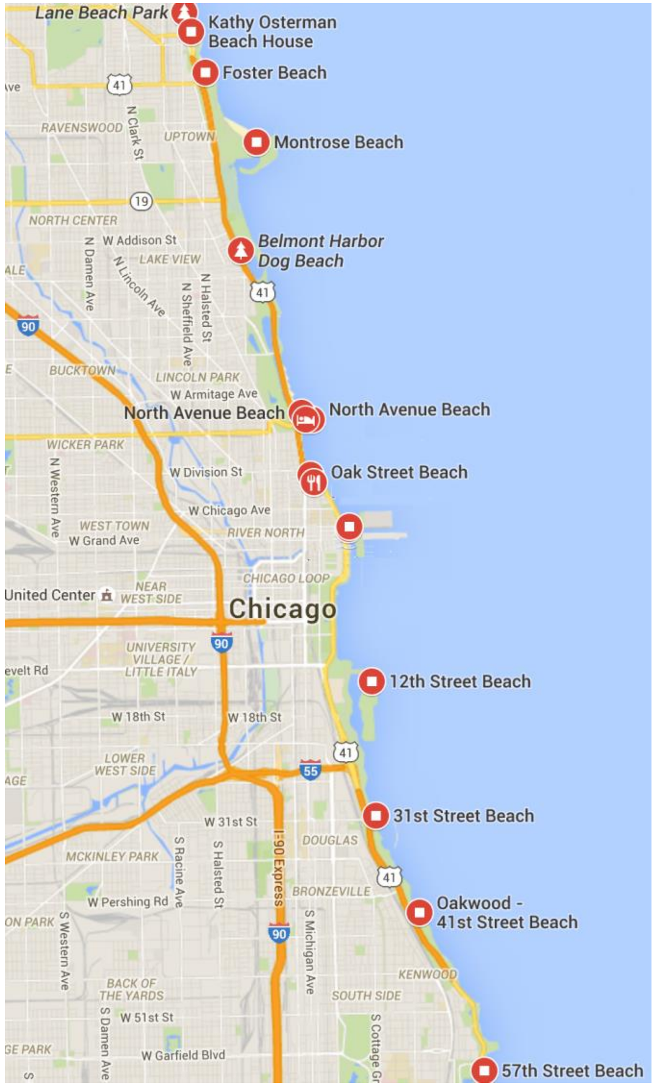
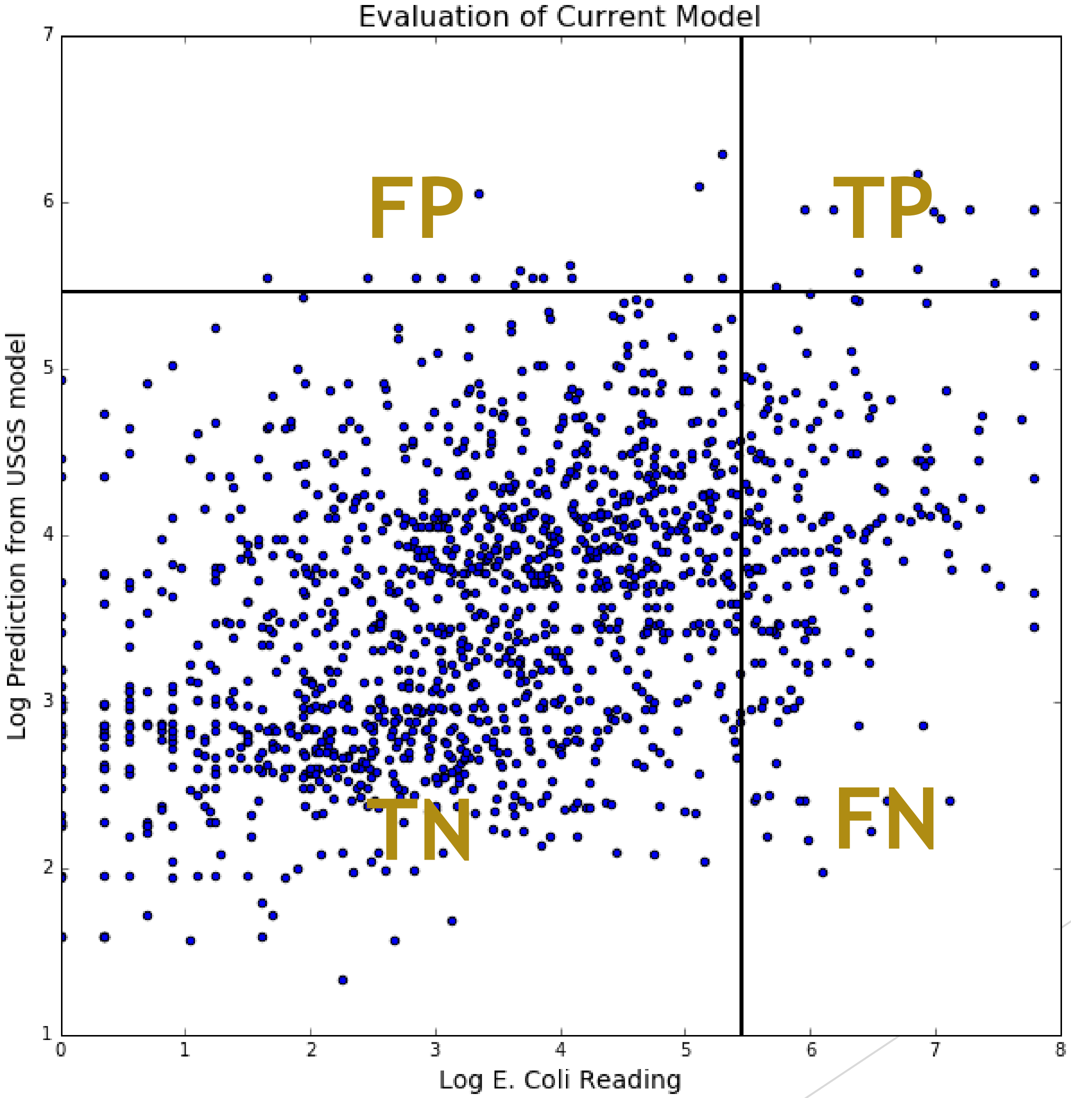
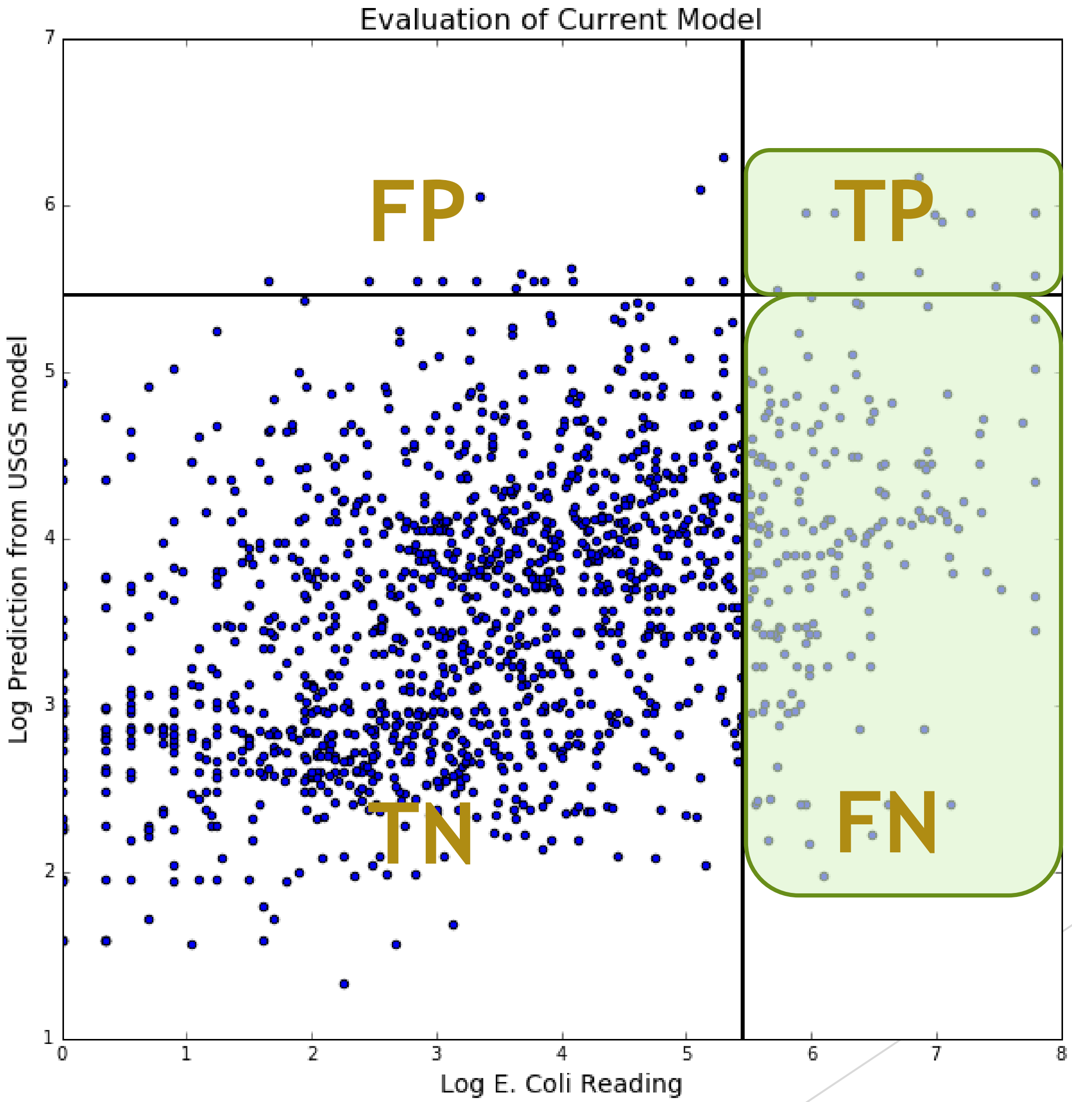




Chicago Beach Monitoring:

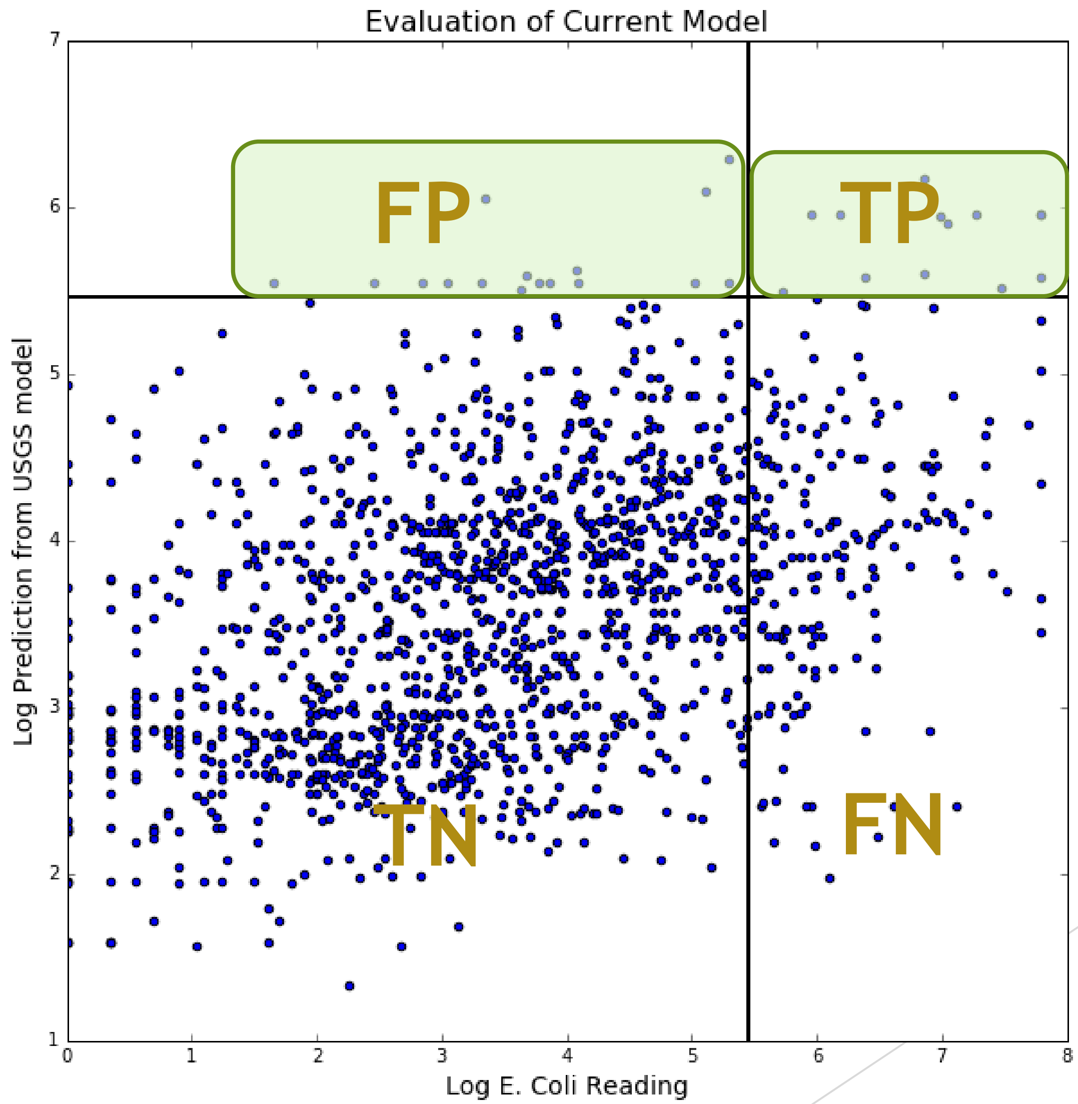
Specificity (Recall or TPR) **: ~6%**
proportion of correctly identified positives



Chicago Beach Monitoring:

Sensitivity (Recall or TPR) : ~6%
proportion of correctly identified positives

Precision : ~42%
proportion of identified that are positives



Chicago Beach Monitoring:

Sensitivity (Recall or TPR) : ~6%
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Precision : ~42%
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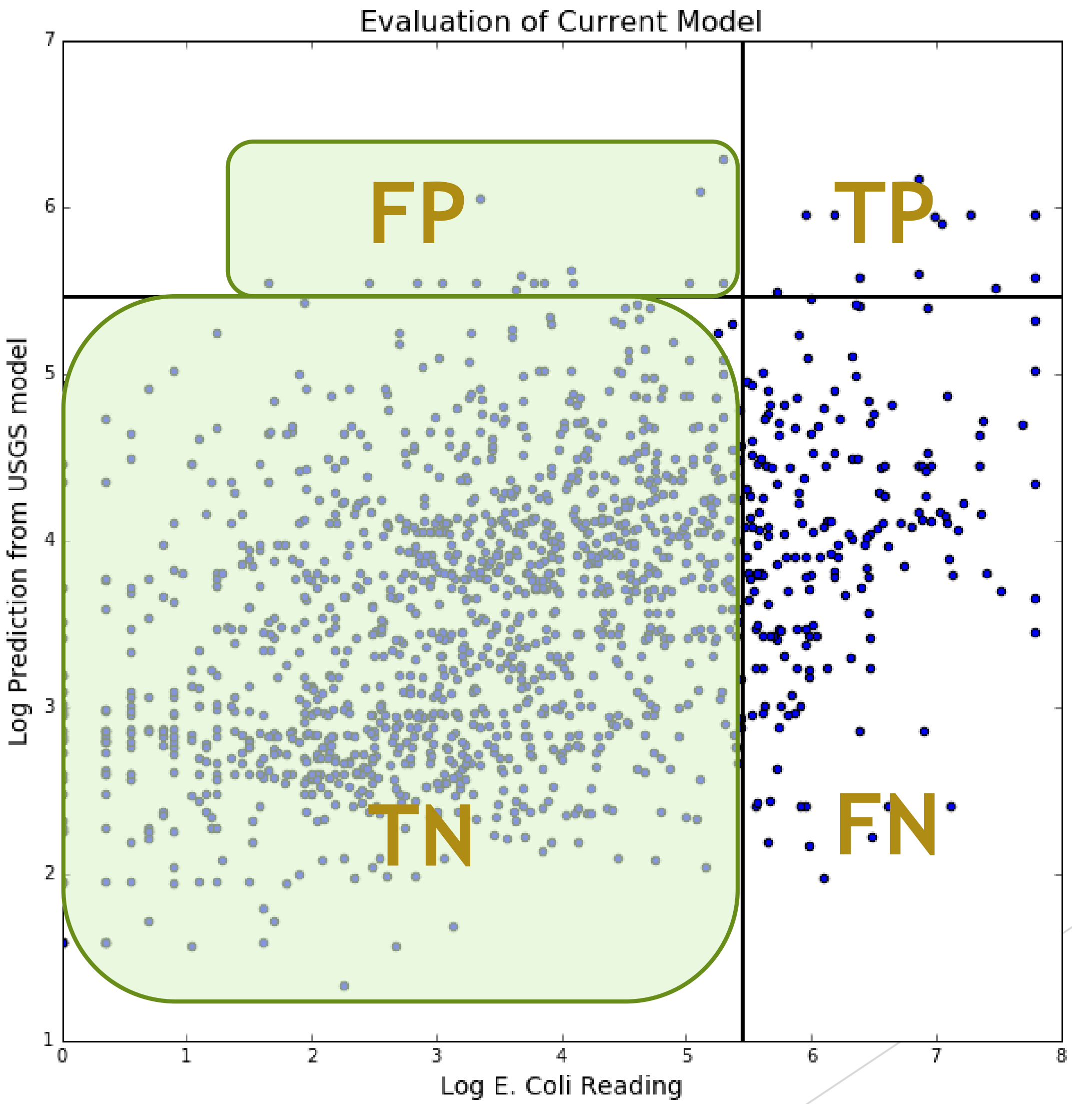
Specificity (TNR): ~98%
Proportion of correctly identified negatives



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Sensitivity (Recall or TPR) : ~6%
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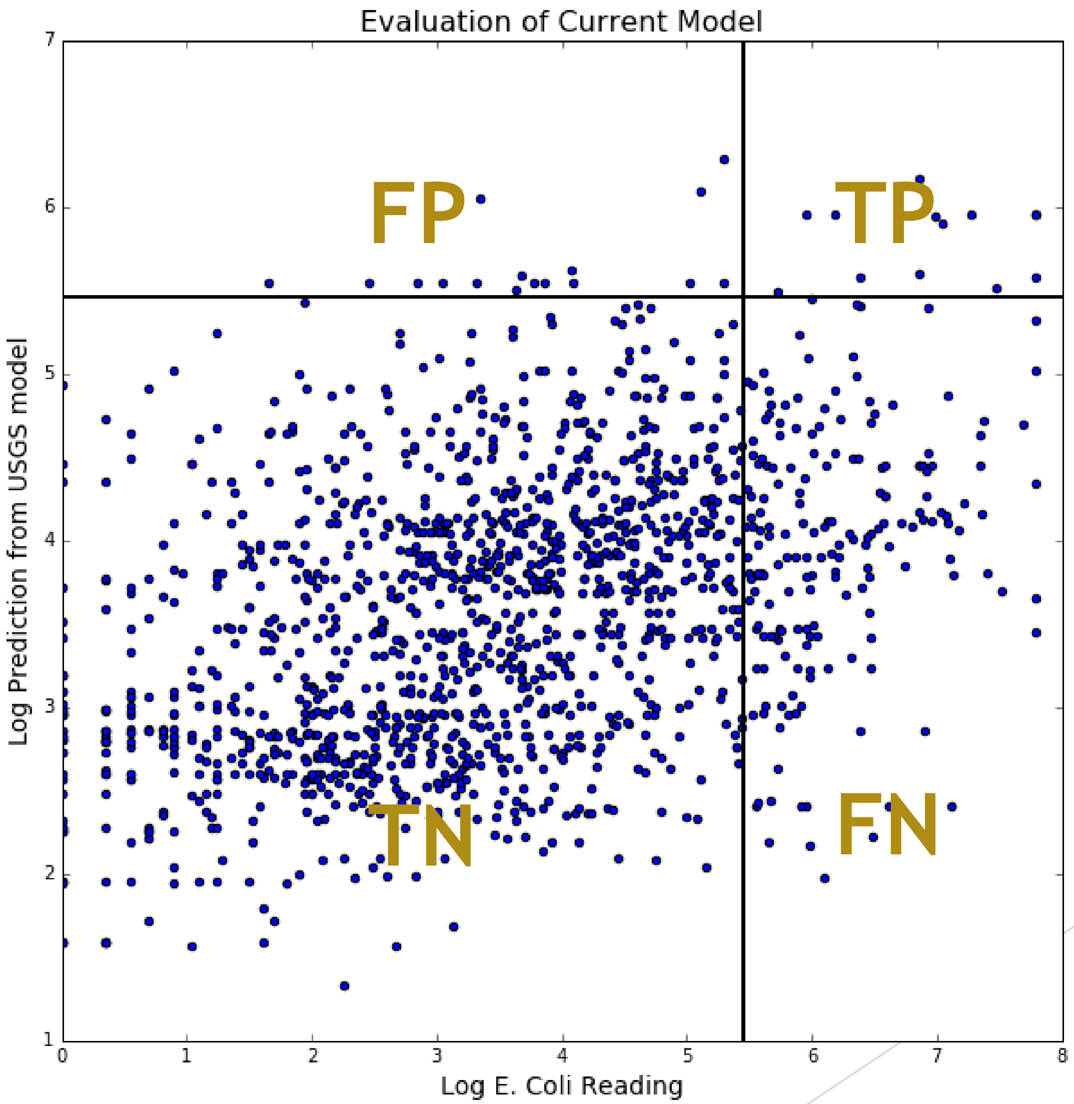
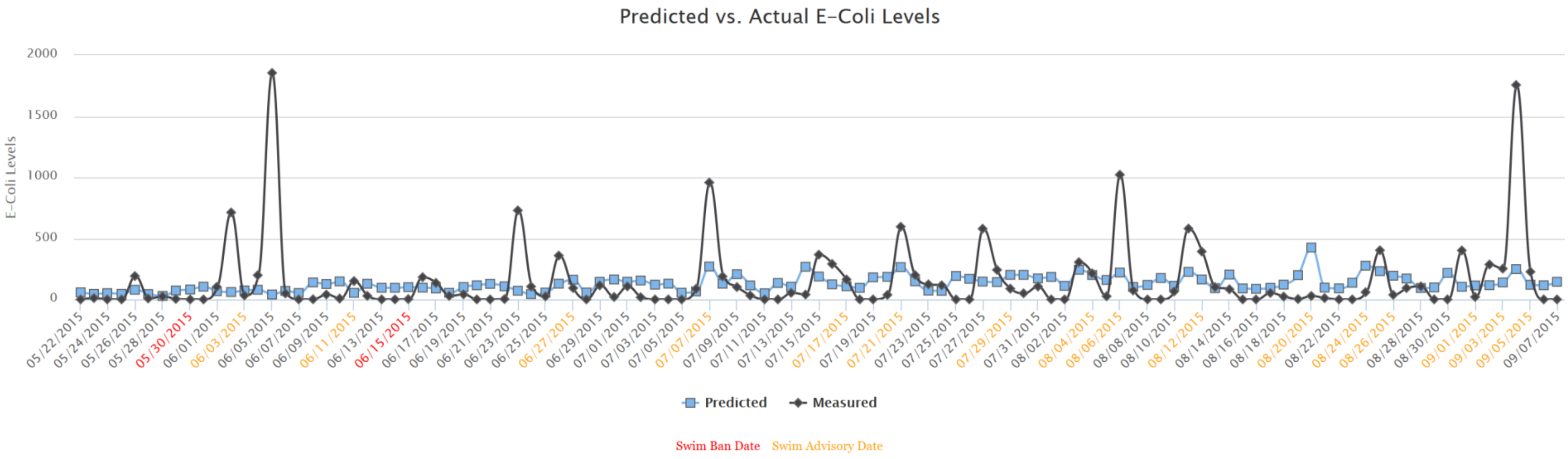
proportion of identified that are positives

Specificity (TNR): ~98%
Proportion of correctly identified negatives

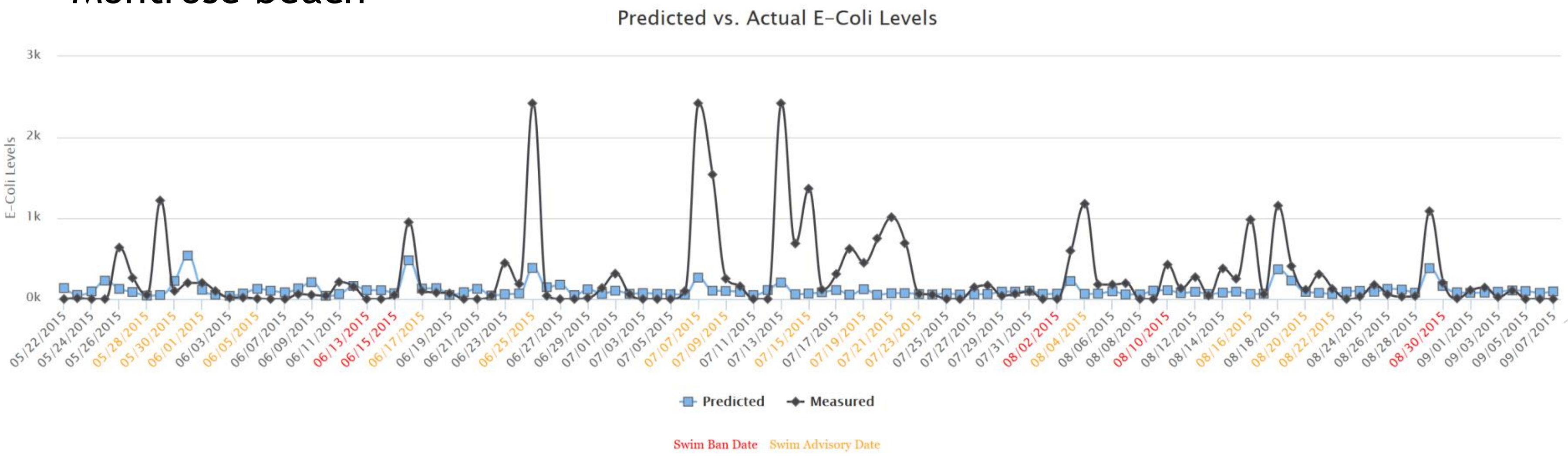
What do we want to maximize?
- Public safety
- Reputation of monitoring system
- Reputation of beaches



Rainbow beach



Montrose beach



From website:
http://drekbeach.org/
by Scott Beslow

Data

<u>Response Variable:</u>

E Coli readings : geometric mean of two readings at each beach.

20 beaches. Measured Mon-Fri. ~75 days per year. 10 years of data.

<u>Predictors:</u>

Weather : temp, wind speed & direction, humidity, rain, pressure, dew point

Water Sensor Readings : turbidity, wave height, chlorophyll, ph levels

Data

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<u>**Predictors:**</u>

Weather : temp, wind speed & direction, humidity, rain, pressure, dew point

~~**Water Sensor Readings :** turbidity, wave height, chlorophyll, ph levels~~

Engineered features : lagged variables, trailing averages,
overnight pressure change, accumulated rain,
North/South wind speed, East/West wind speed

Modeling methods considered: Random Forests and Gradient Boosting

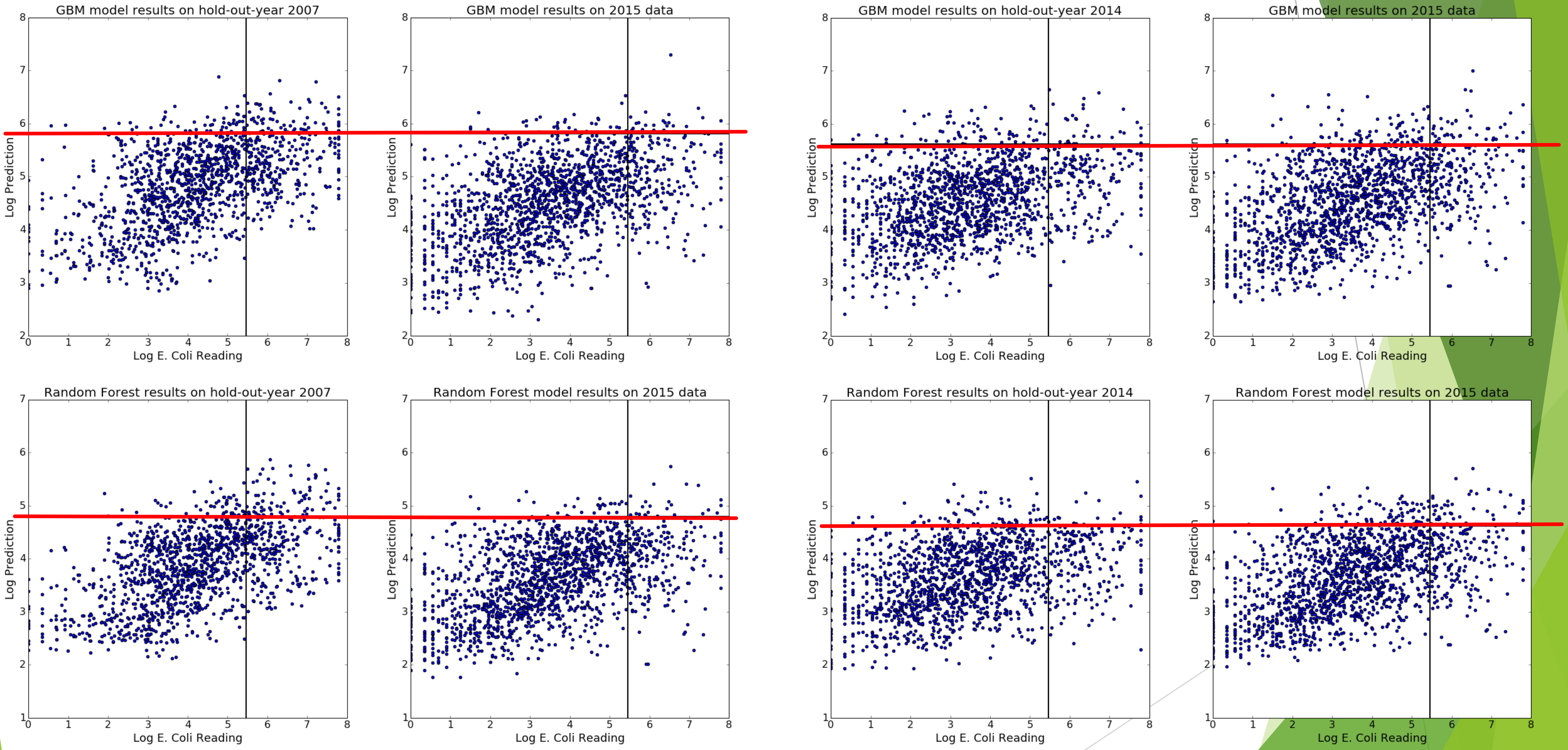
- Bagging (RF) - averaging across independent decision tree models
- Boosting (GBM) – iterative decision tree building to strengthen weak learners
- Use both in combination can lower variance, give more robust results.

Modeling Approach:
Ensembles of Random Forest and
Gradient Boosting Machine Regression Trees

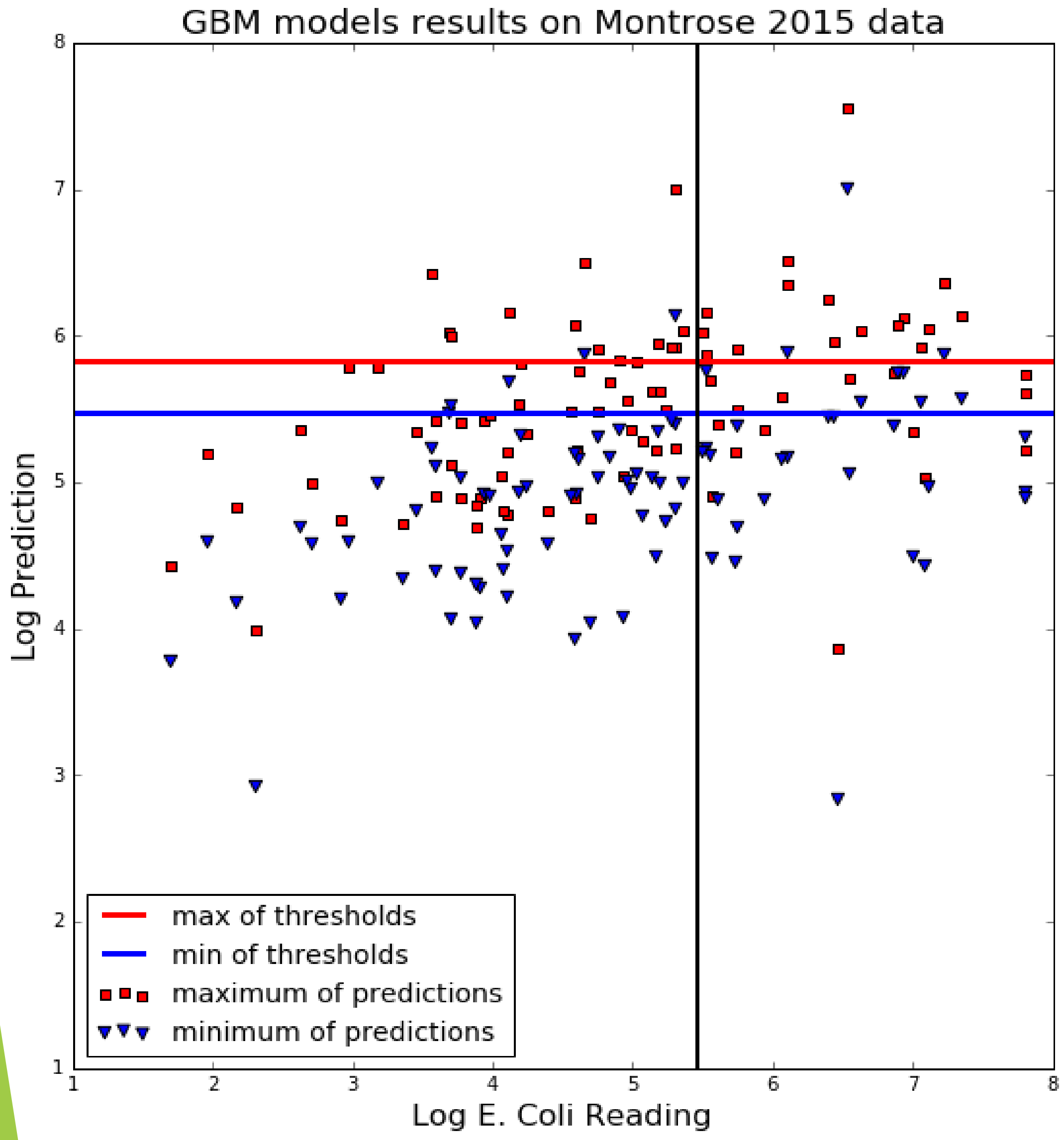
Process:

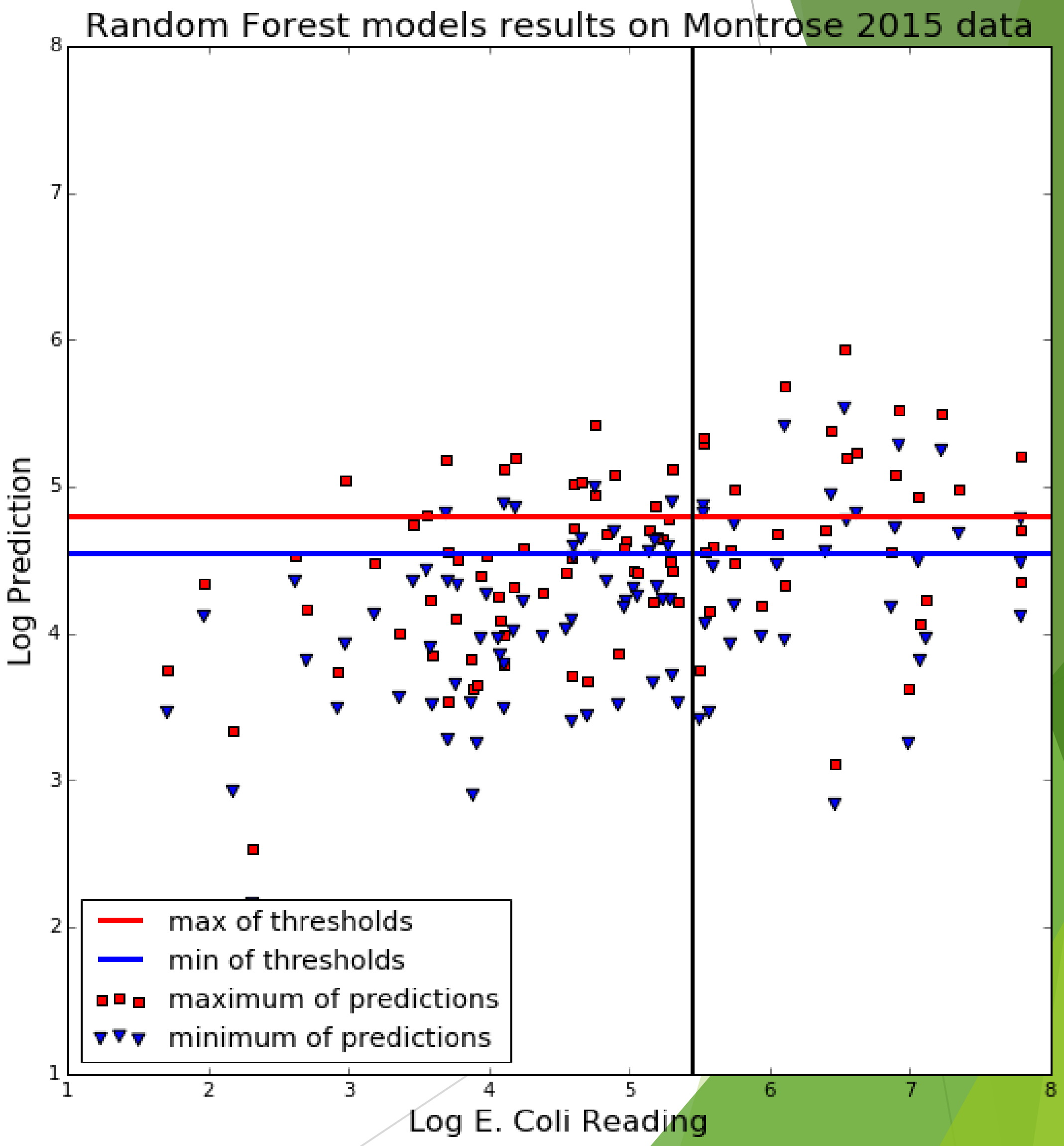
- Remove 2015 from training data. Keep as final test set.
- For each year 2006-2014, hold year of data out of training set and build model.
- Calibrate decision threshold using hold out year. (set False Positive Rate to max 5%)
- Test resulting set of models on 2015 data using calibrated decision thresholds.

Two hold-out-year models. Example of setting and using decision threshold.



Composition and Comparison of Models





Ensemble of ensembles

2006 hold out model	2007 hold out model	…	2013 hold out model	2014 hold out model

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RF prediction & GBM prediction

Final prediction

Ensemble of ensembles

2006 hold out model | 2007 hold out model | each return T/F | 2013 hold out model | 2014 hold out model

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RF prediction & GBM prediction

Final prediction

Ensemble of ensembles

2006 hold out model
2007 hold out model
each return T/F
2013 hold out model
2014 hold out model

2006 hold out model
2007 hold out model
each return T/F
2013 hold out model
2014 hold out model

RF prediction
If any above T then T

&

GBM prediction
If any above T then T

Final prediction

Ensemble of ensembles

2006 hold out model	2007 hold out model	each return T/F	2013 hold out model	2014 hold out model

RF prediction

If any above T then T

&

2006 hold out model	2007 hold out model	each return T/F	2013 hold out model	2014 hold out model

GBM prediction

If any above T then T

Final prediction

If both above T (or if USGS model T) then T

Comparison of Current and Proposed models

Current USGS Model predictions

BEACH	incorrect_warning	correct_warning	missed_warning
Juneway	0	0	5
Rogers	0	0	7
Howard	0	0	7
Jarvis	0	0	2
Leone	0	0	4
Albion	0	0	6
Osterman	0	0	14
Foster	1	0	9
Montrose	1	5	26
North Avenue	0	0	5
Oak Street	0	0	1
Ohio	1	0	13
12th	0	0	11
31st	2	1	12
Oakwood	2	0	6
57th	2	1	4
63rd	2	1	11
South Shore	2	1	13
Rainbow	3	4	17
Calumet	0	0	30

Precision: 42% **Recall: 6%**

Ensemble of Ensemble predictions (FPR of 5%)

BEACH	incorrect_warning	correct_warning	missed_warning
Juneway	1	1	4
Rogers	0	1	6
Howard	1	1	6
Jarvis	1	1	1
Leone	2	0	4
Albion	0	1	5
Osterman	1	2	12
Foster	2	2	7
Montrose	11	17	14
North Avenue	1	0	5
Oak Street	0	0	1
Ohio	2	1	12
12th	3	0	11
31st	7	1	12
Oakwood	4	0	6
57th	4	2	3
63rd	8	1	11
South Shore	7	5	9
Rainbow	16	8	13
Calumet	8	9	21

Precision: 40% **Recall: 24%**

Comparison of Current and Proposed models

Current USGS Model predictions

BEACH	incorrect_warning	correct_warning	missed_warning
Juneway	0	0	5
Rogers	0	0	7
Howard	0	0	7
Jarvis	0	0	2
Leone	0	0	4
Albion	0	0	6
Osterman	0	0	14
Foster	1	0	9
Montrose	1	5	26
North Avenue	0	0	5
Oak Street	0	0	1
Ohio	1	0	13
12th	0	0	11
31st	2	1	12
Oakwood	2	0	6
57th	2	1	4
63rd	2	1	11
South Shore	2	1	13
Rainbow	3	4	17
Calumet	0	0	30

Precision: 42% **Recall: 6%**

Ensemble of Ensemble predictions **(FPR of 2%)**

BEACH	incorrect_warning	correct_warning	missed_warning
Juneway	0	0	5
Rogers	0	0	7
Howard	0	0	7
Jarvis	0	0	2
Leone	0	0	4
Albion	0	0	6
Osterman	1	1	13
Foster	1	1	8
Montrose	3	13	18
North Avenue	0	0	5
Oak Street	0	0	1
Ohio	1	0	13
12th	1	0	11
31st	2	1	12
Oakwood	2	0	6
57th	2	2	3
63rd	3	1	11
South Shore	5	2	12
Rainbow	7	7	14
Calumet	3	3	27

Precision: 50% **Recall: 14%**

Collaborative Data Science : Pros

- Coding improved by collaboration
  - Reinforces better documentation habits
  - Learn from style of more advanced python users
- Opportunity to debate questions of data science
  - Learn from others
  - Teach others
- Familiarity with collaborative tools improved
  - Github, slack, waffle.io

Collaborative Data Science : Cons

- Redundancy of effort
  - Try something, doesn’t work. No report that it was tried.
  - Code not uploaded and shared. Or not documented well enough to make it useable.
- Difficulty bringing people “on-board” mid-project
  - Documentation scattered.
  - Fossilized idiosyncrasies of project.

Beaches with few E. Coli exceedances

Beaches with many E. Coli exceedances