esri Malaysia

Discovering Many Possibilities using Geo-AI

MYSA Technical Talk Series 2/2019

AI is used today literally everywhere…

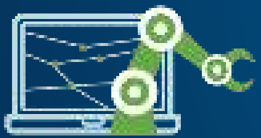
Autonomous Cars

Crime Prediction

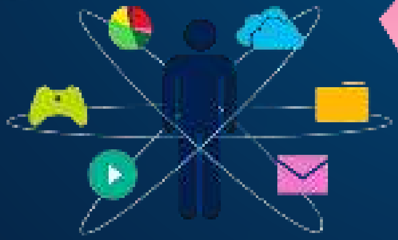
Stock Market Prediction

Sentiment Analysis

Predictive Maintenance



Personalized Marketing



Chatbots

Cancer Detection

Facial Recognition

Advanced Video Analytics

Advanced Satellite Intelligence

War Robots

AI > ML > DL

Artificial Intelligence

Reasoning

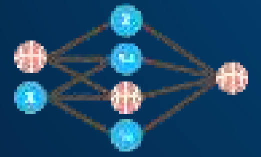
Knowledge Representation

Perception

NLP

Robotics

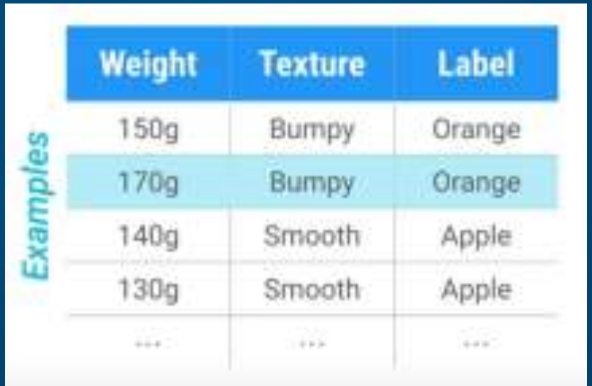
Machine Learning



Machine Learning

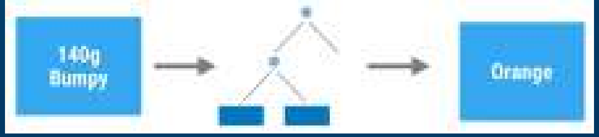
Supervised Learning

1. Training *features* *Labels*



	Weight	Texture	Label
Examples	150g	Bumpy	Orange
	170g	Bumpy	Orange
	140g	Smooth	Apple
	130g	Smooth	Apple
	...	...	...

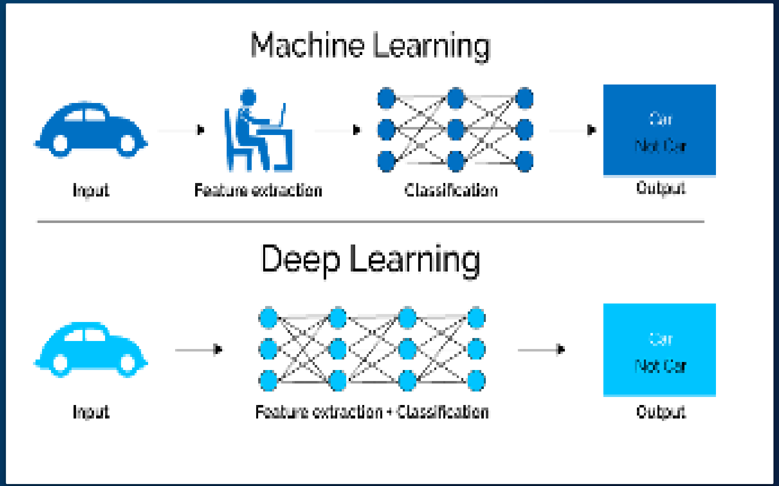
2. Predicting



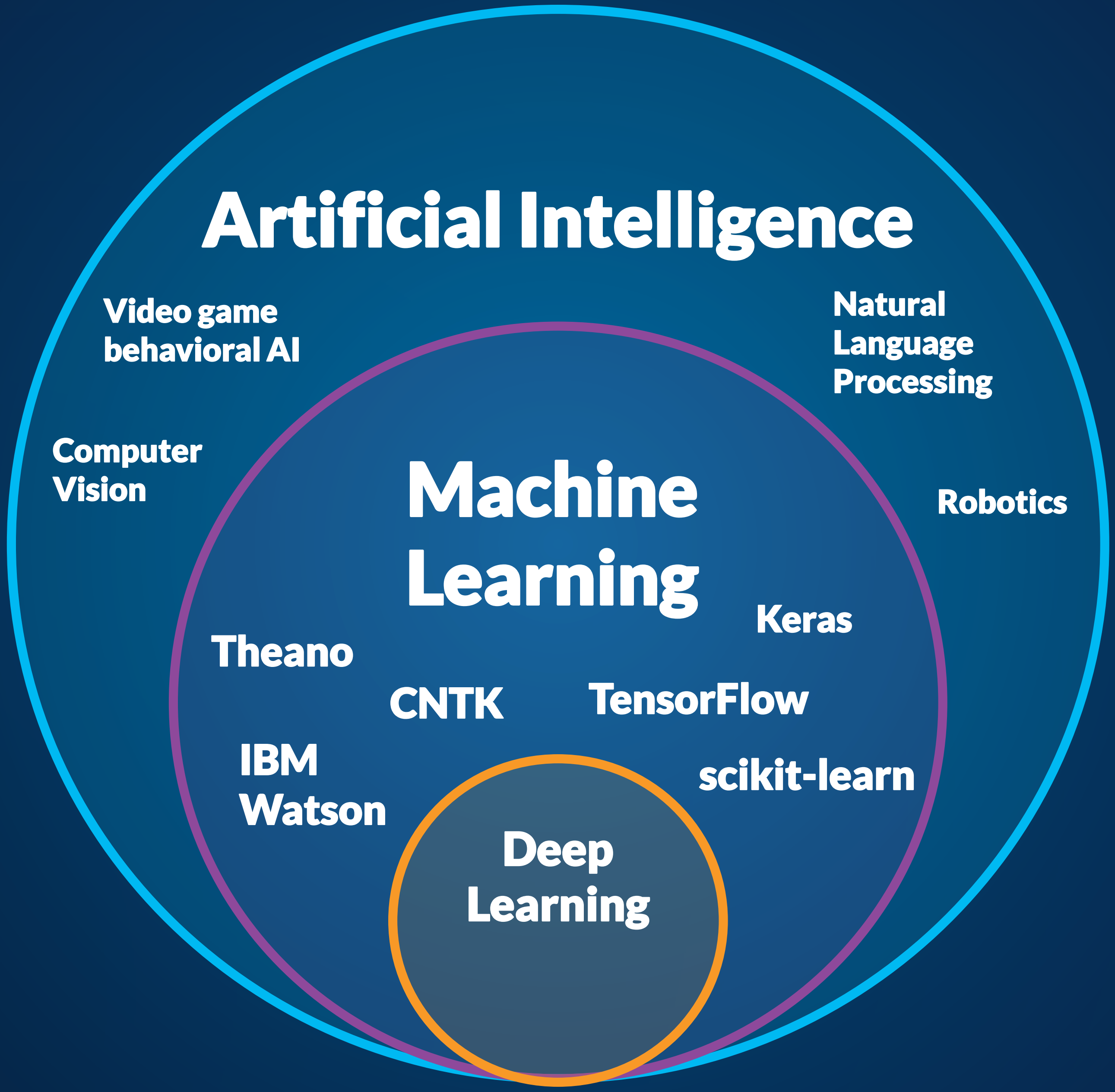
Unsupervised Learning
Reinforcement Learning

Deep Learning

Deep Supervised Learning



Dog



Artificial Intelligence

Video game behavioral AI

Natural Language Processing

Computer Vision

Robotics

Machine Learning

Keras

Theano

CNTK

TensorFlow

IBM Watson

scikit-learn

Deep Learning

How can ArcGIS Geo-AI Capabilities Help you today?

Object Detection

Detecting Objects from Imagery/Videos, Land Cover, Change Detection..

Buildings, Road Segments, Swimming Pools, Blight, Graffiti, Overgrowth, Road Signs, Vehicles from CCTVs, and more

Prediction

Predicting Geospatial Events/Phenomena

Water Pipe Breaks, Asthma Rates, Diseases, Crimes, Crashes, Incidents, Fires, Congestion, 911 Calls

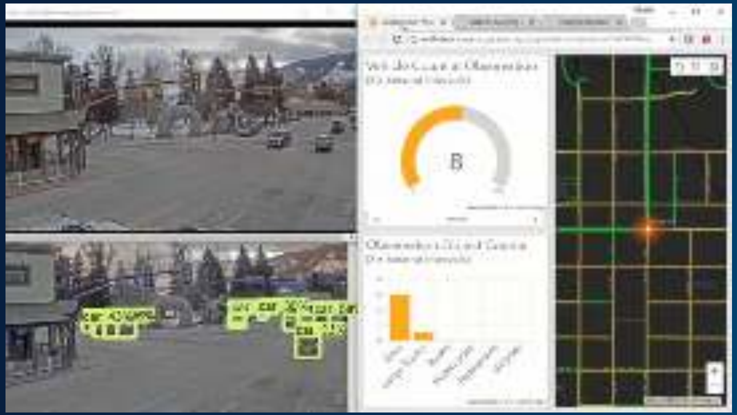
Pattern Detection

Finding Statistically Significant Clusters & Patterns

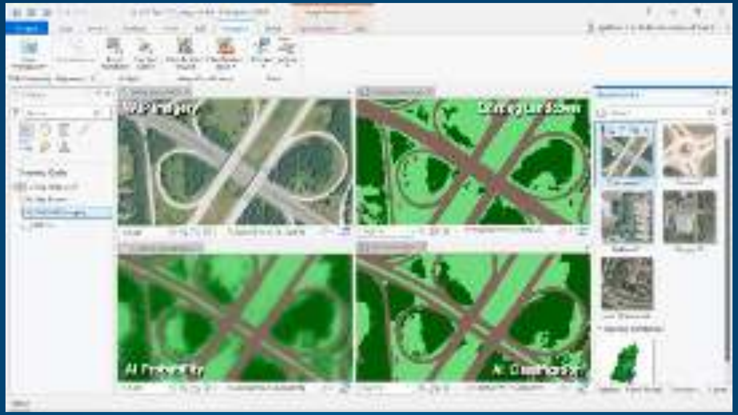
Top Risky Segments, Emerging Hotspots of 911 Calls, Disease Clusters, and more

Geo-AI Sample Use-Cases

Monitor Traffic Congestions



Land Cover Classification



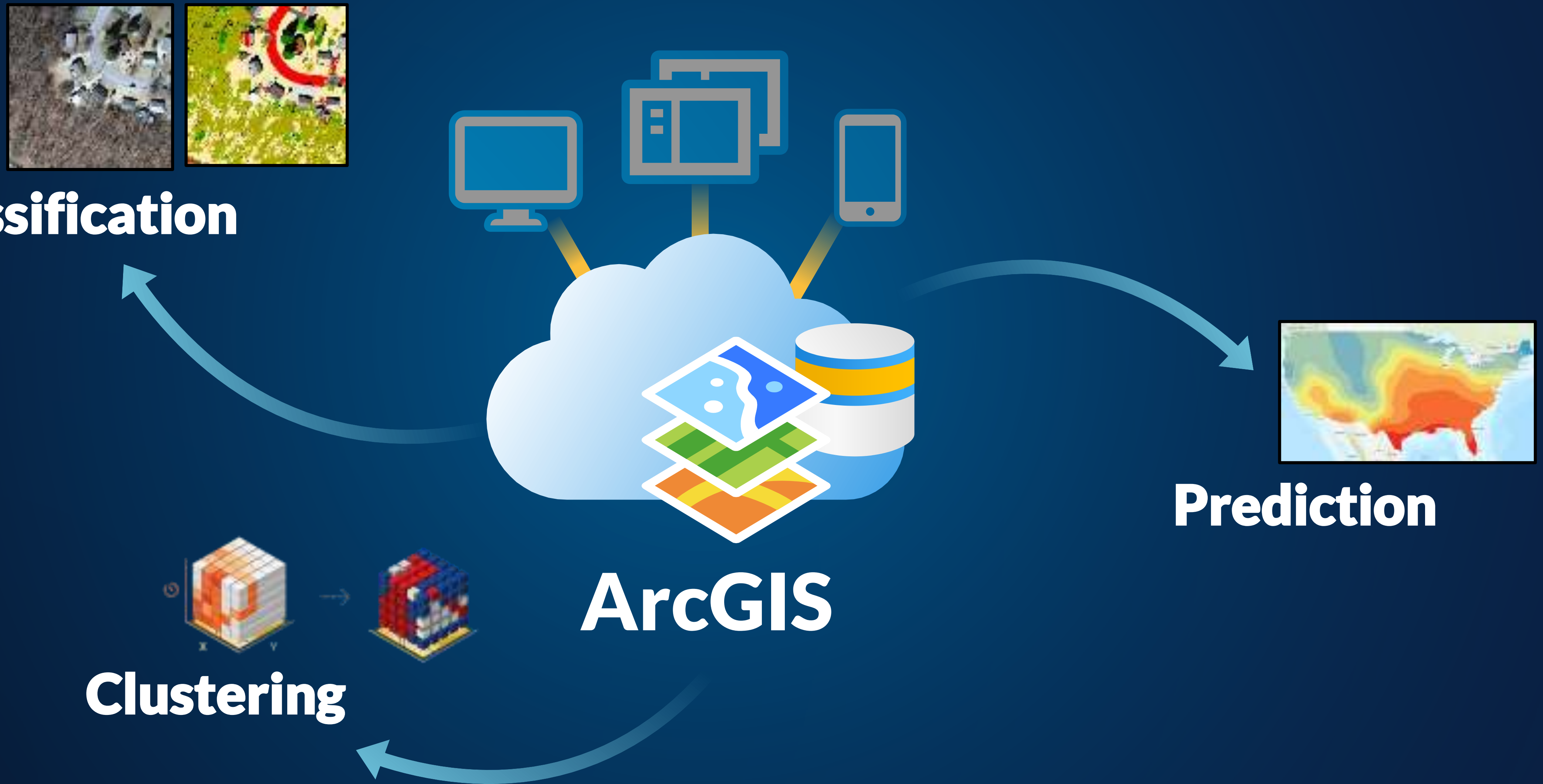
Assess Damaged Infrastructure

Predict Accidents

Assess Trees & Vegetation

Smart Road Digitization

ArcGIS has Machine Learning Tools



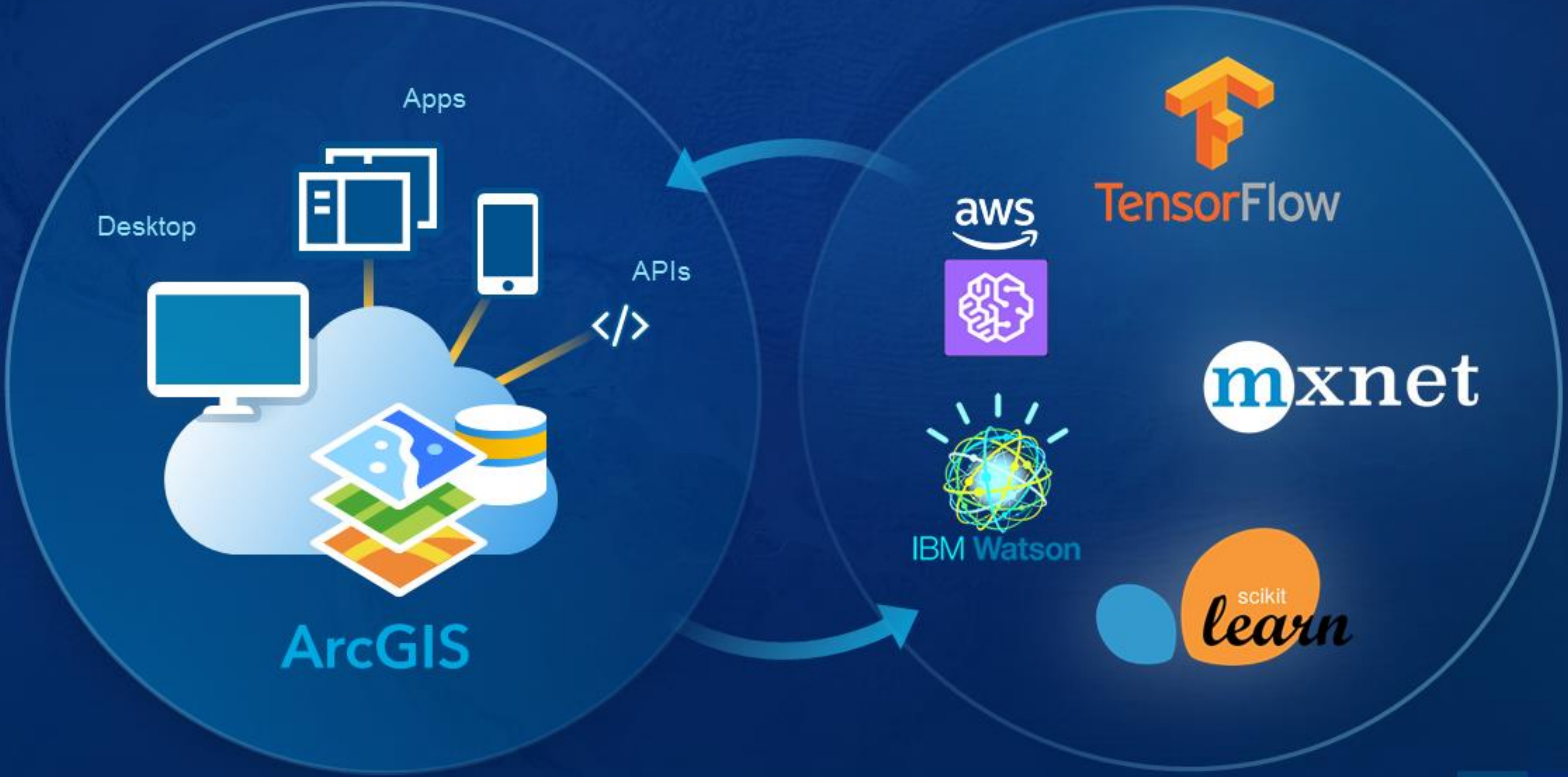
Classification

Prediction

Clustering

ArcGIS

Machine Learning Integration with External Frameworks



Tree Health Assessment

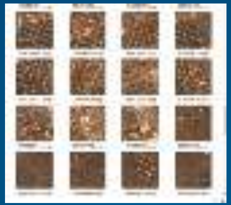
Detecting Stands & Assessment from Imagery

Workflow: Prepare > Train > Detect > Assess

Prepare Training Data

Export Training Data for Deep Learning

Feature Layer + Imagery → Chips



Consume DL Models

Detect Tree & Assess Health

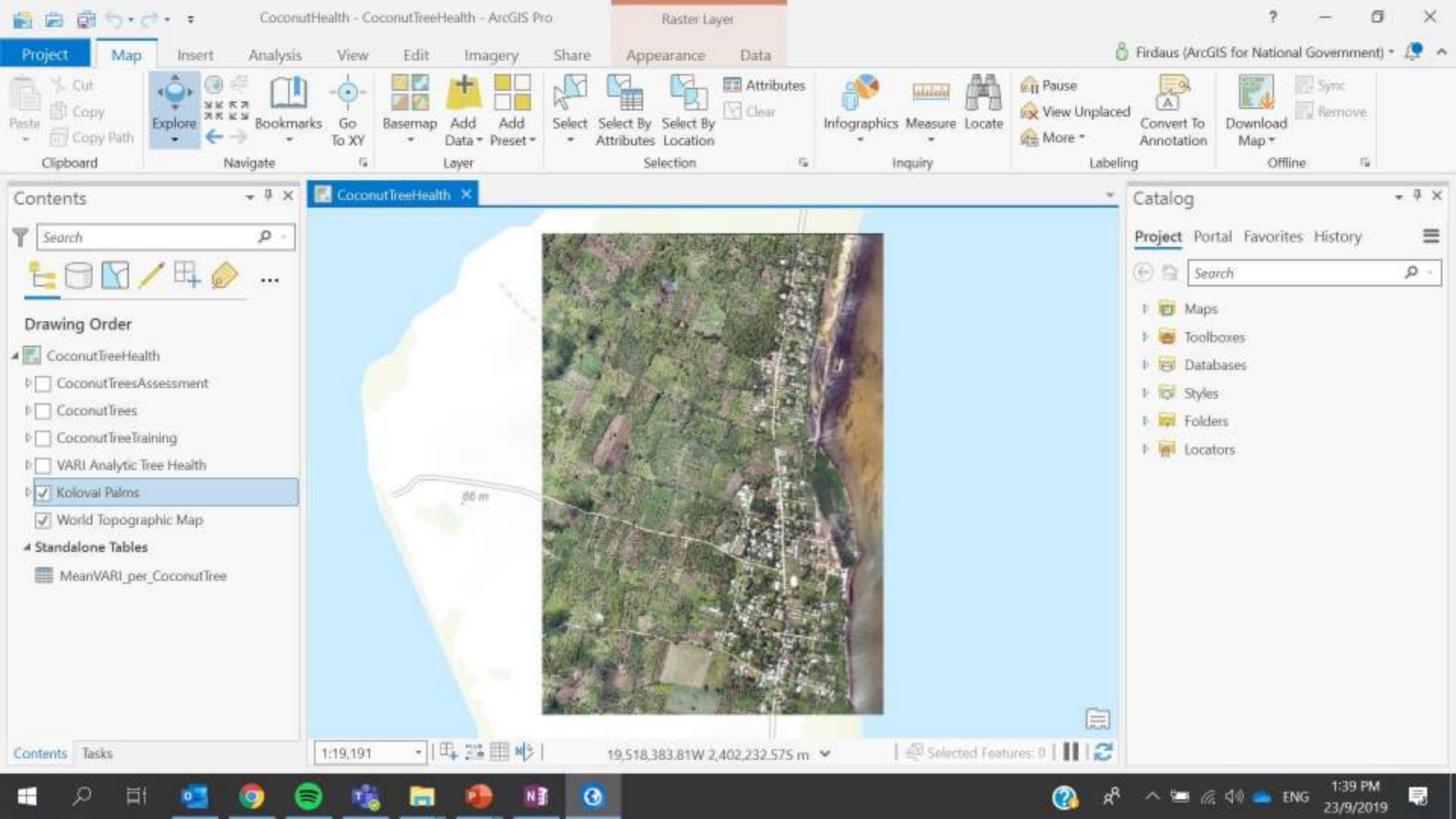
DL Model + Imagery → Detections

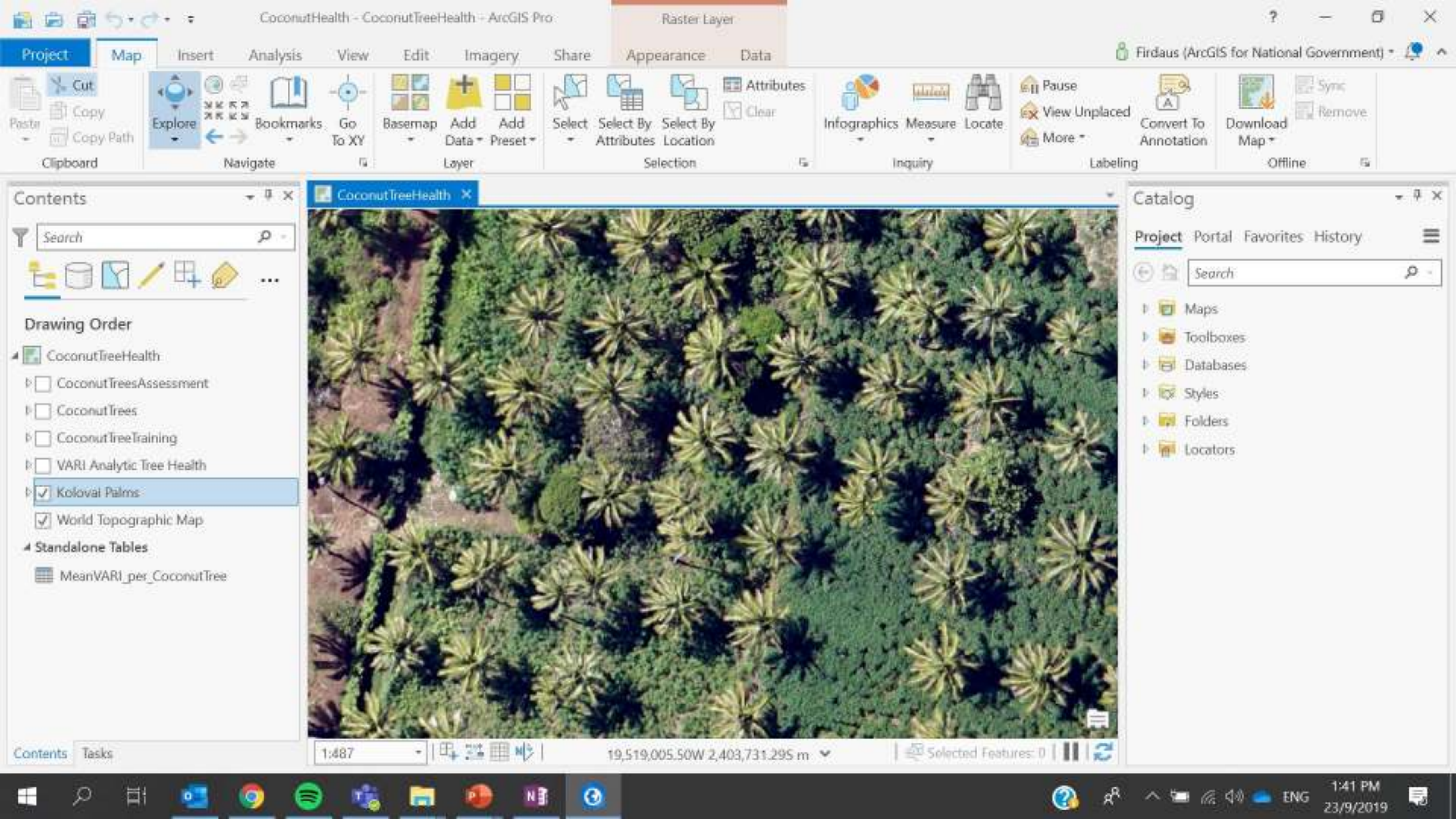
Train DL Models

Generate DL Model

Deploy Output Result

Field Monitoring & Inspection


CoconutHealth - CoconutTreeHealth - ArcGIS Pro
Raster Layer
Project
Map
Insert
Analysis
View
Edit
Imagery
Share
Appearance
Data
Firdaus (ArcGIS for National Government)
Paste
Cut
Copy
Copy Path
Clipboard
Explore
Bookmarks
Go To XY
Navigate
Basemap
Add Data
Add Preset
Layer
Select
Select By Attributes
Select By Location
Attributes
Clear
Selection
Infographics
Measure
Locate
Inquiry
Pause
View Unplaced
More
Convert To Annotation
Labeling
Download Map
Sync
Remove
Offline
Contents
Search
Drawing Order
CoconutTreeHealth
CoconutTreesAssessment
CoconutTrees
CoconutTreeTraining
VARI Analytic Tree Health
Kolovai Palms
World Topographic Map
Standalone Tables
MeanVARI_per_CoconutTree
Contents
Tasks
CoconutTreeHealth
66 m
1:19,191
19,518,383.81W 2,402,232.57S m
Selected Features: 0
Catalog
Project
Portal
Favorites
History
Search
Maps
Toolboxes
Databases
Styles
Folders
Locators
ENG
1:39 PM
23/9/2019

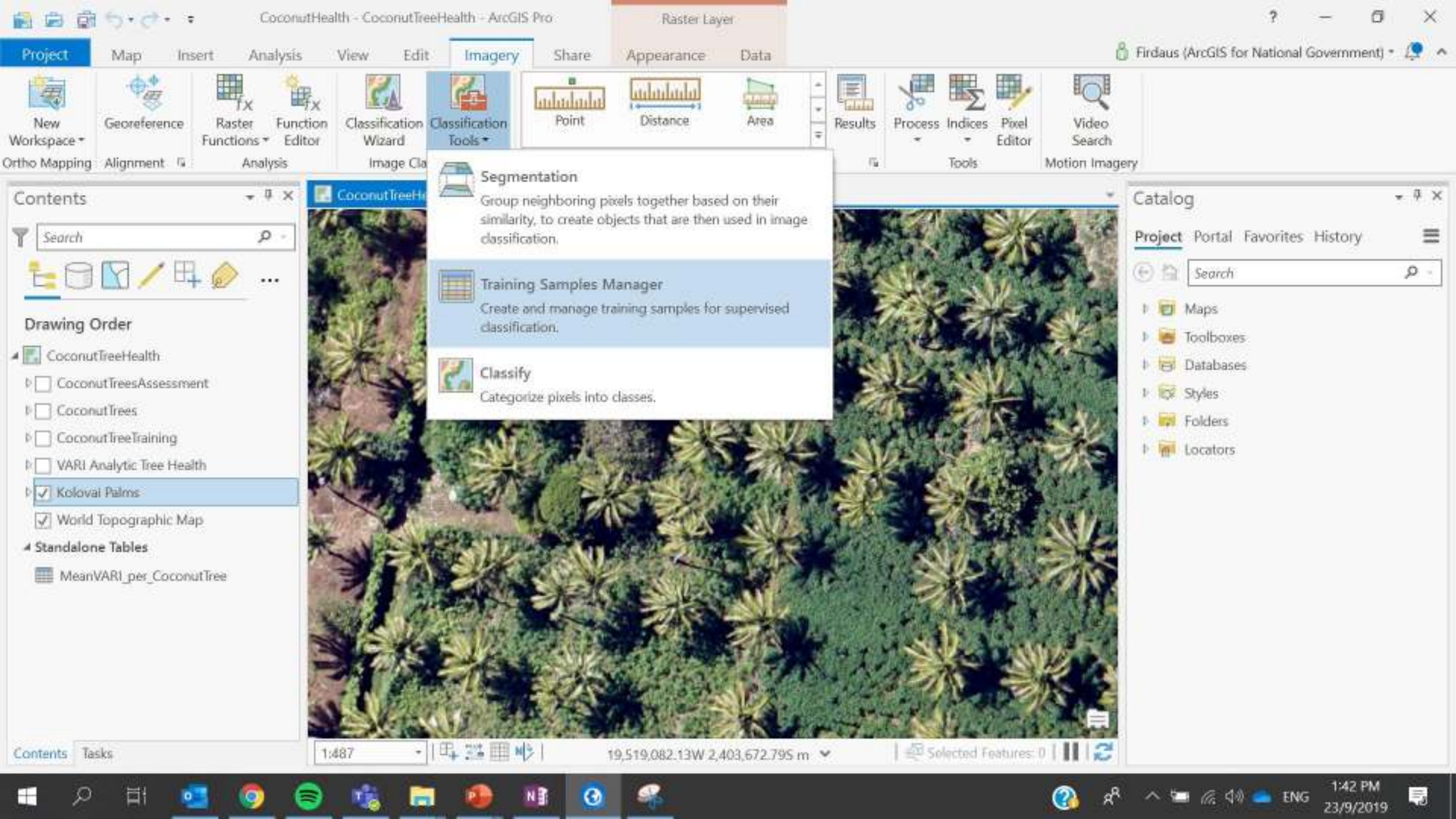


Drawing Order

- CoconutTreeHealth
  - □ CoconutTreesAssessment
  - □ CoconutTrees
  - □ CoconutTreeTraining
  - □ VARI Analytic Tree Health
  - ☑ Kolovai Palms
  - ☑ World Topographic Map
- Standalone Tables
  - MeanVARI_per_CoconutTree

1:487

19,519,005.50W 2,403,731.29S m



Segmentation

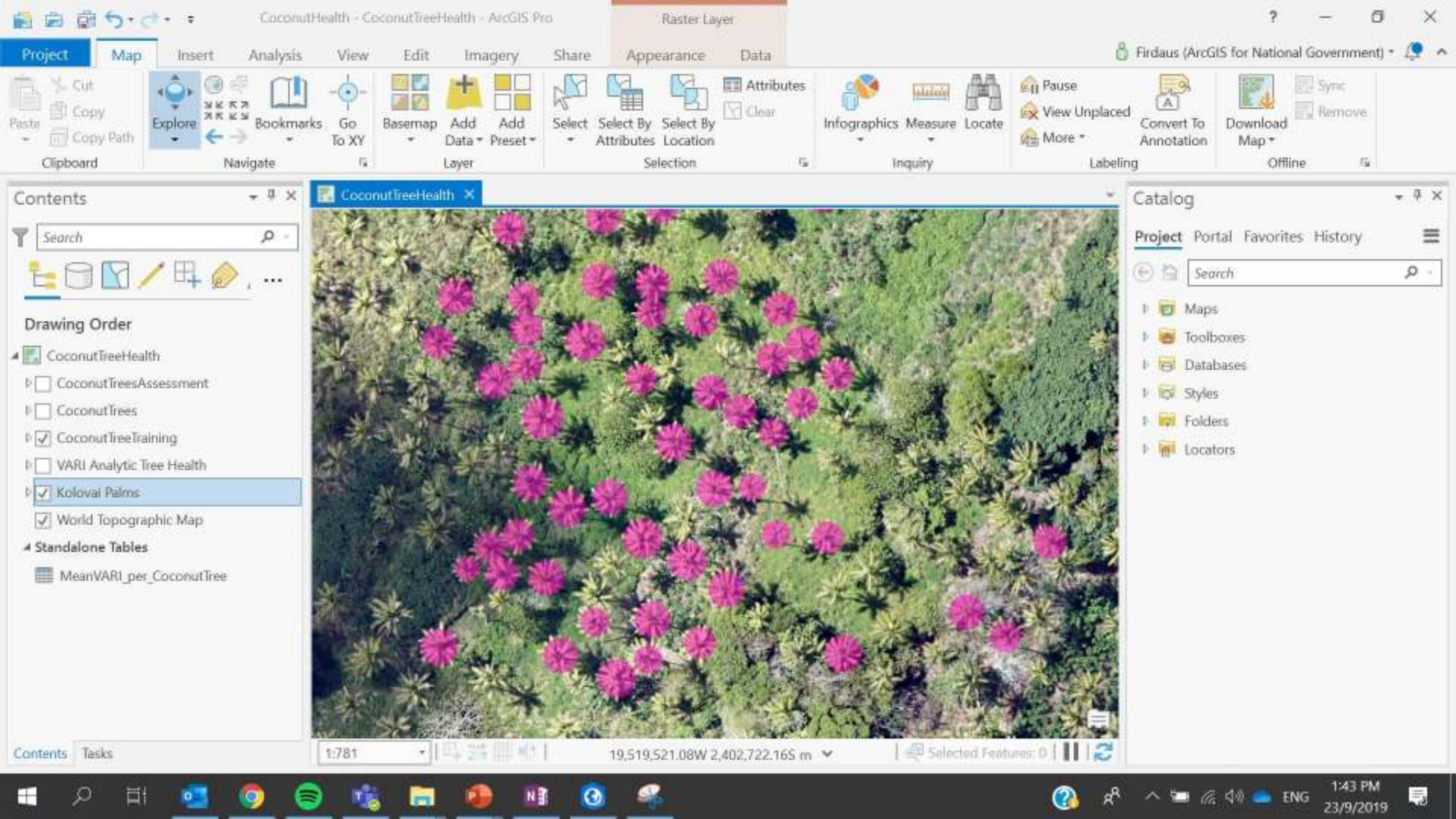
Group neighboring pixels together based on their similarity, to create objects that are then used in image classification.

Training Samples Manager

Create and manage training samples for supervised classification.

Classify

Categorize pixels into classes.



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  - ☑ Kolovai Palms
  - ☑ World Topographic Map
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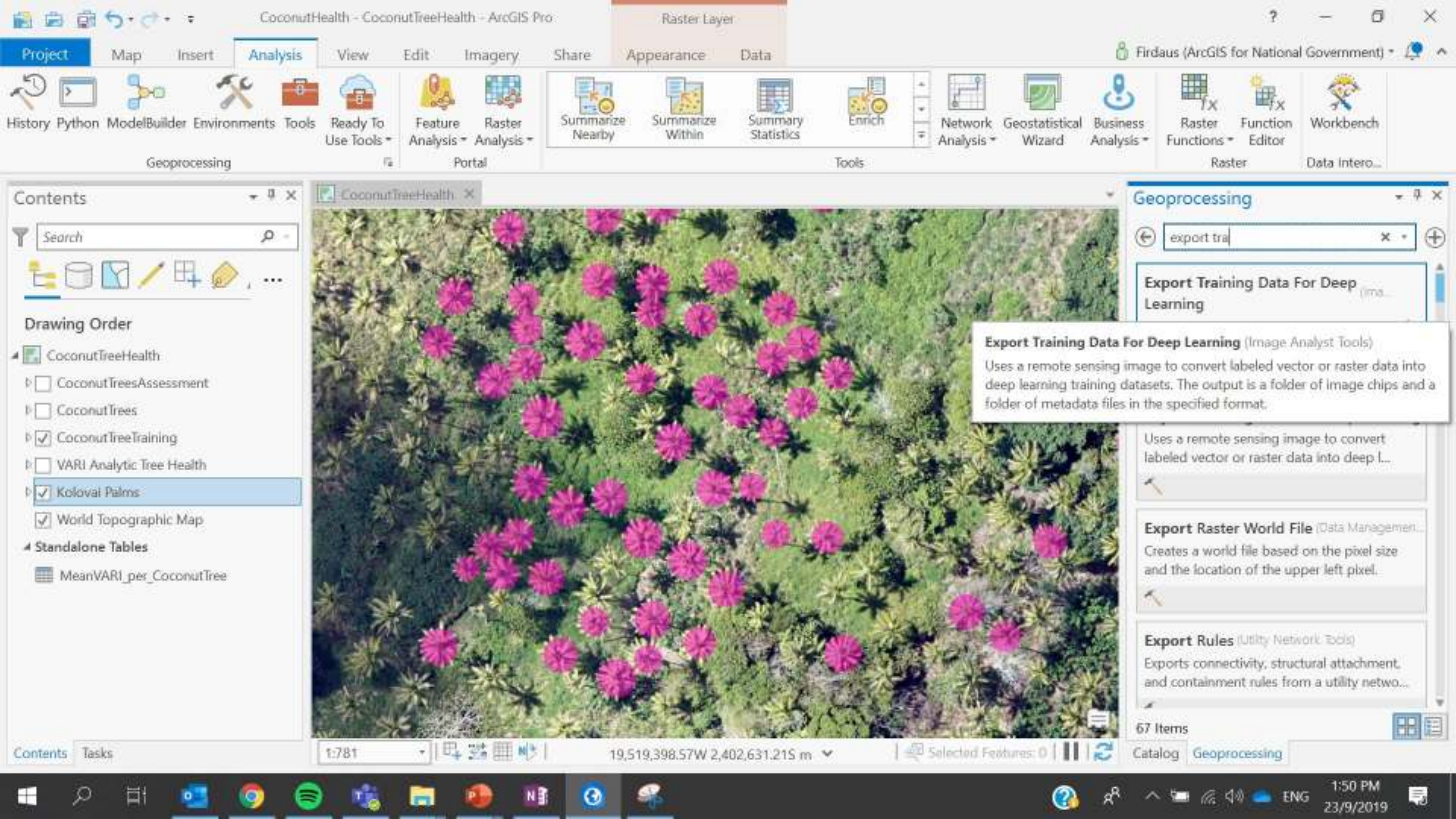
1:781

19,519,521.08W 2,402,722.16S m



Export Training Data For Deep Learning (Ima...

Export Training Data For Deep Learning (Image Analyst Tools)

Uses a remote sensing image to convert labeled vector or raster data into deep learning training datasets. The output is a folder of image chips and a folder of metadata files in the specified format.

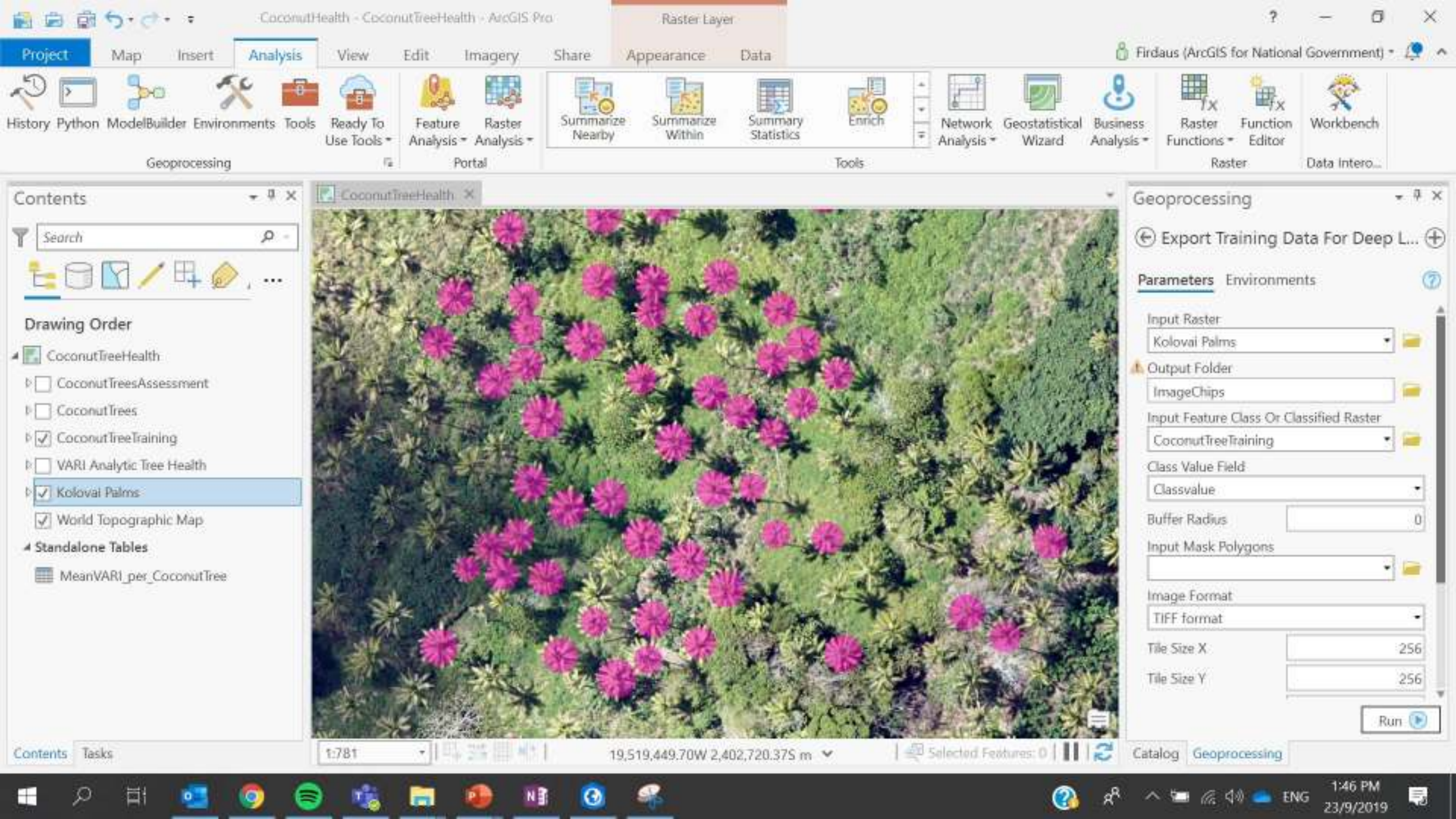
Uses a remote sensing image to convert labeled vector or raster data into deep l...

Export Raster World File (Data Managemen...

Creates a world file based on the pixel size and the location of the upper left pixel.

Export Rules (Utility Network Tools)

Exports connectivity, structural attachment, and containment rules from a utility netwo...



Contents – Drawing Order:

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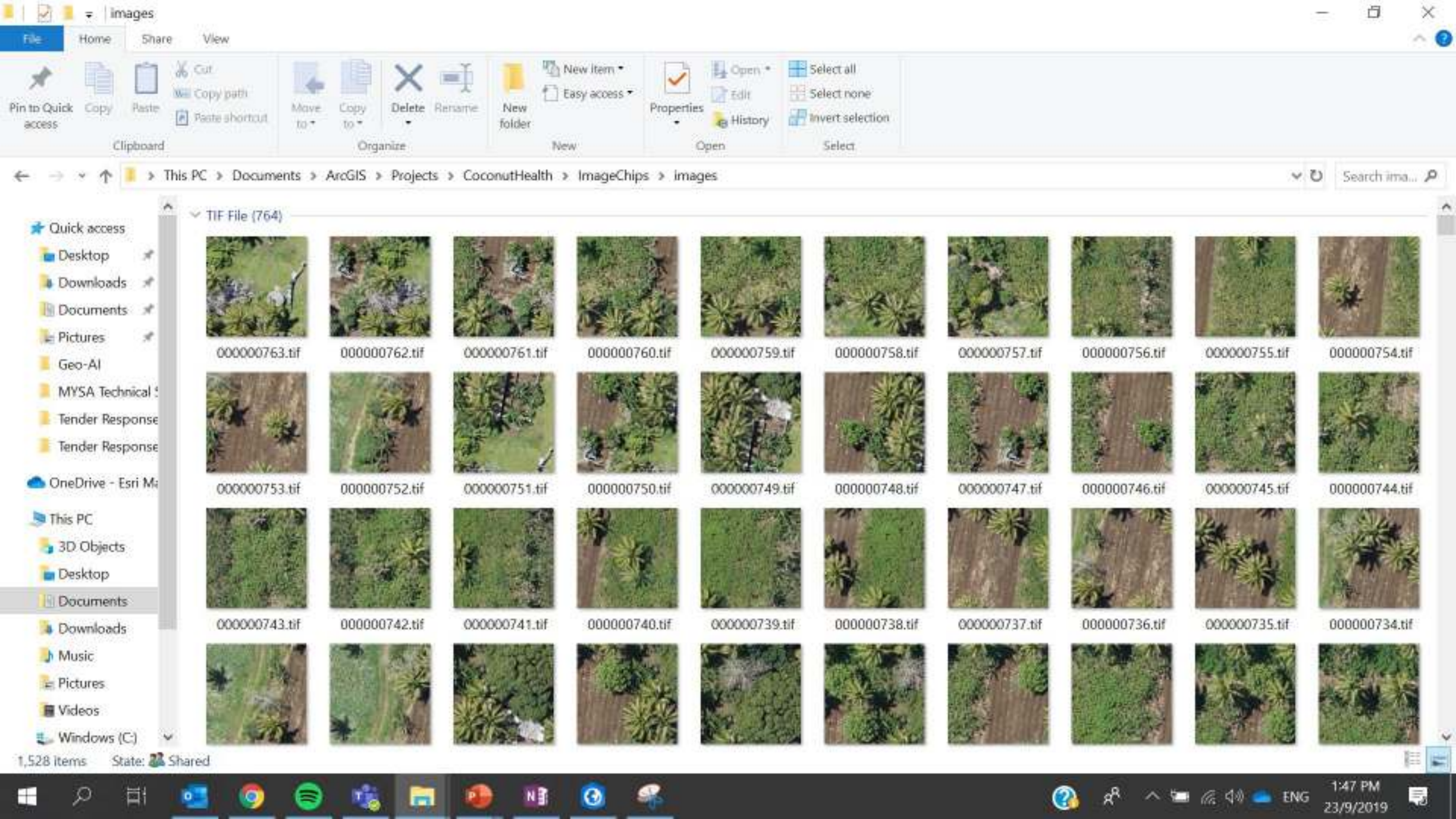
  - □ CoconutTrees
  - ☑ CoconutTreeTraining
  - □ VARI Analytic Tree Health
  - ☑ Kolovai Palms
  - ☑ World Topographic Map
- Standalone Tables
  - MeanVARI_per_CoconutTree

Export Training Data For Deep L...

Input Raster	Kolovai Palms
Output Folder	ImageChips
Input Feature Class Or Classified Raster	CoconutTreeTraining
Class Value Field	Classvalue
Buffer Radius	0
Input Mask Polygons	
Image Format	TIFF format
Tile Size X	256
Tile Size Y	256

1:781

19,519,449.70W 2,402,720.37S m



This PC > Documents > ArcGIS > Projects > CoconutHealth > ImageChips > images

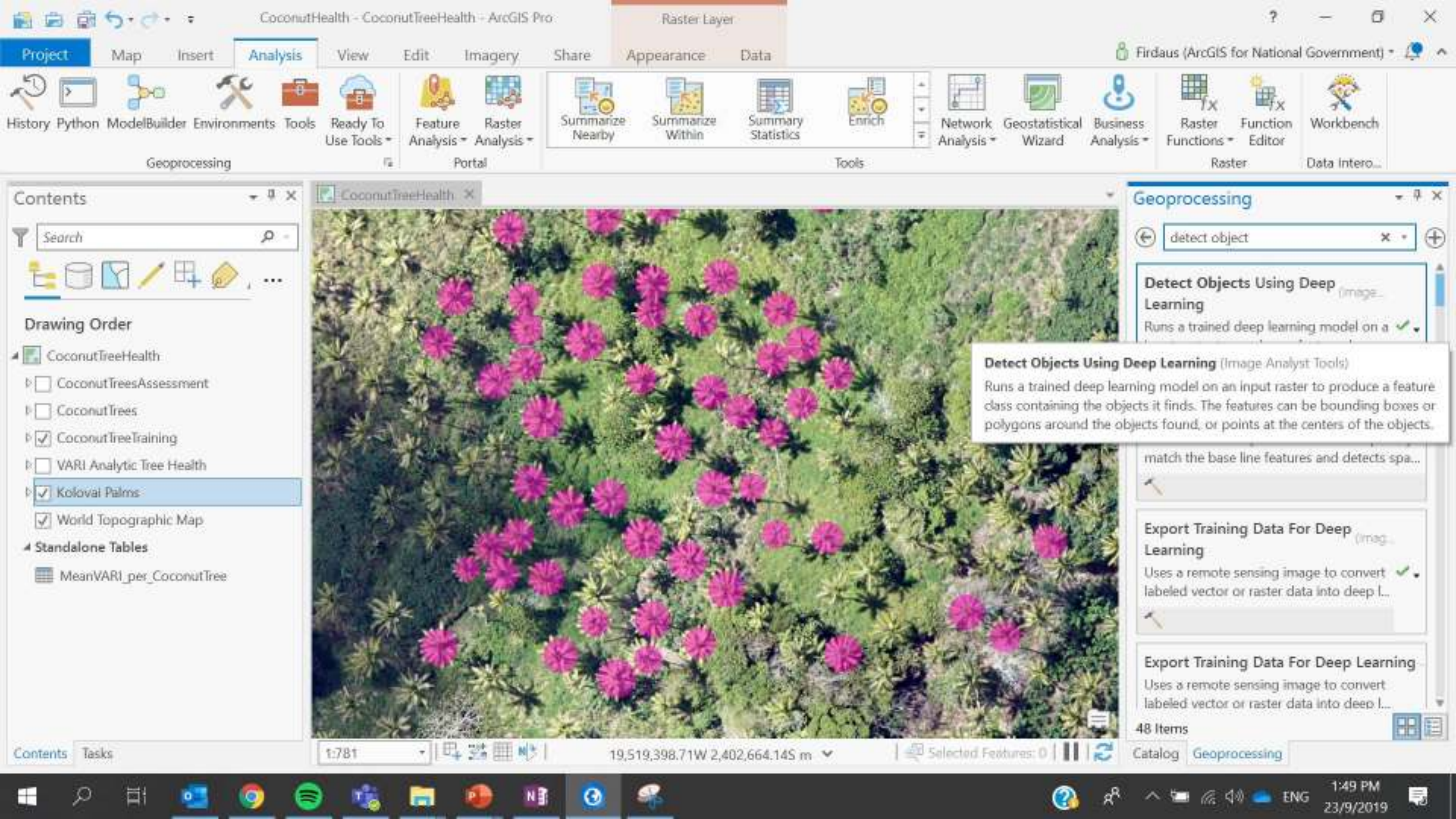
TIF File (764)

000000763.tif 000000762.tif 000000761.tif 000000760.tif 000000759.tif 000000758.tif 000000757.tif 000000756.tif 000000755.tif 000000754.tif

000000753.tif 000000752.tif 000000751.tif 000000750.tif 000000749.tif 000000748.tif 000000747.tif 000000746.tif 000000745.tif 000000744.tif

000000743.tif 000000742.tif 000000741.tif 000000740.tif 000000739.tif 000000738.tif 000000737.tif 000000736.tif 000000735.tif 000000734.tif

1,528 items State: Shared



detect object

Detect Objects Using Deep Learning (Image...

Runs a trained deep learning model on a ...

Detect Objects Using Deep Learning (Image Analyst Tools)

Runs a trained deep learning model on an input raster to produce a feature class containing the objects it finds. The features can be bounding boxes or polygons around the objects found, or points at the centers of the objects.

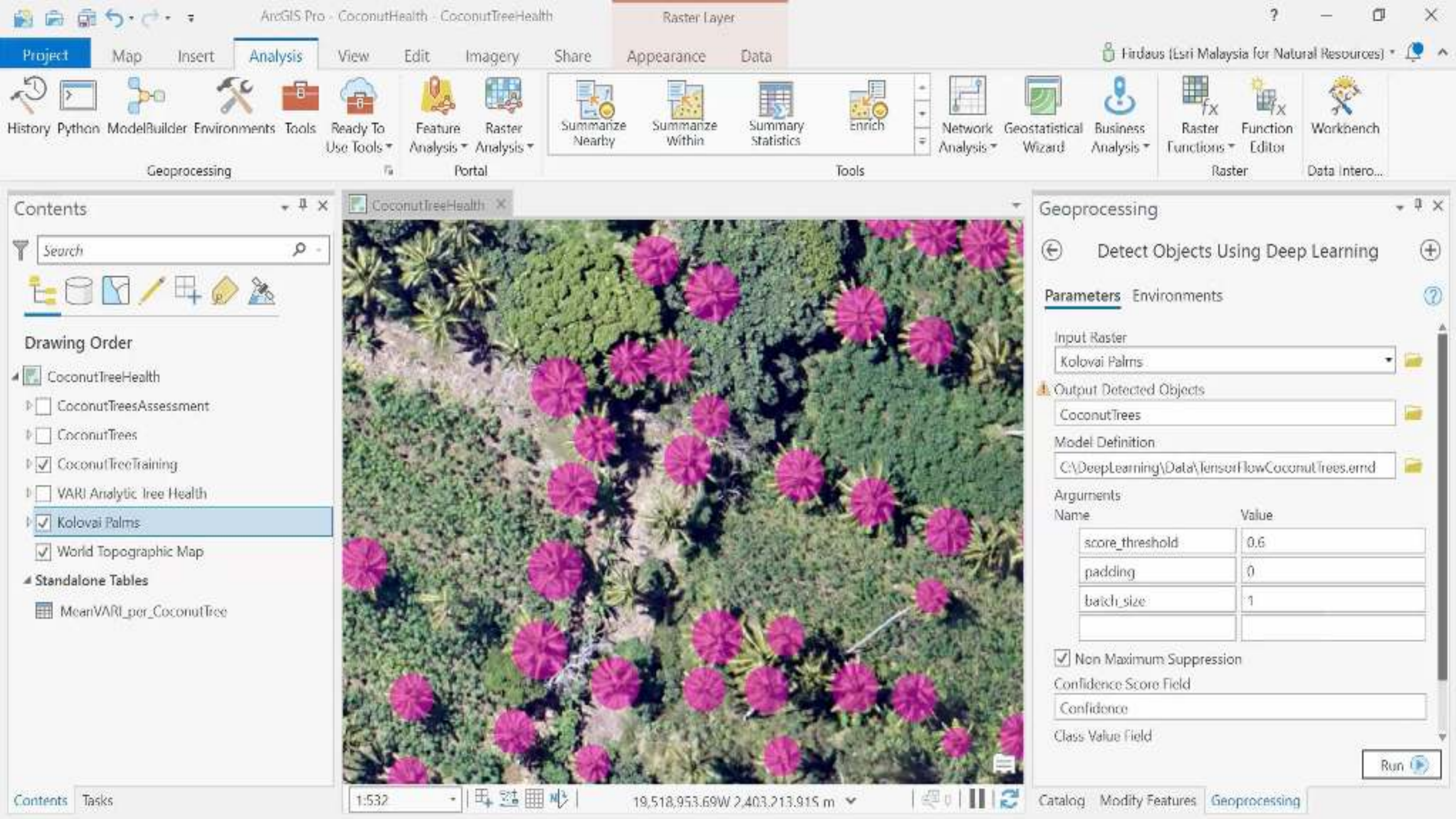
match the base line features and detects spa...

Export Training Data For Deep Learning (Imag...

Uses a remote sensing image to convert labeled vector or raster data into deep l...

Export Training Data For Deep Learning

Uses a remote sensing image to convert labeled vector or raster data into deep l...



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  - □ VARI Analytic Tree Health
  - ☑ Kolovai Palms
  - ☑ World Topographic Map
- Standalone Tables
  - MeanVARI_per_CoconutTree

Detect Objects Using Deep Learning

Input Raster: Kolovai Palms

Output Detected Objects: CoconutTrees

Model Definition: C:\DeepLearning\Data\TensorFlowCoconutTrees.emd

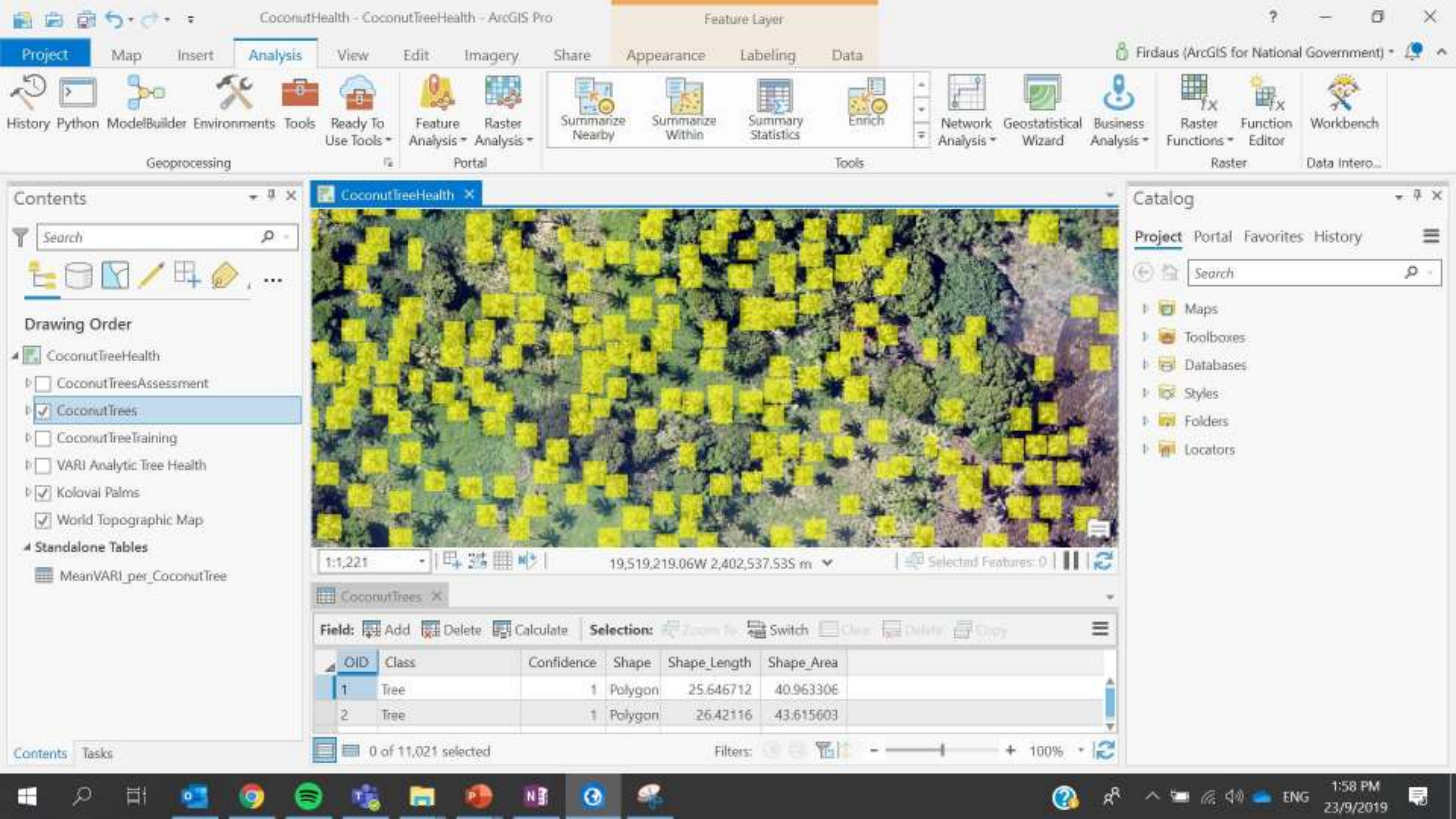
Arguments

Name	Value
score_threshold	0.6
padding	0
batch_size	1

☑ Non Maximum Suppression

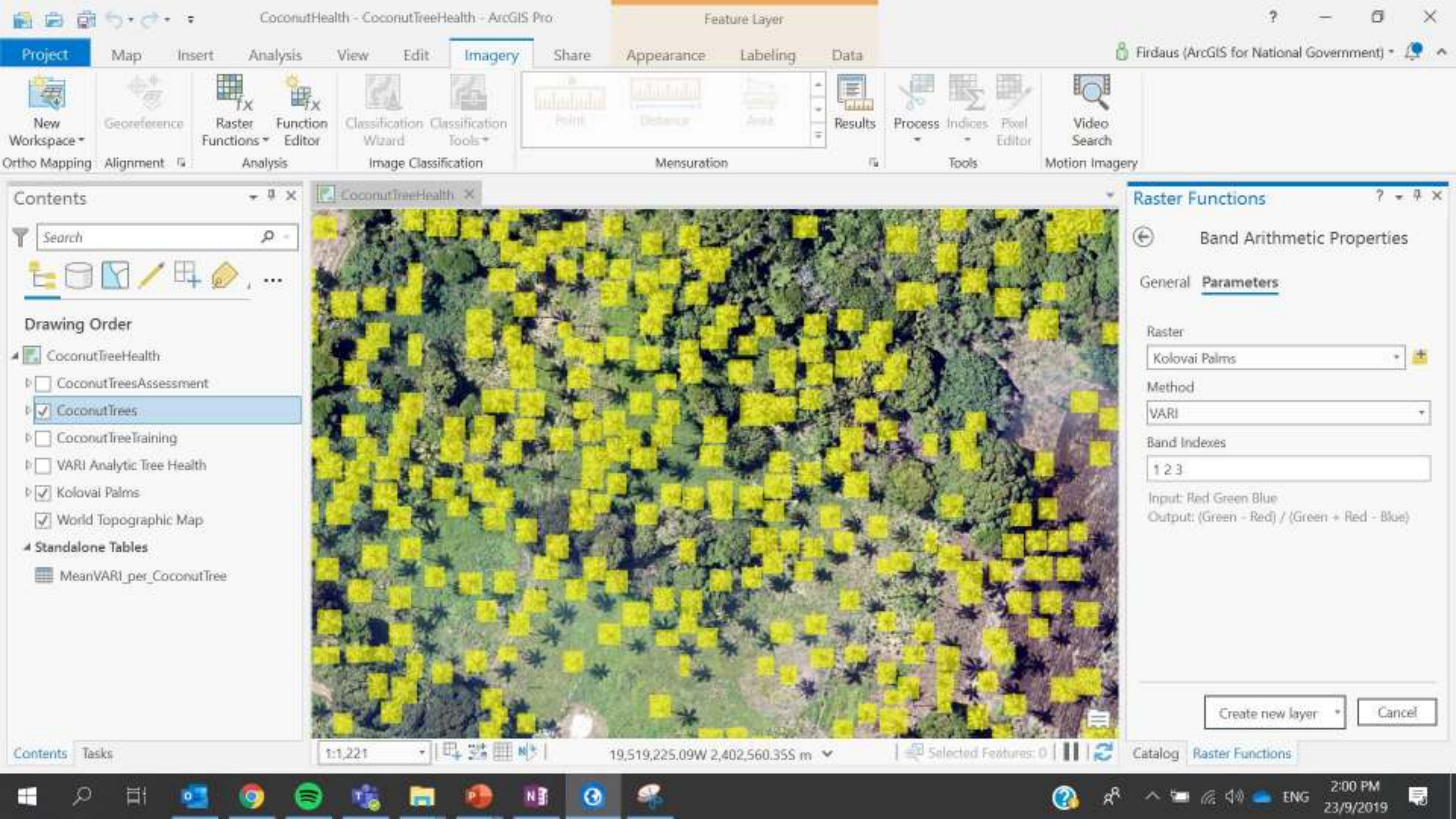
Confidence Score Field: Confidence

Class Value Field



OID	Class	Confidence	Shape	Shape_Length	Shape_Area
1	Tree	1	Polygon	25.646712	40.963306
2	Tree	1	Polygon	26.42116	43.615603

0 of 11,021 selected



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Band Arithmetic Properties

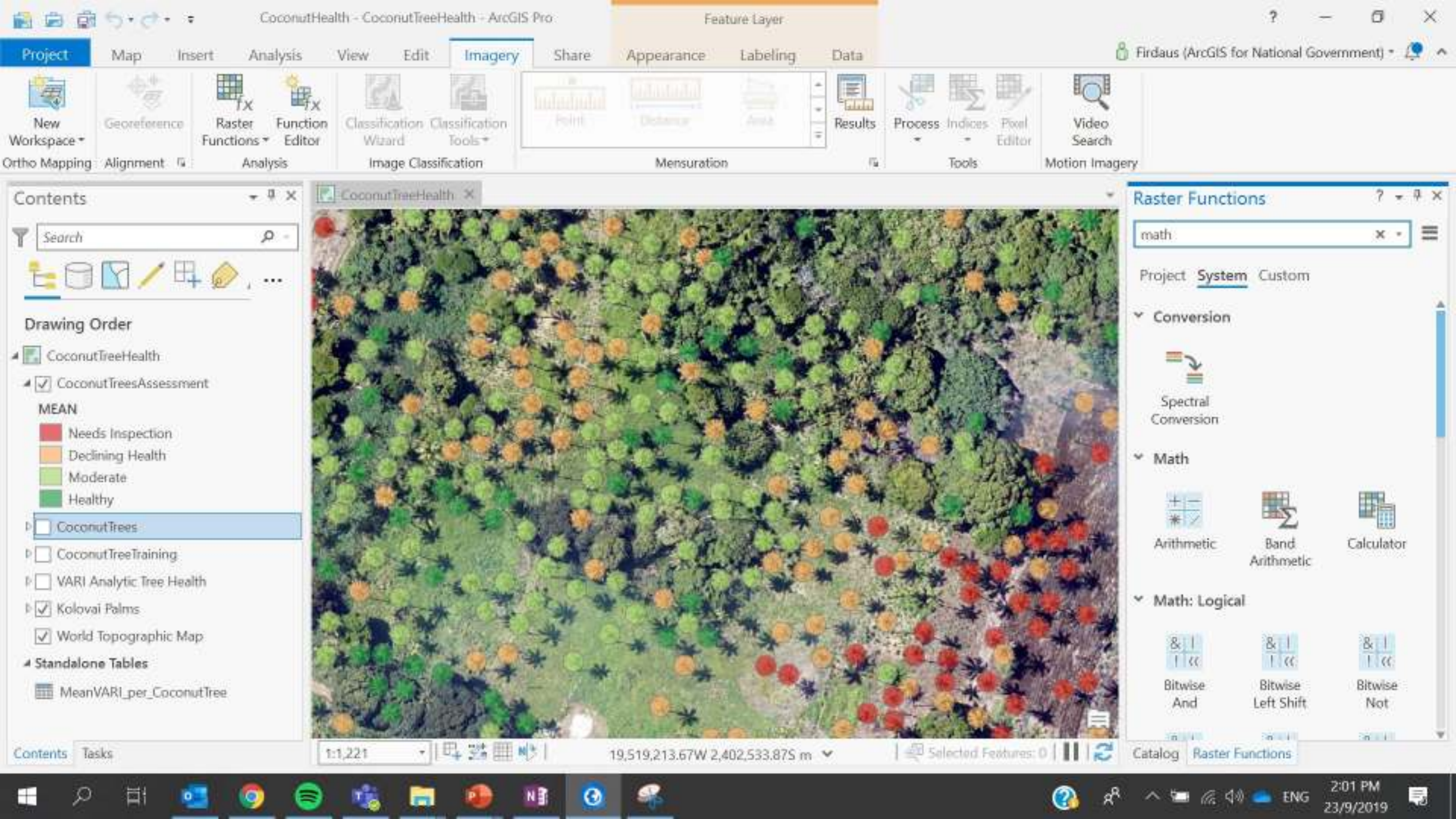
Raster: Kolovai Palms

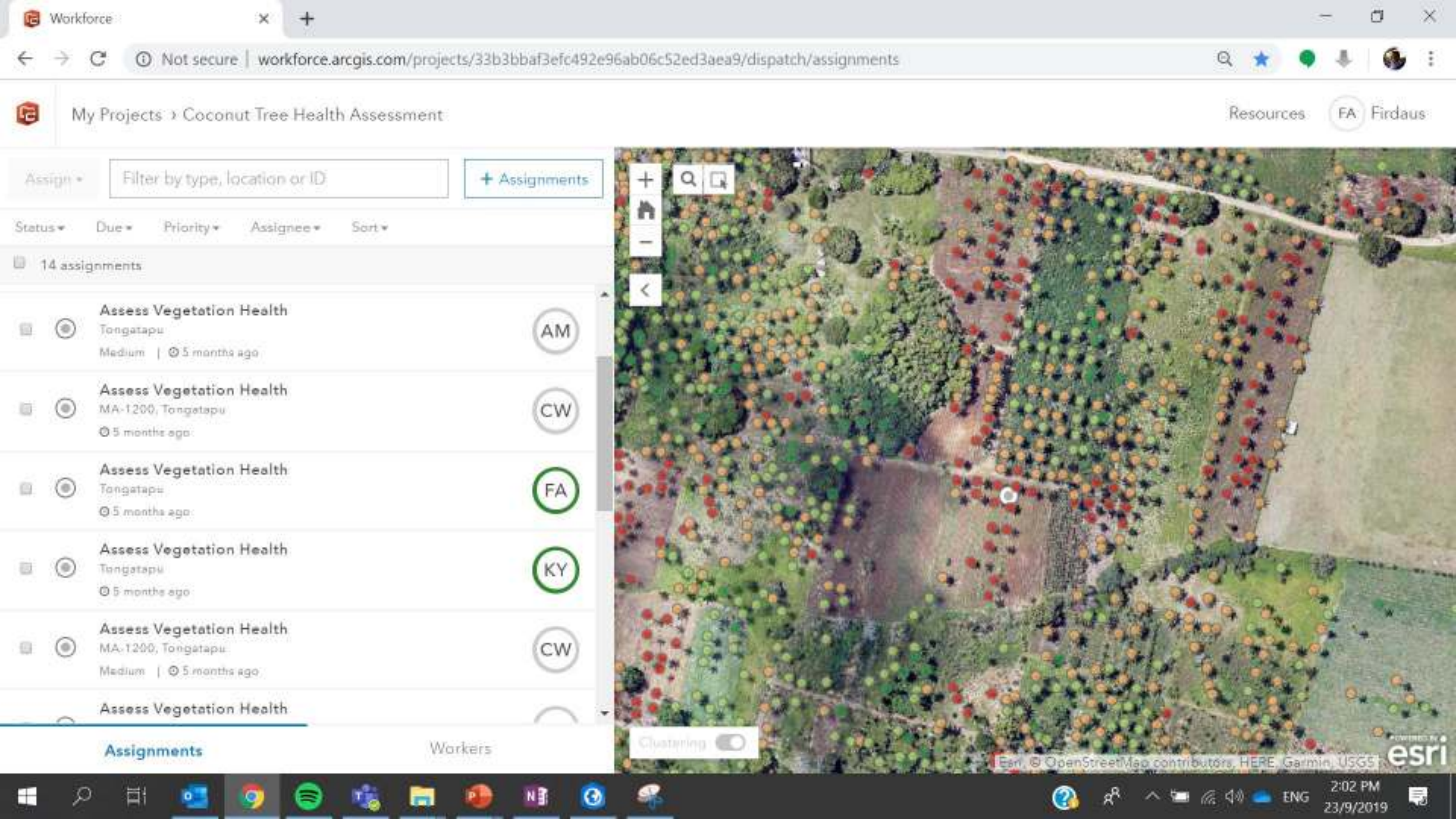
Method: VARI

Band Indexes: 1 2 3

Input: Red Green Blue

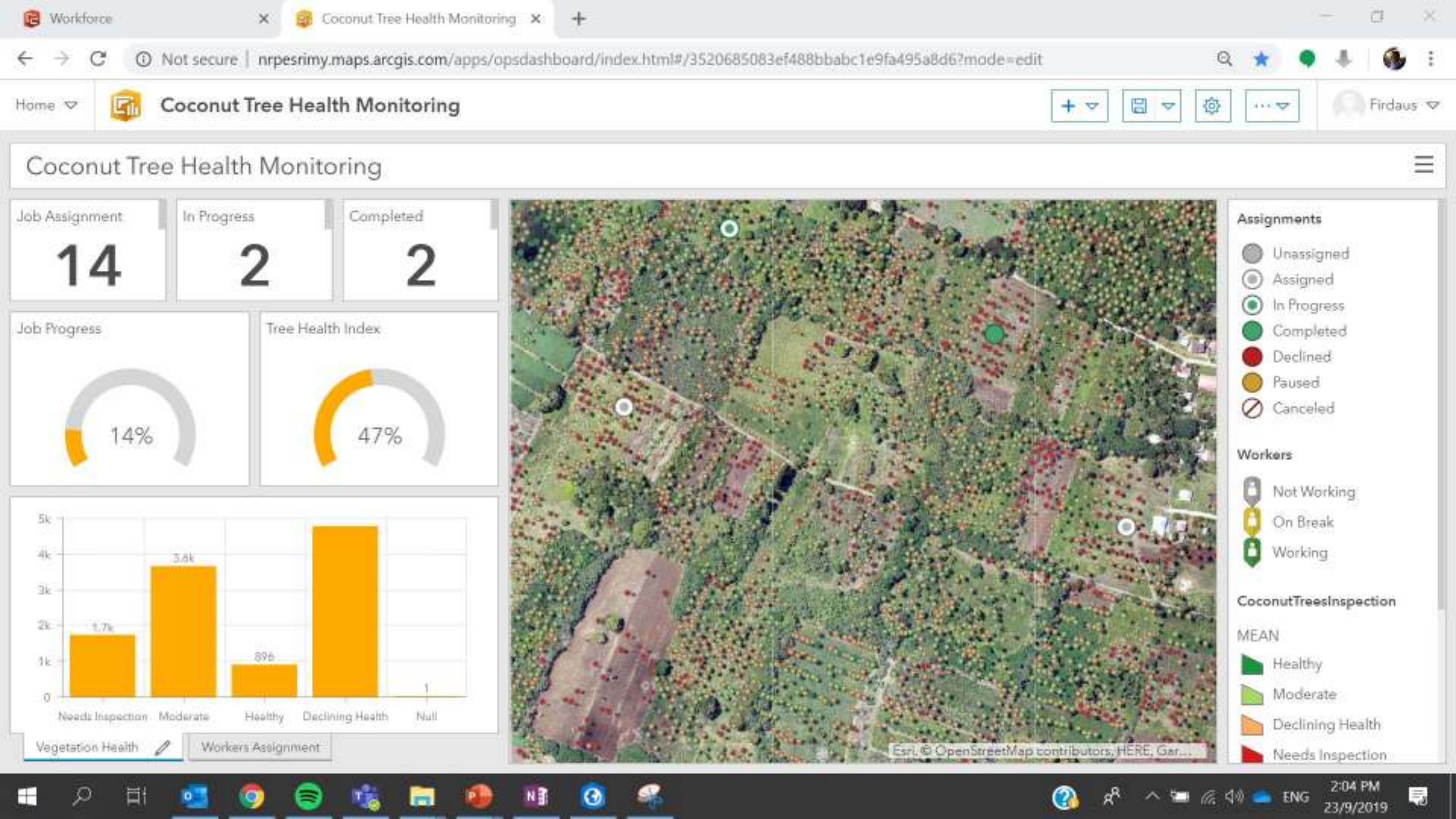
Output: (Green - Red) / (Green + Red - Blue)


CoconutHealth - CoconutTreeHealth - ArcGIS Pro
Feature Layer
Project
Map
Insert
Analysis
View
Edit
Imagery
Share
Appearance
Labeling
Data
Firdaus (ArcGIS for National Government)
New Workspace
Ortho Mapping
Georeference
Alignment
Raster Functions
Function Editor
Analysis
Classification Wizard
Classification Tools
Image Classification
Point
Distance
Area
Mensuration
Results
Process
Indices
Pixel Editor
Tools
Video Search
Motion Imagery
Contents
Search
Drawing Order
CoconutTreeHealth
☑ CoconutTreesAssessment
MEAN
🟥 Needs Inspection
🟧 Declining Health
🟩 Moderate
🟩 Healthy
□ CoconutTrees
□ CoconutTreeTraining
□ VARI Analytic Tree Health
☑ Kolovai Palms
☑ World Topographic Map
Standalone Tables
MeanVARI_per_CoconutTree
Contents
Tasks
CoconutTreeHealth
1:1,221
19,519,213.67W 2,402,533.87S m
Selected Features: 0
Raster Functions
math
Project
System
Custom
Conversion
Spectral Conversion
Math
Arithmetic
Band Arithmetic
Calculator
Math: Logical
Bitwise And
Bitwise Left Shift
Bitwise Not
Catalog
Raster Functions
ENG
2:01 PM
23/9/2019


Workforce
Not secure | workforce.arcgis.com/projects/33b3bbaf3efc492e96ab06c52ed3aea9/dispatch/assignments
My Projects › Coconut Tree Health Assessment
Resources
FA Firdaus
Assign
Filter by type, location or ID
+ Assignments
Status
Due
Priority
Assignee
Sort
Clustering
Esri, © OpenStreetMap contributors, HERE, Garmin, USGS
esri
Assignments
Workers
ENG
2:02 PM
23/9/2019

14 assignments

Assess Vegetation Health Tongatapu Medium | 5 months ago	AM
Assess Vegetation Health MA-1200, Tongatapu 5 months ago	CW
Assess Vegetation Health Tongatapu 5 months ago	FA
Assess Vegetation Health Tongatapu 5 months ago	KY
Assess Vegetation Health MA-1200, Tongatapu Medium | 5 months ago	CW
Assess Vegetation Health	


Workforce
Coconut Tree Health Monitoring
Not secure | nrpesrimy.maps.arcgis.com/apps/opsdashboard/index.html#/3520685083ef488bbabc1e9fa495a8d6?mode=edit
Home
Firdaus
Esri, © OpenStreetMap contributors, HERE, Gar...
ENG
2:04 PM
23/9/2019

Coconut Tree Health Monitoring

Coconut Tree Health Monitoring

Job Assignment	In Progress	Completed
14	2	2

Job Progress: 14%

Tree Health Index: 47%

5k
4k
3k
2k
1k
0
1.7k
3.6k
896
1
Needs Inspection
Moderate
Healthy
Declining Health
Null

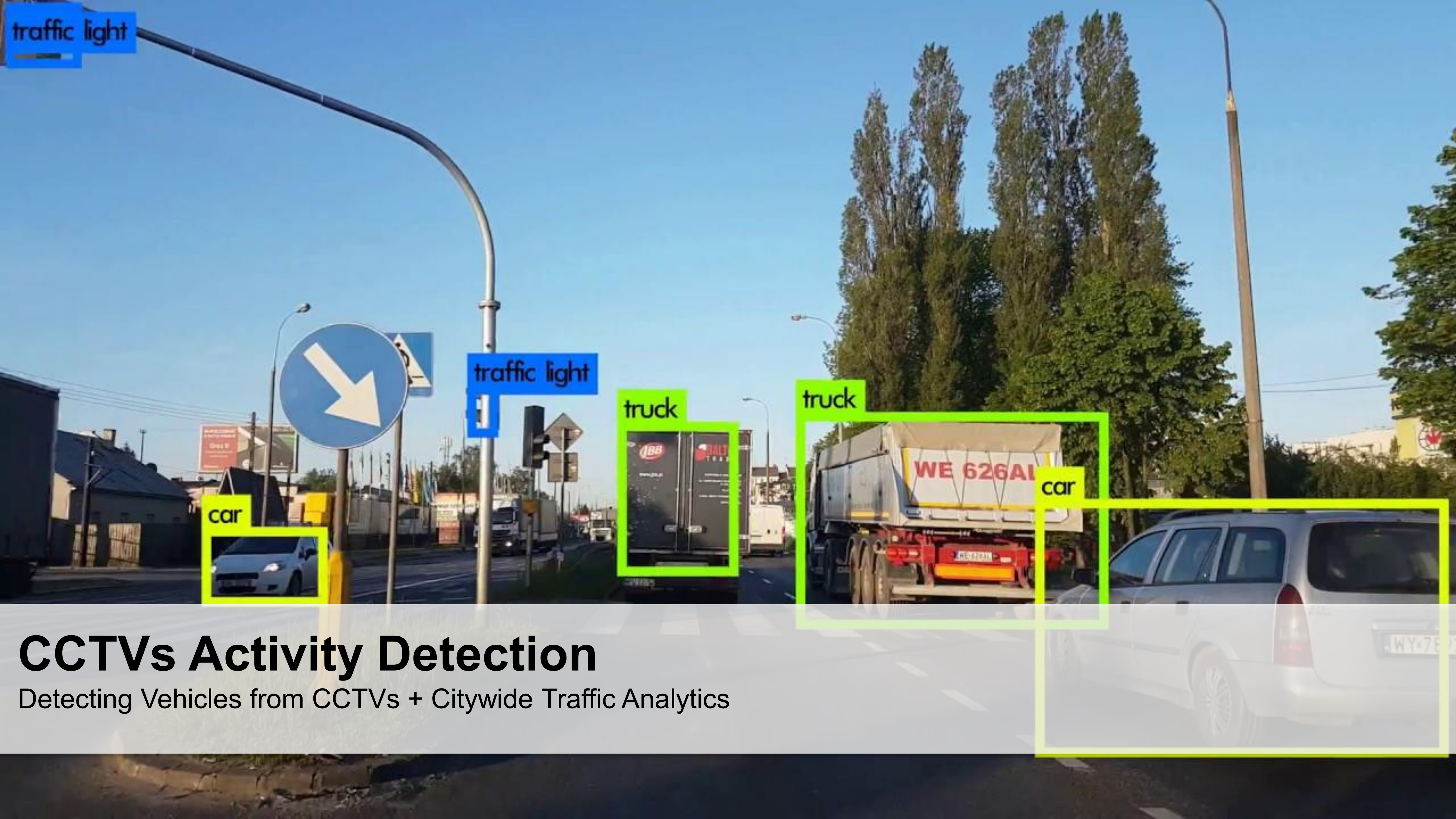
Vegetation Health | Workers Assignment

Assignments
- Unassigned
- Assigned
- In Progress
- Completed
- Declined
- Paused
- Canceled

Workers
- Not Working
- On Break
- Working

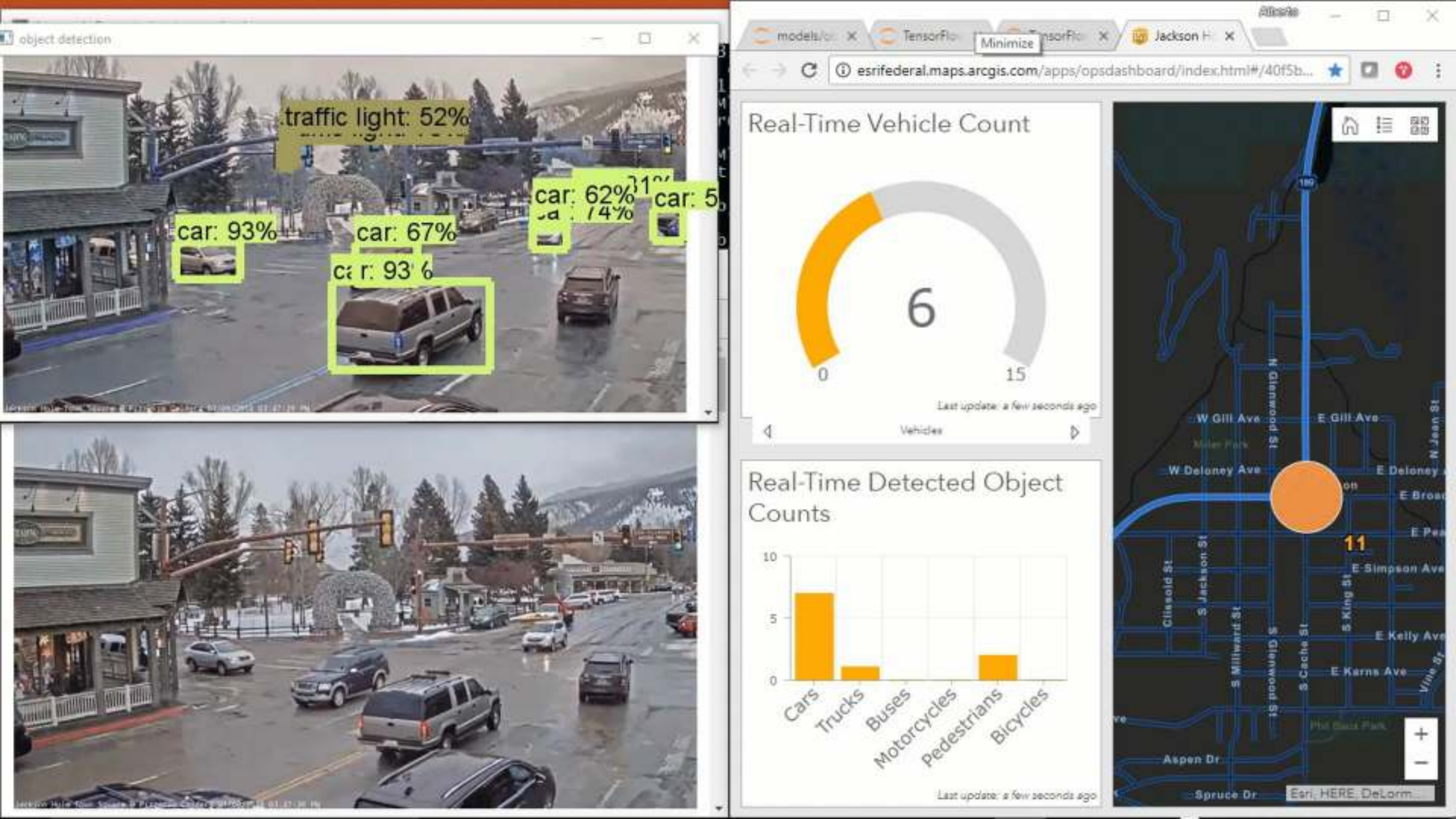
CoconutTreesInspection

MEAN
- Healthy
- Moderate
- Declining Health
- Needs Inspection



CCTVs Activity Detection

Detecting Vehicles from CCTVs + Citywide Traffic Analytics



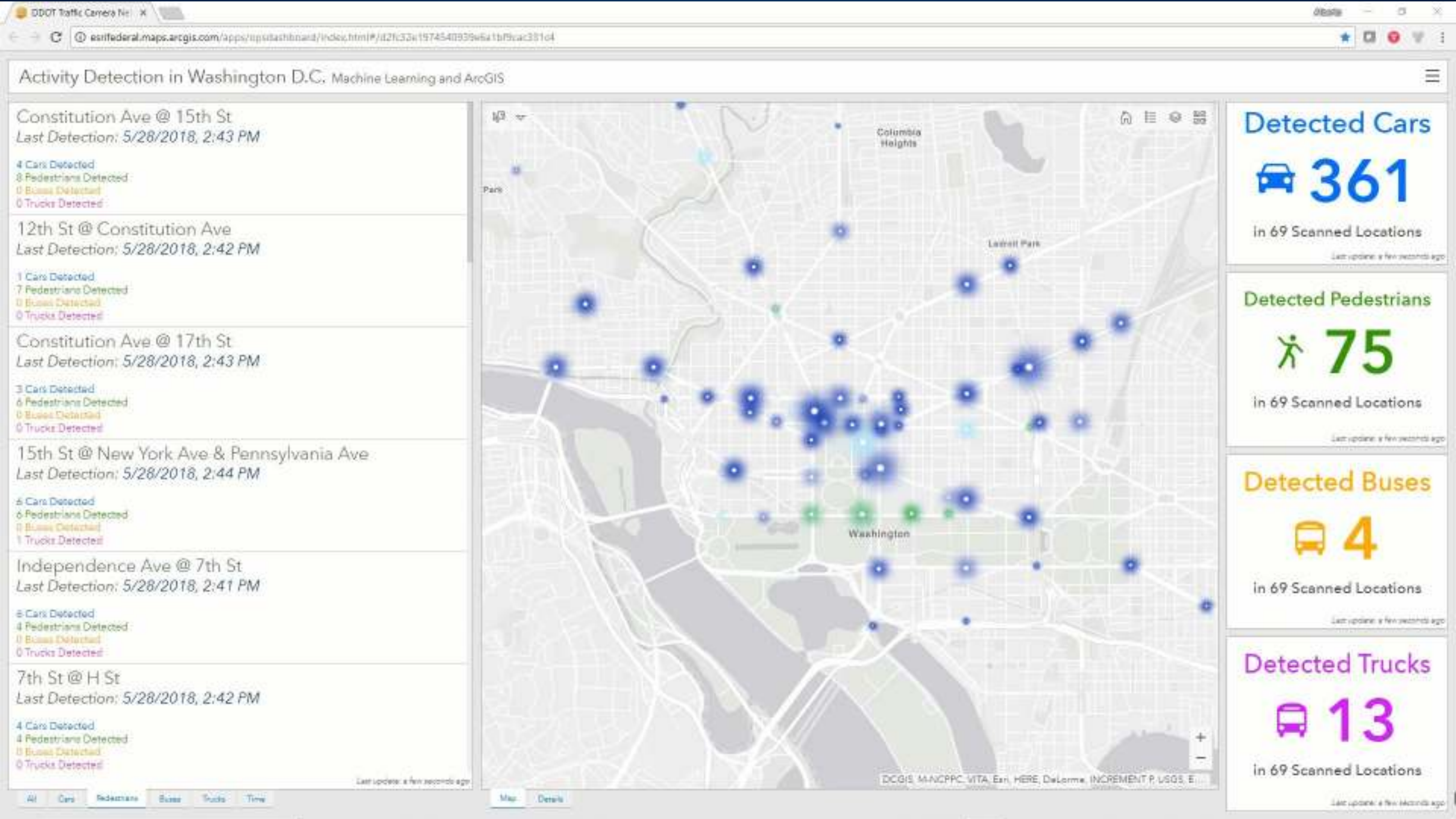
Real-Time Vehicle Count

6

Last update: a few seconds ago

Real-Time Detected Object Counts

Last update: a few seconds ago


DDOT Traffic Camera Ne
esrifederal.maps.arcgis.com/apps/opsdashboard/index.html#/d2fc32e1974540939e6a1bf9cac381d4
Columbia Heights
Park
Ledroit Park
Washington
DCGIS, M-NCPPC, VITA, Esri, HERE, DeLorme, INCREMENT P, USGS, E...
All
Cars
Pedestrians
Buses
Trucks
Time
Map
Details

Activity Detection in Washington D.C. Machine Learning and ArcGIS

Constitution Ave @ 15th St

Last Detection: 5/28/2018, 2:43 PM

4 Cars Detected
8 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

12th St @ Constitution Ave

Last Detection: 5/28/2018, 2:42 PM

1 Cars Detected
7 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

Constitution Ave @ 17th St

Last Detection: 5/28/2018, 2:43 PM

3 Cars Detected
6 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

15th St @ New York Ave & Pennsylvania Ave

Last Detection: 5/28/2018, 2:44 PM

6 Cars Detected
6 Pedestrians Detected
0 Buses Detected
1 Trucks Detected

Independence Ave @ 7th St

Last Detection: 5/28/2018, 2:41 PM

6 Cars Detected
4 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

7th St @ H St

Last Detection: 5/28/2018, 2:42 PM

4 Cars Detected
4 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

Last update: a few seconds ago

Detected Cars

361

in 69 Scanned Locations

Last update: a few seconds ago

Detected Pedestrians

75

in 69 Scanned Locations

Last update: a few seconds ago

Detected Buses

4

in 69 Scanned Locations

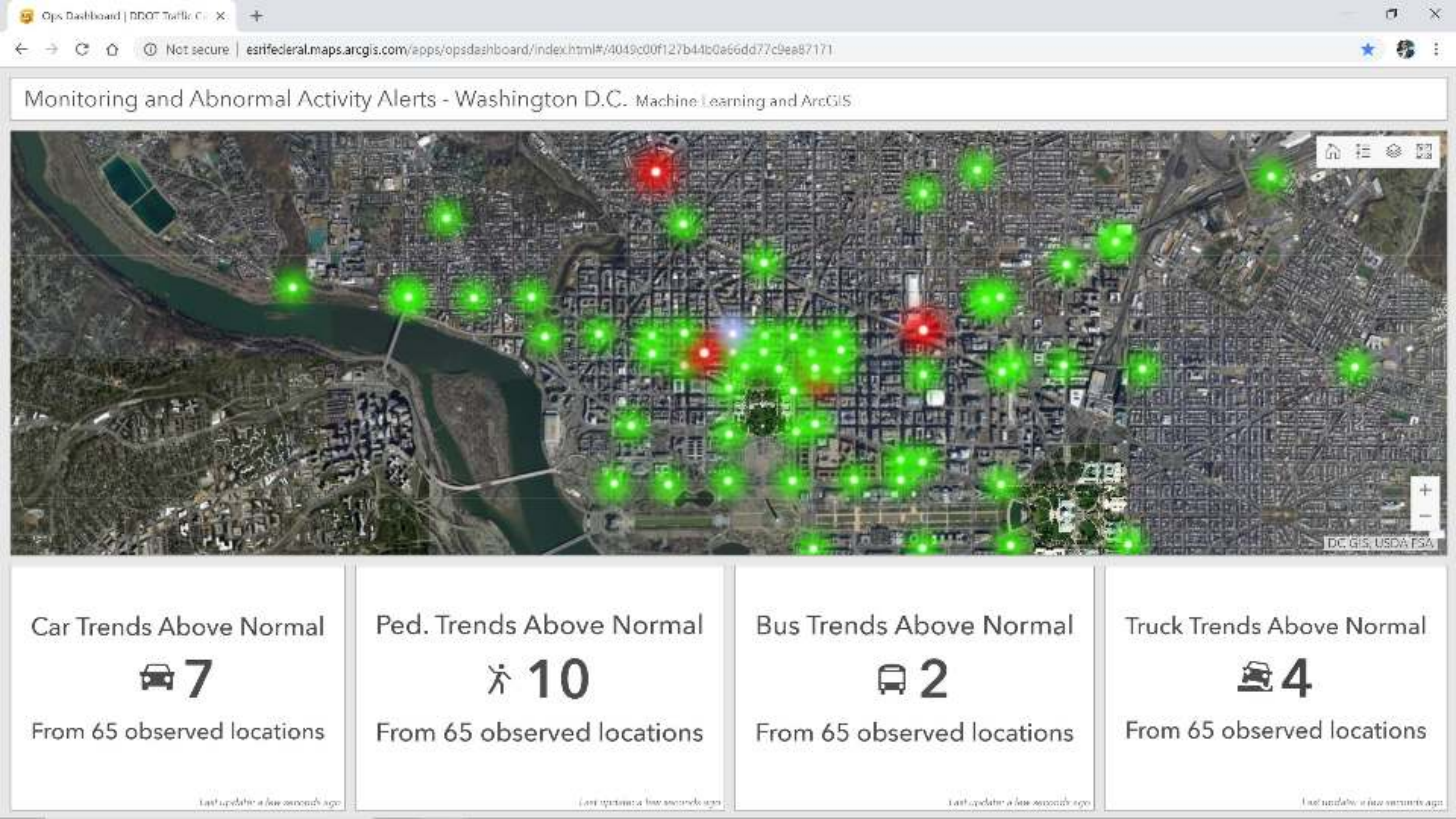
Last update: a few seconds ago

Detected Trucks

13

in 69 Scanned Locations

Last update: a few seconds ago



Ops Dashboard | DDOT Traffic C

Not secure | esrifederal.maps.arcgis.com/apps/opsdashboard/index.html#/4049c00f127b44b0a66dd77c9ea87171

Monitoring and Abnormal Activity Alerts - Washington D.C. Machine Learning and ArcGIS

Car Trends Above Normal

7

From 65 observed locations

Last update: a few seconds ago

Ped. Trends Above Normal

10

From 65 observed locations

Last update: a few seconds ago

Bus Trends Above Normal

2

From 65 observed locations

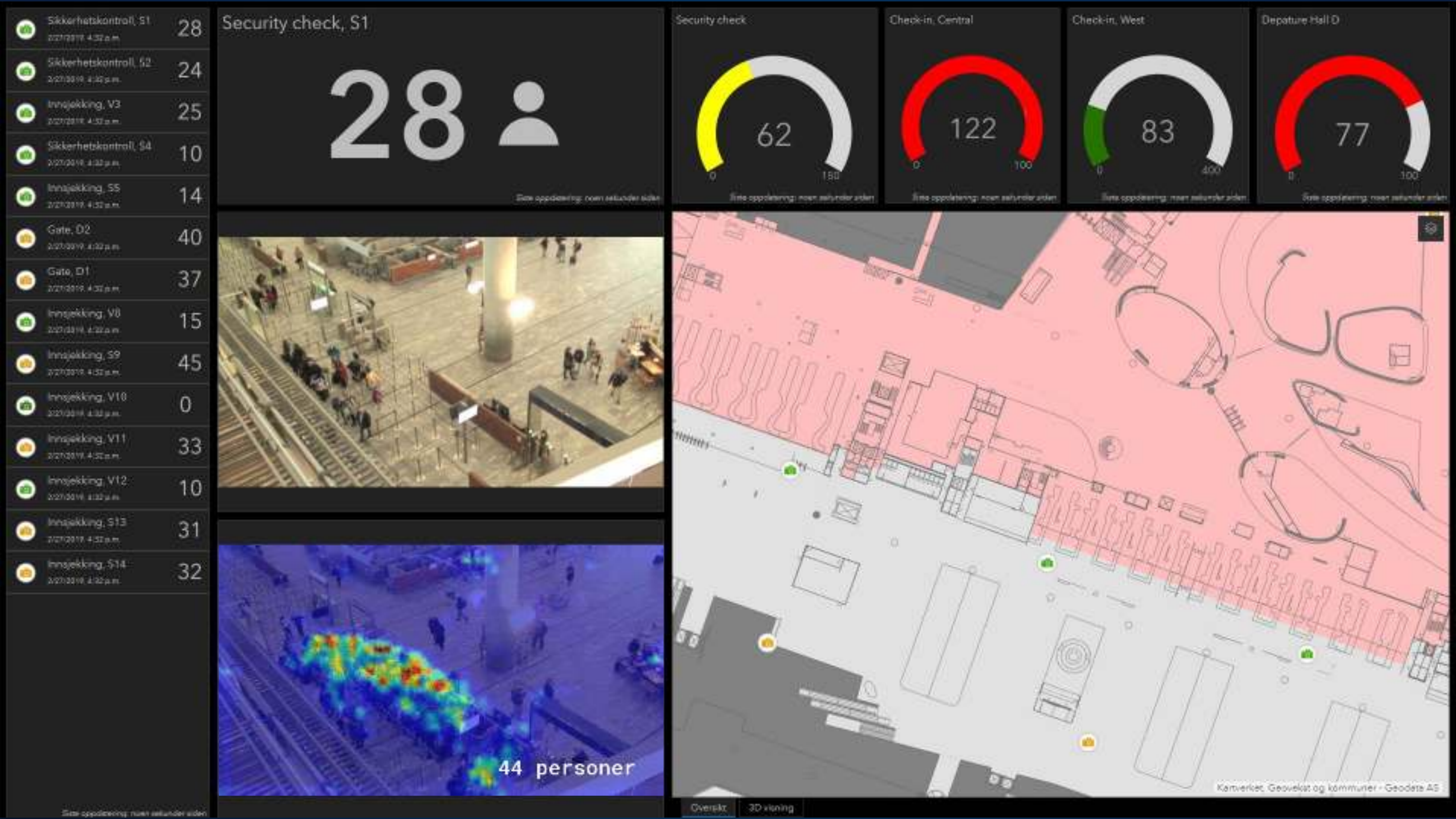
Last update: a few seconds ago

Truck Trends Above Normal

4

From 65 observed locations

Last update: a few seconds ago



Sikkerhetskontroll, S1	2/27/2019, 4:32 p.m.	28
Sikkerhetskontroll, S2	2/27/2019, 4:32 p.m.	24
Innsjekking, V3	2/27/2019, 4:32 p.m.	25
Sikkerhetskontroll, S4	2/27/2019, 4:32 p.m.	10
Innsjekking, S5	2/27/2019, 4:32 p.m.	14
Gate, D2	2/27/2019, 4:32 p.m.	40
Gate, D1	2/27/2019, 4:32 p.m.	37
Innsjekking, V8	2/27/2019, 4:32 p.m.	15
Innsjekking, S9	2/27/2019, 4:32 p.m.	45
Innsjekking, V10	2/27/2019, 4:32 p.m.	0
Innsjekking, V11	2/27/2019, 4:32 p.m.	33
Innsjekking, V12	2/27/2019, 4:32 p.m.	10
Innsjekking, S13	2/27/2019, 4:32 p.m.	31
Innsjekking, S14	2/27/2019, 4:32 p.m.	32

Siste oppdatering: noen sekunder siden

Security check, S1

28

Siste oppdatering: noen sekunder siden

Security check	Check-in, Central	Check-in, West	Depature Hall D
62	122	83	77
0–150	0–100	0–400	0–100
Siste oppdatering: noen sekunder siden	Siste oppdatering: noen sekunder siden	Siste oppdatering: noen sekunder siden	Siste oppdatering: noen sekunder siden

44 personer

Kartverket, Geovekst og kommuner - Geodata AS

Accidents Prediction

Predict Accident Probability per Segment per Hour

What would Cause an Accident?

Temperature
Sun, Mon, Fri..

Wind Speed
Fast, Slow..

Visibility
High/Low

Snow Depth
High/Low

Day of the Week
Sun, Mon, Fri..

Time of the Day
12:45, 23:00

Month
Feb, Dec..

Road Width
20-30 M

Road Alignment
Straight / Curved

Proximity to
Intersections

Speed Limit
120 km/h

Sun Direction
East, West

Daily Traffic
AADT

Proximity to
Billboards

...

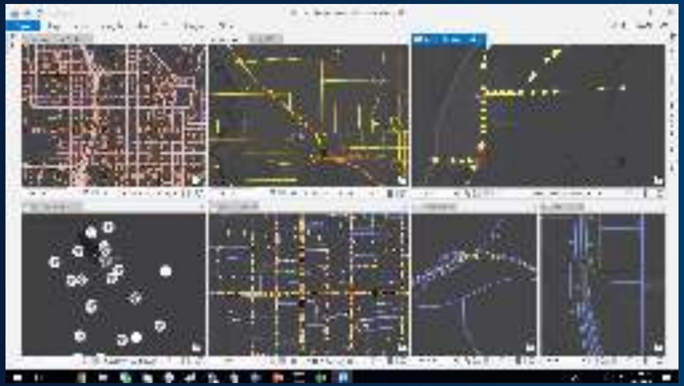
10s of
Variables

7 Years of Data
400,000 Accidents
500,000 Segments

Impossible
to Manually
Analyze

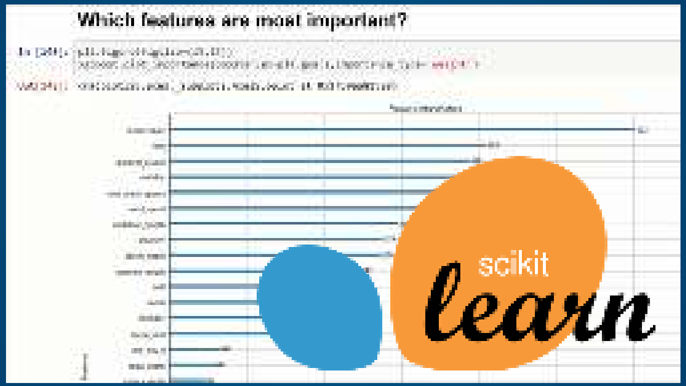
Train a
Machine to
do?

Workflow: Prepare > Machine Learning > Visualization



ArcGIS Pro

Data Exploration
Prepare Input Features



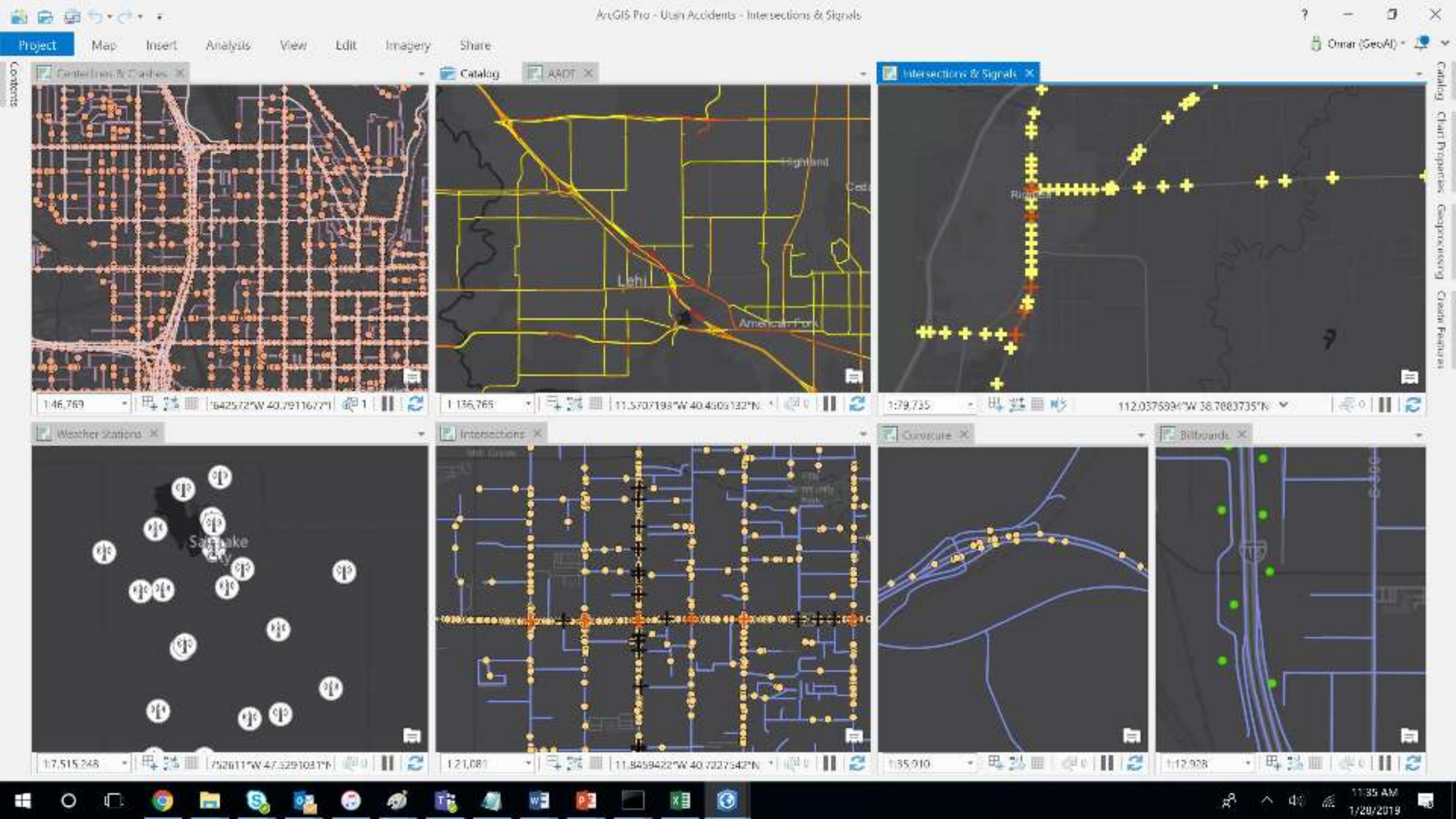
Which features are most important?

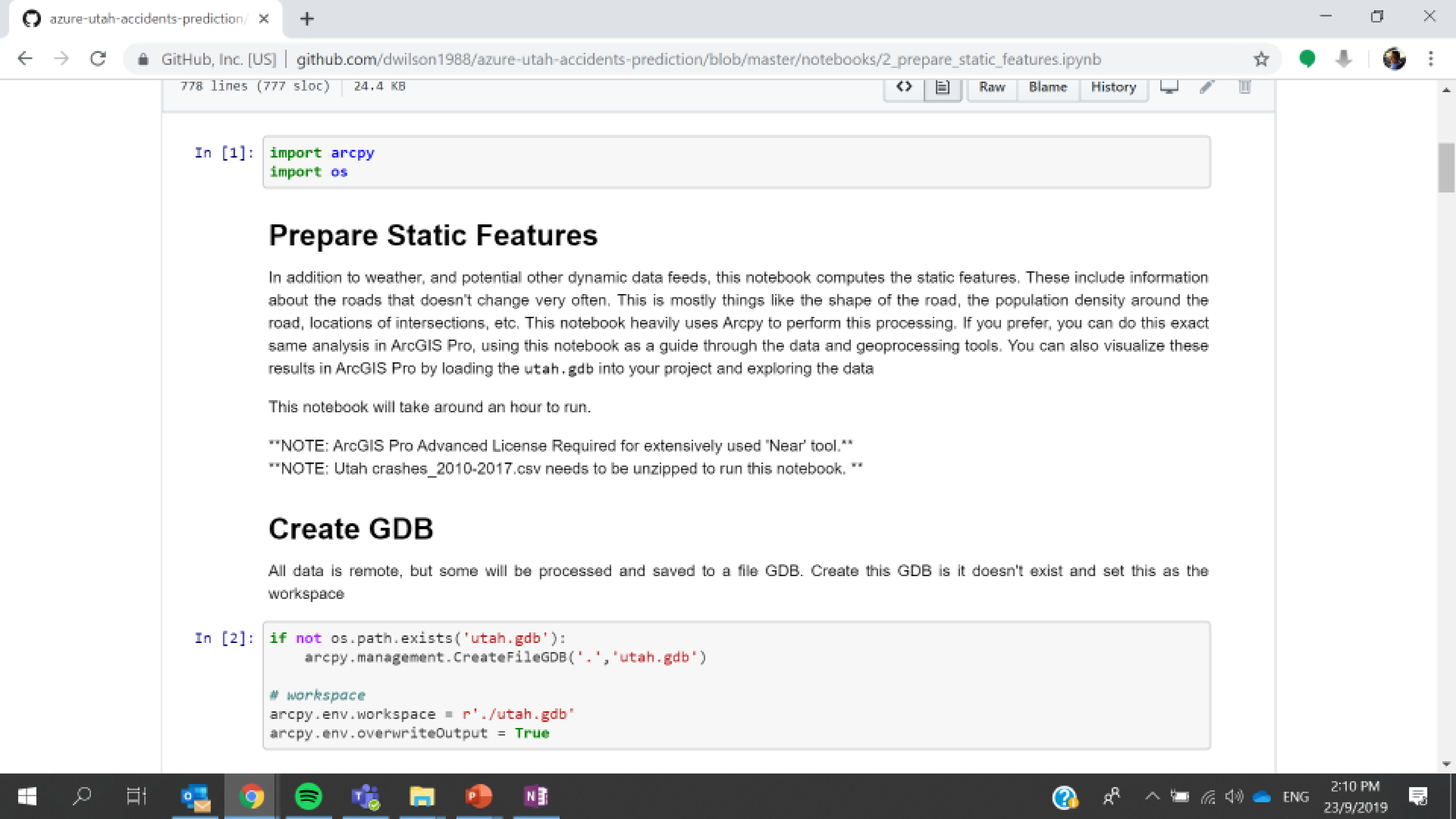
Python Scikit-Learn

Training Data
Model Development

ArcGIS Online

Visualize Results
Operation Awareness


ArcGIS Pro - Utah Accidents - Intersections & Signals
Project
Map
Insert
Analysis
View
Edit
Imagery
Share
Omar (GeoAI)
Contents
Centerlines & Crashes
Catalog
AADT
Intersections & Signals
Catalog
Chart Properties
Geoprocessing
Create Features
Highland
Lehi
American Fork
Riverton
1:46,769
'642572"W 40.7911677"N
1:136,765
11.5707193"W 40.4505132"N
1:79,735
112.0376894"W 38.7883735"N
Weather Stations
Salt Lake City
Intersections
Mill Creek
Curvature
Billboards
1:7,515,248
752611"W 47.5291031"N
1:21,081
11.8459422"W 40.7227542"N
1:35,910
1:12,928
11:35 AM
1/28/2019


azure-utah-accidents-prediction/
GitHub, Inc. [US] | github.com/dwilson1988/azure-utah-accidents-prediction/blob/master/notebooks/2_prepare_static_features.ipynb
778 lines (777 sloc) | 24.4 KB
Raw
Blame
History
ENG
2:10 PM
23/9/2019

In [1]:

```
import arcpy
import os
```

Prepare Static Features

In addition to weather, and potential other dynamic data feeds, this notebook computes the static features. These include information about the roads that doesn't change very often. This is mostly things like the shape of the road, the population density around the road, locations of intersections, etc. This notebook heavily uses Arcpy to perform this processing. If you prefer, you can do this exact same analysis in ArcGIS Pro, using this notebook as a guide through the data and geoprocessing tools. You can also visualize these results in ArcGIS Pro by loading the `utah.gdb` into your project and exploring the data

This notebook will take around an hour to run.

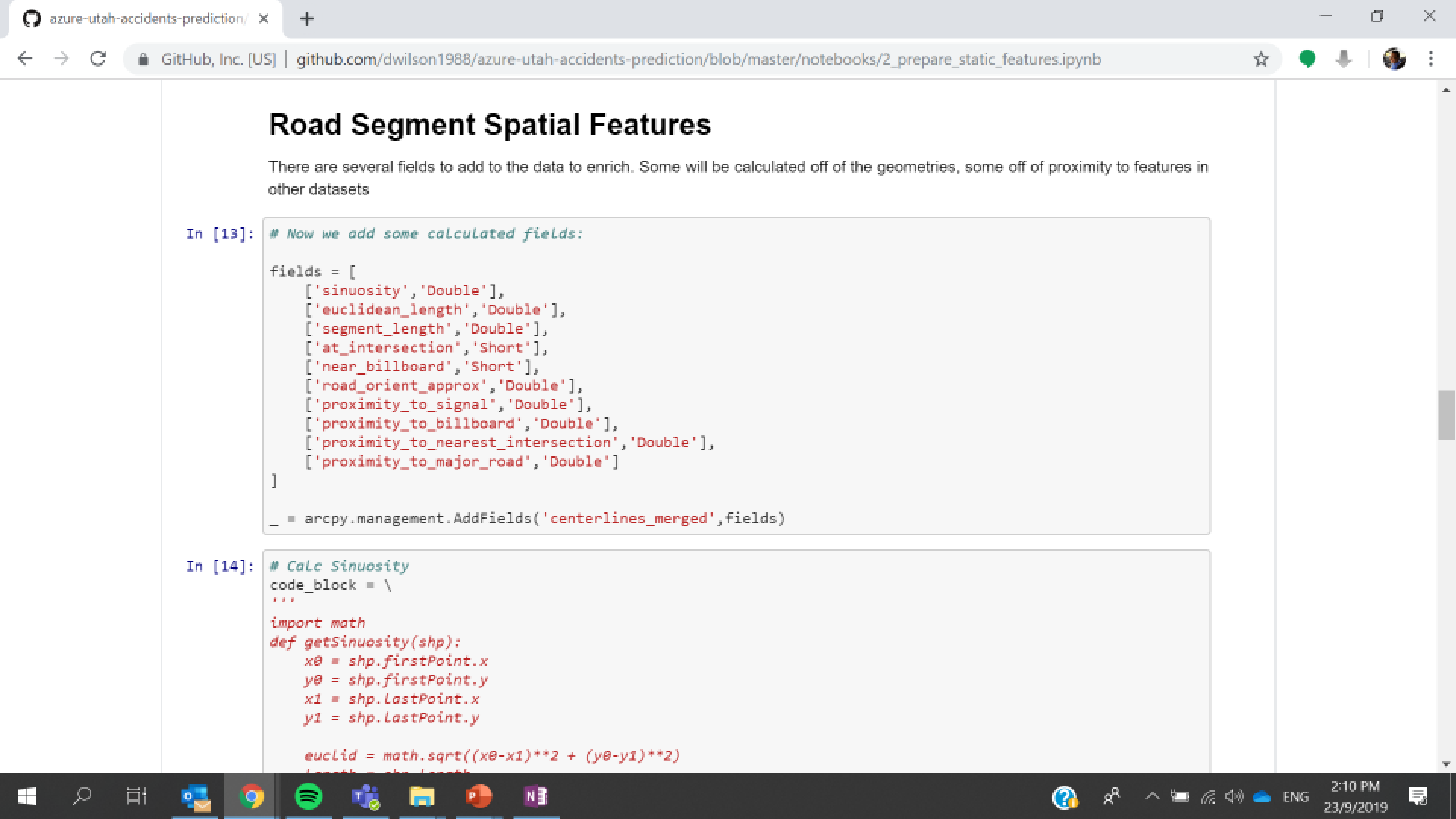
NOTE: ArcGIS Pro Advanced License Required for extensively used 'Near' tool.
**NOTE: Utah crashes_2010-2017.csv needs to be unzipped to run this notebook. **

Create GDB

All data is remote, but some will be processed and saved to a file GDB. Create this GDB is it doesn't exist and set this as the workspace

In [2]:

```
if not os.path.exists('utah.gdb'):
    arcpy.management.CreateFileGDB('.','utah.gdb')

# workspace
arcpy.env.workspace = r'./utah.gdb'
arcpy.env.overwriteOutput = True
```


azure-utah-accidents-prediction/
GitHub, Inc. [US]
github.com/dwilson1988/azure-utah-accidents-prediction/blob/master/notebooks/2_prepare_static_features.ipynb
ENG
2:10 PM
23/9/2019

Road Segment Spatial Features

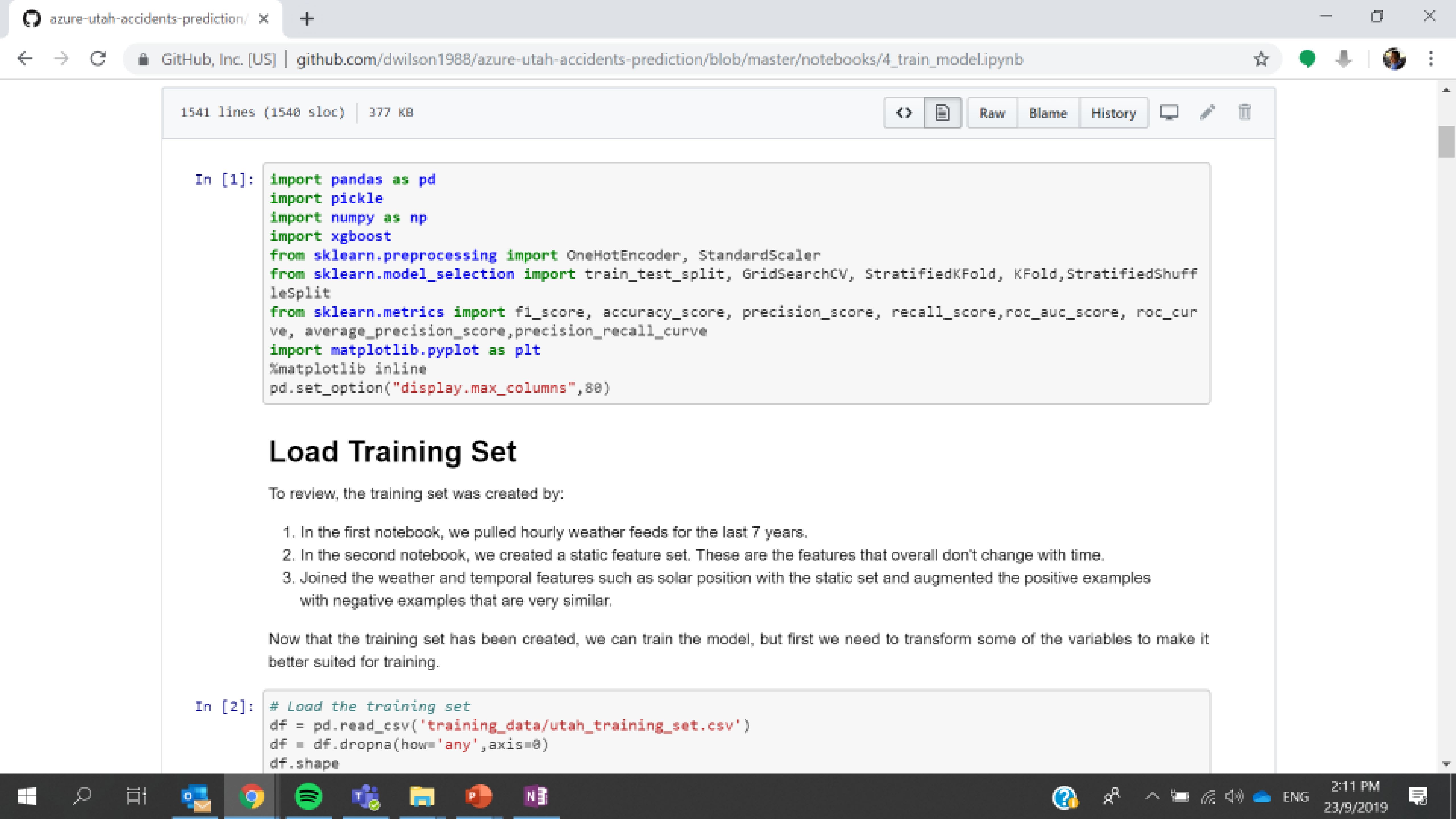
There are several fields to add to the data to enrich. Some will be calculated off of the geometries, some off of proximity to features in other datasets

In [13]:

```
# Now we add some calculated fields:

fields = [
    ['sinuosity','Double'],
    ['euclidean_length','Double'],
    ['segment_length','Double'],
    ['at_intersection','Short'],
    ['near_billboard','Short'],
    ['road_orient_approx','Double'],
    ['proximity_to_signal','Double'],
    ['proximity_to_billboard','Double'],
    ['proximity_to_nearest_intersection','Double'],
    ['proximity_to_major_road','Double']
]

_ = arcpy.management.AddFields('centerlines_merged',fields)
```

In [14]:

```
# Calc Sinuosity
code_block = \
'''
import math
def getSinuosity(shp):
    x0 = shp.firstPoint.x
    y0 = shp.firstPoint.y
    x1 = shp.lastPoint.x
    y1 = shp.lastPoint.y

    euclid = math.sqrt((x0-x1)**2 + (y0-y1)**2)
```


azure-utah-accidents-prediction/
GitHub, Inc. [US] | github.com/dwilson1988/azure-utah-accidents-prediction/blob/master/notebooks/4_train_model.ipynb
1541 lines (1540 sloc) | 377 KB
Raw
Blame
History
ENG
2:11 PM
23/9/2019

In [1]:

```
import pandas as pd
import pickle
import numpy as np
import xgboost
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedKFold, KFold,StratifiedShuff
leSplit
from sklearn.metrics import f1_score, accuracy_score, precision_score, recall_score,roc_auc_score, roc_cur
ve, average_precision_score,precision_recall_curve
import matplotlib.pyplot as plt
%matplotlib inline
pd.set_option("display.max_columns",80)
```

Load Training Set

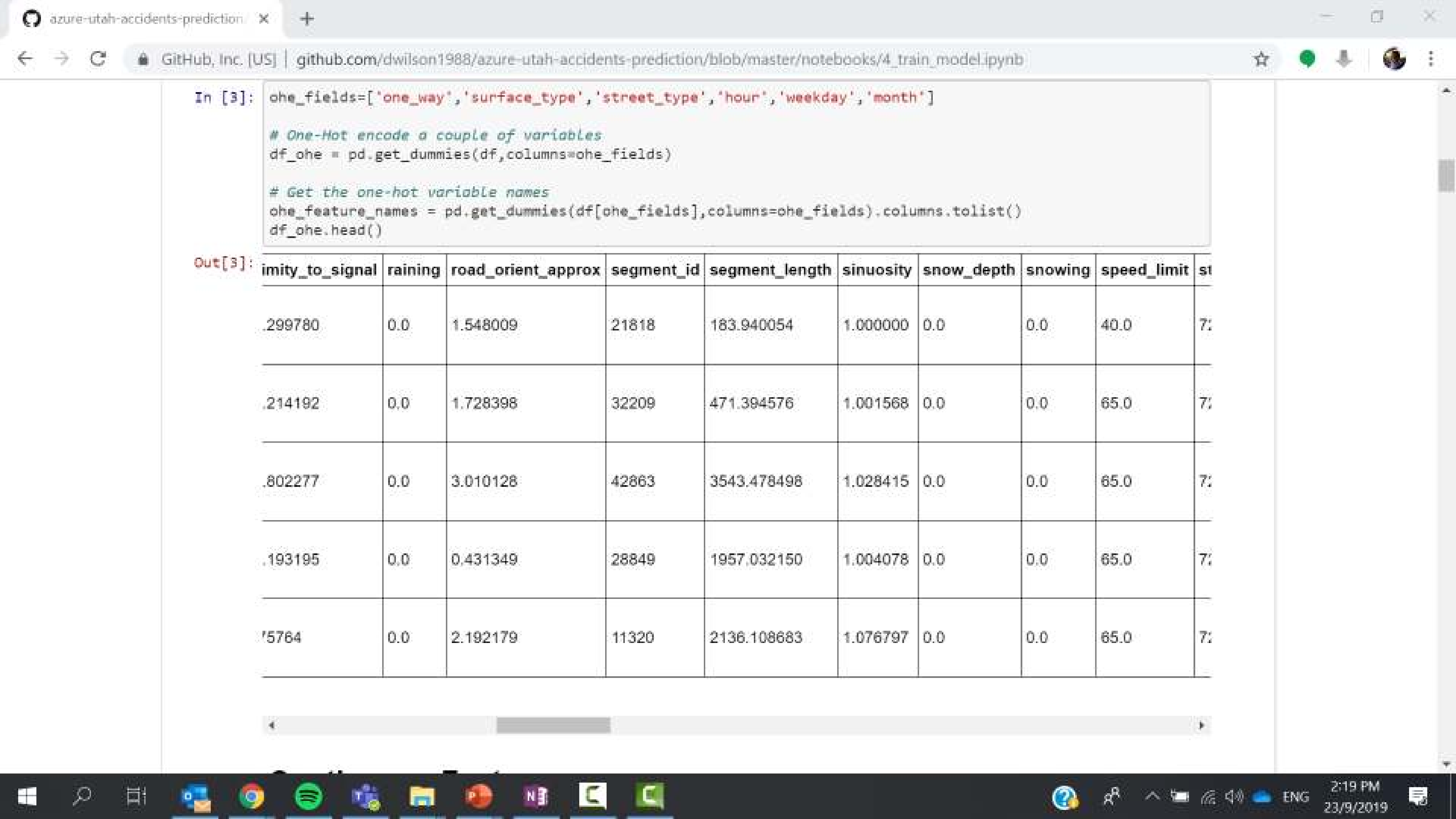
To review, the training set was created by:

1. In the first notebook, we pulled hourly weather feeds for the last 7 years.
2. In the second notebook, we created a static feature set. These are the features that overall don't change with time.
3. Joined the weather and temporal features such as solar position with the static set and augmented the positive examples with negative examples that are very similar.

Now that the training set has been created, we can train the model, but first we need to transform some of the variables to make it better suited for training.

In [2]:

```
# Load the training set
df = pd.read_csv('training_data/utah_training_set.csv')
df = df.dropna(how='any',axis=0)
df.shape
```



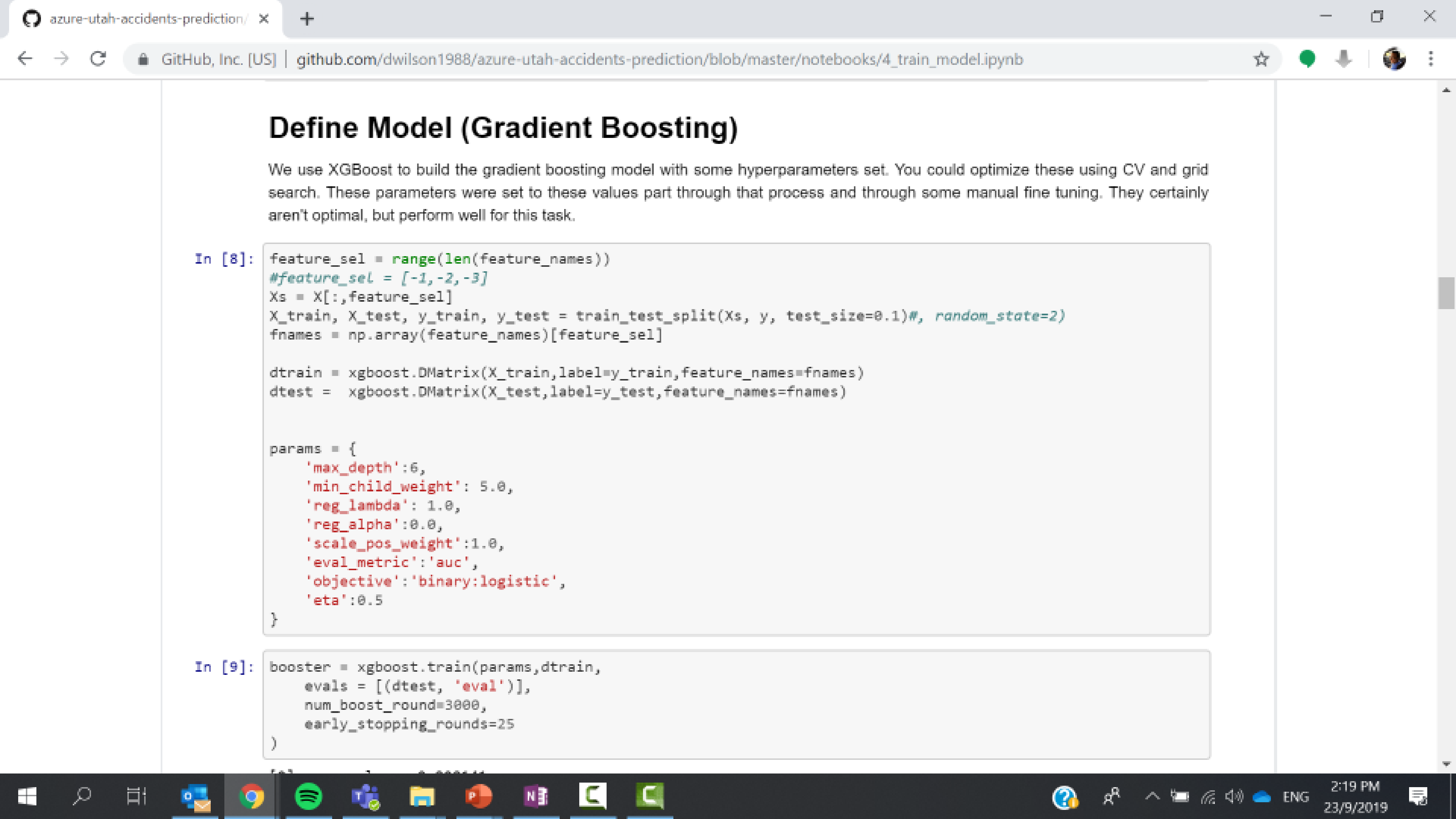
azure-utah-accidents-prediction
GitHub, Inc. [US] | github.com/dwilson1988/azure-utah-accidents-prediction/blob/master/notebooks/4_train_model.ipynb
ENG
2:19 PM
23/9/2019

In [3]:

```
ohe_fields=['one_way','surface_type','street_type','hour','weekday','month']

# One-Hot encode a couple of variables
df_ohe = pd.get_dummies(df,columns=ohe_fields)

# Get the one-hot variable names
ohe_feature_names = pd.get_dummies(df[ohe_fields],columns=ohe_fields).columns.tolist()
df_ohe.head()
```

Out[3]:

imity_to_signal	raining	road_orient_approx	segment_id	segment_length	sinuosity	snow_depth	snowing	speed_limit	st
.299780	0.0	1.548009	21818	183.940054	1.000000	0.0	0.0	40.0	7:
.214192	0.0	1.728398	32209	471.394576	1.001568	0.0	0.0	65.0	7:
.802277	0.0	3.010128	42863	3543.478498	1.028415	0.0	0.0	65.0	7:
.193195	0.0	0.431349	28849	1957.032150	1.004078	0.0	0.0	65.0	7:
'5764	0.0	2.192179	11320	2136.108683	1.076797	0.0	0.0	65.0	7:


azure-utah-accidents-prediction/
GitHub, Inc. [US] | github.com/dwilson1988/azure-utah-accidents-prediction/blob/master/notebooks/4_train_model.ipynb
ENG
2:19 PM
23/9/2019

Define Model (Gradient Boosting)

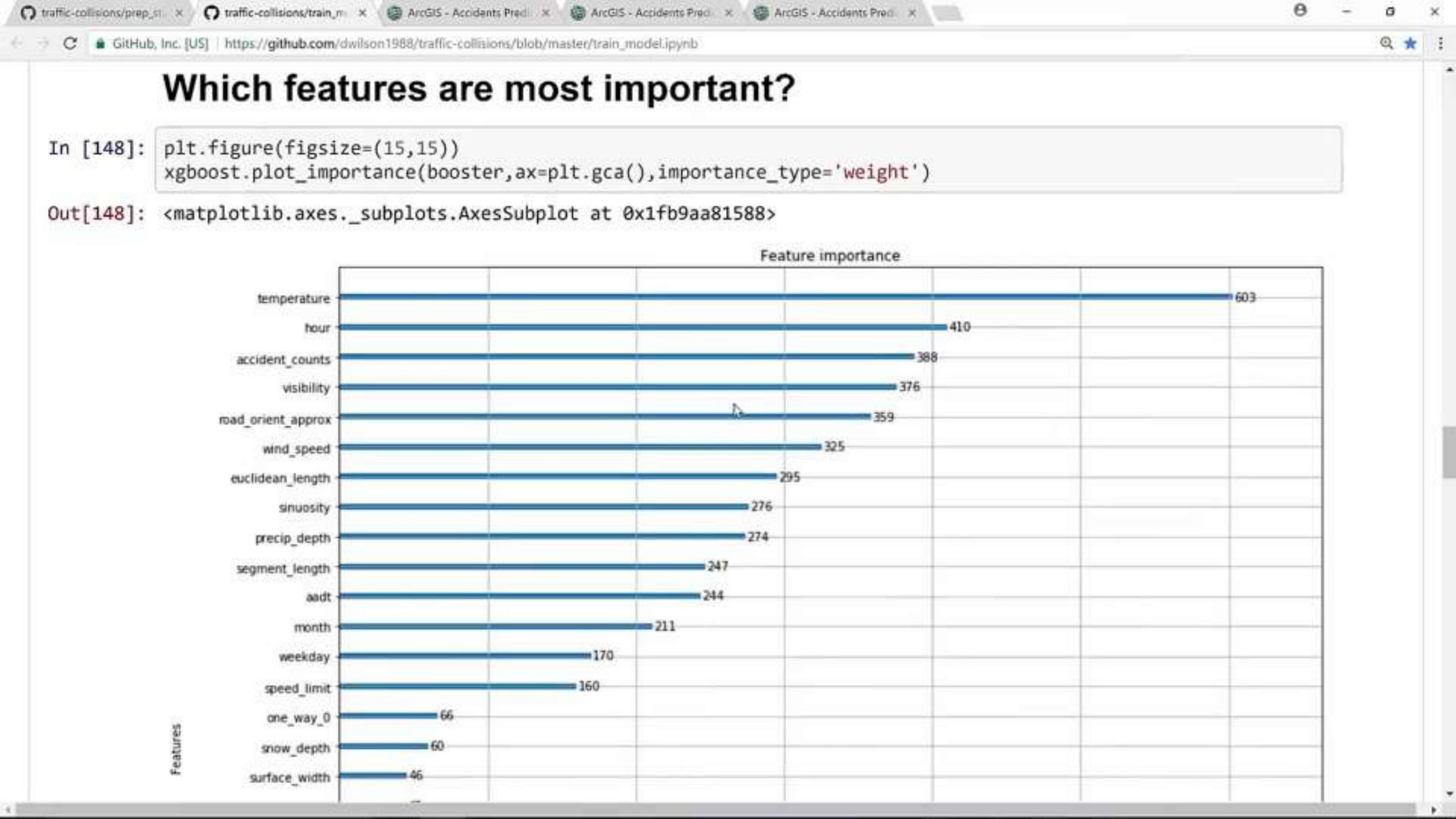
We use XGBoost to build the gradient boosting model with some hyperparameters set. You could optimize these using CV and grid search. These parameters were set to these values part through that process and through some manual fine tuning. They certainly aren't optimal, but perform well for this task.

In [8]:

```
feature_sel = range(len(feature_names))
#feature_sel = [-1,-2,-3]
Xs = X[:,feature_sel]
X_train, X_test, y_train, y_test = train_test_split(Xs, y, test_size=0.1)#, random_state=2)
fnames = np.array(feature_names)[feature_sel]

dtrain = xgboost.DMatrix(X_train,label=y_train,feature_names=fnames)
dtest =  xgboost.DMatrix(X_test,label=y_test,feature_names=fnames)


params = {
    'max_depth':6,
    'min_child_weight': 5.0,
    'reg_lambda': 1.0,
    'reg_alpha':0.0,
    'scale_pos_weight':1.0,
    'eval_metric':'auc',
    'objective':'binary:logistic',
    'eta':0.5
}
```

In [9]:

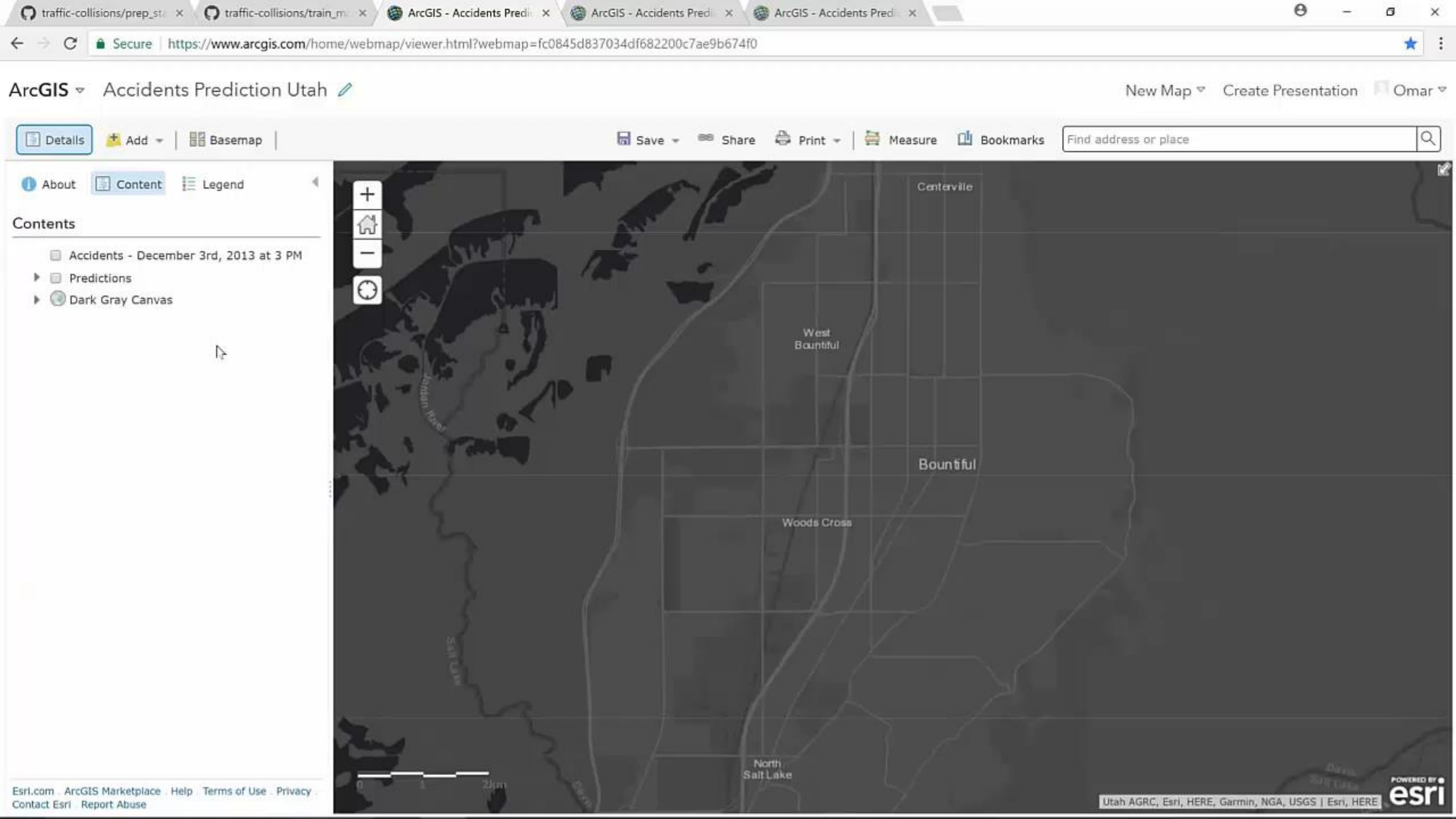
```
booster = xgboost.train(params,dtrain,
    evals = [(dtest, 'eval')],
    num_boost_round=3000,
    early_stopping_rounds=25
)
```



Which features are most important?

```
In [148]: plt.figure(figsize=(15,15))
          xgboost.plot_importance(booster,ax=plt.gca(),importance_type='weight')
```

```
Out[148]: <matplotlib.axes._subplots.AxesSubplot at 0x1fb9aa81588>
```



https://www.arcgis.com/home/webmap/viewer.html?webmap=fc0845d837034df682200c7ae9b674f0

Accidents Prediction Utah

Contents

- □ Accidents - December 3rd, 2013 at 3 PM
- □ Predictions
- Dark Gray Canvas

Geo-AI can help with

Prediction

Object Detection

Clustering

Land Classification

Anomaly Detection

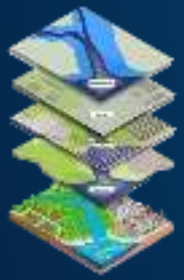
What is the #1 Challenge?

Getting Everyone to SEAMLESSLY work together

Analyst

Data Scientist

End User



Access Imagery, Fix Data, Prepare Training Data, Formulate Ask

Consume Models for Analysis

Build and Optimize Models

Request Data

Information Products

Analysis & Decision Making

Questions…

esri Malaysia