ITCS 8190 Course Project

Predicting Urban Growth using Apache Spark

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This presentation is a limited overview of my project.

Please consult the webpage for more detail:

https://freezurbern.github.io/ITCS8190-CourseProject/

December 17th, 2020

Overview

- Research question: Can we predict urban growth using population, road geometry, and land cover?
- Answer: Yes, but population and road geometry are much better than land cover.

- Using multiple linear regression
  - Independent variables: land cover, population density, road density from **2011**
  - Dependent variable: urban land cover from **2016**
- Running on Google Cloud Platform's Dataproc service

Beyond Linear Regression

- Distributed Prediction
  - Apache Spark DataFrames using Python
  - Using columns for each step of the equation
  - Calculations for each census tract across cluster

- Data Pipeline using R and ArcGIS Pro
  - R:
    - Census tract population estimates and geometry
    - primary/secondary road geometry
  - ArcGIS Pro:
    - National Land Cover Database raster image → CSV

Cool things I learned

- Plotting images in a notebook running in the cloud
- Keep data safe in a Google Cloud Storage ‘Bucket’
  - Accessible by cluster but not stored in the cluster
- GitHub Pages for documentation

Results

Dependent variable from 2016

GEOID	roaddens	popdens	barren	water	nature	agric	urbany	cy
1001020100	0.00678981352	0.00017956058	0.00200455581	0.00145785877	0.65676537585	0.10141230068	0.24036446469	0.24816192176
1001020200	0.00632959225	0.00064757175	0.00215749730	0.00080906149	0.34169363538	0.01672060410	0.64077669903	0.63979962938
1001020300	0.01908926044	0.00062276864	0.00903010033	0.00000000000	0.31739130435	0.09080267559	0.59180602007	0.60003224988
1001020400	0.01431175569	0.00068433141	0.00000000000	0.00014234875	0.30306049822	0.10804270463	0.58875444840	0.59407910920
1001020500	0.00594801379	0.00089086815	0.00015665387	0.00062661549	0.16417325918	0.15485235372	0.68034777160	0.67868136601
1001020600	0.00809658603	0.00042732944	0.00256267409	0.00055710306	0.32345403900	0.14896935933	0.52701949861	0.52894433391
1001020700	0.00484186922	0.00011919023	0.01676888440	0.03505162643	0.50512382579	0.26721527832	0.19260926947	0.19998295296
1001020801	0.00107152947	0.00002342970	0.00222291712	0.04794567109	0.61262100283	0.28207934523	0.05735398086	0.06520516270
1001020802	0.00115896453	0.00005584656	0.00054532804	0.00434852103	0.73789465767	0.18120874781	0.07654807349	0.08438610733
1001020900	0.00070723386	0.00001892776	0.00160465873	0.00395488546	0.73950835466	0.20842154354	0.04811521634	0.05622133741

Independent variables from 2011

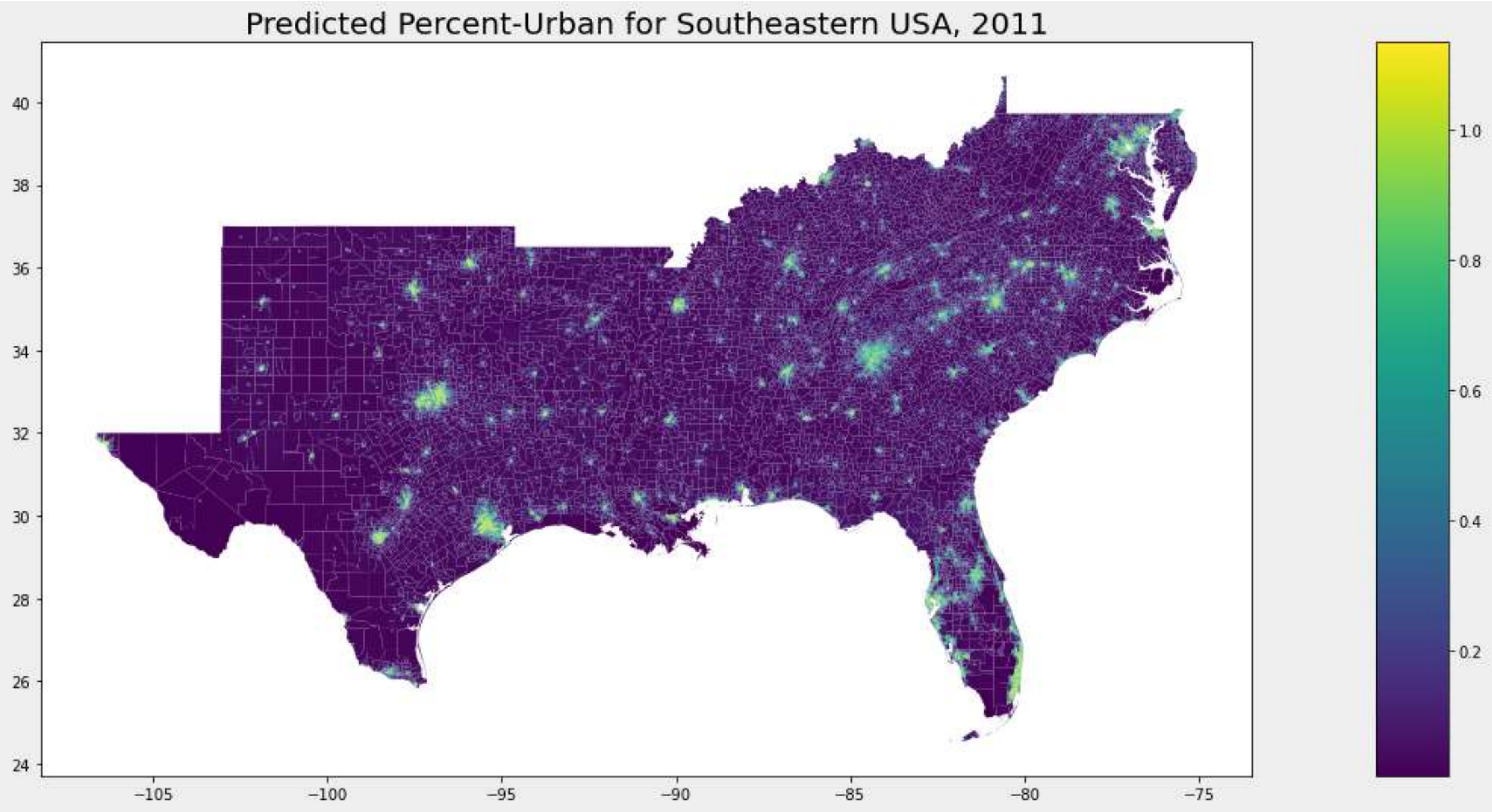
Predicted Urban for 2016

Beta Values	
intercept	0.9828573
roaddens	0.6322004
popdens	4.082916
barren	0.018703736
water	-0.97532403
nature	-0.97348666
agric	-0.9760582

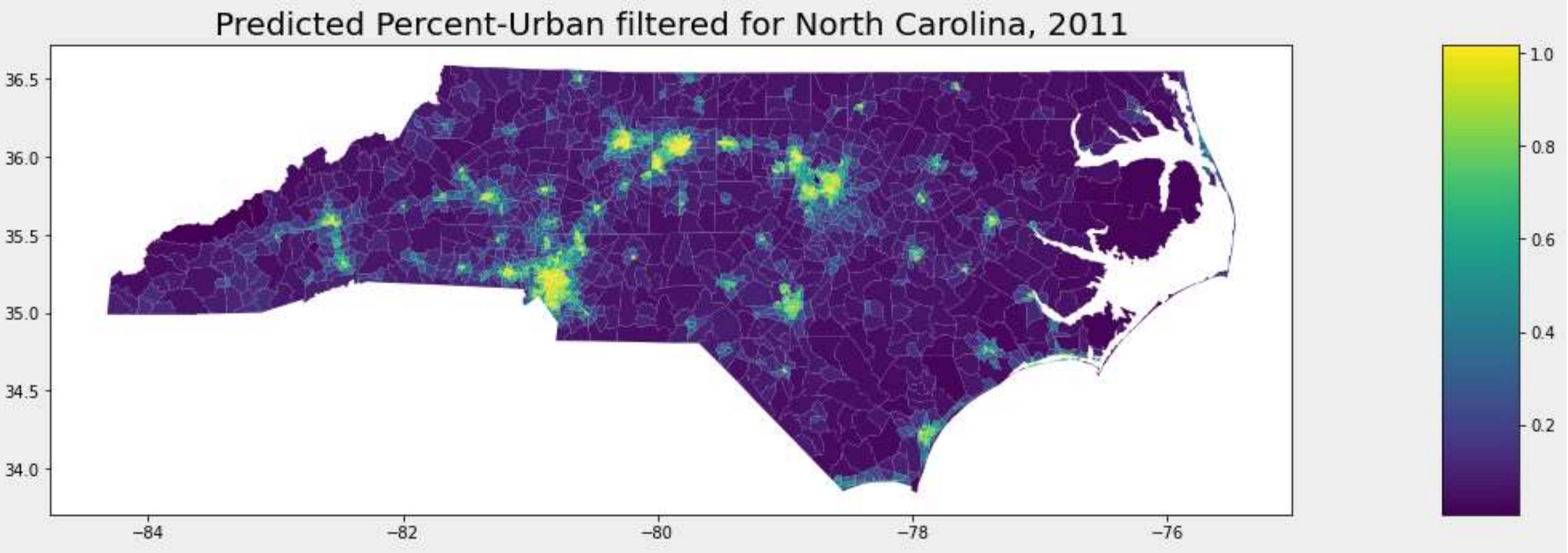
Note:

- Each row is a census tract (n=26,129)
- GEOID is the primary key (text)
- Yellow are independent variables (0..1)
- Purple is the actual value of the dependent variable (0..1)
- Green is the predicted value of the dependent variable (0..1)

Southeastern USA



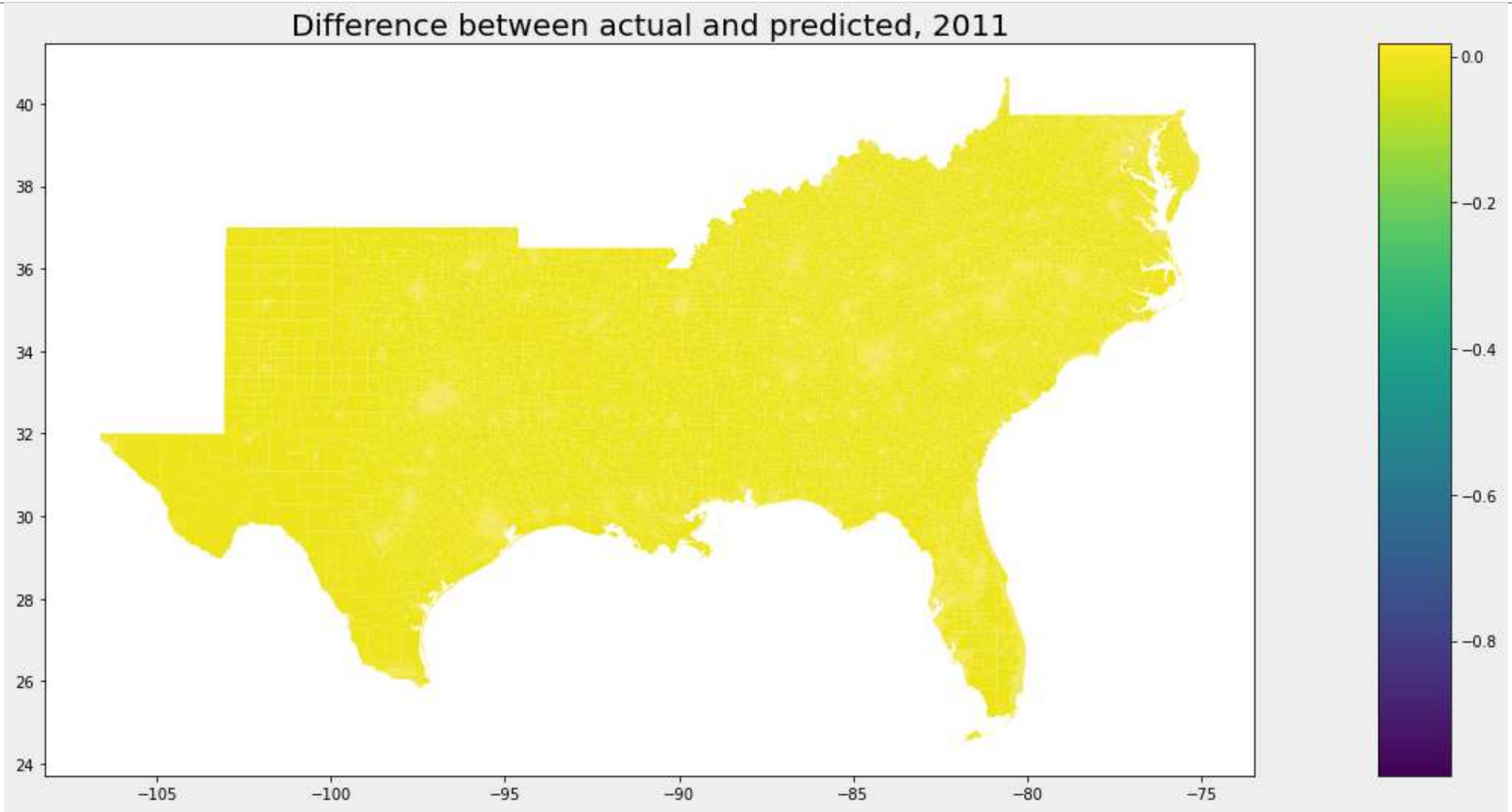
Predictions for North Carolina



Performance Evaluation

- Manually perform prediction
  - Model overestimates percent-urban (Y) by 0.5% for a given census tract
  - 0.5% of a census tract (~2,436 acres) is approximately 121 acres
- R-Squared
  - Calculated in Spark using distributed DataFrames
  - Result: 0.98 → Good enough

Visually inspect performance (less is best)



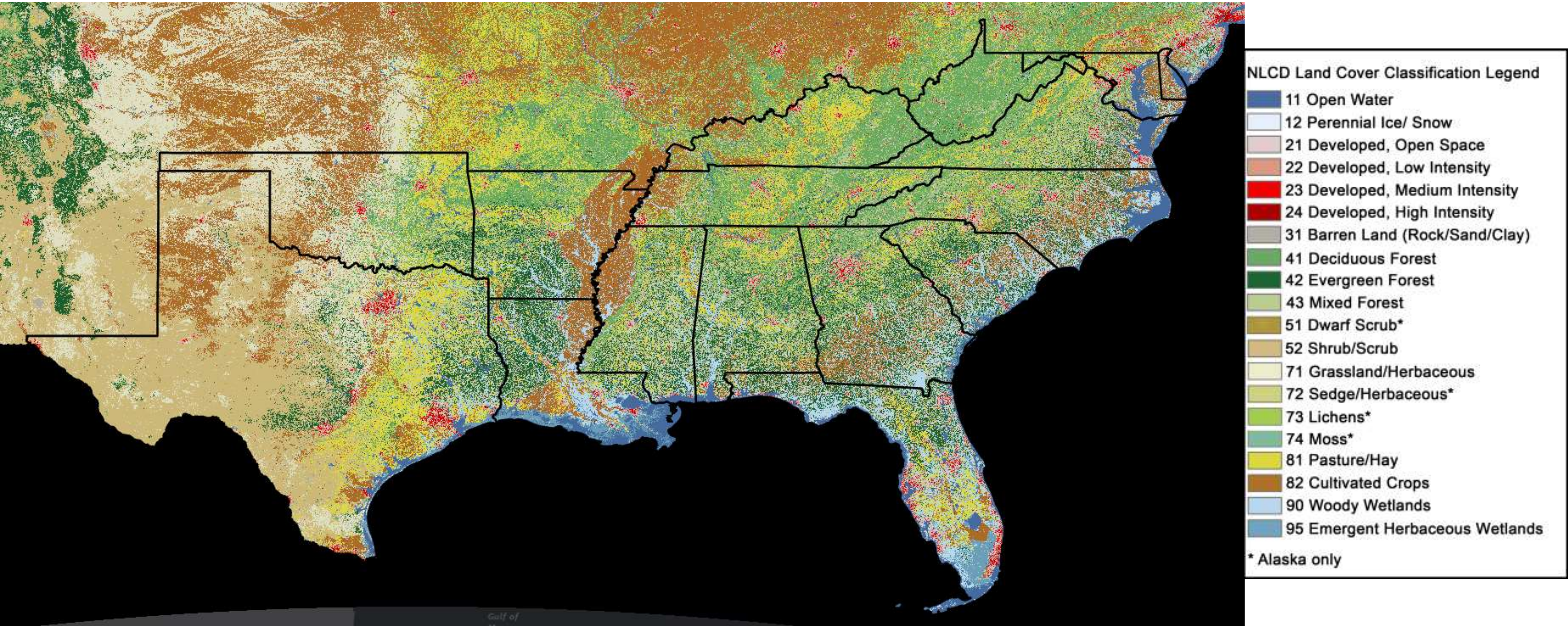
Possible Improvements

- Use RasterFrames on the cluster for raster processing
  - https://rasterframes.io/getting-started.html
  - Removes the ArcGIS Pro dependency in the data pipeline
- Use ‘census’ or ‘CensusData’ packages in Python
  - Removes the R dependency in the data pipeline

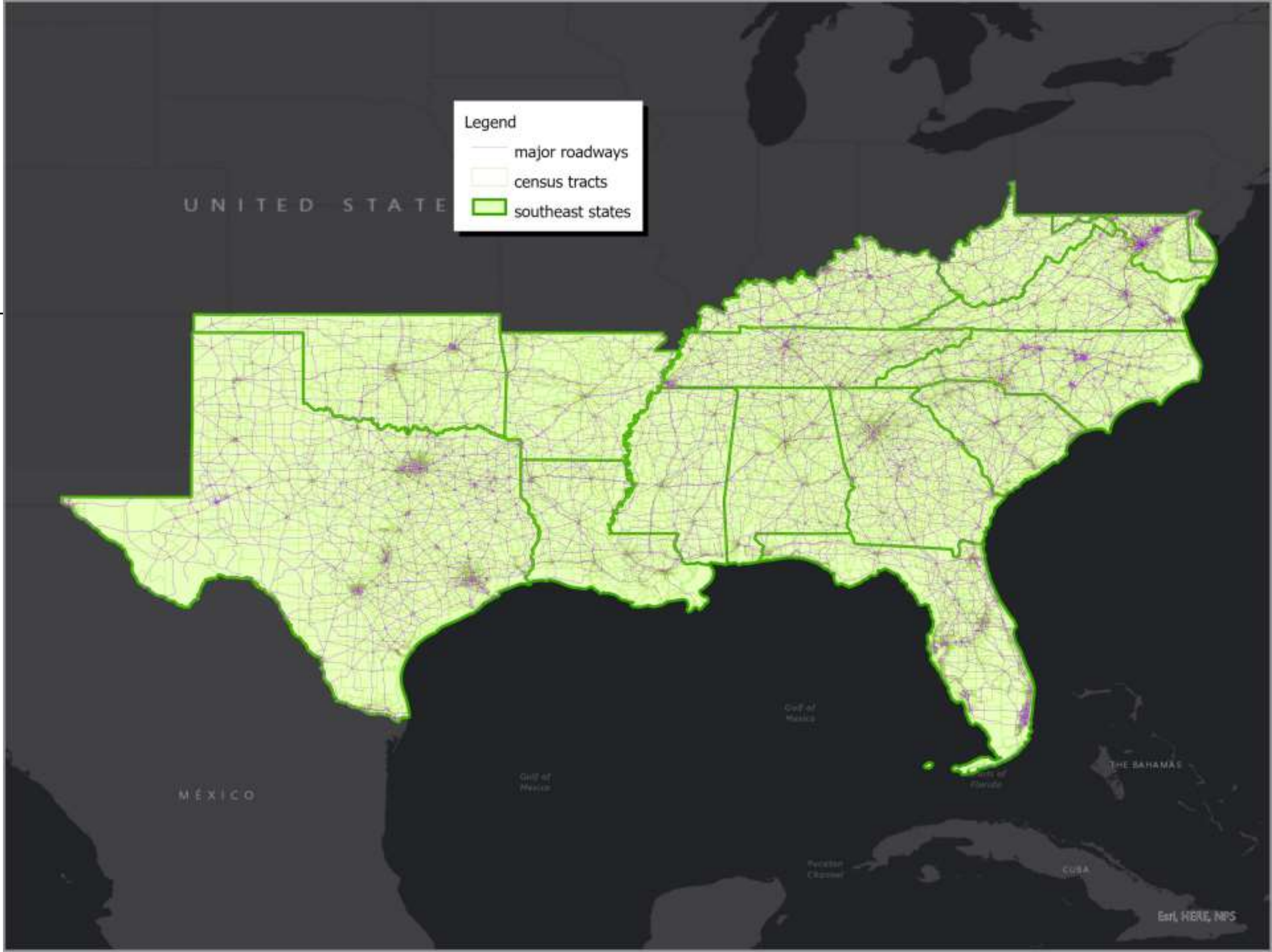
End.

Next: Screenshots

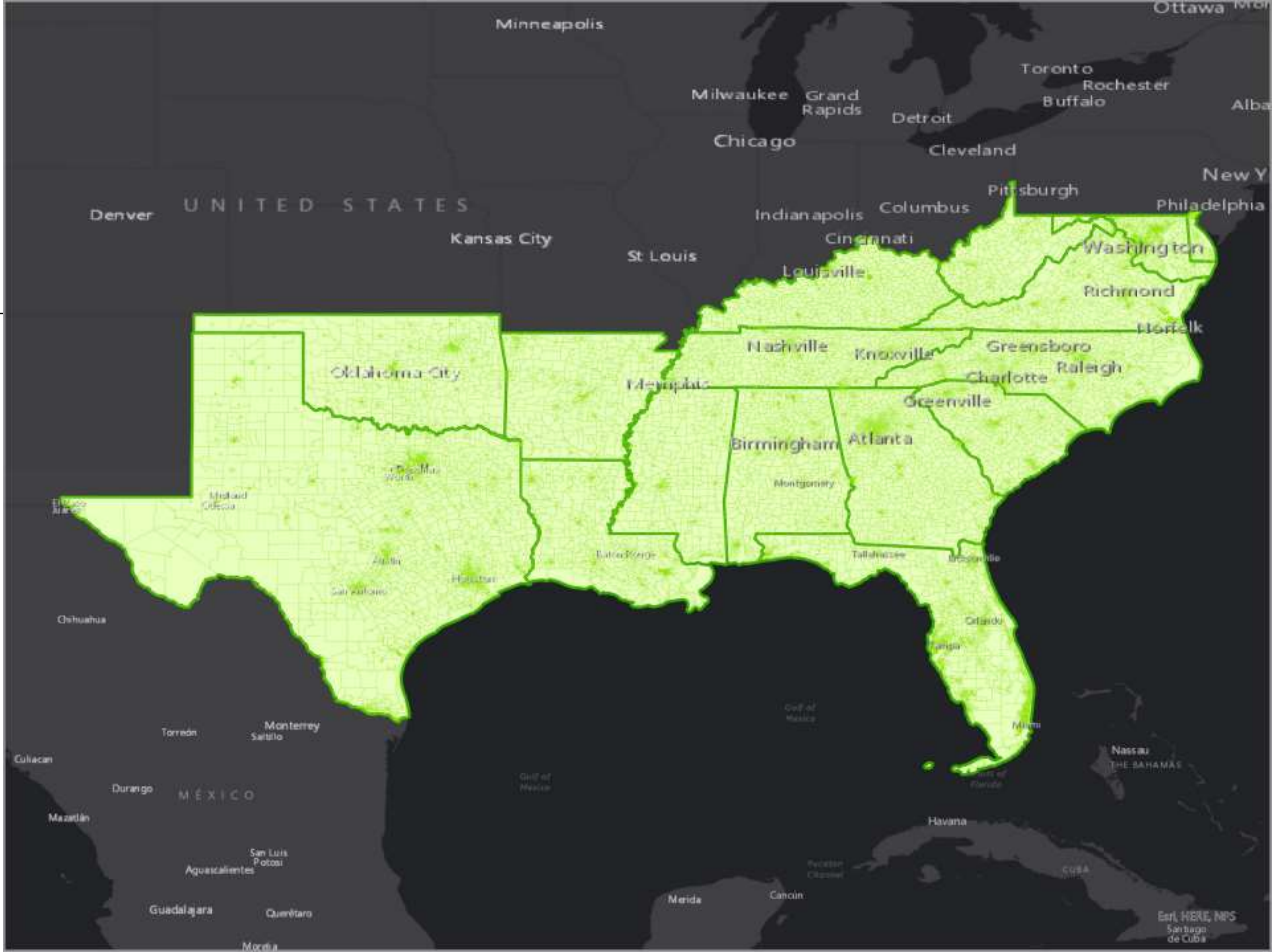
National Land Cover Database



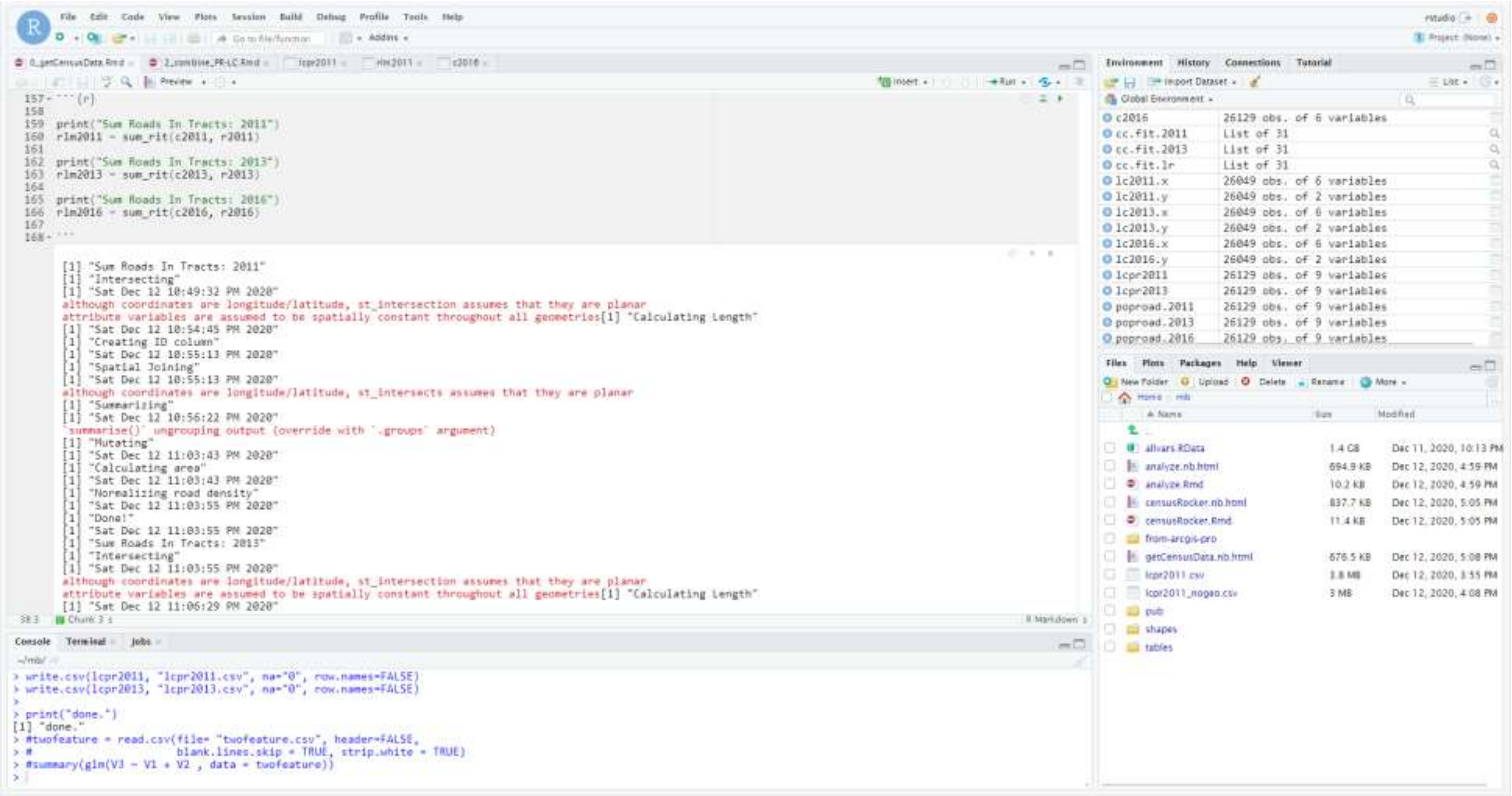
Roadways


Legend
major roadways
census tracts
southeast states
UNITED STATE
MÉXICO
THE BAHAMAS
CUBA
Esri, HERE, NPS

Census Tracts



R Studio



File Edit Code View Plots Session Build Debug Profile Tools Help
Environment History Connections Tutorial
Global Environment
Files Plots Packages Help Viewer
Console Terminal Jobs
print("Sum Roads In Tracts: 2011")
print("Sum Roads In Tracts: 2013")
print("Sum Roads In Tracts: 2016")

Census tract data

0_getCensusData.Rmd | 2_combine_PR-LC.Rmd | lcpr2011 | rlm2011 | c2016

Filter

	GEOID	NAME	variable	estimate	moe	geometry
1	01099076200	Census Tract 762, Monroe County, Alabama	B01003_001	1637	283	list(list(c(-87.784378, -87.781681, -87.780076, -87.771374, -8...
2	01101002100	Census Tract 21, Montgomery County, Alabama	B01003_001	4027	384	list(list(c(-86.299615, -86.294088, -86.290362, -86.288723, -8...
3	01101005302	Census Tract 53.02, Montgomery County, Alabama	B01003_001	2178	272	list(list(c(-86.23964, -86.237495, -86.23762, -86.239558, -86....
4	01101005606	Census Tract 56.06, Montgomery County, Alabama	B01003_001	4203	699	list(list(c(-86.233767, -86.232232, -86.23161, -86.22884, -86....
5	01103000300	Census Tract 3, Morgan County, Alabama	B01003_001	2850	366	list(list(c(-86.984562, -86.976697, -86.972917, -86.967527, -8...
6	01103005303	Census Tract 53.03, Morgan County, Alabama	B01003_001	3871	355	list(list(c(-86.95923, -86.959222, -86.956708, -86.954739, -86...
7	01103005500	Census Tract 55, Morgan County, Alabama	B01003_001	5356	483	list(list(c(-87.028764, -87.027291, -87.025354, -87.023192, -8...
8	01105686800	Census Tract 6868, Perry County, Alabama	B01003_001	1104	279	list(list(c(-87.273701, -87.270902, -87.269211, -87.26494, -87...
9	01111000100	Census Tract 1, Randolph County, Alabama	B01003_001	3325	372	list(list(c(-85.648139, -85.646238, -85.64599, -85.644217, -85...
10	01111000300	Census Tract 3, Randolph County, Alabama	B01003_001	3934	386	list(list(c(-85.651041, -85.651138, -85.650466, -85.641435, -8...

Road density dataset

0_getCensusData.Rmd | 2_combine_PR-LC.Rmd | lcpr2011 | rlm2011 | c2016

Filter

	GEOID.x	length	geometry	area	rlm
1	01001020100	66854.264	*list(list(c(-86.481959, -86.481892, -86.481866, -86.481689, -8...*	9846259 [m^2]	0.0067898135 [1/m^2]
2	01001020200	21181.014	*list(list(c(-86.468275, -86.468, -86.467462, -86.466985, -86.4...*	3346347 [m^2]	0.0063295922 [1/m^2]
3	01001020300	102286.560	*list(list(c(-86.465376, -86.465969, -86.466393, -86.466647, -8...*	5358330 [m^2]	0.0190892604 [1/m^2]
4	01001020400	91580.157	*list(list(c(-86.43807, -86.438116, -86.438141, -86.438229, -86...*	6398946 [m^2]	0.0143117557 [1/m^2]
5	01001020500	68081.788	*list(list(c(-86.411803, -86.411799, -86.411795, -86.411786, -8...*	11446138 [m^2]	0.0059480138 [1/m^2]
6	01001020600	65423.790	*list(list(c(-86.471541, -86.47122, -86.470524, -86.470253, -86...*	8080417 [m^2]	0.0080965860 [1/m^2]
7	01001020700	112282.080	*list(list(c(-86.460182, -86.460117, -86.460087, -86.460081, -8...*	23189821 [m^2]	0.0048418692 [1/m^2]
8	01001020801	141866.303	*list(list(c(-86.460087, -86.460117, -86.460182, -86.460546, -8...*	132396081 [m^2]	0.0010715295 [1/m^2]
9	01001020802	221928.912	*list(list(c(-86.48871, -86.487936, -86.487228, -86.48513, -86....*	191488959 [m^2]	0.0011589645 [1/m^2]
10	01001020900	207412.580	*list(list(c(-86.604386, -86.604383, -86.604392, -86.604404, -8...*	293272980 [m^2]	0.0007072339 [1/m^2]

length (meters) / area (m^2) = rlm (meters of road per square meter of census tract

0_getcensusdata

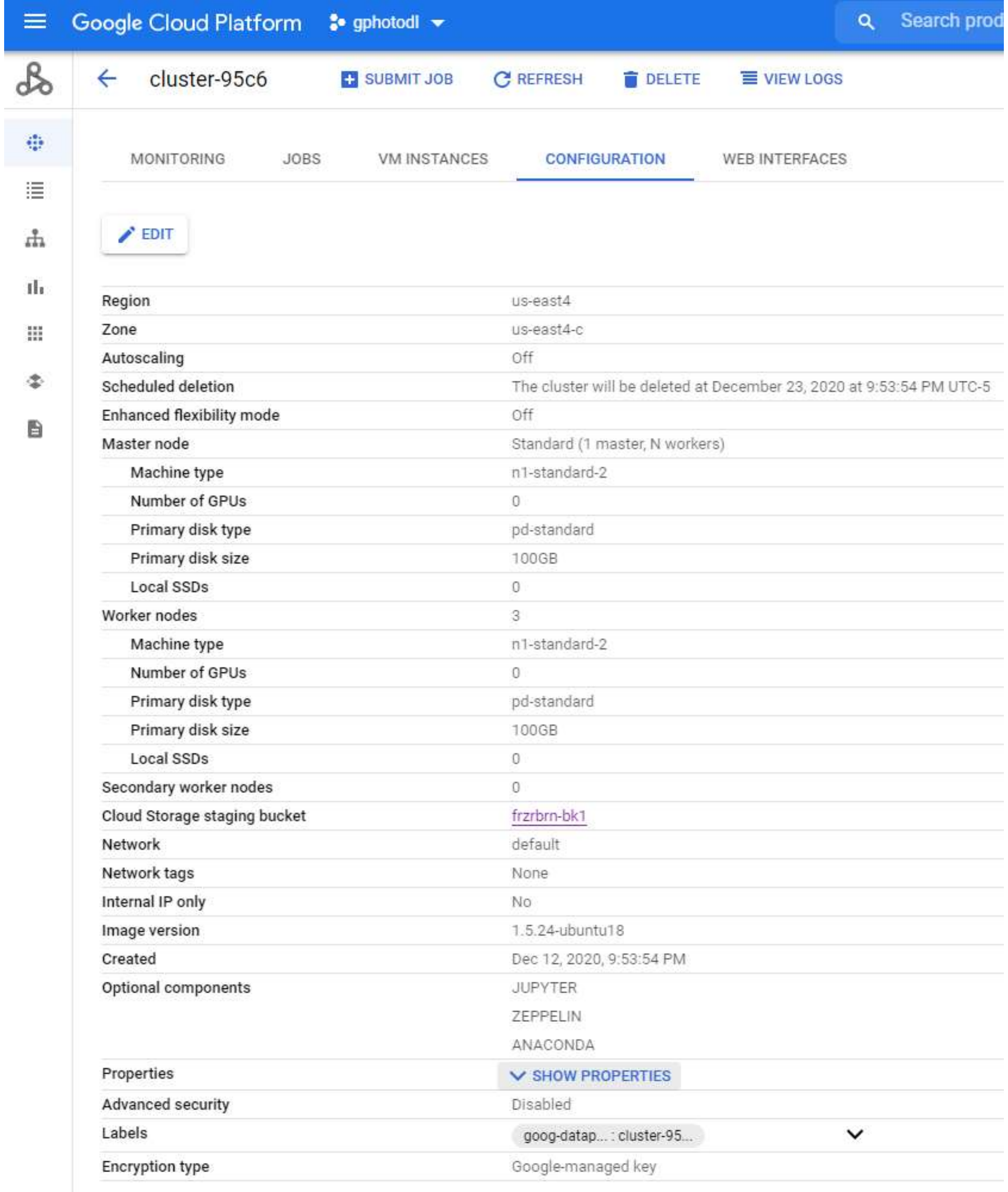
````
# Write shapefiles to disk
## Census Tracts w/ Pop and Road Lines
```{r}
st_write(r2011, "shapes/r2011.shp", delete_layer = TRUE)
st_write(r2013, "shapes/r2013.shp", delete_layer = TRUE)
st_write(r2016, "shapes/r2016.shp", delete_layer = TRUE)

st_write(c2011, "shapes/c2011.shp", delete_layer = TRUE)
st_write(c2013, "shapes/c2013.shp", delete_layer = TRUE)
st_write(c2016, "shapes/c2016.shp", delete_layer = TRUE)
```
````

```
Writing layer `r2011' to data source `shapes/r2011.shp' using driver `ESRI Shapefile'
Writing 159266 features with 5 fields and geometry type Multi Line String.
Writing layer `r2013' to data source `shapes/r2013.shp' using driver `ESRI Shapefile'
Writing 141574 features with 4 fields and geometry type Unknown (any).
Writing layer `r2016' to data source `shapes/r2016.shp' using driver `ESRI Shapefile'
Writing 141041 features with 5 fields and geometry type Unknown (any).
Writing layer `c2011' to data source `shapes/c2011.shp' using driver `ESRI Shapefile'
Writing 26129 features with 5 fields and geometry type Multi Polygon.
Writing layer `c2013' to data source `shapes/c2013.shp' using driver `ESRI Shapefile'
Writing 26129 features with 5 fields and geometry type Multi Polygon.
Writing layer `c2016' to data source `shapes/c2016.shp' using driver `ESRI Shapefile'
Writing 26129 features with 5 fields and geometry type Multi Polygon.
```

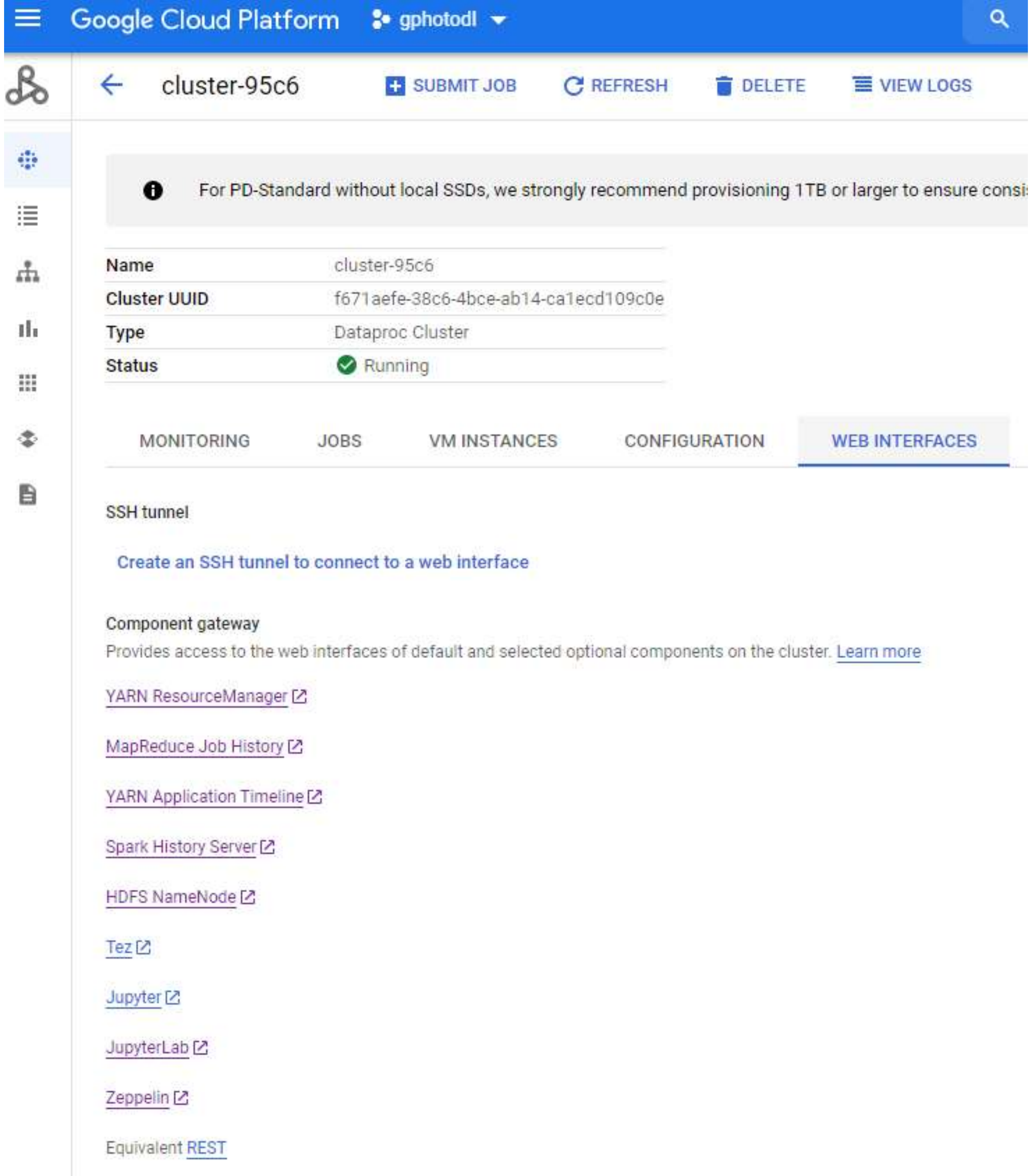
GCP: Dataproc

Cluster configuration page

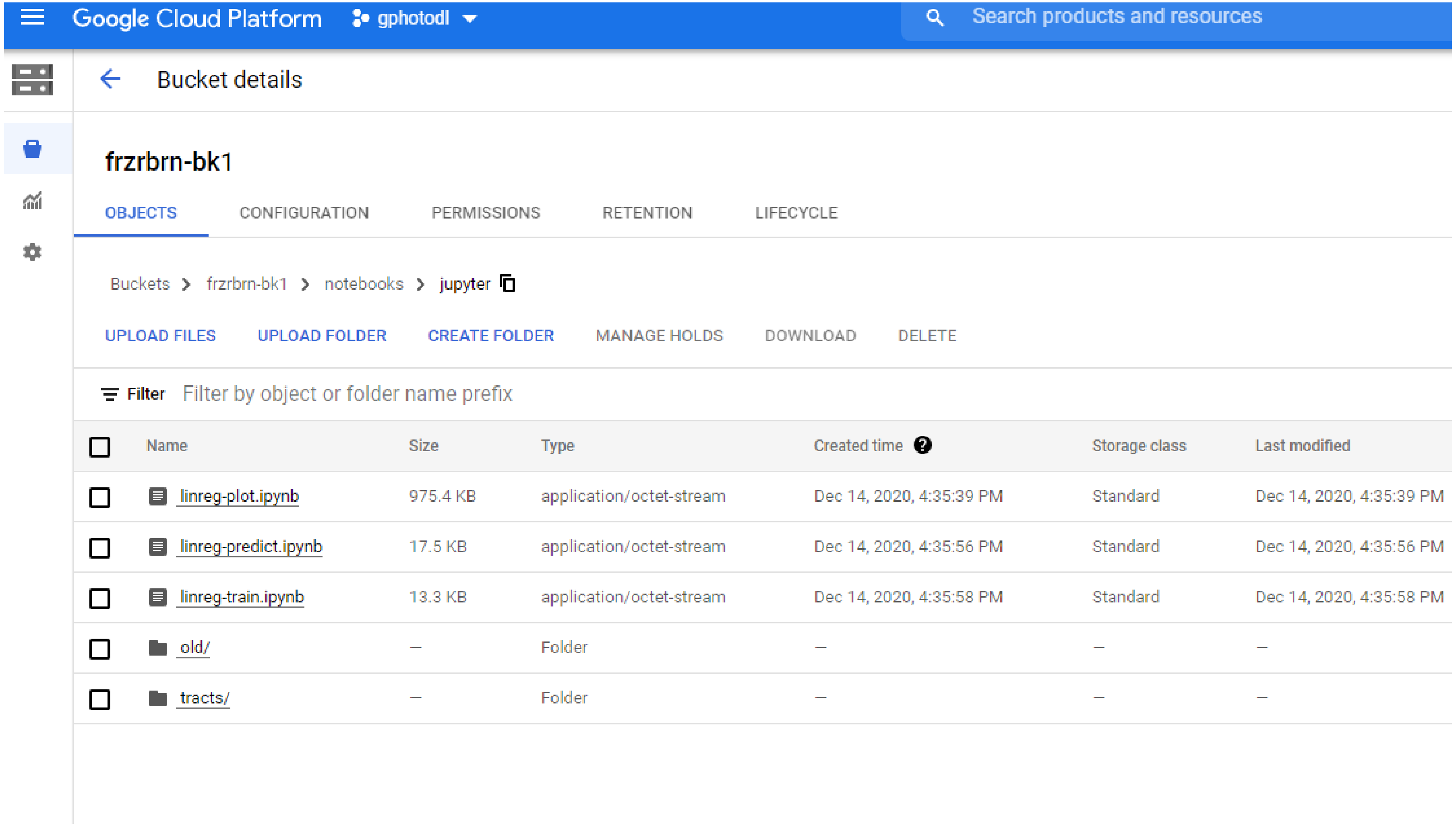


GCP: Dataproc

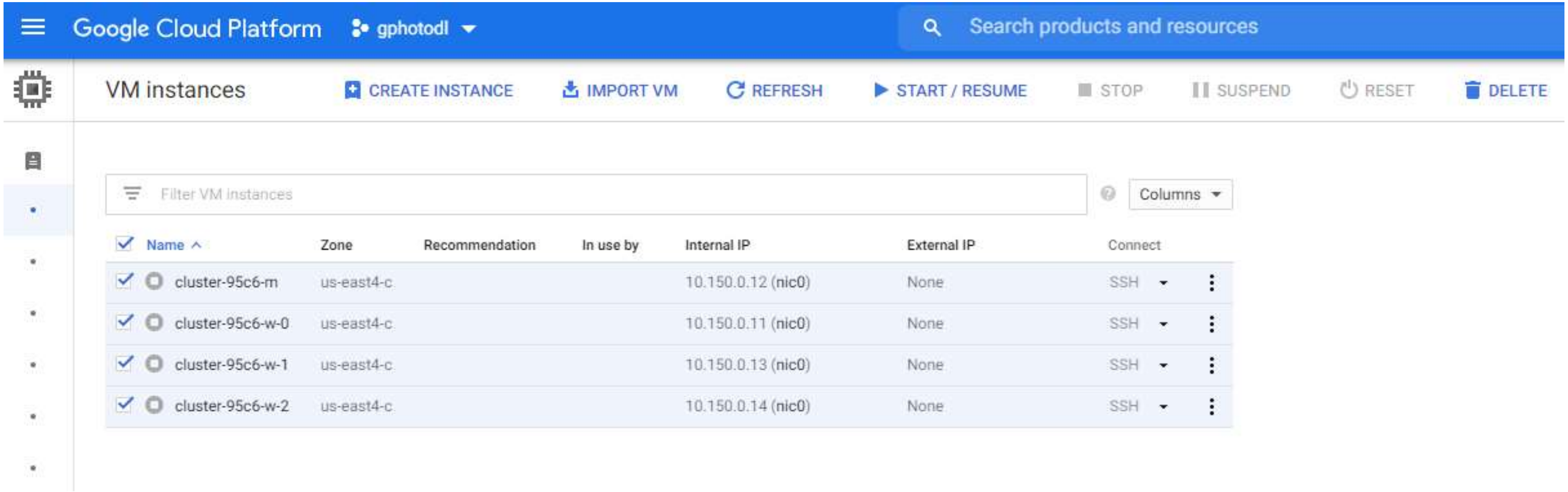
Web interfaces available through 'Component gateway'



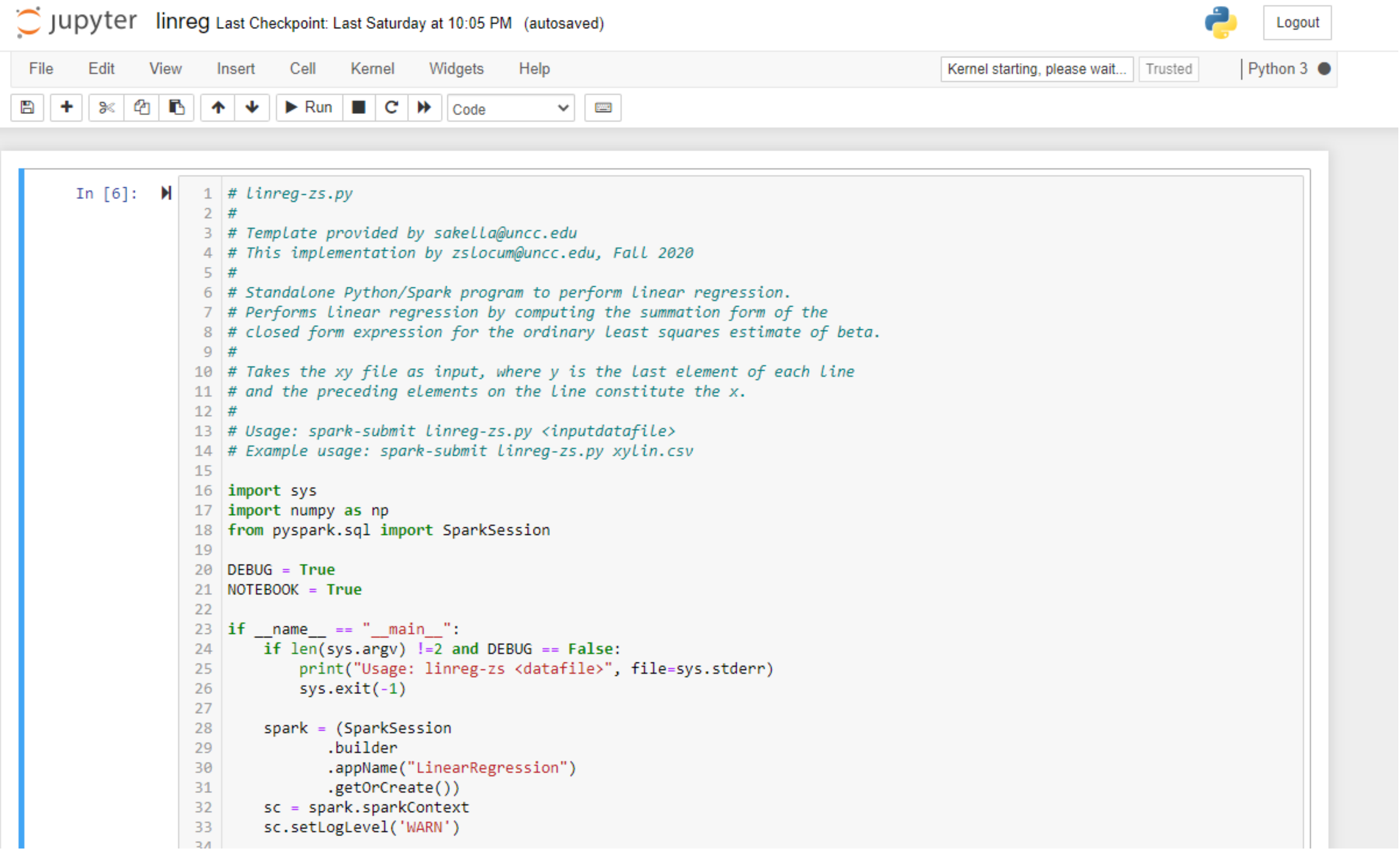
GCP: Bucket access



GCP: Cluster Virtual Machines



Local Jupyter Notebook development



Run Jupyter Notebook Server with pyspark

```
zachery@ubu20lake:~/cc-jnb$ cat run-spark-nb.sh
#!/bin/bash

export PYSPARK_DRIVER_PYTHON=jupyter
export PYSPARK_DRIVER_PYTHON_OPTS='notebook --config /opt/hadoop-3.3.0/pyspark-jnb-config.py'

nohup pyspark &
```

GCP Billing page