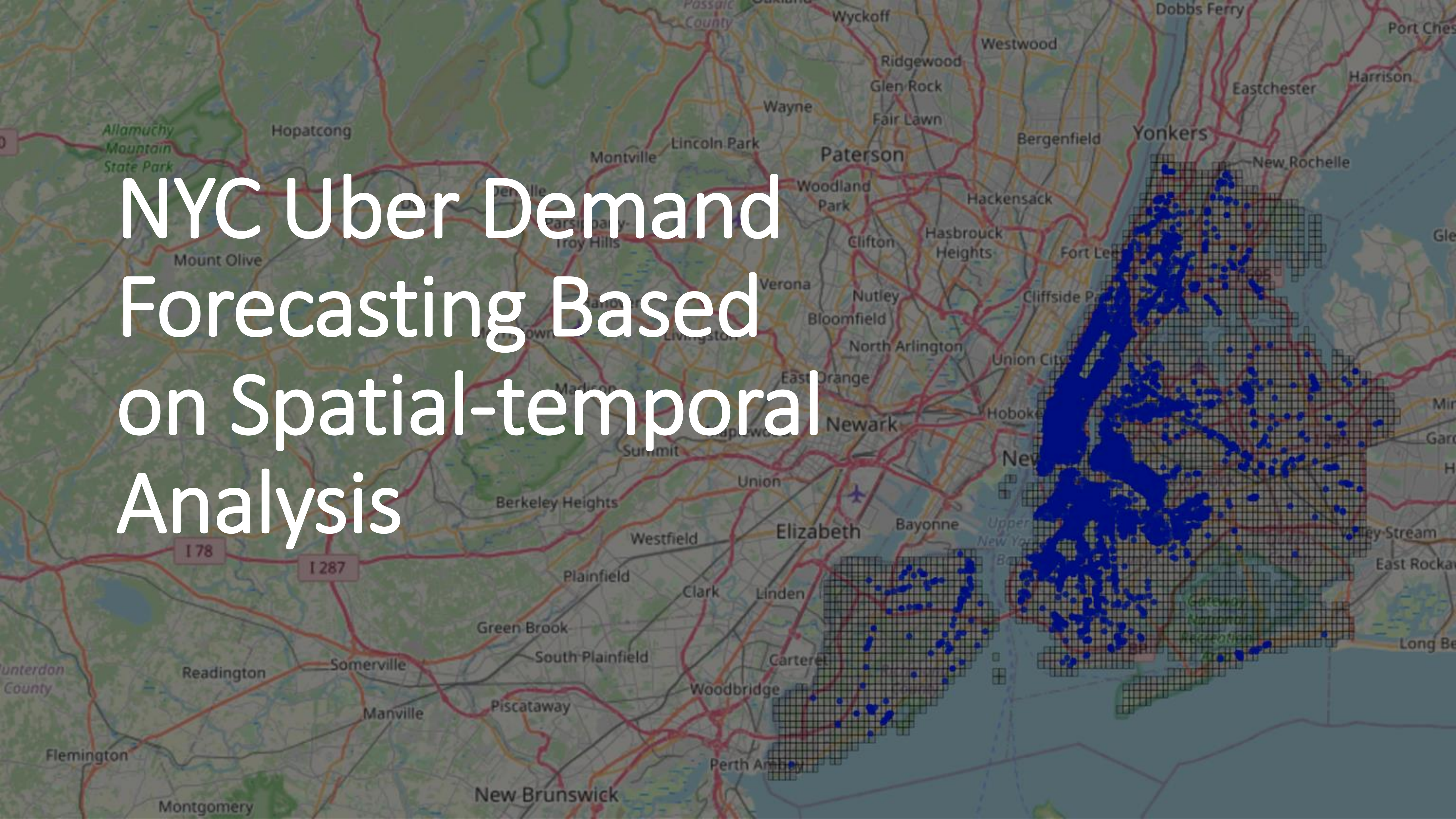
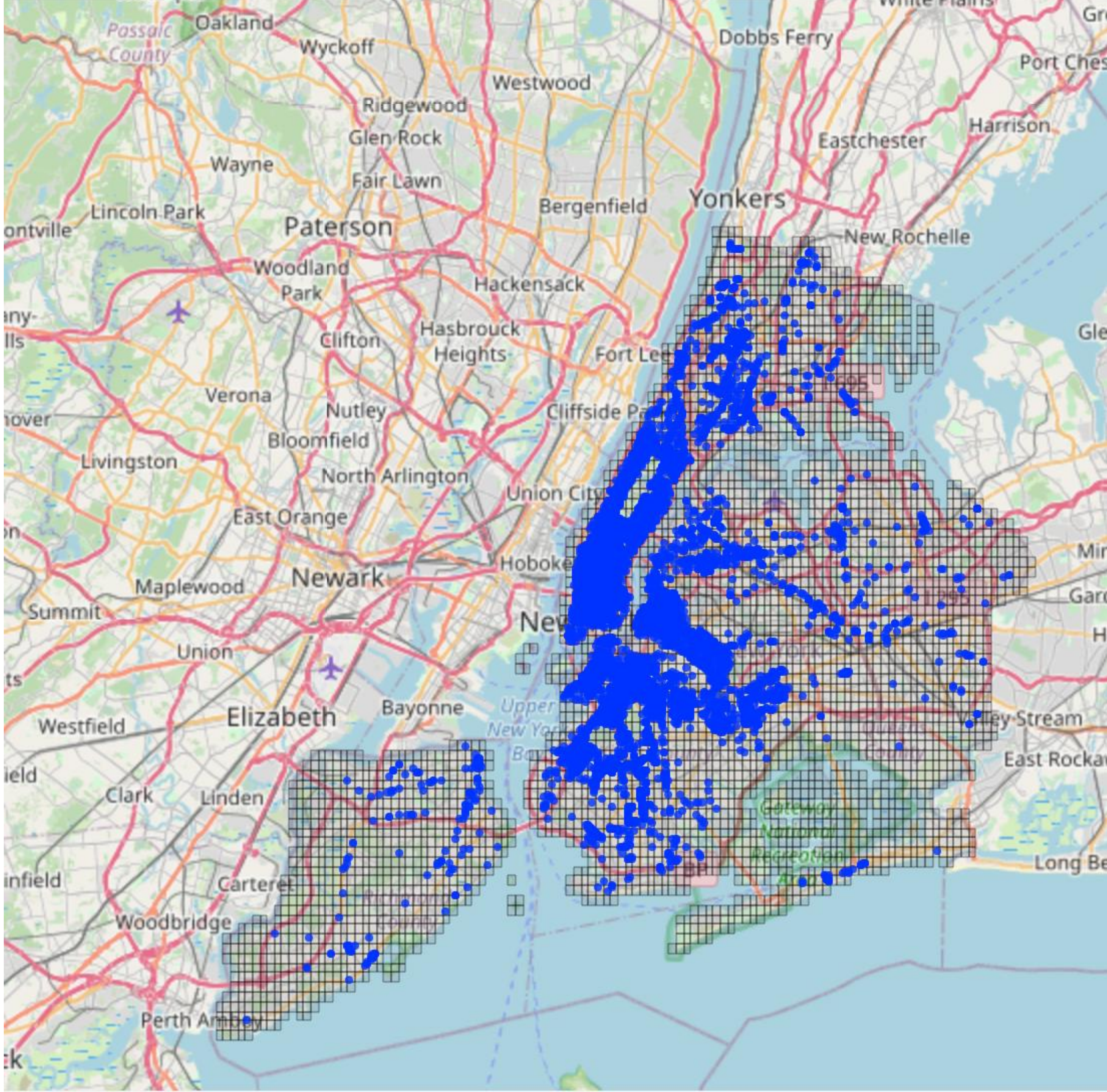
NYC Uber Demand Forecasting Based on Spatial-temporal Analysis



Agenda

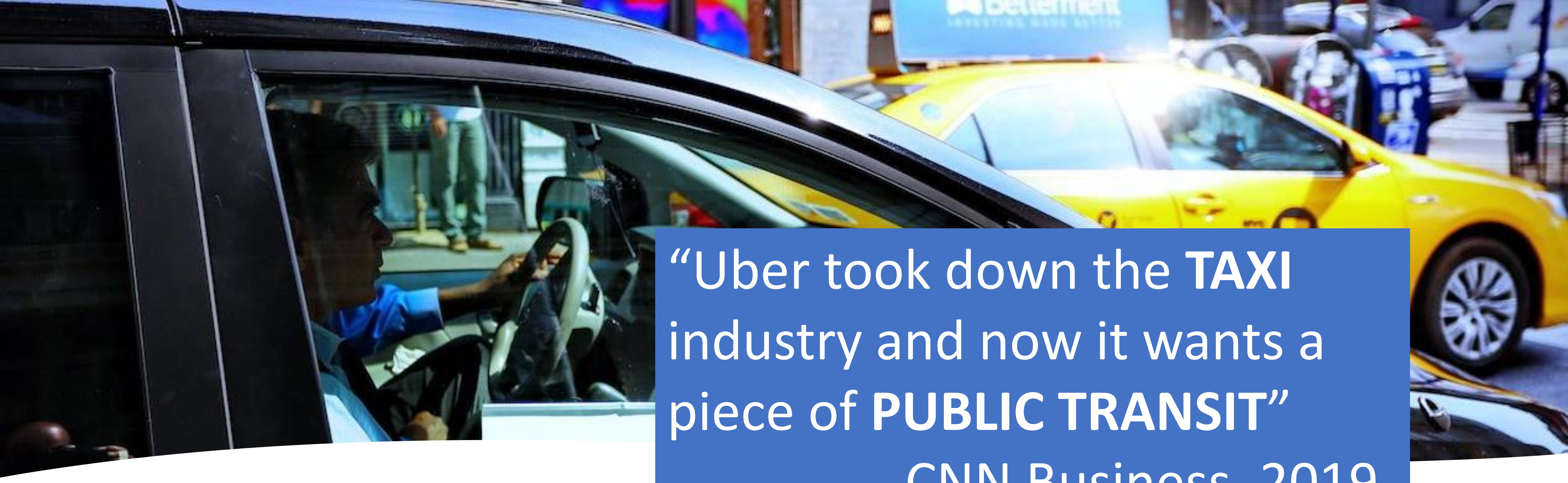
- Purpose of the project
- Methodology
- Exploratory Analysis of NYC Uber Data and it's relationship with other variables
- Model Result : Accuracy

1. Purpose


Oakland
Passaic County
Wyckoff
Dobbs Ferry
Westwood
Port Ches
Ridgewood
Harrison
Glen Rock
Eastchester
Wayne
Fair Lawn
Yonkers
Bergenfield
Lincoln Park
Paterson
New Rochelle
Woodland Park
Hackensack
Hasbrouck Heights
Clifton
Fort Lee
Verona
Nutley
Cliffside Pa
Bloomfield
Livingston
North Arlington
Union City
East Orange
Hoboke
Newark
Maplewood
Summit
Union
Elizabeth
Bayonne
Upper New York Ba
Westfield
Clark
Linden
Carteret
Woodbridge
Perth Amboy
East Rocka
Long Be

Why Forecast Uber Demand

Uber and other ridesharing ideas have become a popular modes and an important part of the transposition system in recent years. To forecast the Uber demand accurately and efficiently will benefit both **Transportation Planners** and **Uber users (drivers & passengers)**



"Uber took down the **TAXI** industry and now it wants a piece of **PUBLIC TRANSIT**"

--- CNN Business, 2019

For Transportation Planners

The collaboration between ridesharing and traditional transportation modes (e.g. transit & taxi) are limited. Transportation planners need to understand the current/future demand of ridesharing to coordinate the transport system as a whole.

For
Uber Users
(driver &
passengers)

Better user experience;

Inform drivers and passengers about the predicted Uber demand will help them to arrange their trip plan and improve the efficiency.

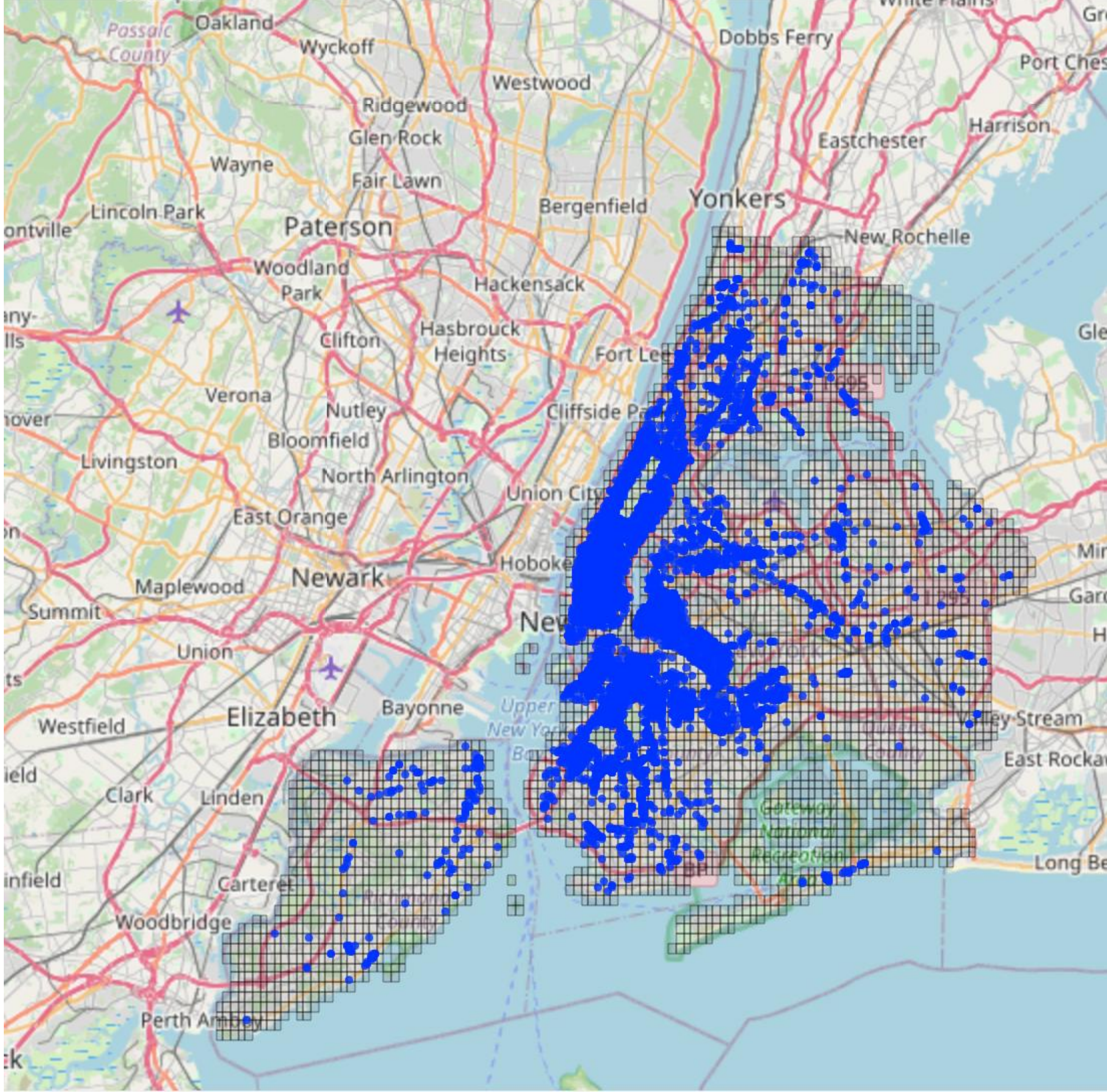
Purposes of the Project

1. Explore the NYC's Uber demand **distribution**

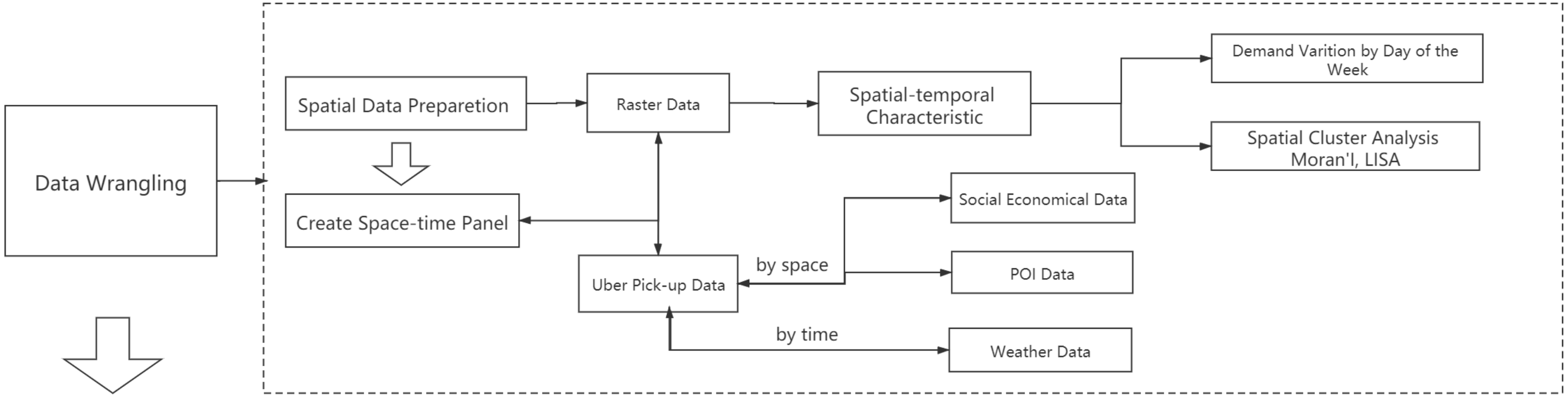
2. Explore which variables **impact** NYC’s Uber demand (pickup)

3. Build an **accurate** predictive model based on Linear regression

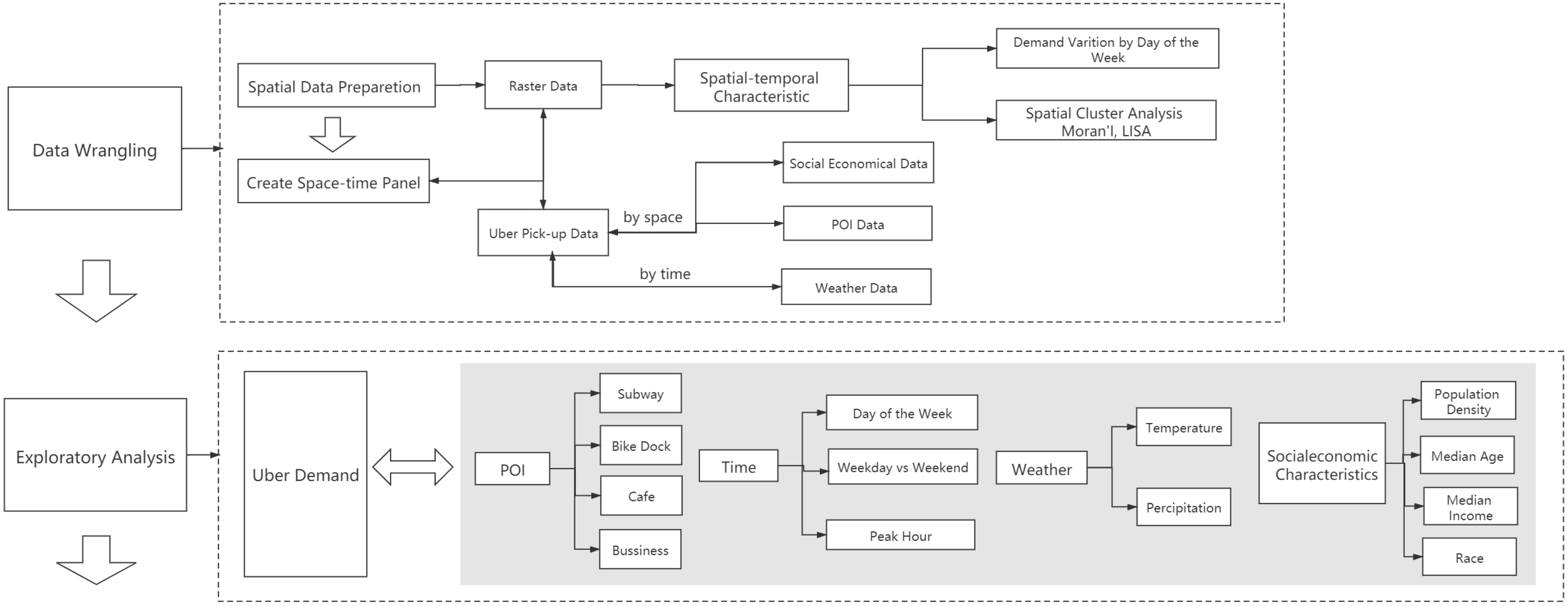
2. Methodology



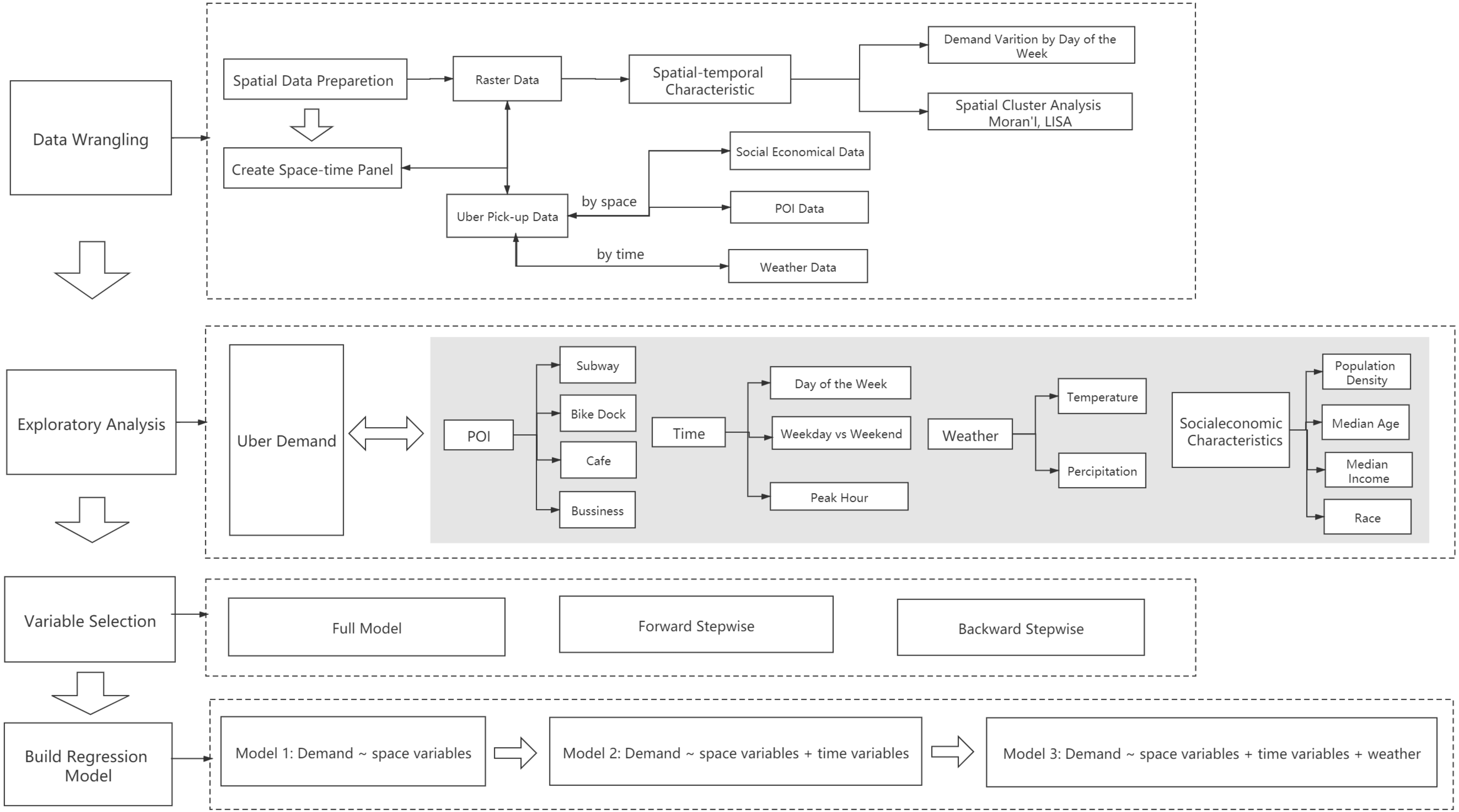
Methodology



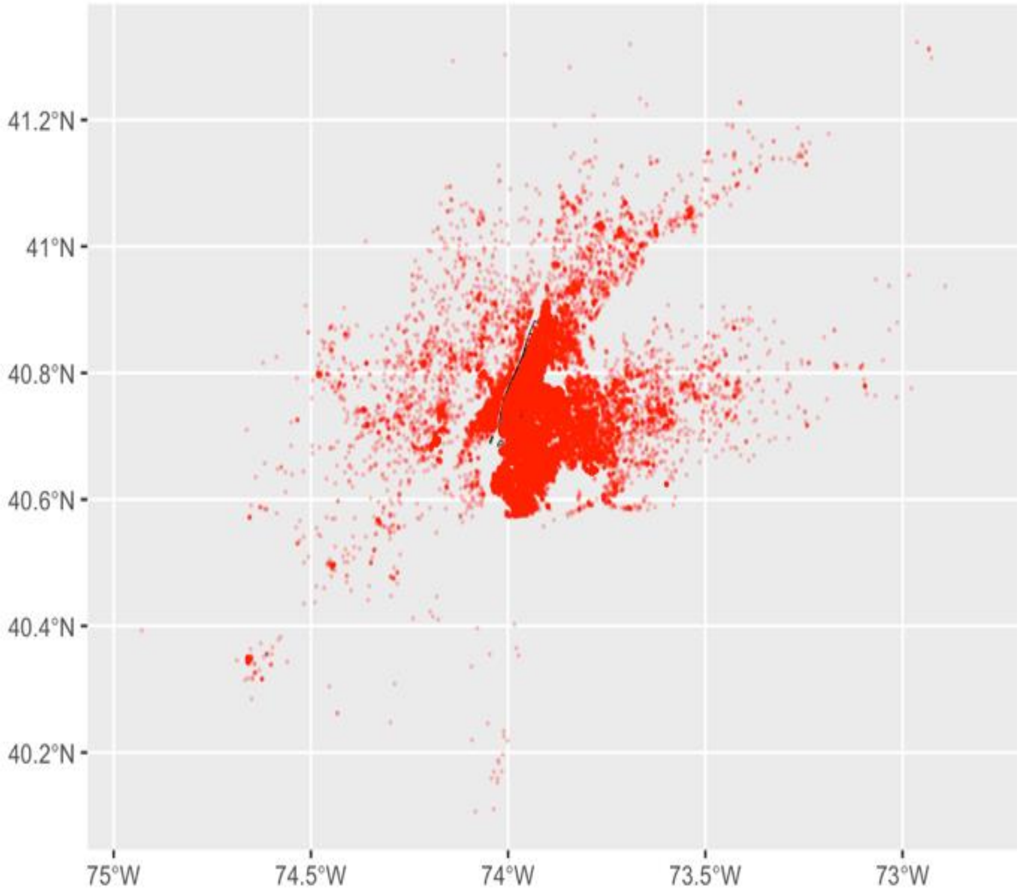
Methodology



Methodology



NYC Uber Pickup data



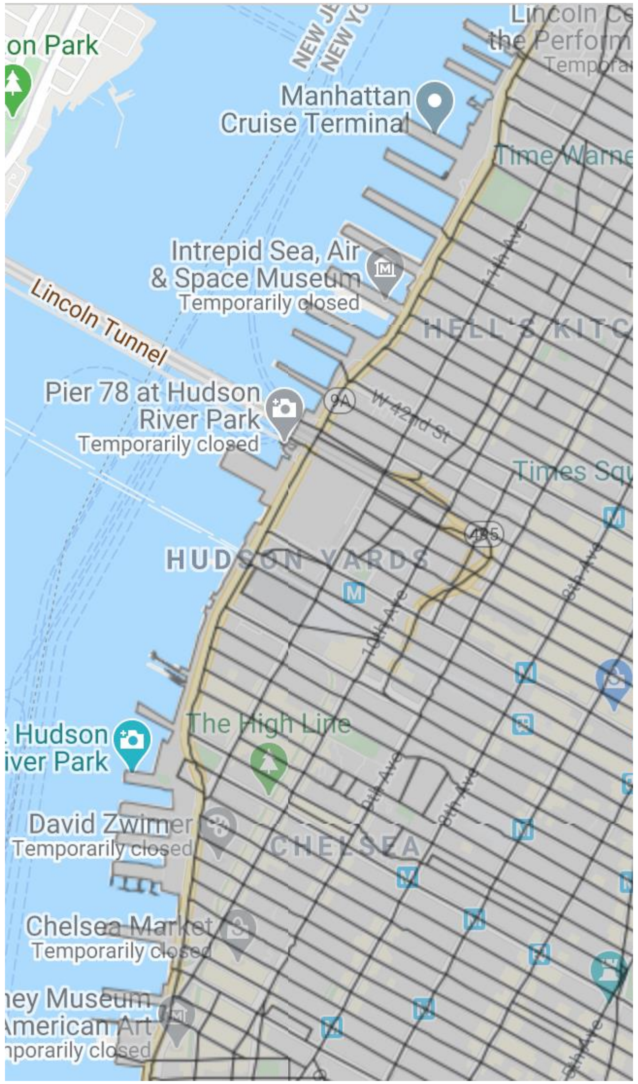
Data Name	2014-May NYC Uber pickup raw data
Source	Kaggle
Size	**652,435 row**

	Date.Time	Lat	Lon
1	5/1/2014 0:02:00	40.7521	-73.9914
2	5/1/2014 0:06:00	40.6965	-73.9715
3	5/1/2014 0:15:00	40.7464	-73.9838
4	5/1/2014 0:17:00	40.7463	-74.0011
5	5/1/2014 0:17:00	40.7594	-73.9734
6	5/1/2014 0:20:00	40.7685	-73.8625

Analysis Unit - Why Raster

NYC Census Tract

NYC Census Block

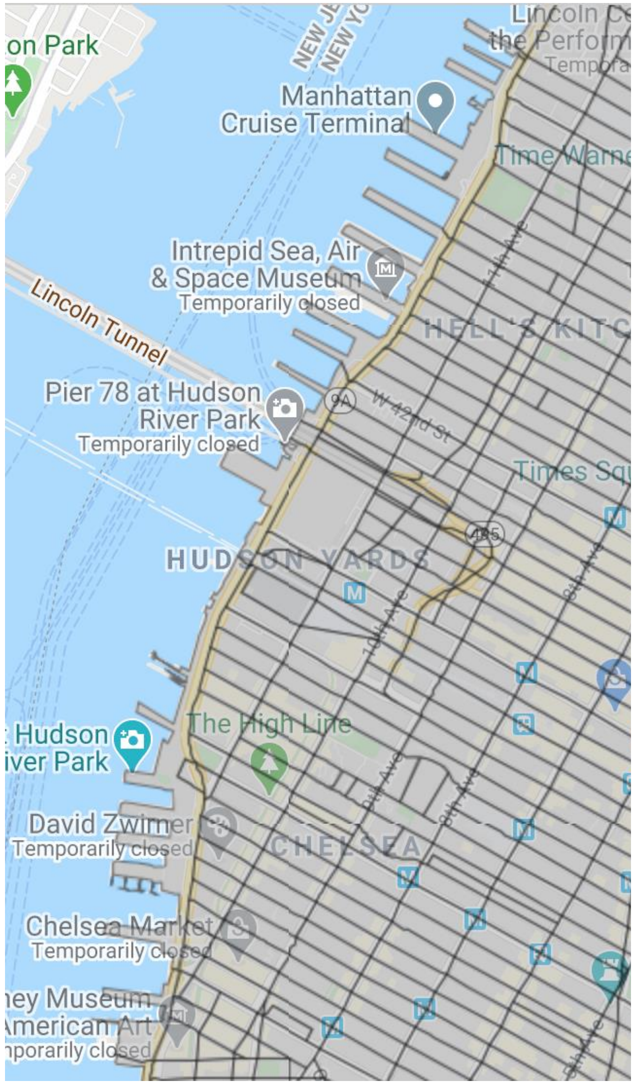


?

Analysis Unit - Why Raster

NYC Census Tract

NYC Census Block



NYC & 500*500m grids

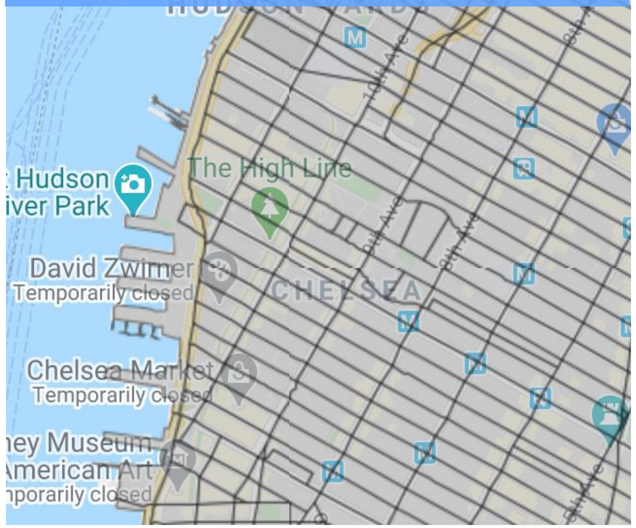
Analysis Unit - Why Raster

NYC Census Tract

The size of census tracts is different, difficult to observe the real demand

NYC Census Block

Size too small, can't count the pickup within the blocks since the boundary is the street



NYC & 500*500m grids

Same size, easier to find out which small grid is the busiest one, and help the Tranpsortation planners or Uber users to make a decision. Because of the coding limitation, we didn't rotate the grids to make it in line with the street direction, but we should.

Related Variables

Time

Weather

Space

NYC Uber Demand Related Variables

Time

Day of Week

Time of Day

Holiday

NYC Uber Demand Related Variables

Time
- Day of Week
- Time of Day
- Holiday

Weather
- Temperature
- Precipitation
- Wind Speed

NYC Uber Demand Related Variables

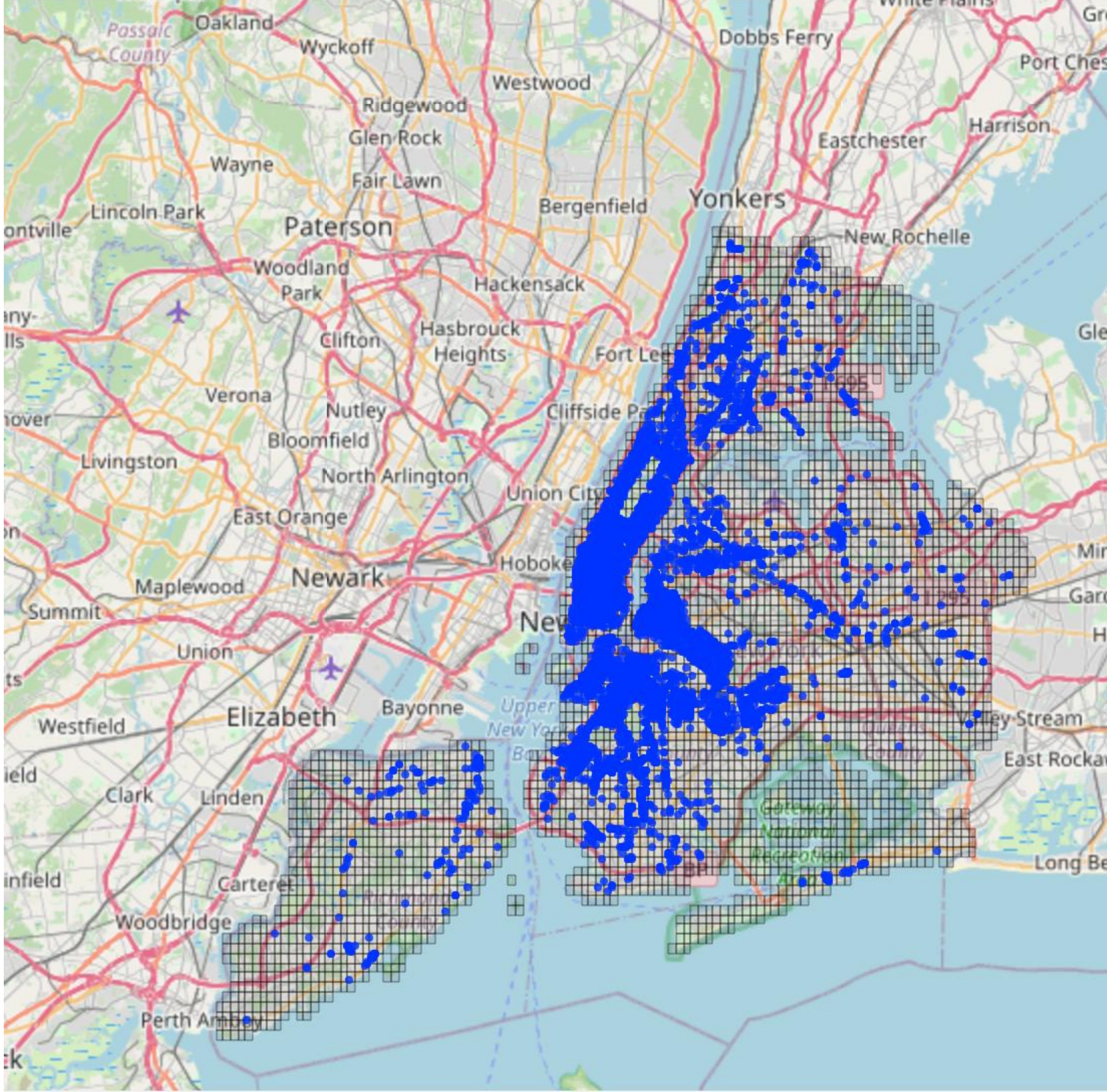
Space

- POI
  - Subway
  - Bike dock
  - Business
  - Neighborhood
  - Café application
- Social Economy
  - Pop Density
  - Med Income
  - Med Age
  - Travel time
  - Number of people taking public transit
  - Café application
  - White %
  - Number of commuter

Related Variables Summary

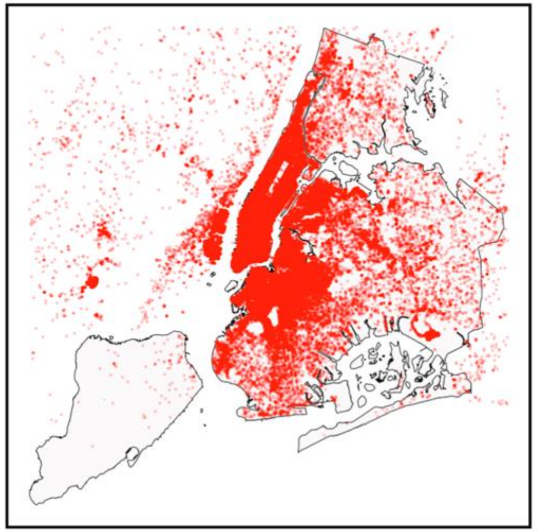
Variable	Data Source	Data Time	Data Size (row)
Bike parking dock	NYC DOT	2017	11734
Subway Entries	NYC open data	2018	1928
Sidewalk Cafe application	NYC open data	2017	1448
Legal operating business	NYC open data	2014	84,383
American Community Survey	ACS	2014	-
Weather		2014-May	-
NYC boundary data	NYC open data	2018	195

3. Exploratory Analysis

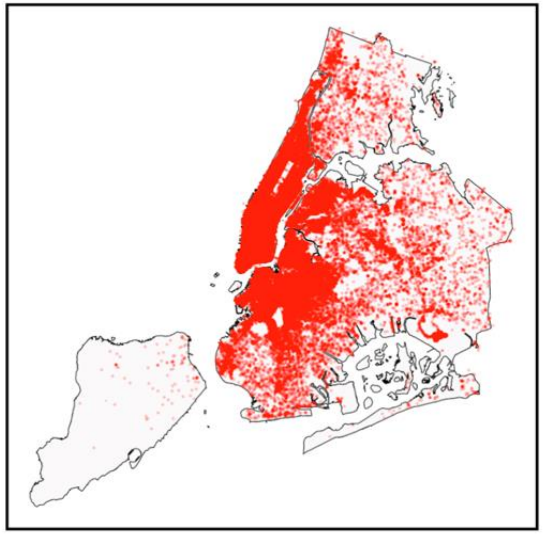


NYC Uber Pickup data

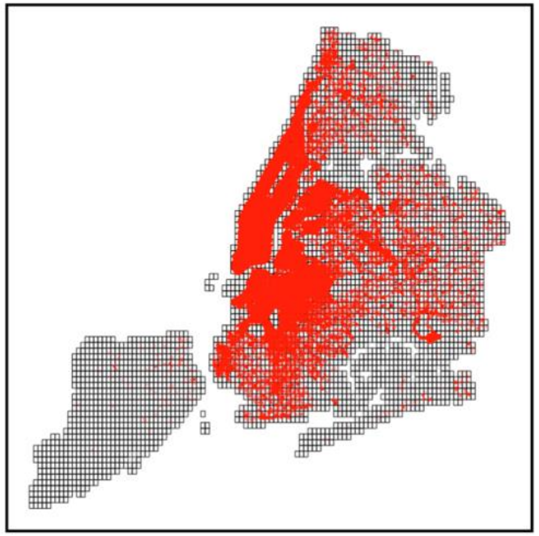
Raw data



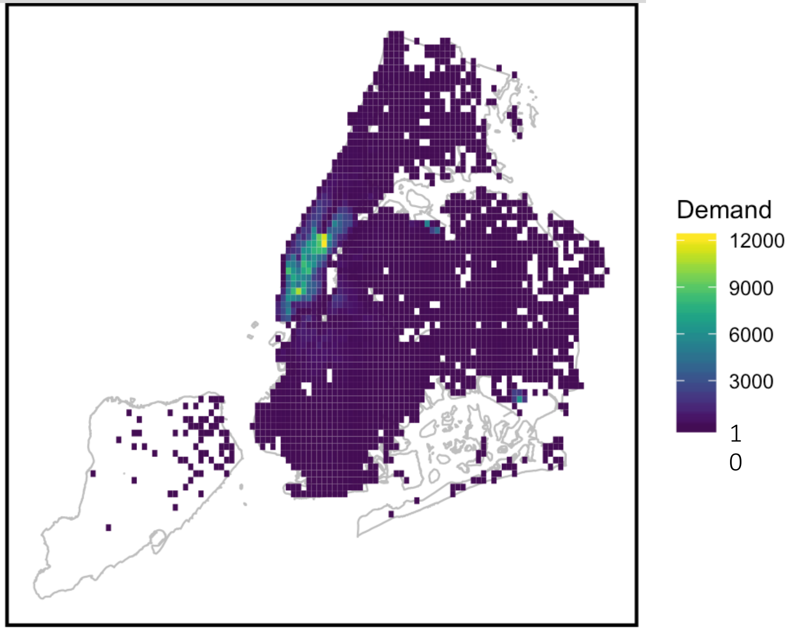
Intersect with NYC boundary



Pickup data with Raster



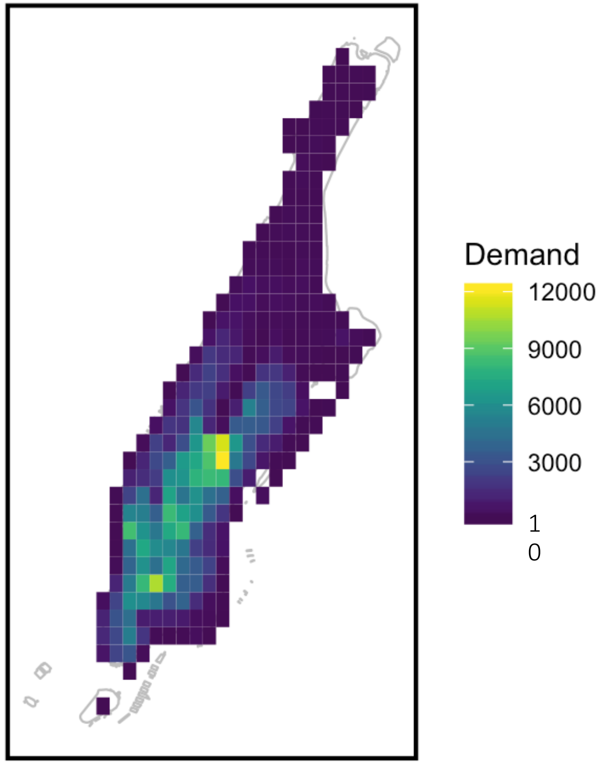
Count of Uber Pickup for each grid



500*500m grid
In total 3949 grids

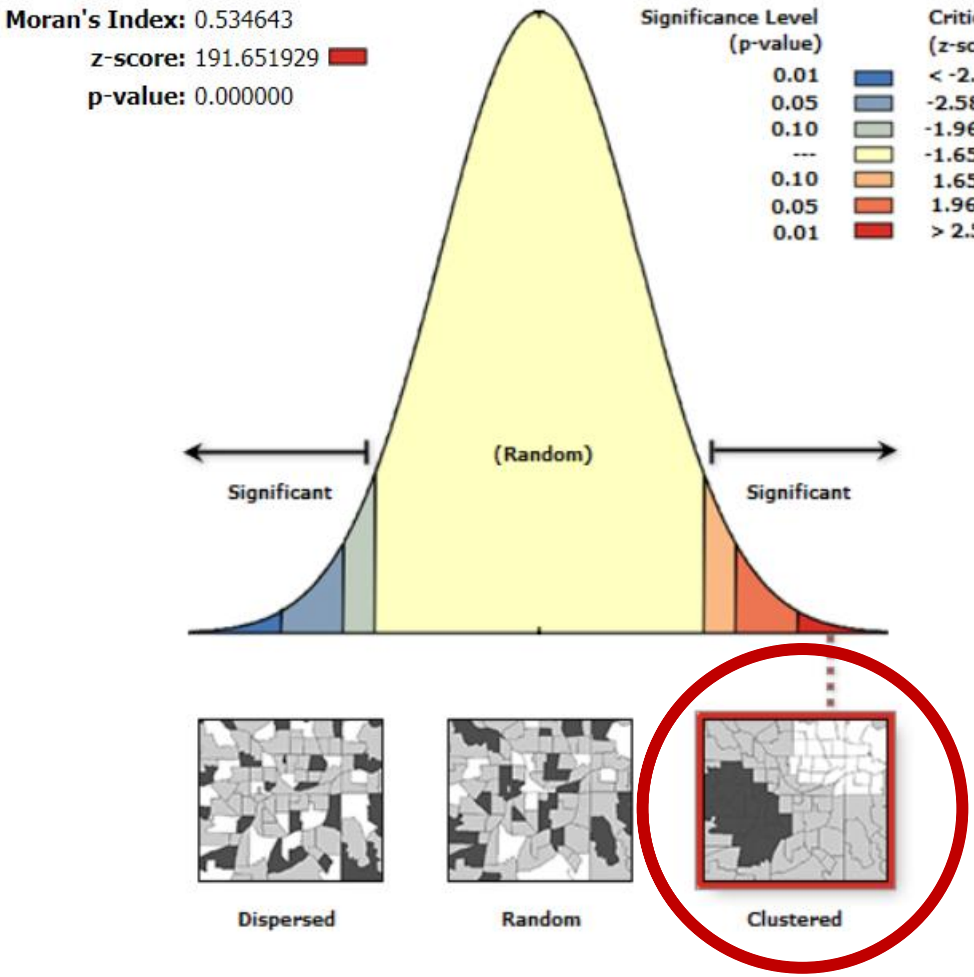
Zoom in to Manhattan

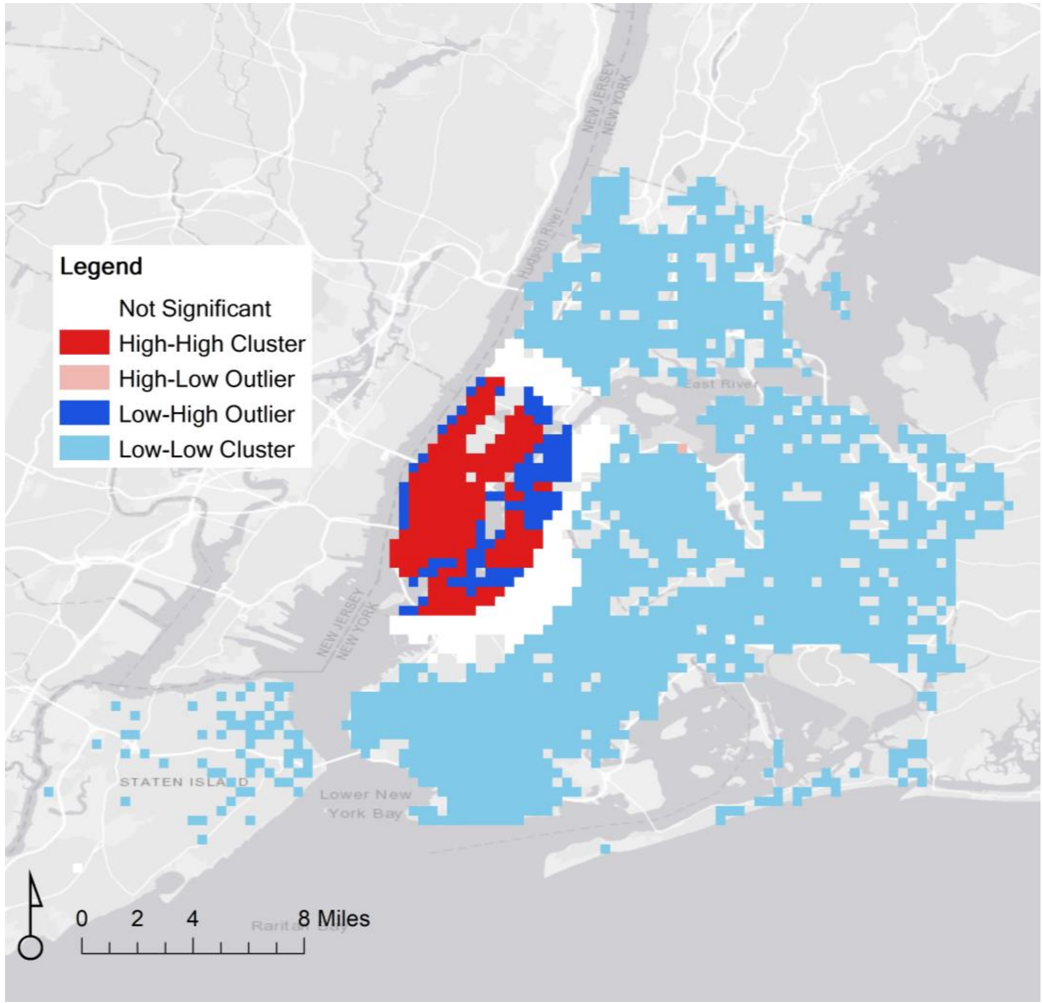
Manhattan Uber Demand



Top 10 Busy Uber Pickup Grid

NYC Uber Pickup - Spatial Cluster Analysis (Moran'I)





Related Variables

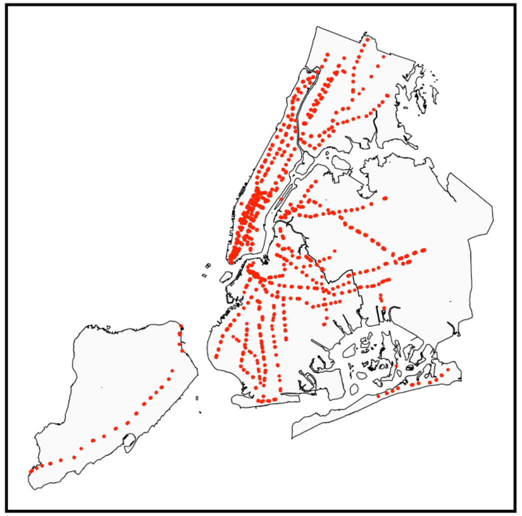
Space

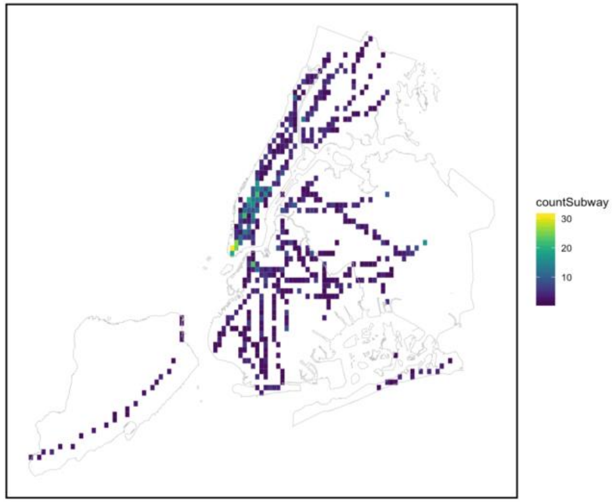
Time

Weather

Exploratory Analysis – Space

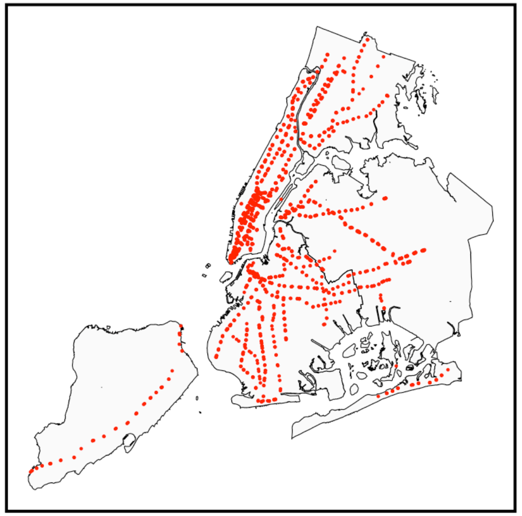
Subway Entrance

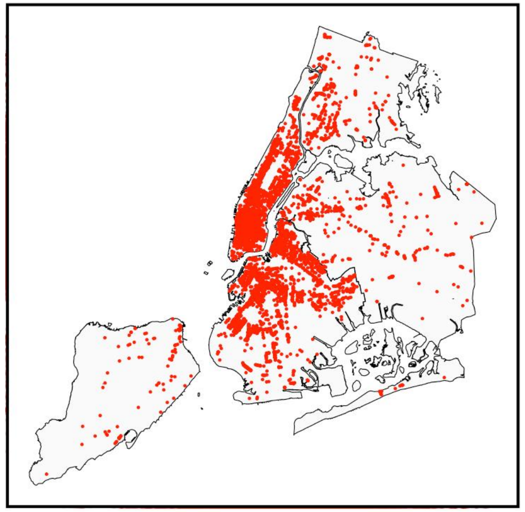


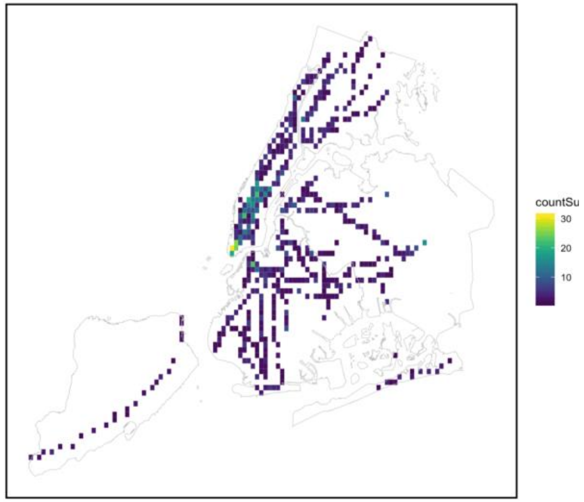


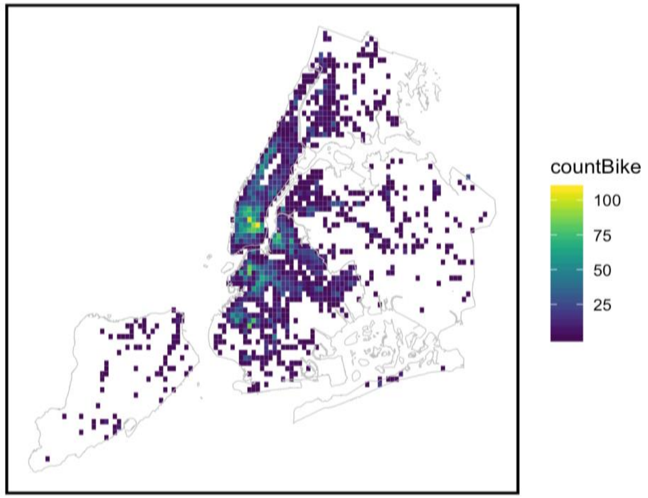
Exploratory Analysis – Space

Subway Entrance	Bike Dock

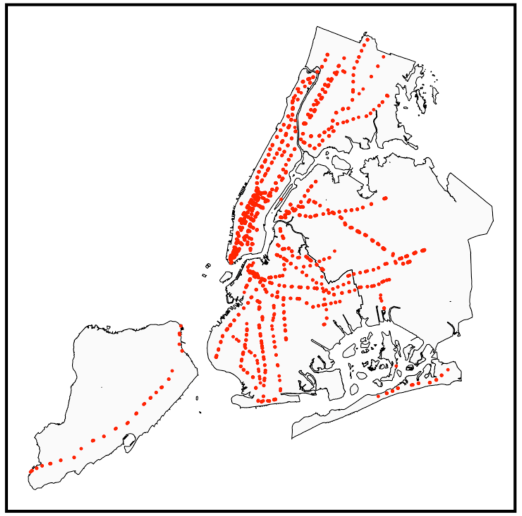
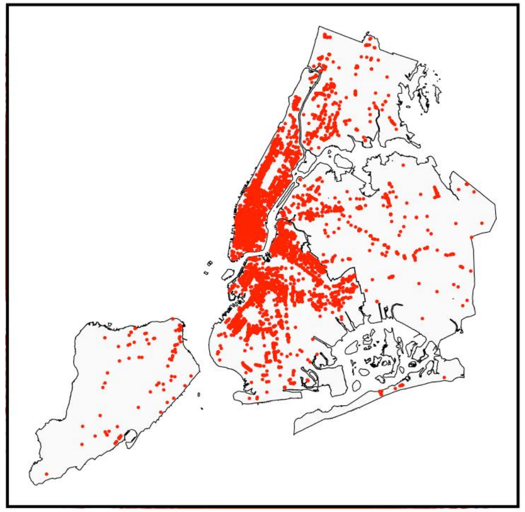
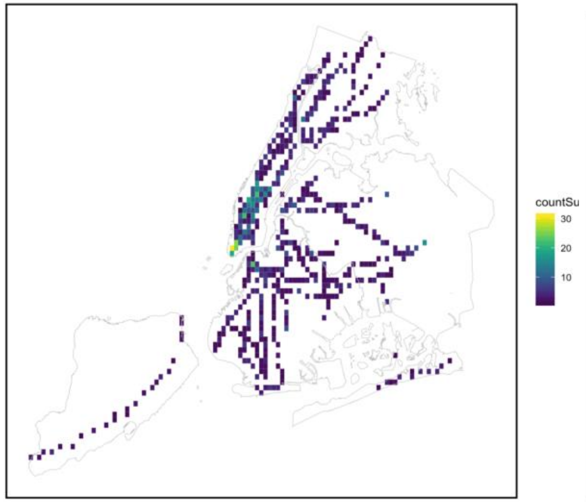
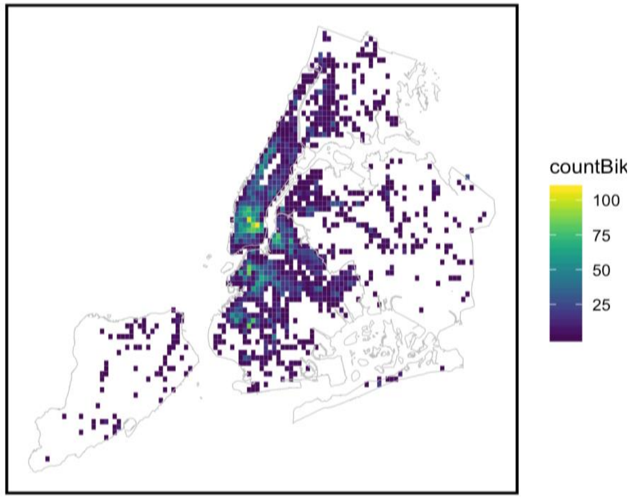
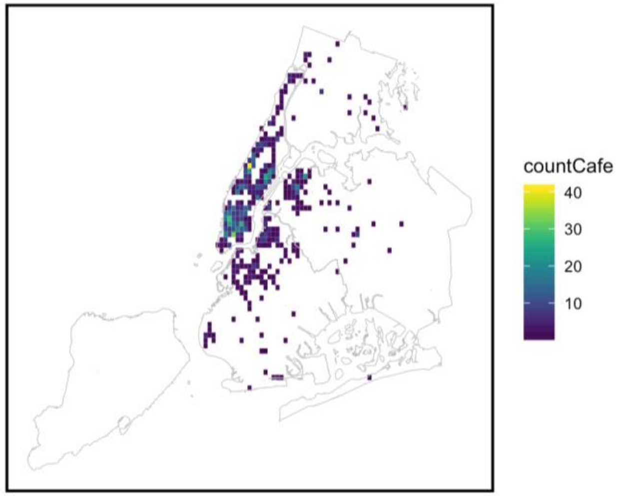






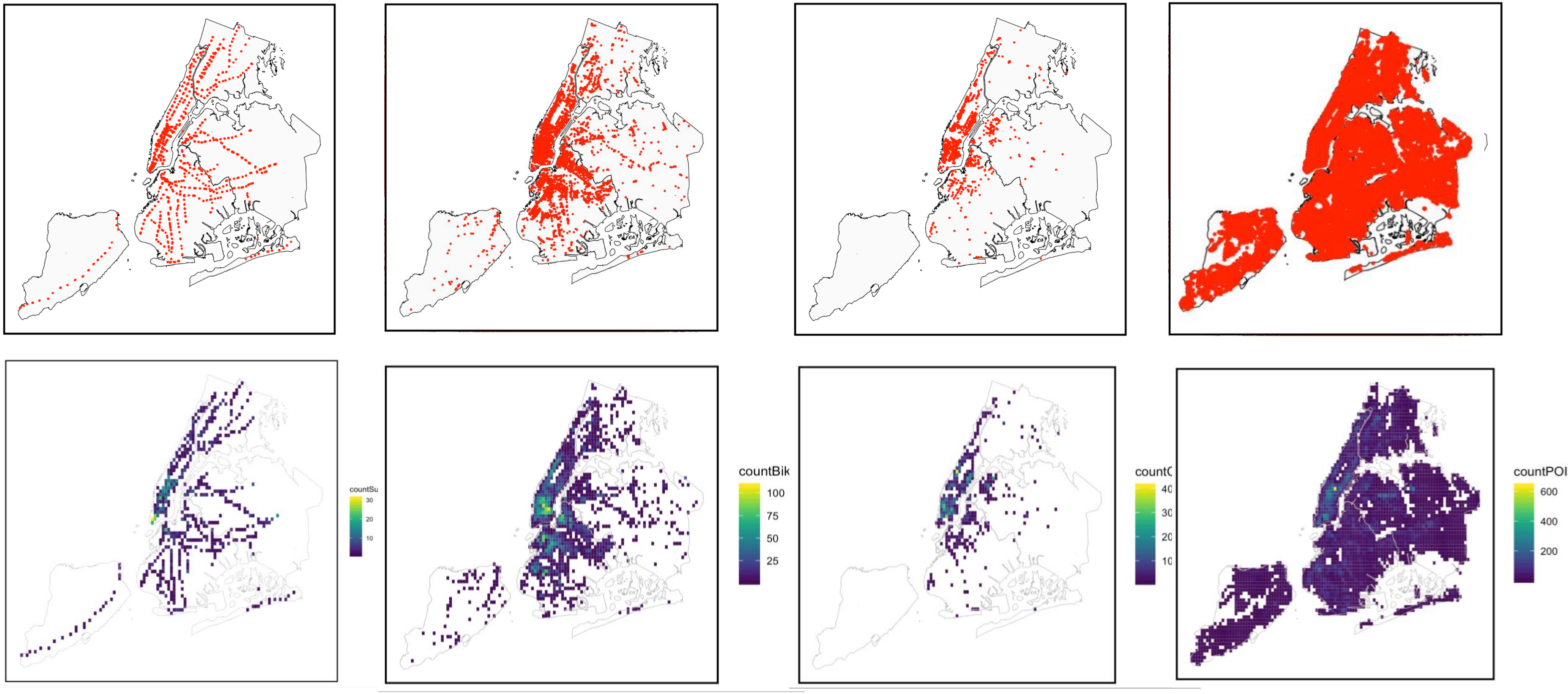


Exploratory Analysis – Space

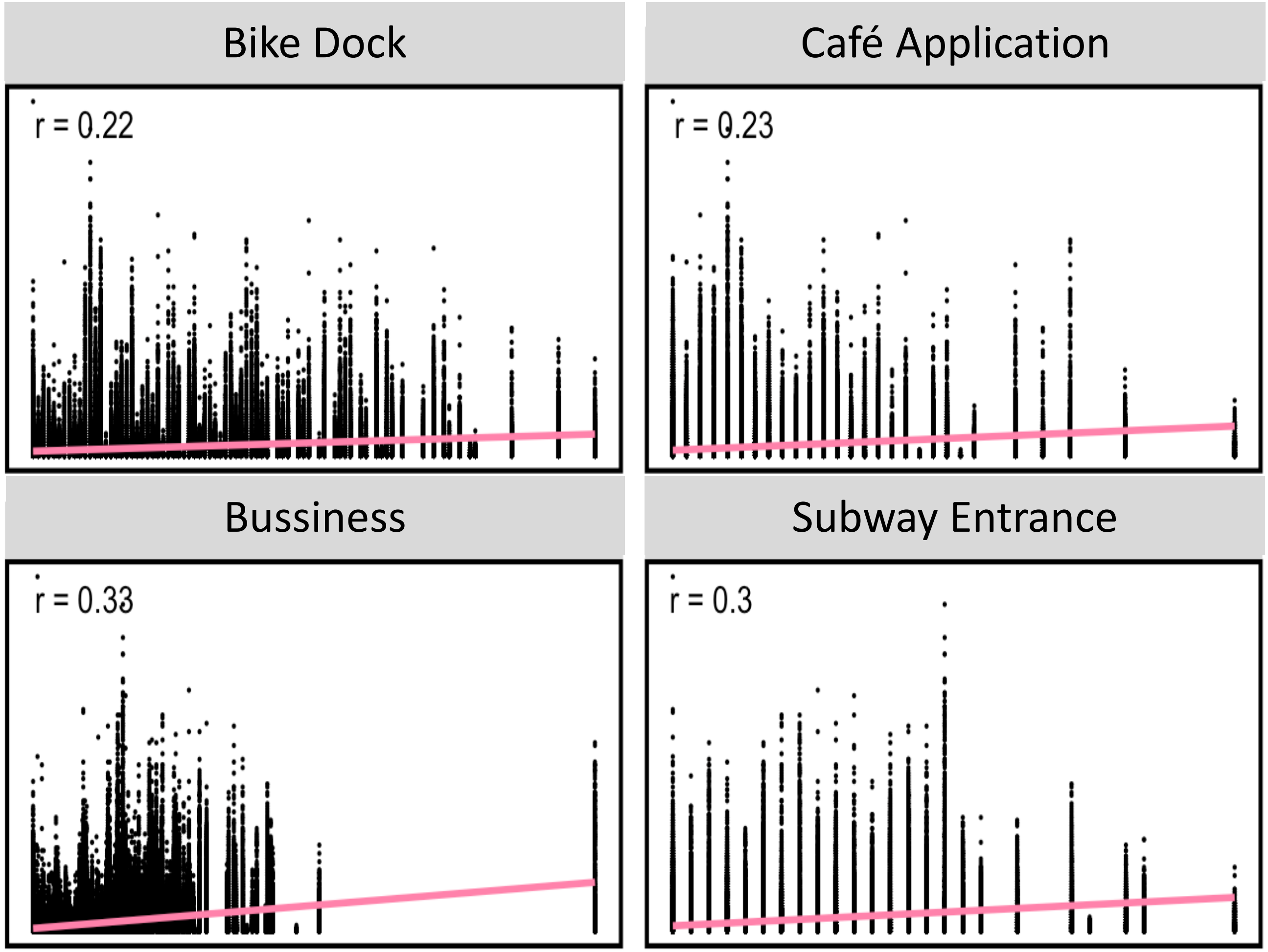
Subway Entrance	Bike Dock	Café Application
		
		

Exploratory Analysis – Space

Subway Entrance	Bike Dock	Café Application	Legal Bussiness

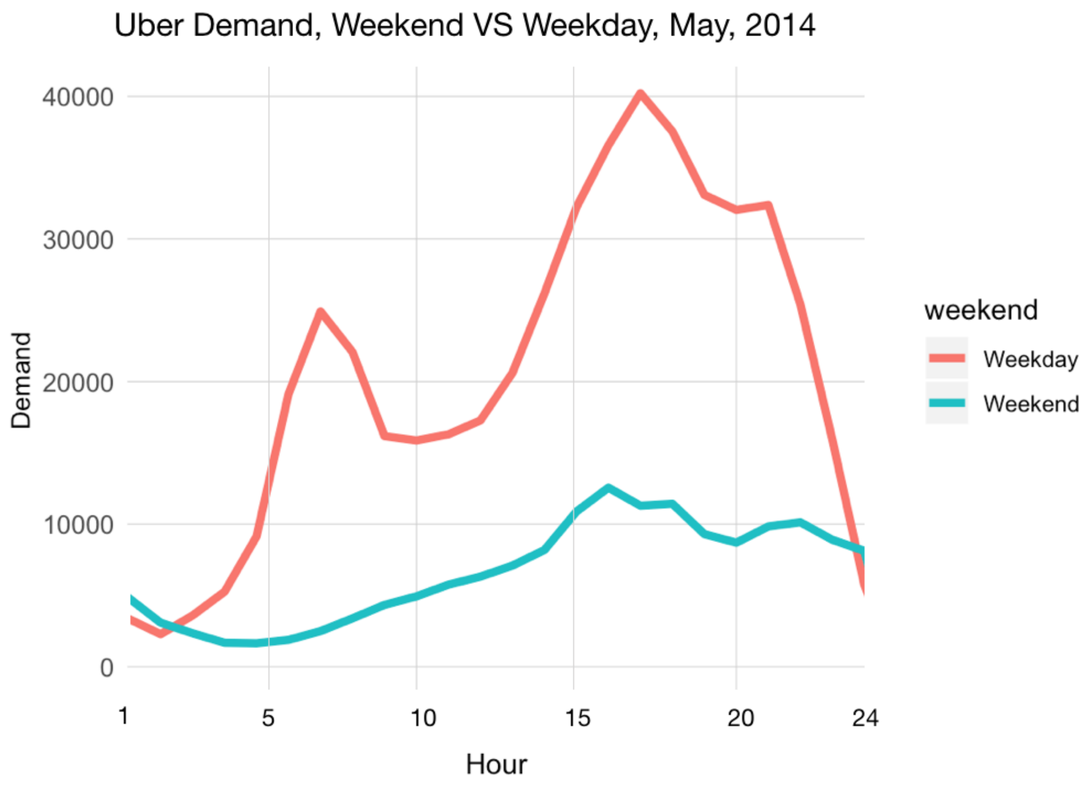


Exploratory Analysis – Space

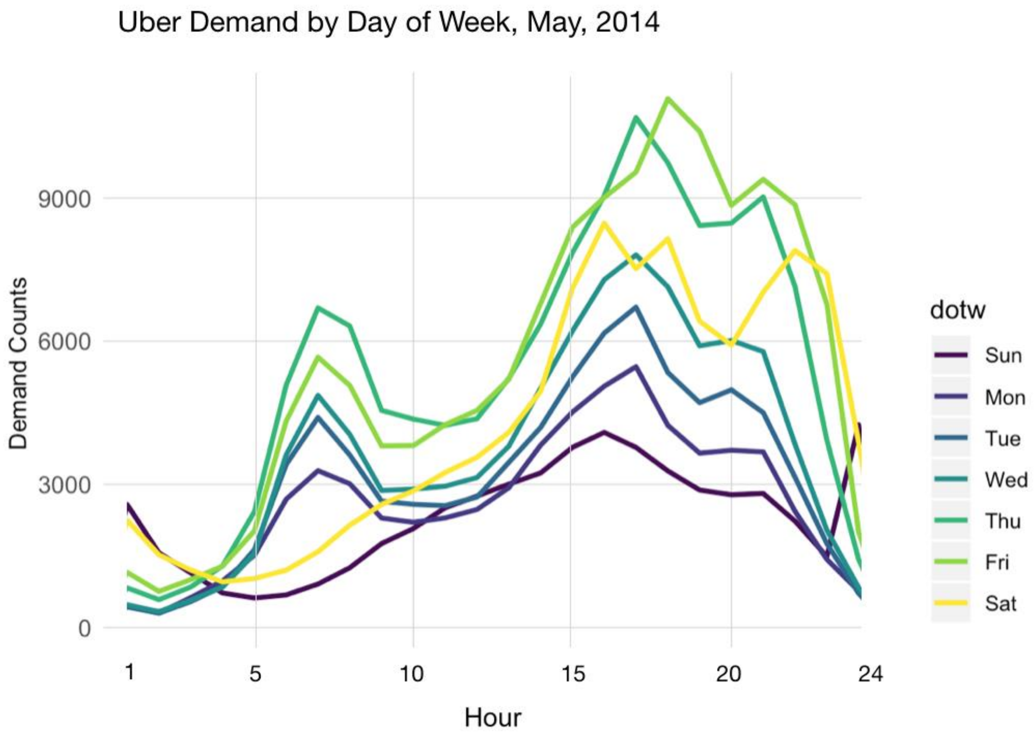


The Demand for Uber has a **positive correlation** with the number of bike dock, subway entrance, business and café within the raster.

Exploratory Analysis – Time

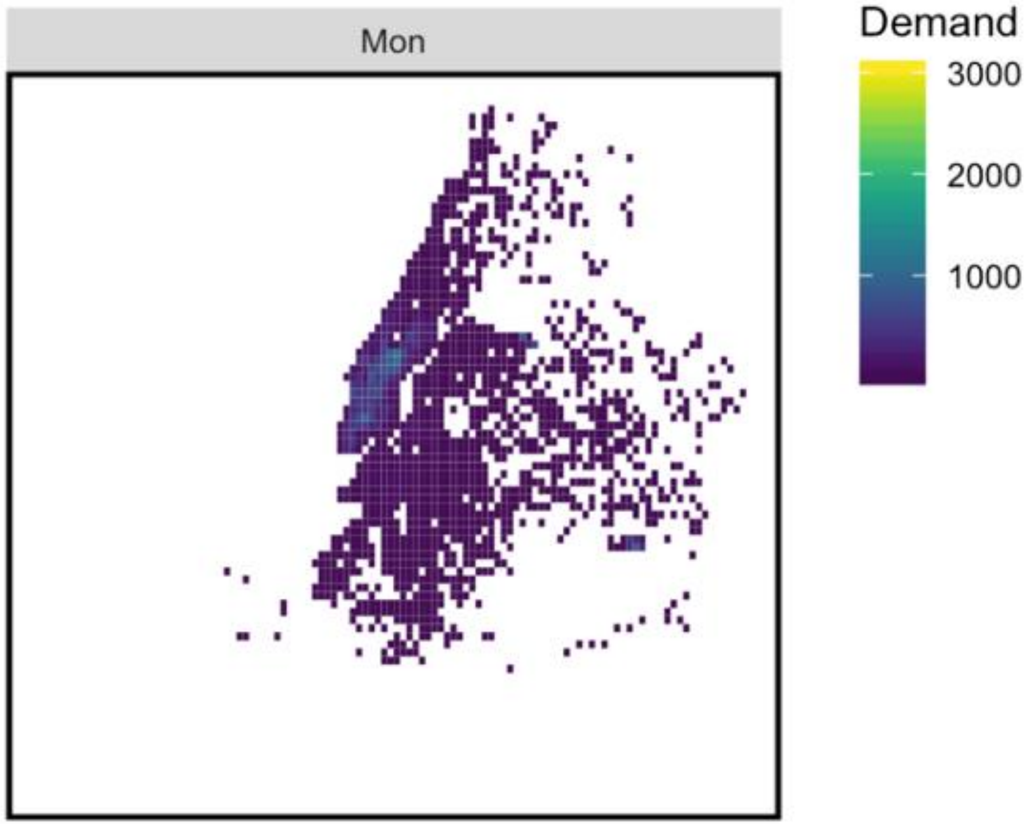


The demand for Uber on weekdays is significantly higher than on weekends and shows a significant **AM and PM peak**, the demand is related to **commuting**.



The demand for Uber increase from Monday to Friday, and then decreases at the weekend.

Exploratory Analysis – Time

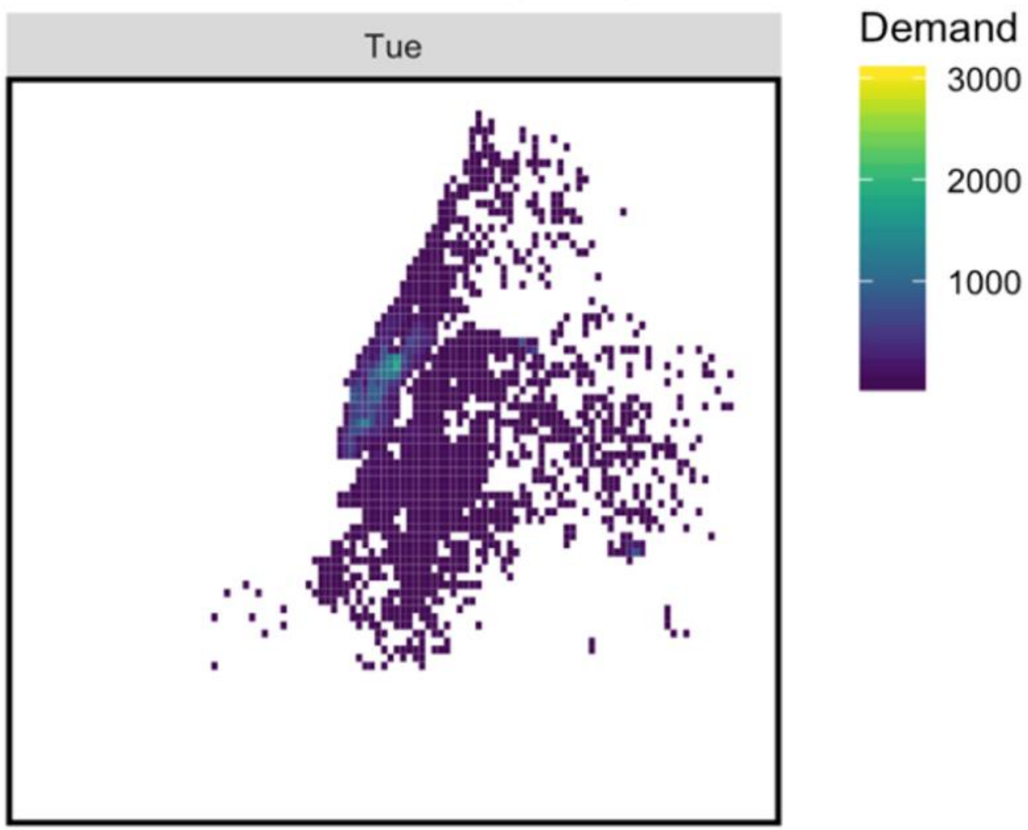


Uber demand distribution evolved for different day of week.

For **Weekday**, the number of Uber pickup is increasingly clustered in Manhattan from Monday to Friday.

For **Weekend**, the number of Uber pickup area related few and no obvious clustering.

Exploratory Analysis – Time



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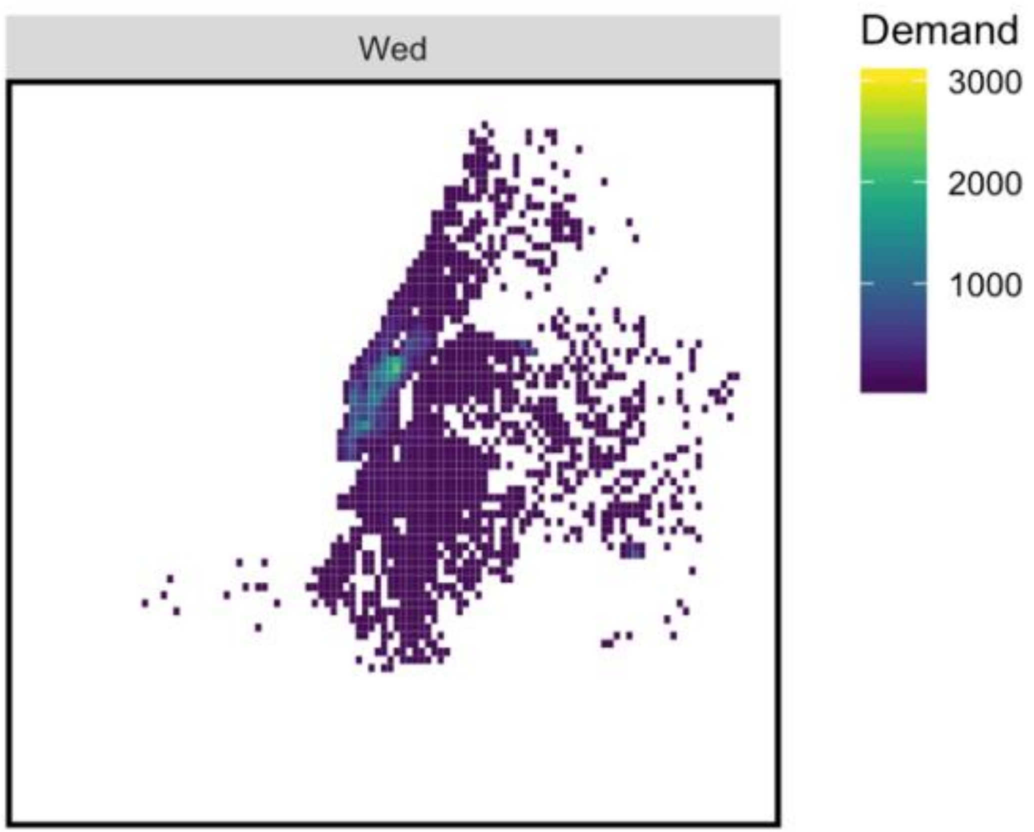

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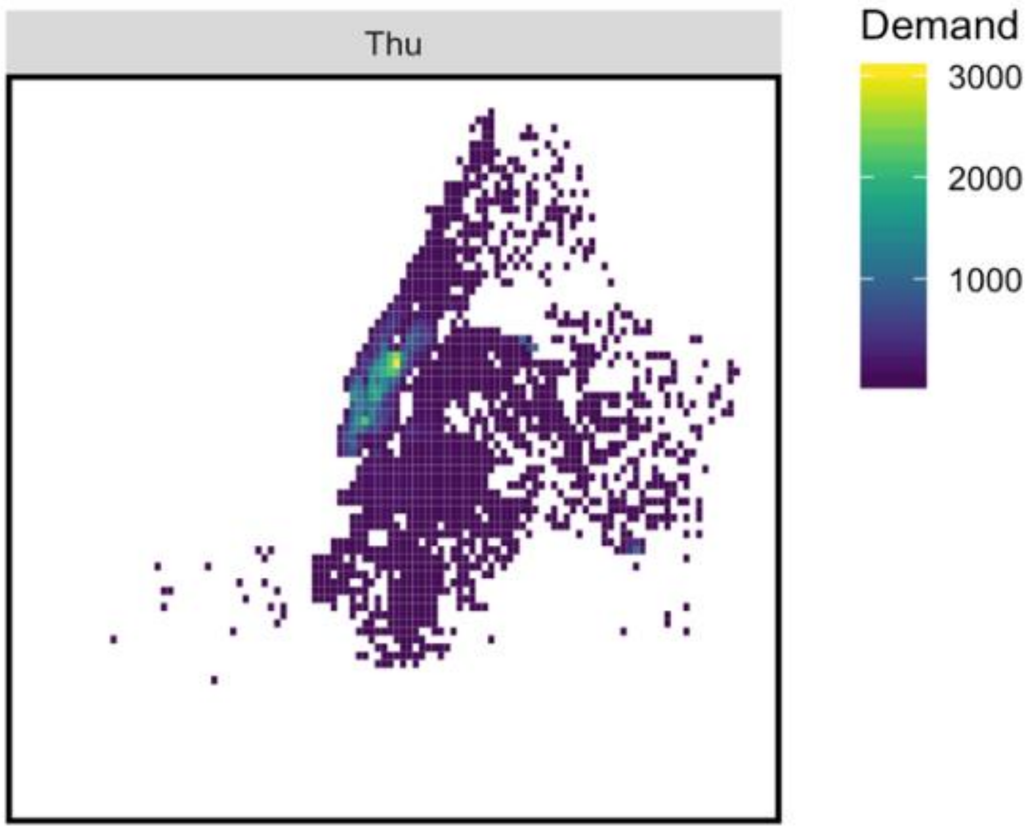

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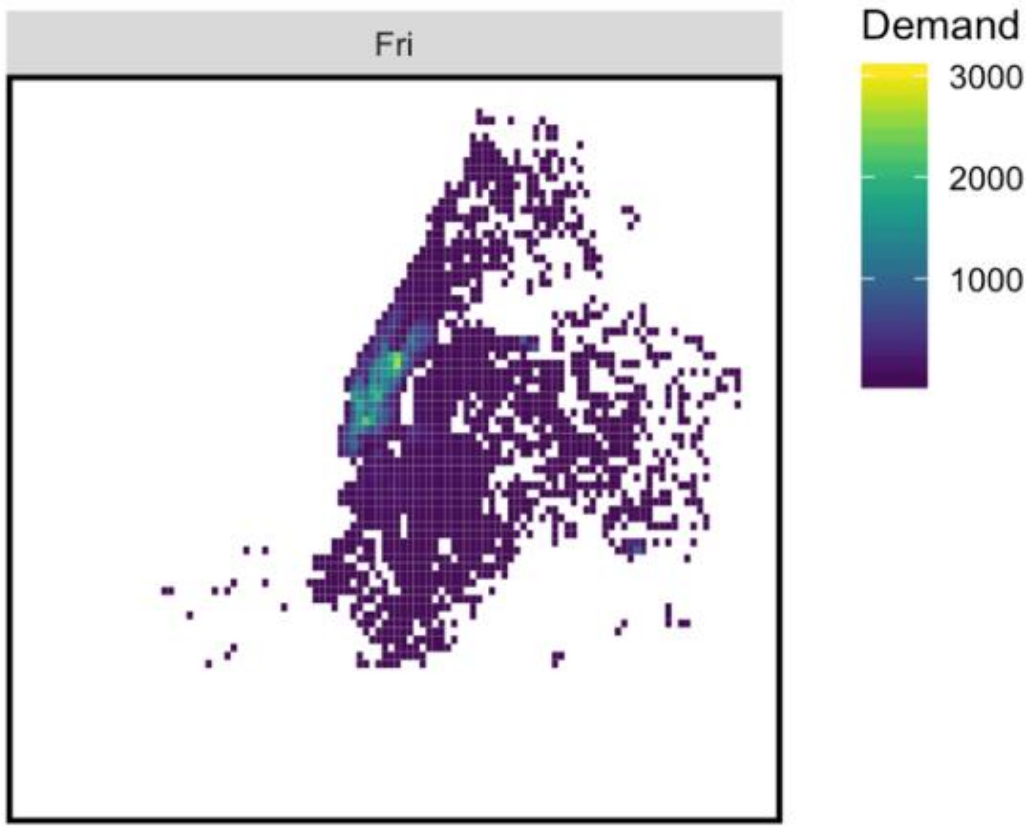

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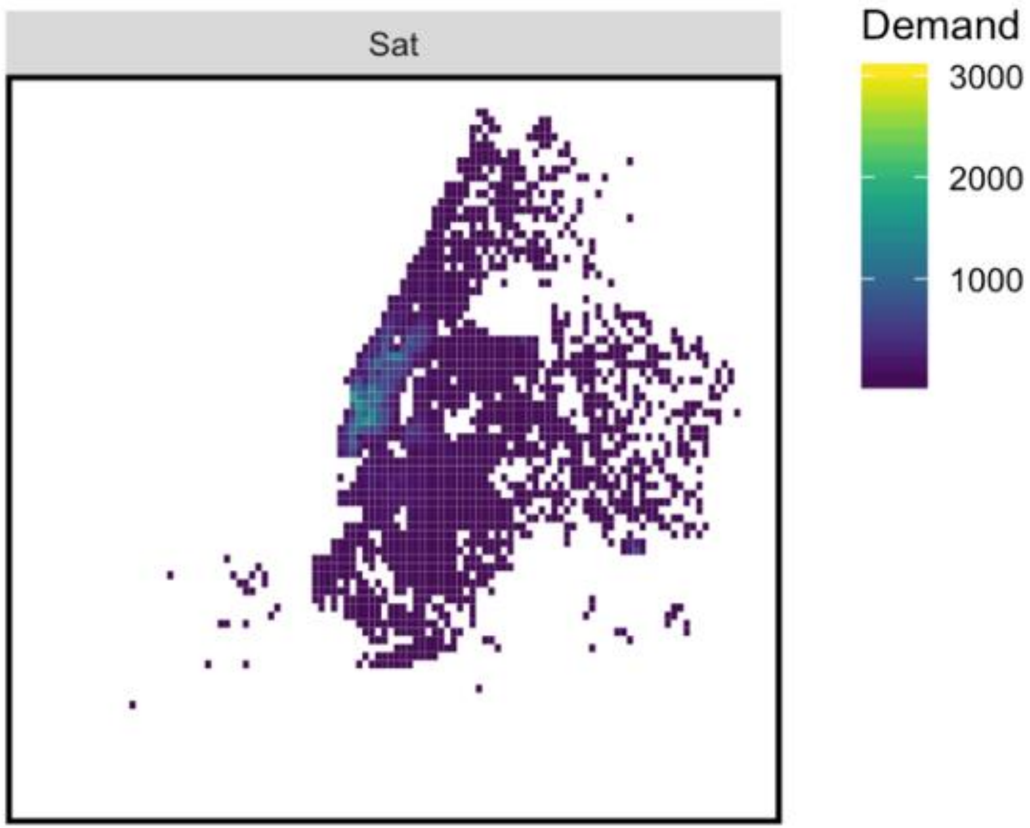

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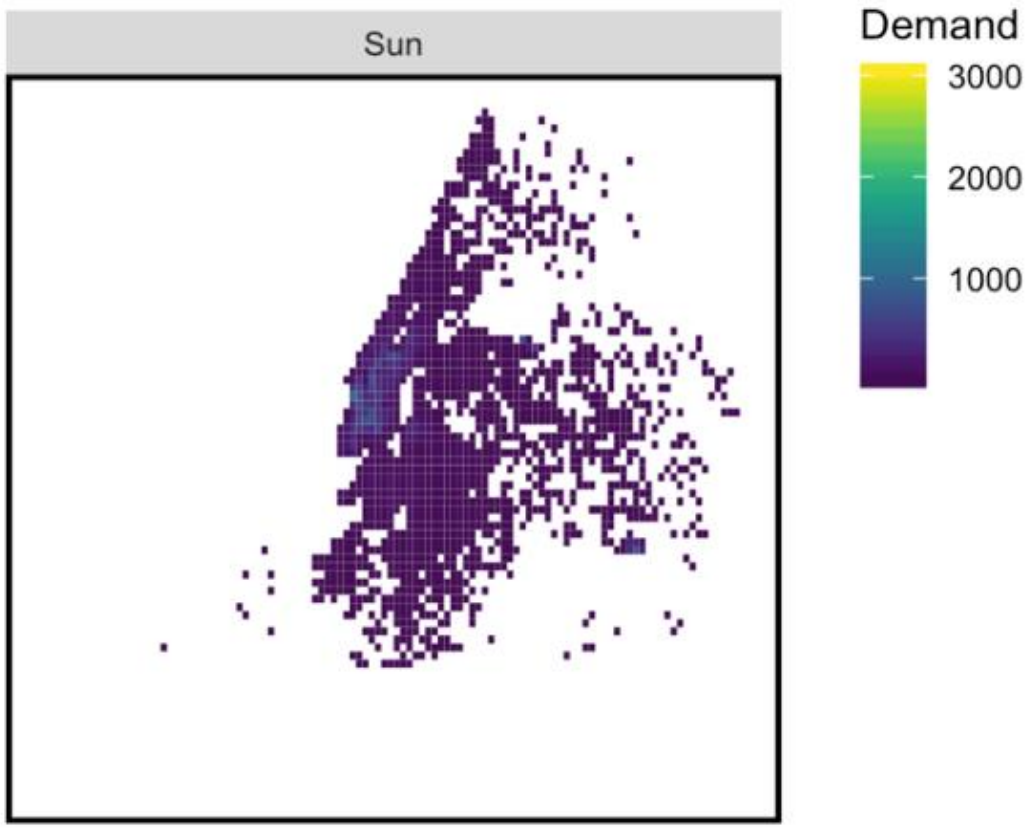

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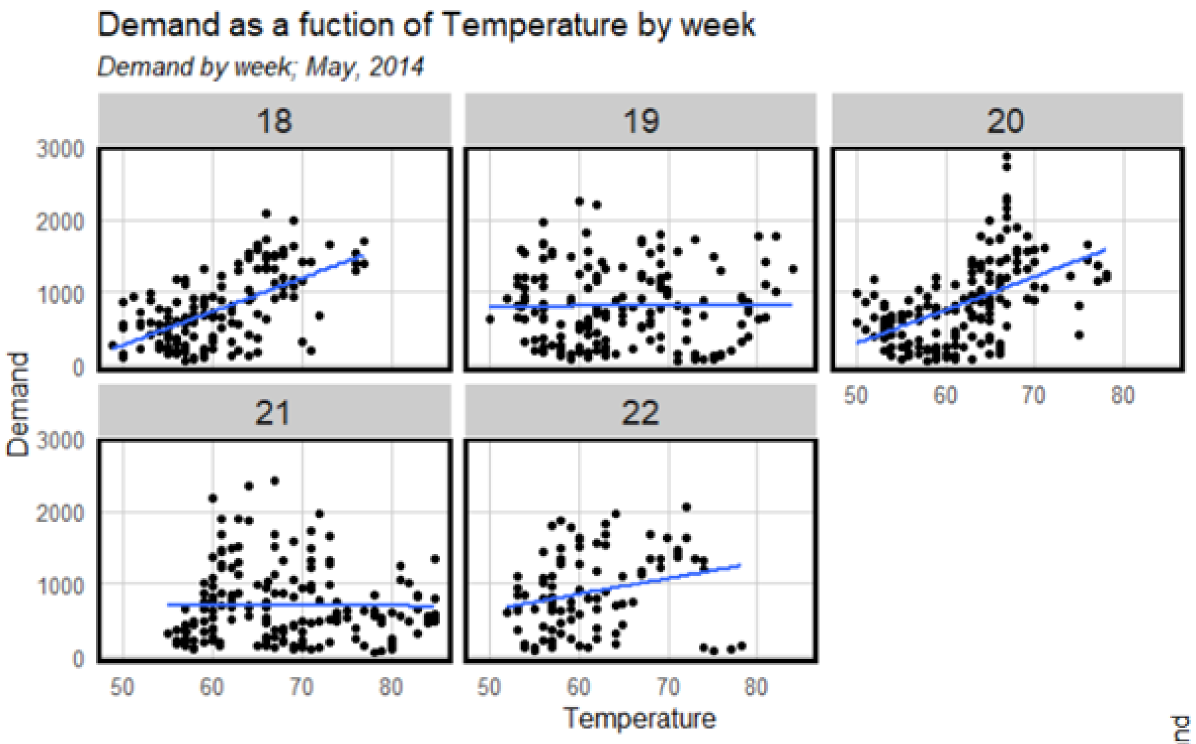
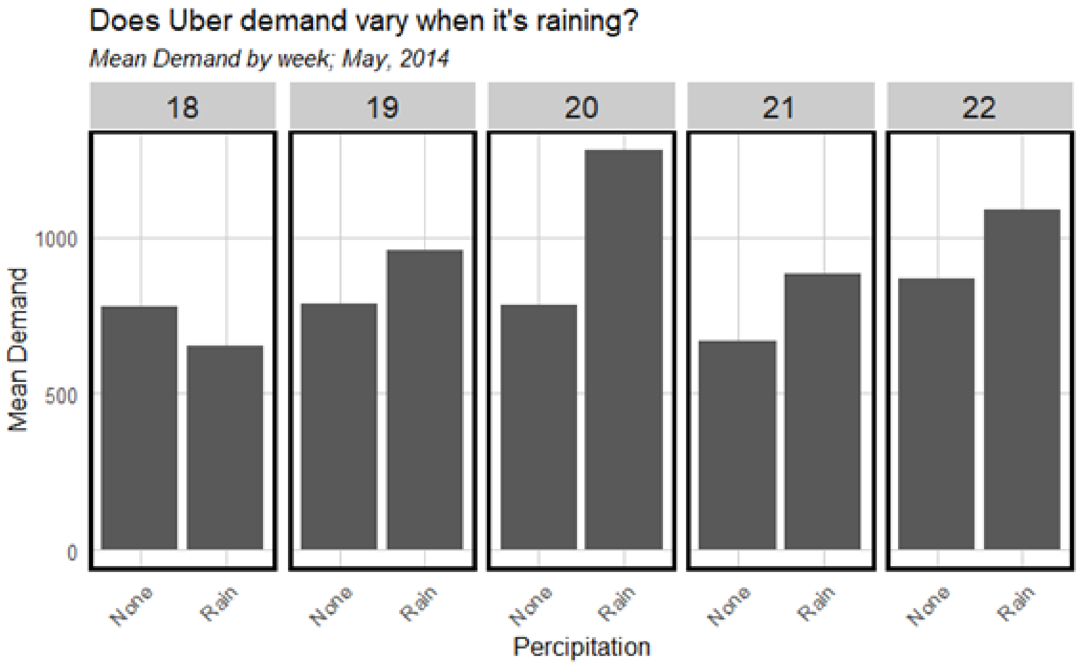
Exploratory Analysis – Weather

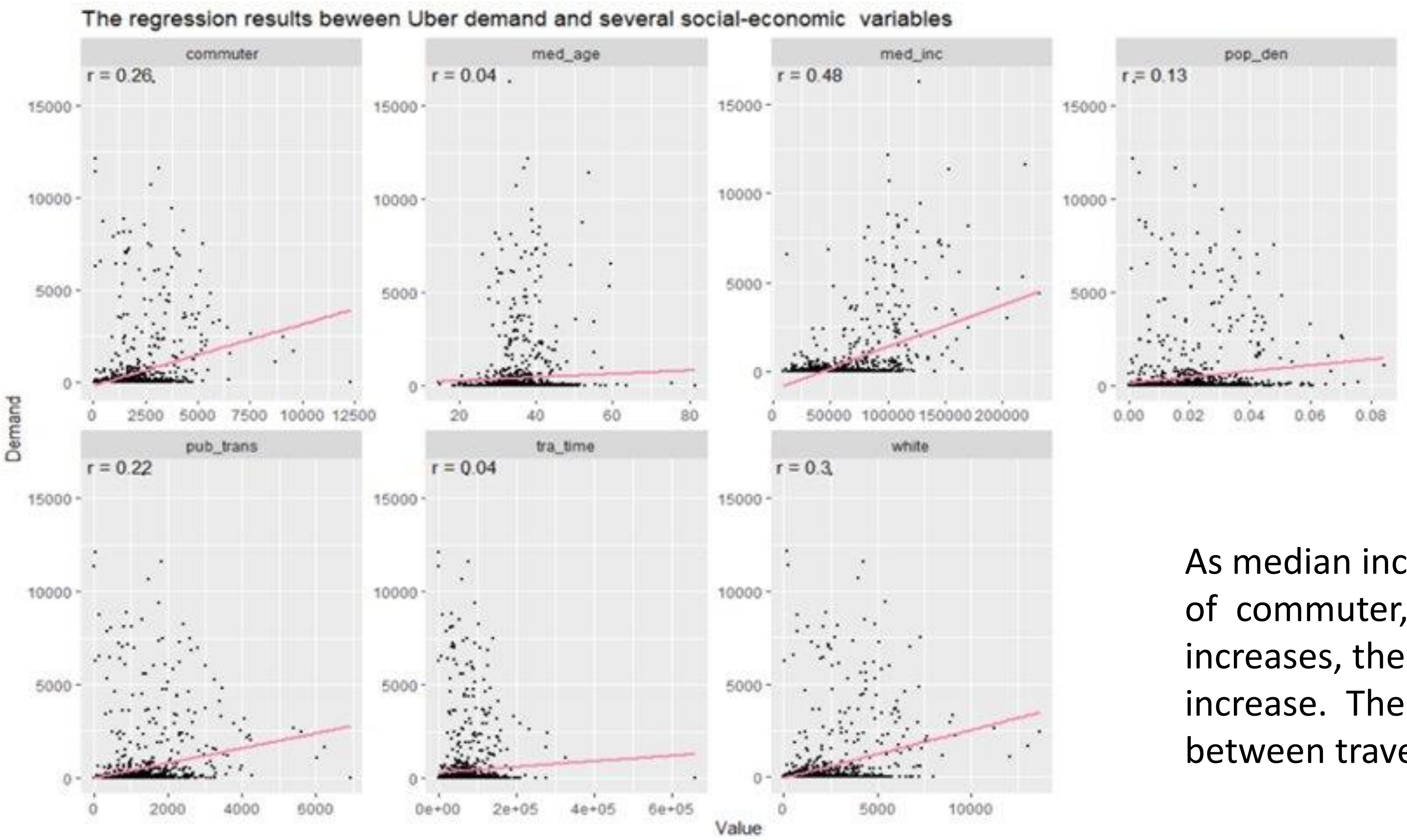


The demand for Uber is higher on raining days, **precipitation** increase the propensity to take Uber



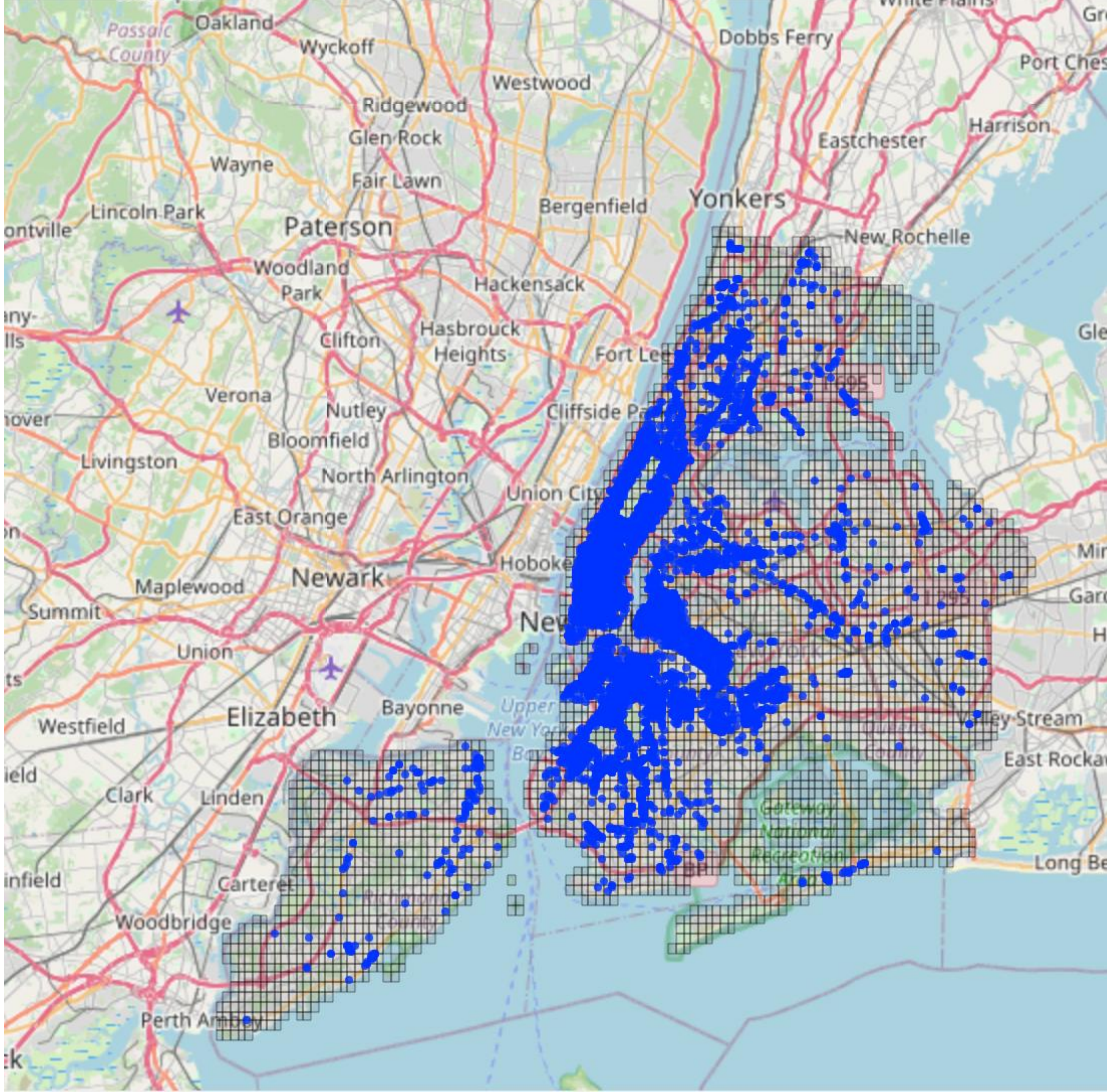
The demand for Uber increases slightly as **temperature warm**

Exploratory Analysis – Social Economic Characteristic



As median income, the number of commuter, and percent of white increases, the demand for Uber increase. There is no significant correlation between travel time and Uber demand

4. Model



Passaic County
Oakland
Wyckoff
Dobbs Ferry
Westwood
Ridgewood
Glen Rock
Wayne
Fair Lawn
Eastchester
Harrison
Yonkers
Bergenfield
Lincoln Park
Paterson
New Rochelle
Woodland Park
Hackensack
Clifton
Hasbrouck Heights
Fort Lee
Verona
Nutley
Cliffside Park
Bloomfield
Livingston
North Arlington
Union City
East Orange
Hoboken
Newark
Maplewood
Summit
Union
Elizabeth
Bayonne
Westfield
Clark
Linden
Carteret
Woodbridge
Perth Amboy
East Rockaway
Long Beach

Model Result – Forward and Backward Stepping

```
Call:
lm(formula = Demand ~ countPOI + hour + med_inc + dotw + tra_time +
    commuter + countBike + countSubway + pub_trans + med_age +
    countCafe + Temperature + pop_den + Wind_Speed + Percipitation +
    white, data = uber)

Residuals:
    Min      1Q  Median      3Q     Max
-13.106  -2.475  -0.714   1.221 125.338
```

No Vriable be dropped by "Forward & Backward Stepping", which means that all the variables that we put are useful to expain the Uber demand.

Model Result – Summary Table

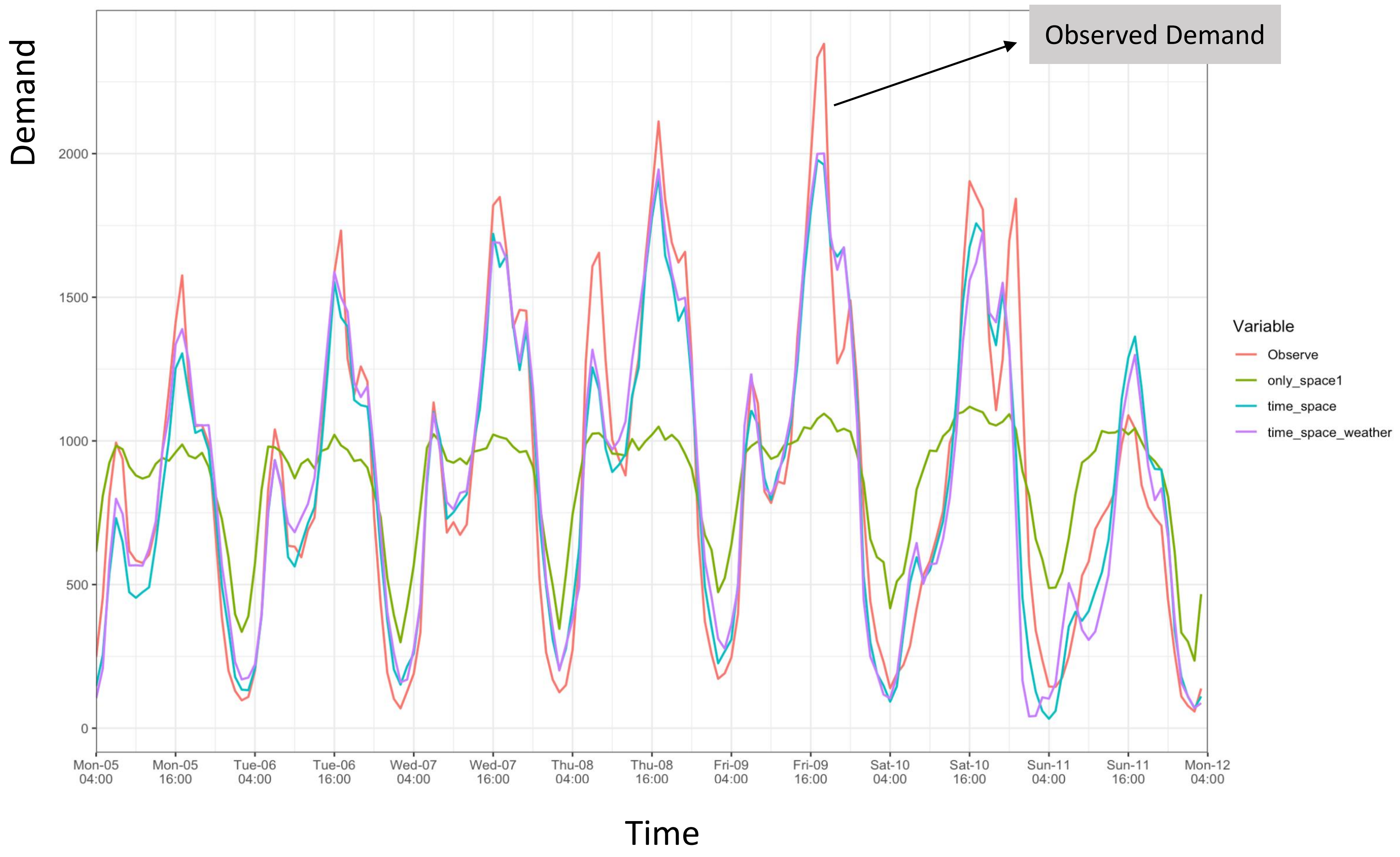
```
Call:
lm(formula = Demand ~ pop + med_age + med_inc + white + commuter +
    tra_time + pub_trans + pop_den + Temperature + isPercip +
    Wind_Speed + countBike + countSubway + countCafe + countPOI +
    dotw + Day_hour + boro_name + ntaname, data = all2)

Residuals:
    Min      1Q  Median      3Q     Max
-13.609  -2.198  -0.490   1.279 124.667

Coefficients: (1 not defined because of singularities)
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                           4.224e+00  6.137e-01   6.883 5.89e-12 ***
pop                                  -1.656e-04  1.808e-05  -9.162  < 2e-16 ***
med_age                               4.606e-02  2.114e-03  21.792  < 2e-16 ***
med_inc                               1.136e-05  4.728e-07  24.022  < 2e-16 ***
white                                 6.227e-05  2.007e-05   3.103 0.001919 **
commuter                             -3.093e-04  5.665e-05  -5.460 4.76e-08 ***
tra_time                             -2.571e-06  7.661e-07  -3.356 0.000791 ***
pub_trans                             4.514e-04  5.816e-05   7.761 8.46e-15 ***
pop_den                               7.962e+00  1.494e+00   5.327 9.97e-08 ***
Temperature                          -3.076e-02  2.066e-03 -14.890  < 2e-16 ***
isPercip1                             5.135e-01  3.801e-02  13.510  < 2e-16 ***
Wind_Speed                           -2.420e-02  4.179e-03  -5.791 7.02e-09 ***
countBike                             1.348e-02  8.710e-04  15.480  < 2e-16 ***
countSubway                           7.712e-02  3.083e-03  25.016  < 2e-16 ***
countCafe                             5.235e-02  2.751e-03  19.027  < 2e-16 ***
countPOI                              5.042e-03  2.614e-04  19.291  < 2e-16 ***
dotwMon                              -1.241e+00  4.619e-02 -26.860  < 2e-16 ***
dotwSat                              -9.888e-01  3.966e-02 -24.929  < 2e-16 ***
dotwSun                              -1.769e+00  4.397e-02 -40.230  < 2e-16 ***
dotwThu                              -3.921e-02  4.118e-02  -0.952 0.341017
dotwTue                              -6.581e-01  4.632e-02 -14.206  < 2e-16 ***
dotwWed                              -3.168e-01  4.453e-02  -7.115 1.13e-12 ***
Day_hour1                            -8.051e-01  1.066e-01  -7.556 4.19e-14 ***
Day_hour10                            2.194e-01  8.999e-02   2.438 0.014774 *
Day_hour11                            4.367e-01  8.966e-02   4.870 1.11e-06 ***
```

- All the variables are **significant** (the screenshot omit some variables like Day_hour and neighourhood)
- While the **R^2 is relatively low**, more related variables need to be added to explain the Uber demand.

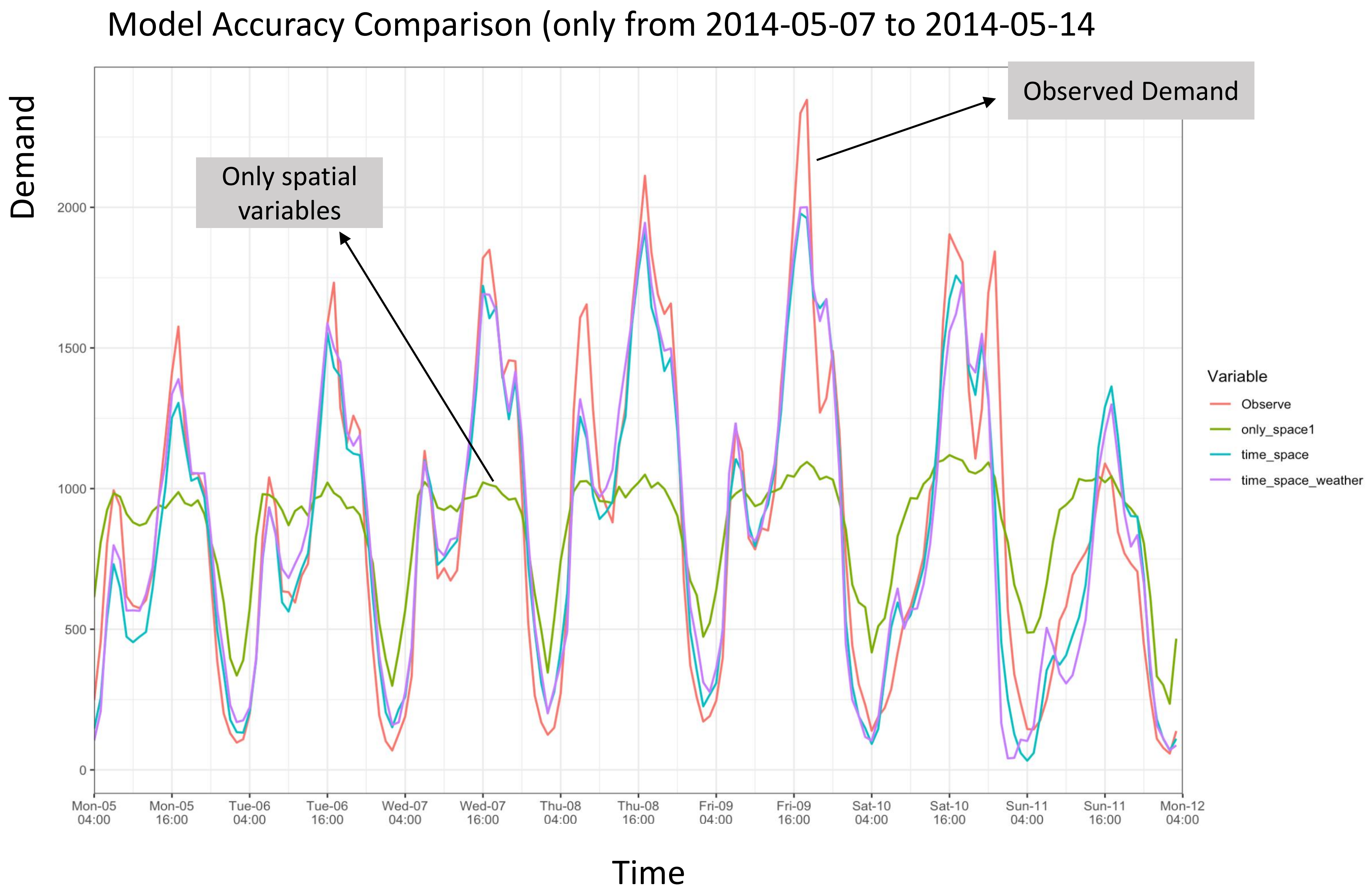
```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.77 on 164228 degrees of freedom
Multiple R-squared:  0.3508,	Adjusted R-squared:  0.3499
F-statistic: 380.9 on 233 and 164228 DF,  p-value: < 2.2e-16
```

Model Result

Model Accuracy Comparison (only from 2014-05-07 to 2014-05-14



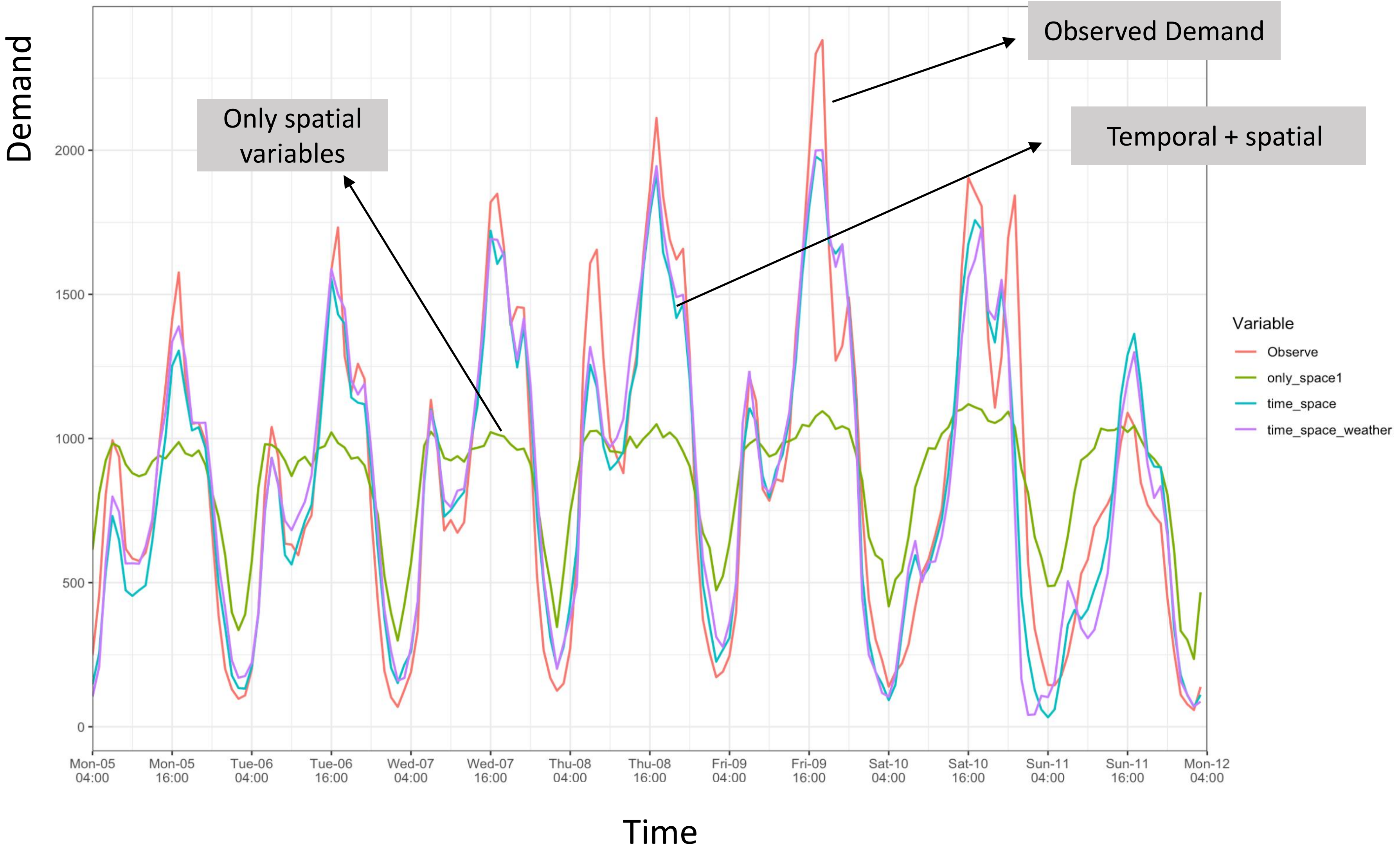
Model Result



Spatial varibales (e.g. neighourhood, POI, subway entries) can't explain all the changes of Uber demand.

Model Result

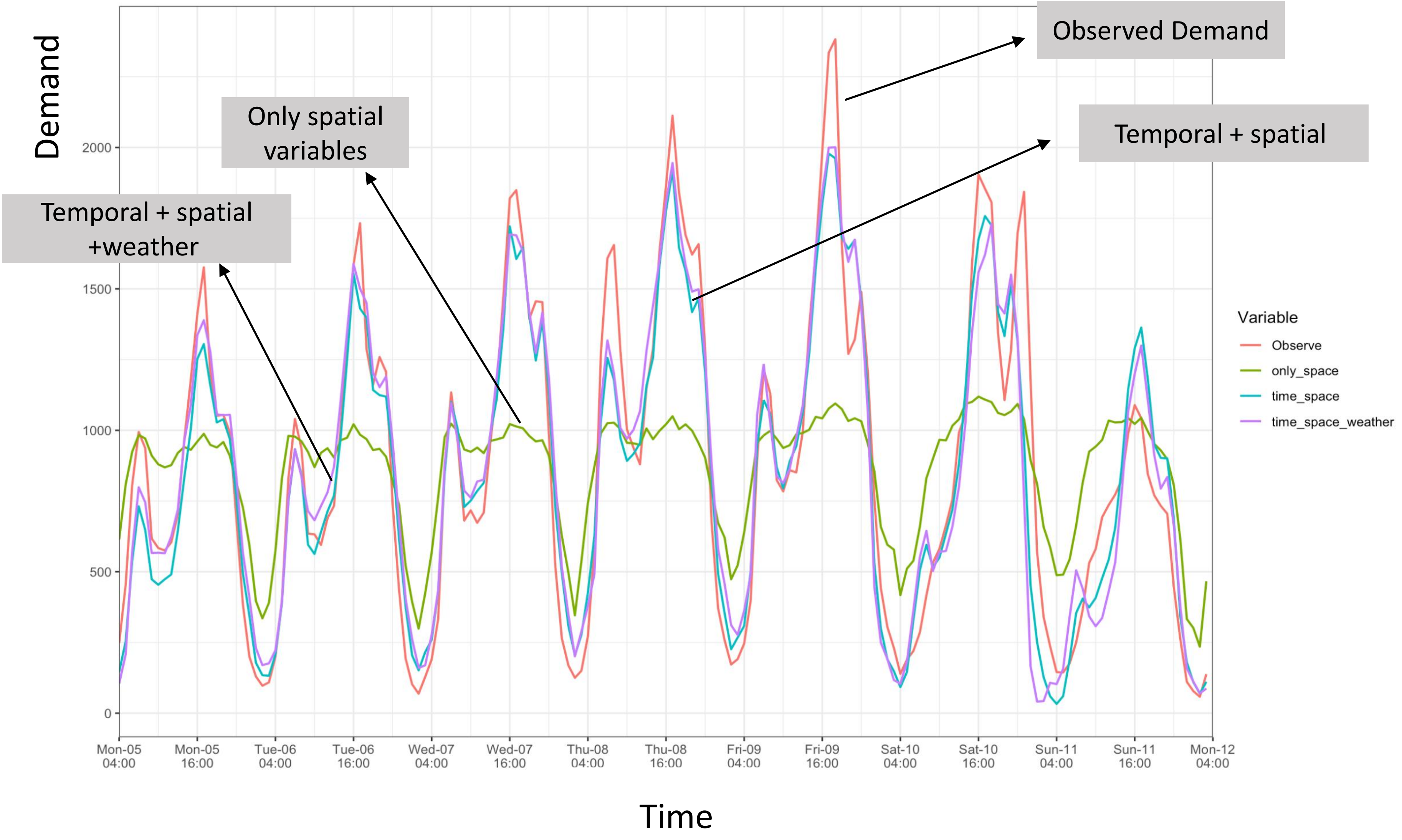
Model Accuracy Comparison (only from 2014-05-07 to 2014-05-14



Additional Temporal varibales
(e.g. day of week, hour of day)
can explain most of the fluctuant demand

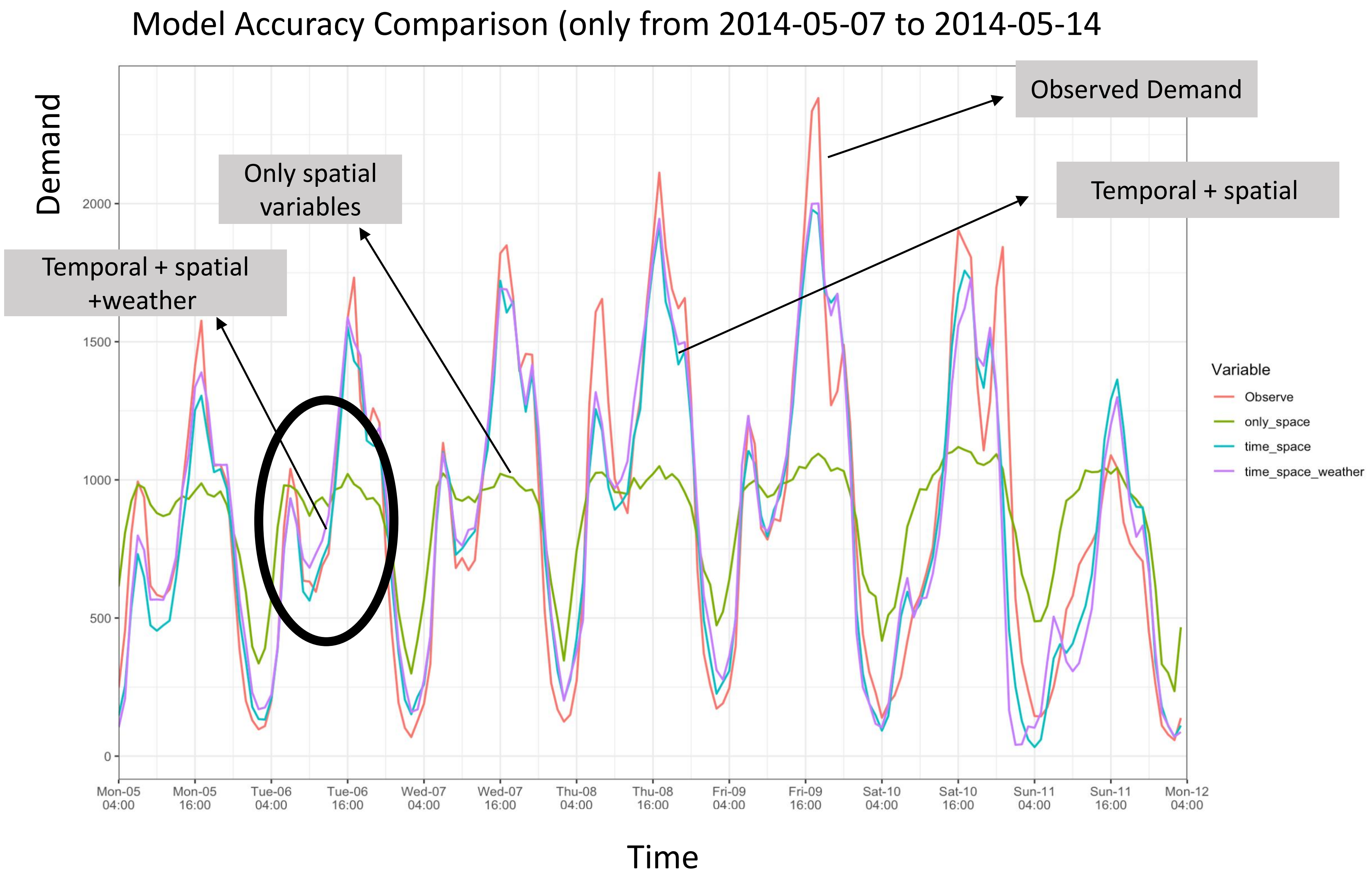
Model Result

Model Accuracy Comparison (only from 2014-05-07 to 2014-05-14



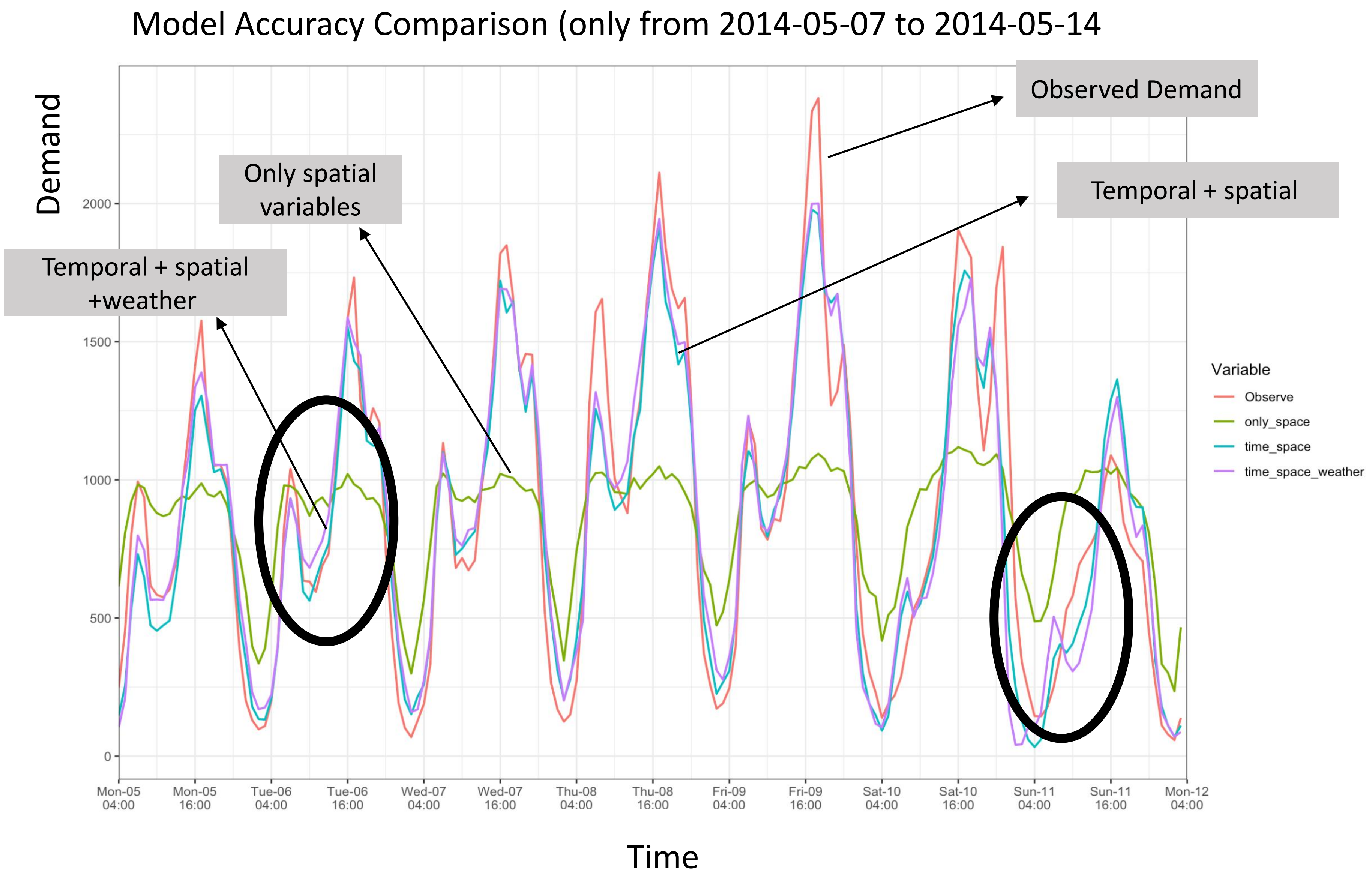
The predictive ability of **Weather related varibales** (e.g. Wind, precipitation) is unstable.

Model Result



The predictive ability of **Weather related varibales** (e.g. Wind, precipitation) is unstable. It increase the accuracy in some days,

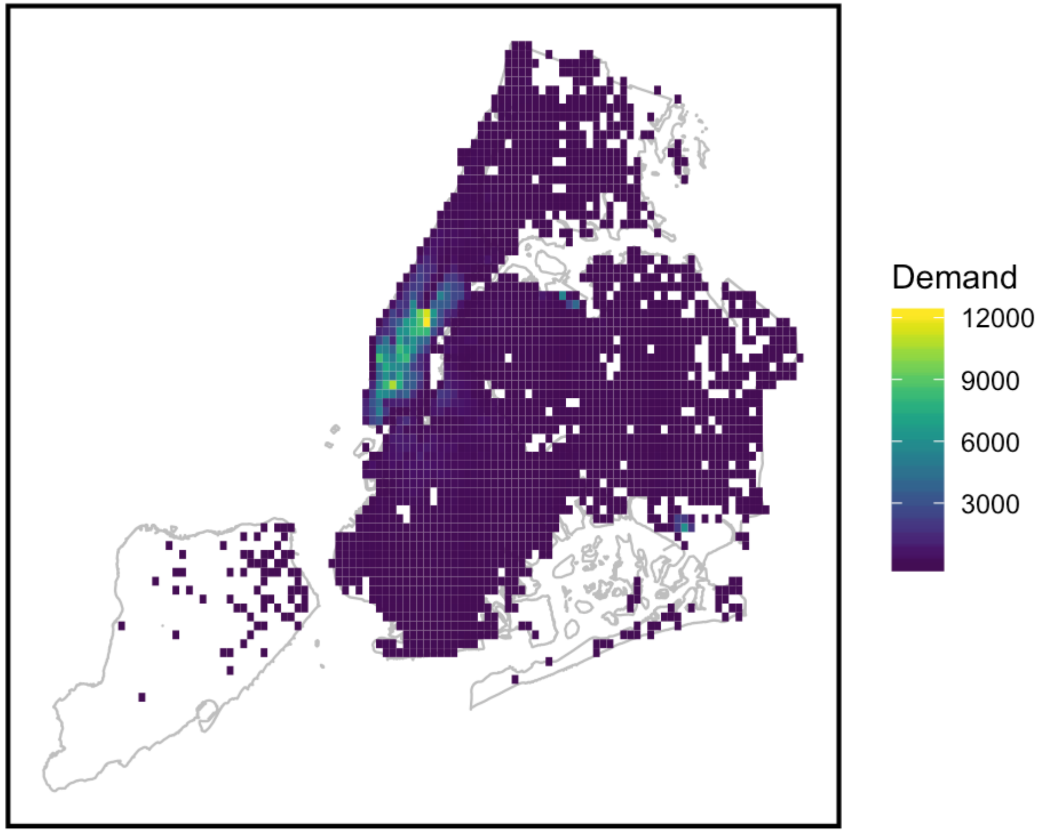
Model Result



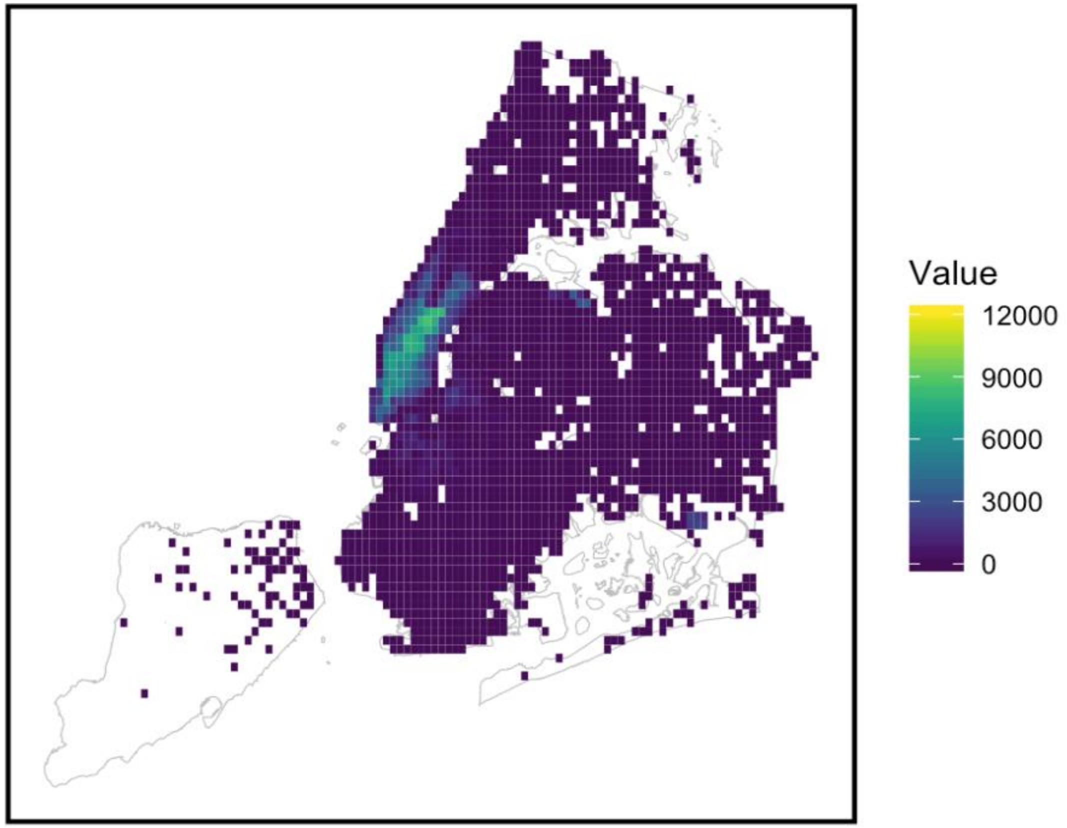
The predictive ability of **Weather related varibales** (e.g. Wind, precipitation) is unstable. It increase the accuracy in some days, while reduce the acccuracy in some cases.

Model Result – Spacial Accuracy

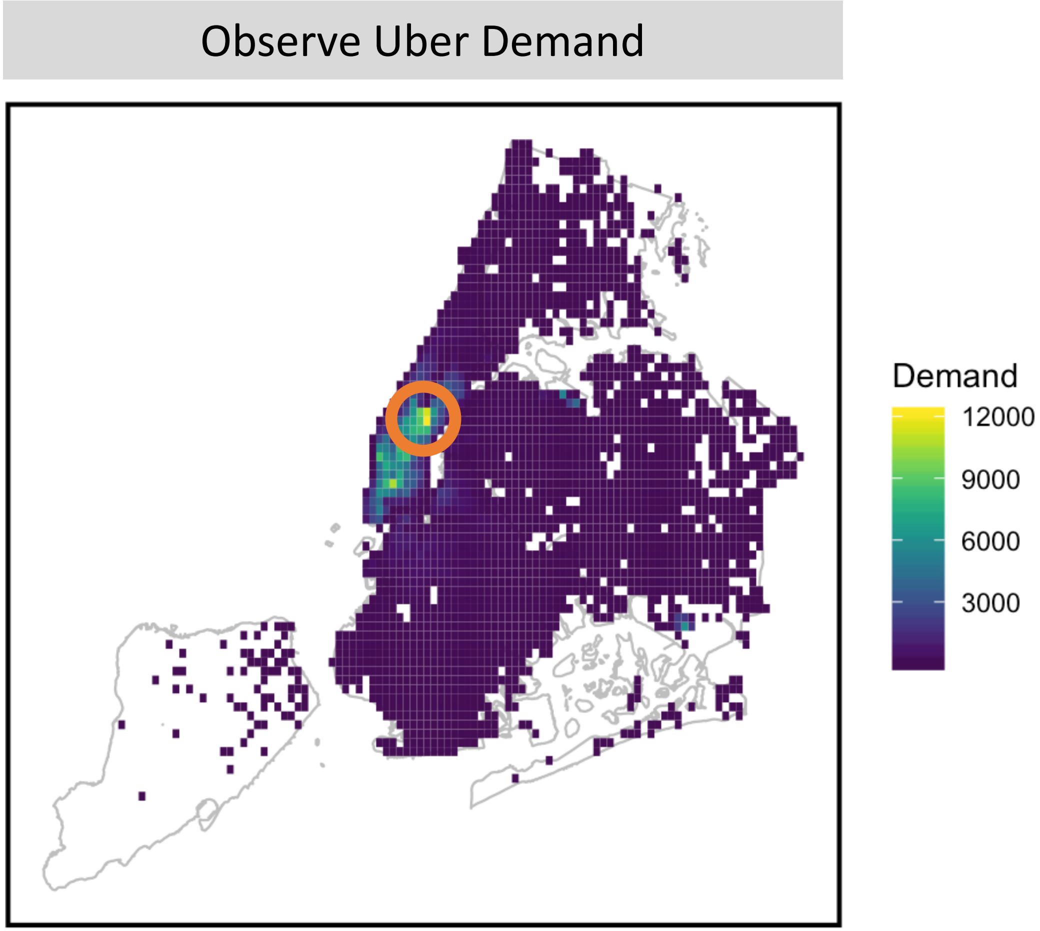
Observe Uber Demand

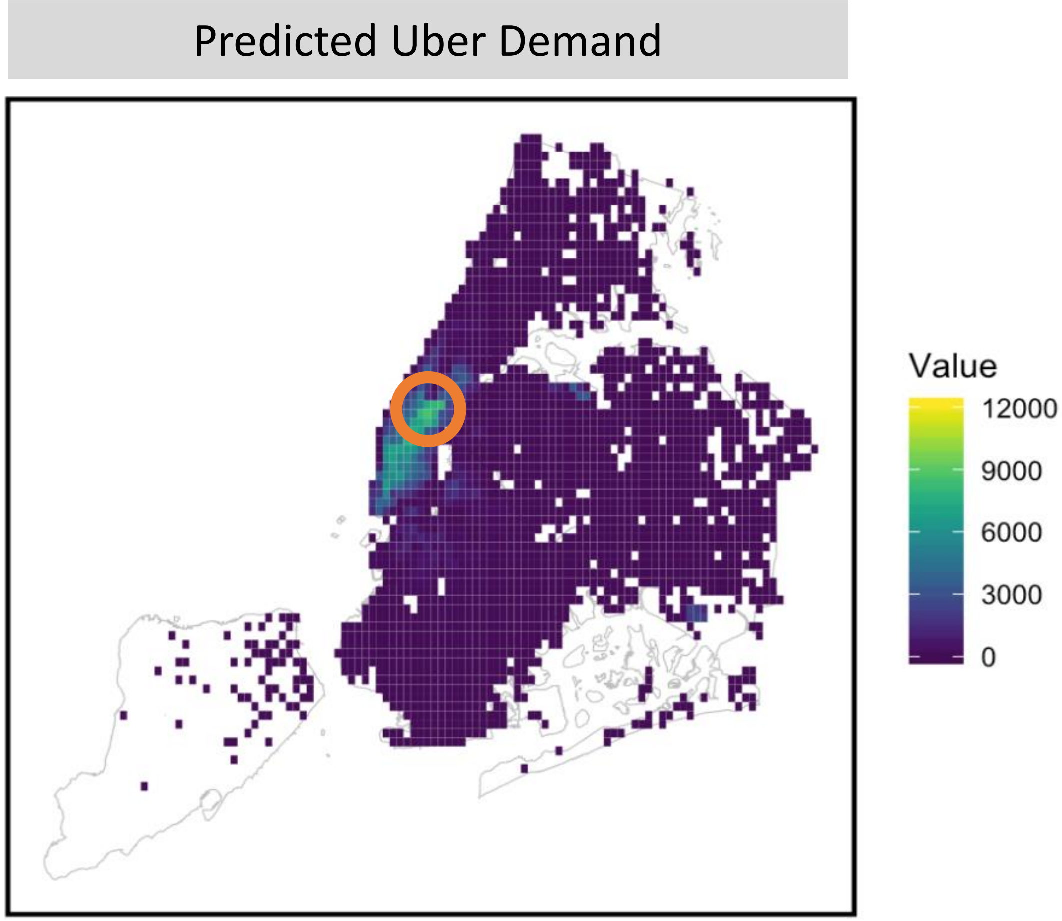


Predicted Uber Demand

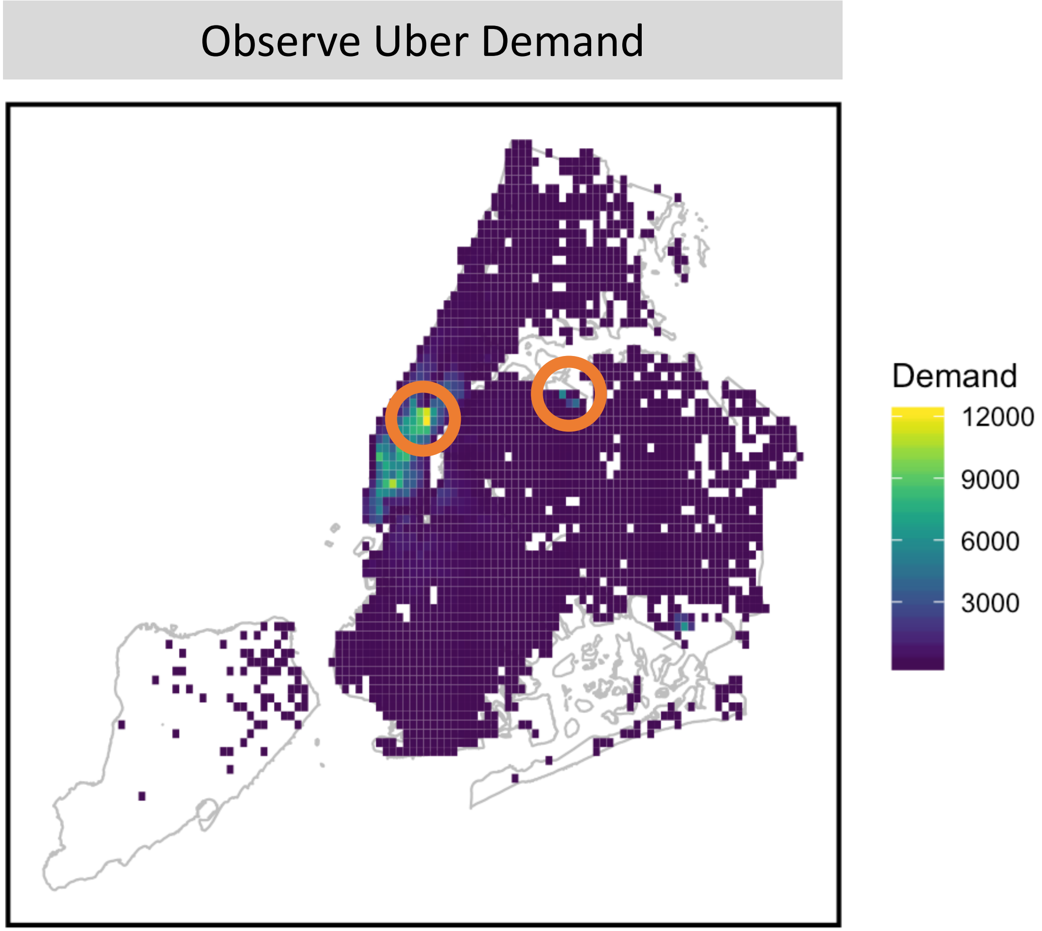


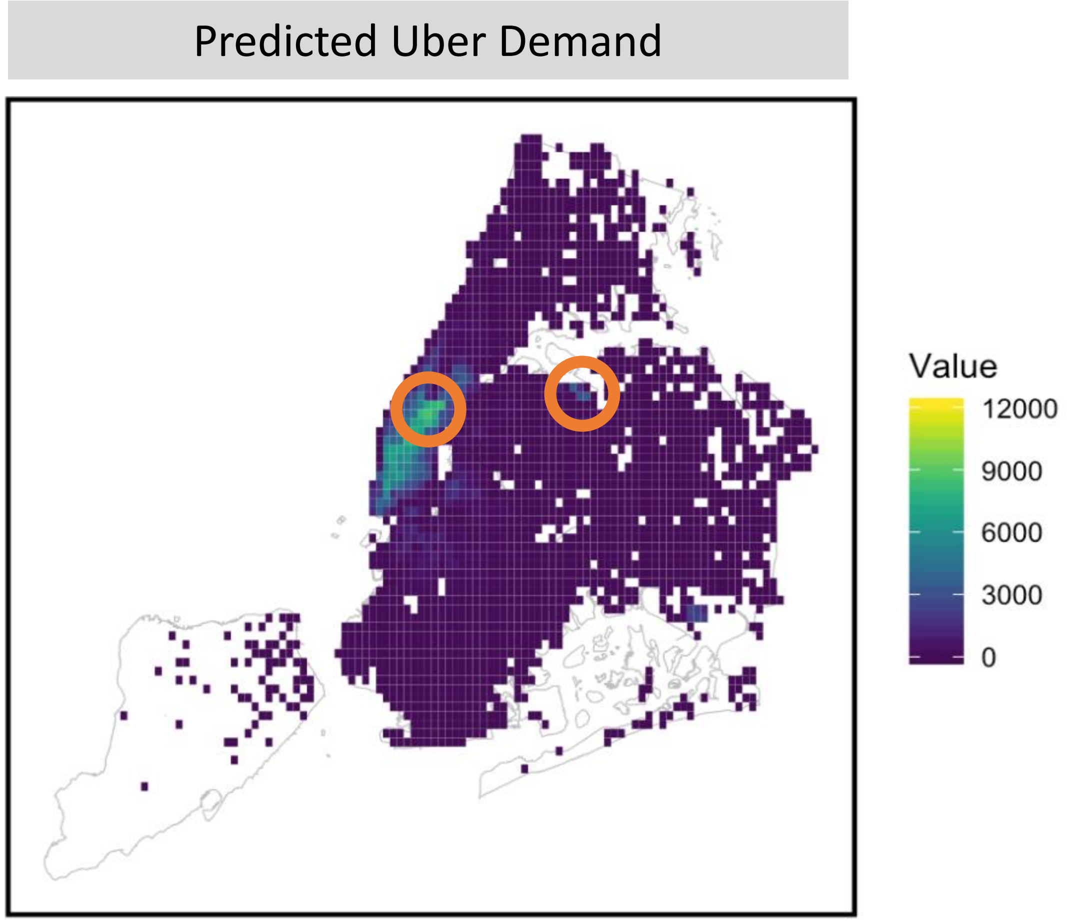
Model Result – Spacial Accuracy





Model Result – Spacial Accuracy

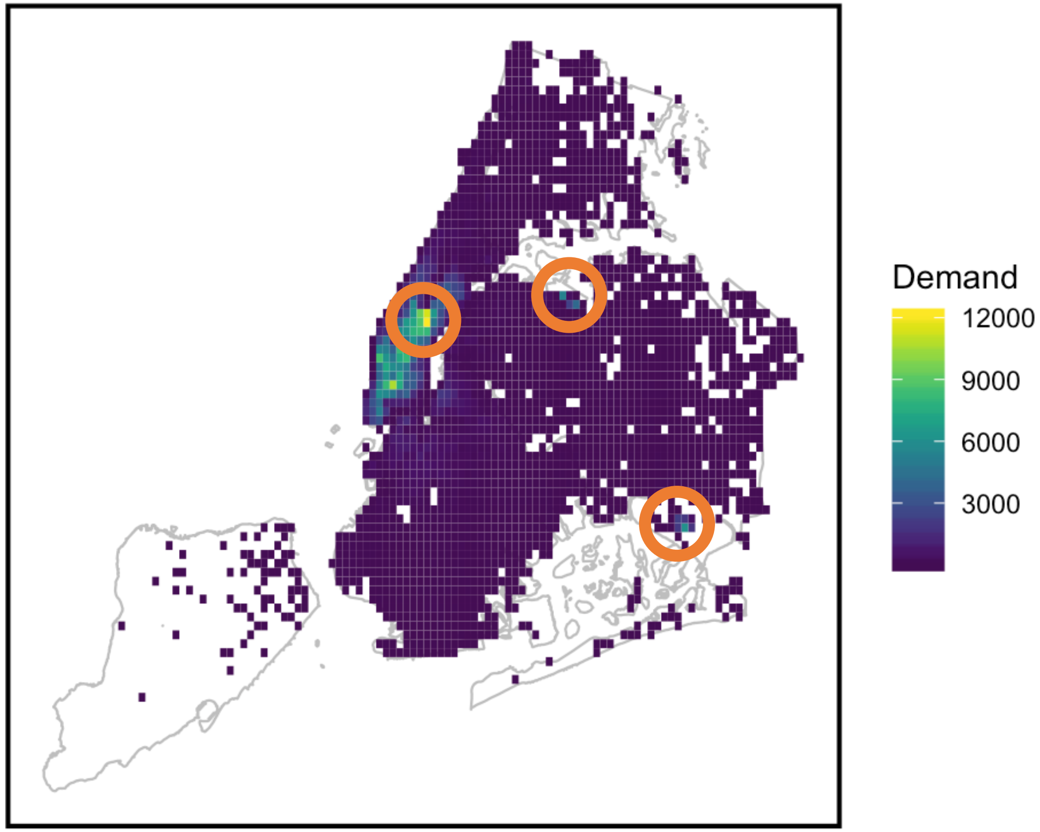




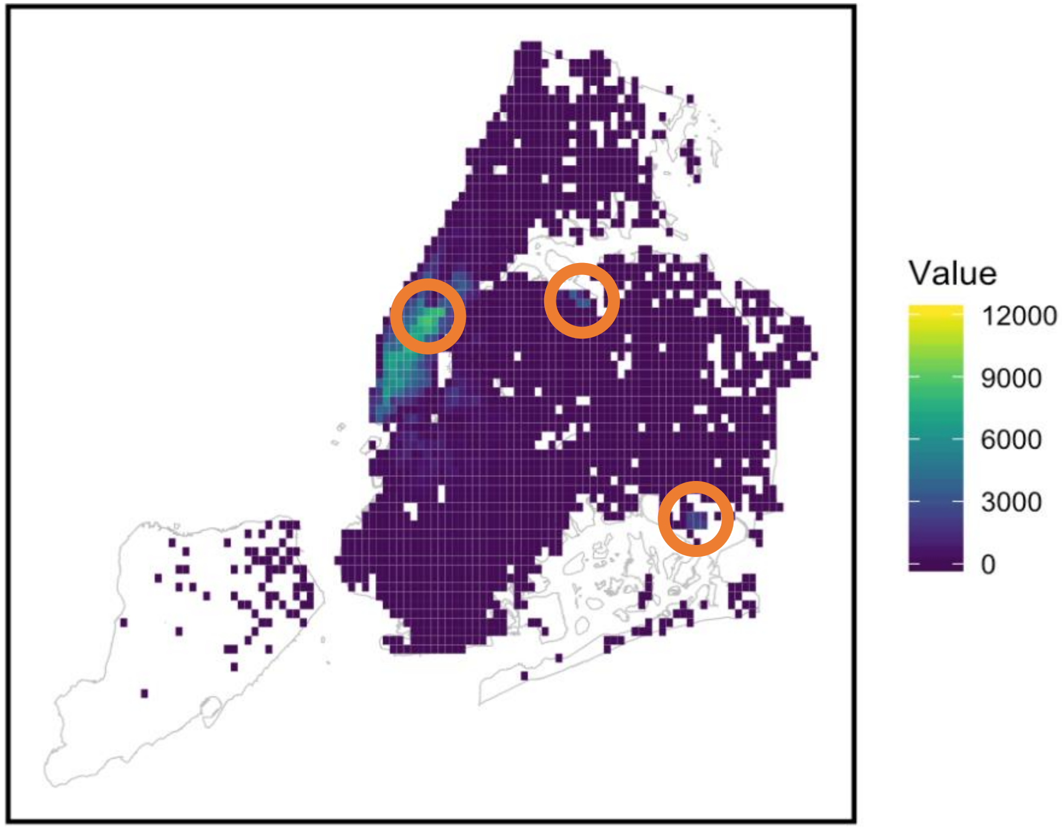
Model Result – Spacial Accuracy

- The model successfully predict the hotspots of Uber demand;
- BUT underestimate the popularity of hotspots;

Observe Uber Demand



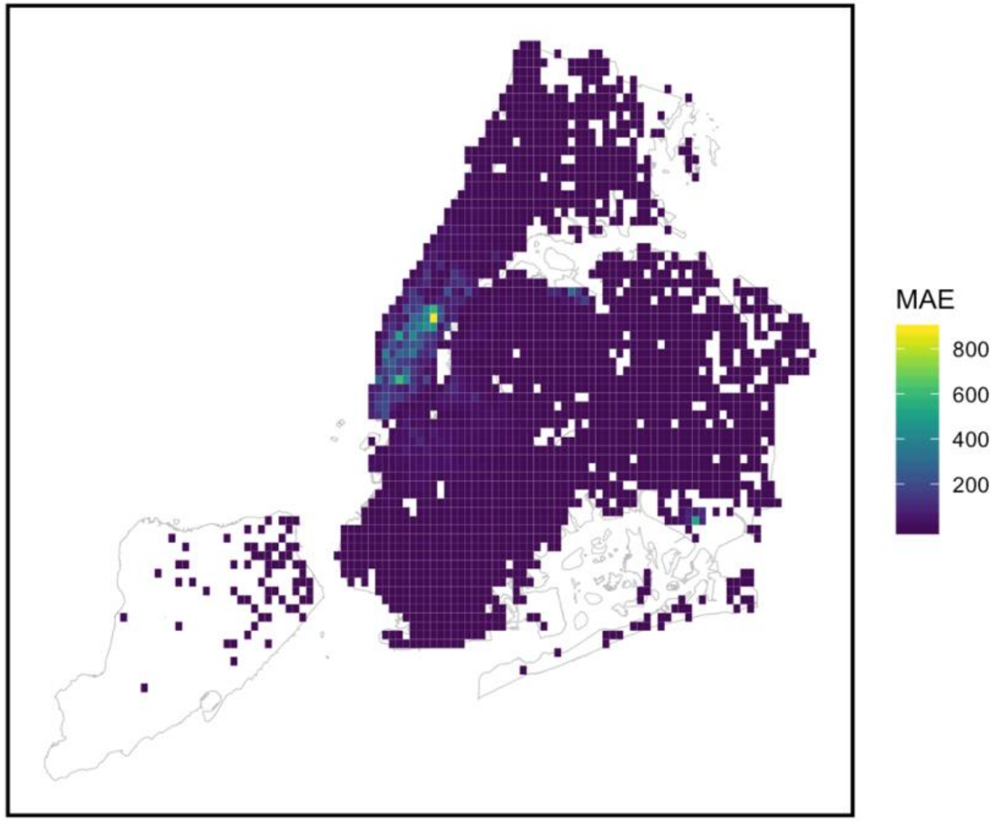
Predicted Uber Demand



Model Result – Spacial Accuracy

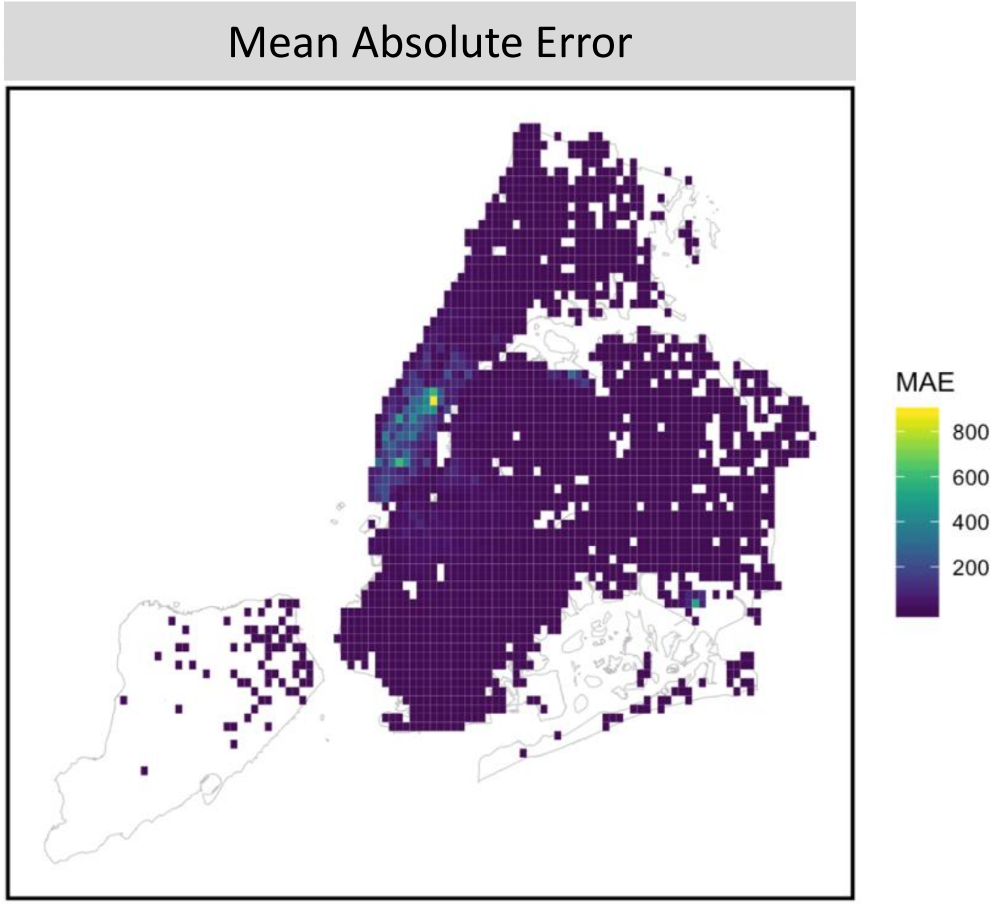
- The model successfully predict the hotspots of Uber demand;
- BUT underestimate the popularity of hotspots;
- Mean Absolute Error: for the busiest area, the predicted demand is 800 less than the observation.

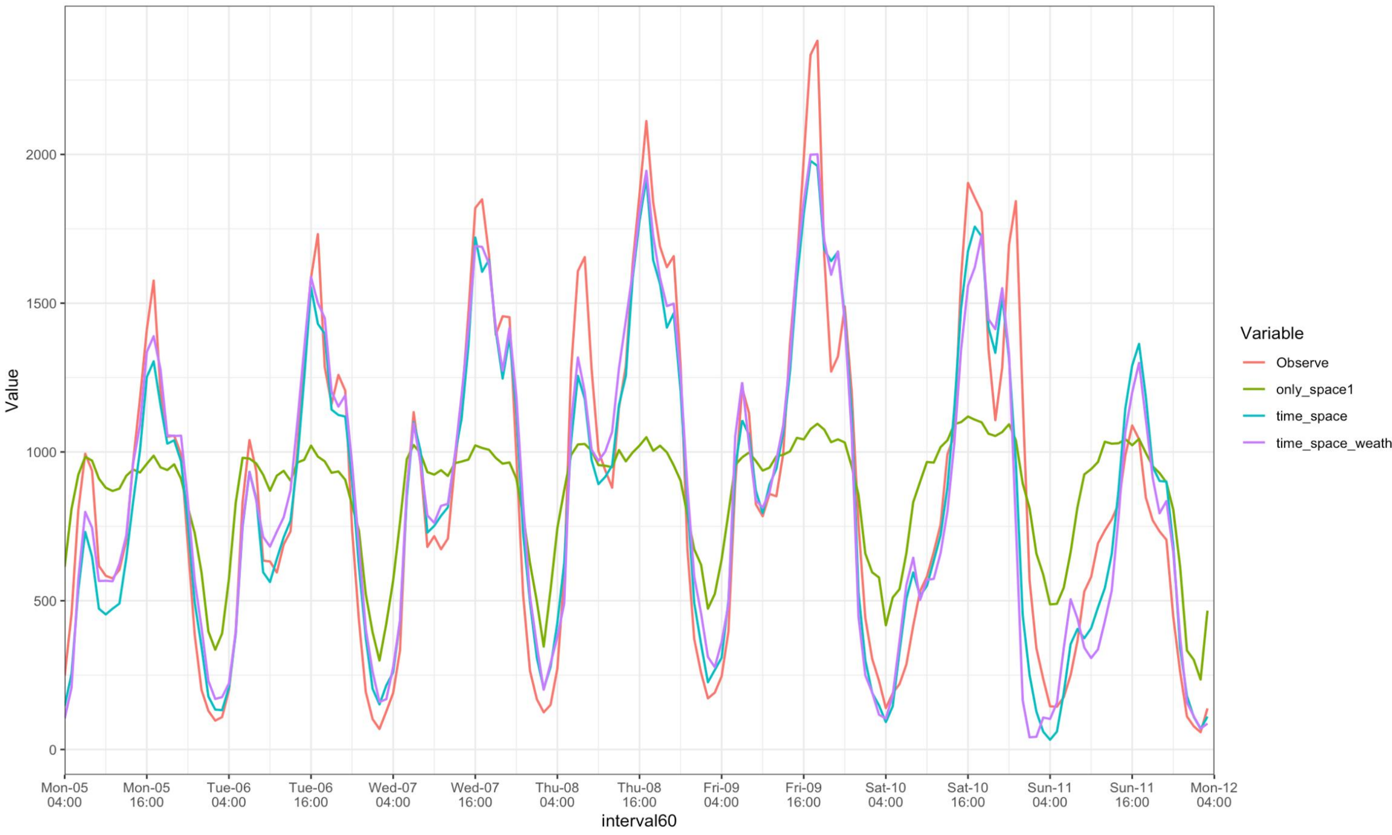
Mean Absolute Error



Model Result – Spacial Accuracy

- Temporal Accuracy tell the same story, the model is underperformed in predicting extremely high demand.





Summary

1. Raster-based analysis (although need to **rotate the grids** make sure they are in line with street direction)

2. Uber demand in NYC is clustered (**Moran's I**).

3. Explored the relationship between Uber demand and 3 types of variables (**spatial, temporal and weather-related**)

4. The model is accurate in general while **underperformed** for area with extremely high Uber demand .