Built environment | Demographic | Socioeconomic | Transit

Spatiotemporal patterns of drug activity in Chicago

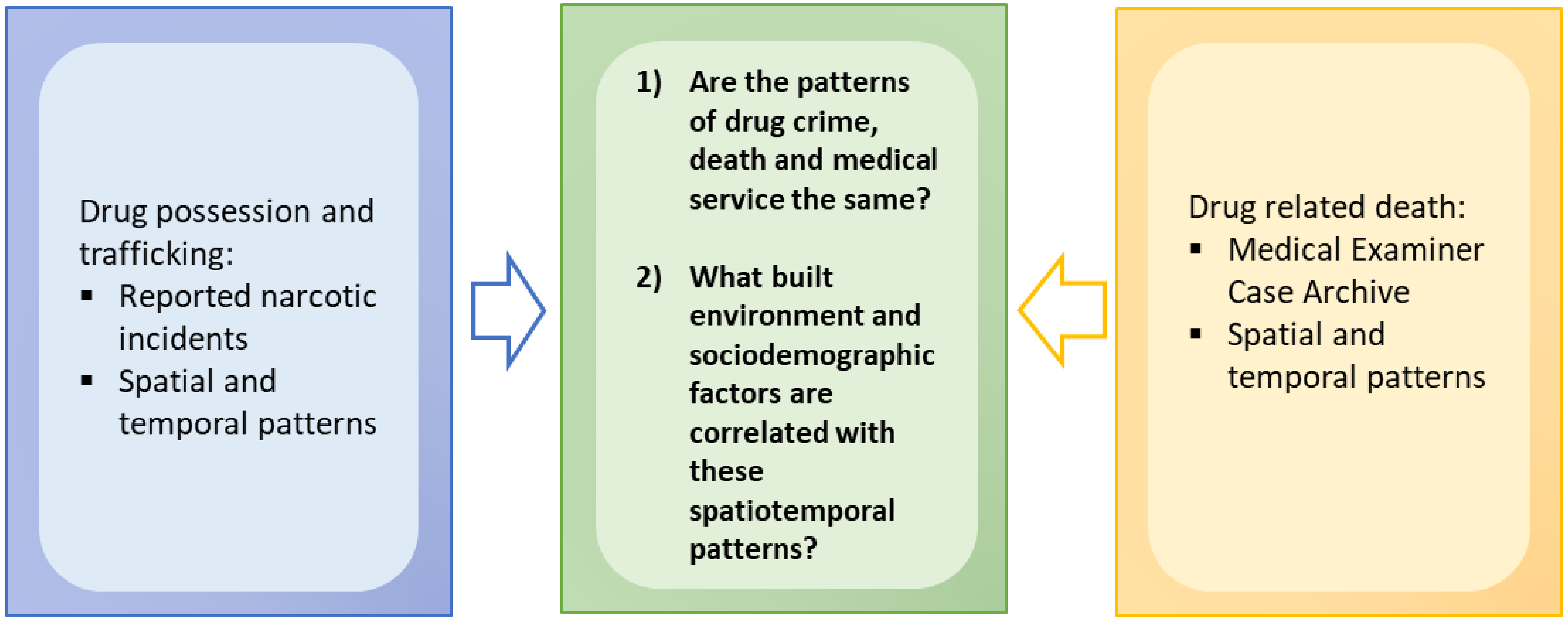
Luna Zhiyue Xia

Three hypothesizes:

1) The spatial patterns of drug activities in city areas are significantly clustered (tested by ESDA and reported in last update)

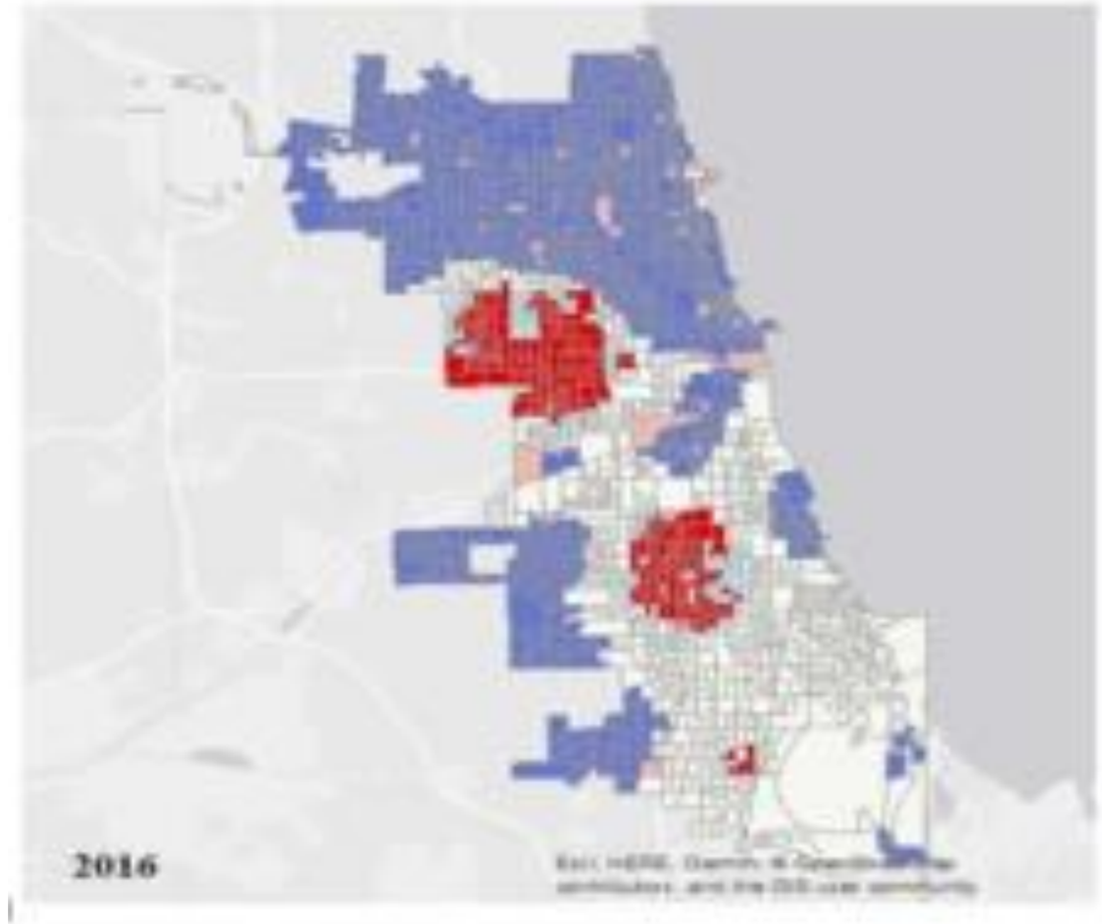
2) Drug arrests (which record times and locations) can be used as a proxy of drug activities

3) The spatial patterns of drug activities are correlated with built environment, demographic and socioeconomic.

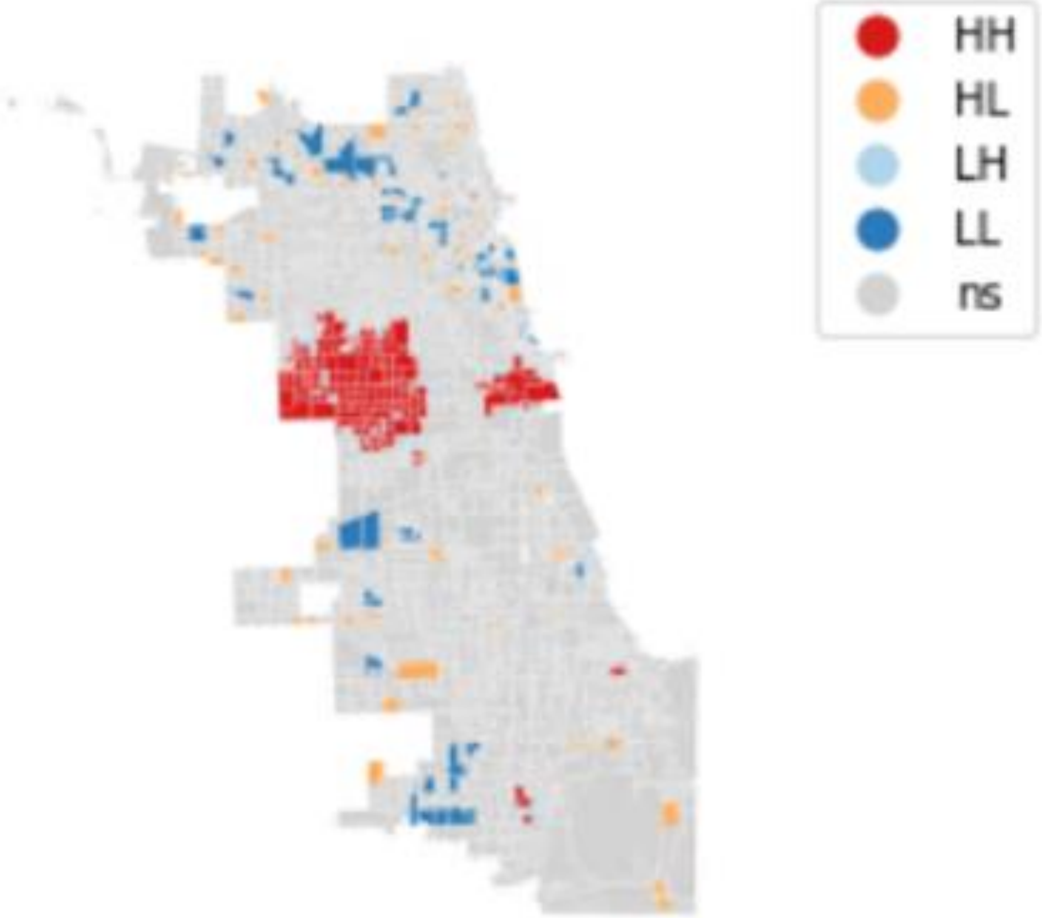


Test H1: Clustering analysis

Drug arrest hotspots, Chicago, 2016
(crime data)

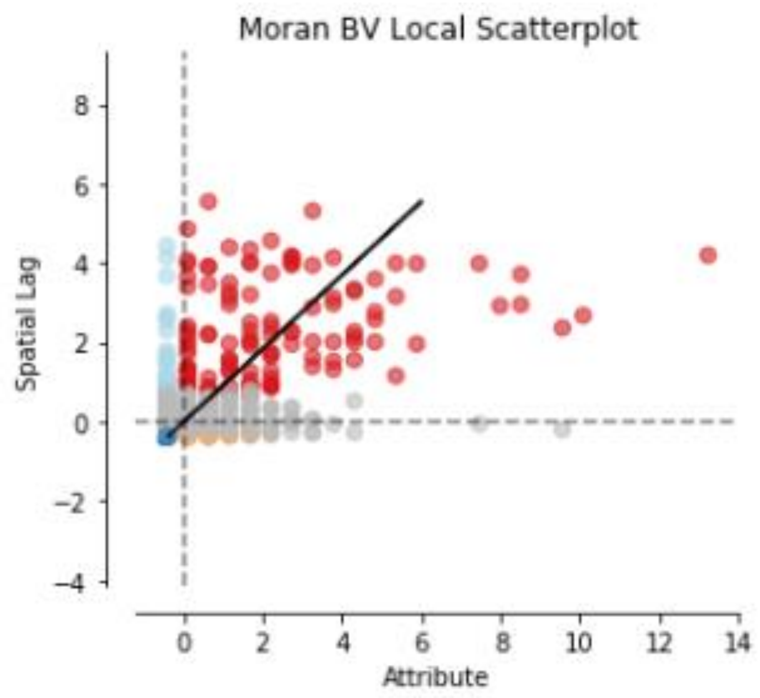


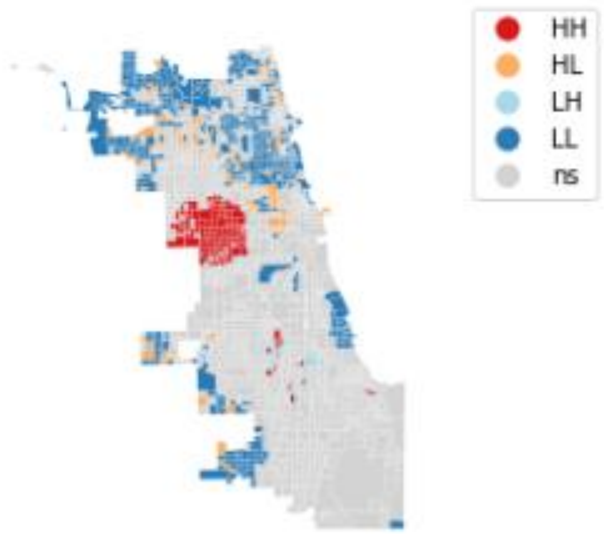
Opioid related death hotspots, Chicago, 2014 - present
(Medical Examiner Case Archive data)



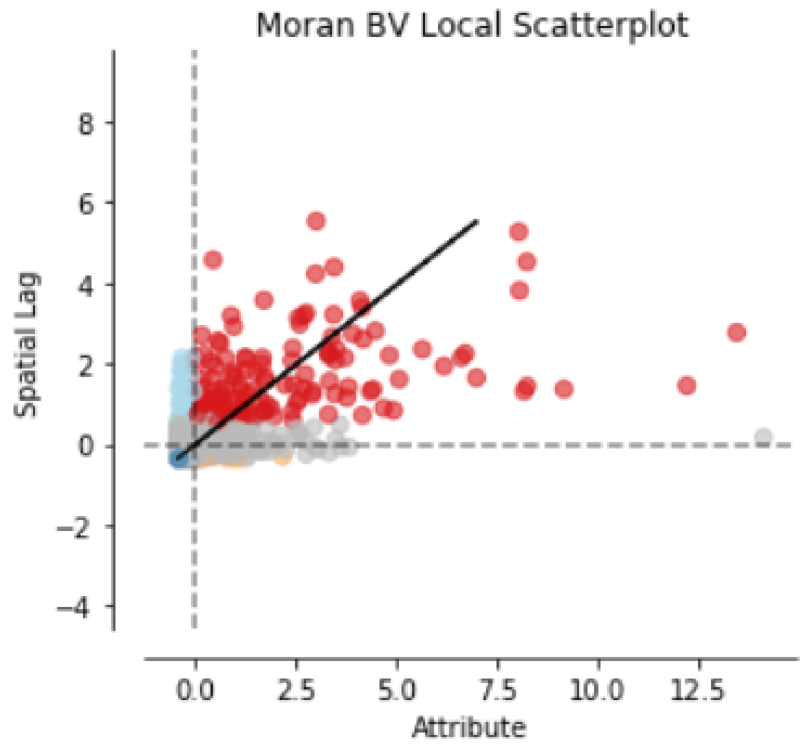
Test H2: Bivariate Moran Statistic

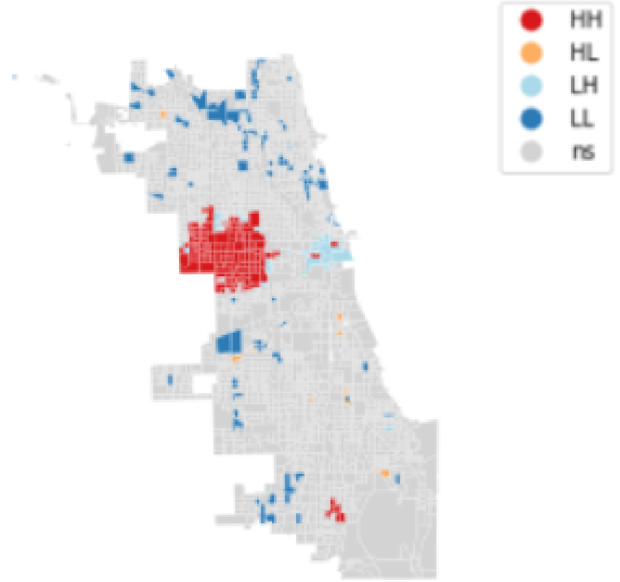
Global bivariate Moran's I is 0.42 with p-value smaller than 0.001
→ Positive correlation between Death and Arrest in nearby areas





Bivariate analysis:
Death surrounded by arrest
HH cluster indicate high death rate
surrounded by high drug arrest





Arrest surrounded by death
HH cluster indicate high frequency of arrest
surrounded by high death rate

GWR and MGWR

Variables:
Total number: 182
Sources: EPA, ACS, ESRI Business, Chicago open data portal

```
list_var = chicago_variable.columns
print(*list_var, sep=", ")
```

```
GEOID10_x, GEOID_Data, geometry, DEATH, FID_x, GEOID, arrest_per1000, FID_y, GEOID10_y, P_WRKAGE, AUTOOWN0, PCT_AO
0, AUTOOWN1, PCT_AO1, AUTOOWN2P, PCT_AO2P, WORKERS, R_LOWWAGEW, R_MEDWAGEW, R_HIWAGEWK, R_PCTLOWWA, EMPTOT, E5_RET
10, E5_OFF10, E5_IND10, E5_SVC10, E5_ENT10, E8_RET10, E8_OFF10, E8_IND10, E8_SVC10, E8_ENT10, E8_ED10, E8_HLTH10,
E8_PUB10, E_FEDT10, E_FEDRET10, E_FEDOFF10, E_FEDIND10, E_FEDSVC10, E_FEDENT10, E_LOWWAGEW, E_MEDWAGEW, E_HIWAGEW
K, E_PCTLOWWA, AC_TOT, AC_WATER, AC_LAND, AC_UNPR, D1A, D1B, D1C, D1C5_Ret10, D1C5_Off10, D1C5_Ind10, D1C5_Svc10,
D1C5_Ent10, D1C8_Ret10, D1C8_Off10, D1C8_Ind10, D1C8_Svc10, D1C8_Ent10, D1C8_Ed10, D1C8_Hlth1, D1C8_Pub10, D1D, D1
_flag, D2A_JPHH, D2B_E5MIX, D2B_E5MIXA, D2B_E8MIX, D2B_E8MIXA, D2A_EPHHM, D2C_TRPMX1, D2C_TRPMX2, D2C_TRIPEQ, D2R_
JOBPOP, D2R_WRKEMP, D2A_WRKEMP, D2C_WREMIX, D3a, D3aao, D3amm, D3apo, D3b, D3bao, D3bmm3, D3bmm4, D3bpo3, D3bpo4,
D4a, D4b025, D4b050, D4c, D4d, D5ar, D5ae, D5br, D5br_Flag, D5be, D5be_Flag, D5cr, D5cri, D5ce, D5cei, D5dr, D5dr
i, D5de, D5dei, NatWalkInd, TrAccess_I, Pop_byTr, Pop_byTr_m, Pop_byTr_1, Pop_byTr_a, Pct_Pop_by, Pct_Pop__1, Pct_
Pop__2, Pct_Pop__3, HU_byTr, HH_byTr, Wrks_byTr, Wrks_byTr_, Wrks_byTr1, Wrks_byT_1, Pct_Wrks_b, Pct_Wrks_1, Pct_W
rks_2, Pct_Wrks_3, LoWgWrks_b, LoWgWrks_1, LoWgWrks_2, MeWgWrks_b, HiWgWrks_b, LoMeWgWrks, LoMeWgWr_1, LoMeWgWr_2,
Pct_LoWgWr, Pct_LoWg_1, Pct_LoWg_2, Pct_LoWg_3, Pct_MeWgWr, Pct_LoMeWg, Pct_LoMe_1, Pct_LoMe_2, Pct_LoMe_3, Jobs_b
yTr, Jobs_byTr_, Jobs_byTr1, Job_byTr_A, Pct_Jobs_b, Pct_Jobs_1, Pct_Jobs_2, Pct_Jobs_3, FID_x, GEOID10_x, TotPop,
TotalHouse, PMale, PFemale, PWhite, PBlack, PAsian, Phispanic, PBachelorHigher, MedianHouseIncome, PPovertyHouse,
PPovertyIndv, PEmploy, Punemploy, PFulltimeEmploy, PParttimeEmploy, POccupyHouse, POwner, PRenter, FID_y, GEOID10_
y, GasStation, VacLot, VacBldg, ParkingLot, AlleyCount, AlleyLen, ParkArea, HighSch
```

Using Random Forest to select 5 important variables to predict frequency of drug arrests
Model : frequency of drug arrest per 1000 population ~ VacantLot + ParkingLot + PBachelorHigher + Pct_LoMeWg + D5ar

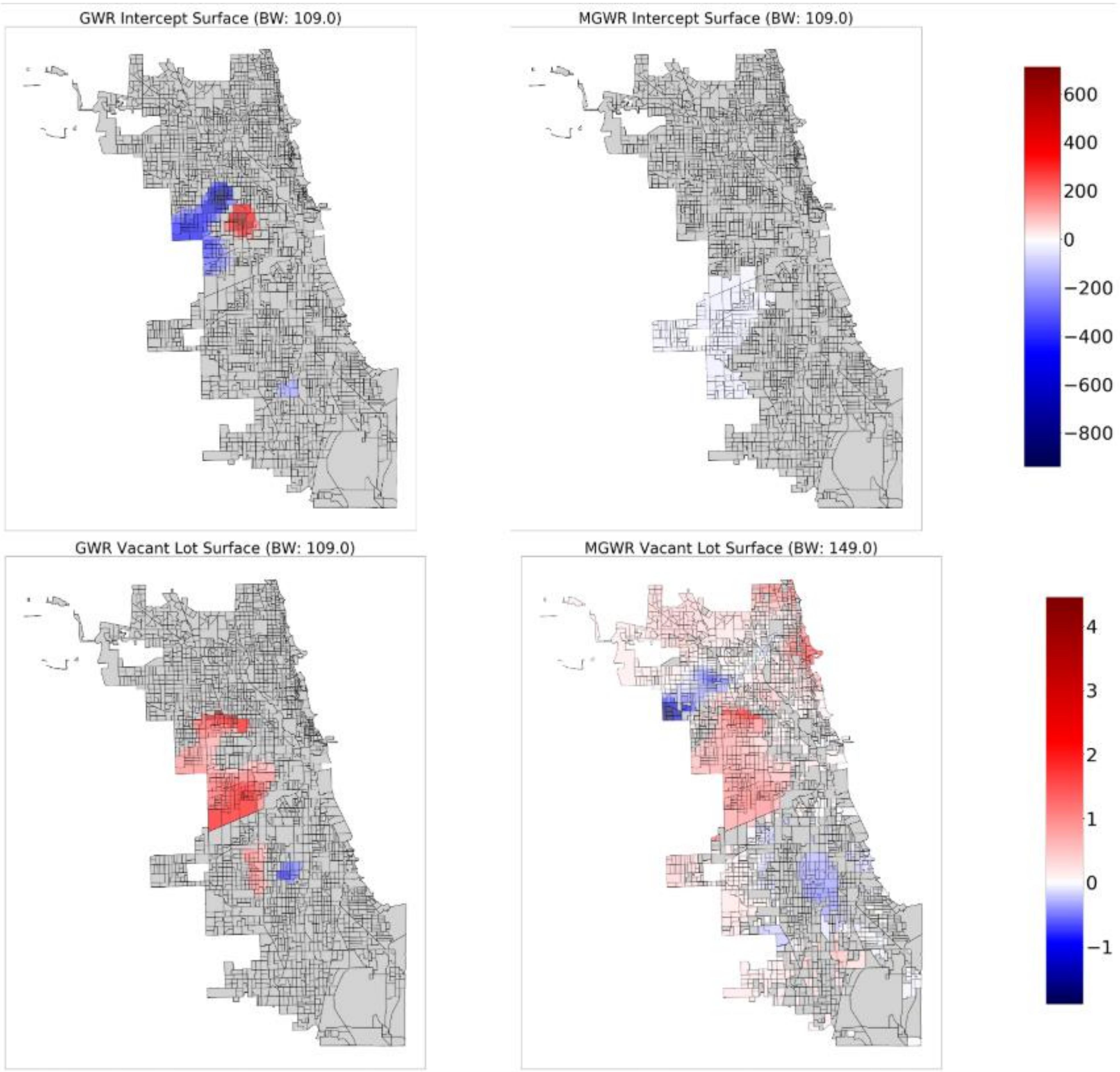
Pct_LoMeWg: percent of low-medium wage workers have accessibility to public transit
D5ar: jobs accessible by 45 min transit

GWR and MGWR

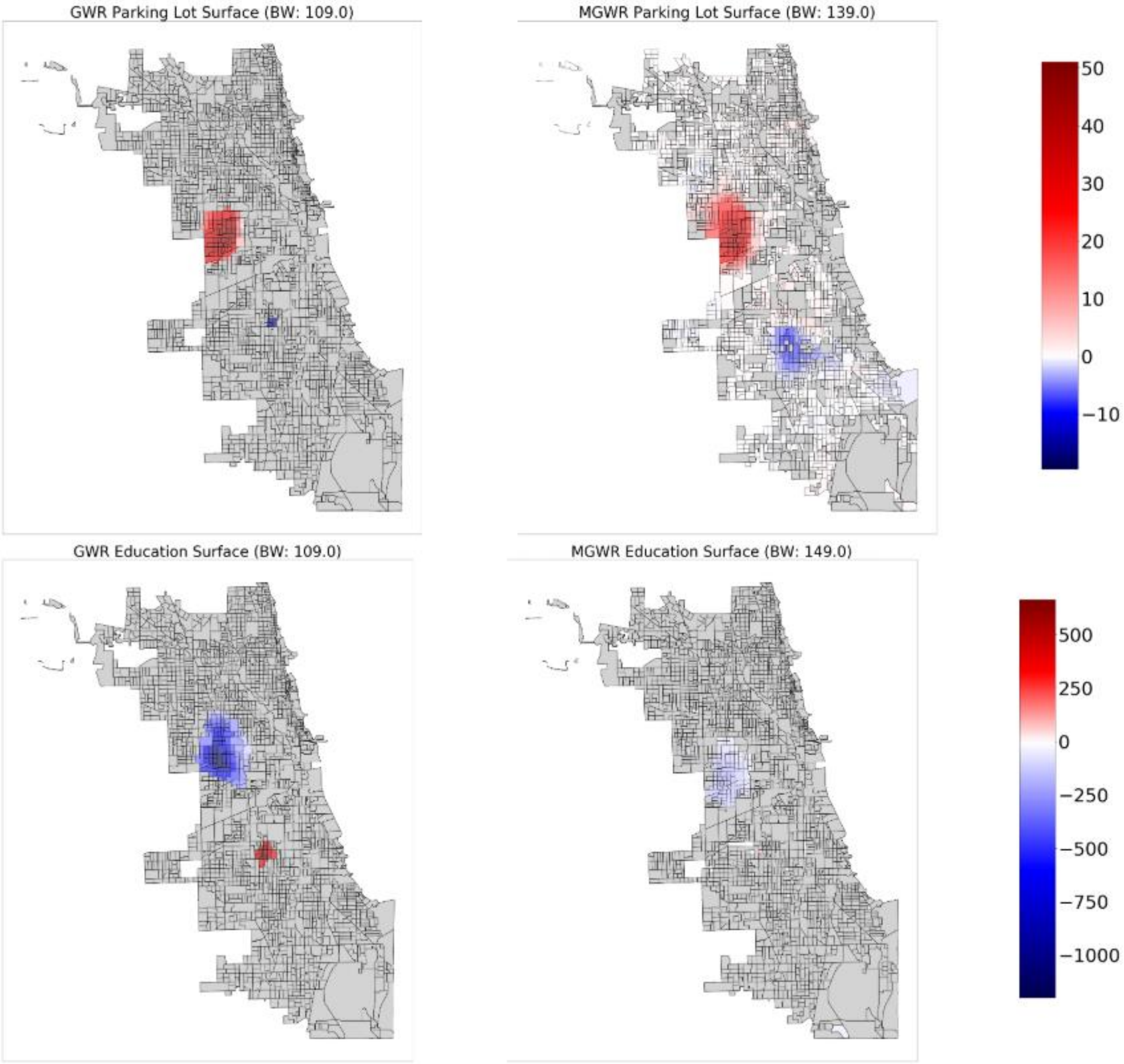
Using Random Forest to select 5 important variables to predict frequency of drug arrests

Model : frequency of drug arrest per 1000 population ~ VacantLot + ParkingLot + PBachelorHigher + Pct_LoMeWg + D5ar

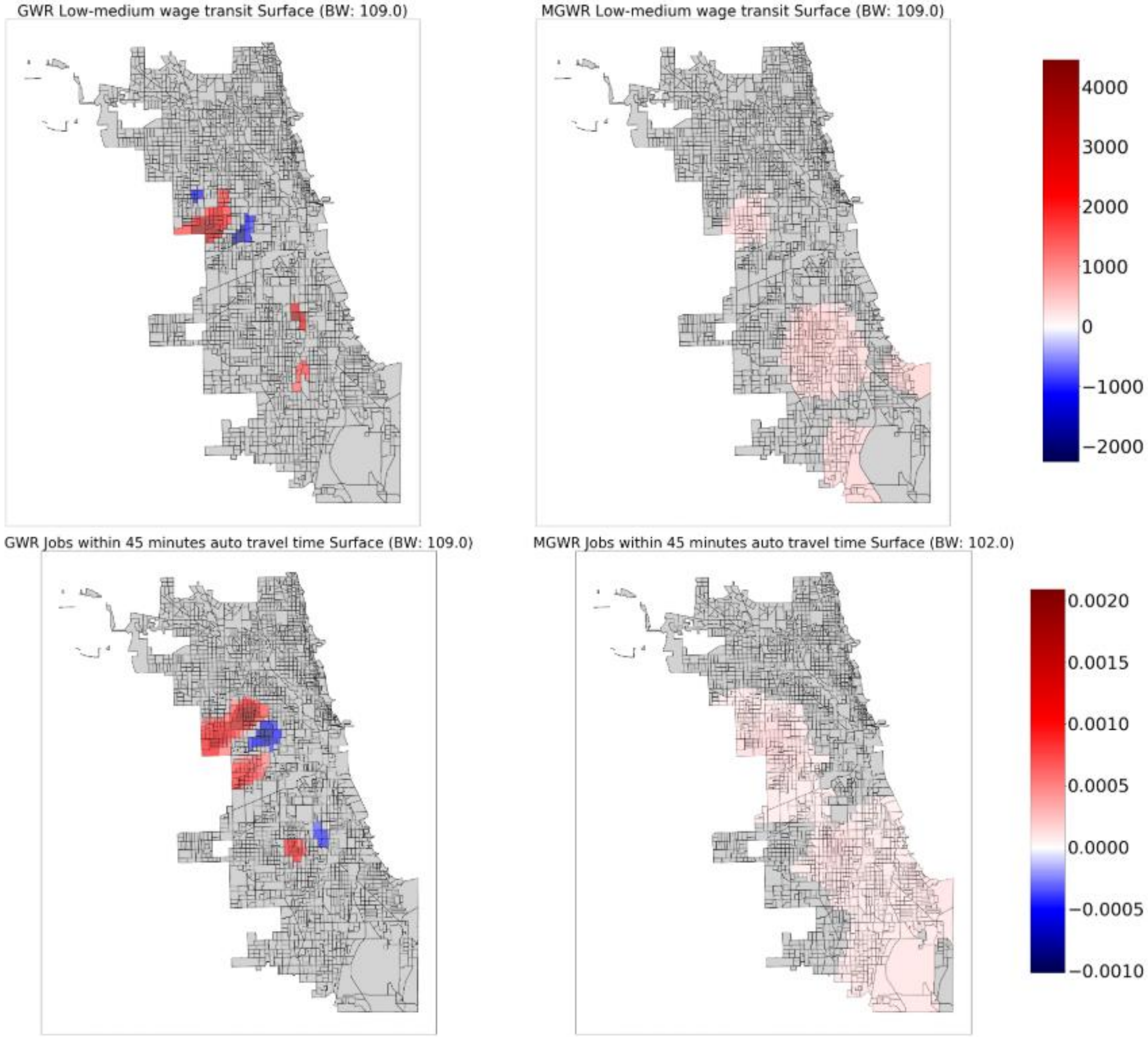
Pct_LoMeWg: percent of low-medium wage workers have accessibility to public transit
D5ar: jobs accessible by 45 min transit



GWR and MGWR


GWR Parking Lot Surface (BW: 109.0)
MGWR Parking Lot Surface (BW: 139.0)
50
40
30
20
10
0
−10
GWR Education Surface (BW: 109.0)
MGWR Education Surface (BW: 149.0)
500
250
0
−250
−500
−750
−1000

GWR and MGWR




```
LinAlgError: Matrix is singular.
```

Backfitting: 100% 200/200 [22:03<00:00, 6.62s/it]

```
[109. 135. 211. 123. 133. 107.]
```

Inference: 0% 0/1 [00:00<?, ?it/s]

Random Forest model

Variables:
Total number: 182
Sources: EPA, ACS, ESRI Business, Chicago open data portal

```
list_var = chicago_variable.columns
print(*list_var, sep=", ")
```

```
GEOID10_x, GEOID_Data, geometry, DEATH, FID_x, GEOID, arrest_per1000, FID_y, GEOID10_y, P_WRKAGE, AUTOOWN0, PCT_AO
0, AUTOOWN1, PCT_AO1, AUTOOWN2P, PCT_AO2P, WORKERS, R_LOWWAGEW, R_MEDWAGEW, R_HIWAGEWK, R_PCTLOWWA, EMPTOT, E5_RET
10, E5_OFF10, E5_IND10, E5_SVC10, E5_ENT10, E8_RET10, E8_OFF10, E8_IND10, E8_SVC10, E8_ENT10, E8_ED10, E8_HLTH10,
E8_PUB10, E_FEDT10, E_FEDRET10, E_FEDOFF10, E_FEDIND10, E_FEDSVC10, E_FEDENT10, E_LOWWAGEW, E_MEDWAGEW, E_HIWAGEW
K, E_PCTLOWWA, AC_TOT, AC_WATER, AC_LAND, AC_UNPR, D1A, D1B, D1C, D1C5_Ret10, D1C5_Off10, D1C5_Ind10, D1C5_Svc10,
D1C5_Ent10, D1C8_Ret10, D1C8_Off10, D1C8_Ind10, D1C8_Svc10, D1C8_Ent10, D1C8_Ed10, D1C8_Hlth1, D1C8_Pub10, D1D, D1
_flag, D2A_JPHH, D2B_E5MIX, D2B_E5MIXA, D2B_E8MIX, D2B_E8MIXA, D2A_EPHHM, D2C_TRPMX1, D2C_TRPMX2, D2C_TRIPEQ, D2R_
JOBPOP, D2R_WRKEMP, D2A_WRKEMP, D2C_WREMIX, D3a, D3aao, D3amm, D3apo, D3b, D3bao, D3bmm3, D3bmm4, D3bpo3, D3bpo4,
D4a, D4b025, D4b050, D4c, D4d, D5ar, D5ae, D5br, D5br_Flag, D5be, D5be_Flag, D5cr, D5cri, D5ce, D5cei, D5dr, D5dr
i, D5de, D5dei, NatWalkInd, TrAccess_I, Pop_byTr, Pop_byTr_m, Pop_byTr_1, Pop_byTr_a, Pct_Pop_by, Pct_Pop__1, Pct_
Pop__2, Pct_Pop__3, HU_byTr, HH_byTr, Wrks_byTr, Wrks_byTr_, Wrks_byTr1, Wrks_byT_1, Pct_Wrks_b, Pct_Wrks_1, Pct_W
rks_2, Pct_Wrks_3, LoWgWrks_b, LoWgWrks_1, LoWgWrks_2, MeWgWrks_b, HiWgWrks_b, LoMeWgWrks, LoMeWgWr_1, LoMeWgWr_2,
Pct_LoWgWr, Pct_LoWg_1, Pct_LoWg_2, Pct_LoWg_3, Pct_MeWgWr, Pct_LoMeWg, Pct_LoMe_1, Pct_LoMe_2, Pct_LoMe_3, Jobs_b
yTr, Jobs_byTr_, Jobs_byTr1, Job_byTr_A, Pct_Jobs_b, Pct_Jobs_1, Pct_Jobs_2, Pct_Jobs_3, FID_x, GEOID10_x, TotPop,
TotalHouse, PMale, PFemale, PWhite, PBlack, PAsian, Phispanic, PBachelorHigher, MedianHouseIncome, PPovertyHouse,
PPovertyIndv, PEmploy, Punemploy, PFulltimeEmploy, PParttimeEmploy, POccupyHouse, POwner, PRenter, FID_y, GEOID10_
y, GasStation, VacLot, VacBldg, ParkingLot, AlleyCount, AlleyLen, ParkArea, HighSch
```

Random Forest modeling is implemented in R

- More customized model setting (enhanced random forest, weighted random forest, regularized random forest, guided regularized random forest…)
- More packages to visualized model results (variable importance, partial dependence plot…)

Spatiotemporal lag variables

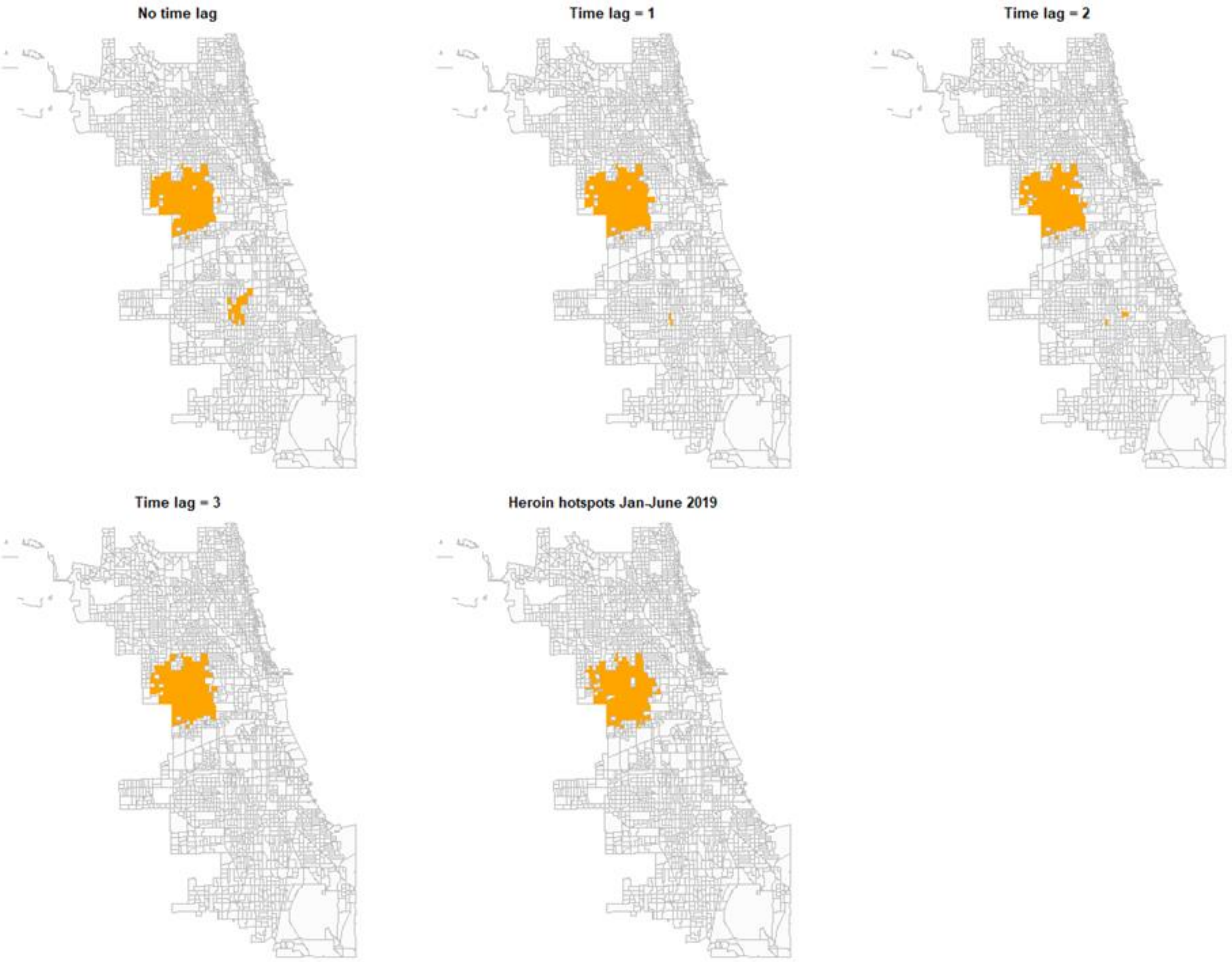
- 3 type of additional variables create
  - Spatiotemporal lag variables – nb (time lag = 1, 2, 3)
    - No. of block groups in neighborhood (Queen adjacency) that belonged to a hotspot in the past time periods (6 mos)
  - Temporal autocorrelation variables – hotspot (time lag = 1, 2, 3)
    - Was this block group in a hotspot in the past time periods? Y/N
  - Trend variables – nb_trend, hotspot_trend
    - Difference between 'nb' for different time lag (eg. 'nb_t-1' – 'nb_t-2')
    - Difference between 'hotspot' for different time lag (eg. 'hotspot_t-2' – 'hotspot_t-3')

Time series analysis

Train Random Forest model using data between 2016 and 2018

Predict in 2019

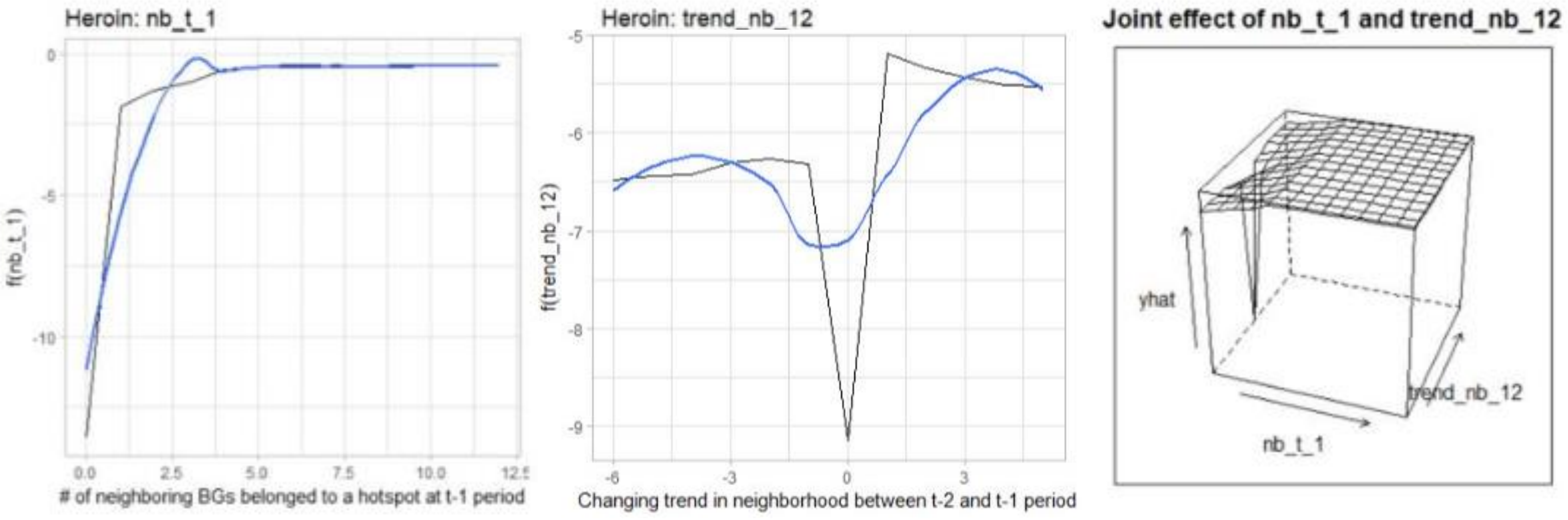
Real patterns between 2016 and 2018



Contribution of spatiotemporal lag var

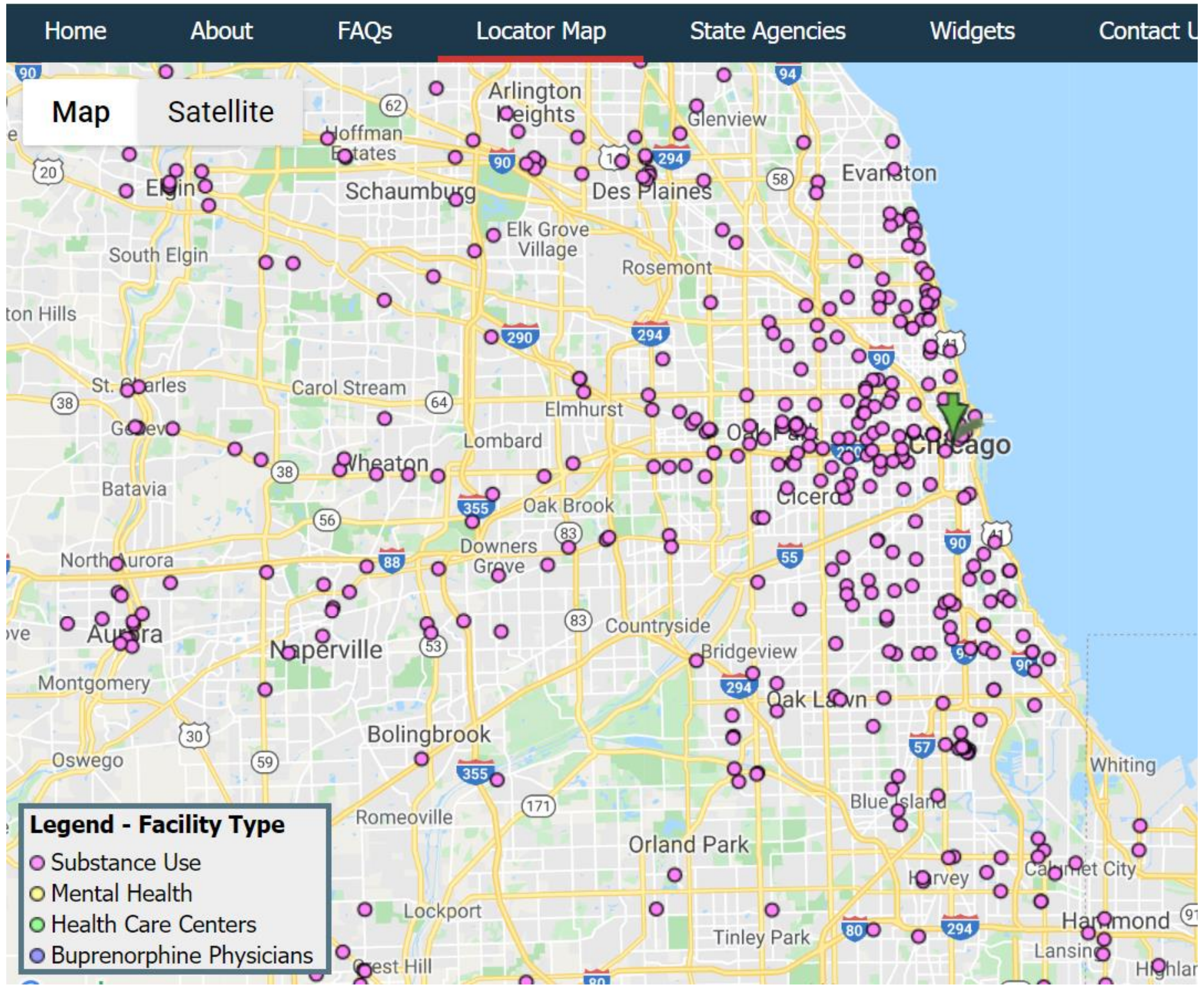
Partial dependence plot of two selected spatiotemporal variables on classifying the case to hotspot class

nb_t_1: the number of BGs belonged to a hotspot at t-1 period
trend_nb_12: nb_t_1 – nb_t_2 (>0: increasing trend; <0 decreasing trend)



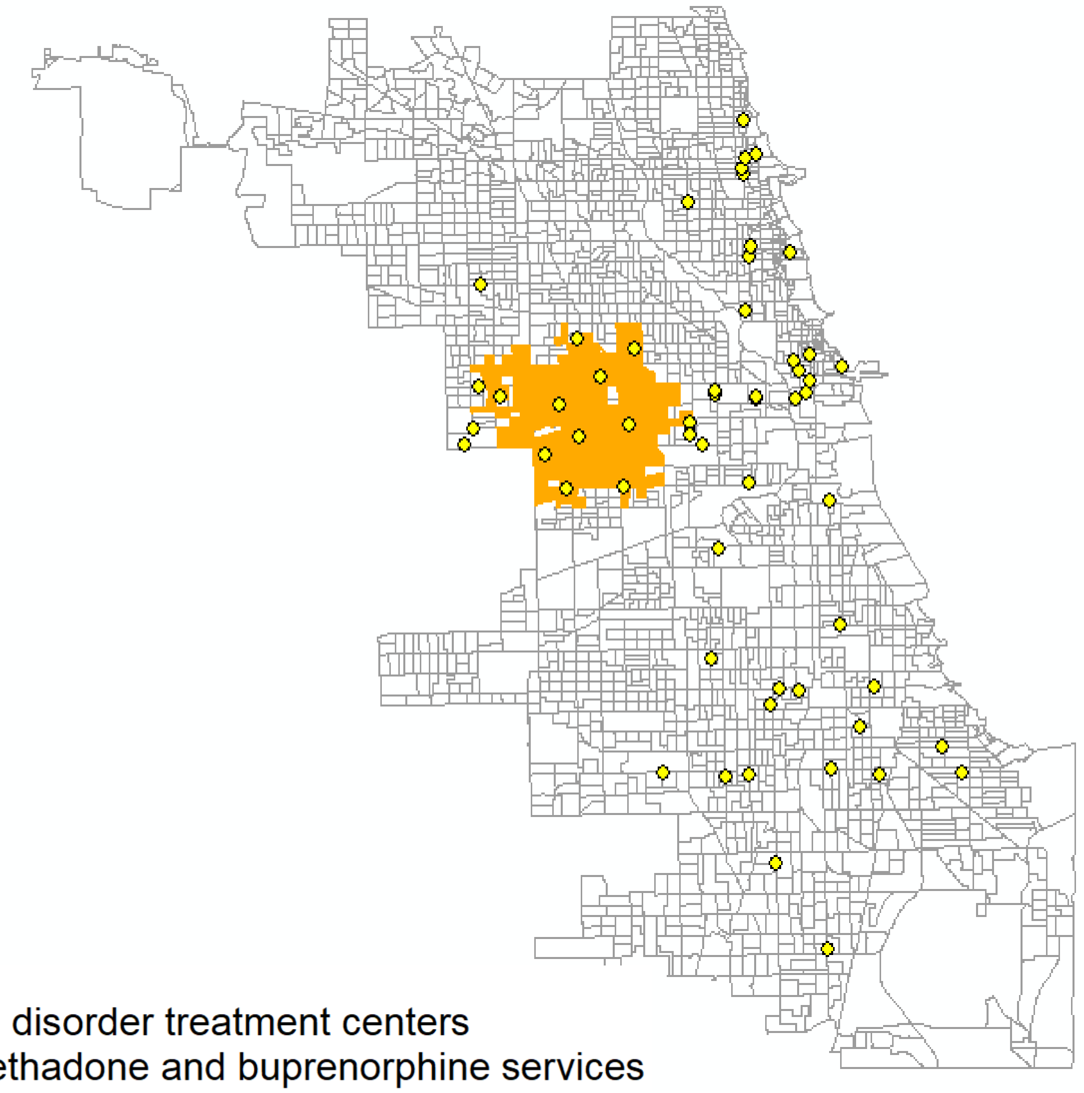
Treatment centers

All substance use treatment centers (some do not provide opioid treatments)



OT	Type of Opioid Treatment	UN	Administers naltrexone
OT	Type of Opioid Treatment	RPN	Relapse prevention from naltrexone
OT	Type of Opioid Treatment	PAIN	Use methadone/buprenorphine for pain management or emergency dosing
OT	Type of Opioid Treatment	MOA	Accepts clients on opioid medication but prescribed elsewhere
OT	Type of Opioid Treatment	NMOA	Does not use medication for opioid addiction
OT	Type of Opioid Treatment	NOOP	Does not treat opioid addiction
OT	Type of Opioid Treatment	ULC	Lofexidine/clonidine detoxification
PHR	Pharmacotherapies	ACM	Acamprosate (Campral®)
PHR	Pharmacotherapies	DSF	Disulfiram (Antabuse®)
PHR	Pharmacotherapies	METH	Methadone
PHR	Pharmacotherapies	BSDM	Buprenorphine sub-dermal implant (Probuphine®)
PHR	Pharmacotherapies	BWN	Buprenorphine with naloxone (Ex. Suboxone®)
PHR	Pharmacotherapies	BWON	Buprenorphine without naloxone
PHR	Pharmacotherapies	BERI	Buprenorphine (extended-release, injectable, for example, Sublocade®)

Locations of opioid treatment centers and heroin hotspots



Opioid use disorder treatment centers provide methadone and buprenorphine services