## E. Details on NC Tracts Data

## E.1. Application Details

The full list of variables used in the clustering analysis is as follows:

Again, the analysis was performed on an Apple Macbook Pro with M1 Pro processor with 32 GB of memory. The scikit-learn clustering package<sup>24</sup> package was used for all experiments to perform comparison K-means clustering as well as handling Gaussian process modeling for the GPSC algorithm and computing clustering metrics. Although we are unable to release the data and auxiliary files for our real world application, the code for clustering and plotting has been submitted along with all the simulation code. For both K-means and GPSC, the full set of data shown in Table 12 including the covariates and spatial data were input into both algorithms.

| Variable       | Description                                     |
|----------------|---|
| Spatial Data S |   |
| LATITUDE       | Latitude coordinate of                          |
|                | population-weighted geographic center of tract  |
| LONGITUDE      | Longitude coordinate of                         |
|                | population-weighted geographic center of tract  |
| Covariates X   |   |
| PRFL_M         | Men in professional occupation                  |
| $PRFL_F$       | Women in professional occupation                |
| LS_HS          | Less than high school education                 |
| SINGLE         | Single with dependent                           |
| HSHLDR_F       | Female head of household                        |
| NHBLK          | Non-Hispanic Black                              |
| PA             | Public assistance                               |
| POV            | Poverty   |
| NO_VHCL        | No vehicle                                      |
| RENT           | Rental housing                                  |
| CROWD          | Crowded housing                                 |
| UNMPLYD        | Unemployment                                    |
| PHONE          | No phone  |
| ACET           | Acetaldehyde                                    |
| BENZENE        | Benzene   |
| BUTA           | 1,3-Butadiene                                   |
| CARBON         | Carbon Tetrachloride                            |
| DIESEL         | Diesel PM2.5                                    |
| ETHYL          | Ethylbenzene                                    |
| FORM           | Formaldehyde                                    |
| HEXANE         | Hexane  |
| LEAD           | Lead compounds                                  |
| MANG           | Manganese compounds                             |
| MERC           | Mercury compounds                               |
| METH           | Methanol  |
| METHYL         | Methyl Chloride                                 |
| NICK           | Nickel  |
| TOLUENE        | Toluene   |
| XYLENE         | Xylenes   |
| Response Y     |   |
| MLCJOINT       | Overall class membership into 8 possible groups |

Table 12: Full set of variables used for NC tracts data application.

# E.2. Additional Real World Application Comparisons

In this section we present additional results of the best performing competitors from the simulation studies (using default parameters) on the CBCS real world example of the main paper, which already contained the comparison to K-means clustering. We also include one algorithm of each type from the set of competitors, again for diversity of results. It can be seen that the different types of clustering models have distinct differences to the results of GPSC as discussed below.

### E.2.1. Gaussian Mixture Model

Here we report the clustering results of the Gaussian Mixture Model. It can be seen that the results are visibly similar to the results of K-means clustering, where again the algorithm appears to mostly center the cluster diversity around the major urban centers of the state, with fewer cluster diversity across the extremities and regions between the urban centers.

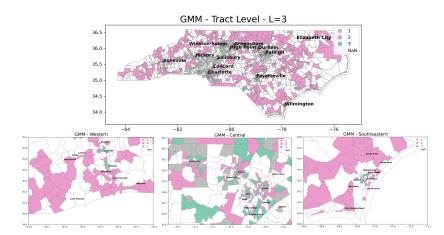


Fig. 29: GMM results for the real world application presented in main paper.

#### E.2.2. Spectral Clustering

Spectral clustering, similar to the spatial hierarchical clustering results presented below, seems to pick up more global trends with lower nuance specifically around the dense city regions of the state.

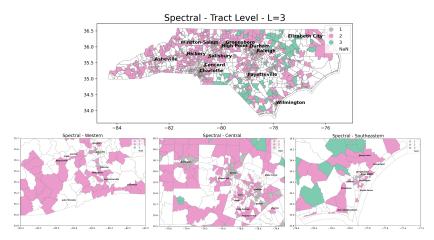


Fig. 30: Spectral clustering results for the real world application presented in main paper.

## E.2.3. Spatial Hierarchical Clustering

Spatial hierarchical clustering is presented here with 5 neighbors (result did not vary significantly over different specifications of the neighbor count). It can be seen that although the algorithm may be picking up on more global trends across the state, there is decreased nuance around the specific city centers of the state.

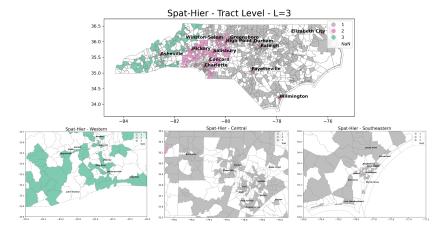


Fig. 31: Spatial hierarchical clustering results for the real world application presented in main paper.

### E.2.4. DBSCAN

Here DBSCAN was chosen over GDBSCAN due to having fewer hyperparameters required to tune (default used), while having similar performance in the simulation studies. It can be seen here that the main challenge of DBSCAN (as well as GDBSCAN) is the inability to mandate the number of clusters, especially in this application where we specifically seek a small number of clusters for interpretability.

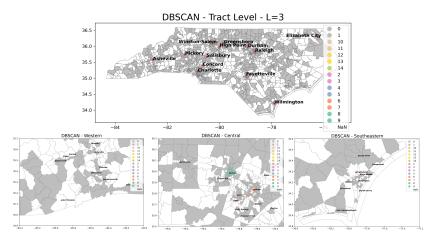


Fig. 32: DBSCAN clustering results for the real world application in the main paper.