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On-Road Mobile Source Pollutant Emissions: Identifying Hotspots and Ranking Roads

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EXECUTIVE SUMMARY

A considerable amount of pollution to the air in the forms of hydrocarbons, carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter (PM) and air toxics comes from the on-road mobile sources. Estimation of the emissions of these pollutants and quantification of the pollutants released are the most important initial steps in the process of controlling the air pollution. This study presents a methodology to rank the roads based on the On-Road Mobile Source Air Pollutant (ORMSAP) emissions using self organizing maps (SOM). This methodology was applied in a case study in Ohio with the historic Average Annual Daily Traffic (AADT) data for highways. This data was obtained from Ohio Department of Transportation (ODOT) and the ORMSAP emission estimates were computed from Motor Vehicle Emission Simulator (MOVES). Traffic was considered as of two types of vehicles, gasoline powered passenger vehicles and diesel powered commercial trucks driven on three types of highways, interstate route, state route and US route. Five ORMSAPs -CO, NO_x, PM₁₀, PM_{2.5} and SO₂- were taken into account in this study. Ohio highway network was classified into groups based on five ORMSAP emissions per road length and also per road segment. Ohio counties were classified according to the total ORMSAP emissions per county and also ORMSAP emissions per highway length, per capita and per area of the county. The results were visualized with the GIS maps.

Keywords: On-road mobile sources, Pollutant, MOVES, Self organizing maps, Traffic

INTRODUCTION

Air pollution is significantly attributed to number of health effects, environmental effects, acid rain, global warming and other climate change effects, and also economical effects. Controlling and mitigating air pollution starts with the understanding of the pollutants and their sources. Air pollutant sources are majorly categorized into three categories; point sources, area sources and mobile sources. Mobile pollutant sources are subclassified into two groups; On-Road Mobile Sources (ORMS) and Non-Road Mobile Sources (NRMS). ORMS (or highway sources) are comprised of the vehicles used for transportation on roads. This ensemble includes light-duty cars, light-duty trucks, heavyduty vehicles and motorcycles. These vehicles are mostly powered by gasoline, diesel, and to a little extent by natural gas, ethanol and electricity. On-Road Mobile Source Air Pollutants (ORMSAP) that are emitted from the ORMS include Hydrocarbons, Carbon Monoxide (CO), Nitrogen Oxides (NO_x), Particulate Matter (PM), Sulfur Dioxide (SO₂), air toxics and greenhouse gases.

Emitted quantity from an on-road vehicle depends on various factors; type of the vehicle, condition of the vehicle, type of the powering fuel, speed the vehicle runs and the distance it travels. Further, the total quantity of ORMSAP present at a time in air is also a function of number of vehicles on road, the time of the day and the surrounding environment. Given the number of the players involving in the pollution mechanism, it is difficult to get an accurate estimate for the ORMSAP emission. MOBILE and MOVES models developed by USEPA hold the capabilities to estimate the emission factor for a vehicle from its type, fuel type and other vehicle specific inputs (USEPA, 2003; USEPA, 2007; USEPA, 2010). Claggett and Miller presented a methodology to estimate the emission of mobile source air toxics using MOBILE 6.2 (Claggett and Miller, 2006).

In the process of controlling on-road mobile source induced air pollution, in addition to the estimation of the emission per vehicle, it is also important to identify the volume of traffic with respect to location and time. On-road air pollution increases with the number of vehicle in motion. Hence identifying the road sections of high emission (emission hotspots) and the temporal factor in the emission becomes crucial in the decision

making stage of air pollution control. This necessitates a model for delineating the transportation network into clusters based on amount of ORMSAP emission. This clustering process also helps to rank the roads according to the on-road mobile air pollution severity. Identifying such similar ORMSAP based road clusters in different parts of an interested region (such as a county or a state or even the whole country) would help to explore further to compare the other factors such as socioeconomic parameters present within each cluster. 'Total Emission per Length of the road' (TEL) classification can be used to evaluate the intensity of the ORMSP pollution along the transportation system, and 'Total Emission per Segment' (TES) classification can be used to identify the road segments according to their pollutant contribution.

The objective of this study is to develop a methodology for clustering the roads and the regions based on the traffic counts and the ORMSAP emission estimates so that the heavily polluted roads and regions can be identified and delineated for designing and planning alternative traffic routes. This methodology is elaborated with the case study using the Ohio highway traffic data.

METHEDOLOGY

The methodology for achieving the objective is presented into four consecutive steps:

Step 1: Identification of vital ORMSAPs

Step 2: Derivation of emission metrics of vital ORMSAPs

Step 3: Quantification of available vital ORMSAPs

a. Road ORMSAP estimation

b. Areal ORMSAP estimation

Step 4: ORMSAP analyses

a. ORMSAP based clustering of the roads

b. ORMSAP based clustering of the regions

Figure 1 shows the schematic of the methodology.

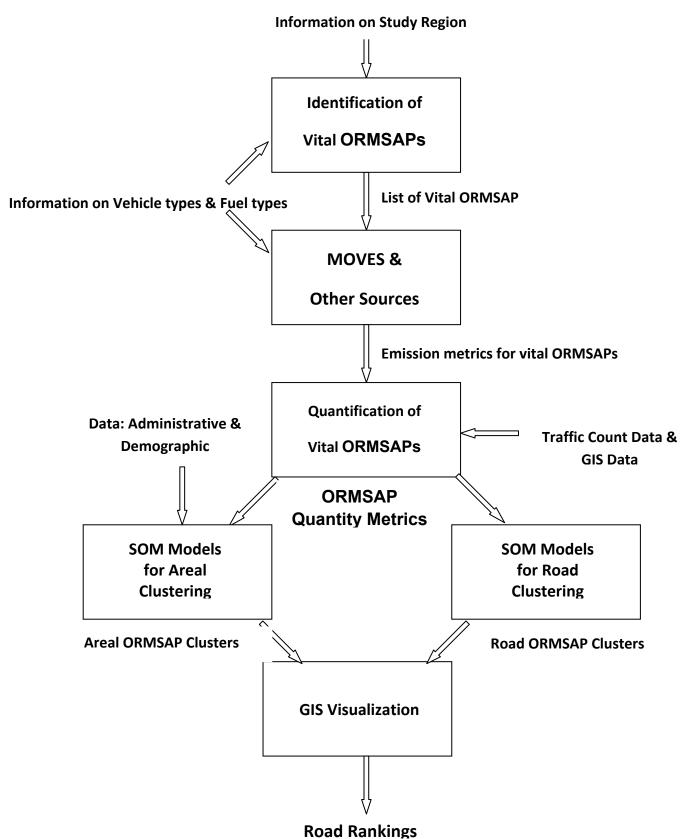


Figure 1: Schematic of the Methodology

Step 1: Identification of vital ORMSAPs

ORMSAPs (released in a transportation network) depend on the vehicle type and the fuel type. Hence it is important in the first place to identify the vital ORMSAPs released in a transportation network by analyzing the vehicle types and the fuel types in the traffic data. A typical list of ORMSAPs that were released in a road network includes CO, NOx, PM and important mobile source air toxics (USEPA, 2008) for a gasoline powered vehicle. SO₂ may be included for a vehicle operated with diesel.

Step 2: Derivation of emission estimates for vital ORMSAPs

Once the vital ORMSAPs for a road network are identified, the emission estimate set is composed of the ORMSAP emissions from each type of fuel-vehicle combinations per vehicle per length of road. These values are obtained either by running MOVES program with the appropriate data or by using the reasonable emission estimates available in the literature. A short description of MOVES is given in the next section.

Step 3: Quantification of available vital ORMSAPs

In the Step 3, total quantity of each ORMSAP released for a time period such as an hour or a day is calculated using the emissions estimated in Step 2, and the traffic count data. Traffic count data consists of observation locations, diversity data of vehicle types and traffic contribution for day.

a. Road ORMSAP quantity metrics estimation

Two types of road ORMSAP quantity metrics, TEL and TES are computed. For each road segment, TEL is the metric of all individual ORMSP emissions per length. Each TEL metric is computed as the product of estimated emission of an ORMSP for a vehicle per mile and the number of the vehicles in the segment. TEL metrics are computed as the products of ORMSP emission estimates and the traffic counts. TES for a segment is the metric of all individual ORMSP emissions. It is equivalent to the product of Vehicle Miles Traveled (VMT) and actual emissions of ORMSPs per mile. When the vehicles are counted at one location per segment, TES metrics are computed by multiplying TEL of the particular segment by the length of the segment.

b. Areal ORMSAP emission quantity estimation

Once the ORMSP - TES metrics for the roads are computed, they are summed up to the needed regional scale (such as a county) to account for the total ORMSP emissions for the region. Once this is done, three categories of average emissions for the region is computed; emissions per area, emissions per capita and emissions per road length.

Step 4: ORMSAP analyses

Once the road and areal emissions are computed for the transportation network, one family of unsupervised artificial neural networks, Self Organizing Map (SOM) is used to cluster the roads and the regions into groups. Hence roads (or routes) are clustered into two ways; based on the TEL metrics and TES metrics. Regional clustering is done in five ways; based on the total areal emissions, emissions per area, emissions per capita, emissions per road length and all the above four categories together. The basic theory of SOM is explained in the next section.

Finally the clustering results are visualized in GIS.

Modeling Techniques Used

MOVES

MOtor Vehicle Emission Simulator, MOVES in short, was developed and is maintained by U. S. Environmental Protection Agency for providing the best estimates for mobile source pollutant emissions under various conditions (EPA, 2010). MOVES comes with a quality controlled database of the parameters that are needed for the emission estimations. This database is updated time to time. A user can use either this default database or the user's own datasets for the estimation purpose depending on the scale of the project.

With the problem in hand, a modeler can specify geographical regions, road types such as urban roads and rural roads, vehicle types such as passenger cars and trucks,

vehicle operating conditions such as speed, operating time periods such as night and day, pollutants such as PM and CO, and fuel types such as gasoline and diesel. Once the conditions are set and the model is run, it will execute a series of computations to estimate emissions. The output is saved on a database that can be read and saved as text files by post processing tools in MOVES.

Figure 2 shows a screen shot of the features in MOVES. This study used MOVES2010a version for its estimation.

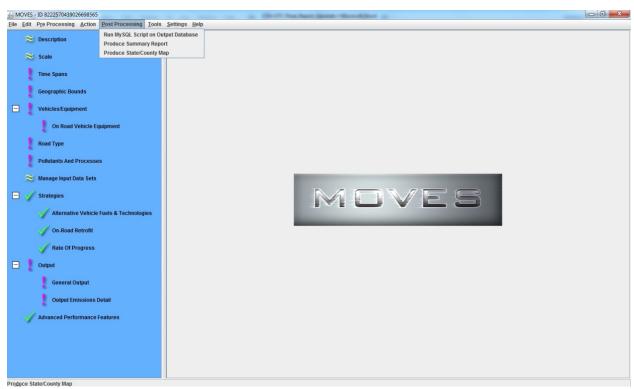


Figure 2: MOVES Graphical User Interface

Self Organizing Maps (SOMs)

One of the most popular types of unsupervised artificial neural network, generally known as Self Organizing Map (SOM) can be used to extract underlying relationships among the variables from data. It was first conceptualized by Kohonen, and has been extensively explored in many fields for the purposes of classification and pattern recognition (Kohonen, 2001).

In a SOM network, the competitive learning process is done with inputs. These networks are comprised of the input layer with original data and the output layer that is mapped with the reduced two dimensional data. In such a network each input layer neuron represents an input variable and this input neuron is connected to each of the mapped output layer using a nonlinear projection (Figure 3).

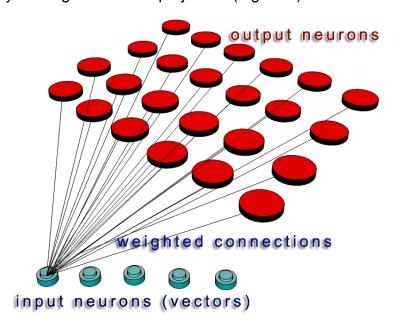


Figure 3: Components of a self organizing map

The high dimensional input data is reduced to two dimensional through the iterative selforganization process elaborated below, and consequently the input data is grouped into the cells. This is followed by the similar cells being grouped into clusters. Analyzing the extracted relationships among the input variables, the system can be understood (Kohonen, 1990; Kohonen, 2001).

SOM Training

Let us say the input vector is $\{X(t)\}$ with N variables in each vector

Step 1: Weight of each neuron is randomly initialized within the interval [0,1].

Step 2: At an instance, this input vector is compared with the weights using Euclidean distance.

Step 3: Best Matching Unit (BMU) for an input vector is decided as the neuron with the shortest Euclidean distance.

Step 4: The weights are updated by reducing the distances between them and the input values using a neighborhood function.

Step 5: Steps 2-4 are iteratively done till the results converge to the desired range

The SOM size (number of cells the SOM is composed of) affects the classification. If the cells are few it may suppress some cluster differences that should explain few underlying patterns. If many cells make the SOM map the important subtle differences may not be distinguished. SOM selection criteria use two iterative error values to select the optimal SOM size. Quantization error that measures map resolution is the average distance between each data vector and its BMU. Topographic error that measures topology preservation is the proportion of all data vectors for which first and second BMUs are not adjacent units. Figure 4 presents an example for how the iterative errors change with the number of cells in the SOM map. Number of cells is chosen when both errors are relatively low in the iterative process. However this selection process is subjective too.

Once the SOM map size is decided, U-matrix that is composed of the distances between neighboring map units is used to decide the number of clusters (Figure 5). The light color of the cells shows the input vectors that are similar and the dark color shows the input vectors that are dissimilar. Light areas can be considered as clusters while dark areas can be used as the cluster separators. Mathematically, the minimum value of the Davies-Bouldin index can be used to decide the number of the clusters (Figure 6). Figure 7 shows a clustered SOM. In this study, MATLAB-Neural Networks Toolbox is used to develop SOM maps.

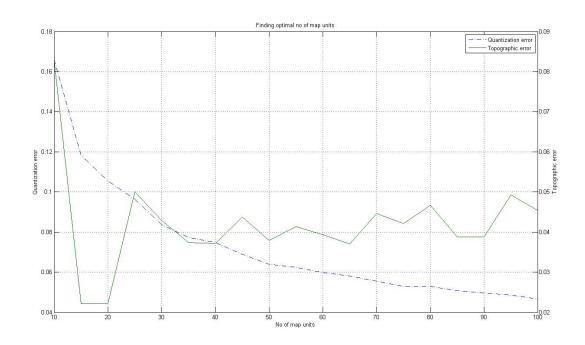


Figure 4: Change of quantization and topographic errors with the size of SOM

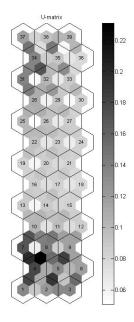


Figure 5: U-Matrix of a SOM

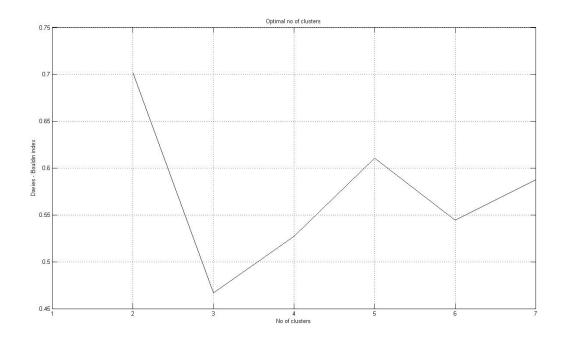


Figure 6: Davis-Bouldin Index for choosing the optimal number of clusters

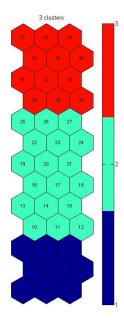


Figure 7: SOM clusters and the cells in those clusters

CASE STUDY

Annual Average Daily Traffic (AADT) count data for two categories -passenger vehicles and trucks- for three types of routes (state route, US route and interstate route) for six year period (2003-2008) in Ohio was obtained from ODOT. Figure 8 shows the Ohio highways network.

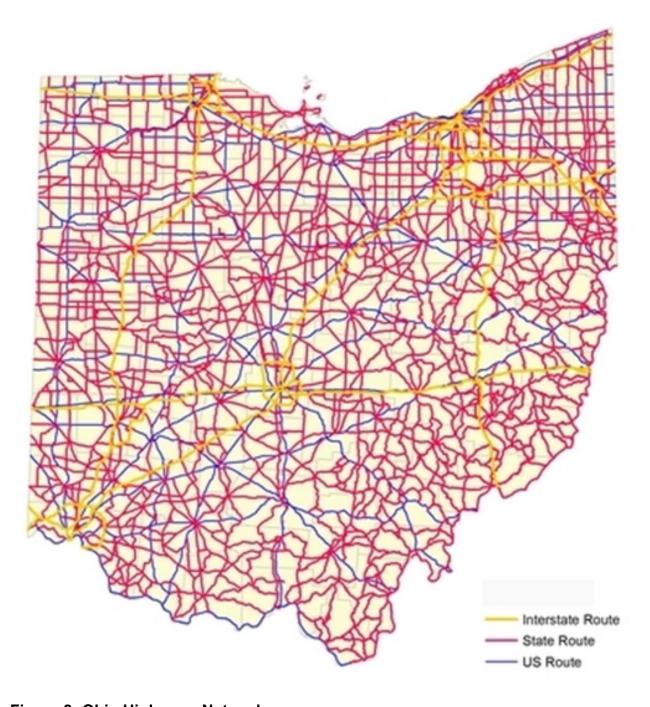


Figure 8: Ohio Highways Network

Five ORMSAPs, CO, PM (PM_{2.5} and PM₁₀), NO_x and SO₂ were identified as the vital pollutants with the safe assumption that cars or light duty trucks were powered with gasoline and heavy duty trucks were powered with diesel (Diesel Net, 2010; RITA, 2010). Three different sets of ORMSAP emission estimates per vehicle per mile – two from the literature and the third from running MOVES- were considered for computing total emissions. Based on these values two detailed studies were performed; one study was done with one of the literature based emission data, the allowable emissions provided in Tier 2 standard (Diesel Net, 2010). The second study was pursued with MOVES estimates. These results are provided in the next section.

TEL and TES metrics were computed in EXCEL. Classification was done with MATLAB— Neural Network toolbox. The final visualization was performed on ARCGIS.

RESULTS

Available traffic data, AADT was an annually cumulative traffic data averaged per day. AADT was also computed in phases throughout Ohio counties for six year period. Hence this averaged data was not much sensitive to the change in the weather parameter. It did not reflect the various levels of seasonal fluctuations in the traffic either. Hence while computing the ORMSAP estimates with MOVES and the national data, a summer month, August was selected. MOVES was executed for ORMSAPs in two different type of counties in Ohio; heavily urban Cuyahoga County and the mostly rural Morgan County. As an example, the screen shots of consequent steps in MOVES for computing SO₂ in Cuyahoga County are given in Appendix A.

Table 1 provides ORMSAP estimates per vehicle per mile computed for Cuyahoga County and Morgan County. Table 2 presents the ORMSAP estimates presented in the literature and the estimates made with the results presented in Table 1. It was not found that the differences between the estimates from these two counties were not negligible.

Vehicle	Fuel	Pollutant		Emission (g/mile/\	
Туре	Туре	Type	Road Type	Cuyahoga	Morgan
7,7	7,70	. , , ,		County	County
			Rural Unrestricted	0.023	0.022
Passenger	Gasoline		Urban Restricted	0.029	N/A
Truck		D14	Urban Unrestricted	0.022	N/A
		PM _{2.5}	Rural Unrestricted	1.564	1.565
Heavy duty	Diesel		Urban Restricted	1.618	N/A
Truck			Urban Unrestricted	1.563	N/A
December			Rural Unrestricted	0.040	0.040
Passenger	Gasoline		Urban Restricted	0.046	N/A
Truck		DM	Urban Unrestricted	0.038	N/A
11		PM ₁₀	Rural Unrestricted	1.685	1.685
Heavy duty	Diesel		Urban Restricted	1.740	N/A
Truck			Urban Unrestricted	1.678	N/A
December			Rural Unrestricted	0.062	0.062
Passenger	Gasoline		Urban Restricted	0.076	N/A
Truck		DM	Urban Unrestricted	0.059	N/A
Heavy duty		PM	Rural Unrestricted	3.250	3.250
	Diesel		Urban Restricted	3.358	N/A
Truck			Urban Unrestricted	3.241	N/A
December			Rural Unrestricted	6.122	7.828
Passenger	Gasoline		Urban Restricted	7.058	N/A
Truck		СО	Urban Unrestricted	6.082	N/A
Lloon, duty		CO	Rural Unrestricted	3.751	3.751
Heavy duty	Diesel		Urban Restricted	3.752	N/A
Truck			Urban Unrestricted	3.751	N/A
Daggarar			Rural Unrestricted	1.061	1.231
Passenger Truck	Gasoline		Urban Restricted	1.045	N/A
HUCK		NO	Urban Unrestricted	1.043	N/A
Lloon, duty		NO _x	Rural Unrestricted	14.930	14.703
Heavy duty Truck	Diesel		Urban Restricted	14.856	N/A
Truck			Urban Unrestricted	14.930	N/A
Dooongor			Rural Unrestricted	0.022	0.017
Passenger Truck	Gasoline		Urban Restricted	0.023	N/A
HUCK		80	Urban Unrestricted	0.022	N/A
Hoove duty		SO ₂	Rural Unrestricted	0.068	0.068
Heavy duty Truck	Diesel		Urban Restricted	0.068	N/A
HUCK			Urban Unrestricted	0.068	N/A

Table 1: MOVES estimates for ORMSAP emissions in two counties of Ohio

Pollutant Type						
	CO (g/mi)	NO _x (g/mi)	PM (g/mi)	PM ₁₀ (g/mi)	PM _{2.5} (g/mi)	SO ₂ (g/mi)
Vehicle Type						
Light Duty Vehicle FTP Tier 2 Standard	4.2	0.6	0.08			
Medium Duty Vehicle FTP Tier 2 Standard	7.3	0.9	0.12			
Light Duty Truck (2008) National Average	12.49	0.94				
Heavy Duty Truck (2008) National Average	2.31	8.61				
Light Duty Truck (2008) MOVES	7.85	1.25	0.08	0.05	0.03	0.02
Heavy Duty Truck (2008) MOVES	3.75	15.00	3.35	1.75	1.6	0.07

Table 2: ORMSAP emission estimates for a single vehicle in Ohio

Once the ORMSAP emissions per mile per vehicle were estimated, TEL and TES for each segment of the roads were computed, and they were used as inputs to run SOMs.

Total emissions for each ORMSAP in a county were computed by adding the emissions from all three types of the roads (TES values) within the particular county.

Like the classifications of the routes were done based on TEL and TES values, the counties were classified based the following per county; emissions per area, emissions per capita, emissions per road length and combination all the above three metrics.

Table 3 summarizes the classification results in the cluster level based on MOVESestimated ORMSAP emissions. Tables in Appendix B summarize the groupings of the counties in the SOM cell-scale.

The results are visualized Appendix C.

	Co	ounty		Cluster numbe	er according e	missions per	
No	Name	Abbreviation	Total	Road length	Area	Population	All Three
1	Adams	ADA	2	4	3	5	4
2	Allen	ALL	1	2	2	3	1
3	Ashland	ASD	1	2	2	3	2
4	Ashtabula	ATB	1	2	2	3	1
5	Athens	ATH	2	3	3	4	3
6	Auglaize	AUG	1	2	2	4	2
7	Belmont	BEL	1	2	2	3	1
8	Brown	BRO	2	3	3	5	3
9	Butler	BUT	1	1	1	2	1
10	Carroll	CAR	2	5	4	5	4
11	Champaign	CHP	2	4	3	5	4
12	Clark	CLA	1	1	1	2	1
13	Clermont	CLE	1	2	2	3	1
14	Clinton	CLI	1	2	2	4	2
15	Columbiana	COL	1	3	2	4	2
16	Coshocton	COS	2	4	3	5	4
17	Crawford	CRA	2	3	3	4	3
18	Cuyahoga	CUY	1	1	1	1	1
19	Darke	DAR	2	3	3	5	3
20	Defiance	DEF	2	3	3	4	3
21	Delaware	DEL	1	1	1	2	1
22	Erie	ERI	1	2	2	3	1
23	Fairfield	FAI	2	3	2	4	2
24	Fayette	FAY	1	2	2	4	2
25	Franklin	FRA	1	1	1	1	1
26	Fulton	FUL	1	2	2	3	2
27	Gallia	GAL	2	3	3	5	3
28	Geauga	GEA	2	3	2	4	3
29	Greene	GRE	1	2	2	3	1
30	Guernsey	GUE	1	2	2	3	2
31	Hamilton	HAM	1	1	1	1	1
32	Hancock	HAN	1	2	2	3	1
33	Hardin	HAR	2	4	3	5	3
34	Harrison	HAS	2	4	4	5	4
35	Henry	HEN	2	3	3	4	3
36	Highland	HIG	2	4	3	5	4
37	Hocking	HOC	2	4	3	5	4
38	Holmes	HOL	2	4	3	5	4
39	Huron	HUR	2	3	3	4	3
40	Jackson	JAC	2	3	3	4	3
41	Jefferson	JEF	2	3	3	4	3
42	Knox	KNO	2	4	3	5	4
43	Lake	LAK	1	1	1	2	1
44	Lawrence	LAW	2	4	3	5	4

Table 3: Ohio Counties: Groups based on MOVES-emission estimates

	Co	unty		Cluster numb	per according em	nissions per	
No	Name	Abbreviation	Total	Road length	Area	Population	All four
45	Licking	LIC	1	1	1	2	1
46	Logan	LOG	2	3	3	4	3
47	Lorain	LOR	1	1	1	2	1
48	Lucas	LUC	1	1_	1	1_	1
49	Madison	MAD	1	2	2	3	2
50	Mahoning	MAH	1	1	1	2	1
51	Marion	MAR	2	3	2	4	3
52	Medina	MED	1	11_	1	2	1
53	Meigs	MEG	2	5	4	5	4
54	Mercer	MER	2	3	3	4	3
55	Miami	MIA	1	2	2	3	1
56	Monroe	MOE	3	5	4	5	4
57	Montgomery	MOT	1 3	1	1	1	1
58 59	Morgan Morrow	MRG MRW	1	5 2	2	5 3	4 2
60	Muskingum	MUS	1	2	2	3	1
61	Noble	NOB	2	4	3	5	3
62	Ottawa	OTT	2	3	3	4	3
63	Paulding	PAU	2	4	4	5	4
64	Perry	PER	2	5	4	5	4
65	Pickaway	PIC	2	3	2	4	2
66	Pike	PIK	2	4	3	5	3
67	Portage	POR	1	<u>.</u> 1	1	2	1
68	Preble	PRE	1	2	2	3	2
69	Putnam	PUT	2	4	3	5	4
70	Richland	RIC	1	2	2	3	1
71	Ross	ROS	1	2	2	3	2
72	Sandusky	SAN	1	2	2	3	1
73	Scioto	SCI	2	3	3	4	3
74	Seneca	SEN	2	3	3	5	3
75	Shelby	SHE	1	2	2	3	2
76	Stark	STA	1	1	1	2	1
77	Summit	SUM	1	1	1	1	1
78	Trumbull	TRU	1	1	1	2	1
79	Tuscarawas	TUS	1	2	2	3	2
80	Union	UNI	1	2	2	4	2
81	Van Wert	VAN	2	3	3	4	3
82	Vinton	VIN	3	5	4	5	4
83	Warren	WAR	1	1	1	2	1
84	Washington	WAS	2	3	2	4	2
85	Wayne	WAY	1	2	2	3	2
86	Williams	WIL	1	2	2	4	2
87	Wood	WOO	1	1	1	2	1
88	Wyandot	WYA	2	d on MOVES	3	4	3

Table 3: Ohio Counties: Groups based on MOVES-emission estimates (Cont.)

DISCUSSION

FTP Tier 2 based emission estimates

These estimations were done considering the passenger vehicles as light duty vehicles and trucks as medium duty vehicles. Since for a vehicle, any emission per mile was defined with the allowable emission for that particular vehicle, the type of the fuel was not an interest (Diesel Net, 2010).

Based on FTP Tier 2 – TEL metrics, three distinct levels of on-road mobile pollution were identified along the Ohio Highway network (Appendix C.1.1) with decreasing severity of the pollution with the ascending number level. Except very few sections that fell into Cluster 2, rest of the interstate highway segments were almost in the highest emission group (Cluster 1). Sections of state and US highway routes and US highway routes fell into all three groups with the US highway that ran closer to interstate routes fell into Cluster 1. It was found that the higher order pollution on US and state highways was released around the metropolitan areas in the state. ORMSAP pollutant hotspots were found around Cleveland (Cuyahoga County), Columbus (Franklin County) and Cincinnati (Hamilton County) metropolitan areas.

Map based on Based on FTP Tier 2 – TES metrics show four classes, but without any geographically identifiable pattern. TES metrics were the product of the TEL metrics and the respective segment lengths of the routes. Hence, even a small section of a road with large traffic may yield more emission than a longer section with low traffic. However the TES based class map would be helpful in identifying a road section according to its pollutant contribution level. Knowing this level is helpful in diverting traffic or in taking preventive actions.

Collective ORMSAP emission per county was higher in the northern region of Ohio than in the southern region of Ohio except in Cincinnati metropolitan area (Appendix C.1.3.x). It has been demonstrated that the self organizing maps can be used to classify the transportation network based on the ORMSAP emissions.

Among the two types of vehicles we studied, passenger vehicles were found to contribute a larger portion in to the pollution, though a truck (heavy duty vehicle) emits more than a car (light duty vehicle) emits. This approach can be improved by incorporating better individual pollutant emission estimates for a vehicle using programs like MOVES (EPA, 2010).

MOVES based emission estimates

These estimations were done considering the passenger vehicles as light duty trucks running on gasoline and commercial trucks as heavy duty trucks running on diesel (Diesel Net, 2010).

There are 88 counties in Ohio with few are heavily urban and the others are rural. As it has explained under Case study and in the results, one heavily urban county (Cuyahoga County) and one heavily rural county (Morgan County) were taken to compute the emission estimate per vehicle using MOVES. Also it should be said that despite the varying speeds of the vehicles along the roads MOVES assumed the same value with its default in its computation. This value was lower than actual speeds in many segments of the routes. Emission estimation with the route specific data is cumbersome and has to be done in the MOVES-project level with the other user-specific data. However except the annual traffic count that was averaged for a day no required user-specific data was available. Hence the national-level data was forced to be input into these two Ohio counties in the estimation process for a token month (August).

Table 1 shows that there was no significant difference between the emissions in the unrestricted rural routes and the unrestricted urban routes for a chosen ORMSAP. It was also found that the differences among the emission estimates for an ORMSAP in different type of the road in a county were minimal with the assumptions that were taken. ORMSAP emission estimates were chosen from these computed values, and tabulated on Table 2. Comparisons of the MOVES-emission estimates for CO and NO_x

with those found in the literature show the agreements in the levels despite the difference in numbers.

Appendix C.2.1 shows three pollutant levels based on MOVES-TEL metrics. With respect to the pollution, the emission map with MOVES-TEL metrics show higher level in the rural areas and lower level in the urban areas than the emission map with MOVES-TEL metrics show. This could be due to the following reason. As shown for FTP Tier 2 case in Table 4, the ratios between the estimated emission values assumed for the passenger vehicles and the commercial trucks were around 0.6. However for MOVES case, the ratios were really low for all ORMSAPs but for CO where the ratio was comparatively high. With the MOVES estimates, the estimated emissions from a truck were relatively higher than a passenger vehicle except for CO. In other words, few trucks could yield the same amount ORMSAPs that many cars can yield. While the ratio of number of passenger vehicles to commercial trucks was high in and around the urban areas, this ratio was low in rural areas. Hence with the MOVES estimates, the pollution levels in rural areas were higher than that were in FTP Tier2 case and the vice versa was true regarding the urban area. Appendixes 2.3.1- 2.3.5 visualize the emitted ORMSAP quantities.

Criterion	Emission Estimate Ratio	CO	NOx	PM	PM10	PM2.5	SO2
FTP Tier 2	Light Duty Vehicle / Medium Duty Vehicle	0.58	0.67	0.67			
MOVES	Light Duty Vehicle / Heavy Duty Vehicle	2.09	0.08	0.02	0.03	0.02	0.29

Table 4. Emission estimate ratio between passenger vehicle & commercial trucks

In the county scale, Table B.1 and Appendix 3.2.2 shows the road classification according to total pollutants. It clearly shows the counties with interstate routes were clustered as the highest polluted group. However Tables B.2-B.4 and Appendixes 3.2-3.4 show that considering the emission per area or emission per road length or emission per capita in a county puts only the counties around urban centers in the highest level. Six cities were identified as these centers; Cleveland (Cuyahoga County), Columbus (Franklin County), Cincinnati (Hamilton County), Dayton (Montgomery County), Toledo (Lucas County) and Akron (summit County) (Appendix 3.4). With all the

above metrics considered, the less polluted counties concentrated on the northwestern region and the southeastern region of the state.

Considering the two types of the estimates, FTP Tier 2 based and MOVES based, MOVES based estimates are much desirable since they are based on the real national data in contrast to the theoretical assumption with the FTP Tier 2 allowable values.

FUTURE RESEARCH

In the future, this approach can be improved by incorporating better individual pollutant emission estimates for a vehicle with the consideration of the adjustments for seasonal changes in the traffic and vehicle speed. Also, vehicles can be further categorized and additional ORMSAPs can be taken into account. In addition, an estimate of noise pollution can be added as an input in the classification.

CONCLUSIONS

Reasonable assumption of an estimate for emission is very important in the clustering the roads and the counties. Cleveland (Cuyahoga County), Columbus (Franklin County), Cincinnati (Hamilton County), Dayton (Montgomery County), Toledo (Lucas County) and Akron (summit County) were found to have the highest levels of emissions. Rural counties with less traffic -especially those counties that do not have any interstate highway passing through them - received the lowest quantities.

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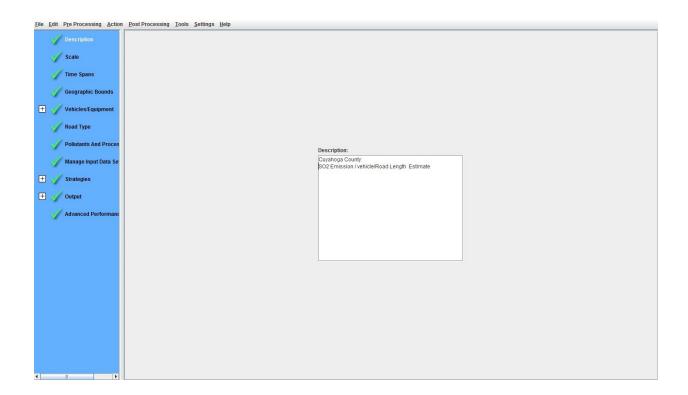
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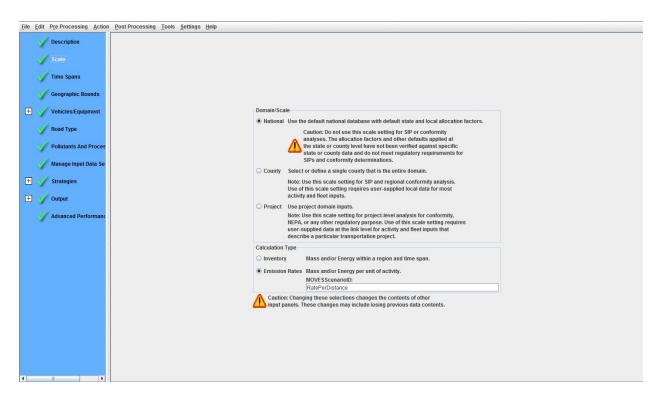
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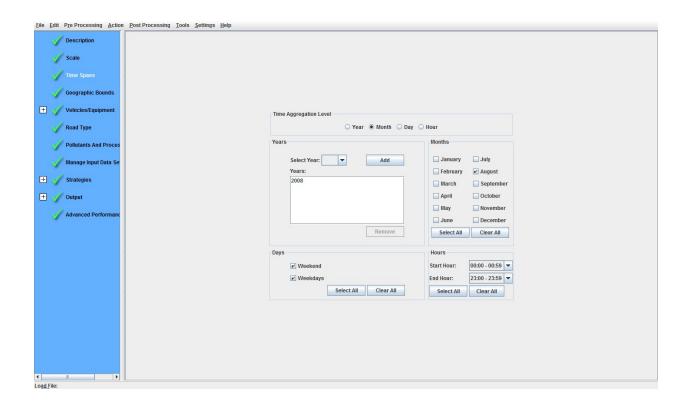
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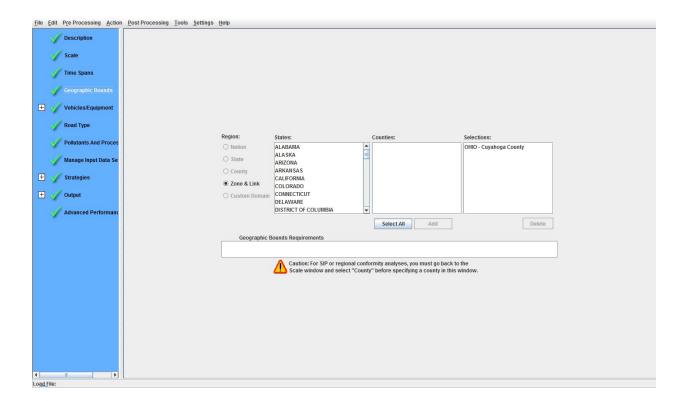
APPENDIX A

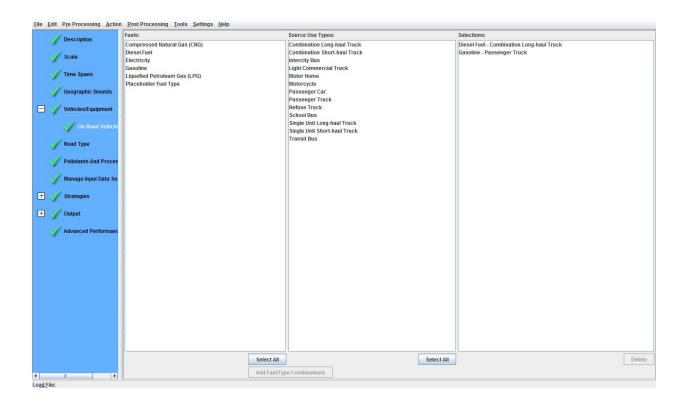
Working with MOVES: Screen Shots

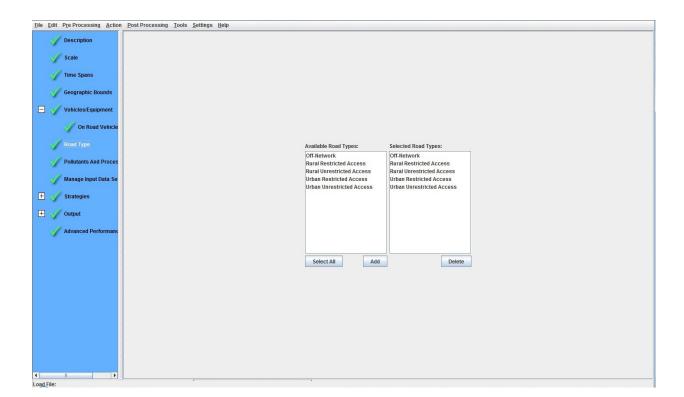


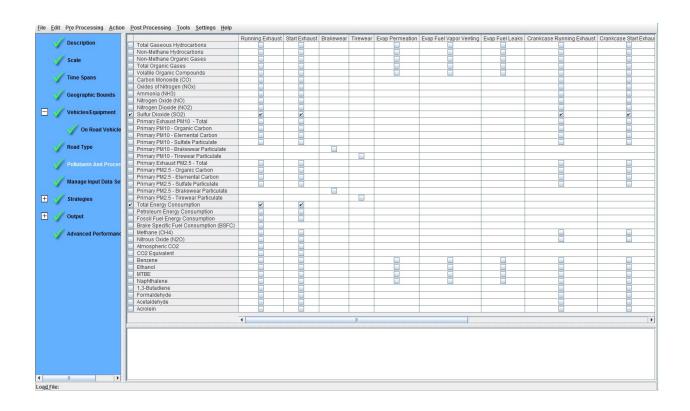


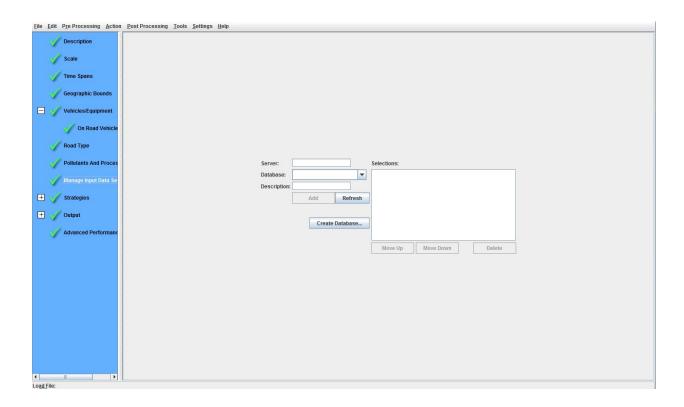


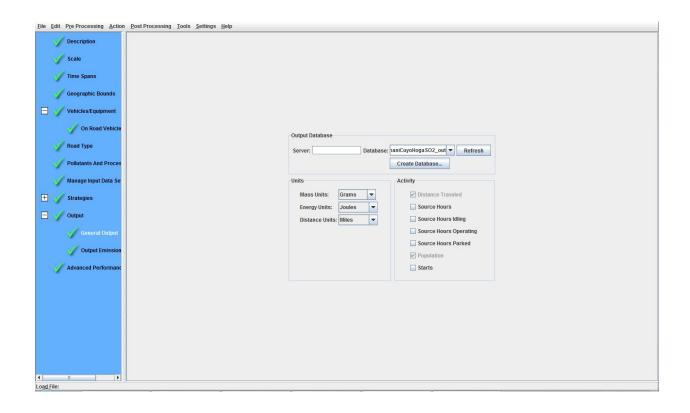


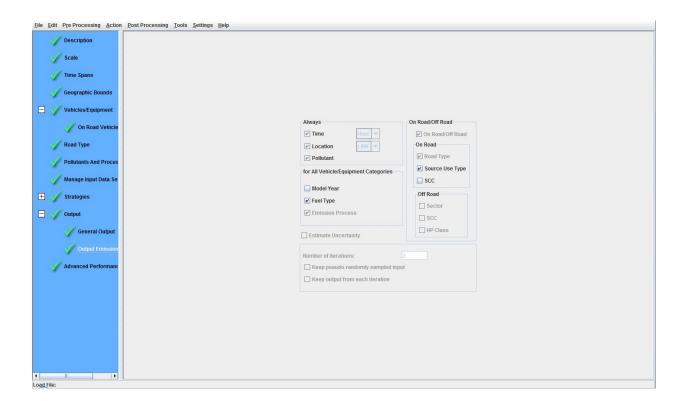


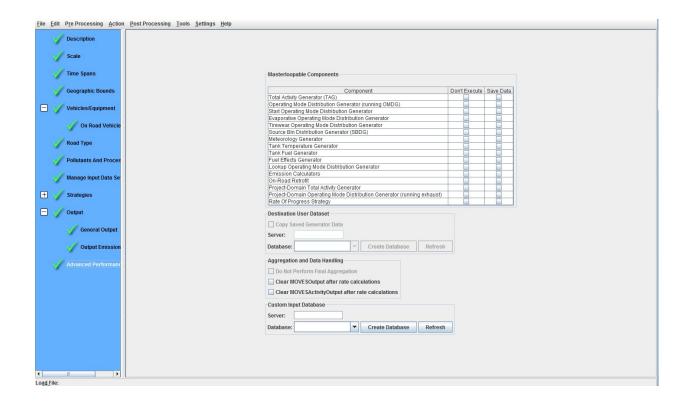












APPENDIX B

Tables of SOM Cells: MOVES estimate based Classifications in the County Scale

Cluster	No	Cell No	Count		Cou	nty Numb	er (Refe	r Table 3	3 for cour	nties)	
	1	1	5	18	25	31	57	77			
	1	2	1	48							
	1	3	0								
	1	4	1	87							
	1	5	8	9	43	45	47	50	76	78	83
	1	6	4	12	21	52	67				
	1	7	1	13							
	1	8	1	22							
	1	9	4	4	29	55	70				
	1	10	6	2	7	32	49	60	72		
	1	11	2	79	85						
	1	12	1	30							i
	1	13	0								
	1	14	8	3	6	24	26	59	68	75	86
	1	15	3	15	71	80					
	1	16	1	14							
	2	17	3	23	65	84					
	2	18	0								
	2	19	5	5	28	41	51	73			i
	2	20	2	46	62						
	2	21	0								
	2	22	5	35	39	40	81	88			
	2	23	3	8	19	74					
	2	24	4	17	20	27	54				
	2	25	1	66							
	2	26	1	61							\ <u></u>
	2	27	6	1	11	36	37	42	44		\ <u></u>
	2	28	1	16							\ <u></u>
	2	29	2	38	69						\ <u></u>
	2	30	1	33							\ <u></u>
	2	31	2	10	64						\ <u></u>
	2	32	3	34	53	63					
	3	33	1	82							<u> </u>
	3	34	1	56							
	3	35	1	58							
	3	36	0								
Table	R 1	Ohio	Counti	<u> </u>	M coll	locati	one for	COLLD	tios ba	cod on	total

Table B.1: Ohio Counties: SOM cell locations for counties based on total ORMSAP emissions in a county (MOVES-emission based estimates)

Cluster No	Cell No	Count		Coun	ty Numb	er (Refe	r Table 3	for cour	nties)	
1	1	5	18	25	31	57	77			
1	2	1	48							
1	3	3	43	47	87					
1	4	5	45	50	67	78	83			
1	5	4	9	21	52	76				
1	6	1	12							
2	7	3	4	29	70					
2	8	8	2	7	22	32	49	55	60	72
2	9	3	13	79	85					
2	10	2	3	30						
2	11	3	14	71	80					
2	12	7	6	24	26	59	68	75	86	
3	13	6	15	23	28	51	65	84		
3	14	0								
3	15	3	41	46	62					
3	16	5	35	39	40	81	88			
3	17	5	5	8	19	73	74			
3	18	4	17	20	27	54				
4	19	4	11	42	44	66				
4	20	2	33	61						
4	21	4	1	36	37	38				
4	22	2	16	69						
4	24	2	34	63						
5	23	2	53	64						
5	25	2	58	82						
5	26	2	10	56	4.	•	4.			11015

Table B.2: Ohio Counties: SOM cell locations for counties based on ORMSAP emissions per road length in a county (MOVES-emission based estimates)

Cluster No	Cell No	Count	County Number (Refer Table 3 for counties)								
1	1	5	18	25	31	57	77				
1	2	1	48								
1	3	3	43	47	87						
1	4	5	45	50	67	78	83				
1	5	4	9	21	52	76					
1	6	1	12								
2	7	4	4	13	29	70					
2	8	8	2	7	22	32	49	55	60	72	
2	9	2	79	85							
2	10	2	3	30							
2	11	3	14	71	80						
2	12	7	6	24	26	59	68	75	86		
2	13	6	15	23	28	51	65	84			
2	14	0									
3	15	3	41	46	62						
3	16	5	35	39	40	81	88				
3	17	5	5	8	19	73	74				
3	18	4	17	20	27	54					
3	19	4	11	42	44	66					
3	20	1	61								
3	21	4	1	36	37	38					
3	22	3	16	33	69						
4	23	2	53	64							
4	24	2	34	63							
4	25	2	58	82							
Table B 2	26	2	10	56	a a ti a ma	for or		basad		MCAD	

Table B.3: Ohio Counties: SOM cell locations for counties based on ORMSAP emissions per area in a county (MOVES-emission based estimates)

Cluster No	Cell No	Count	County Number (Refer Table 3 for counties)						
1	1	4	18	25	31	77			
1	2	1	57						
1	3	1	48						
2	4	1	87						
2	5	4	9	43	47	76			
2	6	5	45	50	67	78	83		
2	7	2	21	52					
2	8	1	12						
3	9	3	4	13	29				
3	10	6	7	22	32	60	70	72	
3	11	2	55	85					
3	12	3	2	30	49				
3	13	2	71	79					
3	14	5	3	26	59	68	75		
4	15	2	14	80					
4	16	3	6	24	86				
4	17	7	15	23	28	51	62	65	84
4	18	3	39	46	88				
4	19	3	5	41	73				
4	20	6	17	20	35	40	54	81	
5	21	4	8	19	44	66			
5	22	2	27	74					
5	23	7	1	11	36	37	38	42	69
5	24	3	16	33	61				
5	25	6	10	53	56	58	64	82	
5	26	2	34	63					

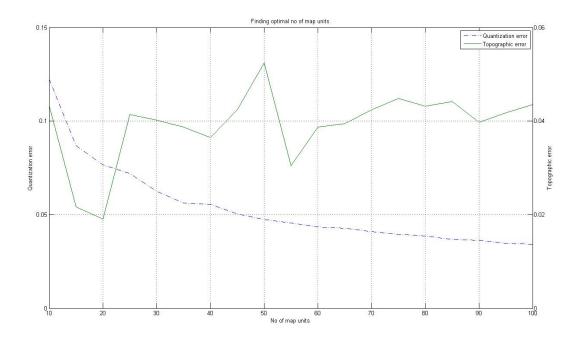
Table B.4: Ohio Counties: SOM cell locations for counties based on ORMSAP emissions per capita in a county (MOVES-emission based estimates)

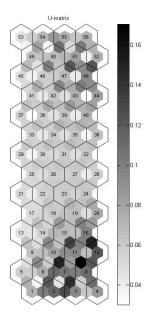
Cluster No	Cell No	Count	County Number (Refer Table 3 for counties)								
1	1	3	43	47	87						
1	2	6	18	25	31	48	57	77			
1	3	3	12	21	52						
1	4	7	9	45	50	67	76	78	83		
1	5	9	2	4	7	22	32	55	60	70	72
1	6	2	13	29							
2	7	7	3	26	30	49	59	68	75		
2	8	2	79	85							
2	9	4	6	14	24	86					
2	10	6	15	23	65	71	80	84			
3	11	2	62	88							
3	12	5	28	39	41	46	51				
3	13	6	17	20	35	40	54	81			
3	14	3	5	73	74						
3	15	3	33	61	66						
3	16	3	8	19	27						
4	17	2	63	69							
4	18	8	1	11	16	36	37	38	42	44	
4	19	4	10	56	58	82					
4	20	3	34	53	64						

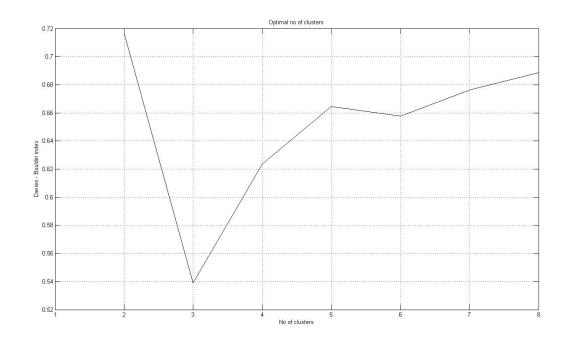
Table B.5: Ohio Counties: SOM cell locations for counties based on all four ORMSAP emission metrics in a county (MOVES-emission based estimates)

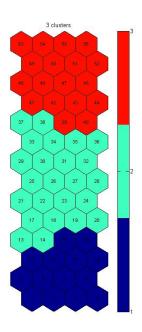
APPENDIX C
C.1: Classification based on FTP Tier 2 emission Estimates

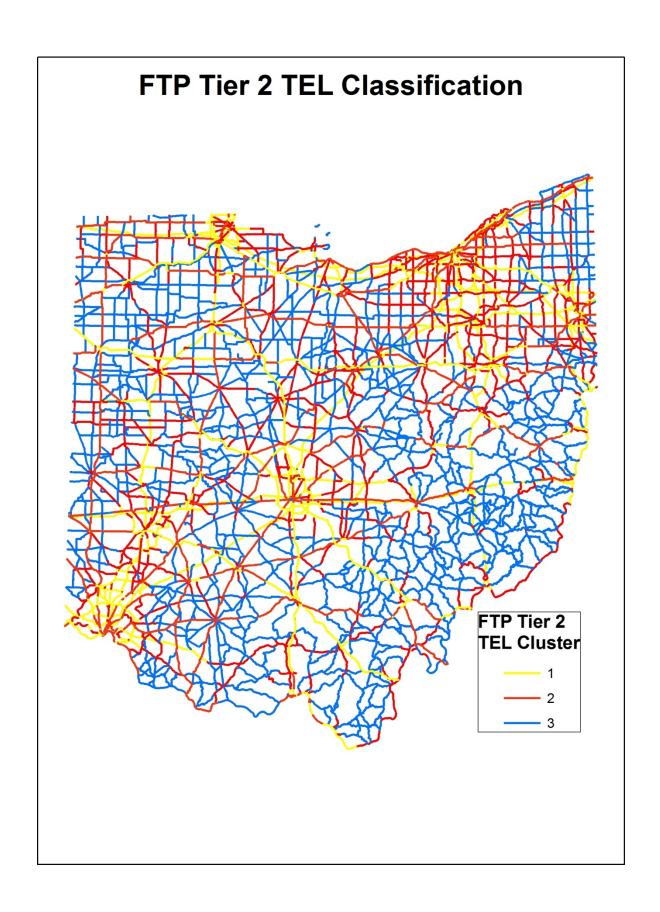
C.1.1: Classification based on TEL metrics constructed from FTP Tier 2 estimates



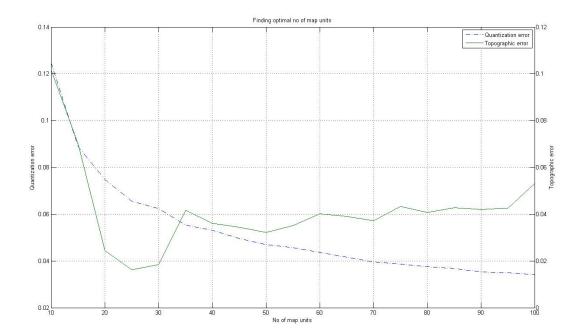


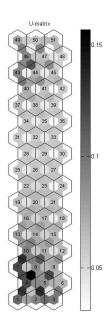


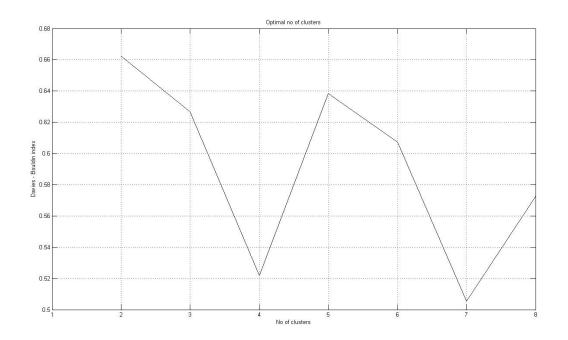


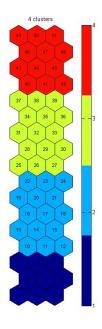


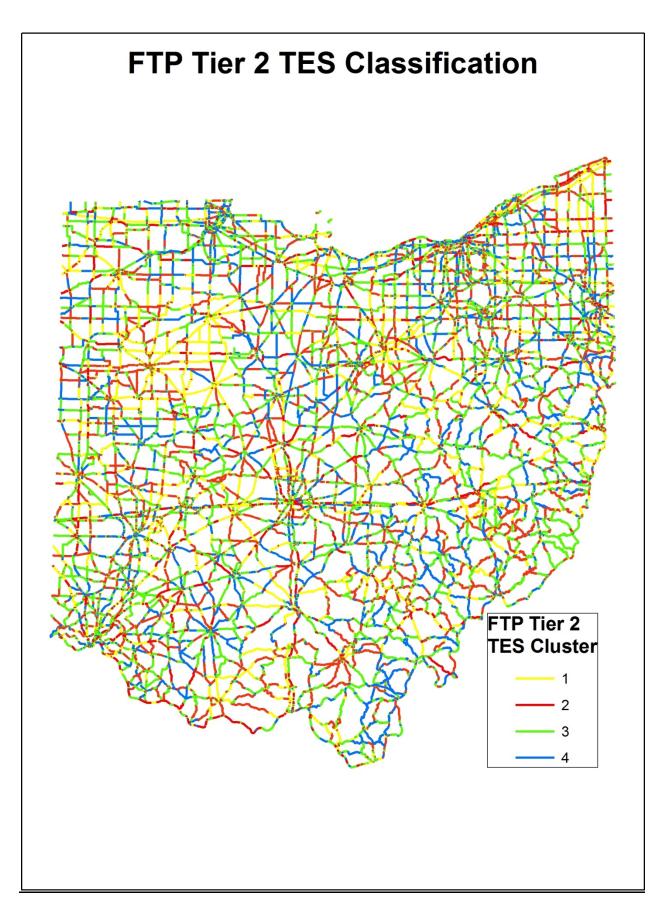
C.1.2: Classification based on TES metrics constructed from FTP Tier 2 estimates



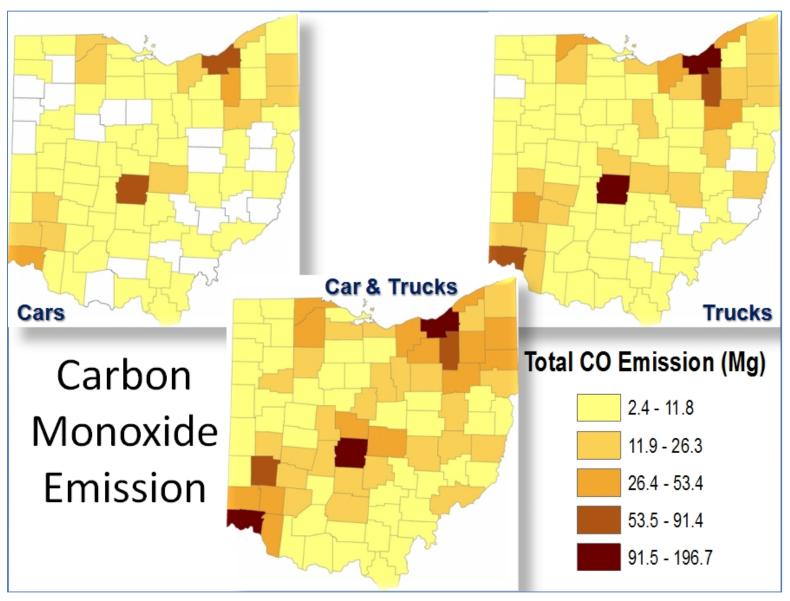




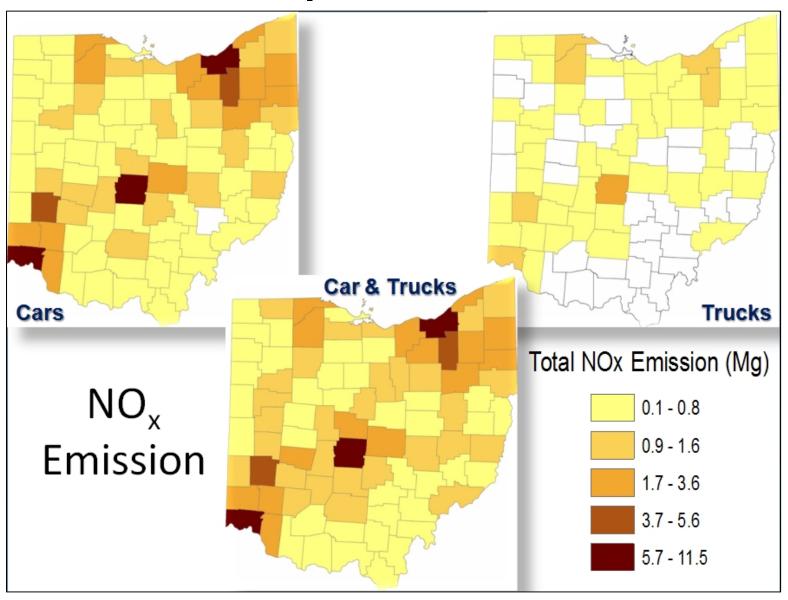




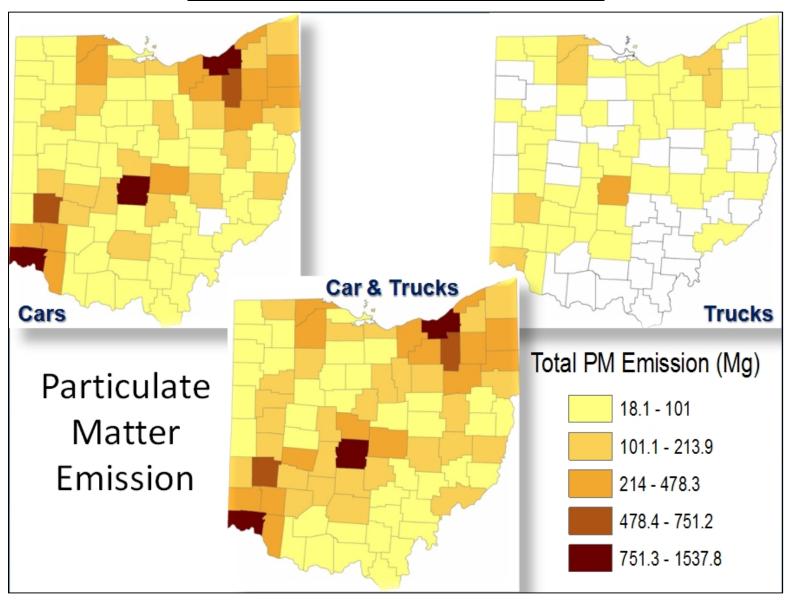
C.1.3.1: Total CO Emission based on FTP Tier 2 estimates



C.1.3.2: Total NO_x Emission based on FTP Tier 2 estimates

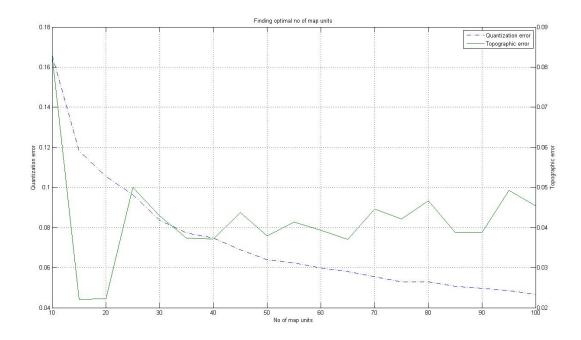


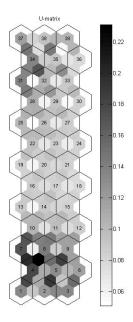
C.1.3.3: Total PM Emission based on FTP Tier 2 estimates

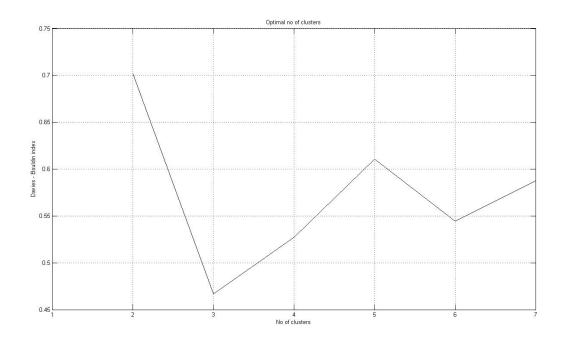


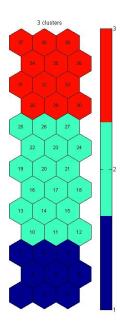
C.2: Classification based on MOVES emission Estimates

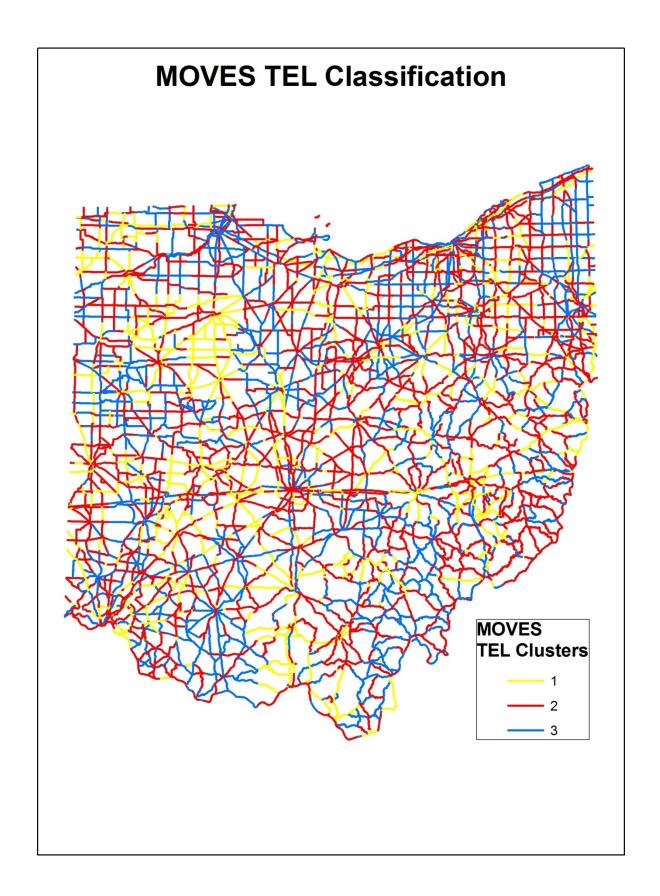
C.2.1: Classification based on TEL metrics constructed from MOVES estimates



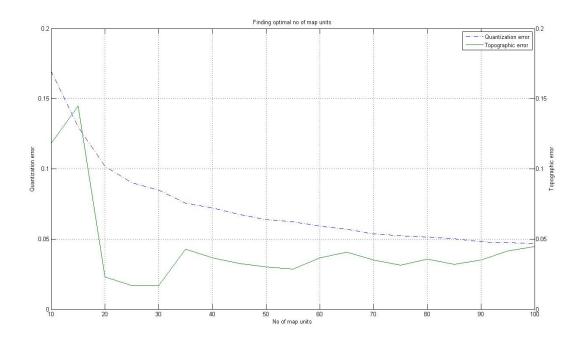


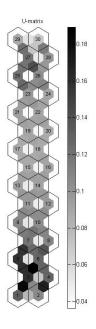


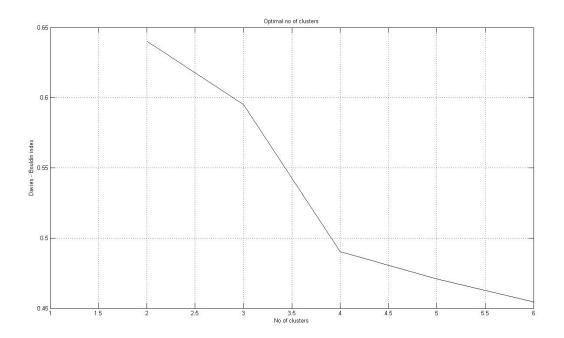


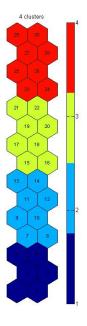


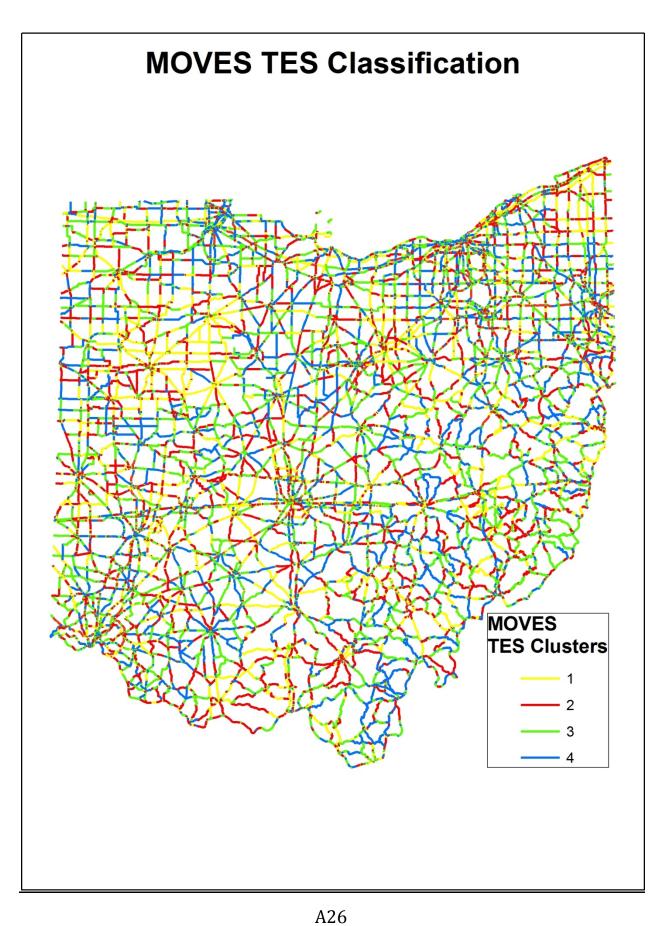
C.2.2: Classification based on TES metrics constructed from MOVES estimates



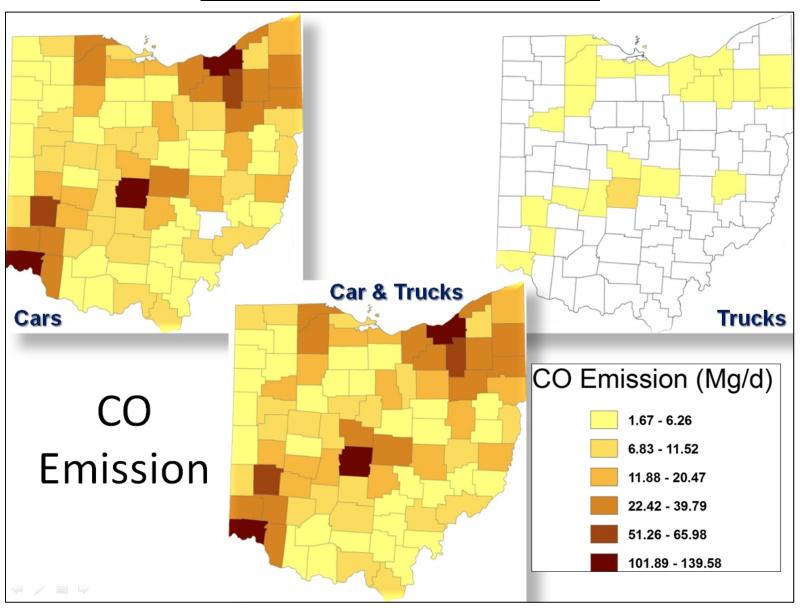




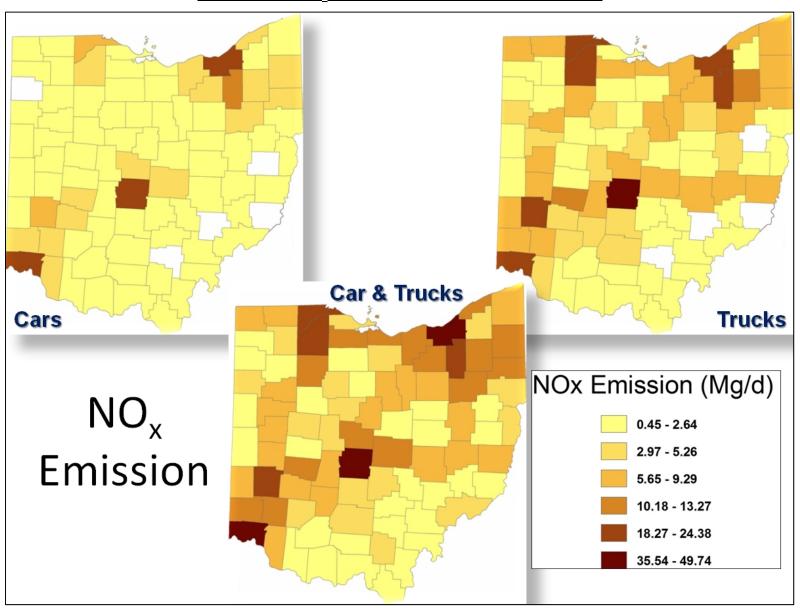




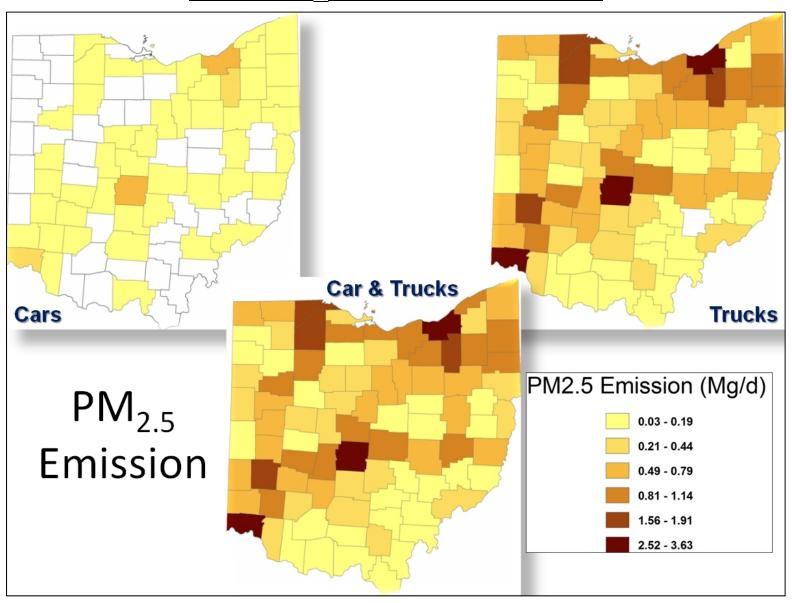
C.2.3.1: Total CO Emission based on MOVES estimates



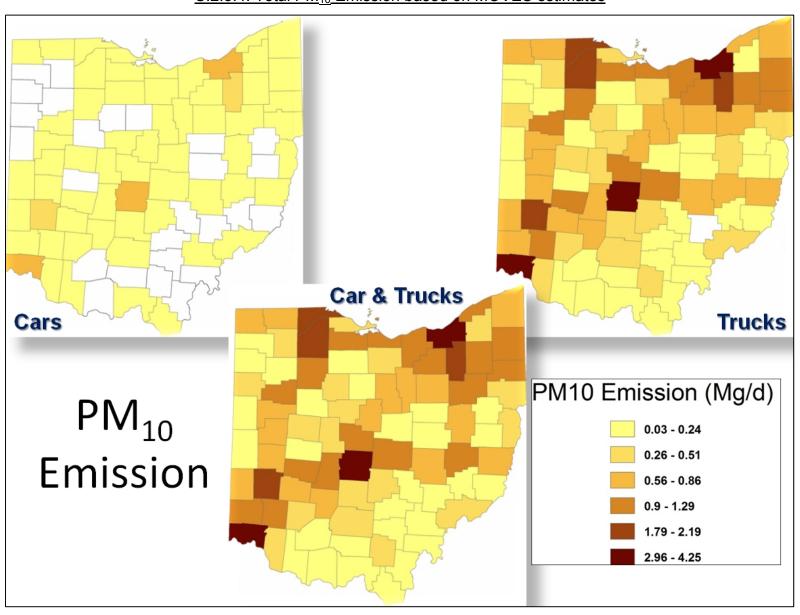
C.2.3.2: Total NO_x Emission based on MOVES estimates



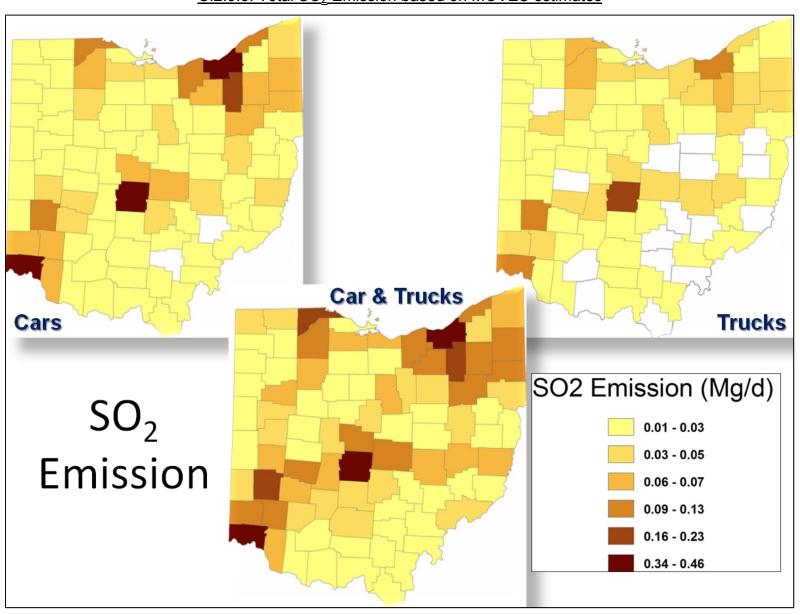
C.2.3.3: Total PM_{2.5} Emission based on MOVES estimates



C.2.3.4: Total PM₁₀ Emission based on MOVES estimates

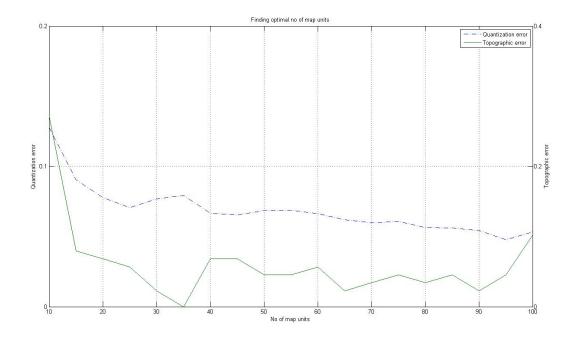


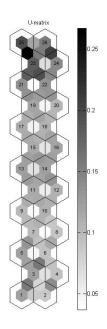
C.2.3.5: Total SO₂ Emission based on MOVES estimates

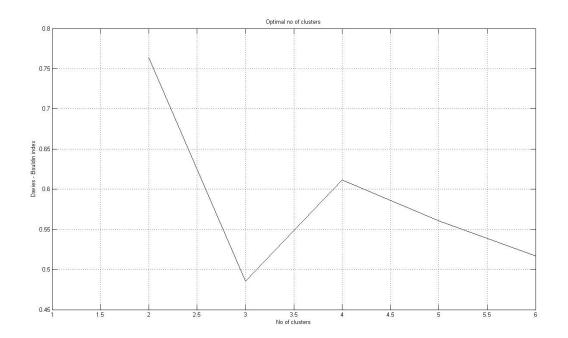


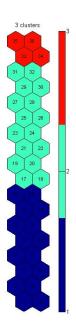
C.3: Classification of Counties based on MOVES emission Estimates

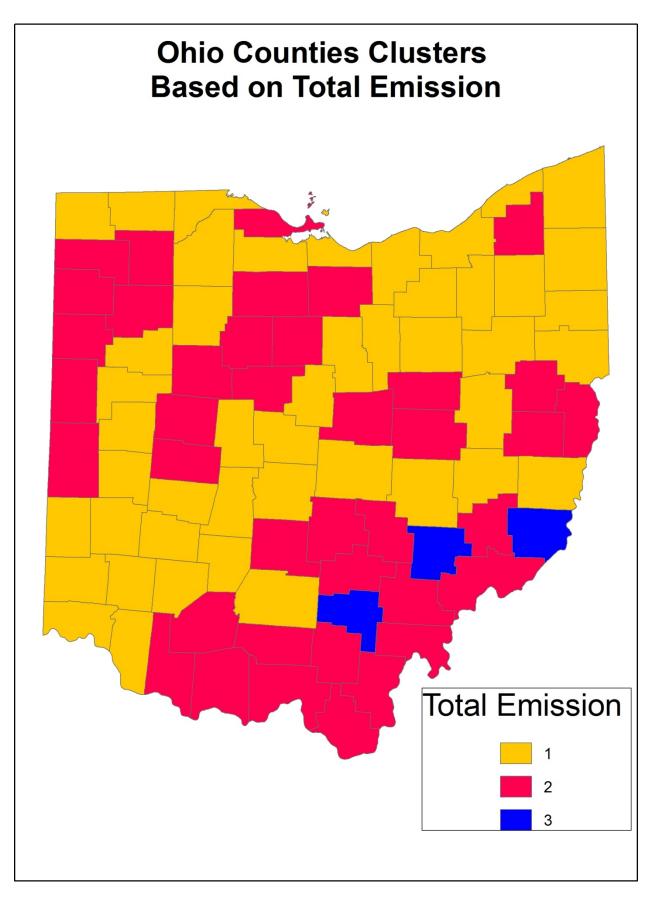
C.3.1: Classification based on total ORMSAP emission estimates



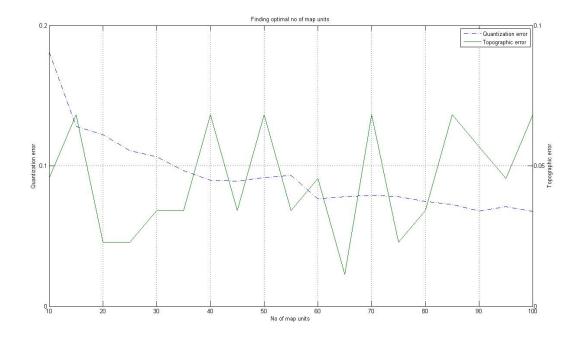


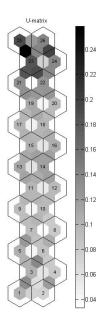


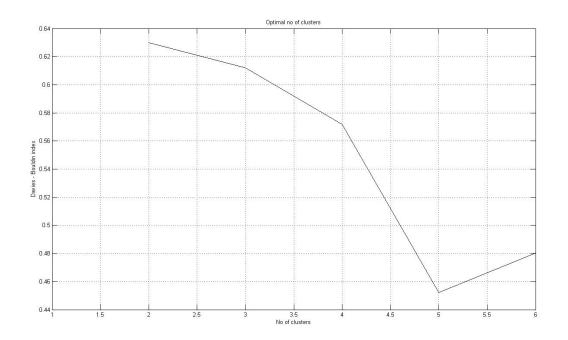


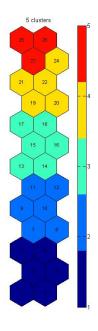


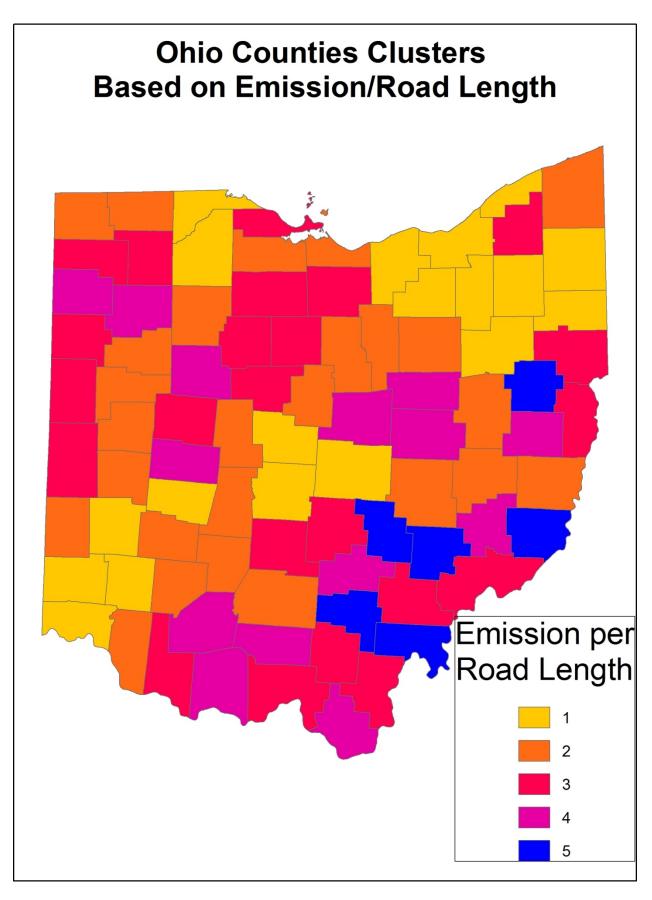
C.3.2: Classification based on ORMSAP emission estimates per road length



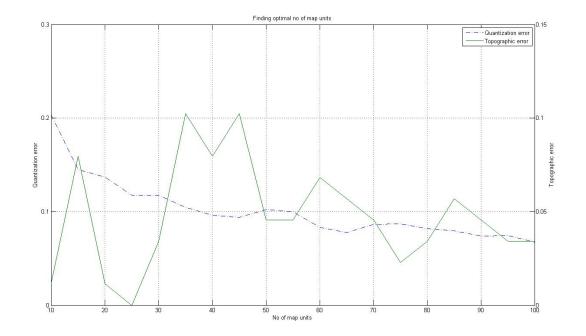


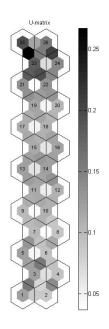


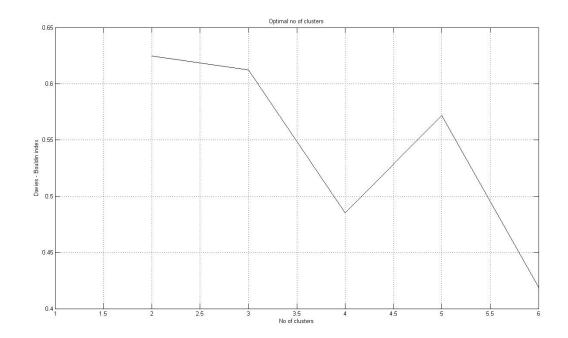


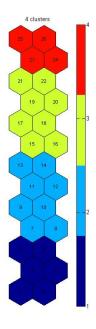


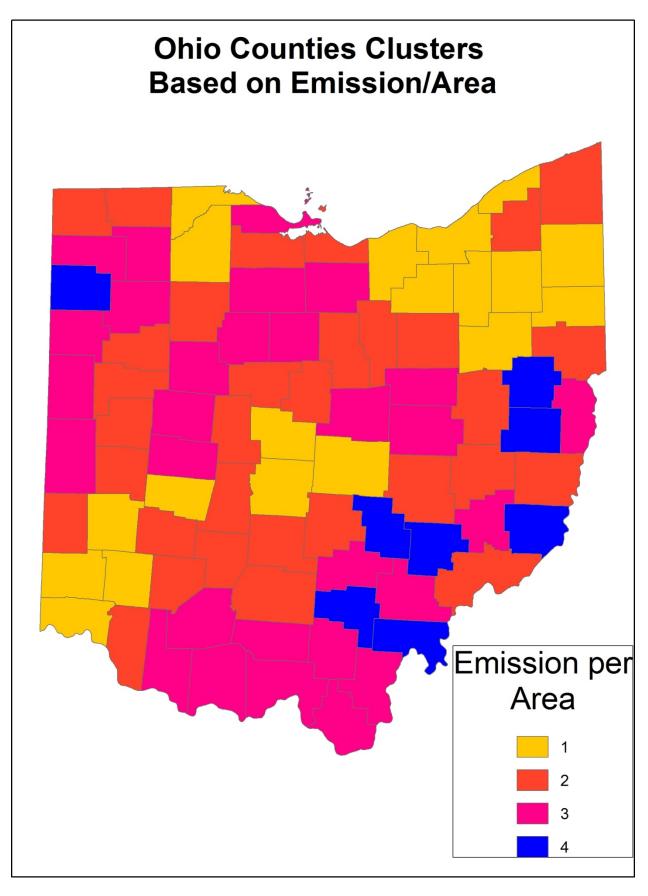
C.3.3: Classification based on ORMSAP emission estimates per land area



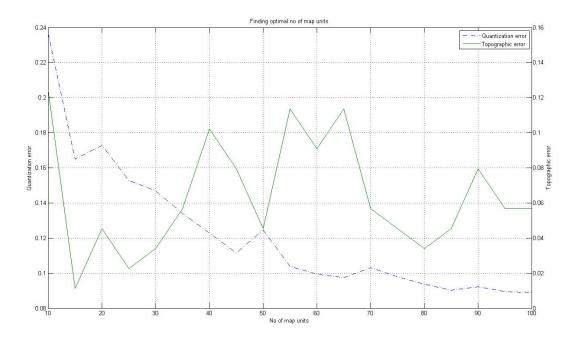


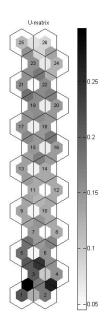


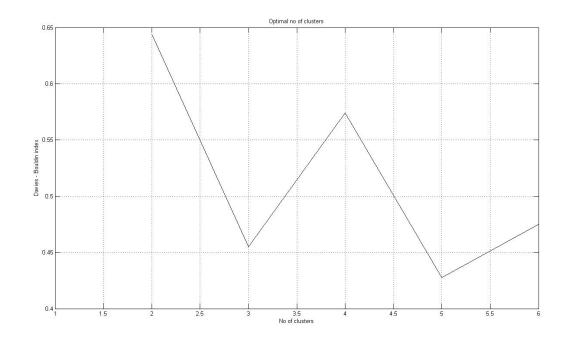


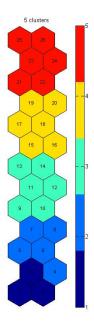


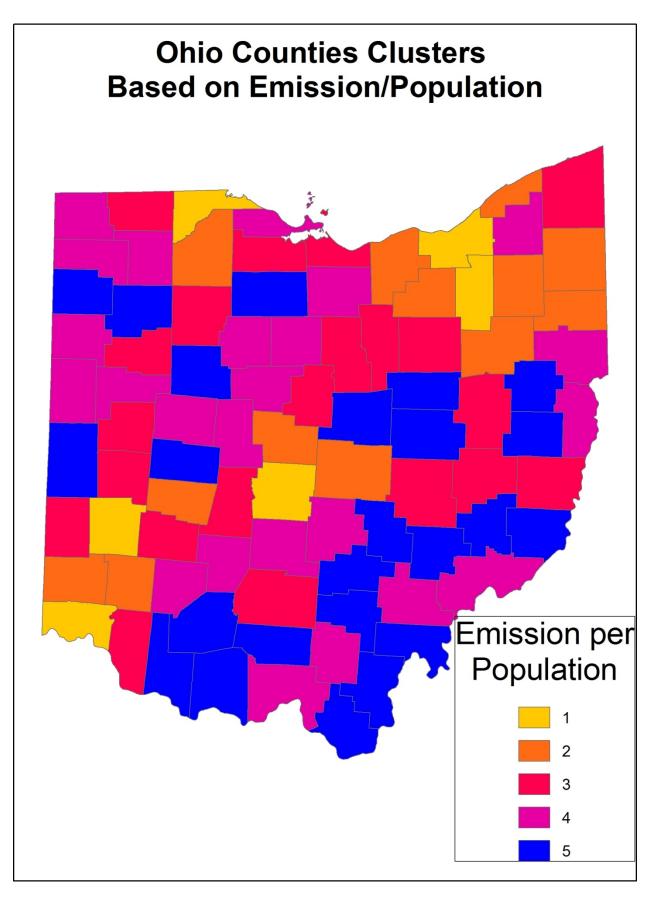
C.3.4: Classification based on ORMSAP emission estimates per population



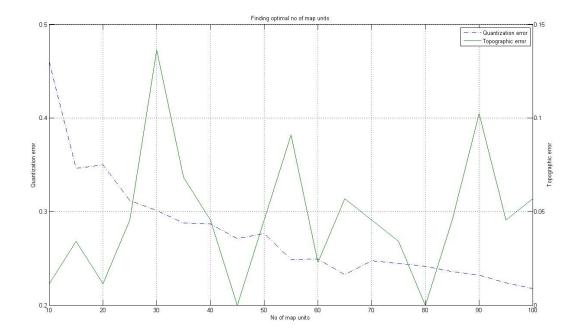


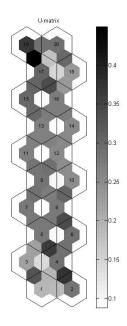


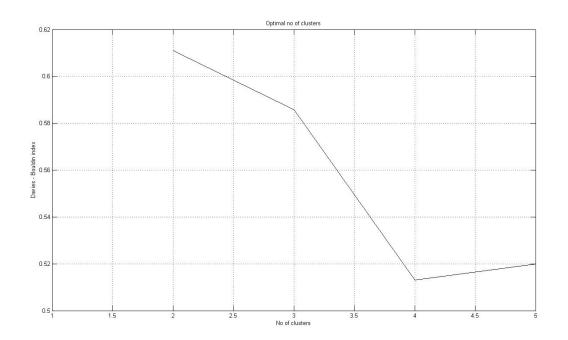


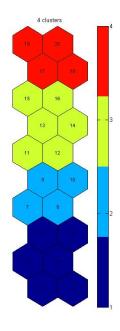


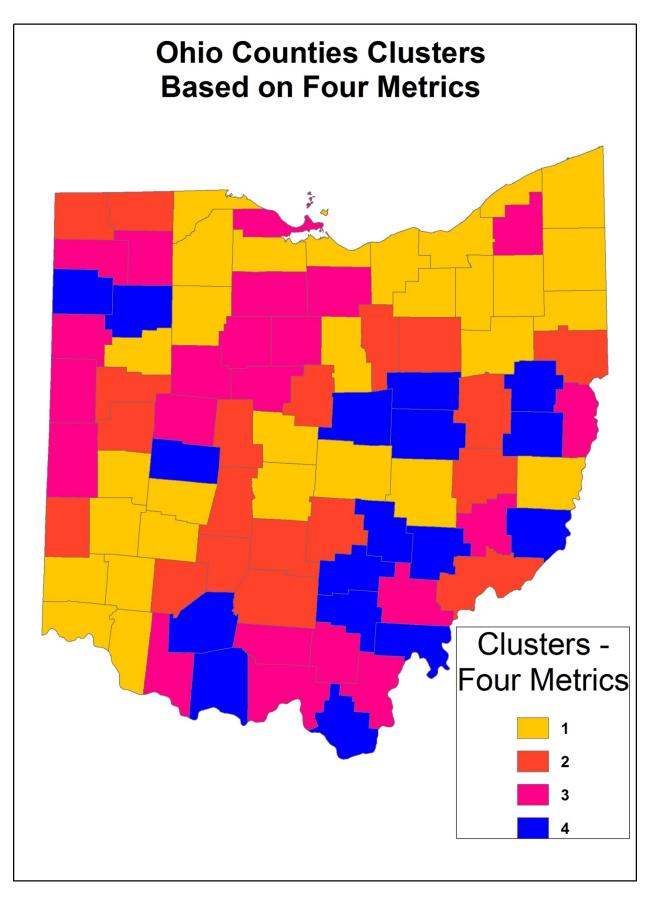
C.3.5: Classification based on all four ORMSAP emission estimate metrics











APPENDIX D

RELATED PUBLICATIONS AND PRESENTATIONS

Meade Wilbert and Kandiah Ramanitharan. 2009. *A Methodology to Estimate the Annual Average Daily On-Road Mobile Source Pollutant Emissions*. 5th Annual Dayton Engineering Sciences Symposium, Wright State University, Fairborn, OH. October 26, 2009

Andrè Morton. 2010. Classification of Urban Districts based on Mobile Carbon Monoxide Exposure Using Self Organizing Maps. OTC Undergraduate Student Paper Competition winner.

Andrè Morton, John Davenport and Ramanitharan Kandiah. 2010. *Comparison of the Traffic Counts in Three Counties in Miami Valley, Ohio*. 6th Annual Dayton Engineering Sciences Symposium, Wright State University, Fairborn, OH. October 25, 2010

Tinina Hale and Ramanitharan Kandiah. 2010. *Using MOVES to Estimate On-Road Motor Vehicle Emission in the Miami Valley, Ohio*. 6th Annual Dayton Engineering Sciences Symposium, Wright State University, Fairborn, OH. October 25, 2010

Ramanitharan Kandiah, Andrè Morton and John Davenport. 2010. *Estimating on-road mobile Source Pollution in Ohio*. Ohio UTC Student Research Conferenceium, University of Akron, Akron, OH. November 10, 2010

Ramanitharan Kandiah, John Davenport and Andrè Morton. 2010. *Using Datamining in Classifications of Traffic Counting Locations: A Case Study in Ohio*. Ohio UTC Student Research Conferenceium, University of Akron, Akron, OH. November 10, 2010

Tinina Hale and Ramanitharan Kandiah. 2010. *Estimating On-Road Motor Vehicle Emission using MOVES*. Ohio UTC Student Research Conferenceium, University of Akron, Akron, OH. November 10, 2010. (Poster session)