Spatial Analysis of Traffic Growth and Variations and Their Implications to the Operations of a Traffic Monitoring Program

Ehsan Bagheri, PhD Student, Department of Civil and Environmental Engineering,
University of Waterloo, Waterloo, O.N., Canada N2L 3G1; mebagher@uwaterloo.ca

Ming Zhong, Associate Professor, Department of Civil Engineering,
University of New Brunswick, Fredericton, N.B., Canada E3B 5A3; ming@unb.ca

James Christie, Professor, Faculty of Science, Applied Science & Engineering,
University of New Brunswick, St. John, N.B., Canada; Christie@unbsj.ca

Paper prepared for presentation
at the Best Practices in Transportation Planning Session
of the 2012 Conference of the
Transportation Association of Canada
Fredericton, New Brunswick

ABSTRACT

Annual Average Daily Traffic (AADT) is one of the most important indicators of travel demand with many applications in different areas of transportation engineering. Highway agencies commit significant resources to traffic monitoring programs to obtain AADTs, among others. Although many guidelines exist at the national or the provincial levels about how to best operate a traffic monitoring program, there are still quite a few steps relying on subjective judgements, such as how to apply traffic growth rate and how to assign short-term traffic counts (STTCs) to permanent traffic counts (PTCs) or permanent traffic counter groups (PTCGs). In order to reduce risks of potentially significant AADT estimation errors due to the above subjective judgements, PTC data from the province of Alberta, Canada are used to examine spatial correlation in traffic seasonality as well as traffic growth rate for all the road segments covered by its PTC program. The results show that roads in a functional class group can have several seasonal traffic patterns, and there is no definitive relationship between functional class and traffic seasonality. The finding indicates that the STTCs to PTCGs assignment procedure in the Federal Highway Administration’s (FHWA) method may not be appropriate, as it is based on a road’s functional class only. The results also demonstrate that traffic growth rates are highly clustered in the study area, and the correlation analysis revealed that growth rates applied to short-term counting sites should be taken from the closest PTC on a road from a similar functional class. In this regard, Geographical Information Systems (GIS) analyses provide a clear portrait of how traffic growth distributes over a jurisdiction and thus reduces the judgmental errors associated with the task.

INTRODUCTION

Annual Average Daily Traffic (AADT) is one of the most important indicators of travel demand with many applications in different areas of transportation engineering. Highway agencies commit significant resources to traffic monitoring programs to obtain AADTs, among others. Although many guidelines exist at national or provincial level about how to best operate a traffic monitoring program, there are still quite a few steps relying on subjective judgements, such as how to apply traffic growth rate and how to assign short-term traffic counts (STTCs) to permanent traffic counts (PTCs) or permanent traffic counter groups (PTCGs).

In general, two types of traffic monitoring programs are identified by the Traffic Monitoring Guide [1]. First, AADTs can be obtained using a Permanent Counting program. In this method, traffic volume on a road segment is counted continuously using loop detectors underneath the road surface. These counters provide traffic volume for 24 hours a day and 365 days a year, which can easily be used to obtain the AADT.

Second, AADT can also be estimated using STTCs. In this method, traffic volume on a road is counted for a short period of time usually between 24 and 72 hours. These counts are then converted to AADTs using seasonal adjustment factors derived from a continuous count program as described above. This type of counting program is suitable when there are budget restrictions which prevents installing PTCs on all desired locations as PTC units are expensive to install and maintain, or where special extra traffic volume studies are necessary. However, the challenge associated with this type of AADT estimation is the conversion of STTCs to AADTs, where engineers are required to decide from which PTC or PTC group the adjustment factors and annual growth rates should be used.

Since the adjustment factors are based on the variation in the seasonal pattern, the best PTC site to derive these factors is the one that its seasonal pattern has the highest similarity to the one of the STTC site. The annual growth rates are also needed when STTCs are collected in years before the study year and the traffic volume on the site should be converted to its equivalent in the study year. This conversion requires a perfect knowledge about how traffic volumes change in the study area over years, and which PTC has the similar annual traffic growth as the STTC site.

The Federal Highway Administration (FHWA) method may be the most widely used in practice for estimating AADTs from STTCs, which is presented in the Traffic Monitoring Guide [1]. In this method, in order to estimate AADTs from STTC sites, the following steps are performed:

1. Permanent Traffic Counters are grouped based on the functional class of the roads where they are installed (i.e. Arterial, Local, Expressway, etc.). In the grouping process some geographical and other engineering judgement can also be considered.
2. Short-Term Traffic Counts with duration of usually between 24 and 72 hours are collected once every few years or based on the counting requirements.
3. STTCs are assigned to one of the PTC groups developed in Step one based on the functional class of the road where they are collected.
4. AADTs are estimated using STTCs and the adjustment factors derived from the assigned PTC groups.

Since the purpose of using adjustment factors is to take into account traffic seasonal variation it appears that the FHWA method assumes that roads within a functional class have similar seasonal patterns.

Another method in use to estimate AADT from STTCs is based on a regression analysis. In this method, a regression analysis is performed between pairs of a given STTC site and each PTC and a coefficient of determination, R^2, is calculated for these pairs. The aim of this regression analysis is to identify the pair of the STTC site and an individual PTC with the highest R^2, which signalizes they have the highest similarity between their seasonal traffic patterns. In this approach, in contrast to the FHWA method, PTCs are not grouped and adjustment factors are derived from individual PTCs.

Several other methods exist in the literature, which intend to improve the estimation of AADT from short-term traffic counts. Some of these methods are: artificial neural network [2]; Bayesian assignment of STTCs to PTC groups [3]; and using historical STTCs to improve the assignment of STTC sites to PTCs or PTC pattern groups [4]. All of these methods try to assign a STTC site to a PTC with the highest similarity in seasonal pattern. However, previous studies have not systematically studied how traffic seasonality and growth change over space and therefore they have limited values to the operation of a traffic monitoring program. In this regard, this paper uses GIS to study the spatial correlation of traffic seasonality and growth.

METHODOLOGY

In this section, Geographical Information Systems (GIS) tools are described, which will be used for spatial correlation analysis of traffic growth and seasonality in this paper.

Spatial statistics are defined as tools, methods, and techniques that use parameters in space such as area, length, proximity, etc. to describe any special pattern, relationship, or distribution among geographical features [5]. Spatial autocorrelation is one of the spatial statistical methods that examine the characteristics of the geographic patterns. Some of these tools are described in the following.

Global/Local Moran's I:

Distribution of features or values in a space always has a pattern. This pattern can be completely dispersed, random, or completely clustered. To understand a pattern, geographic features or their attributes can be plotted on a map. When possible, the patterns can be observed visually, or statistical tools such as Moran's I can be used to identify the relationship between features in a space.

Global Moran's I uses features attributes to identify spatial patterns. In this method, the differences between the value of a target feature and the mean value of all its neighbouring features are calculated. Features are identified as clustered if the differences between neighboring features are less than the average total differences among all the features in the study area.

In order to calculate the Moran's Index for the features in the study area, the mean value of all the features should be calculated and then the value of each pair of features is subtracted from the mean and their cross product are calculated and multiplied by their weight as presented in Equation (1). This process is repeated for all the features in the study. A variance is also calculated for all the features as presented in Equation (2). And finally the Moran's Index is calculated using Equation (3) by dividing Equation (1) by (2).

$$\sum_i \sum_j W_{ij} (X_i - \bar{X})(X_j - \bar{X}) \tag{1}$$

$$\sum_i \sum_j W_{ij} \frac{\sum_i (X_i - \bar{X})^2}{n} \tag{2}$$

$$I = \frac{n \times \sum_i \sum_j W_{ij} (X_i - \overline{X})(X_j - \overline{X})}{\sum_i \sum_j W_{ij} \sum_i (X_i - \overline{X})^2} \tag{3}$$

Where,

W_{ij} : The weight associated between features i and j

$\mathrm{X_i}, X_j$: Value of features i and j

$\overline{\mathrm{X}}$: Mean of all the features' values in the study area

n : Total number of features

The indices calculated from the above equation are indicators to determine if features in the area are clustered or not. As presented in Table 1, if the index is more than one, features are clustered; if they are less than zero they are dispersed; and otherwise they are randomly distributed in the area.

Local Moran's I is also used to identify features with similar values (clustered) in a study area. This tool is a more detailed version of the Global Moran's I that can identify where clustered features are located and in which areas the distributions of features do not follow any patterns. The mathematical representation of the Local Moran's I is presented by Equation (4). For every feature in the study area an Index value is calculated.
The significance of the above results is presented by a Z-score. This value measures whether the similarity among the features are due to a chance or not. As shown in Equation (6), in order to calculate the Z-score, first, using a random distribution the expected values for all the features in the area are calculated. These values are subtracted from the actual values. The expected values of the features are

$$I_i = \frac{(X_i - \overline{X})}{s^2} . \sum_j W_{ij} (X_j - \overline{X}) \tag{4}$$

calculated using Equation (5). A positive and higher Z-score indicates feature in the area are clustered.

$$E(I_i) = \frac{-\sum_j W_{ij}}{n-1} \tag{5}$$

$$Z(I_i) = \frac{I_i - E(I_i)}{\sqrt{\mathrm{var}(I_i)}} \tag{6}$$

Where,

$E(I_i)$: The expected Index value for feature i

A Hot-Spot analysis is also used in this study to identify areas with features having significantly high or low values. As shown in Figure 1 and Figure 2 this tool can also illustrate the distribution of features in the study area and identify where they are highly clustered by providing P-values and the Z-score.

In this study, a geostatistical tool called Kriging is used to visualize the magnitude of values in different area by creating distribution surfaces. This tool can also be used to predict values for areas where no data available by using existing data from nearby places.

STUDY DATA AND RESULTS

In this section, Geographical Information Systems (GIS) tools are used to achieve the following objectives:

1. To examine the FHWA assignment method based on the functional class similarity and if there is any correlation between roads functional classes and their seasonal traffic patterns.
2. To understand if there is any spatial correlation between roads' annual traffic growth rates, which helps to better understand which PTC traffic growth rates should be applied to a STTC site.

In this study, data from province of Alberta, Canada are used. In total, there are 365 PTCs available throughout the province and data for the years between 2002 and 2009 are obtained from the Alberta Department of Transportation (DOT) website. These data contain hourly traffic volume. Location of all the PTCs as well as road network and their functional class are also obtained as GIS shapefiles from Alberta DOT.

A program was developed in MATLAB software to analyze the data. Monthly Average Daily Traffic (MADT) and AADT volumes for all the PTCs in the study area were calculated, which were used to create PTCs' seasonal patterns. Using a K-mean clustering method in MATLAB, PTCs based on the seasonal patterns are assigned into 6 seasonal pattern groups as shown in Figure 3. These groups are: Summer Recreational; Winter Recreational; Rural Long Distance; Regional Commuter; Commuter 1; and Commuter 2. Figure 4 compares these pattern groups in terms of their shape and relative magnitudes. The study area with the road network and location of PTCs and their seasonal patterns are presented in Figure 5.

By visually examining the roads' functional classes versus seasonal patterns of the PTCs on the roads, it can be seen that on a road with a specific functional class, there may be PTCs with different seasonal patterns. This finding indicates the weakness with the FHWA AADT estimation method, which assigns STTCs to functional class groups based on the assumption that roads within a same functional class should have a same/similar seasonal pattern. For instance, Figure 6 shows highway 1 passing through the city of Calgary. As can be seen in the marked area, approaching from the east to the city, traffic seasonality on this road follows a "Commuter" pattern, while after the city toward the west the pattern changes to a "Regional Commuter" and further to "Rural Long-distance".

The Average Nearest Neighbor method was used to analyze the distribution of seasonal patterns in the study area. This tool analyzes geographic features to find if they cluster together in space. The results are shown in Table 2, which indicates that commuter roads follow a cluster pattern as they are mostly located near cities. Rural Long Distance roads have a dispersed pattern, while Winter Recreational roads are randomly distributed. The results also show that Regional Commuter roads are somewhat clustered but this may be due to a random chance.

Annual traffic growth rates for all the PTCs in the study area between the years 2002 and 2009 were calculated using MATLAB and Equation (7). As an example the growth rates between years 2008 and 2009 are plotted using different colors as shown in Figure 7. It can be seen that annual growth rates are highly clustered in different areas. In this figure, high annual growth rates are clustered around Calgary, Edmonton, and Lethbridge cities, while low rates are located in the center and west part of the study area, which show a decline in the traffic volume.

$$GR_{(n,n+1)k} = \frac{AADT_{n+1}}{AADT_n} \tag{7}$$

Where,

n: The year (i.e. 2008)

$GR_{(n,n+1)k}$: Growth Rate for PTC (k) between years (n) and (n+1)

Spatial autocorrelation of traffic growth rates are examined using Global and Local Moran's I. The results are presented in Table 3. For instance between the year 2008 and 2009 the calculated Global Moran's Index is 0.09 with the Z-score of 5.17 standard deviation, which shows that growth rates are highly clustered over the study area.

An example of Local Moran' I analysis for the growth rates between years 2008 and 2009 is presented in Figure 8. The results show that from all the 288 PTCs in the study area regarding their annual growth rates, 190 follow a clustered pattern, while 9 have random distribution, and 89 are dispersed.

The Kriging method is also used to visualize the distribution of traffic growth rates in the study area. An interpolated surface and a 3D surface are created for the entire province shown in Figure 9 and Figure 10, which show that neighbor locations have similar growth rates. This finding indicates that in order to estimated AADTs from STTCs, growth rates should be obtained from the closest PTCs to the STTC site.

The above results are further investigated using Hot-Spot analysis to identify regions with high and low traffic growth rates. Traffic growth rates obtained from PTC data are used as the inputs to the Getis-Ord Gi* method and the results for growth rates between years 2008 and 2009 are presented in Figure 11.

The results from all the above analysis show that, in the study area, nearby PTCs are very likely to have similar growth rates. In order to further investigate this similarity, a correlation analysis was performed to examine the growth rates among nearby PTCs by defining four criteria that constrain whether the closest PTCs are:

1. Only on the same road;
2. Only on the same functional class but not on the same road;
3. On the same road or on the same functional class (closest PTC on the same functional class);
4. Near to each other with no constraint.

The growth rates from all the years between 2002 and 2009 are used to calculate a correlation coefficient for each pair of nearest PTC. The correlation coefficient is a number between -1 and 1 with -1 meaning a very strong "negative" correlation, 0 indicating no correlation, and 1 representing a high correlation between a pair of PTCs.

In this study, correlation coefficients greater than 0.7 (a defined threshold in this study) are counted and a percentage is calculated. The results show that 'PTCs on the same road' group has the highest correlation with the value of 49%. However, there are many unmatched PTCs in this category since there may not be another PTC on the same road. There are 27% of correlation coefficients greater than 0.7 in the category of 'only on the same functional class but not on the same road'; this number is 35% for the category of 'on the same road or on the same functional class'; and 32% for the PTCs 'near to each other with no constraints'.

A box-plot of all the correlations for each category is created and shown in Figure 12. The figure shows that the nearby PTCs located on the same road have the highest correlation; however, there are several unpaired PTCs in this category. So the next best category 'on the same road or on the same functional class (Closest PTCs on the same functional class)' is recommended in this study as the best criteria to "borrow" a traffic growth rate for a STTC site.

SUMMARY AND CONCLUSION

In this study, Geographic Information Systems (GIS) is used to examine the distribution of traffic growth rates and seasonality among road segments in the province of Alberta. Several tools such as Global/Local Morans' I, Hot-Spot analysis, Average Nearest Neighbor, and Kriging methods are used to investigate any existing correlations or patterns.

The spatial correlation analysis of the seasonal traffic patterns shows that there is no definitive relationship between a road's functional class and its seasonal pattern. This means that along a road of a particular functional class, different seasonal patterns may be observed. This finding indicates that there is a weakness with the FHWA AADT estimation method, for which a STTC is assigned to a PTC group based on the functional class, although Traffic Monitoring Guide does emphasizes the importance of basing the assignment methods on traffic seasonality. Study results also show that most of the commuter roads are clustered around the large cities, while roads with other seasonal patterns are randomly distributed in the area or have a dispersed pattern.

Spatial correlation analysis of traffic growth rates shows that they are highly clustered in the study area. This finding indicates that nearby roads are likely to have similar growth rates. Further, based on the correlation analyses of growth rates from the nearby roads under the four different criteria, it is recommended that the growth rate from a nearby road on the same functional class be used as it has the highest correlations with the STTC site.

It is believed that the findings from this study would help highway agencies to improve the operation of their traffic monitoring programs in the following two areas: (1) assigning SSTC to a PTC or PTC group with a similar seasonal traffic pattern and (2) assigning a more accurate traffic growth rate for the STTC site under investigation.

ACKNOWLEDGEMENTS

The authors are thankful to the Alberta Department of Transportation for the study data and Natural Science and Engineering Research Council (NSERC), Canada for the financial support.

REFERENCES

1. FHWA**.** *Traffic Monitoring Guide.* s.l. : U.S Department of Transportation, Federal Highway Administration, Office of Highway Policy Information, 2001.

2. *Estimation of Annual Average Daily Traffic on Low-Volume Roads: Factor Approach Versus Neural Networks.* Sharma, Satish C., et al., et al. s.l. : Transportation Research Board of the National Academies, 2000, Transportation Research Record, Vol. 1719, pp. 103-111.

3. *Bayesian Assignment of Coverage Counts Location to Factor Groups and Estimation of Mean Daily Traffic.* Davis, Gray A. and Guan, Yuzhe. s.l. : Transportation Research Board of the National Academies, 1996, Vol. 1542.

4. *Improving Group Assiginment and AADT Estimation Accuracy of Short-Term Traffic Counts Using Historical Seasonal Patterns.* Bagheri, Ehsan, Zhong, Ming and Christie, James. s.l. : American Society of Civil Engineers (ASCE), 2011. International Conference on Transportation Information and Safety (ICTIS). pp. 1548-1554.

5. Kemp, Karen K. *Encyclopedia of geographic information science.* s.l. : SAGE, 2008.

6. ESRI. How Hot Spot Analysis (Getis-Ord Gi*) works. *ArcGIS Resource Center.* [Online] ESRI, 2010. http://help.arcgis.com.

LIST OF TABLES

Table 1: Representation of distribution of features in an area by Moran's Index

Value of Moran's I	Pattern
I>0	Clustered
I=0	Random
I<0	Dispersed

Table 2: Average Nearest Neighbor analysis results show how different seasonal patterns are distributed in the study area.

Pattern Group	Z-Score	P-Value	Index	Interpretation
Commuter 1	-8.79	0.01	0.57	There is less than 1% likelihood that this clustered pattern could be the results of random chance.
Commuter 2	-6.33	0.01	0.7	There is less than 1% likelihood that this clustered pattern could be the results of random chance.
Rural Long Distance	2.3	0.05	1.4	There is less than 5% likelihood that this dispersed pattern could be the results of random chance
Regional Commuter	-1.32	N/A	0.88	While somewhat clustered, the pattern may be due to random chance.
Winter Recreational	0.57	N/A	1.07	The pattern is neither clustered nor dispersed (randomly distributed).

Table 3: Global Moran's Index for the traffic growth rates in the study area.

Years	Moran's Index	Z-Score	Interpretation
2002-2003	0.03	2.09	There is less than 5% likelihood that this clustered pattern could be the results of random chance.
2003-2004	0.17	9.25	There is less than 1% likelihood that this clustered pattern could be the results of random chance.
2004-2005	0.05	3.43	There is less than 1% likelihood that this dispersed pattern could be the results of random chance
2005-2006	0.14	7.86	There is less than 1% likelihood that this dispersed pattern could be the results of random chance
2006-2007	0.02	1.06	While somewhat clustered, the pattern may be due to random chance.
2007-2008	0.05	3.13	There is less than 1% likelihood that this dispersed pattern could be the results of random chance
2008-2009	0.09	5.17	There is less than 1% likelihood that this dispersed pattern could be the results of random chance

LIST OF FIGURES

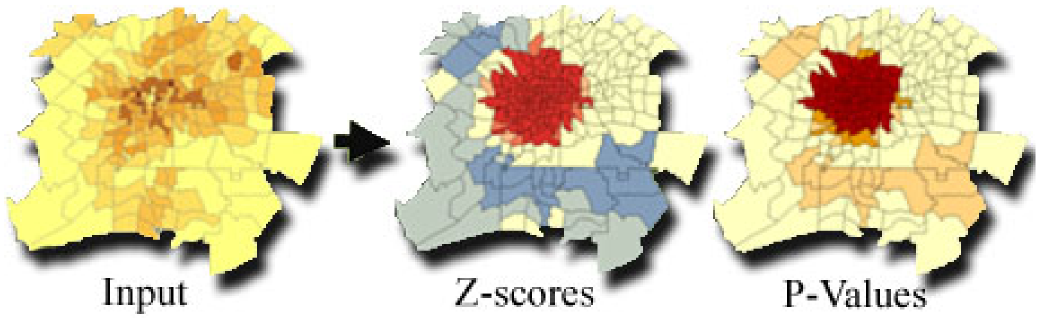

Figure 1:Hot-Spot analysis [6]

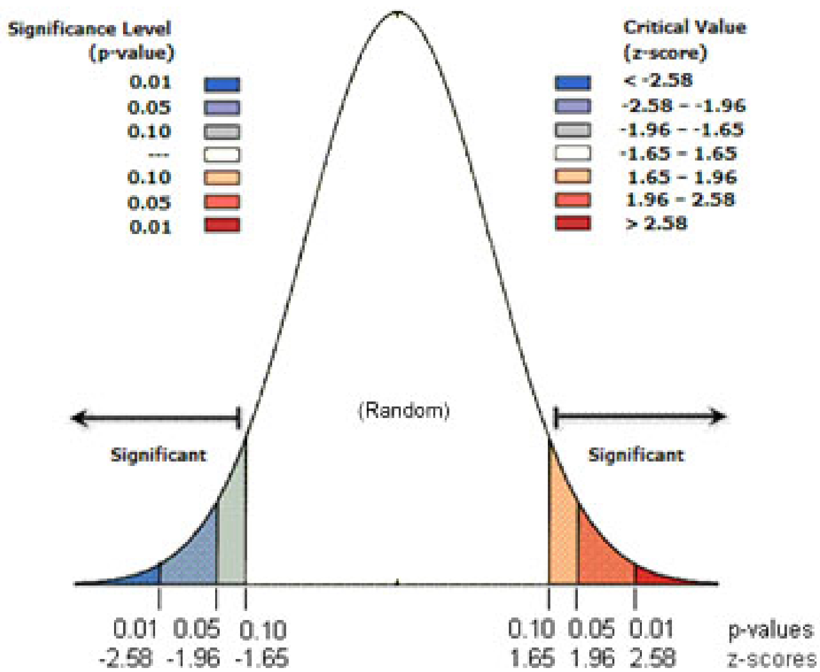

Figure 2: Z-scores and P-values provided by Hot-Spot analysis [6].

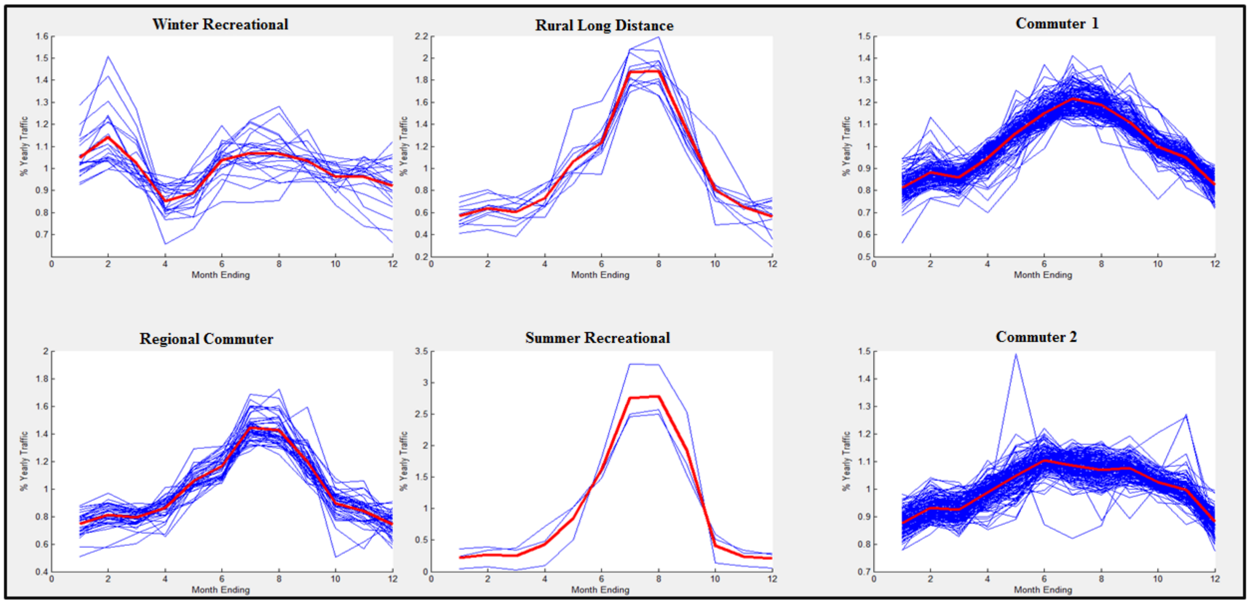

Figure 3: Six seasonal pattern groups identified for all the PTCs in the province of Alberta, Canada

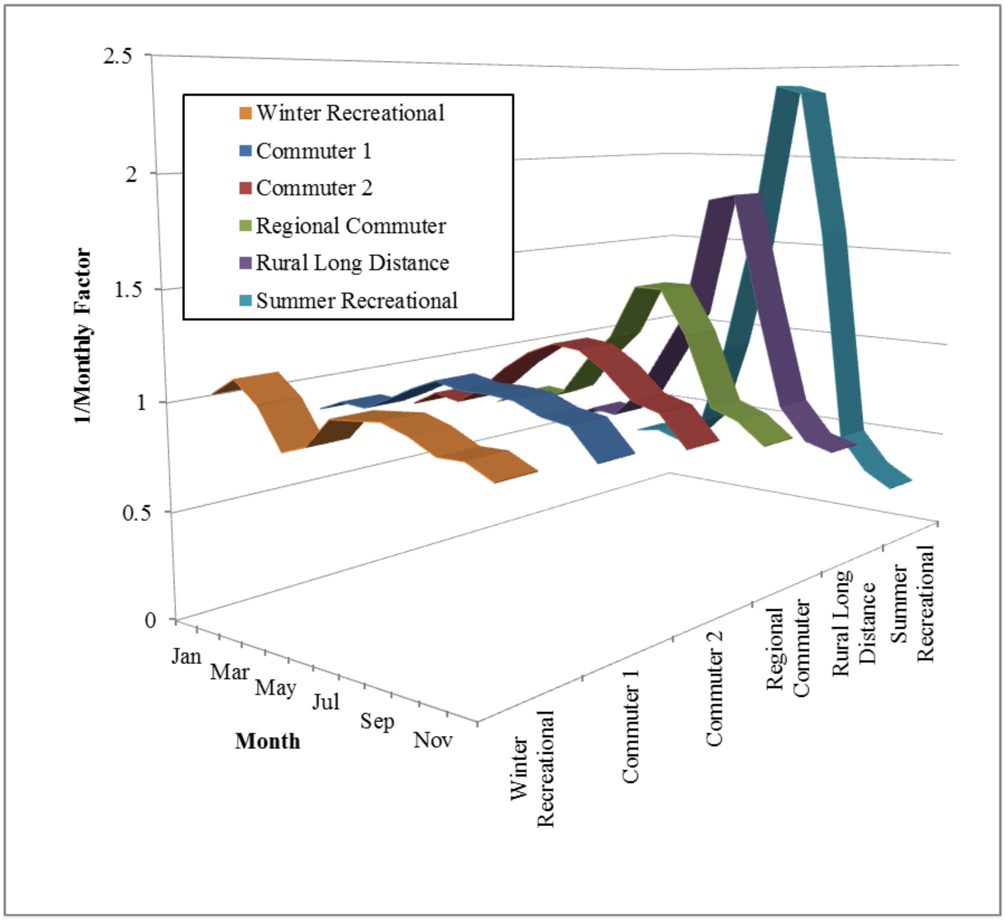

Figure 4: Comparison between six seasonal pattern groups in the study area.

Figure 5: Study area with PTCs locations and their seasonal pattern; and roads with their functional class group.

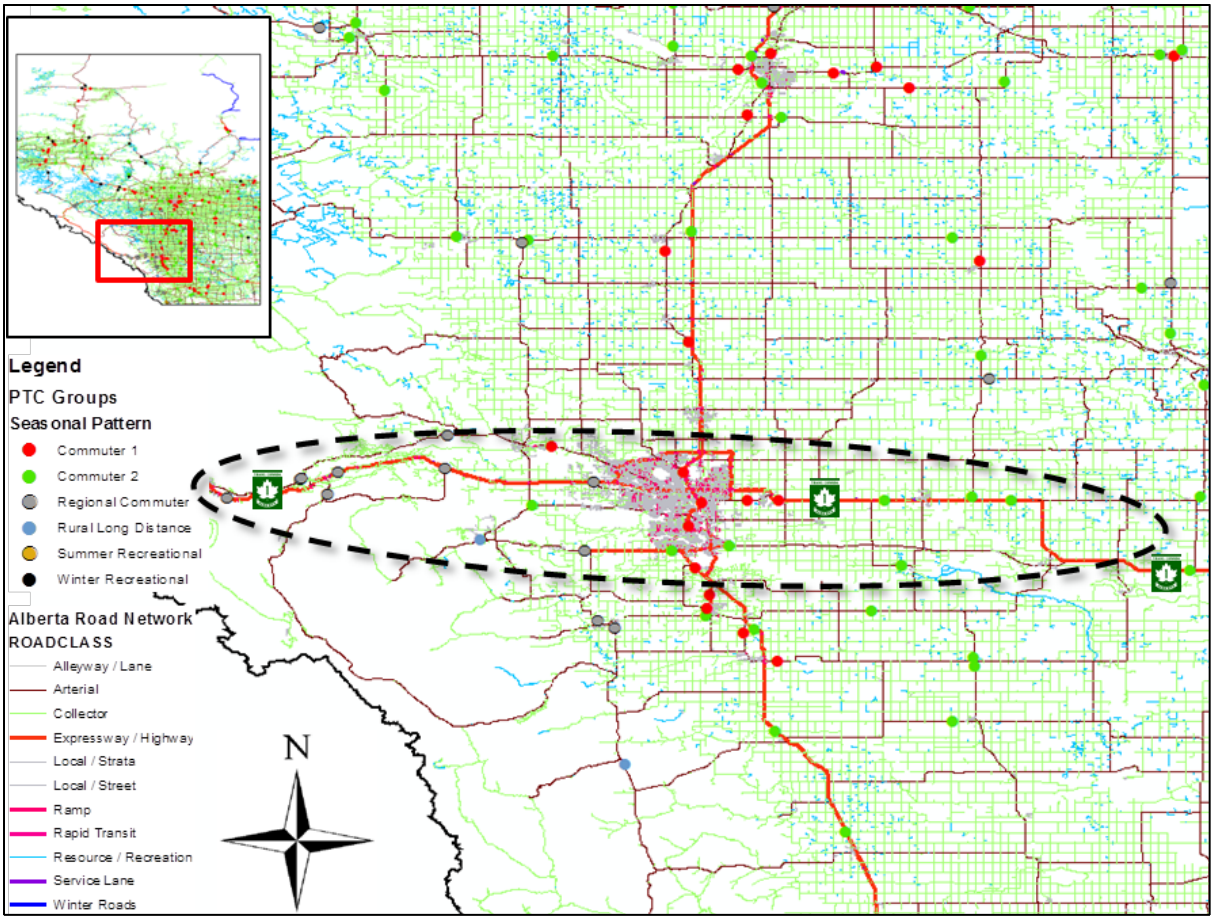

Figure 6: Change in the seasonal pattern along Highway 1 near city of Calgary, Alberta.

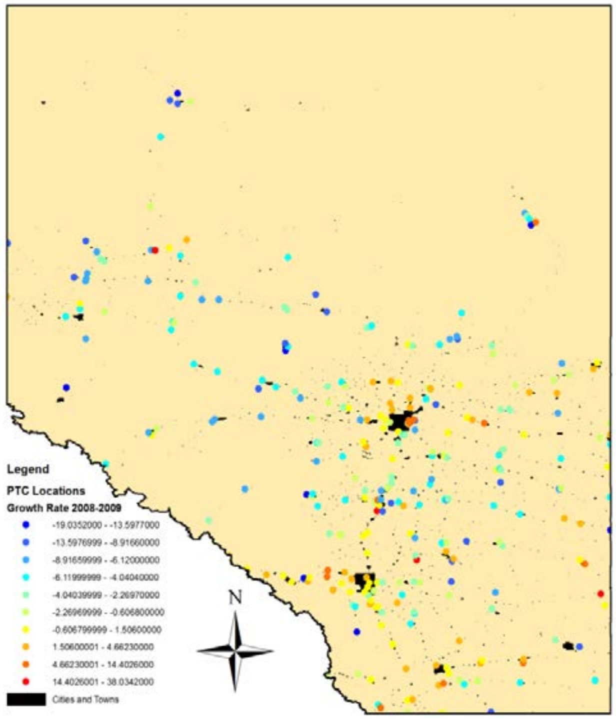

Figure 7: Annual growth rate associated to each PTC site between years 2008 and 2009

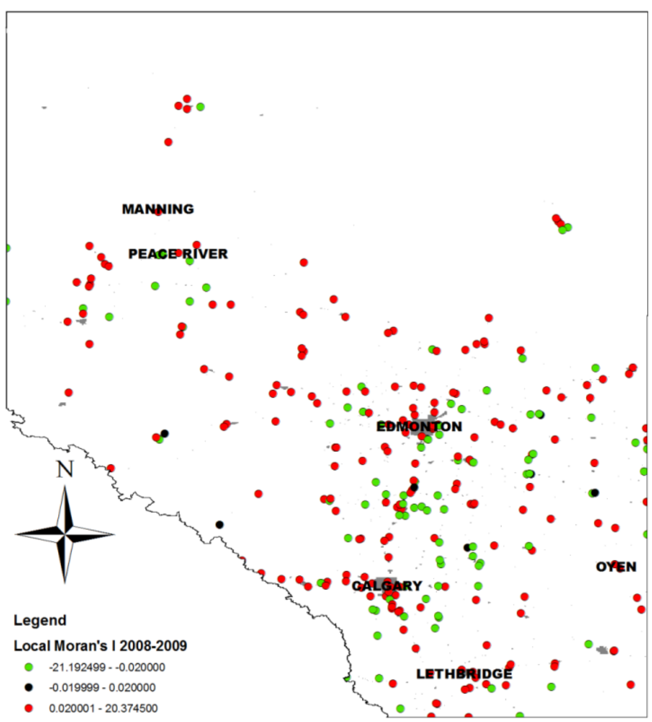

Figure 8: Local Moran's I analysis for the PTCs annual growth rates in the study area between years 2008 and 2009

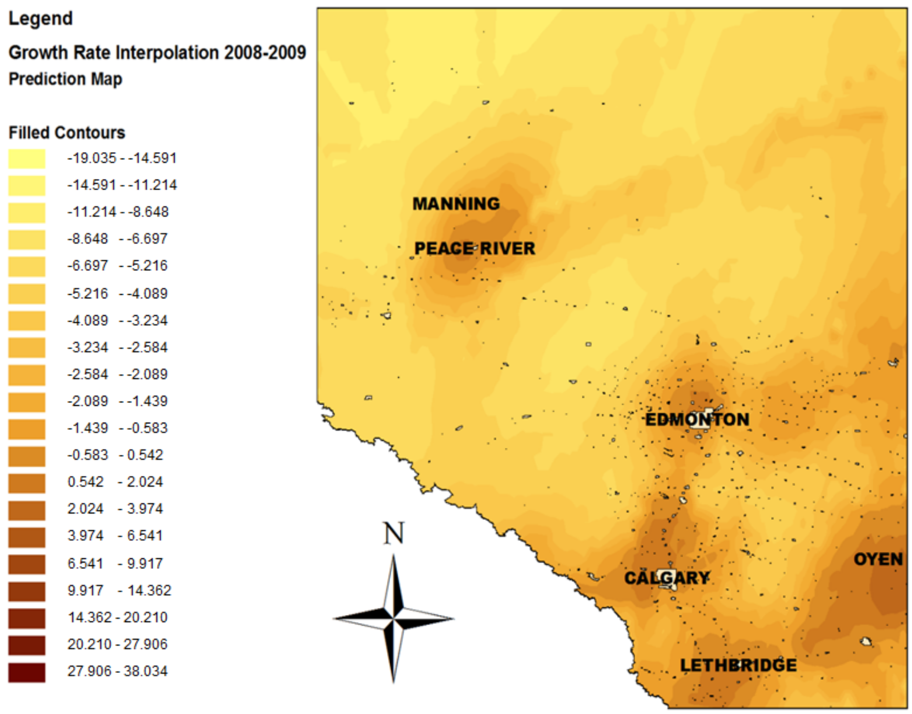

Figure 9: Distribution of the traffic growth rates in the study area using Kriging method.

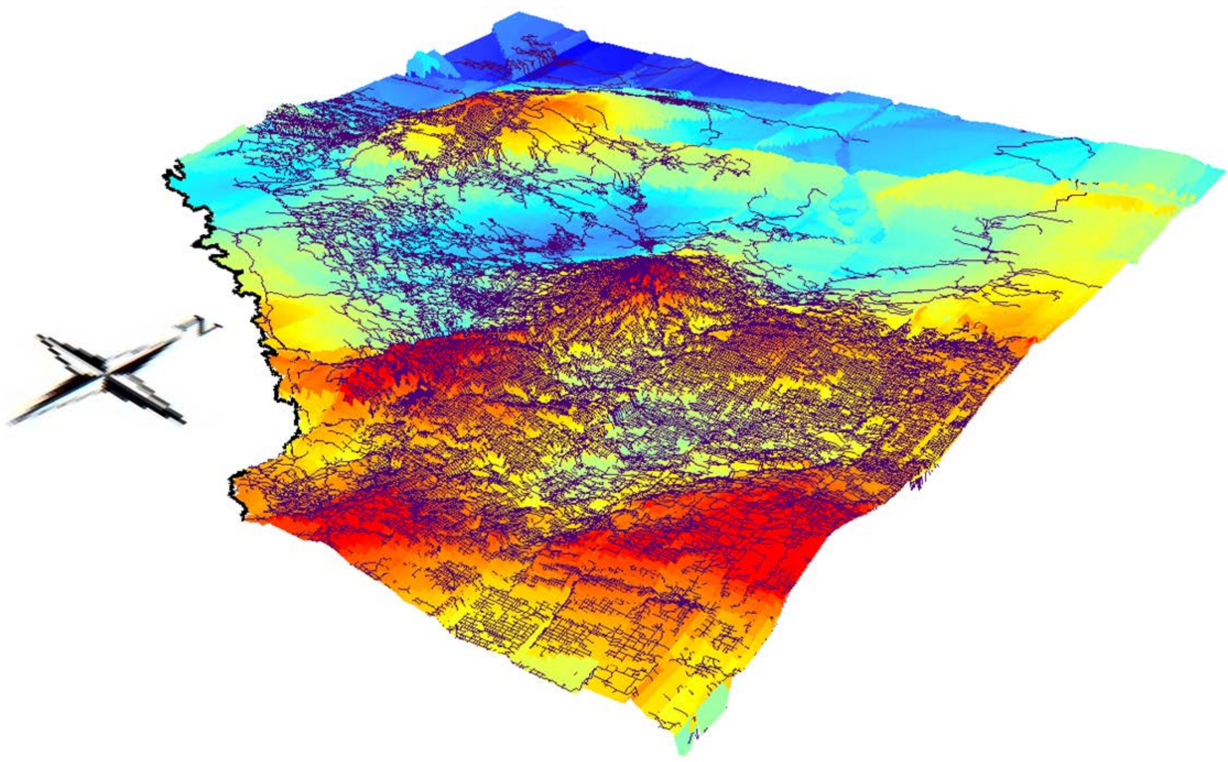

Figure 10: 3D Surface showing magnitudes of traffic growth rates using Kriging method.

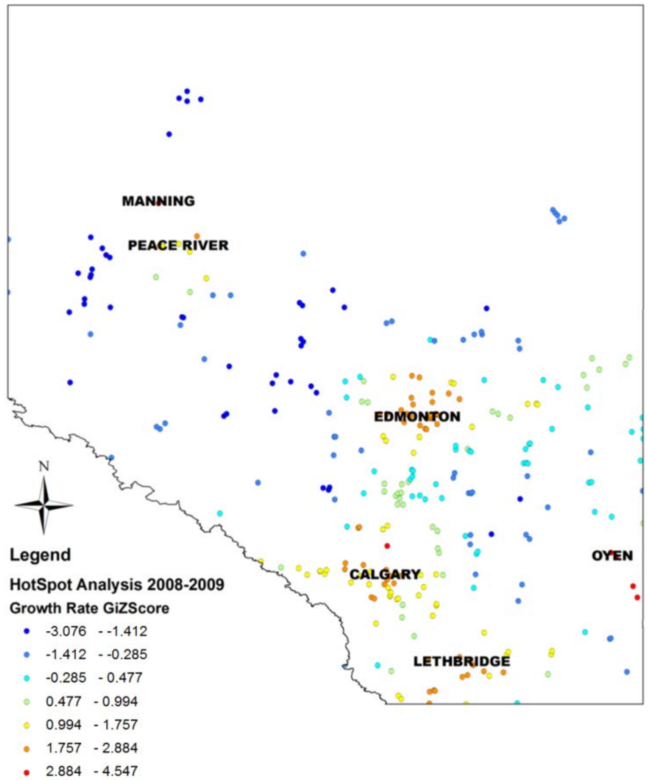

Figure 11: Hot-Spot analysis of annual growth rates between the years 2008 and 2009

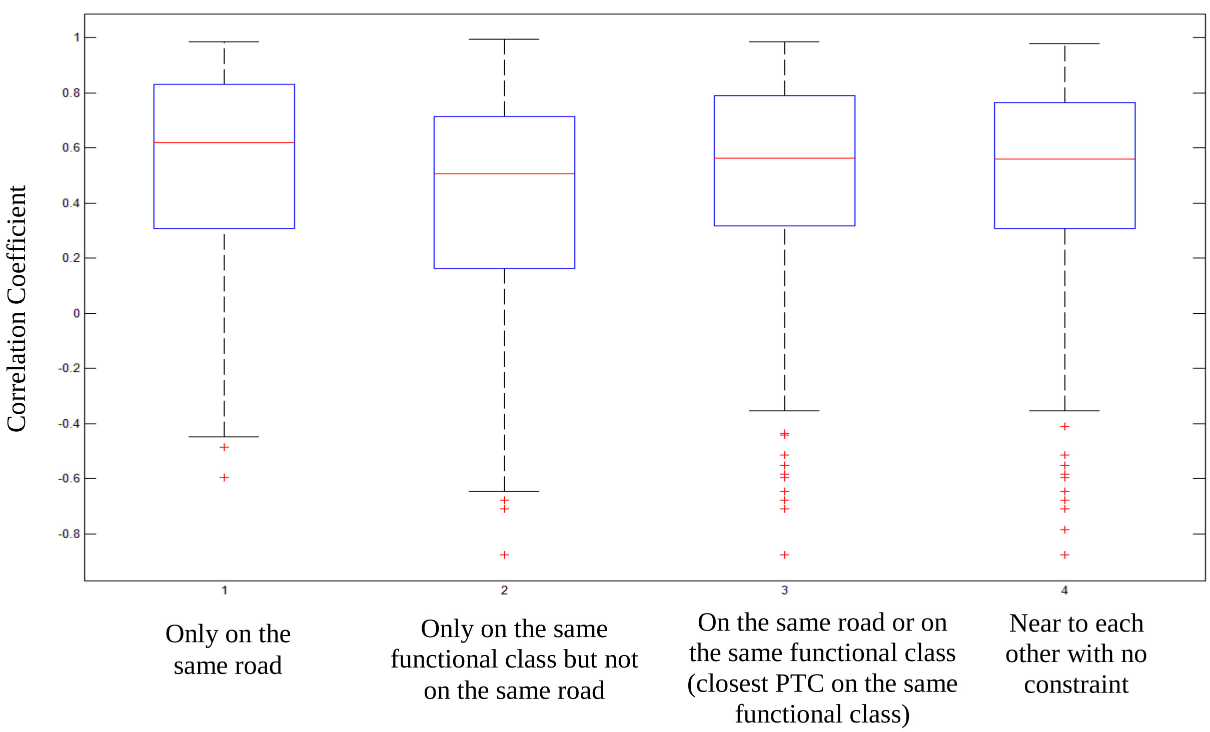

Figure 12: Box-Plot analysis of PTCs' traffic growth rates correlation in the study area.