# Analysis of Relationships Between Road Traffic Volumes and Weather: Exploring Spatial Variation

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## ABSTRACT

Weather is known to have a strong effect on traffic volumes. In this paper, we suggest a spatial approach to the modelling of traffic volumes. The relationship between weather variables and traffic volume is first modelled at a global level in a regional city centre in Finland. As strong a spatial dependency is found between the variables in the model, spatial variation is incorporated into the model. This local approach provides a more accurate model, as well as new insights into the data.

## **Categories and Subject Descriptors**

G.3 [Probability and Statistics]: Correlation and regression analysis

## **General Terms**

Measurement, Theory.

## Keywords

Weather, traffic volume, spatial modelling.

# 1. INTRODUCTION AND BACKGROUND

The modelling of traffic flows and volumes has been an important topic of research in varied fields and has previously been studied with the use of a raft of methods and techniques [3, 5]. One element that is lacking in previous studies into how the weather affects traffic volumes is the incorporation of spatial variation.

Previous studies that have examined the influence of weather variables upon traffic volumes have assumed that any relationships that are determined hold constant for the whole study area. In this paper we explore whether this assumption is valid or whether there are intrinsic differences in the relationships affecting traffic volumes which can be identified at disparate locations across the study area.

# 2. DATA

Traffic volume data was received from the city of Oulu, Finland. The data is for the whole of 2012 and consists of the daily totals James Culley Department of Real Estate, Planning and Geoinformatics Aalto University Espoo, Finland james.culley@aalto.fi

of traffic volumes from 59 crossroads as measured by sensors located at each of them.

Weather data was received from the Finnish Meteorological Institute. From the data measured every ten minutes we obtained variables relating to the daily average temperature, amount of precipitation, and average road friction.

# 3. MODEL DESCRIPTION

#### 3.1 Ordinary least squares

Ordinary least squares (OLS) regression is applied to the data first. This is a global model that results in a single estimation of each parameter for the entire study area [2]. The classic OLS regression model is written as

 $Y_i = b_0 + \sum_k b_k X_{ik} + \varepsilon_i$ 

where Y is the dependent variable,  $X_k$  is the kth explanatory variable, and b are the regression coefficients to be estimated by the model from the observed data.

In the model we adopted, the normalised traffic volume is the dependent variable. The explanatory variables are the days of the week, school and public holidays, the summer period, and weather variables for temperature, precipitation, and friction.

# 3.2 Local model

The most common method for modelling spatially non-stationary relationships is through geographically weighted regression (GWR) [1]. Whilst we would have liked to use GWR for our study, the data does not lend itself favourably to an analysis, with 59 crossroads locations, with 365 events at each location.

Therefore we propose two solutions to this problem. First, we will run a separate regression at each location to study the spatial autocorrelation. Second, we will use a simple form of GWR: A regression model is calibrated on all data that lies within the distance d of the regression point, a crossroads, and the process is repeated at all the regression points. We shall term moving window regression MWR in this paper.

#### 4. RESULTS

#### 4.1 Global model

All the coefficients in the global regression model are statistically significantly different from zero. The  $R^2$  value, which is a goodness-of-fit statistic that shows how much variation in the traffic volume is explained by the model, is 0.76.

The results show that on days when there was precipitation there was 2% more traffic. A rise in temperature of 10 degrees Celsius

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results in 0.6% more traffic and the maximum possible increase in friction equals a 6% increase in traffic compared to the median in the model.

## 4.2 Local model

To study if spatial dependency exists in the data, first, regression models are created for all the crossroads individually. Moran's I values [4] are then calculated for the coefficients to study the spatial autocorrelation.

All the Moran's I values for the coefficients show a positive spatial autocorrelation. Thus the relationship between the weather variables (as well as the time variables) and the amount of traffic varies spatially. This indicates that when studying the effect of these variables upon traffic volumes we need to take the location into account.

For the MWR we need to determine a suitable bandwidth distance d to use in the model. Different values were tested and the results presented here were calculated with the value of 1500 metres.

The coefficients from the local models can be shown on a map to study how the variables explain the traffic volumes in different areas.

Figure 1 presents the local coefficients for the precipitation variable. It shows that in the central area and northern part of Oulu the coefficients are bigger than in the other areas on the outskirts, which means that in those areas the traffic increase on days when there is precipitation is bigger, up to almost 4%. One reason for this may be that cyclists in the Oulu area switch to cars when it rains or snows and there are more cyclists in the centre than in the outskirts. The local coefficients for the other weather variables show a similar pattern.



Figure 1. Local coefficients for the precipitation variable.

The temporal variables can be studied in a similar manner to reveal the effects of different days of the week, as well as holidays. For example, on weekdays the increase in traffic is at its biggest south of the centre. One reason for this is that the area has lots of industrial, commercial, and office buildings.

The goodness of fit can also be studied locally by plotting the local  $R^2$  values. The values are better than for the global model, except in the central areas. Thus it seems that in the central area there are possibly explanatory variables missing from the model.

# 5. CONCLUSION AND DISCUSSION

This study strongly indicates that modelling the correlation between traffic volumes and weather variables needs a spatial approach. This is because the relationship between the variables depends on location. The centre of the city is especially different from other areas.

Possibly the biggest constraint for the research is the time span for the data. As only the data from one year is used, seasonal variation is not analysed and long-term trends cannot be seen.

The results help when predicting traffic volumes in Oulu. As the amount of traffic affects travelling time, this can be used for navigational purposes. In order to create a better spatial model, more sensors are needed outside the city centre.

Because the concept of spatially non-stationary relationships is scarce in the traffic modelling literature, we decided to approach the topic with a simple method, suitable for preliminary investigation. The purpose of adopting this technique was to identify whether there was any evidence to support the concept of non-stationary spatial relationships in the traffic modelling. The next stage in this research will be to determine a more suitable technique to investigate the apparent spatial aspects.

# 6. ACKNOWLEDGEMENTS

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