

IMPACT OF METEOROLOGICAL FACTORS ON THE NUMBER OF INJURY ACCIDENTS

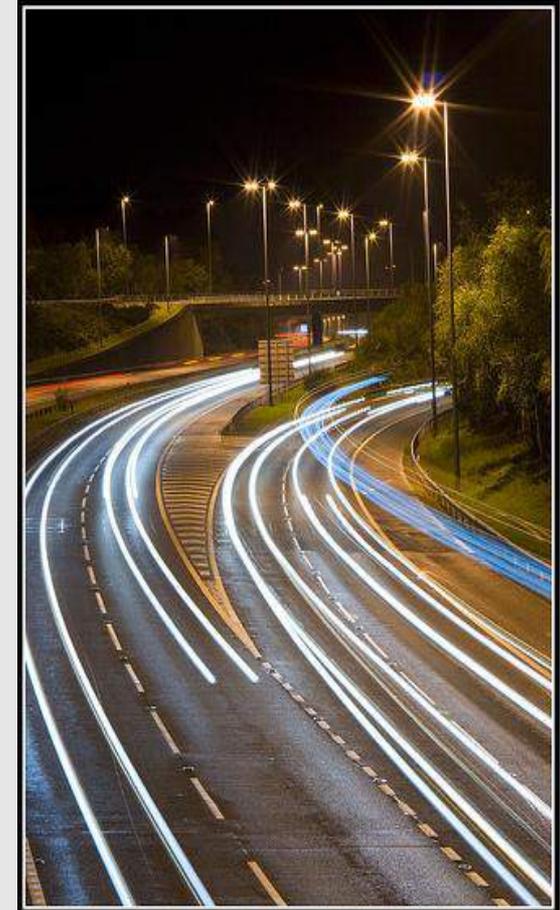


The 13th World Conference
on Transport Research
Julho 15- 18, 2013
Rio de Janeiro, Brasil

George Yannis, Associate Professor, NTUA
Constantinos Antoniou, Assistant Professor, NTUA
Dimitris Katsochis, Researcher-Manager, PLANET S.A.

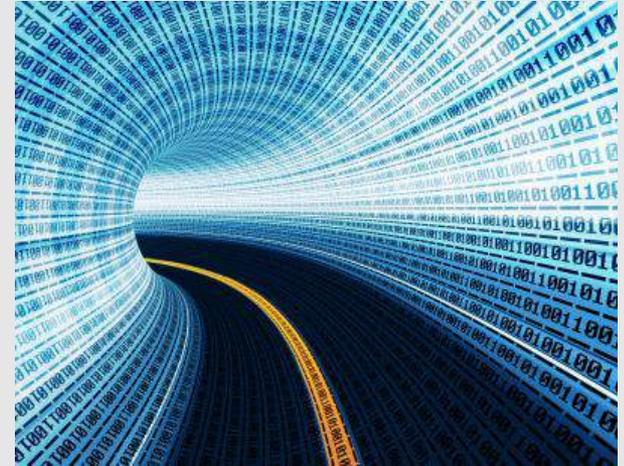
Objectives

- Objective: exploration of meteorological indicators' (temperature and precipitation) impact on the number of total accidents and fatalities in the wider Athens area.
- Using data from:
 - the Hellenic Statistical Authority (EL.STAT.) [road accidents and fatalities]
 - the National Observatory of Athens (NOA) [*daily average temperature and total precipitation*];
 - combined with data from the Shimatari toll station to the north of Athens [*monthly traffic data*].



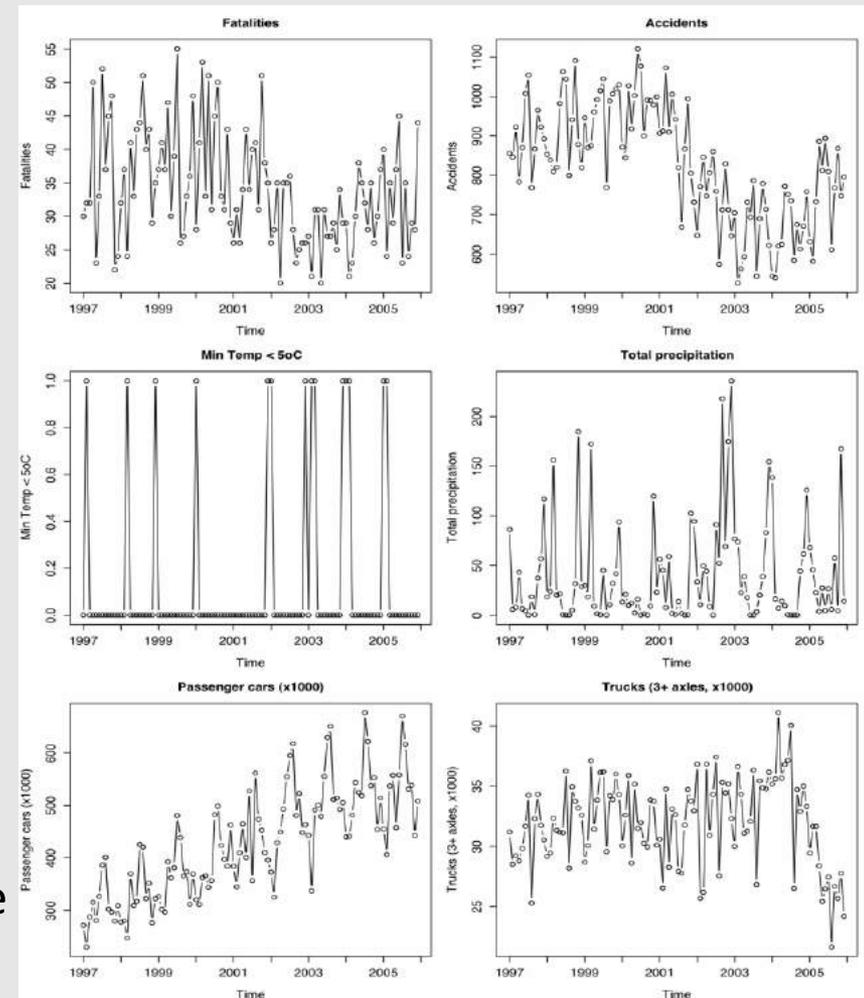
Data

- Road accident / fatalities data:
 - for the period 1997-2005 (9 years / 108 months), in
 - the wider Athens area (Attica, Greece);
- are correlated with meteorological parameters:
 - Temperature (the same 108-month period);
 - Precipitation.
- Temporal correlation of accidents / fatalities with meteorological variables is examined through:
 - Generalized linear models (GLM) –a family of models including the negative binomial, Poisson and quasi-Poisson distributional assumptions;
 - Dynamic GLM (or state-space) models.



Data Organization

- Daily meteorological data (temp./precip.):
 - as kept by NOA & NSSG;
 - undergone some processing.
- Monthly data:
 - Aggregate temperature and precipitation;
 - Toll station as a proxy to the entire traffic in the Athens area;
 - in an attempt to also consider exposure data.



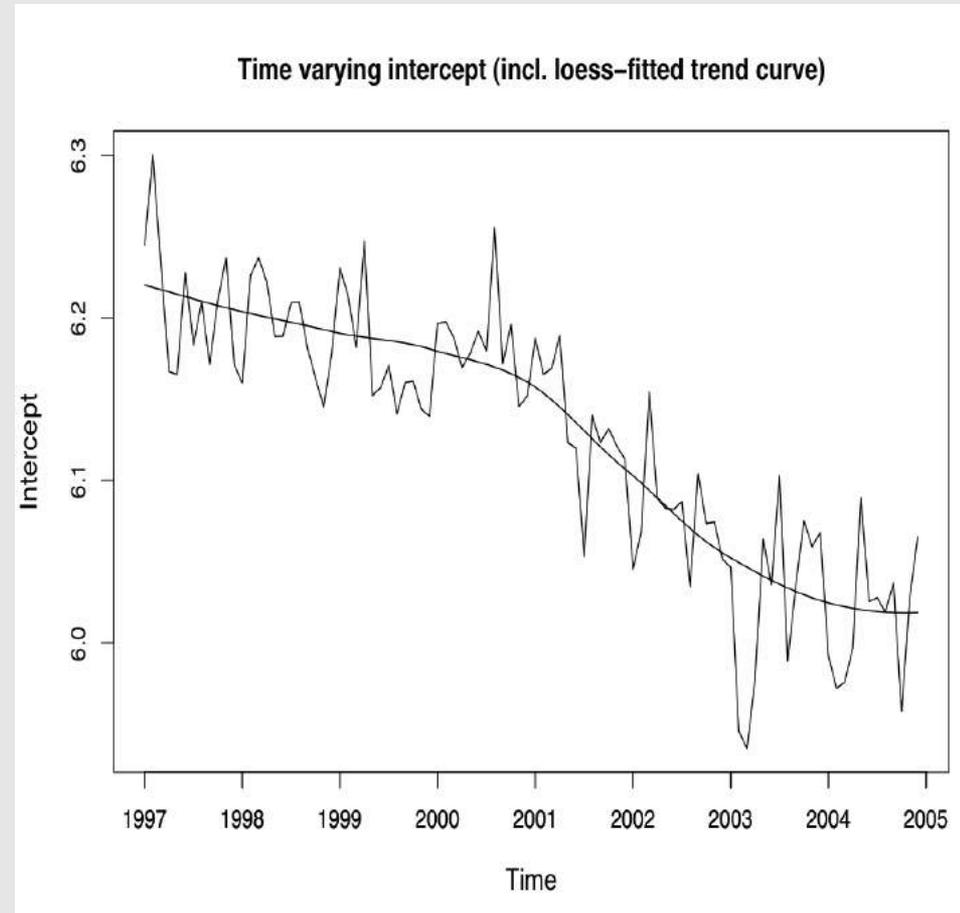
Methodology

- **The selected data-set is split in two parts, using:**
 - a first part to fit the models and test estimation performance;
 - a second part to validate models' predictive performance.
- **Generalized linear models (GLM):**
 - facilitate analysis of explanatory variables' effects resembling the analysis of covariates in a standard linear model;
 - with less confining assumptions; by specifying a *link function*;
 - linking the systematic component of the linear model with a wider class of outcome variables and residual forms;
 - model defined through a set of independent random variables, each with a distribution from the exponential family.
- **Dynamic GLM (or state-space / SS) models:**
 - A certain form of SS models; run at this context using the Poisson distribution and log link for the dependent variable;
 - and as GLM (using Poisson distribution with a log link function).



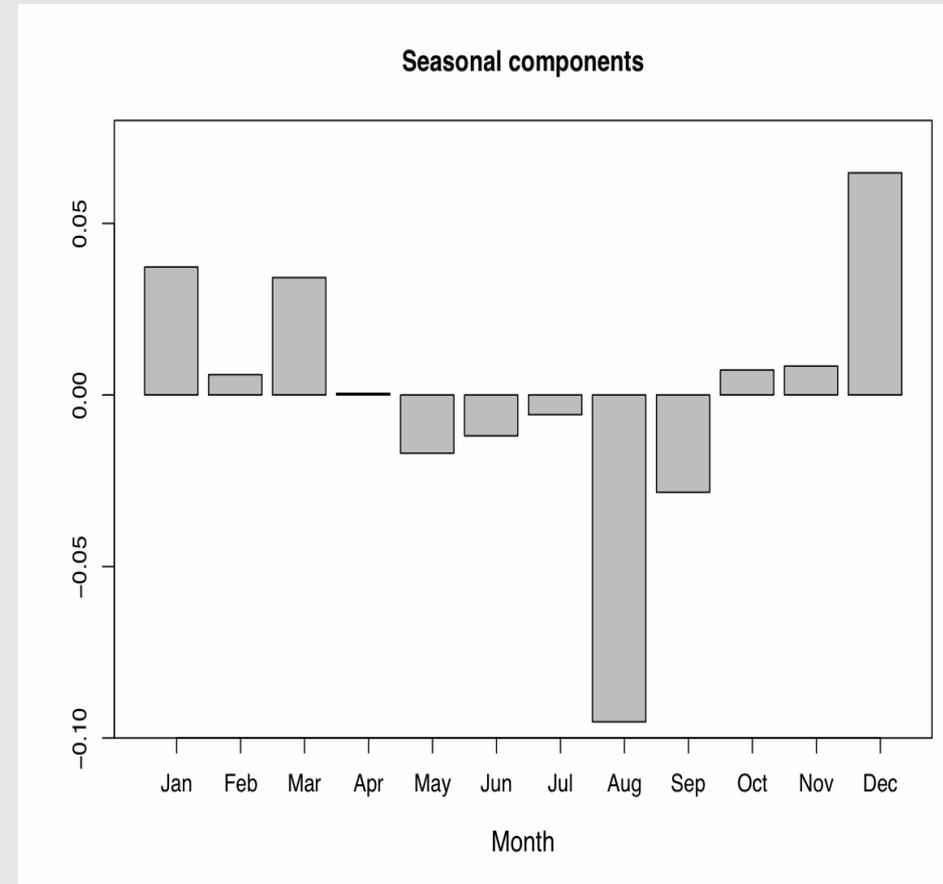
Dynamic Generalized Linear Model / DGLM (1/2)

- Approach selected as:
 - it allows explicit modelling of serial correlation;
 - measurement equation distributions fall within the exponential family.
- Explanatory variables:
 - binary (0/1) variable with value of "1" if min. mean temp. of one day in a month was less than 5 C;
 - sum of total precipitation during a month (mm);
 - number of heavy trucks passing from the toll station during a month;
 - number of motorized two-wheelers.



Dynamic Generalized Linear Model / DGLM (2/2)

- Time-varying intercept:
 - loess-fitted trend line;
 - for illustration purposes of the decreasing trend.
- Unstructured seasonal pattern in the form of:
 - month-specific seasonal components;
 - verifying a lower number of accidents during the summer months;
 - possibly due to low exposure and improved weather conditions; and
 - comparatively more accidents during winter;
 - possibly due to inclement weather conditions.



GLM – Poisson assumption (1/2)

➤ Model estimation results:

- a model without dummies for the months is presented first;
- followed by a model with month dummies.

	GLM Poisson (glm1.p)		GLM Poisson with month dummies (glm2.p)	
	Coef.	t-test	Coef.	t-test
Intercept	6.119	155.165	6.057	147.94
Min Temp < 5oC	4.851x10-2	3.549	1.934x10-2	1.322
Total Precip.	1.602x10-4	2.14	1.118x10-4	1.324
Heavy Trucks	-9,891x10-3	-8.387	-8.263x10-3	-6.810
Motor.2wheel.	1.863x10-3	42.163	1.882x10-3	41.787
Dummy Jan	N/A		7.207x10-2	5.079
Dummy Aug	N/A		-2.111x10-3	-2.068
Dummy Dec	N/A		6.198x10-2	3.921
Null deviance	2669.6	(95 d.o.f.)	2669.6	(95 d.o.f.)
Residual deviance	391.54	(91 d.o.f.)	352.0	(88 d.o.f.)
AIC	1222.3		1188.8	

- The 2nd model (month dummies) somewhat approximates the seasonal components of the state-space model.

GLM – Quasi-Poisson assumption (2/2)

➤ Model estimation results:

- the same structuring process as under Poisson assumption;
- again, the model with month dummies approximates SS model better.

	GLM quasi-poisson (glm1a.p.disp)		GLM quasi-poisson with month dummies (glm2.p.disp)	
	Coef.	t-test	Coef.	t-test
Intercept	6.107	72.877	6.043	72.072
Min Temp < 5oC	5.316x10-2	1.932	2.079x10-2	0.718
Total Precip.	---	---	1.251x10-4	0.730
Heavy Trucks	-9.647x10-3	-3.982	-8.507x10-3	-3.468
Motor.2wheel.	1.83x10-3	20.341	1.925x10-3	20.611
Dummy Jan	N/A		7.013x10-2	2.430
Dummy Aug	N/A		-2.360x10-3	-1.098
Dummy Dec	N/A		6.460x10-2	1.959
Null deviance	605.372	(95 d.o.f.)	649.594	(95 d.o.f.)
Residual deviance	91.335	(92 d.o.f.)	86.958	(88 d.o.f.)
AIC	280.26		296.69	

- The coefficients for most (but not all) parameters are significant at the 95% level.

Estimation / prediction accuracy of models (1/2)

➤ General remarks:

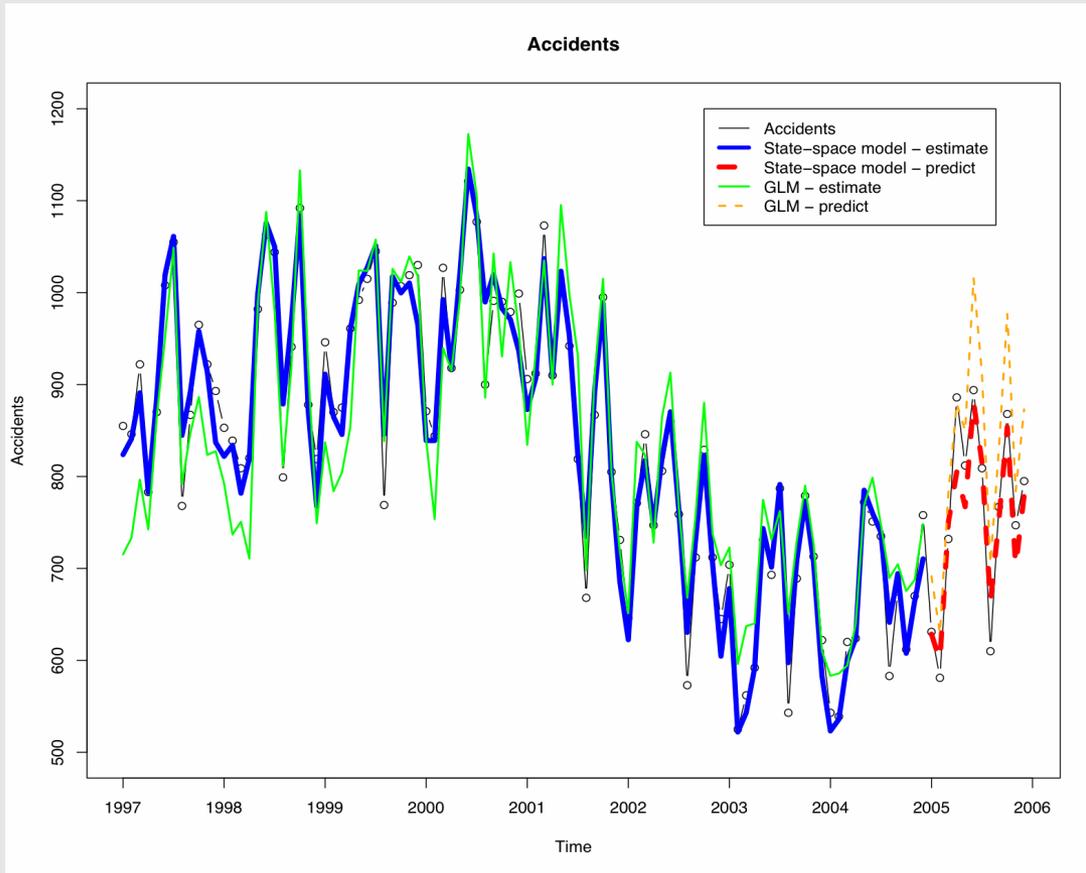
- various GLM models show similar estimation and prediction performance;
- models not modelling over-dispersion correctly underestimate standard errors and may give false positive indication of some values' significance.

RMSPE	Estimation	Prediction
State Space model	0.0386	0.0461
GLM Poisson (glm1.p)	0.0727	0.0984
GLM Poisson – month dummies (glm2.p)	0.0684	0.0914
GLM quasi-Poisson (glm1a.p.disp)	0.0730	0.0981
GLM quasi-Poisson – month dummies (glm2.p.disp)	0.0685	0.0948

- Dynamic GLM/state-space models show a considerably improved performance over the GLM models.
- Use of the RMSPE metric reveals satisfactory performance, with an estimation error between ~ 7% (GLM) and <4% (state-space model).

Estimation / prediction accuracy of models (2/2)

➤ Visual representation confirms models' quantitative results:



- reasonable differentiation across months within a year;
- June yields more accidents than autumn period months, probably because more vehicle-km are driven on most road networks during early summer;
- it appears that low temperature corresponds to some reduction of recorded accidents (mostly in winter);
- the same is the case as total precipitation increases, probably due to reduced mobility under rainy weather.

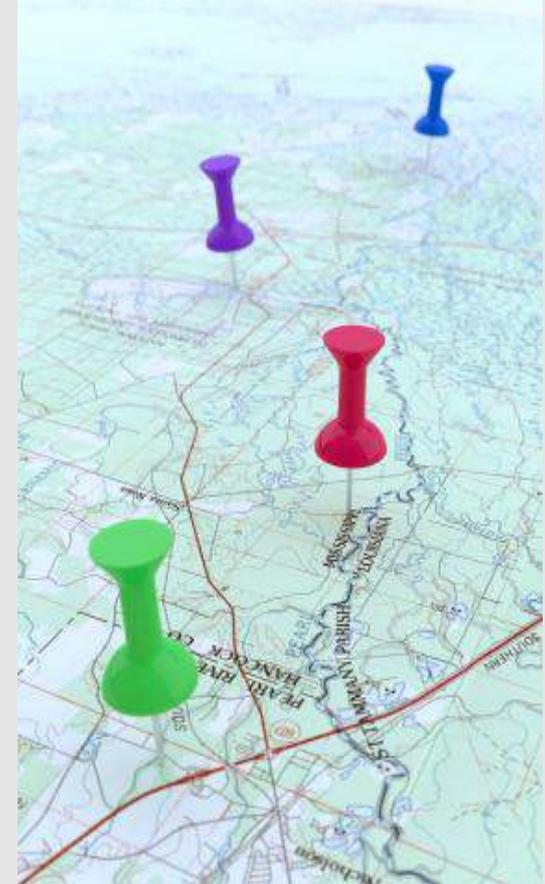
Concluding remarks (1/2)

- Models solely built around meteorological variables only demonstrate limited potential in interpreting trends and may only be used as indicative descriptive tools.
- Model diagnostics and goodness-of-fit measures demonstrate the explanatory and predictive power of the more involved dynamic GLM models (DGLM / SS).
- In terms of predictive performance, the error is <10% for the GLMs and well below 5% for the state-space model.
- These rather simple models demonstrate a reasonable differentiation across months within a year, with:
 - June yielding more accidents than each month of the autumn period;
 - probably because more vehicle-km are driven on most road networks during early summer.



Concluding remarks (2/2)

- Better understanding of the subtle difference among different model functional forms can yield more reliable forecasts.
- Models that can accurately assess the impact of meteorological parameters on traffic safety can help establishing base-line conditions, to assess safety measures & campaigns' performance.
- Recommendations for practical use of results may include:
 - shaping public policy/measures (e.g. VMS operation under rain);
 - strengthening focused road safety campaigns (e.g. lights/tyres; significance of car service, overall).



IMPACT OF METEOROLOGICAL FACTORS ON THE NUMBER OF INJURY ACCIDENTS

Apoio



Patrocinadores

