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FURTHER DEVELOPMENTS
OF TWO POINT PROCESS MODELS
FOR FINE-SCALE TIME SERIES

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Abstract

Two point processes, the Autoregressive Conditional Duration (ACD) model and the Bartlett-Lewis Pulse (BLP) model, are further developed and used to model fine scale time series.

Six different ACD models are specified and fitted to two sets of real stock transaction data. The Akaike Information Criterion (AIC), Takeuchi Information Criterion (TIC) and Generalized Information Criterion (GIC) are the information-theoretic criteria for model evaluation. This is the first time that ACD models have been evaluated and ranked based on the information-theoretic criteria, and makes the comparison of ACD models with different autoregressive and error structures straightforward. A newly proposed ACD model with a mixed lognormal-gamma error term distribution is identified as the best model with minimum predictive error.

The original BLP model was developed and fitted to 60 years of 5-minute rainfall series from Kelburn, a place near Wellington, New Zealand, by Cowpertwait et al. (2007). The BLP model can be used to produce realistic simulation samples of fine scale rainfall series that are required in many applications, e.g. urban drainage system design. Following the continuous distributions of storm types approach as first proposed by Cowpertwait (2010), a more general BLP process characterization framework is formulated under which the original BLP model can be recovered as a special case. Statistical properties up to third order are derived for the BLP model characterized by continuous distributions of storm types. Without an increase in model parameters, a modified BLP model is specified, in which a conditional mean exponential distribution is used to represent the pulse depths distribution and a continuum of storm types within a process is assumed. Simulation studies show that the modified model improves the fit to the observed proportion of dry periods significantly, whilst retaining a good fit to moment properties. Also a better fit is obtained to the annual extreme rainfall values at the 5 minutes and 12 hours aggregation levels whilst retaining a good fit at other aggregation levels, and significant improvement is achieved in the goodness-of-fit to extremes for the individual months. The improvements of the original BLP model's performance are mainly due to the successful implementation of the within cell pulse depths dependence structure using a conditional mean exponential distribution.

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Main abbreviations and symbols

$\exp(\cdot)$	exponential function such that $\exp(1) = e$
$\log(\cdot)$	the natural logarithm function such that $\log(e) = 1$
iid	independent and identically distributed
pdf	probability density function
pmf	probability mass function
$\Pr[\]$, or $P[\]$	probability
$E[\]$	expected value, mean value
$\text{Var}[\]$	variance
$\text{Cov}[\]$	covariance
$L(\underline{\theta})$	likelihood function for the parameter $\underline{\theta}$
MLE	maximum likelihood estimator or maximum likelihood estimate
QMLE, quasi MLE	quasi-maximum likelihood estimator or estimate
M-estimator	maximum likelihood-type estimator
EDA	exploratory data analysis
qq-plot	quantile-quantile plot
$G(x), g(x)$	the distribution and density functions representing the true distribution from which the observed sample data are generated
\hat{G}, \hat{g}	the empirical distribution and density functions of the true distribution
$F(x \underline{\theta})$ or $f(x \underline{\theta})$	a fitted distribution or density function, which is specified to approximate the true distribution
$\underline{x} = \{x_1, x_2, \dots, x_n\}$	a random sample data set of n observations generated from the true distribution $G(x)$
$\{y_t\} = \{y_1, y_2, \dots, y_n\}$	an observed time series which consists of n values sampled at discrete times $1, 2, \dots, n$
AR model	(standard time series) Autoregressive model
MA model	(standard time series) Moving-average model
ARMA model	(standard time series) Autoregressive Moving-average model
L-B statistic	Ljung-Box statistic (see Section A.3)
Q-statistic	Pearson's Q-statistic (see Section 2.5.2)

K-L information	Kullback-Leibler information
$I(g; f)$	symbol for K-L information (see Section 2.3.2)
AIC	Akaike Information Criterion
AICc	the small sample bias-corrected AIC
BIC	Bayesian Information Criterion
DIC	Deviance Information Criterion
TIC	Takeuchi Information Criterion
GIC	Generalized Information Criterion
EMD	effective model dimension
W_i	Akaike weights (see Section 2.4.1)
ACD model	Autoregressive Conditional Duration model (finance model)
EACD(1,1), EACD(2,2)	the first, second order ACD models that have an exponential distribution error term structures (see Section 3.3.1)
WACD(1,1), WACD(2,2)	the first, second order ACD models that have a Weibull distribution error term structures (see Section 3.3.1)
mixedE-ACD(1,1)	a first order ACD model that has a mixed exponential distribution error term (see Section 3.3.2)
mixedLG-ACD(1,1)	a first order ACD model that has a mixed lognormal-gamma distribution error term (see Section 3.3.2)
NSRP model	Neyman-Scott rectangular pulse model (rainfall model)
BLRP model	Bartlett-Lewis rectangular pulse model (rainfall model)
BLP model	Bartlett-Lewis pulse model (rainfall model)
CV	coefficient of variation
AC	autocorrelation
PD	proportion dry
FIT-O1	the original BLP model specification, single process of storms (six parameters in total) (see Section 6.3)
FIT-O	the original BLP model specification, superposition of two independent FIT-O1 processes (11 parameters in total) (see Section 6.3)
FIT-C1	based on FIT-O1, but with a within cell pulse depths dependence structure characterization (see Section 6.3)
FIT-C	superposition of two independent FIT-C1 processes (11 parameters in total) (see Section 6.3)
FIT-C-PD	based on FIT-C, but with the sample PD properties further included in the fitting procedure (see Section 6.3)

FIT-C1- $\beta z \theta z$	based on FIT-C1, specification with continuous distributions of storm types in terms of cell origins generation rate $\beta(z) = \beta_0(1 - z) + \beta_1 z$ and mean pulse depth $\theta(z) = \theta z$ (see Section 7.2.3)
FIT-C1- $\xi z \theta z$	based on FIT-C1, specification with continuous distributions of storm types in terms of pulse generation rate $\xi(z) = \xi_0(1 - z) + \xi_1 z$ and mean pulse depth $\theta(z) = \theta z$ (see Section 7.2.3)
FIT-C1- $\beta z \xi z$	based on FIT-C1, specification with continuous distributions of storm types in terms of cell origins generation rate $\beta(z) = \beta_0(1 - z) + \beta_1 z$ and pulse arrival rate $\xi(z) = \xi_0(1 - z) + \xi_1 z$ (see Section 7.2.3)
FIT-C1- $\beta z \xi z \theta z$	based on FIT-C1, specification with continuous distributions of storm types in terms of cell origins generation rate $\beta(z) = \beta_0(1 - z) + \beta_1 z$, pulse arrival rate $\xi(z) = \xi_0(1 - z) + \xi_1 z$, and mean pulse depth $\theta(z) = \theta z$ (see Section 7.2.3)
FIT-C-8	based on FIT-C, but with the assumption of a common mean storm lifetime, a common rain cell origins generation rate and common mean cell duration for the two distinct processes of storms (a reduced FIT-C, eight parameters in total)
FIT-C-9	based on FIT-C, but with the assumption of a common mean storm lifetime, a common cell origins generation rate for the two distinct processes of storms (a reduced FIT-C, nine parameters in total)
FIT-C-10	based on FIT-C, but with the assumption of a common mean storm lifetime for the two distinct processes of storms (a reduced FIT-C, 10 parameters in total)
FIT-C1- $\beta z \theta z(6)$	based on FIT-C1, specification with continuous distributions of storm types in terms of cell origins generation rate $\beta(z) = \beta(1 - z)$ and mean pulse depth $\theta(z) = \theta z$ (six parameters in total, see Section 8.1.1)
FIT-C1- $\beta z \theta z E$	based on FIT-C1, specification with continuous distributions of storm types in terms of cell origins generation rate $\beta(z) = \beta e^{-z}$ and mean pulse depth $\theta(z) = \theta z$ (six parameters in total, see Section 8.1.1)
FIT-C- $\beta z \theta z E$	superposition of two independent FIT-C1- $\beta z \theta z E$ processes