Simulating hourly rainfall occurrence within an equatorial rainforest, Borneo Island

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Abstract The ability to simulate characteristics of the diurnal cycle of rainfall occurrence, and its evolution over the seasons is important to the forecasting of hydrological impacts resulting from land-use and climate changes within the humid tropics. This stochastic modelling study uses a generalized linear model (GLM) solution to second-order Markov chain models, as these discrete models are better at describing binary occurrence processes on an hourly time-scale than continuous-time approaches such as stochastic state-space models. We show that transition probabilities derived by the Markov chain method need to be time-varying rather than stationary to simulate the evolution of the diurnal cycle of rainfall occurrence over a Southeast Asian monsoon sequence. The conceptual and pragmatic links between discrete diurnal processes and continuous processes occurring over seasonal periods are thereby simulated within the same model.

Key words generalized linear model (GLM); hourly rainfall; Markov chain; Monte Carlo simulation; time-varying transition probabilities; tropical climate; weather generator

Simulation de l'occurrence de pluie horaire au sein de la forêt équatoriale, Ile de Bornéo

Résumé L'aptitude à simuler les caractéristiques du cycle diurne d'occurrence des pluies et de son évolution au fil des saisons est importante pour la prévision des impacts hydrologiques de changements d'occupation du sol et de climat en zones tropicales humides. Cette étude de modélisation stochastique utilise une résolution de modèle linéaire généralisé (GLM) de modèles de type chaîne de Markov de second ordre, ces modèles discrets étant meilleurs pour décrire des processus d'occurrence binaire à pas de temps horaire que les approches continues telles que les modèles d'état stochastiques. Nous montrons que les probabilités de transition dérivées par la méthode de la chaîne de Markov doivent être évolutives au fil du temps plutôt que stationnaires pour simuler l'évolution du cycle diurne d'occurrence des pluies pendant une séquence de mousson en Asie du sud-est. Les liens conceptuel et pragmatique entre les processus diurnes discrets et les processus continus intervenant lors des périodes saisonnières sont simulés au sein du même modèle.

Mots clefs modèle linéaire généralisé (GLM); pluie horaire; chaîne de Markov; simulation de Monte-Carlo; probabilités de transition évolutives; climat tropical; générateur météorologique

INTRODUCTION

Many studies have simulated the statistical properties of daily rainfall data (e.g. Wilks & Wilby, 1999; Leander *et al*., 2005). Very few studies however, have simulated hourly rainfall data (Katz & Parlange, 1995). Such models would have particular benefits for hydrological research within tropical rainforest regions where streamflow and sediment sources are very sensitive to sub-daily rainfall characteristics (Chappell *et al*., 2001, 2004a, 2006; Bonell, 2004; Bidin & Chappell, 2006). Markov chains are the most common method of modelling the statistical properties of daily rainfall occurrence, i.e. duration of wet and dry days (Stern & Coe, 1984). Further, the weighted least squares (WLS) technique involved with Markov chain procedures is normally undertaken assuming that the transition probabilities are stationary. However, Klugman & Klugman (1981), Gregory *et al*. (1993), and Katz & Parlange (1995) have shown that this assumption often leads to underestimation of the variance in the modelled rainfall dynamics, particularly where hourly data are analysed. Consequently, within this study we apply the generalized linear model (GLM) for binary data (McCullagh & Nelder, 1989) to simulate hourly rainfall data for an equatorial

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rainforest site. In particular, we examine the impact of relaxing the stationarity assumption, by estimating transition probabilities that vary smoothly through the day, across days and across years.

LOCATION OF RAINFALL OBSERVATIONS

The data for this hourly rainfall modelling study were monitored at automatic raingauge "R3" within the Baru experimental watershed (Chappell *et al*., 1999, 2004a, 2006), close to the Danum Valley Field Centre (DVFC) in the Malaysian State of Sabah on Borneo Island, Southeast Asia. This raingauge is called "Site 3" within Bidin & Chappell (2006), and is located at 4°57′50″N; 117°49′6″E, 50 km inland from the eastern coast of Sabah. The Baru watershed and wider DVFC locality forms the focus of ongoing hydrological research on rainfall, throughfall and wet-canopy evaporation (Chappell *et al*., 2001; Bidin & Chappell, 2006); soil-water regulation of landscape ecology; streamflow generation mechanisms (Chappell & Sherlock, 2005); rainfall–runoff modelling (Chappell *et al*., 1999, 2006) and erosion (Chappell *et al*., 1999, 2004a). All of this work could be advanced with a better model of the hourly characteristics of rainfall.

The vegetation at the locality of the raingauge is "lowland, evergreen dipterocarp" forest, with the upper canopy being dominated by *Parashorea malaanonan*, *P. tomentella* (both White Seraya), *Shorea johorensis* (Red Seraya) and *Rubroshorea* spp. The area is managed by Yayasan Sabah for commercial timber production and conservation.

Daily rainfall has been measured at the DVFC meteorological station since 1986, and over the 20-year monitoring period (1986–2005) an average annual rainfall (AAR) of 2799 mm (with σ being 456 mm) has been recorded. Hourly monitoring in the DVFC locality began in 1990 with tilting-siphon raingauges (model R208, RW Munro Ltd, Woodford Green, UK); these were replaced in 1994 with tipping-bucket raingauges (model 103755D-04, Casella CEL Ltd, Kempston, UK) connected to Newlog dataloggers (Technolog Ltd, Wirksworth, UK) recording the time of every 0.20 mm of rainfall. Raingauge R3 was installed in a large canopy gap and placed on Bornean ironwood (*Eusioderoxylon zwageri*) towers at a height of 6 m to prevent disturbance from wild boar or cover by regenerating vegetation. All tipping-bucket rainfall data were totalled over 5-minute periods. The time-series used within this study extended from 1 July 1995 to 30 June 1996 (Fig. 1), giving approx. 105 408 5-min sampled observations and approx. 8784 observations re-sampled on an hourly basis.

MODELLING METHODS

The stochastic approach that we use to model the hourly rainfall data from raingauge R3 follows the methodology of Stern & Coe (1984), where the maximum likelihood (ML) estimation of smooth transition probabilities of the Markov chain for the occurrence process is obtained using the GLM. We use the GLM function in S-Plus (Insightful, Seattle, USA), with an approach usually applied in medical studies, where at each experimental unit (here meaning "'observation") there is an associated binary response (i.e. 0 or 1) and a vector of covariates. For our application, these covariates are the indicator variables, $Z_{hij}(t)$, for hours through the day, and days through the year. The link function we use is the logit:

$$\hat{p}_{i,j}(t) = h\left(\hat{g}_{i,j}(t)\right)^{-1} = \frac{\exp\left(\hat{g}_{i,j}(t)\right)}{\left[1+\exp\left(\hat{g}_{i,j}(t)\right)\right]} \qquad \text{for } i, j = 0, 1 \tag{1}$$

where $\hat{p}_{i,j}(t)$ is the time-varying Markov chain parameter for probability of rainfall occurrence at time t given its occurrence in last two samples i and j (these terms have values of 0 or 1), and the function $\hat{g}_{ij}(t)$ is modelled as a Fourier series. To demonstrate the improvement in model fit derived by relaxing the stationarity assumption, we fit the second-order transition probabilities as a Fourier series, firstly with the assumption of stationarity:

$$\hat{g}_{i,j}(t) = a_{i,j,0} + \sum_{k=1}^{l_{i,j}} \left[a_{i,j,k} \sin\left(\frac{2\pi h_k}{24}\right) + b_{i,j,k} \cos\left(\frac{2\pi h_k}{24}\right) \right] \tag{2}$$

then as a Fourier series with harmonics (defined by terms $m_{i,j}$ and $l_{i,j}$) varying through the day and across days:

$$\hat{g}_{i,j}(t) = a_{i,j,0} + \sum_{k=1}^{m_{i,j}} \left[a_{i,j,k} \sin\left(\frac{2\pi h_k}{24}\right) + b_{i,j,k} \cos\left(\frac{2\pi h_k}{24}\right) \right] + \sum_{k=1}^{l_{i,j}} \left[a_{i,j,k} \sin\left(\frac{2\pi d_k}{366}\right) + b_{i,j,k} \cos\left(\frac{2\pi d_k}{366}\right) \right] \tag{3}$$

where the index h relates to the indicator variable for the 24 hours through the day, and index d relates to the indicator variable for the 366 days through that year. To apply the GLM function of S-Plus within the binomial family, we construct the response variable as a two-column matrix, with the first column given by the number of successes and the second given by the number of failures for each trial (Venables & Ripley, 1997). To estimate the four, second-order transition probabilities for the hourly data, we used the eight $Z_{hij}(t)$ terms, where h, i, j = 0 or 1. To estimate the probability that it starts to rain at time $t = p_{00}(f)$ we build a response matrix where the first column is given by $Z_{001}(t)$ and the second is given by $Z_{000}(t)$. The observations which have both values of Z equal to 0 are discarded by the function. The covariates are the indicator variables for hours, days, and seasons and can be treated as variables or as factors. The number of harmonics was chosen using the ANOVA analysis presented in Table 1, where all the harmonics included in the stationary model are shown by symbol *, and in the time-varying model by symbols * and +. To check the adequacy of the model, a Monte Carlo testing procedure with 100 realizations is used. The two modelling approaches are then compared by examination of four performance indicators. These are: (a) a visual comparison of the diurnal rainfall pattern and its seasonal evolution; (b) a comparison of the variance over differing periods; (c) a comparison of the number of wet spells observed throughout the day, over 366 days and over 12 months; and (d) a comparison of the length of the wet and dry periods.

RESULTS AND DISCUSSION

The stationary and time-varying second-order transition probabilities for our rainfall data that were derived by GLM techniques are shown in Fig. 2. In order to consider the impact of these on the simulated rainfall characteristics, notably variance, we present the observations in graphical and statistical form (Fig. 3, Table 2).

Observational characteristics

The 5-min rainfall time-series from station R3 re-sampled to hourly occurrence data are presented in Fig. 3. It is clear from observation of the 5-min and hourly occurrence data, that most of the rain falls in the afternoon with relatively little falling at night and in the morning (Figs 1 and 2). This pattern seems to evolve over the year ("seasonality"), with night/morning falls becoming more important in the November–February period. The 6-month period of the Northeast Monsoon within Sabah runs from November to April (Bidin & Chappell, 2003, 2006) and, thereby, includes this period of greater night/morning rainfalls. The dominance of mid-afternoon rainfall in most periods could be the result of localized convective rain-events from cumulus clouds developed by solar heating through the day (Battan, 1979; Riehl, 1979). Similar mid-afternoon peaks are seen at other inland tropical localities in Peninsular Malaysia (Ramage, 1964; Oki & Musiake, 1994; Sorooshian *et al.*, 2002) and the Amazon (Lloyd, 1990). This contrasts with the oceans (and small islands), which show an early morning rainfall peak due to nocturnal cooling or sea-air temperature differences (Sorooshian *et al.*, 2002; Bonell *et al.*, 2004). Coastal regions have diurnal distributions which include elements of either land and ocean phenomena (Chen & Houze, 1997) or a distinctive regime resulting from the effects of land and sea breezes (Ramage, 1964; Sorooshian *et al.*, 2002).

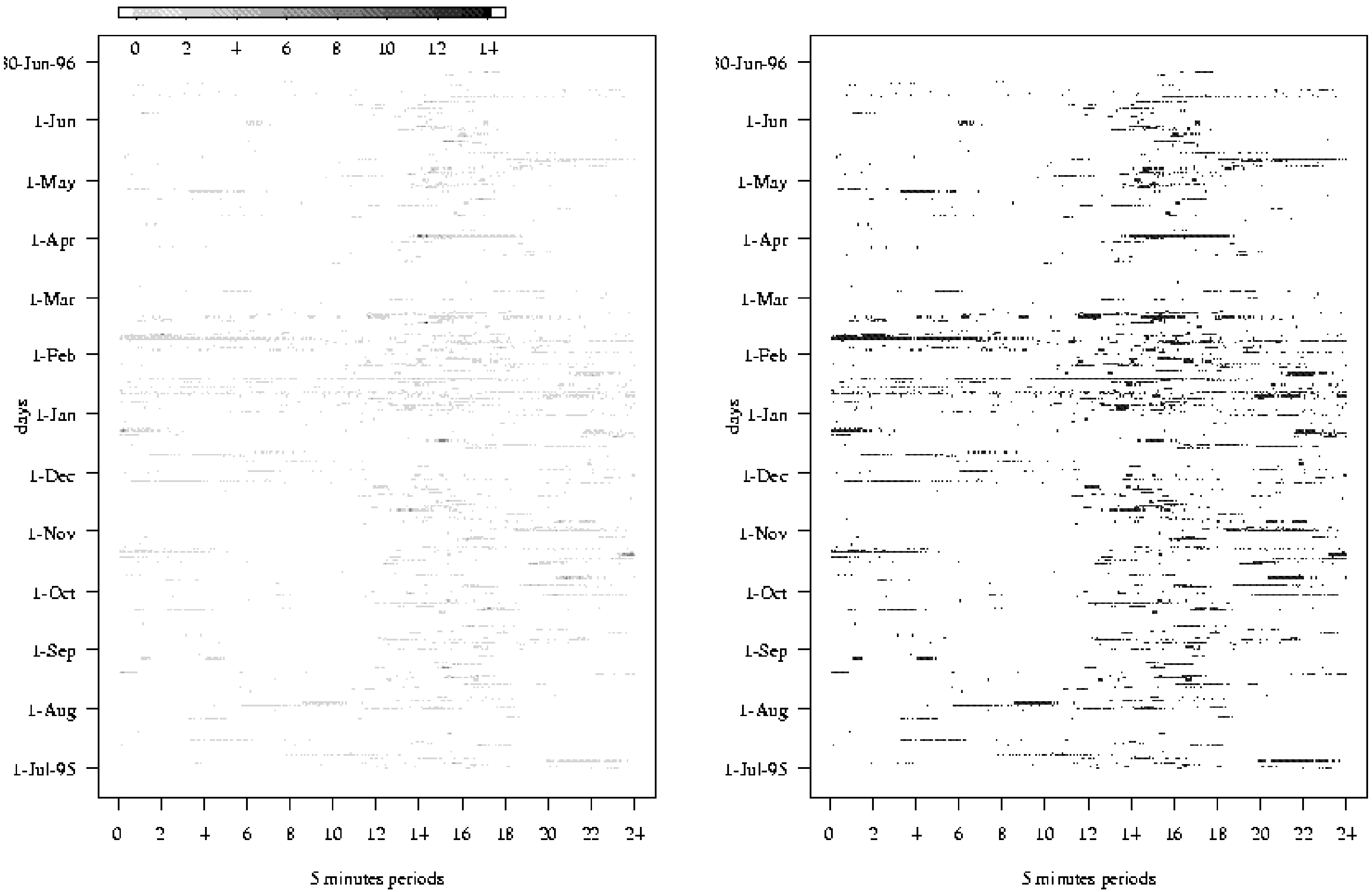

Fig. 1 Seasonal evolution of diurnal rainfall characteristics sampled on a 5-minute basis: (a) rainfall intensity (mm/5-min), and (b) rainfall occurrence (i.e. 1 or 0).

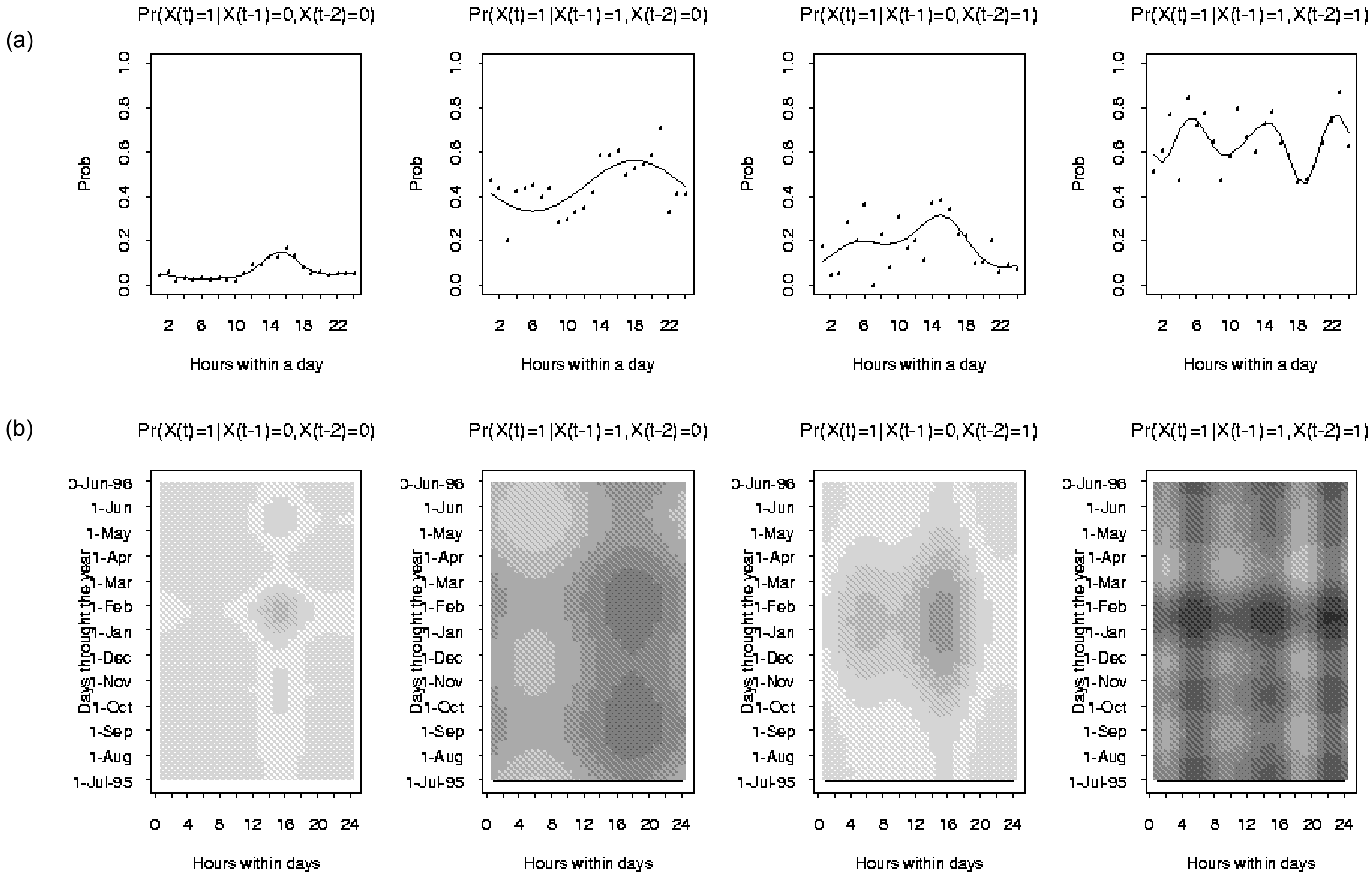

Fig. 2 The second-order transition probabilities for the R3 raingauge data sampled every hour over the period 1–30 June 1996, where (a) shows the stationary transition probabilities, and (b) the time-varying transition probabilities.

Table 1 ANOVA table for the stationary and time-varying models of hourly rainfall occurrence at raingauge R3 within the Baru watershed, Malaysian Borneo.

Harmonics	$p_{00}(t)$		$p_{01}(t)$		$p_{10}(t)$		$p_{11}(t)$	
	Df. resid.	Dev. resid.	Df. resid.	Dev. resid.	Df. resid.	Dev. resid.	Df. resid.	Dev. resid.
Null	7060	3218.099*	522	724.189*	522	501.646*	676	892.767*
1 hour	7058	3105.400*	520	711.309*	520	488.951*	674	889.322*
2 hours	7056	3076.502*	518	710.170	518	484.046*	672	884.208*
3 hours	7054	3072.979	516	706.764	516	482.548	670	867.904*
4 hours	7052	3071.668	514	704.662			668	865.957*
5 hours	7050	3065.794	512	701.257				
1 day	7052	3060.214^{+}	518	707.079^{+}	516	459.904*	666	857.510^{+}
2 days	7050	3051.573^{+}	516	703.884^{+}	514	458.403	664	851.510^{+}
3 days	7048	3016.918^{+}	514	703.569	512	456.924	662	847.037^{+}
4 days	7046	3006.255^{+}					660	843.825^{+}
5 days	7044	3002.012						

* harmonics used to fit stationary transition probabilities; $^{+}$ harmonics used to fit time-varying transition probabilities.
Df.: degrees of freedom; Resid.: residual; Dev.: deviation.

Table 2 Summary statistics of the 5-min, hourly and daily rainfall for raingauge R3 within the Baru watershed, Malaysian Borneo. The period "Summer 95" covers 1 July–26 November 1995, "Winter" – 27 November 1995–10 March 1996, and "Summer 96" – 11 March 1996–30 June 1996.

	Rainfall (mm)	Mean rainfall (mm per period)	SE	Max.	No. of wet spells	% of wet spells	Mean rainfall per wet spell (mm per period)
5-min:							
All	3100.0	0.029	0.263	14.0	4423	4.196	0.701
Summer 95	1289.4	0.030	0.278	9.0	1608	3.747	0.802
Winter	1161.8	0.038	0.270	14.0	20022	6.687	0.575
Summer 96	648.8	0.020	0.235	9.4	793	2.458	0.816
Hourly:							
All	3100.0	0.353	2.149	57.6	1200	13.661	2.583
Summer 95	1289.4	0.361	2.289	47.6	416	11.633	3.100
Winter	1161.8	0.457	2.088	36.0	542	21.305	2.144
Summer 96	648.8	0.244	2.002	57.6	242	9.084	2.681
Daily:							
All	3100.0	8.470	14.829	167.0	279	76.230	11.111
Summer 95	1289.4	8.654	12.472	55.6	112	75.168	11.513
Winter	1161.8	10.960	19.228	167.0	88	83.919	13.202
Summer 96	648.8	5.845	12.428	89.8	79	71.171	8.213

The summary statistics of the 5-minute and re-sampled data (Table 2) show that the statistical distributions are very skewed, with the skew increasing as the integration period reduces. The overall proportion of wet hours is about 13.7%, but there is a marked seasonality in the rainfall occurrence. Notably, the hourly data show that the proportion of the time that is wet in the winter months (strictly 25 November 1995–10 March 1996) is almost double that in the summer, while the mean intensity of rain per wet hour is much less in the winter.

Comparison of model performance indicators

Given the marked diurnal and seasonal cyclicity seen within the graphs and statistics of the hourly rainfall data from this equatorial rainforest site (Fig. 3, Table 2), we now compare those simulated by the Markov chain models using stationary and time-varying transition probabilities. The four performance indicators used are: (a) a visual comparison of the diurnal rainfall pattern and its seasonal evolution; (b) a comparison of the variance over differing periods; (c) a comparison of the

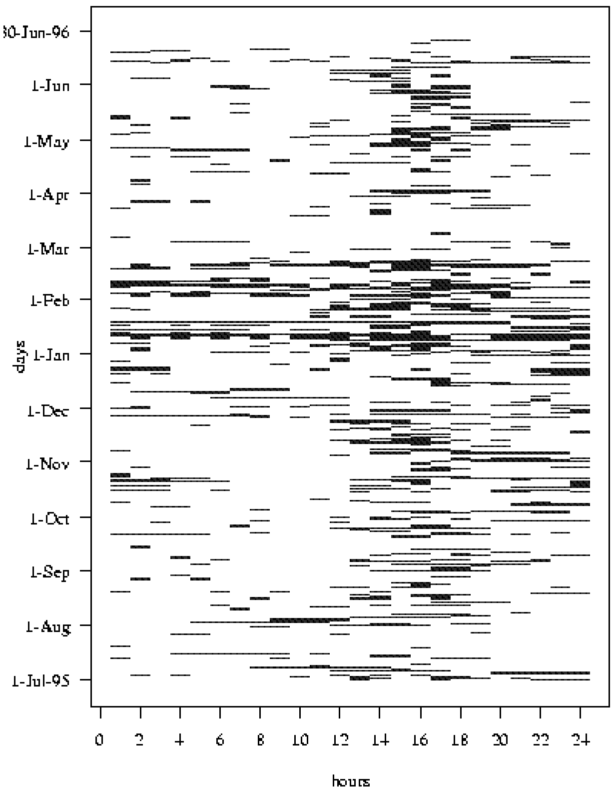

Fig. 3 Seasonal evolution of diurnal rainfall occurrence observed at Site 3 (R3) raingauge, Baru watershed (Malaysian Borneo), re-sampled on an hourly basis.

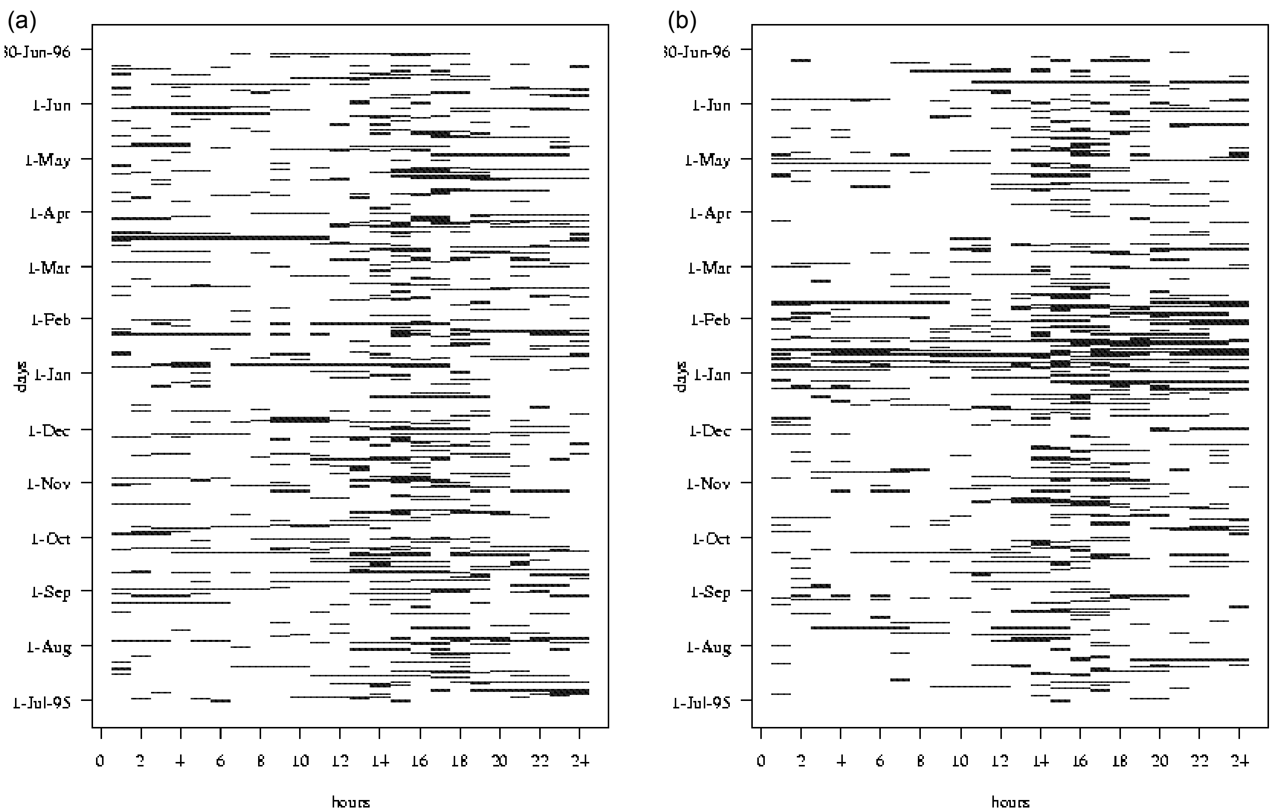

Fig. 4 Seasonal evolution of diurnal rainfall occurrence on an hourly basis simulated using: (a) stationary transition probabilities and (b) time-varying transition probabilities.

Table 3 Observed variance in rainfall from raingauge R3 within the Baru watershed, Malaysian Borneo (for the period: 1 July 1995–30 June 1996) together with variances simulated by GLM Markov chains using stationary and time-varying transition probabilities.

	Hourly	Daily	Monthly
Observed	603.1304	12.5139	3013.273
Stationary	628.1638	9.3374	322.002
Time-varying	612.3512	11.1884	2728.939

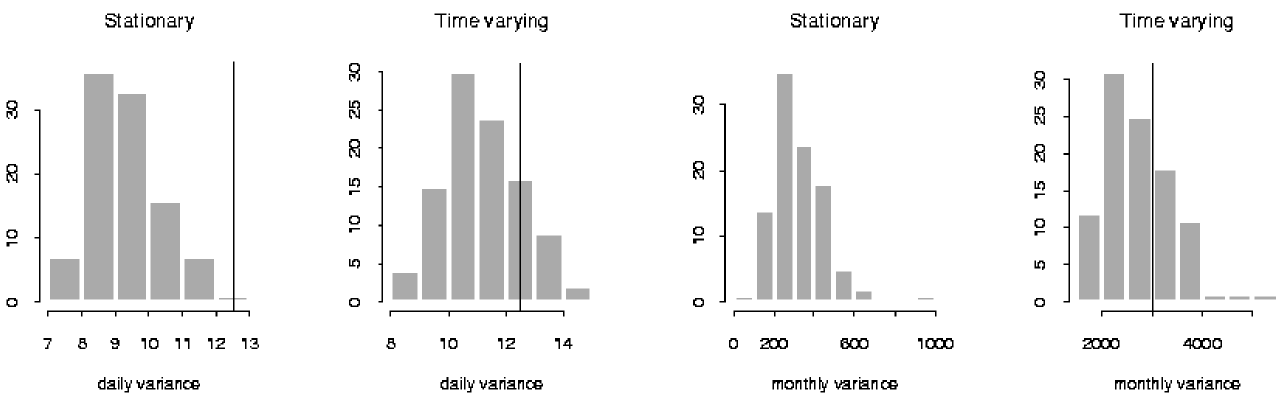

Fig. 5 The statistical distributions of the daily and monthly variance simulated by the models with either stationary or time-varying transition probabilities. The frequency of occurrence is plotted on the y-axis and the solid vertical line shows the variance in the observations.

number of wet spells observed throughout the day, over 366 days and over 12 months; and (d) a comparison of the length of the wet and dry periods.

One hundred realizations of models with either stationary or time-varying transition probabilities were undertaken. Figure 4 shows two representative realizations, one from each model structure. While both models fitted well to the total number of wet hours of 1200, the model with stationary transition probabilities (Fig. 4(a)) is visually very different from the observed patterns (Fig. 3). Notably, the diurnal pattern of rainfall occurrence exhibits little seasonality (Fig. 4(a)). In contrast, the realization incorporating time-varying transition probabilities (Fig. 4(b)) exhibits a seasonal evolution of the diurnal cycle similar to that of the observations (Fig. 3).

Table 3 shows the variance in the hourly observations and simulations when compared on a daily and monthly basis, while Fig. 5 shows the simulated distributions of the daily and monthly variance for the stationary and time-varying models. While the stationary model only slightly

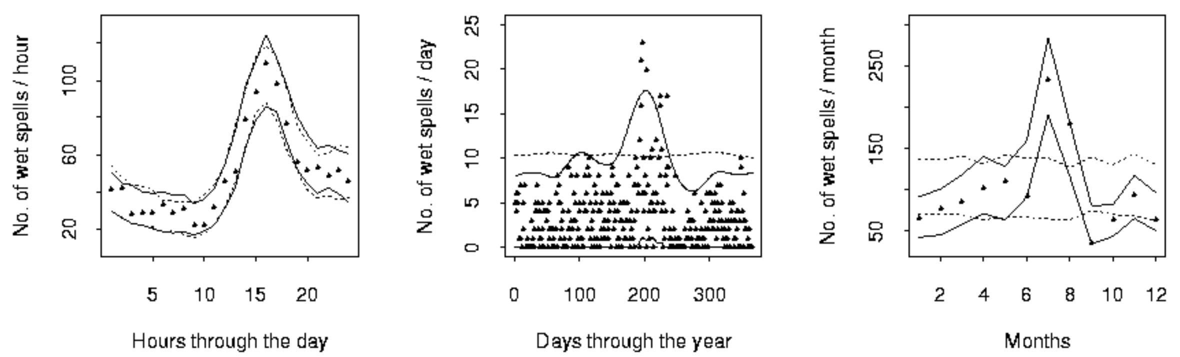

Fig. 6 Number of wet spells observed throughout the day, over 366 days and over 12 months. Observations are shown with asterisks, uncertainty bands for the model with time-varying transition probabilities by a solid line, and with stationary transition probabilities by a broken line. The frequency of occurrence is plotted on the y-axis.

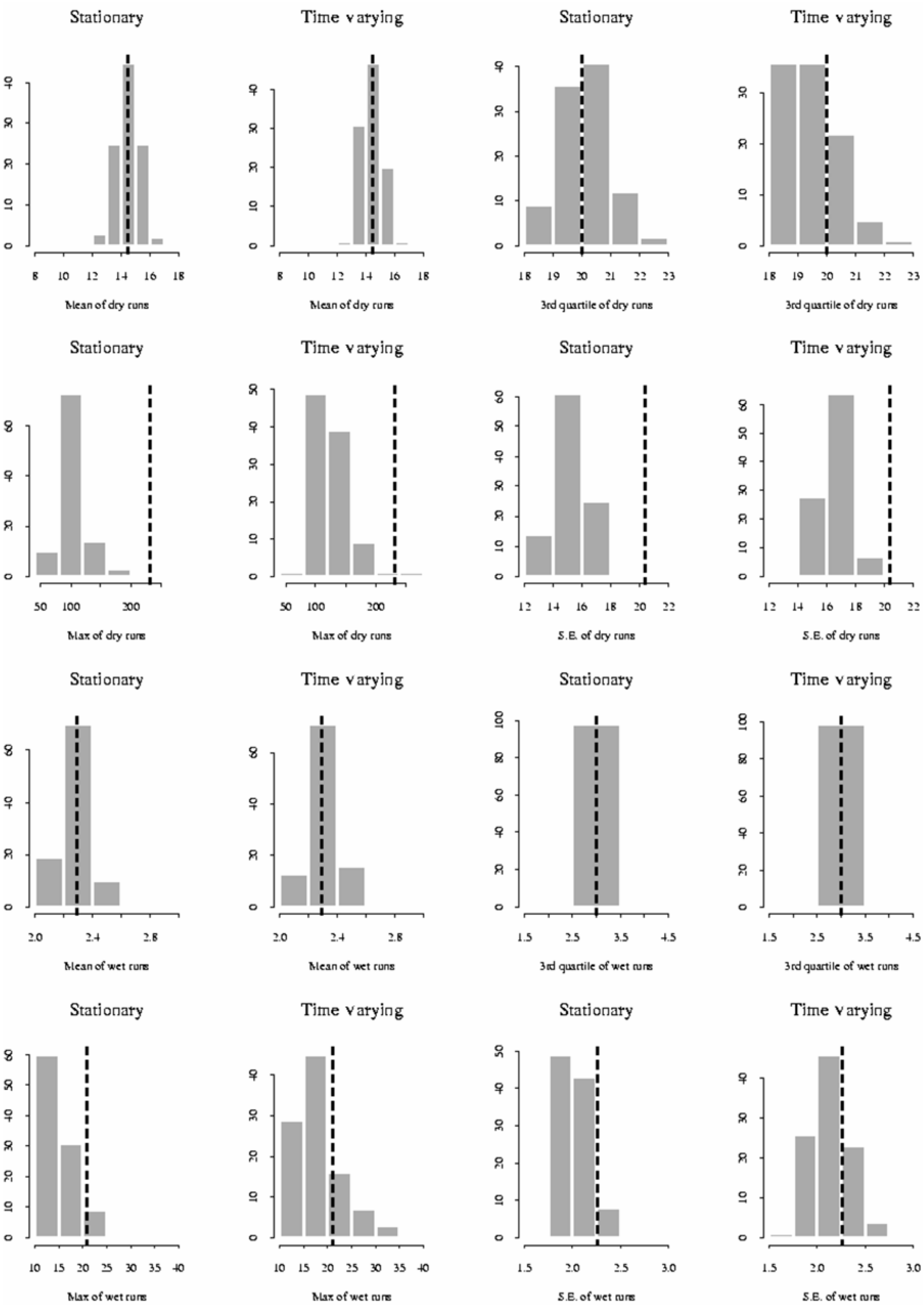

Fig. 7 Stochastic distributions of the statistical properties of the duration of the wet spells and dry spells at raingauge R3, produced by model realizations with stationary transition probabilities and with time-varying transition probabilities.

underestimates the daily variance, it dramatically underestimates the monthly variance (i.e. 322 against an observed 3013).

Figure 6 shows the observed number of wet spells per hour, per day and per month, together with the 95% Monte Carlo envelopes from the 100 realizations of each method. The envelope for the time-varying model is plotted as a solid line, while that for the stationary model is plotted as a broken line. For the simulation of the cycles of wet spells through the day, both models encompass the observations. This is in some contrast to the situation over 366 days and 12 months, where the model with stationary transition probabilities fails to capture any of the seasonal dynamics seen within the observations.

Figure 7 shows the stochastic distributions of the statistical properties of the duration of the wet spells and dry spells produced by model realizations with stationary transition probabilities and time-varying transition probabilities. Both approaches are seen to reproduce the mean and third quartile of the statistical distribution for both wet and dry spells. While both models are seen to underestimate the standard error (SE) and maximum number of dry or wet spells, the model with the stationary transition probabilities shows the greatest underestimation.

CONCLUSIONS

This study has shown that the statistical properties of the diurnal rainfall cycle at an equatorial rainforest site, and the evolution of this cycle over the monsoon seasons can be simulated using hourly data where time-varying transition probabilities are used in Markov chain models. Application of the same approach using stationary transition probabilities produces results that: (a) have seasonal patterns that are visually very different from the observed patterns; (b) dramatically underestimate the monthly variance in rainfall occurrence; (c) produce Monte Carlo envelopes that fail to capture any of the seasonal dynamics seen within the observations; and (d) show greater underestimation of the standard error and maximum number of dry or wet spells. These discrete stochastic models, through their seasonal character, create a conceptual and pragmatic link between finer temporal resolution of the hourly scale and longer time scales, where a continuous approach can be applied, using seasonal stochastic state-space models such as dynamic harmonic regression (DHR, Young *et al.*, 1999; Chappell *et al*., 2001). The relative success of the Markov chain model using time-varying transition probabilities applied to hourly rainfall data, means that we can now use it within our ongoing modelling exercises (Chappell *et al*., 2004b, 2007; Solera-Garcia *et al*., 2006) of land-use change impacts on the hydrology of managed tropical rainforests.

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