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LAND USE IMPACTS ON HYDROLOGIC RESPONSE IN THE MAE CHAEM CATCHMENT, NORTHERN THAILAND

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ABSTRACT

As part of an international project exploring the impact of changing agroforestry mosaics on catchment water yield and quality in Southeast Asia, a study of the hydrological response in the Mae Chaem catchment in Northern Thailand is being carried out. The main interest is being able to predict the flow under significant changes in land use, as well as at ungauged sites. This paper reviews some of the data analysis techniques available, and the results of applying these to data from gauges in the Mae Chaem catchment.

1 INTRODUCTION

Loss of forest cover in developing countries is increasing the risk of erosion, and subsequent degradation of water quality. Managing catchments to maintain an adequate supply of clean water for downstream users is an ongoing issue, particularly in catchments where forest cover in steep terrain is being converted to agricultural land uses. As part of a study of the effect of agroforestry mosaics on watershed functions, an investigation of land use impacts on hydrologic response is being conducted in Indonesia and Thailand. The adopted approach is to use regionalisation of catchment response characteristics such as the runoff coefficient and flow duration curve to define the response characteristics at ungauged sites, with a view of using the derived characteristics for ungauged sites to calibrate or at least constrain the parameters of the IHACRES rainfall-runoff model (Jakeman *et al*. 1990, Jakeman and Hornberger, 1993). This paper discusses the initial findings based on data analysis techniques for the study site in Thailand.

2 STUDY SITE

The Mae Chaem catchment is a ~3740km^2 catchment (area defined by gauge at Ob Luang) in northern Thailand. The elevation within the Mae Chaem catchment ranges from 250 to 2570 m above sea level. The subcatchments are generally steeply sloping with only limited areas suitable for paddy agriculture. Over a 5 year period from 1985 to 1990, the forest cover decreased from approximately 3380 to 2980km^2. The region has a monsoonal climate with almost all the annual rainfall occurring during the wet season which starts in May and extends into October. The location of the catchment, and the rainfall and streamflow gauges (and corresponding catchment areas) are shown in Figure 1.

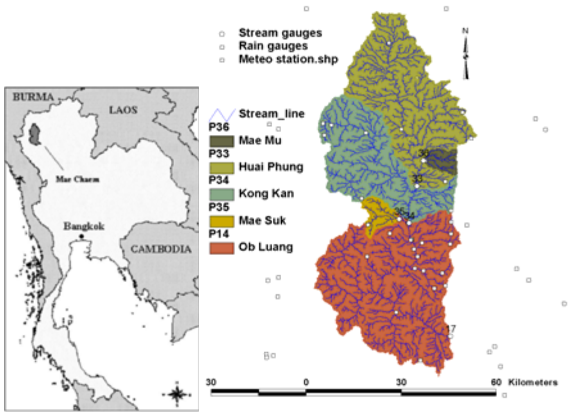

Figure 1: Mae Chaem catchment, with rainfall and stream gauges used (with corresponding sub-catchments).

3 ESTIMATING RAINFALL

Areal rainfall estimates were obtained using a weighted Theissen polygon approach where the rainfall in each polygon is varied spatially based on a long-term mean rainfall surface. The rainfall surface was derived using the ANUSPLIN software (Hutchinson, 1995) which employs thin plate smoothing splines to the recorded annual rainfall for each gauge in the region (extending a considerable distance outside the catchment to minimise edge effects), using the spatial coordinates of the gauges (x, y and z) as the independent variables. The streamflow and areal rainfall estimates for gauge P14 are shown in Figure 2.

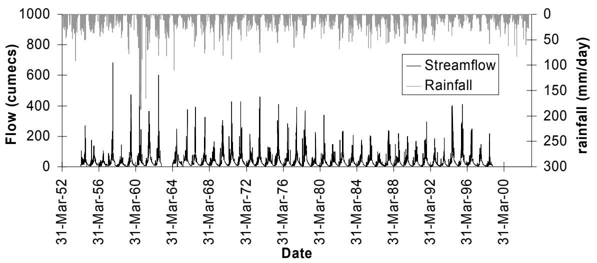

Figure 2: Observed streamflow and estimated areal rainfall for gauge P14.

4 DATA ANALYSIS

Four data analysis tools were used to explore the data quality and some of the response characteristics: cross correlation of streamflow with rainfall; flow and rainfall exceedence curves; analysis of the power spectrum of rainfall and streamflow; and baseflow filtering.

4.1 Cross Correlation Analysis

As with comparing data from different rainfall gauges, a simple technique for checking rainfall and streamflow data is cross correlation analysis. The cross correlation of rainfall and streamflow shows how flow relates to rainfall. Generally, there is a modest peak (~0.4-0.6) in the correlation function for a lag either zero, or a small positive value, with the width of the peak depending on both the width of the rainfall autocorrelation function, and the unit hydrograph response curve. The absence of a clear peak in the rainfall-streamflow cross correlation function indicates a likely variable timing error in either the rainfall or streamflow timeseries (or both).

With well behaved datasets (long record of evenly sampled data values with no missing values), the Fourier transform can be used to derive the cross correlation function for any 2 timeseries. Due to the presence of a significant number of missing values, an alternative method had to be employed. For each lag value, the set of all points with valid data in both datasets was obtained, normalised to have a mean of zero and a standard deviation of one, and the correlation coefficient determined. This is less computationally efficient than using the Fourier transform, but makes the maximum use of the available data. An example of the cross correlation function is shown in Figure 3 (gauge 14). The top panel shows the effect of the seasonality of rainfall on the rainfall autocorrelation function, and evidence for a 20 day lag in the "seasonal" correlation peak, and a 50 day lag in the minimum value, demonstrating the buffering effect of the baseflow.

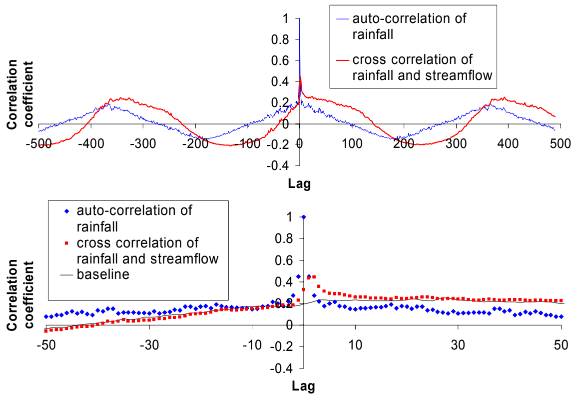

Figure 3: Cross correlation analysis for gauge 14 (Ob Luang). Top panel shows the seasonal delay in streamflow response compared to the rainfall signal (delay in correlation function compared with autocorrelation of rainfall). The bottom panel shows the correlation between daily rainfall and streamflow, with the peak in streamflow delayed by 1 to 2 days. The baseline curve is the correlation function shifted by 365 days (i.e. the correlation between this years streamflow and last years rainfall) and represents the influence of the seasonal variation in rainfall.

Gauges P14, P33 and P34 show a strong peak (0.4 to 0.5)at a one timestep lag, while gauges P35 and P36 show only a broad correlation peak (with subsequent reduction in peak height to less than 0.3). Since these gauges have relatively small catchment areas, this indicates a potential timing error in the data for these catchments. The timing error will result in difficulties in calibrating the rainfall-runoff model for these catchments (note the poorer fit compared to gauges P33 and P34 in the baseflow filtering section).

While use of the Fourier transform requires continuous datasets, this restriction can be overcome by using the correlation functions. The Fourier transform of the cross correlation of two functions **x** and **y** can be written as $\mathbf{XY}^*$ where **X** and **Y** are the Fourier transforms of **x** and **y** respectively, and $\mathbf{Y}^*$ is the complex conjugate of **Y**. Thus, if **x** is given by the convolution of **y** with **z** (in this case, the unit hydrograph), then the Fourier transform of **z** can be estimated from the cross correlation of **x** with **y** and the autocorrelation of **y**:

$$\mathbf{Z} = \mathbf{X}/\mathbf{Y} = \left(\mathbf{X}\mathbf{Y}^*\right)/\left(\mathbf{Y}\mathbf{Y}^*\right) \qquad (1)$$

This will only be approximate as the autocorrelation of the observed rainfall is used for **y** rather than the autocorrelation of effective rainfall, and the unit hydrograph is assumed to be constant in time. The use of rainfall rather than effective rainfall is not likely to be a significant influence on the hydrograph peak, as this will mainly affect the seasonal pattern (less rainfall becoming streamflow at the start of the wet season compared with the remainder of the wet season due to the variation in soil moisture). The assumption that the unit hydrograph is constant in time is potentially the greatest constraint on the information that can be derived from Fourier deconvolution, though the noise introduced by such variations does not greatly affect the peak of the unit hydrograph profile (as seen in Figure 4). The subsequent profile is an estimate of an average UH response curve.

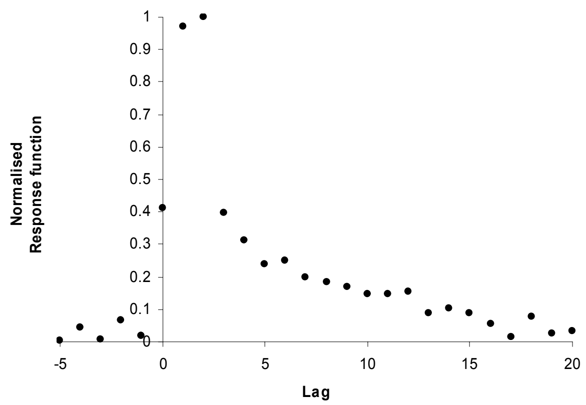

Figure 4: Unit hydrograph for P14 (normalised to have a peak of 1) derived using Fourier deconvolution of the auto- and cross correlation functions shown in Figure 3.

Using the Fourier deconvolution technique described above, the peak of the unit hydrograph for gauge P14 (Figure 4) has a delay of between 1 and 2 days, and a full width at half maximum (FWHM) of a little less than 3 days. The values for negative lags (streamflow leading rainfall) show the noise level within the deconvolved profile as these values should be zero. Thus the profile peak has a signal to noise of approximately 15, with the S/N decreasing to 2 at a lag of about 10 days.

Analysis of the temporal variation in the unit hydrograph was unable to identify a significant correlation with land use change due to the noise in the rainfall and streamflow data. In particular, relative timing errors between rainfall and streamflow, particularly gauges P35 and P36 (where the delay in the flow peak varied from between 0 and 3 days), were the principle source of noise in the estimated unit hydrographs. Given this difficulty, there was some evidence for a decline in the width of the hydrograph peak for gauge 36 between the late 1980's and mid 1990's, though this is well within the scatter in the annual widths. For gauge P14 (station with the longest record of observed flow, and the gauge with the largest catchment area), there is no evidence of a change in width, though this does not imply there was no actual variation present.

4.2 Flow and rainfall exceedence curves

Flow and rainfall exceedence curves (Figure 5) are a useful means of representing the probability distributions of flow and rainfall (note, flow exceedence curves are sometimes called flow duration curves). When plotted on a log-normal plot (see Figure 6) the flow exceedence curve typically shows a nearly linear relationship, with the probability distribution being almost symmetrical about the 0.5 probability point. In comparison, the rainfall exceedence curve extends to just over 50% (that is, there is no rainfall on just under 50% of the days). The difference between the curves for flow and rainfall is due mainly to the influence of the smoothing out of the effective rainfall by the unit hydrograph response curve. A secondary factor in determining the shape of the flow exceedence curve is the redistribution of rainfall into effective rainfall (affected by variations in soil moisture).

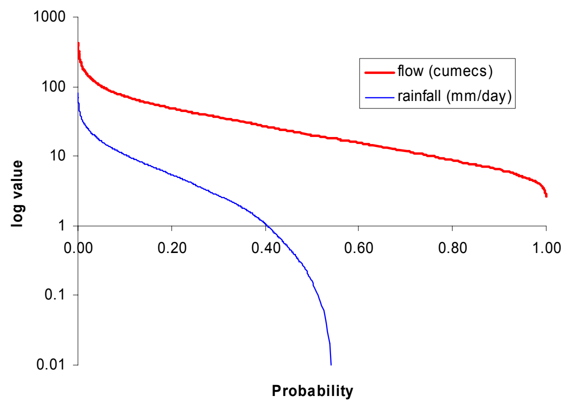

Figure 5: Rainfall and flow exceedence curves for gauge P14 plotted against probability.

Comparing a time series of the ratio of the rainfall and streamflow exceedence curves gives an indication of the variation of the influence of the unit hydrograph coupled with the conversion of rainfall to effective rainfall. While variation was detected, no correlation with the change in forest cover post 1985 was detectable. This suggests that the variation is either climate driven, or due to errors in the data. Rainfall and flow exceedence curves yield little information from a data analysis viewpoint, but can be very useful in calibration and testing of rainfall-runoff models.

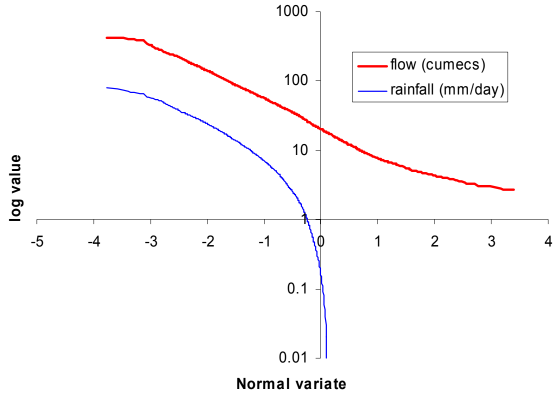

Figure 6: Rainfall and flow exceedence curves for gauge P14 plotted against the normal variate.

4.3 Power Spectrum Analysis

Another use of the Fourier transform in investigating the properties of a timeseries is the estimation of the power spectrum or power spectral density (PSD). There are techniques for calculating the PSD for data with variable sampling rate (e.g. Lomb, 1976; Scargle, 1982), though these have not been used here. Rather, a subset of data that does not have gaps has been used for each catchment. The power spectrum for areal rainfall and streamflow for gauge P14 are shown in Figure 7. A least squares linear regression gives slopes in log-log plots of –0.74 and –1.01 for the rainfall and streamflow power spectra, respectively. However, weighted regressions should be used to reduce the weight given to high frequency components due to the distribution of data values. This would result in a slightly lower slope for the streamflow power spectrum. The difference in the slopes in the rainfall and streamflow power spectra is due primarily to the influence of the unit hydrograph, particularly the baseflow component, though the redistribution of rainfall into effective rainfall can also contribute. The influence of the unit hydrograph on the power spectrum will be strongest at high frequencies (of the order of 1 day^{-1}) and minimal at low frequencies (of the order of 1 year $^{-1}$).

The power spectrum of a function x (normalised by the mean square amplitude) can be derived from its Fourier transform X:

$$
\begin{aligned}
P(0) &= \frac{1}{N^2}\left|X_0\right|^2 \\
P(f_k) &= \frac{1}{N^2}\left(\left|X_k\right|^2 + \left|X_{N-k}\right|^2\right) \qquad k = 1,2,\ldots,\left(\frac{N}{2}-1\right) \\
P(f_{N/2}) &= \frac{1}{N^2}\left|X_{N/2}\right|^2
\end{aligned}
\tag{2}
$$

where the frequency f_k is given by:

$$
f_k = 2 f_{N/2}\frac{k}{N} \tag{3}
$$

To reduce the noise in each frequency bin, the data was divided into 11 equal segments (with 50% overlap) of 2048 timesteps, and the resulting power spectrum averaged. To minimise leakage between frequencies (signal from one frequency bin appearing in a nearby frequency bin due to aliasing of the signal) a Bartlett window function was used (triangular window function that drops to zero at the ends of each segment).

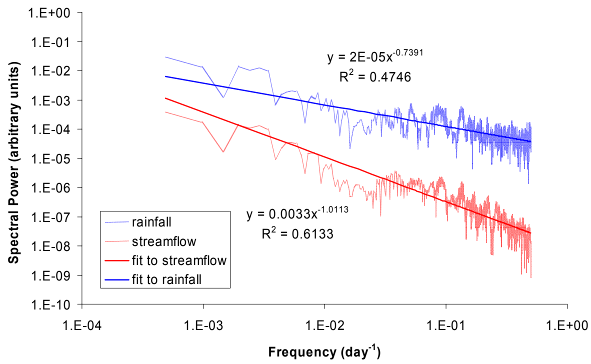

Figure 7: This plot shows the power spectra for rainfall and streamflow, along with the fitted power law in each case.

A common use of power spectrum analysis is investigating the multifractal nature of a time series (e.g. Pandey *et al.* (1998), particularly from the viewpoint of scaling, with a scaling field having a power-law dependency between the power spectrum and the frequency. While the power spectra found here do show a power law behaviour, the multifractal analysis has not been performed.

4.4 Baseflow Filtering

Estimation of the baseflow component of observed streamflow is instrumental in determining the influence of water use on the environment. There are several methods for estimating the baseflow component. The simplest are mathematical filters that do not attempt to represent the processes taking place. These include the Lyne-Hollick filter (Lyne and Hollick, 1979), and the Baseflow Index (BFI – Gustard et al. 1992). The lack of physical basis for the Lyne-Hollick filter requires the user to determine when the derived baseflow looks “right” and does not inform the user, but confirms his/her preconceived notion regarding the form of the baseflow. The BFI approach simply attempts to give a lower envelope for the observed flow, which can then be assumed to correspond to the baseflow. An alternative to the BFI is the running minimum filter (Croke et al. 2001) which uses a running minimum filter of variable width (typically 5 days is used) followed by a running average filter with the same width.

A more sophisticated approach uses an assumed functional form for the baseflow recession – typically an exponential decay. Examples of such forms can be found in Chapman (1999). The simplest form is the filter proposed by Chapman and Maxwell (1996) which has one parameter. The other filters discussed by Chapman (1999) were the two-parameter Boughton filter (derived from the AWBM model of Boughton (1993)) and the three-parameter IHACRES filter (derived from the IHACRES model of Jakeman et al. 1990 and Jakeman and Hornberger, 1993). Recently, Furey and Gupta (2001) proposed a new filter based on their groundwater discharge model (Furey and Gupta, 2000).

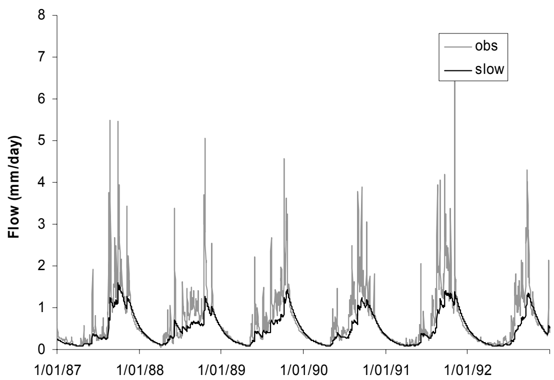

Figure 8: Estimated baseflow for gauge P14

Table 1: Baseflow filter parameters for all gauges, with effective rainfall constrained to be less than the observed rainfall.

gauge	R^2	Bias	X1	U1	ARPE	V_s	T_q	T_s
P14	0.67	6.7	0.16	-0.13	0.22	0.82	2.3	43
P33	0.90	1.4	0.10	-0.08	0.03	0.666	1.24	65
P34	0.96	0.5	0.08	-0.07	0.01	0.730	1.55	63.4
P35	0.78	-1.3	0.02	-0.07	0.11	0.909	1.9	92
P36	0.74	0.5	0.03	-0.02	0.11	0.825	1.13	95

In this study, the IHACRES filter (Chapman, 1999) was used, with the effective rainfall constrained to being less than the areal rainfall estimate for that day (Croke et al, 2002). In this filter, the values for three parameters need to be determined. Since the effective rainfall is generated by the filter, after an initial guess at the quick flow and slow flow recession rates, the values for these parameters were refined using the simple refined instrumental variable (SRIV) technique (Jakeman and Hornberger, 1993) used in the IHACRES rainfall runoff model. The filter was then run using the refined values, and the procedure iterated until the combined change in the quick and slow flow decay rates was less than 0.001. The remaining parameter (the slow flow volume) was adjusted in each pass through the baseflow filter to set the fraction of timesteps for which the baseflow flow filter exceeded the observed flow at a nominated value (typically 1% is used).

Table 2: Baseflow filter parameters for all gauges, with effective rainfall set to zero if there has been no increase in the observed daily mean flow.

gauge	R^2	Bias	X1	U1	ARPE	V_s	T_q	T_s
P14	0.93	2.7	0.14	-0.10	0.01	0.733	2.48	53
P33	0.90	1.4	0.10	-0.08	0.03	0.666	1.24	65
P34	0.89	2.4	0.15	-0.11	0.03	0.783	2.28	57
P35	0.78	-2.1	-0.01	-0.07	0.08	0.903	2.2	105
P36	0.70	3.4	0.16	-0.09	0.06	0.831	2.1	101

The R^2 value is the model efficiency defined by Nash and Sutcliffe (1970). The X1 and U1 indicators are the one timestep lag correlation coefficients between model error and modelled streamflow (X1) and modelled effective rainfall (U1) and indicate potential errors in the model structure if the absolute values are significantly larger than 0 (a value of 0.2 would indicate a significant correlation between the model estimates and the model errors). The ARPE (Arithmetic Relative Parameter Error, Jakeman *et al.* 1990) is an indicator of the relative error in the parameters of the linear module, and should typically be significantly less than 0.1. These indicators show that there is a significant error when rainfall is used to constrain the effective rainfall for gauges P14, P35 and P36. The indicators generally improve for these gauges when streamflow is used to constrain the effective rainfall, though this is most noticeable for gauge P14.

This approach was also applied to 4 year periods from 1/1/1966 to 31/12/1998. While the estimates for the values of the v_s parameter showed evidence for an increase in baseflow component since 1966, this is correlated with a decrease in the values of the τ_s parameter, and may be due to the influence of correlation between the parameters rather than an actual variation in the baseflow component. There was little variation found post 1985.

5 CONCLUSIONS

Climate variability and the uncertainties in the data and the derived quantities make it difficult to identify effects of land use change on the hydrologic response of the Mae Chaem catchment. Additionally, the effect of water extractions through the catchment will mask any natural signal that may be present.

The cross correlation analysis has shown there are considerable timing errors within the available data, particularly for gauges P35 and P36. This limits the information that can be extracted from any analysis tool (including rainfall-runoff models) unless a technique to remove the timing error can be developed. Given this difficulty, there is some evidence for a decline in the width of the hydrograph peak for gauge P36 between the late 1980's and the mid 1990's. However, the change in width is this well within the scatter in the annual widths. At gauge P14, there is no evidence of a change in the width, though this does not imply there was no variation.

Baseflow filtering can avoid the timing error issue, and can thus potentially yield information on the dynamics of the catchment response. Using daily data, no information is available on the quick flow time constant except for large catchments where the time constant is considerably greater than a day. However, the slow flow volume and time constant can be estimated. For the gauged sites in the Mae Chaem catchment, the smaller gauges sites (P35 and P36) tend to have higher baseflow volumes, and longer time constants that the gauges on the Mae Chaem River (P14, P33 and P34). Assuming this difference is not driven by the influence of extractions, this may indicate an influence from natural drivers (e.g. vegetation, soils, geology).

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