Environmental Foresight and Models: A Manifesto
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CHAPTER 14

Structural Effects of Landscape and Land Use on Streamflow Response

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14.1 INTRODUCTION

At present there are no credible models to predict the effect on hydrological response of land-use change in gauged catchments or of climate change in ungauged catchments. It seems to be increasingly accepted within the hydrological community that instead of developing complex process representations of hydrological response, more effort should be directed towards measurements of hydrological phenomena and landscape attributes that drive such phenomena (Goodrich and Woolhiser, 1991; Vertessy et al., 1993; and Chapter 12). Such efforts are required to further understanding of the mechanisms and controls of hydrological processes, and to provide estimates of water fluxes within the landscape that are frequently required to assess impacts of different management practices.

Improving understanding is an issue having more of a scientific nature, of course, and it can be pursued at a relatively small scale in experimental sites specifically established for research purposes. But even in extensively instrumented research sites hydrological systems present appreciable difficulties for modellers; in the wakes of Chapters 8 and 12, this will come as no surprise. These difficulties arise from the sheer complexity of internal system behaviour involving dynamic and multi-dimensional interactions that are physical, and possibly chemical and biological in character. In addition, such interactions vary spatially due to heterogeneity of the media where they occur and – of crucial significance for this monograph – often also temporally, reflecting changing dominant controls of the system (Jakeman et al., 1994), as we have already seen in Chapter 5. Compounding this complexity is our incapacity to measure internal system states as comprehensively and accurately as we would like and – again, as we have now seen from the arguments of the preceding chapter – to control the inputs in order to excite the system in a deliberate manner for the purposes of enhanced learning.

Providing estimates of water fluxes in the landscape is a more practical matter. Key scientific advances required for such problems include the capacity to predict hydrological fluxes in ungauged catchments and in response to land-use changes. In these cases, where the scale involved is usually much larger, the need for a sufficient amount of observations becomes even more critical. Remotely sensed data can provide some assistance here. It is foreseeable that acquisition of spatially distributed data will become easier and more affordable with constantly improving sensing techniques. However, remotely sensed data tend to represent only indirect measurements of the phenomena of interest, and thus sufficiently long records of on-site measurements of hydrological fluxes will continue to be needed. In short, currently, and in the near future, hydrologists are often faced with questions that need to be answered with only restricted amounts of data available.

When only limited data are at hand it is of paramount importance to deal with uncertainties inherent in the modelling results. To do this in an objective, statistically rigorous manner we argue in this chapter that the model applied to simulate the hydrological system should preferably be of a relatively simple structure. Statistical techniques may then be applied to determine whether the model has captured the dynamics of the system sufficiently well. In many disciplines, such as industrial control and economics, it is the norm for models to be statistically justifiable. In hydrology, largely due to the problems mentioned above, this kind of approach has gained only restricted advocacy.

A goal of hydrological modelling should be to capture, or to quantify, as parsimoniously as possible, the hydrological response of a catchment. Hydrological response is understood here as the manner in which a catchment reacts, in terms of streamflow volume and dynamics, to a specified climatic forcing. Thus it is a climate-independent or standardised property, and is a function of landscape and land-use characteristics. However, substantial climate dependency exists in the actual relationships between the factors driving the system (precipitation, evapotranspiration) and the output of the system (streamflow). This is due to two factors. Firstly, water storage within the catchment induces memory in the system, so that soil moisture conditions antecedent to a precipitation event have a significant effect on the resulting streamflow magnitudes. Secondly, there is a long-term effect of climate on catchment biota structure and function, the state of which will affect storage and dynamic response characteristics of the catchment (Eagleson, 1978). Such a long-term effect is not considered here.

Removing the climate signal from observed hydrological data enhances the likelihood of revealing relationships between the hydrological response of a catchment and its terrain and land-use properties. Herein, we adopt this strategy to separate out the different factors influencing the hydrological behaviour of a catchment. As a result we are able to explore in two case studies how catchment-scale runoff processes relate to (a) different terrain properties between catchments belonging to the same region and (b) land-use changes occurring through time in the same catchment.

Our approach differs from the more standard procedures in hydrological modelling, where all the anticipated controls are included in complex models *a priori*, and parameters subsequently estimated. Here, the emphasis is on identification of separate controls on hydrological response: climate, landscape, and land use. The knowledge gained at the identification step can then lead to more model complexity, if significant controls worth quantifying are detected. This is consistent with the "data and theory to model" approach in Jakeman et al. (1994). It is an alternative approach to modelling environmental systems – to begin with simple assumptions, and build up the level of model detail by testing additions and refinements to the structure and prior assumptions, by recourse to evaluation of their consistency with system observations and theory. In a sense, looking back over Chapters 11, 12, and 13, one can see a migration from the use of somewhat higher-order models (HOMs) to relatively low-order models (LOMs) in this chapter – and we shall indeed return to the role of HOMs in Chapter 17. Here, we demonstrate how to use our approach (with LOMs) in order to address problems encountered in catchment hydrology, but the lessons clearly have wider applicability, as illustrated for instance by Dietrich et al. (1989), Young and Lees (1992), and Young (1993). The interplay between the two approaches, of the "large" and the "small", has already been at the focus of the preceding chapter; and we shall echo elements of that discussion, of finding the dominant modes of a system's behaviour, in what we have to say in this chapter. Two case studies will be used. The first shows how parameterisation of the rainfall–runoff relationship can be made a function of the catchment's landscape attributes. The second considers how construction of farm dams has altered the structure of a catchment's hydrological behaviour. Irrespective of the means of incorporating additional process mechanisms, the objective is to create a model which could be applied to conditions where no observed data are available, that is, to be capable of extrapolating process behaviours into the future, or predicting responses for areas where no sufficient amount of measurements exist (the remarks of Chapter 8 notwithstanding).

14.2 THE MODEL AND SOME PRELIMINARIES

The first of our two case studies is taken from the Coweeta Hydrologic Laboratory located in the Nantahala Mountain Range of North Carolina, in the south-eastern United States. The 2185 ha laboratory consists of two adjacent basins, of which Coweeta Basin (1626 ha) has been the primary site for hydrological experimentation. Since the establishment of Coweeta in the early 1930s, 32 weirs have been installed to monitor stream flows. Currently 17 catchments, with areas ranging from 9 to 61 ha, are gauged for streamflow (Post et al., 1998). Average annual precipitation, ranging from 1870 mm at low elevations to 2500 mm at higher elevations, is relatively evenly spread, having a slight maximum in March, and minimum in October. Less than 2%

of the total precipitation falls as snow (Post et al., 1998). Deciduous oak species dominate canopy vegetation, with an abundant evergreen undergrowth consisting of rhododendron and mountain laurel. A comprehensive description of the Coweeta Hydrologic Laboratory is given in Swank and Crossley (1988).

The Yass catchment (388 km^2) in the Murrumbidgee Basin, New South Wales, Australia, forms our second case study. The predominant land use is grazing, but there are also some areas of cropping. Average annual rainfall (633 mm) has a slight summer maximum and a winter minimum. Most of the runoff (mean annual 220 mm) occurs in the winter and autumn months from June to November.

14.2.1 Model

The IHACRES rainfall-runoff model is used as the basis for our analyses. Its development derives from the idea of selecting the model to encapsulate the response characteristics of a catchment with a complexity matching the information content of the available data. Additional model complications are only incorporated if they both result in a more accurate reproduction of the observations and do not cause the parameter covariation to become intolerably large (Jakeman et al., 1994).

The model consists of two modules. The nonlinear rainfall loss module converts rainfall to rainfall excess or effective rainfall, which is defined to be the share of rainfall that eventually becomes streamflow. The linear module represents the transformation of rainfall excess to streamflow. The nonlinear modules used in the two case studies to be presented in this paper differ in structure. In the first case study, which discusses relationships between the hydrological response of a catchment and its terrain properties, the nonlinear module has the form as described in Jakeman and Hornberger (1993). The effective rainfall at time step k, u_k, is computed from

$$u_k = s_k r_k \tag{14.1}$$

where r_k is rainfall, and s_k is a catchment wetness index at time step k. The index s_k is calculated by a weighting of the rainfall time series, the weights decaying exponentially backward in time, namely

$$s_k = (1/c)r_k + (1 - \tau_w^{-1})s_{k-1} \tag{14.2}$$

The parameter τ_w is approximately the time constant, or inversely, the rate at which the catchment wetness declines in the absence of rainfall. The parameter $1/c$ represents the increase in storage index per unit rainfall in the absence of evapotranspiration. It is not really a free parameter, but is chosen so that the volume of effective rainfall is equal to the total streamflow volume over the calibration period. To account for seasonal fluctuations in evapotranspiration, the following simple function of temperature (T_k, at time step k) is used

$$\tau_w(T_k) = \tau_w \exp[(20 - T_k)f] \tag{14.3}$$

where f is a temperature modulation parameter on the rate of evapotranspiration.

In the second case study, where effects of land use on the catchment response are investigated, the model has a nonlinear module structure as described in Evans and Jakeman (1998). The basic difference is that this module is capable of delivering, in addition, an estimate of catchment evapotranspiration; it is basically a store that is recharged by precipitation P and depleted by evapotranspiration E and effective rainfall U. However, the state of the store is not expressed as a water level but as a catchment moisture deficit CMD. The catchment moisture store accounting scheme is given at time step k by

$$CMD_k = CMD_{k-1} - P_k + E_k + U_k \tag{14.4}$$

Evapotranspiration, E_k at time step k, is characterised here as a function of potential evaporation (or temperature T_k, as a surrogate for potential evapotranspiration, PET_k) and catchment moisture deficit. Effective rainfall is assumed to be dependent on catchment moisture deficit only. The parameterisations for evapotranspiration and effective rainfall are defined as

$$E_k = c_1 \, T_k \exp(-c_2 CMD_k) \tag{14.5}$$

$$U_k = -(c_3/c_4)CMD_k + c_3, \text{ for } CMD_k < c_4; \;\; U_k = 0, \text{ for } CMD_k \geq c_4 \tag{14.6}$$

$U_k = c_3 - CMD_k$, for $CMD_k < 0$; where c_1, c_2, c_3, and c_4 are model parameters. Interested readers are referred to Kokkonen and Jakeman (2001) for further discussion of different IHACRES nonlinear modules.

The linear module of IHACRES allows for a flexible configuration of linear stores connected in parallel and/or series. Use of statistical identification procedures suggests that the most appropriate form for the Coweeta basin catchments is two stores in parallel (Jakeman and Hornberger, 1993). For the Yass catchment, due to its ephemeral nature, only one store can be identified. When the linear module has two parallel stores it is fully described by three parameters, which are:

τ_q (days), the time constant governing the rate of recession in the quicker of the two parallel stores;

τ_s (days), the time constant governing the rate of recession in the slower of the two stores;

v_q (dimensionless), the partitioning coefficient between the two stores, i.e., the proportion of quickflow to total flow.

Only one parameter, a time constant, is required to describe the linear module in the case of a single store model structure.

The equations underlying the linear module, and its link to a transfer function model, can be found in Jakeman et al. (1990) and Jakeman and Hornberger (1993).

14.2.2 Assessment Criteria

On this occasion the deviations of observed flow from modelled flow are assessed by using two statistics. These were efficiency (F), defined as

$$F = 1 - (\sigma_e^2 / \sigma_q^2) \tag{14.7}$$

where σ_e^2 is the variance of the residual errors $e_k = q_k - \hat{q}_k$ between the observed (q_k) and modelled ($\hat{q}_k$) streamflow and σ_q^2 is the variance of the observed discharge, and the relative water balance error ($RWBE$), given as

$$RWBE = 100[(\sum \hat{q}_k - \sum q_k) / \sum q_k]\% \tag{14.8}$$

14.2.3 Removing Climate Dependency

When investigating the nature of the controls exerted by landscape and land use on the hydrological response of a catchment, it is desirable to filter out first the influence of other effects, such as climate variability, since this may obscure the sought-for relationships. Gan and Burges (1990) reported that there may be considerable climate dependency in rainfall-runoff model parameters, indicating that the model has not been capable of removing climatic effects appropriately. In an attempt to find out how well our model performs in terms of eliminating climatic dependencies from further analysis, the model was calibrated to the same catchment using data from two climatically very different periods. The catchment selected for this exercise is Coweeeta 36, one of the experimental catchments at the Coweeta Hydrologic Laboratory. The first period of time is from 4 October, 1947, to 17 October, 1950, and is a wet period having an average rainfall of 7.2 mm/d, well above the average of the entire record (6.0 mm/d). It also includes the largest value for daily runoff in the entire record, 115 mm. The second period is relatively dry, this being from 20 September, 1984, to 1 November, 1987. Average rainfall is 4.6 mm/d, while the largest daily runoff in this period is half that of the first period, 57.5 mm.

The most obvious and simplest way of assessing whether the different climatic sequences in the two periods affect calibration results is to examine how well the parameters calibrated on one of the periods are capable of reproducing the runoff time series for the other. Statistics of fit for all four combinations are listed in Table 14.1. In terms of efficiencies model performance is affected little when the parameters calibrated on one period are transferred to the other. When dry-period parameters are used for predicting runoff for the wet period, an efficiency of 0.84 is achieved, which is only marginally inferior to the efficiency yielded by the calibration on the wet period (0.86). The same is true when dry-period runoff is predicted with wet-period parameters. In this case the efficiency drops to 0.76 when compared with the value of 0.78 obtained in calibration. The absolute value of the relative water balance error increases to 2.68% from 1.76% when wet-period parameters are applied to the dry period instead of using the parameters calibrated on the dry

Table 14.1

Fit statistics for calibrations and simulations on two climatologically different periods.

Prediction period	Parameters calibrated on the dry period		Parameters calibrated on the wet period	
	F	*RWBE* (%)	*F*	*RWBE* (%)
Dry	0.78	1.76	0.76	–2.68
Wet	0.84	7.6	0.86	–0.22

Table 14.2

Linear module parameter 95% confidence intervals for two climatologically different periods

	τ_q	τ_s	v_q
Dry	1.50–1.82	35.78–48.09	31.76–36.59
Wet	1.47–1.67	43.99–62.96	41.26–45.37

period. And when the wet-period runoff is estimated with the dry-period parameters, a relative water balance error of 7.60% is obtained, as opposed to the almost negligible value of –0.22% when calibration is performed on the wet period.

In conclusion, the model performance drops substantially only when the relative water balance error obtained by application of dry-period parameters to the wet period is considered and even in this case the relative water balance error would be considered tolerable in many cases.

Another way of investigating the climate independence of the model is to consider the parameter values yielded by the two climatically different calibration periods. The optimisation method for determining linear module parameters also delivers an estimate of the covariance between the parameters, which enables an objective comparison of the similarity between the two sets of linear module parameters. Table 14.2 lists 95% confidence intervals for the linear module parameters for both calibration periods. Neither of the time constants (τ_q and τ_s), at the given confidence level, is significantly different when calibrated on the two time periods, yet the partitioning coefficient (v_q) appears to be higher when calibrated on the wetter period. Figure 14.1 shows confidence intervals for the instantaneous unit hydrographs (IUHs) for both calibration periods. These impulse response functions depict the speed with which effective rainfall entering the linear routing module of the model emerges as streamflow. As such, they reflect the combined effects of all three model parameters in a single figure. A lack of identifiability is known to be present in the model's structure, in the sense that there may be both relatively high estimation error variances associated with some individual parameters and high covariances amongst the errors attaching to two or more of these parameters. The IUHs reflect succinctly all the consequences of these variances and covariances. They are a more complete assessment of the similarity of the linear module parameters, since the uncertainty of individual parameters is increased by interrelations between them. The two IUHs are distinct from each other, although their confidence intervals overlap in part of the domain. The main difference is that the IUH for the wet period has a higher peak than the IUH calibrated on the dry period, indicating thus that in the wet period the transformation of rainfall excess into streamflow occurs more quickly. This result is consistent with the earlier finding that the parameter depicting the share of quickflow, v_q, is higher for the wet period. Perhaps the hydrological response is indeed somewhat "flashier" during wet periods and, since this is not accounted for in the model structure (the climate history only affects the volume of generated runoff, not the timing), climate dependency *is* accordingly detected in model parameters. The parameter shift, although significant, is relatively small, however. In fact, it is much smaller than that when catchments exhibiting clearly different hydrological behaviour are calibrated to a common time period. Figure 14.2 shows IUH confidence intervals for three Coweeta catchments with substantially different hydrological responses, with calibration of each being achieved for the period from 1 January 1955 to 30 October 1958.

In spite of the fact that we cannot convince ourselves of being able to remove completely the effects of climate on the hydrological response, we nevertheless assert that the climatic "signature" can be removed to an extent sufficient to facilitate detection of how other factors may control the hydrological behaviour of a

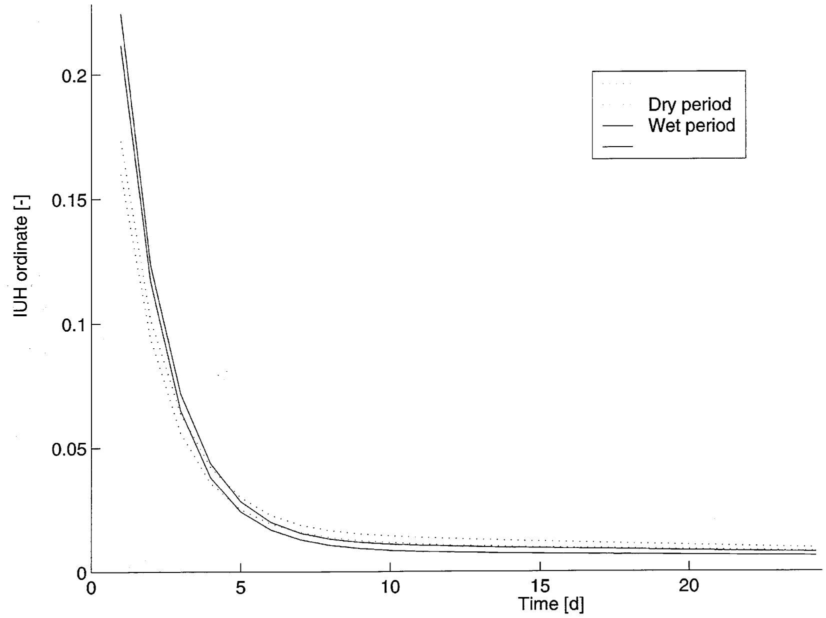

Fig. 14.1. Confidence intervals for the Instant Unit Hydrographs (IUHs) as calibrated for Coweeta catchment 36 over two periods of time (one dry, the other wet).

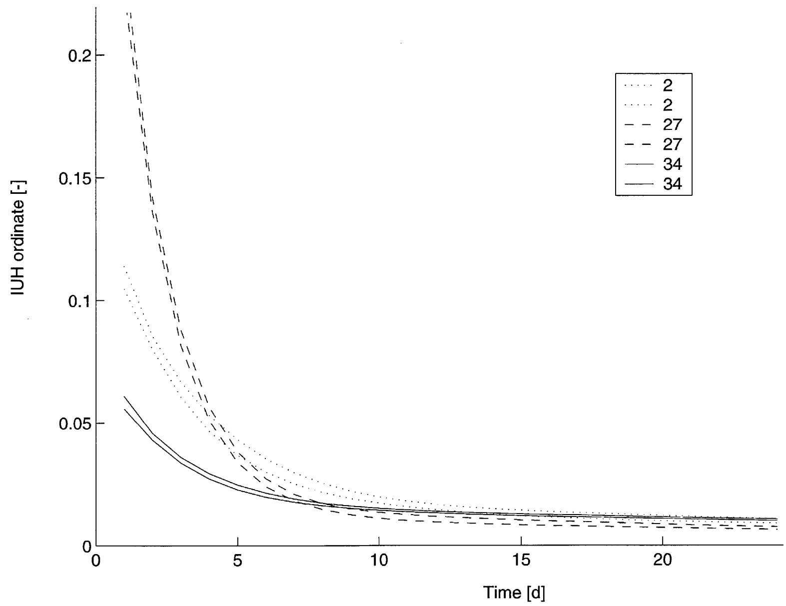

Fig. 14.2. IUH confidence intervals for Coweeta catchments 2, 27, and 34.

catchment. This assumption is grounded by the following: (a) the model performs reasonably well when parameters used for runoff prediction are adopted from a period with a substantially different climate sequence; and (b) the differences between parameters calibrated for two climatologically different periods are small.

14.3 CASE STUDY 1: COWEETA, USA

Regionalisation can be defined as the transfer of information from one catchment to another (Blöschl and Sivapalan, 1995). Such a transfer is called for when no flow records of sufficient length are available at the site of interest; it is often achieved by establishing a relationship between the hydrological response of a catchment and its physical attributes. In the present case the hydrological response can be taken as having been quantified through the parameters of IHACRES, while the physical attributes include the weir elevation and the mean slope of the catchment. These two attributes were screened from a much larger set of potential explanatory variables on the grounds of statistical significance and physical plausibility of their influence over the rainfall-runoff process. In essence, what we are seeking is a relationship suggested by the general form of equation 5.4 in Chapter 5, i.e., parameterisation of any identified parameteric variation (in this case from one catchment to another, as opposed to changes with time).

IHACRES has been calibrated for all 13 catchments at Coweeta. Ideally, we should have been able to choose one common span of time for all the catchments under study, with complete sets of observations, but this would have restricted the number of catchments available to only eight. By choosing two windows of the record, 13 catchments, having data for either (or both) of the periods, can be included in the analysis. Period 1 is from 1 November 1937 to 31 August 1939; the second refers to 1 January 1955 to 30 October 1958. The model fits well the discharge of all the catchments, with efficiencies ranging from 0.84 to 0.92, and the absolute value of the relative water balance error always being less than 10%. All the fit statistics are shown in Table 14.5 (first column).

Table 14.3 lists correlations between the catchment attributes and model parameters. Those correlations which are significant (two-tailed test) at the 5% level are given in bold-face type. Elevation appears to be a major driver of hydrological response in the Coweeta catchments, correlating significantly with four out of six parameters, while slope is identified as having significant correlations with three model parameters. Two of these relationships are shown as scatter plots in Figures 14.3 and 14.4, respectively for the partitioning parameter v_q *versus* slope, and for the water balance parameter c *versus* weir elevation. In fact, we take this line of exploration further through regression analysis. Each catchment is treated as if it were ungauged and its data excluded from the regressions. Since there are thirteen catchments in total, thirteen different regionalisation equation sets can thus be formed. Only small differences, if any, however, may be expected in the screening of significant explanatory variables for the thirteen different data sets. Having analysed three of the thirteen data sets, always arriving at an identical set of explanatory variables, these explanatory variables were accepted to reflect the regression relationships across all the catchments. In the full account of the analysis (Kokkonen et al., 2002), three different regression methods were employed, of which two were capable of taking into account correlation between dependent variables (i.e., the rainfall-runoff model parameters in this case). No significant difference in performance was detected between any of the regression methods, however. Accordingly, only the results yielded by the simplest method are repeated here. In this method ordinary least squares (OLS) regression is applied to explain each parameter individually using those catchment attributes that maximise the significance of the overall regression as independent variables. The following list gives the identified relationships: τ_w from weir elevation; f constant; c from weir elevation; τ_q from weir elevation; τ_s from weir elevation; and v_q from slope. Recalling the cross correlations

Table 14.3

Correlations between catchment characteristics and IHACRES parameters. Those that are significant at the 5% confidence level are shown in bold.

	τ_w	f	c	τ_q	τ_s	v_q
ELEV	**–0.68**	–0.12	**–0.78**	–0.56	–0.68	0.37
SLOPE	**–0.56**	–0.42	–0.51	–0.12	**–0.62**	0.66

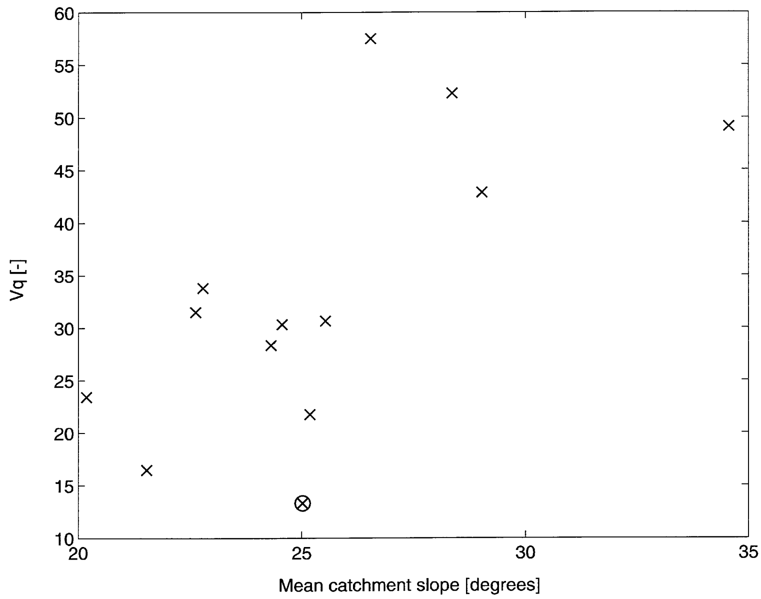

Fig. 14.3. Parameter v_q plotted against the mean catchment slope (catchment 34 is circled).

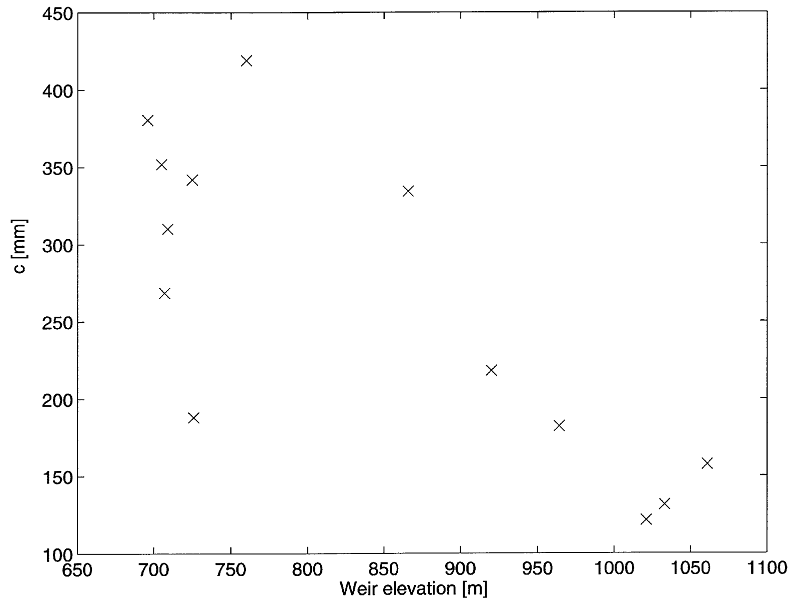

Fig. 14.4. Parameter c plotted against weir elevation.

Table 14.4

IHACRES parameter values as predicted from regression. Calibrated values shown in parentheses. No refers to a catchment number.

No.	τ_w [d]	f [–]	c [mm]	τ_q [d]	τ_s [d]	v_q [–]
1	12.0 (15.1)	12.8 (14.0)	331 (352)	3.1 (3.0)	49.3 (48.9)	30.7 (28.3)
2	12.7 (10.5)	13.1 (10.4)	336 (310)	3.1 (3.0)	50.4 (40.8)	33.7 (30.7)
6	12.4 (14.4)	12.6 (17.3)	332 (381)	3.2 (2.8)	49.8 (48.3)	25.8 (31.5)
13	11.5 (15.6)	12.6 (16.4)	321 (342)	3.0 (3.2)	48.7 (46.6)	25.9 (33.8)
14	12.9 (9.9)	13.0 (12.1)	344 (269)	3.3 (2.1)	49.8 (45.1)	19.6 (23.4)
17	11.1 (13.2)	13.0 (11.6)	291 (419)	2.6 (5.3)	47.0 (49.0)	33.9 (57.5)
18	13.2 (4.1)	13.2 (9.5)	343 (188)	3.1 (2.6)	47.4 (55.3)	33.6 (21.8)
27	4.4 (5.6)	12.8 (14.7)	134 (157)	1.8 (1.8)	38.0 (31.5)	38.6 (52.3)
28	6.9 (6.4)	12.9 (13.8)	195 (182)	2.1 (2.2)	40.0 (37.8)	31.2 (30.3)
32	7.7 (8.5)	12.9 (13.7)	217 (218)	2.4 (1.7)	40.6 (47.4)	25.3 (16.5)
34	8.5 (14.1)	12.9 (13.2)	239 (334)	2.5 (2.6)	42.4 (53.5)	33.8 (13.3)
36	6.1 (3.5)	13.1 (10.3)	173 (121)	1.9 (2.1)	36.4 (42.4)	41.8 (42.9)
37	5.8 (3.7)	13.1 (11.1)	163 (131)	1.9 (1.8)	39.5 (29.7)	64.0 (49.1)

between catchment attribute and model parameter from Table 14.3, these relationships can be explained in words as follows. Elevation correlates negatively with c, which means that higher elevated catchments with smaller c values have lower storage and a more rapid increase in catchment wetness index in response to a rainfall event, relative to the lower catchments. Hence more of the rainfall is converted into effective rainfall and these catchments have higher runoff coefficients. Higher elevated catchments also have a quicker response, which is indicated by the decrease in both time constants of the linear module, τ_q and τ_s, with elevation. The partitioning coefficient, v_q, increases with slope, so that the more steeply sloping catchments have a larger share of quickflow, and hence exhibit a flashier behaviour than catchments with shallower slopes. The temperature modulation parameter, f, was not successfully related to any of the catchment characteristics and appears, therefore, as a constant in the regression equations. Table 14.4 lists estimated IHACRES parameter values as produced by the corresponding regression relationship – from catchment attributes – along with the estimates previously identified from the original catchment (precipitation, streamflow) data. The regression coefficients themselves for all thirteen sets of equations are not shown, as the cross correlations between the catchment characteristics and model parameters (Table 14.3) essentially provide the same information.

An obvious means of validating these results is to predict the daily streamflow time series using the parameters for IHACRES that are generated from the regression relationships. Recall that separate relationships between the model parameters and attributes were derived for the thirteen different subsets of twelve Coweeta catchments. Here daily runoffs are reproduced for all catchments using the regressed parameters, hence considering each to be ungauged for streamflow. Since

Table 14.5

Performance statistics using calibrated and predicted IHACRES parameters.

Catchment No.	Calibrated		Predicted	
	F	*RWBE* (%)	*F*	*RWBE* (%)
1	0.90	–3.5	0.90	–5.6
2	0.88	5.6	0.85	–5.0
6	0.89	–5.2	0.76	17.8
13	0.91	–4.5	0.90	–3.5
14	0.89	1.4	0.83	–8.1
17	0.90	–4.1	0.84	17.9
18	0.84	9.5	0.84	4.7
27	0.89	–2.2	0.87	6.1
28	0.92	–1.3	0.91	2.2
32	0.91	0.0	0.86	–3.1
34	0.92	–0.2	0.52	–1.2
36	0.89	–1.4	0.88	–9.3
37	0.87	–2.1	0.85	0.6

these catchments are in fact gauged, the accuracy of the predictions may be assessed by comparison against the observed flows. Table 14.5 lists fit statistics (*F* and *RWBE*) for all catchments and for both calibrated and estimated parameter values. Overall the regionalised parameters produced daily runoff predictions not greatly inferior to those given by calibration. Figure 14.5 shows predicted streamflows, based on the regionalised parameters, and measured streamflows for one catchment (number 1), where good results were obtained. However, there are two catchments whose runoffs were poorly reconstructed when regionalised parameters were applied. Most noticeably, even though the overall water balance for catchment 34 is adequately reproduced, peak values are consistently over-predicted (Figure 14.6). This occurs because the predicted value for v_q is much greater than it should be according to calibration (Table 14.4). Figure 14.3, which plots v_q against slope, shows catchment 34 as a clear outlier, having a far smaller value for v_q than the slope–v_q relationship would suggest. Another catchment where regionalised parameters perform inadequately is catchment 6, which has the largest f parameter value of all the catchments. Since f was found not to be related to any catchment characteristics, there is no way a regionalisation procedure can account for this feature. The large f value could be due to an unknown control, but more likely it is merely an artifact of calibration. It is worth pointing out that calibration was performed in this case study on a completely objective basis according to a fit criterion where no expert reasoning was taken into account.

While elevation and slope have been found useful in explaining the hydrological response of the Coweeta catchments, some of the other characteristics, such as those describing the stream network structure of the catchments, were rejected in the screening analysis as not being plausible in differentiating among catchments in

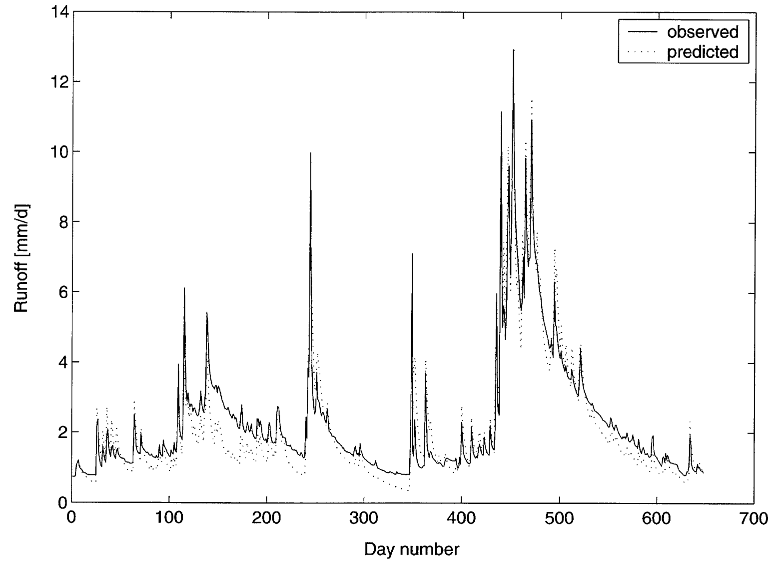

Fig. 14.5. Observed and predicted runoff for Coweeta catchment 1 for November 1, 1937, to August 31, 1939 (using regionalised parameters).

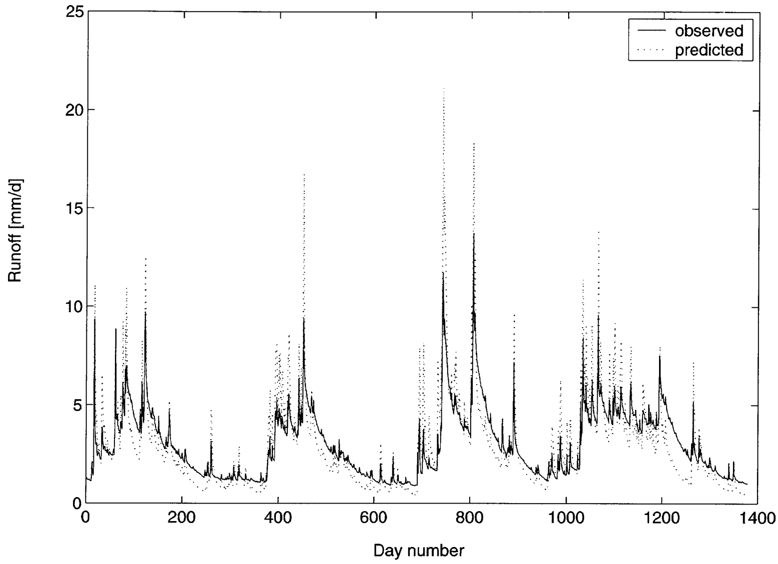

Fig. 14.6. Observed and predicted runoff for Coweeta catchment 34 for January 1, 1955, to October 30, 1958 (using regionalised parameters).

terms of their hydrological behaviour. This result reinforces the complex, system-dependent nature of factors influencing catchment response. In other words, factors which may logically seem important – at the outset – in determining the hydrological behaviour can be insignificant in the area of interest, for instance, because their effects have been masked by more powerful drivers of the hydrological response. This outcome casts doubt on the underpinning of complex models where so-called understanding is imposed *a priori* upon model structure and variables.

14.4 CASE STUDY 2: YASS RIVER

One might hypothesize that diverting water for irrigation purposes should result in an increase in evaporative losses within a catchment, and that the share of precipitation seen as streamflow should correspondingly diminish. Whether this is the case for the catchment of the Yass River, which has been subject to intensive farm dam development in the recent years, is the central issue now to be addressed (as discussed more fully in Schreider and Jakeman, 1999).

Our analysis is based on a concept of potential streamflow response (PSR), which is defined to be the ability of a catchment to generate streamflow in response to climatic excitation under given land use and vegetation conditions. As this is a climate-independent characteristic the effect of the climatic signal on streamflow must again be first removed. Suppose the rainfall-runoff model – here IHACRES – is calibrated for a part of the record, thus capturing the PSR at that time. Suppose further the model is then applied over the entire record using the climate time series as input. If the PSR of a catchment is reduced (after the calibration period) as a consequence of the increasing number of farm dams, the model should clearly overestimate streamflows when applied under the changed conditions of land use. Similarly, if prior to the calibration period the PSR has been greater due to fewer farm dams, the streamflow estimates yielded by the model when applied to that prior time should be smaller than the observed. The identification problem here is to investigate whether there is a significant trend in the model residuals, indicating a constant reduction in the PSR of a catchment, which could be attributed to the increased storage capacity of the farm dams. The approach adopted to address this problem can be outlined as follows:

- Calibrate IHACRES to a part of the existing record of daily streamflow and climatic data for the catchment of interest (calibration period was one year here);
- Using the calibrated parameters, simulate streamflow over the entire record;
- Compute daily residuals between modelled and observed streamflow;
- Calculate moving-average time series for the daily residuals (averaging, or smoothing, period being two years);
- Test whether there is a statistically significant trend in the time series constructed at the previous step.

Some further comments are warranted to clarify the procedure outlined above. Firstly, there is a trade-off in selecting the length of the calibration period. A long time period is preferred in order to minimise residual and parameter error variance in the calibration, yet a short period would be better in terms of ensuring stationarity with respect to the level of farm dam development. Secondly, the model residuals need to be smoothed to account for the periods of no rainfall. The Yass catchment streamflow is highly ephemeral, which leads to long periods where model residuals are zero, irrespective of whether the PSR of a catchment has changed. Because there is seasonality involved when a catchment experiences dry spells, the smoothing period needs to be long enough to extend over the entire seasonal cycle. Finally, fitting a trend to the model residuals revealed discrepancies between the linear trend and the model residuals that were found to be auto-correlated. Ordinary least squares regression estimates are inefficient when serial correlation is present and the standard error estimates are biased, so that judgements about the significance of the trend line may be seriously undermined. For these reasons, the estimated generalised least squares method (Judge et al., 1980) was employed to fit the trend line.

Figure 14.7 shows observed and modelled moving averages for the streamflow in the Yass River, along with the moving average of the model residuals and a trend line fitted to the residual time series. The model was calibrated to a one year time period starting on 1 January 1979. Visual inspection of the figure suggests that the model indeed increasingly overpredicts the flow, indicating that the PSR of the catchment is decreasing with time. This result is supported by statistical analysis, according to which the trend line is significant at the 5% risk level. On the basis of this trend line

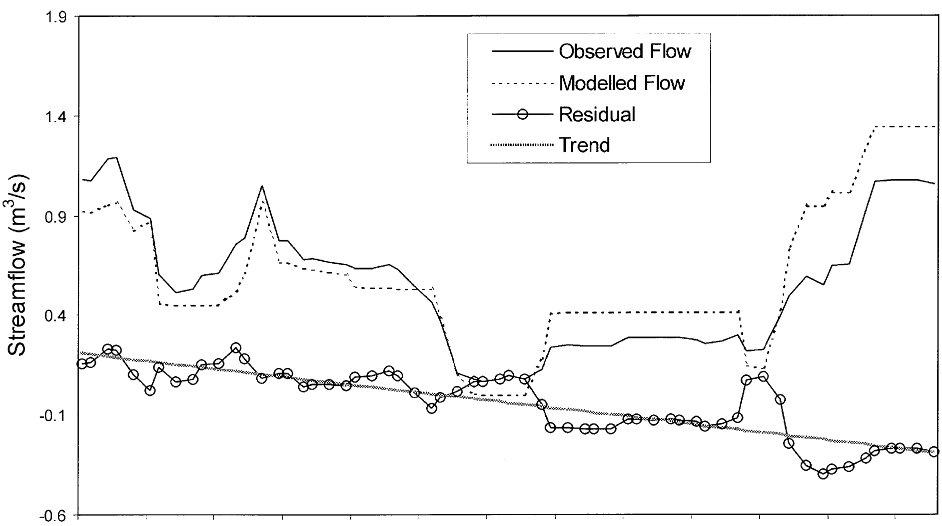

Fig. 14.7. Observed, modelled, and residual moving averages of streamflow in the Yass catchment. The trend of the residual time series is shown.

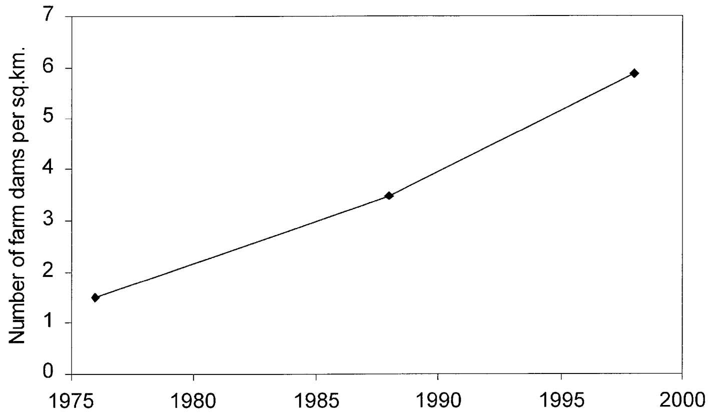

Fig. 14.8. Development of farm dam density in the Yass catchment.

the runoff volume is found to be decreasing by 9.5% every year. Figure 14.8 shows the increase in numbers of farm dams over the period of analysis, as estimated from aerial photography. Four representative cross-sections of the catchment were analysed, the average values of which are depicted in the figure. Other changes potentially affecting the water balance in the Yass River catchment include hobby farming associated increases in tree planting, and more use of perennial pasture which has higher water requirements than native pasture. However, it is assumed that the predominant factor in reduction of the PSR will have been the farm dams.

Our analysis has allowed us to gain an appreciation of the effects of farm dams on streamflow response. Given that there is a significant trend it ought to be possible to develop a more complex model accounting explicitly for these impacts. In fact, this can be achieved by extending the model structure through an additional module, the storage of water in farm dams "upstream", as it were, of the nearest stream-gauge (where it would be recorded as streamflow). In order to avoid identification problems, however, it will be necessary to keep the number of additional parameters requiring calibration in this module as low as possible. Further, given the lumped nature of the basic rainfall-runoff model, the impact of all farm dams must be represented as a single, equivalent (conceptual) farm dam. This is essentially an additional store within the catchment, which is recharged by direct precipitation and runoff from other parts of the catchment, and depleted by irrigation water consumption and evaporation. The total surface area of the dams controls two of the above mentioned processes – direct precipitation to the dams and evaporation. An estimate of changes in total surface area of dams through time can be extracted from aerial photography, and then inserted into the model. Spatial analysis incorporating digital elevation models and dam locations might be used to estimate the proportion of catchment area draining to the dams, which is required to assess the amount of water the dams receive as runoff from the surrounding area. Estimates of consumption of stored water could, in principle, be retrieved from farmers.

14.5 CONCLUSIONS

The various factors influencing the hydrological response of a catchment can be identified separately. The effects of a climate signal on the streamflow data can first be extracted, thus improving the chances of revealing how other factors, such as landscape properties and land use, control the hydrological response of a catchment. Our approach has been to start with a basic LOM, thus to identify parametric variation, or structural inadequacy, all the more crisply, and then to extend the model accordingly (Jakeman et al., 1994).

Although it may not be possible to eliminate the effect of climate completely, the rainfall-runoff model of our two case studies proved to be relatively insensitive to the climate of the calibration period. In the first of these, parameterisation of the relationship between landscape attributes and the *parameters* of a simple low-order model (LOM) could be demonstrated for a catchment in the Coweeta Basin, North Carolina. The weir elevation and the mean slope of a catchment were identified as causal variables and could be used to extrapolate hydrological response from one point in space (if not time) to another. Overall these predictions were only slightly inferior to those given by direct calibration of the same model to the streamflow data. Some of the landscape attributes one might beforehand have presumed would control hydrological behaviour of the catchment (such as those that describe the stream network structure), were not found to be important.

For the Yass catchment – our second case study – changes with time (as opposed to space) were more significant. But in this instance they were revealed in the residual errors of model fit instead of through the model's parameters, which in turn suggested a means of adapting and improving the model's structure. It seems likely the effects of the upward trend in farm dam construction, once accounted for and parameterised within the extended model structure, for example, through a time constant (τ_f, say) and a partitioning coefficient of some kind (v_f, say), could then be extrapolated into the future. We would be able to explore structural change in the hydrological behaviour of the catchment through this parametric variation, $\tau_f(t^+)$ and $v_f(t^+)$, into the future (t^+).

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