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Evaluating explicit and implicit routing for watershed hydro-ecological models of forest hydrology at the small catchment scale

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Abstract:

This paper explores the behaviour and sensitivity of a watershed model used for simulating lateral soil water redistribution and runoff production. In applications such as modelling the effects of land-use change in small headwater catchments, interactions between soil moisture, runoff and ecological processes are important. Because climate, soil and canopy characteristics are spatially variable, both the pattern of soil moisture and the associated outflow must be represented in modelling these processes. This study compares implicit and explicit routing approaches to modelling the evolution of soil moisture pattern and spatially variable runoff production. It also addresses the implications of using different landscape partitioning strategies. This study presents the results of calibration and application of these different routing and landscape partitioning approaches on a 60 ha forested watershed in Western Oregon. For comparison, the different approaches are incorporated into a physically based hydro-ecological model, RHESSys, and the resulting simulated soil moisture, runoff production and sensitivity to unbiased error are examined. Results illustrate that both routing approaches can be calibrated to achieve a reasonable fit between observed and modelled outflow. Calibrated values for effective watershed hydraulic conductivity are higher for the explicit routing approach, which illustrates differences between the two routing approaches in their representation of internal watershed dynamics. The explicit approach illustrates a seasonal shift in drainage organization from watershed to more local control as climate goes from a winter wet to a summer dry period. Assumptions used in the implicit approach maintain the same pattern of drainage organization throughout the season. The implicit approach is also more sensitive to random error in soil and topographic input information, particularly during wetter periods. Comparison between the two routing approaches illustrates the advantage of the explicit routing approach, although the loss of computational efficiency associated with the explicit routing approach is noted. To compare different strategies for partitioning the landscape, the use of a non-grid-based method of partitioning is introduced and shown to be comparable to grid-based partitioning in terms of simulated soil moisture and runoff production.

KEY WORDS flow routing; modelling lateral soil moisture flux; landscape representation; hydro-ecological modelling; TOPMODEL

INTRODUCTION

Representing the distribution and lateral flux of soil water is a critical component of modelling hydrological and ecological processes and the impacts of disturbances such as forest harvesting at the small watershed (<100 km^2) scale. Watershed models used to assess and understand these impacts must consider the vertical and horizontal interactions within the forest-canopy–soil system that involve hydrological processes, including interception, evapotranspiration, surface and subsurface runoff production and stream flow. This paper examines the issue of representing lateral soil-water flux on the behaviour and sensitivity of a watershed hydro-ecological model. The intention is to better specify the type of approach required in order to adequately

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capture hydrological response, including spatially variable soil moisture conditions, runoff production and ultimately ecologically significant variables such as evaporation, within a hydro-ecological modelling context.

The explicit and implicit routing approaches used in this study represent two basic approaches to modelling lateral soil moisture flux. Explicit routing approaches have been applied in models such as TOPOG (O'Loughlin, 1990), VSAS (Bernier, 1985), CLAWS (Duan, 1996) and DHSVM (Wigmosta *et al*., 1994), which explicitly transfer water between connected cells. These explicit routing models generally are applied over areas where sufficient information on the spatial variability of the topographic and soil parameters that control water movement is available. In these situations, landscape representation, both in terms of the size and the shape of modelling units, can influence simulation results. The need for generalizing from intensely studied sites to broader landscapes with sparse data sets presents a problem for these explicit routing approaches. At the same time, particularly in mountainous regions, high spatial variability within a watershed may preclude the use of averaged values (Band, 1993), particularly when ecological variables of interest, such as evapotranspiration, respond non-linearly to available soil moisture.

Spatial variability in soil moisture also can be addressed implicitly using statistical distribution methods such as TOPMODEL (Beven and Kirkby, 1979), which distribute saturation deficit across a non-spatial distribution of hydrological parameters within a catchment. Statistical methods can be thought of as providing a compromise between the processing intensive explicit routing methods and mean value or bucket model approaches. Statistical approaches use readily available topographic information to incorporate estimates of variability in hydrological properties. Processing efficiency is much greater for these approaches in comparison with explicit routing methods, but the information about connectivity between specific areas is lost. Statistical approaches, such as TOPMODEL, can also reduce data requirements by using coarser scale information to estimate distributions of required hydrological parameters. Previous work, however, has shown that the modelled streamflow response is sensitive to the resolution of the topographic information used to derive this distribution of hydrological parameters (Wolock and Price, 1994; Zhang and Montgomery, 1994; Bruneau *et al*., 1995).

Two basic approaches have been implemented for this study. One approach is an explicit routing model based upon a modified form of the distributed hydrological soil and vegetation model, DHSVM (Wigmosta *et al*., 1994). The other is TOPMODEL (Beven and Kirkby, 1979), an implicit approach to modelling spatially variable soil moisture and runoff production. In comparing the explicit and implicit routing approaches, the implications of (i) including information about connectivity and (ii) maintaining a finer resolution of response and soil moisture variability during model simulations are explored. This paper examines how the behaviour of each approach influences the spatial and temporal dynamics of the hydro-ecological model when only the subsurface routing scheme is varied and considers the relative sensitivity of each approach to error in input information. This paper also examines the role played by landscape representation when the explicit routing approach is used. The potential for gaining flexibility and efficiency is illustrated by adapting the grid-based routing scheme, traditionally used in the DHSVM and other explicit routing approaches, to allow the size and shape of modelling units to vary and incorporate information about local hydrological characteristics.

Comparisons are done for a small catchment within the H. J. Andrews watershed, which is a long-term ecological research (LTER) site. This site represents an area with considerable field data within a larger region where understanding the impacts of forest harvesting is an important issue. Part of the impetus for this comparison is to assess the potential for using modelling to assess impacts on soil moisture, runoff and ecologically significant variables such as evapotranspiration in similar areas within a broader region, where less information may be available for model parameterization and calibration.

REPRESENTATION OF DISTRIBUTED SOIL MOISTURE

TOPMODEL (implicit routing)

TOPMODEL is a statistically based approach that distributes water based on an index of hydrological similarity. TOPMODEL has been incorporated into biophysical models such as RHESSys (Band *et al*., 1993), TOPLATS (Famiglietti and Wood, 1994) and several soil–vegetation–atmosphere transfer models, SVATS, such as Troch *et al.* (1996).

TOPMODEL distributes a mean soil moisture deficit (s) based on a local wetness index

$$w_i = \ln\left(\frac{aT_i}{T_o \tan\beta}\right) \tag{1}$$

where T_i and T_o are local and mean watershed saturated soil transmissivity, respectively, $\tan\beta$ is local slope and a is upslope contributing area. Soil transmissivity is calculated as

$$T = \int_{s_i}^{\infty} K_o e^{\left(-\frac{s_i}{m}\right)} ds \tag{2}$$

where K_o is saturated hydraulic conductivity at surface, s is depth expressed as a saturation deficit, s_i is local saturation deficit and m is a soil parameter, which scales hydraulic conductivity with depth.

Local saturation deficit is computed as

$$s_i = \bar{s} + m(\lambda - w_i) \tag{3}$$

where λ is mean wetness index value, s_i and $\bar{s}$ are local and mean watershed saturation deficit.

TOPMODEL generates saturation excess flow for rain falling on areas with local saturation deficit, s_i, less than or equal to zero. In RHESSys, saturation excess flow is not routed but assumed to reach the stream within a daily time step. TOPMODEL also computes a catchment level baseflow, which is subtracted from the mean catchment saturation deficit. Baseflow, q_b, is calculated as

$$q_b = e^{(-\lambda)} e^{\left(\frac{-\bar{s}}{m}\right)} \tag{4}$$

where, λ is the mean watershed wetness index calculated as

$$\lambda = \frac{1}{A} \int \left[\ln\left(\frac{a_i T_i}{T_o \tan\beta_i}\right)\right] da \tag{5}$$

where A is basin area.

As a statistically based approach, TOPMODEL represents a simplified method that has been applied and tested against observed outflow responses for a number of catchments, as reviewed by Beven (1997). TOPMODEL relationships are based on the assumption that saturated hydraulic conductivity varies exponentially with depth; that water table gradients can be approximated by local topographic slope, that recharge is spatially invariant and that steady state flux is achieved within the modelling time step. The implications of these assumptions have been explored by comparing TOPMODEL predictions of saturation deficits with observed values in several catchments. In general, TOPMODEL assumptions appear to hold in humid catchments with rolling topography. Several studies (Barling *et al.*, 1993; Ostendorf and Manderscheid, 1997; Woods *et al.*, 1997) have found that the assumption of steady state flux is violated during drier periods. In drier periods, areas of the catchment may become disconnected and thus the extent of effective contributing areas becomes more local. In contrast, the TOPMODEL assumptions lead to a constant distribution of contributing area and a constant catchment water table shape through time. Moore and Thompson (1996) found a reasonable correspondence with the TOPMODEL steady state assumption for a humid mountainous catchment in British Columbia but found a weak correspondence between saturation deficit and TOPMODEL predictions. This catchment has similar topographic and climatic conditions to the H. J. Andrews catchment used in this study. Moore and Thompson (1996) attribute the difference in model and predicted saturation deficit to sensitivity to input errors in both soil parameters and topographic information. Burt and Butcher (1986) also cite the potential for error resulting from soil properties, including situations where the TOPMODEL calculation of soil transmissivity may not be valid (i.e. where hydraulic conductivity does not decay exponentially with depth or where hysteretic behaviour occurs). In very shallow soil layers, for example, the assumption of exponential decay with depth may not be valid. TOPMODEL has been modified to consider other relationships (i.e. parabolic and linear) between hydraulic conductivity and depth (Ambroise *et al.*, 1996). However, the model will always be sensitive to the appropriateness of the chosen relationship.

Explicit routing

The explicit routing approach used in this study is a modified form of an algorithm used in the DHSVM model (Wigmosta *et al.*, 1994). The DHSVM routing scheme assumes that throughflow from pixel a to pixel b is given as

$$\mathrm{q(t)}_{a,b} = \left[\mathrm{T(t)}_{a,b} \tan\beta_{a,b}\omega_{a,b}\right] \tag{6}$$

where ω is flow width, $\tan\beta$ is local slope, and T is soil transmissivity as defined above for the TOPMODEL implementation. Flow widths are assumed to be 0·5 × grid size for cardinal directions and 0·354 × grid size for diagonal directions, after Quinn *et al.* (1991). The original DHSVM approach is adapted and generalized here to consider irregularly shaped patches, such that the usual use of grid cells can be considered a special case. The advantage of this broader definition of a patch is that it allows the landscape to be represented as ecologically meaningful units rather than arbitrary grid cells. Previous studies such as Band *et al.* (1991) have shown that definition of modelling units based upon ecological properties can reduce within-unit variance. This definition of patches also provides a method for increasing efficiency by reducing the number of modelling units, without losing important spatial information.

An assumption of exponential decay of hydraulic conductivity with depth is also used with the explicit routing approach. As with TOPMODEL, however, this profile can be replaced with alternative functions, including a prescribed bedrock–soil interface.

The partitioning of the landscape into patches used in this paper is described below. Throughflow is calculated using Equation (6), where flow widths are summed along the shared boundary between adjacent patches. Connectivity between patches is derived using automated GIS-based routines. Neighbours and associated perimeters between irregular areas or patches are extracted from an image of defined patches. Slopes are calculated based on the mean elevation for each patch area.

Routing between patches permits multiple flow paths. Stream patches, defined by an imposed stream network, however, are restricted to single, steepest descent pathways. This is consistent with Quinn *et al.* (1991), who observe that multiple flow methods yield more realistic patterns in watersheds but single flow paths are more appropriate for stream flow routing. There is no catchment level baseflow defined for the explicit routing scheme as baseflow contributions are assumed to be produced directly from saturation subsurface throughflow from patches adjacent to the stream network.

Connectivity between patches is traversed to detect pits or circular flow. O'Callaghan and Mark (1984) note that actual pits are rarely observed in mountainous regions at the scales used in this study. Thus, pits are considered to be spurious products of the digital elevation model (DEM) or the alternative patch partitioning strategy. Pits are removed by redirecting flow going into the pit to the minimum elevation upslope patch that points to a receiving patch lower than the bottom patch in the pit. All patches in the pit are then assigned to point to this receiving patch. This method is similar to that used by O'Callaghan and Mark (1984).

Figure 1 compares the landscape representation used in the explicit routing approach with TOPMODEL. The explicit routing approach removes the steady state assumption included in TOPMODEL and permits the shape of the water table to vary through time. This explicit routing scheme, however, makes similar assumptions about soil transmissivity and hydraulic gradients. Both models will, therefore, be sensitive to errors in soil hydraulic conductivity and topographic information. The inclusion of information about spatial connectivity between modelling units in the explicit routing approach may change the sensitivity to these errors relative to the TOPMODEL implementation.

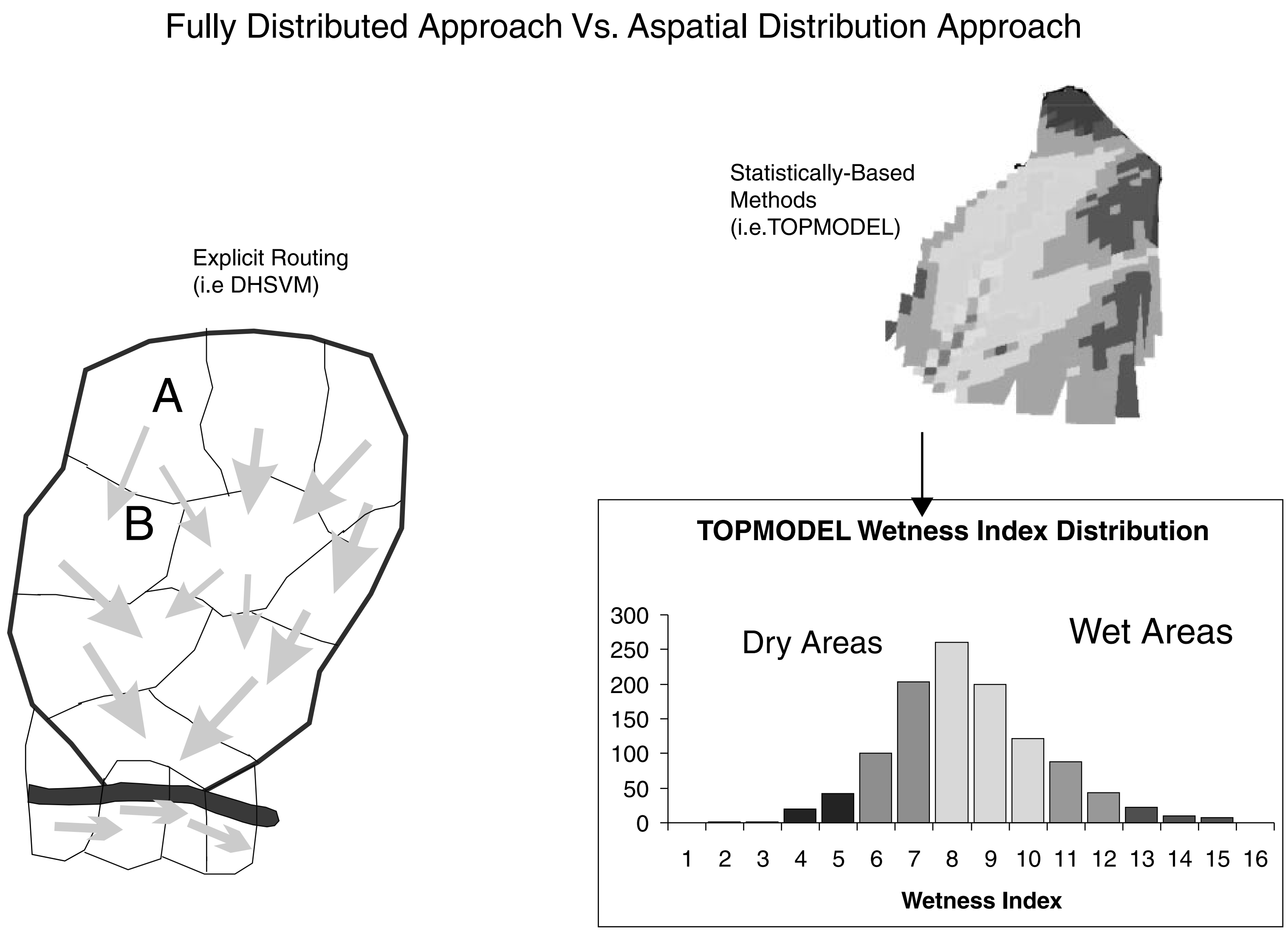


Figure 1. Comparison of landscape representation for explicit and implicit routing approaches—explicit routing approach uses contiguous spatial patches, whereas Implicit routing uses a statistical distribution of aspatial patch types

LANDSCAPE PARTITIONING STRATEGIES AND MODEL IMPLEMENTATION

Both TOPMODEL and the explicit routing approach are incorporated into RHESSys (regional hydrological ecosystem simulation system). RHESSys is an ecological modelling system that combines distributed flow modelling with an ecophysiological canopy model, based on BIOME_BGC (Running and Hunt, 1993) and a climate interpolation scheme based on MTN_CLIM (Running *et al.*, 1987). These submodels are combined within a GIS framework to allow for organized and efficient modelling of landscape systems. Outputs from RHESSys include both hydrological and carbon fluxes at a daily time step. By incorporating both explicit and implicit approaches to modelling distributed hydrology into RHESSys, hydro-ecophysiological feedback and responses, such as evapotranspiration and unsaturated zone dynamics, do not vary between the two approaches. Similarly, climate forcing, i.e. radiation, temperature and precipitation, does not vary between the two approaches. The different approaches are compared in terms of the resulting runoff production and the spatial pattern of soil moisture and evapotranspiration. Evapotranspiration, as part of the ecophysiological canopy model, is calculated using the Penman–Monteith (Monteith, 1965) approach.

Partitioning strategy

The TOPMODEL wetness index distribution can be derived from assumptions made about the shape of the catchment or computed from a DEM. In the former case, TOPMODEL can be run when detailed DEM information is not available. We chose the latter approach following Lammers *et al.* (1997). For explicit routing, the resolution of modelling units is directly tied to the resolution of input information. In addition, because modelling units are spatially explicit, shape can be important. In order to investigate the implications of using variable-shaped patches, which include information about hydrological organization, three different partitioning strategies are explored. The first is based on 30-m DEM pixels (PR) and is used as the baseline of finer resolution grid-based information. Two methods of reducing resolution: grid-based aggregation (SQ) and irregular-shaped, hydrologically defined patch aggregation (TR) are also compared. Partitioning is implemented using an automated GIS-based scheme. The aggregation scheme for developing irregular patches (TR) uses landscape information to derive patches of similar soil moisture characteristics according to the TOPMODEL wetness interval. Aggregation is accomplished by using a connected component routine applied to a combination of the wetness index image and an image of 50-m elevation intervals, as shown in Figure 2. Explicit routing using patches defined by wetness indices can be thought of as a hybrid of TOPMODEL and explicit routing approaches. The hypothesis is that as the wetness index tends to denote areas of hydrological similarity, routing between patches defined by the TOPMODEL wetness index will provide an efficient method of aggregation and minimize the loss of information resulting from aggregation. The 50-m elevation intervals are included as an additional limitation on patch size.

Figure 3 illustrates the different partitioning strategies used for the explicit routing and for the TOPMODEL implicit routing approach. The number of effective modelling units with TOPMODEL is usually significantly smaller (<20 wetness intervals) and less variable with scale in comparison with the explicit routing approach, which requires 654 modelling units for the pixel based landscape representation for the 60-ha study catchment. As shown in Figure 3, for the explicit routing approach, spatially explicit modelling units vary significantly in number and shape as a function of the partitioning strategy.

Study site and calibration

The study site is a small 60 ha unlogged catchment, Watershed 2, in the H. J. Andrews Experimental Forest in the Western Cascade region of Oregon, with an elevation range of 500–1000 m. Climate in this region is characterized by warm, dry summers and cool, wet winters. Annual precipitation for the years used for calibration and testing ranges from 1500 to 2300 mm. During the winter, climate in this basin is often at the threshold between rain and snow, where heavy rain, rain-on-snow and snowmelt are all common runoff and potential flood-producing events. During the summer, precipitation is much lower, and the maintenance of

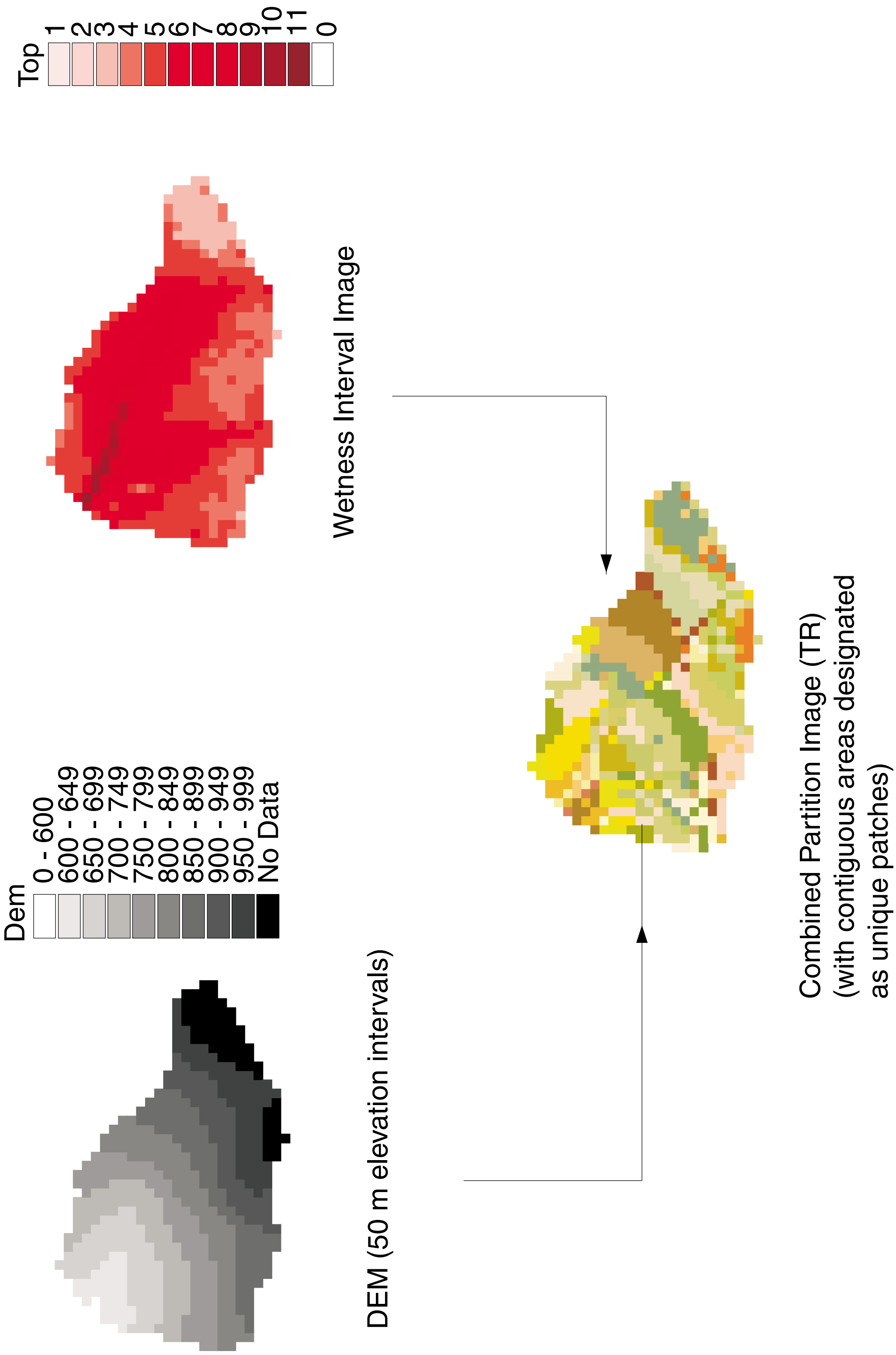
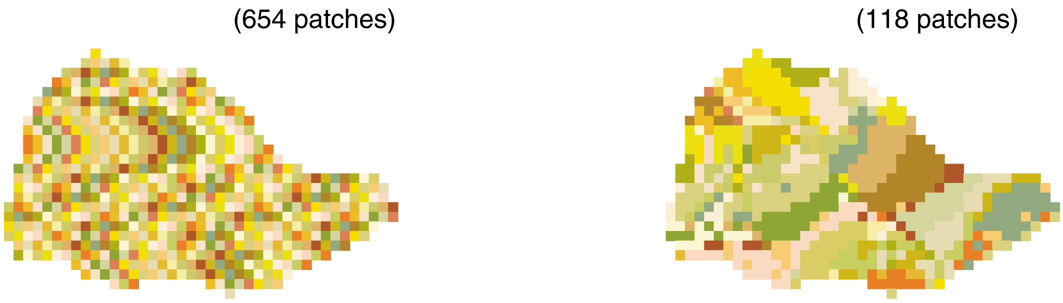
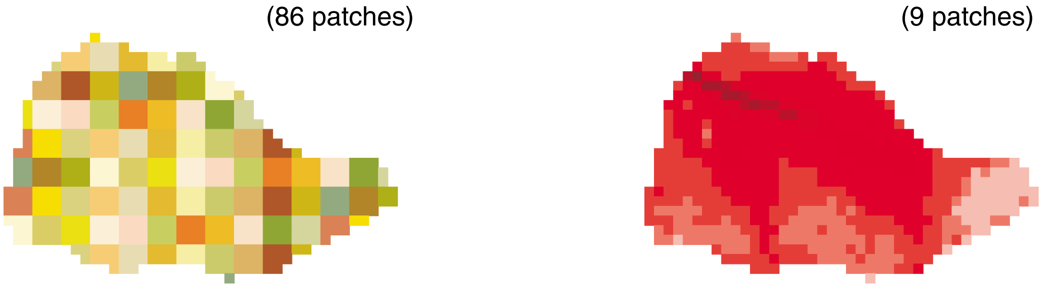


Figure 2. Construction of patches based on using the overlay of a wetness index and a DEM GIS-based image



a) PR - Partitioning based on 30 m pixels; highest resolution approach

b) TR - Partitioning based on a combination of wetness index and 50 m elevation intervals; spatially contiguous patches



c) SQR - Partitioning based on 90 m pixels

d) TOPMODEL Partitioning based on unit interval wetness intervals; with non-contiguous patches

Figure 3. Landscape partitioning strategies including 30-m pixels, contiguous patches based on a combination of a wetness index image and a DEM, 90-m pixels and non-contiguous patches based on a wetness index

low flows can become an important ecological issue. Watershed 2 is covered primarily by mature–old growth Douglas fir. Outflows for this basin, during the study period, range from 850 to 1300 mm/year.

Soils. Topographically, stream erosion, landsliding and glaciation have produced a steep and highly dissected landscape. Soils range from clay to sandy and gravelly loam. In general, soils are characterized by both high porosity and hydrological conductivity owing to the aggregated character of the soil material and in many areas a high stone content as a result of glacial or mass movement deposition (Ranken, 1974). Some areas, however, contain subsoils of lower porosity and permeability. Underlying bedrock is volcanic material from Oligocene to lower Miocene, including basalts, tuffs and breccias. Solid bedrock in many areas is covered by a thick layer of weathered, unconsolidated material (Rothacher *et al.*, 1967), which also facilitates rapid subsurface flow to the stream.

Parameters for the two models of distributed hydrology are derived from a 30-m DEM, and 30-m soil texture maps derived from a 1 : 15 000 soil survey map. Calibration is done separately for the explicit routing and TOPMODEL approaches and for each of the different partitioning strategies. Calibration of the model applies a scale factor to the initial estimates for two soil parameters, m and K_{sat}, which together define soil transmissivity. The same scale factor is applied to the entire watershed so that calibration does not alter the initial spatial distribution of the soil parameters. The initial values for the specific soil parameters, m and hydraulic conductivity, K_{sat}, are derived from soil map information as described below. The initial values of m and K_{sat} fix the spatial distribution of relative transmissivity within the catchment. Other soil parameters, porosity, air entry pressure, and pore size index are not calibrated and are set based upon literature estimates, shown in Table I, for different soil textures following Clapp and Hornberger (1978).

The different approaches are calibrated for 1988, a relatively wet year (annual precipitation = 2319 mm). Each approach is subsequently tested for 1987, which received less annual precipitation (1607 mm), and 1986, which received a slightly larger amount (2427 mm). Calibration maximizes the Nash–Sutcliffe efficiency (Nash and Sutcliffe, 1970) for 1988.

To set initial parameters, the m parameter is estimated from point measurements by Rothacher *et al.* (1967) of soil percolation rates taken for different soil depths (z) for a selection of soils with measured porosity, $\phi = 0{\cdot}5$, in the H. J. Andrews watershed as follows

$$m = \varphi \times \frac{z}{\ln\left(\dfrac{K(z)}{K_{\mathrm{o}}}\right)} \tag{7}$$

The range of m is 0·05 to 0·2. In this implementation of TOPMODEL and the explicit routing scheme, soil depth is indirectly defined by m, as m controls the depth of active hydraulic conductivity.

Lateral and vertical saturated hydraulic conductivity, K_{sat}, in this region are very high, with some measured soil sample values above 150 m/day, in part illustrating the effect of high stone content (Dryness, 1969). Conductivity is also highly variable, thus it is not realistic to derive K_{sat} from a limited number of point samples. As an approximation, hydraulic conductivity for the most common texture (gravelly loam) is estimated from average values for different soil samples described in Dryness (1969). Values for other texture classes are extrapolated from that of gravelly loam using typical relationships between texture and conductivity following Clapp and Hornberger (1978). Some stone content is assumed for all matric soils and increases hydraulic conductivity for all soil types, equally. Thus, the relative variation in conductivity between rocky and loamy soils, which typically have a much lower conductivity, is reduced. Table I shows the values used.

Calibration of hydraulic transmissivity through m and K_{sat} is necessary in both the explicit and implicit routing approaches because measurement of soil matrix hydraulic conductivity does not completely determine resistance to water flux given by the soil. The inclusion of macropores for example can increase the rate at which water is able to move through the soil. Calibration estimates an effective conductivity that includes those pathways involved in controlling the movement of water through a patch.

Table I. Hydrological parameter values for specific soil classifications in Watershed 2, derived from field measurements (Dryness, 1969) and typical literature values (Clapp and Hornberger, 1978)

Soil texture class	K_{sat} (m/day)	Porosity	Air entry pressure (m)	Pore size index	Areal of W2 (%)
Rocky	200	0·45	0·001	0·28	3·77
Cobbly	160	0·5	0·007	0·26	1·98
Cobbly loam	140	0·5	0·005	0·25	0·81
Gravel–sandy loam	100	0·6	0·008	0·22	35·99
Gravelly loam	80	0·6	0·01	0·2	45·18
Gravel–clay loam	60	0·6	0·012	0·18	5·84
Light clay loam	0·1	0·5	0·1	0·12	1·18
Poorly drained	0·01	0·5	0·12	0·1	5·27

It also should be noted that the explicit routing approach has the potential to incorporate much greater parameter uncertainty than the TOPMODEL approach because each patch could be parameterized separately. In TOPMODEL, on the other hand, the distribution of subwatershed variability in hydrological parameters (hydraulic conductivity) is characterized by only two parameters. In this paper, the explicit routing approach uses an initial grid-cell-scale distribution of soil parameters. Calibration as described above, however, is based on watershed scale parameters that scale m and K_{sat} in all cells or patches equally. This effectively reduces the number of calibration parameters used in the explicit routing approach to that of the TOPMODEL approach.

Climate and vegetation. Precipitation and temperature inputs are taken from a single base station within the catchment. Variation in incoming radiation with elevation and aspect is accounted for using MTN_CLIM logic (Running *et al.*, 1987). Precipitation lapse rates with elevation are derived from PRISM (Daly *et al.*, 1994). Use of PRISM and the density of climate stations (i.e. there are more than six climate stations within the H. J. Andrews Basin, including one within Watershed 2) allows the complex patterns of local precipitation to be accounted for. Temperature lapse rates were estimated by Rosentrater (1997) using the multiple climate stations available in the H. J. Andrews watershed to account for temperature inversions associated with this area and improve the temperature interpolation associated with the MTN_CLIM approach. As both routing approaches are implemented within the larger RHESSys simulation framework, both receive the same climate forcing, canopy coverage and soil distribution information.

Given the high density of climate station input in this region, error in climate input should be small. One exception to this is the estimation of snow versus rainfall events based upon temperature. The meteorology station records do not distinguish between precipitation falling as rain or snow—the model assumes that the snow/rain proportion varies linearly from −3C (all snow) to 3C (all rain). Watershed 2 can often contain the boundary between precipitation falling as rain and as snow and, therefore, presents a complex pattern of rain versus snow across the landscape and over time. In addition snowmelt processes in this region are complex, including 'rain on snow' melt events. Considerable error, particularly in the timing of snowmelt processes can be expected given the daily time step snowmelt model used in RHESSys. Although Watershed 2 does not maintain a seasonal snowpack in the winter, daily to weekly snow accumulation events and subsequent melt can alter the timing and characteristics of runoff events over a period of several days. Snowfall events during the simulation period, however, were few and thus this source of error is not expected to be significant for these simulations.

Vegetation is represented as a uniform coverage of Douglas fir. Evapotranspiration within RHESSys is computed using the Penman–Monteith equation. Soil moisture controls on vegetation response are included through stomatal conductance, which is calculated using the Jarvis model (Jarvis, 1976). Canopy parameters such as estimated LAI, and ecophysiological parameters for Douglas fir forests are assigned using literature values following Running (1994) and Jarvis and Leverenz (1986).

RESULTS

Explicit versus implicit routing—watershed outflow and evapotranspiration

Final calibrated values of m and K_{sat} for TOPMODEL and the explicit routing scheme are shown in Table II. Calibration differences between the different partitioning strategies used for explicit routing are small. Calibrated effective transmissivity for the explicit routing implementations are substantially larger than those used for TOPMODEL (i.e. both m and K_{sat} calibrated values are larger for routing). The larger transmissivities required for explicit routing may reflect the sensitivity of explicit routing to local conditions. The explicit flowpaths associated with the modified DHSVM approach, for example, may create areas of convergence with relatively low initial hydrological connectivity, which will force required transmissivities to increase. In addition, the explicit routing model allows for re-infiltration of surface runoff generated by upslope patches, which may slow the transport of water to the stream. In comparison, the TOPMODEL approach assumes that all surface runoff generated reaches the stream within the daily time step. TOPMODEL also implicitly assumes full connectivity, as pointed out by Barling *et al.* (1993). Transmissivity values for the TOPMODEL method are, therefore, more representative of watershed level organization rather than local patch flowpaths and thus are less susceptible to local irregularities in the pattern of flow.

TOPMODEL also differs in its approach to modelling baseflow. In TOPMODEL, baseflow is calculated on a catchment-wide basis. Local flow connectivity is assumed in TOPMODEL and does not need to be maintained for baseflow to occur. Thus, baseflow can partially reflect deeper groundwater sources, organized at the watershed level. For explicit routing, baseflow is implemented as a local process in patches adjacent to the stream and therefore is sensitive to seasonal changes in local connectivity patterns and to the representation of local areas near to the stream. Baseflow, in this case, is a function of local gradient and transmissivity of the streamside patch. The assumption that the local hydrological gradient is parallel to topographic slope, as is assumed in this explicit routing implementation, may not be appropriate for baseflow production from streamside areas. In these areas, low topographic gradients may increase the importance of matric-potential in controlling flow. The larger calibrated transmissivity associated with the explicit routing approach therefore may compensate for an underestimation of local streamside hydraulic gradient.

High calibrated transmissivity values for the explicit routing approach also suggest that, even for this more physically based method, m and K are essentially tuning parameters and do not necessarily reflect observable soil properties, although they may reflect dominant physical processes. The high calibrated transmissivities may reflect the importance of macropore flow over soil matrix properties in controlling the hydrological response. Calibrated transmissivity is therefore an effective value rather than a reflection of soil-based measurements. Initial soil texture classifications, however, do indicate within-watershed (i.e. between 30-m patches) variability in hydrological properties.

Table III shows predicted ET and annual outflow values for the different approaches. In all cases the total annual outflow is underestimated by both explicit and implicit approaches, although underprediction is greater for the TOPMODEL approach. This could suggest an overestimation of ET. Error in the estimation of leaf area index inputs based on stand age and literature rather than measured values may result in lower ET values.

Figure 4 compares 3-day averaged winter (January–March) and summer (June–September) observed outflow with TOPMODEL implicit routing and the explicit routing implementation, using the full pixel landscape partitioning. Both models capture the pattern of response fairly well. The explicit routing implementation produces flashier hydrograph responses than the corresponding TOPMODEL response. In general explicit routing implementations tend to overestimate the rate of peak flow decay. TOPMODEL tends to underestimate it. Both models overestimate summer baseflow, as shown in Table IV. TOPMODEL also shows a consistent delay in stormflow response.

TOPMODEL and the explicit routing implementation are applied in RHESSys with the same canopy evapotranspiration, snowmelt and vertical unsaturated flow submodels. Thus, differences between them reflect differences in rates of flow through the watershed to the stream network. The rapid peak flow decay associated with the explicit routing approach reflects its corresponding large values for calibrated transmissivity. High

Table II. Comparison between different routing strategies and landscape representation approaches showing calibration results and the number of spatial patches

Method	m	Mean K_s (m/day)	Efficiency	Number of patches	Patch shape	Average patch size
$PR_{Routing}$	0·17	120	0·68	507	Grid (30 m)	900 m^2
$TR_{Routing}$	0·17	150	0·60	113	Irregular	4000 m^2
$SQ_{Routing}$	0·17	150	0·58	92	Grid (90 m)	5000 m^2
TOPMODEL	0·09	6	0·47	9 (wetness intervals)	Non-spatial	Non-contiguous areas

Table III. Evapotranspiration and Outflow for 1986 to 1988; Comparison between implicit and explicit routing schemes and landscape partitioning strategies

Method	1986		1987		1988	
	ET (mm)	Outflow (mm)	ET (mm)	Outflow (mm)	ET (mm)	Outflow (mm)
$\mathrm{PR}_{\mathrm{Routing}}$	914	1455	728	861	816	1442
$\mathrm{TR}_{\mathrm{Routing}}$	908	1463	718	873	810	1446
$\mathrm{SQ}_{\mathrm{Routing}}$	913	1452	728	869	815	1437
TOPMODEL	1061	1312	855	844	1083	1133
Observed		1641		979		1539

transmissivities are required for the explicit routing implementation in order to match peak flows. The Nash–Sutcliffe calibration metric used in this study is more sensitive to high flows and thus matching peak flows may occur at the expense of adequately modelling recession periods. In the case of explicit routing, high rates of peak flow decay may also reflect the lack of explicit treatment of baseflow. In TOPMODEL, however, the assumption that the water table follows the shape of the topography may create a limitation in calibrating to fit both peak and recession flow conditions.

The difficulty in matching the pattern of peak flow, recession and low flow periods in both approaches may be related to the calibration of effective conductivity. As noted above, the calibrated hydrological conductivity is typically higher than that recorded for particular soils. This effective value takes into account other processes involved in the transport of water in addition to matric flow through soil pores. In particular, pipe flow and preferential flow paths through root channels, bedrock fractures, etc., are included in this effective conductivity. McDonnell (1990) notes that access to these preferential flow paths, however, may change with soil water content. In this case, calibrated effective conductivity will vary over time. To account for this effect, an extension of the model and calibration procedure to include both matric and preferential flow paths as separate processes would be necessary. In this case the density of macropores across the watershed and as a function of saturation deficit would need to be estimated. Again assumptions could be made based on relationships between macropore density and catenary sequence or soil type. In the current model, the assumption of a temporally constant effective conductivity independent of conditions controlling macropore flow may prevent matching both peak and recession flow periods. Similarly, the assumption that conductivity decays exponentially with depth may not always be valid and may limit the ability of the model to capture all flow dynamics. Modelling of spatially variable profile functions, however, would considerably increase the complexity of the model and the degree of required parameterization.

Both approaches are also sensitive to other sources of error in the model, including error in climate input, vegetation characteristics, snowmelt modelling and errors in measured outflow. As noted above, error in the estimation of vegetation parameters, particularly LAI, may account for the overall (annual) underestimation of outflow response. The inaccurate estimation of snow versus rain events may also account for some of the differences between observed and modelled hydrographs. During low flow periods, small values may be within the precision of weir measurements. There are no available estimates of deeper groundwater flow that may be lost from the catchment and not measured by the weir. These are assumed to be negligible. In addition, the daily time step used in the model means that differences in rainfall intensities are ignored. Seasonal differences in rainfall intensities, i.e. high intensity convective storms during the summer versus low intensity rainfall during winter months, may account for some differences in summer versus winter hydrograph responses. Given the high infiltration capacities associated with humid forest soils, however, these effects are likely to be small.

Explicit versus implicit routing—spatially distributed soil moisture patterns

Differences between implicit and explicit routing approaches are reflected more dramatically by the pattern of soil moisture distribution. The pattern of soil moisture deficit across Watershed 2 is shown in

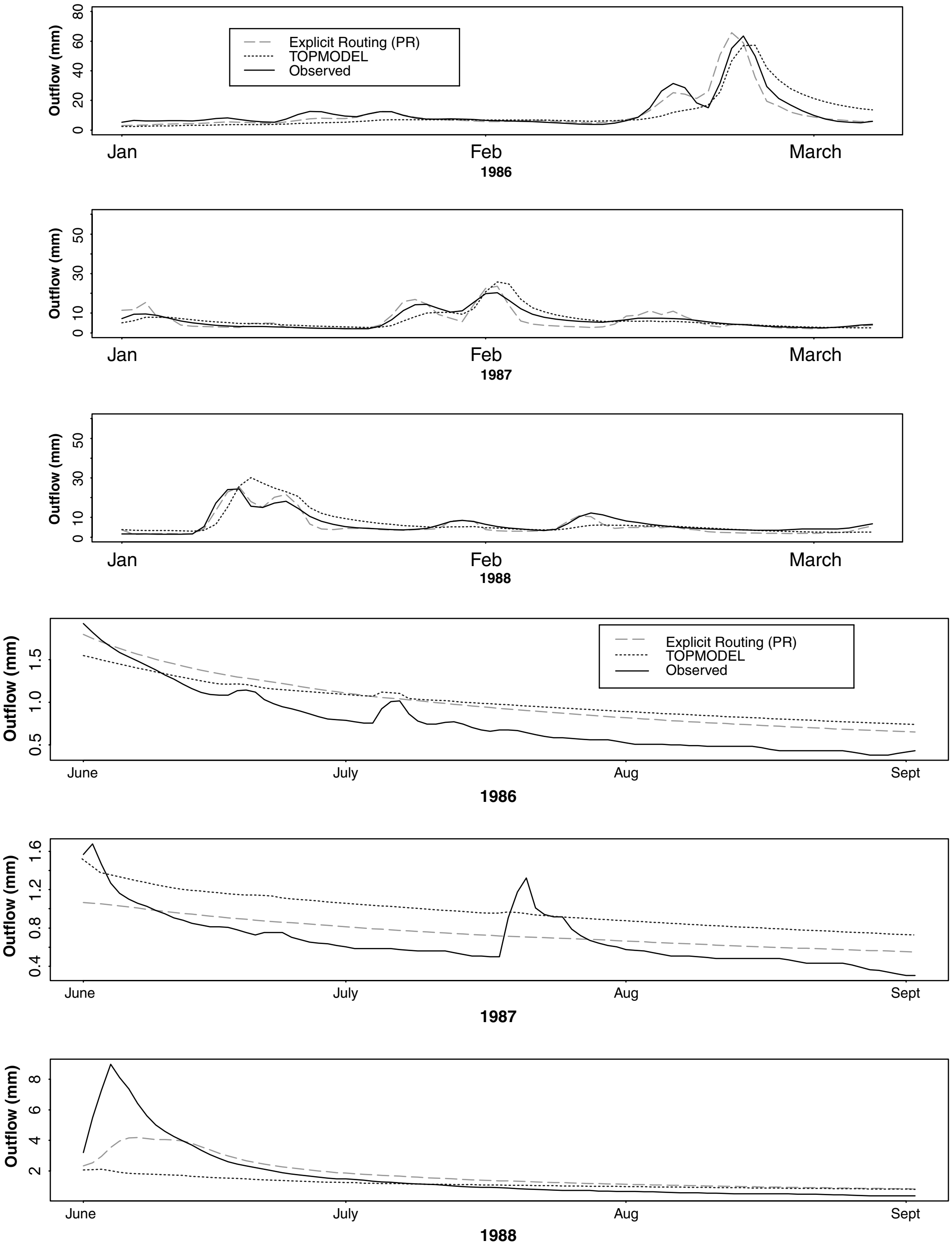


Figure 4. Watershed 2 outflow, comparison between simulations using TOPMODEL (implicit routing), explicit routing and observed outflow for 1986–1988

Table IV. Summer outflow comparison between observed and modelled outflow using TOPMODEL and explicit routing with various landscape partitioning strategies

Method	June–September outflow (mm)			June–September evapotranspiration (mm)		
	1986	1987	1988	1986	1987	1988
$PR_{Routing}$	95	70	164	189	163	238
$TR_{Routing}$	96	71	175	184	156	233
$SQ_{Routing}$	95	69	164	187	163	238
TOPMODEL	95	90	110	124	155	374
Observed	72	63	155			

Figures 5 and 6 for two sample days — 10 January 1988 and 20 August 1988, a wet and dry day respectively. TOPMODEL and the explicit routing patterns match fairly well for the wet day. For the dry day, however, TOPMODEL predicts a significantly different pattern of saturated area for the same amount of generated outflow (0·4 mm). Comparing upland and streamside soil moistures during wet and dry periods depicts a clear and potentially field testable difference between the two approaches. TOPMODEL assumes a constant difference between upland and bottomland areas, whereas routing predicts an increased divergence during drier summer periods.

TOPMODEL is restricted by the assumption that the water table follows the shape of the topography. Routing, on the other hand, permits the water table shape to vary over the watershed and throughout the year. Figure 7 illustrates saturation deficit along a single flowpath, from the ridge to the stream, for both January and August. The pattern of saturation deficit illustrates the invariance in water table shape associated with TOPMODEL and the ability of the explicit routing model to capture the production of local, subcatchment patterns of soil moisture.

Monthly soil moisture patterns, shown in Figure 8, further illustrate the dynamic versus static spatial variation in soil moisture associated with explicit routing and TOPMODEL respectively, for a single watershed within Watershed 2. With explicit routing there is a decreased spatial variability in saturation deficit as the watershed goes from the dry period in August to nearly full saturation in January. TOPMODEL, however, does not capture this pattern to the same extent.

Over the year, these differences in soil moisture patterns between the two approaches result in a higher annual evapotranspiration (Table III) for TOPMODEL. In local areas, however, evapotranspiration from the explicit routing can be higher, owing to the greater variability in soil moisture associated with the explicit routing approach. This suggests that the explicit routing approach offers a significant improvement over the TOPMODEL approach in terms of the ability to capture the seasonal dynamics that control the pattern of soil moisture. These differences influence secondary prediction of ecologically important variables such as evapotranspiration and, by extension, productivity.

SENSITIVITY ANALYSIS

Landscape representation

Using various methods of aggregation can reduce the input information that is required for the pixel-based explicit routing approach. These methods also serve to simplify the landscape representation. As discussed above, a grid-based and a variable-shape partitioning strategy are considered. Neither of the two approaches to aggregation produce significant differences in outflow in comparison with the pixel- (30 grid cell) based approach for calibrated and test years. Aggregation does slightly alter the pattern of soil moisture deficit, although to a lesser degree, than the quasi-spatial TOPMODEL approach. Aggregation smoothes the landscape

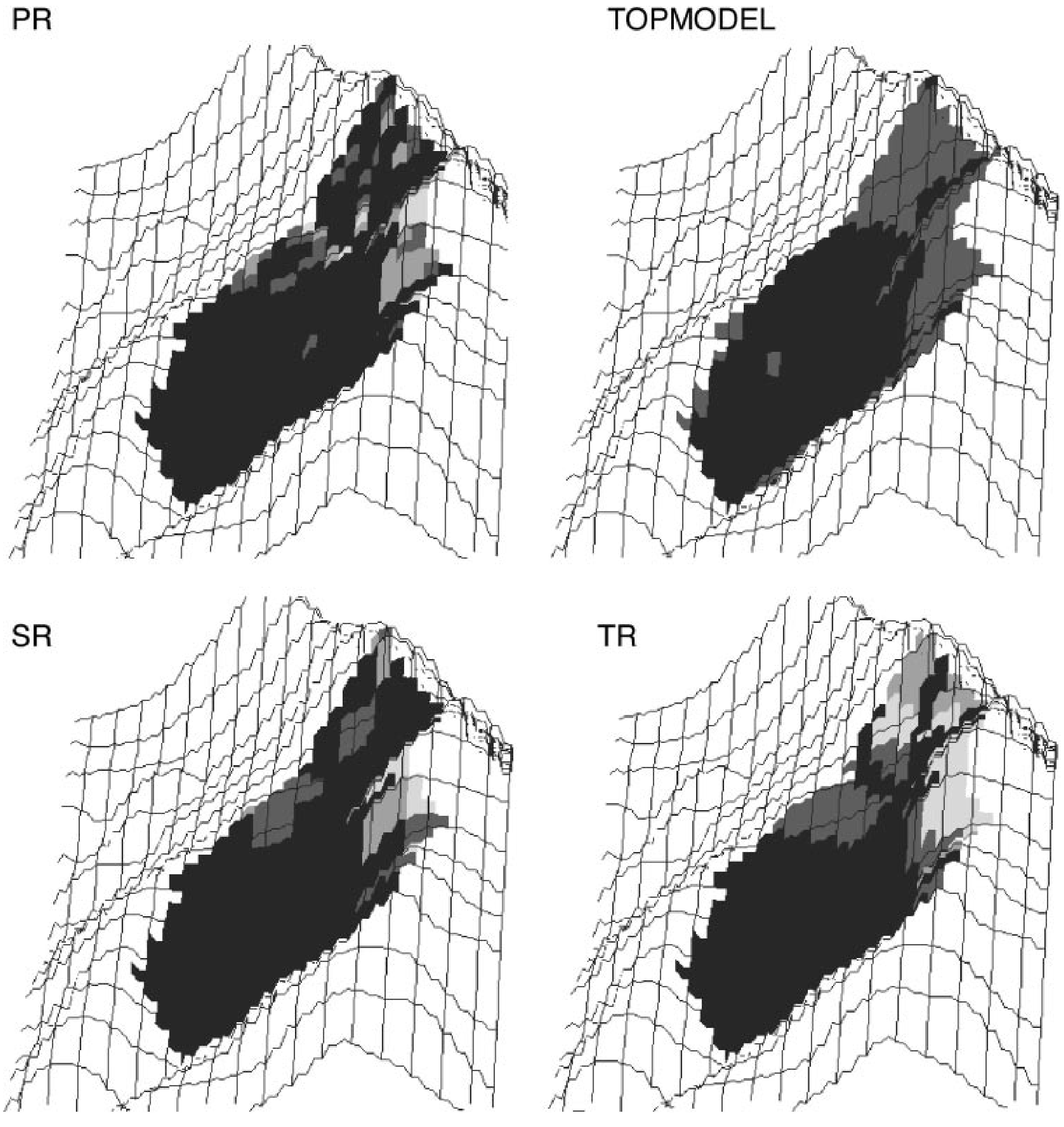


Figure 5. Soil moisture distribution for 10 January 1998—comparison between different routing approaches

topography and consequently can change the pattern of flow. Figures 5 and 6 compare results from the fine resolution pixel-based routing (PR) and the two approaches for reducing resolution (i.e. aggregating by wetness index (TR) versus aggregation by squares (SQ)). The pattern of soil moisture shown in Figures 3 and 4 are inconclusive in terms of the superiority of grid cell versus variable shape aggregation strategies in best matching the finer (30-m pixel) soil moisture patterns. In these simulations, the grid-based approach and the variable shaped partitioning strategies both show some degradation of soil moisture patterns. Both

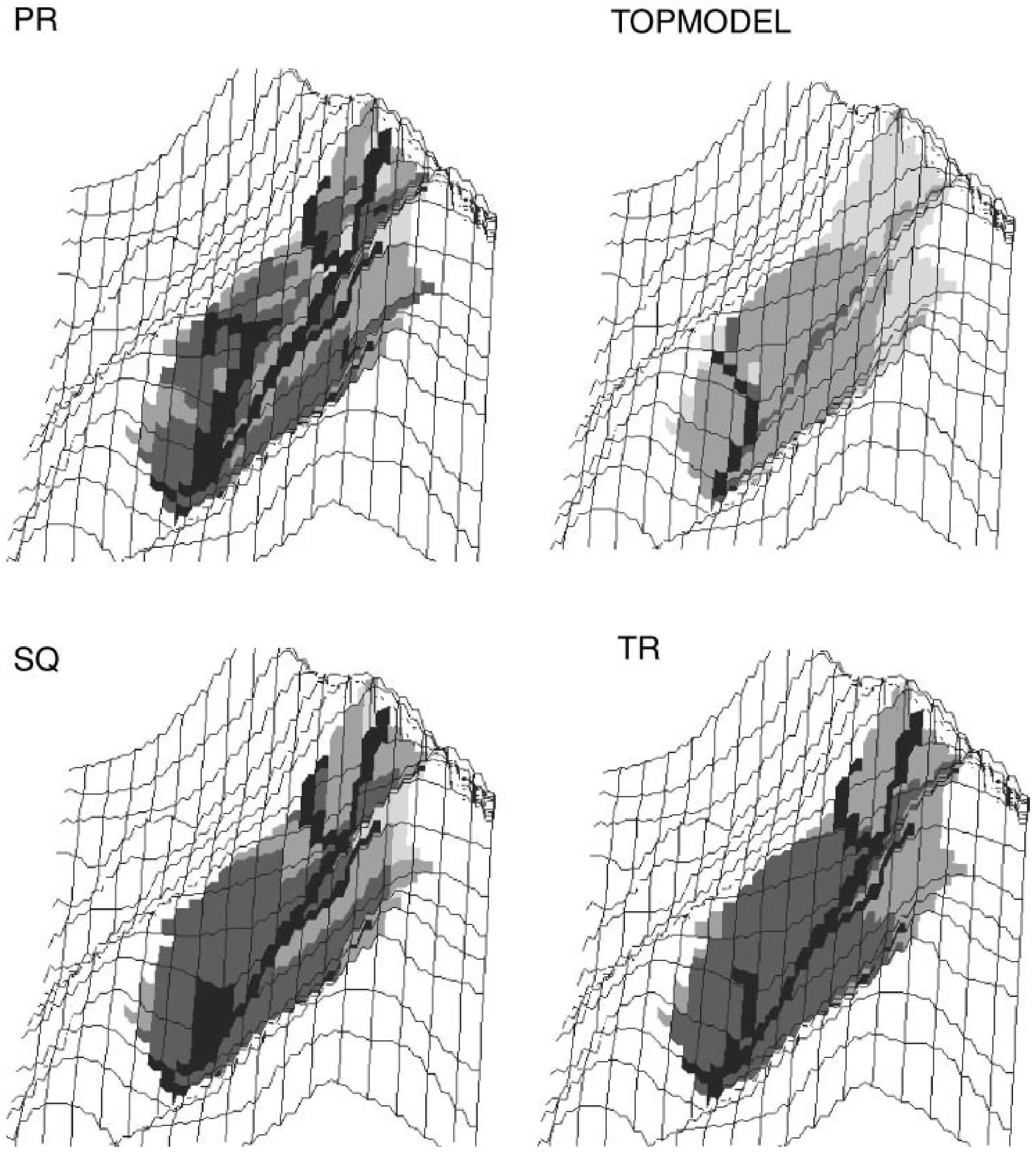


Figure 6. Soil moisture distribution for 20 August 1998—comparison between different routing approaches

methods of aggregation show a loss of finer resolution variability in soil moisture. Similarly in Figure 8 the pattern of wetting and drying illustrated by monthly watershed soil moisture deficit is fairly consistent across the different approaches, with some loss in fine resolution detail for both aggregation approaches. Comparison of ET, shown in Figure 9, shows that the resulting differences in ET are also small, although

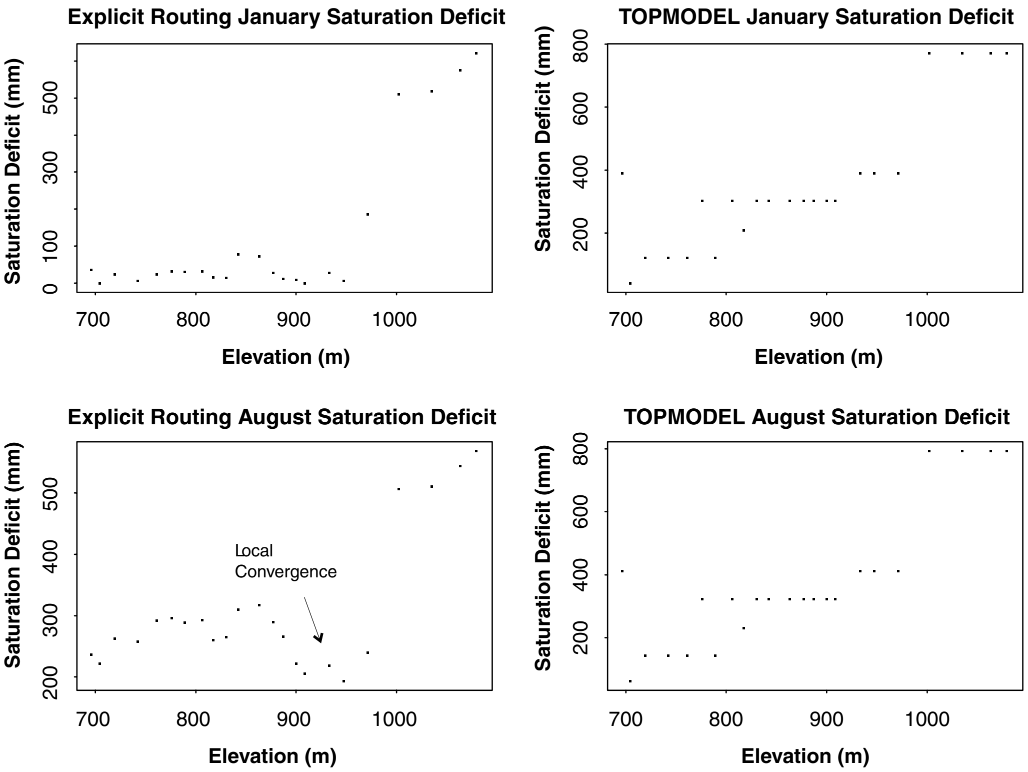


Figure 7. Saturation deficit along a single flow path—from stream to ridge. Comparison between TOPMODEL and explicit routing for January (wet period) and August (dry period)

the aggregate approaches tend to underestimate late summer transpiration reductions. During the summer dry period, larger evapotranspiration rates are associated only with a fairly small area of significantly higher soil moisture. Aggregation results in an effective expansion of these areas, which results in a small net increase in catchment mean evapotranspiration. This effect can be explained by non-linearity in evapotranspiration–soil-moisture relationships. In RHESSys, soil moisture control on evapotranspiration occurs through a non-linear modification of stomatal conductance. When areas of high soil moisture are concentrated in relatively small areas, aggregation can produce relatively greater or smaller net ET, depending on the magnitude and pattern of soil moisture.

Effect of error in DEM and soils

The inclusion of connectivity information in the explicit routing approach permits the pattern of local contributing area to vary seasonally. Including this information, however, may make the explicit routing approach more sensitive to errors in both soil and topographic input information. To explore this issue, the sensitivity of both the explicit routing and TOPMODEL approaches to input information degraded by Gaussian noise is examined.

Sensitivity analysis comprises additional simulations based on (i) a DEM corrupted with Gaussian noise (with zero mean and a standard deviation, σ, equal to 5 m—RMSE estimate for US Geological Survey 30-m DEM is 7·5 m) and (ii) a soil hydraulic conductivity image corrupted with Gaussian noise. For soil hydraulic conductivity two scenarios are considered, high and low noise cases. The high noise case adds noise to the soil hydraulic conductivity image with zero mean and a standard deviation equal to 1/6 of the K_{sat} range (0·5 to 200 m/day) for the watershed studied. Note that variation in K_{sat} in the context of local point variation

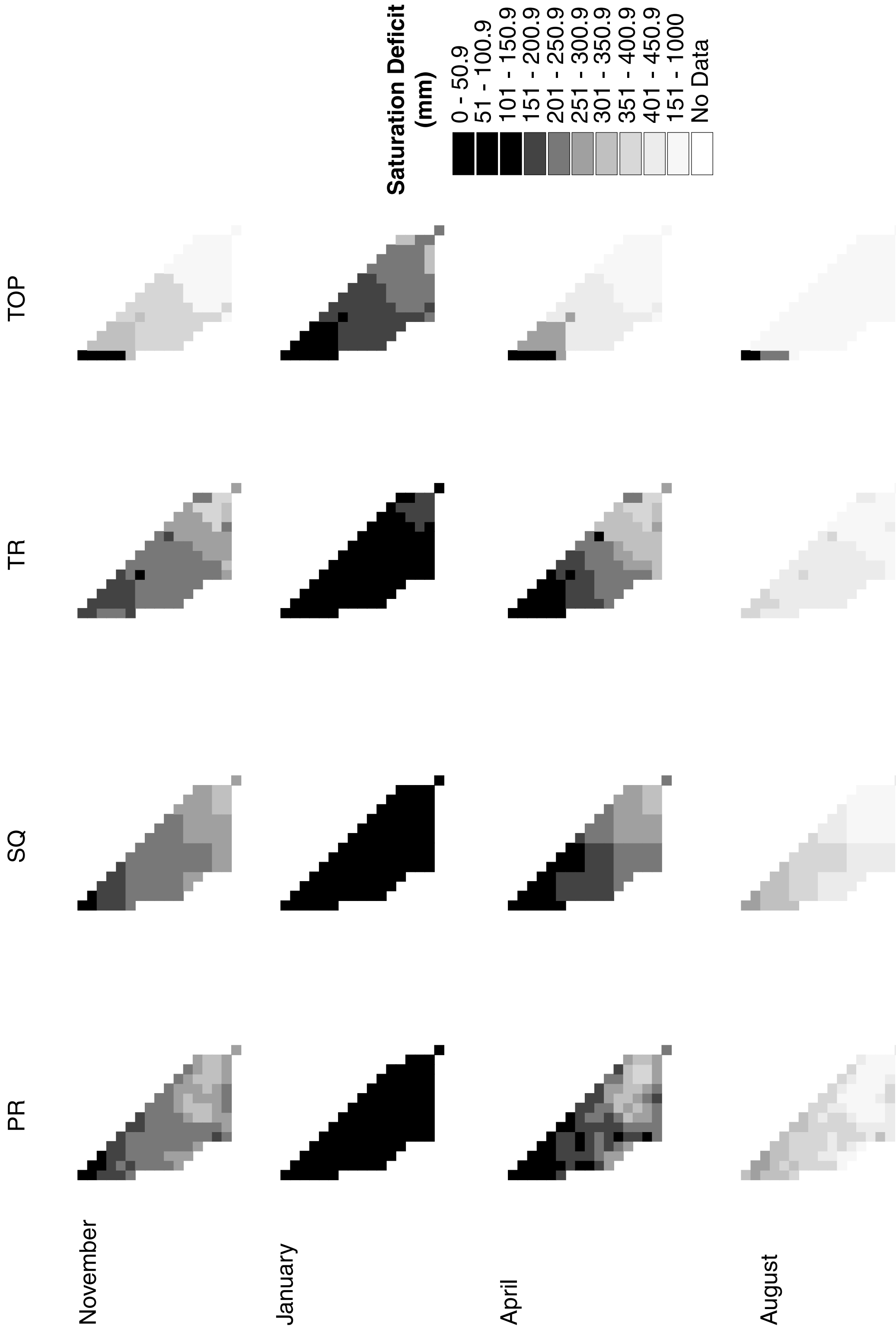


Figure 8. Spatially distributed mean monthly saturation deficits for a small subhillslope in Watershed 2—comparison between different routing methods

Figure 9. Simulated late-summer evapotranspiration—comparison between pixel-based 30-m grid (PR), and aggregation by grids (SQ) and irregular aggregation (PR) landscape partitioning approaches

in hydraulic conductivity can be much higher than these ranges. For larger patches, however, variation in effective and averaged conductivity should be lower. The low noise scenario uses Gaussian noise with standard deviation equal to 1/30 of the K_{sat} range. Use of the corrupted soil hydraulic conductivity image permits testing of the effect of changing the spatial pattern of soil properties on hydrological response and assesses the robustness of the model for applications in other catchments with potentially less information available.

Table V shows the sensitivity to error in input topographic and soil information for the two approaches. Sensitivity is expressed as both a mean daily relative and a mean daily absolute difference in simulated outflow obtained using initial and corrupted input information. Daily relative difference is defined as

$$\sum_{\text{all}_i} \frac{(q_i - q_{\text{obs}_i})}{q_{\text{obs}_i}} \tag{8}$$

where q_{i} is modelled outflow and q_{obs} is observed outflow.

Figure 10 illustrates the daily relative difference between simulations with degraded and original input information for both routing approaches. Both TOPMODEL and the explicit routing approach result in a reasonably small (<5%) mean difference in daily outflow for both the DEM noise and for noise in soil K_{sat} inputs. In terms of absolute error, TOPMODEL is significantly more sensitive to noise in both the input DEM

Table V. Sensitivity of outflow to error in soil and topographic input information for explicit and implicit routing approaches

Modelling approach	Sensitivity to degradation of DEM by Gaussian noise ($\mu = 0$; $\sigma = 5$ m)		Sensitivity to degradation of soil hydraulic conductivity, K_{sat}, by Gaussian noise ($\mu = 0$; $\sigma = 8$ m/day)		Sensitivity to degradation of soil hydraulic conductivity, K_{sat}, by Gaussian noise ($\mu = 0$; $\sigma = 40$ m/day)	
	Mean daily relative difference (%)	Mean daily absolute difference (mm)	Mean daily relative difference (%)	Mean daily absolute difference (mm)	Mean daily relative difference (%)	Mean daily absolute difference (mm)
TOPMODEL	1·4	0·92	1·0	0·63	3·0	1·60
Explicit routing	0·5	0·15	0·1	0·008	2·0	0·11

and input K_{sat} information. In terms of relative error, TOPMODEL and the explicit routing approach show a more similar response, although TOPMODEL is still more sensitive.

However, on a daily basis, explicit routing shows relative differences in outflow for corrupted simulations of up to 20% during the summer, shown in Figure 10. TOPMODEL simulations show differences of up to 150% during the winter. Figure 10 also illustrates that TOPMODEL sensitivity to noise is more pronounced during peak flow events. Explicit routing shows a somewhat greater sensitivity to noise during summer low flow events and a consistent reduction in summer outflow response with the addition of noise for both K_{sat} and DEM inputs. In the case of TOPMODEL, the impacts of Gaussian noise are reflected in changes in the distribution of the wetness index, as shown in Figure 11. Runoff production in TOPMODEL is particularly sensitive to the upper tail of this distribution, which expands with the addition of noise for the DEM and high noise K_{sat} scenarios. For TOPMODEL, changes in the distribution of the wetness index translate local noise into catchment scale changes, because baseflow is computed at the watershed rather than individual patch scale. In the explicit routing approach, the effects of noise remain more local. In the winter, flow is dominated by the catchment-scale topographically driven flow patterns and the effects of noise on the explicit routing approach remain small and unbiased. In summer, however, subcatchment flow networks play a relatively stronger role in runoff production and the addition of noise disrupts the dominant local runoff production mechanisms.

CONCLUSIONS

This study has explored the behaviour and sensitivity of watershed hydrological and ecological processes to different lateral subsurface water flux models and to different landscape representations within these models. Comparison between an explicit routing approach and an implicit routing approach, TOPMODEL, illustrates the implications of the simplification of landscape representation associated with the latter approach. In summary, the following trade-offs exist between the two approaches. TOPMODEL is simpler and computationally more efficient. Specifically by removing information about connectivity and by decreasing the effective modelling resolution, the implicit routing or TOPMODEL approach results in a computationally more efficient approach where the number of modelling units is reduced by more than a factor of 10 and processing time decreases by a similar amount. Even with considerable computational power often available for modelling work, the need for multiple, multiyear simulations for large-scale landscapes, particularly for calibration and scenario development, means that processing efficiency remains an issue. TOPMODEL also does not require information about connectivity and thus potentially can be parameterized with less information. In this study the topographic information used to derive the wetness index distribution came from the same resolution DEM that was used by the explicit routing approach. Franchini *et al.* (1996), however, showed that the effect of scale (of the DEM) used to derive the topographic index distribution can be modelled and potentially

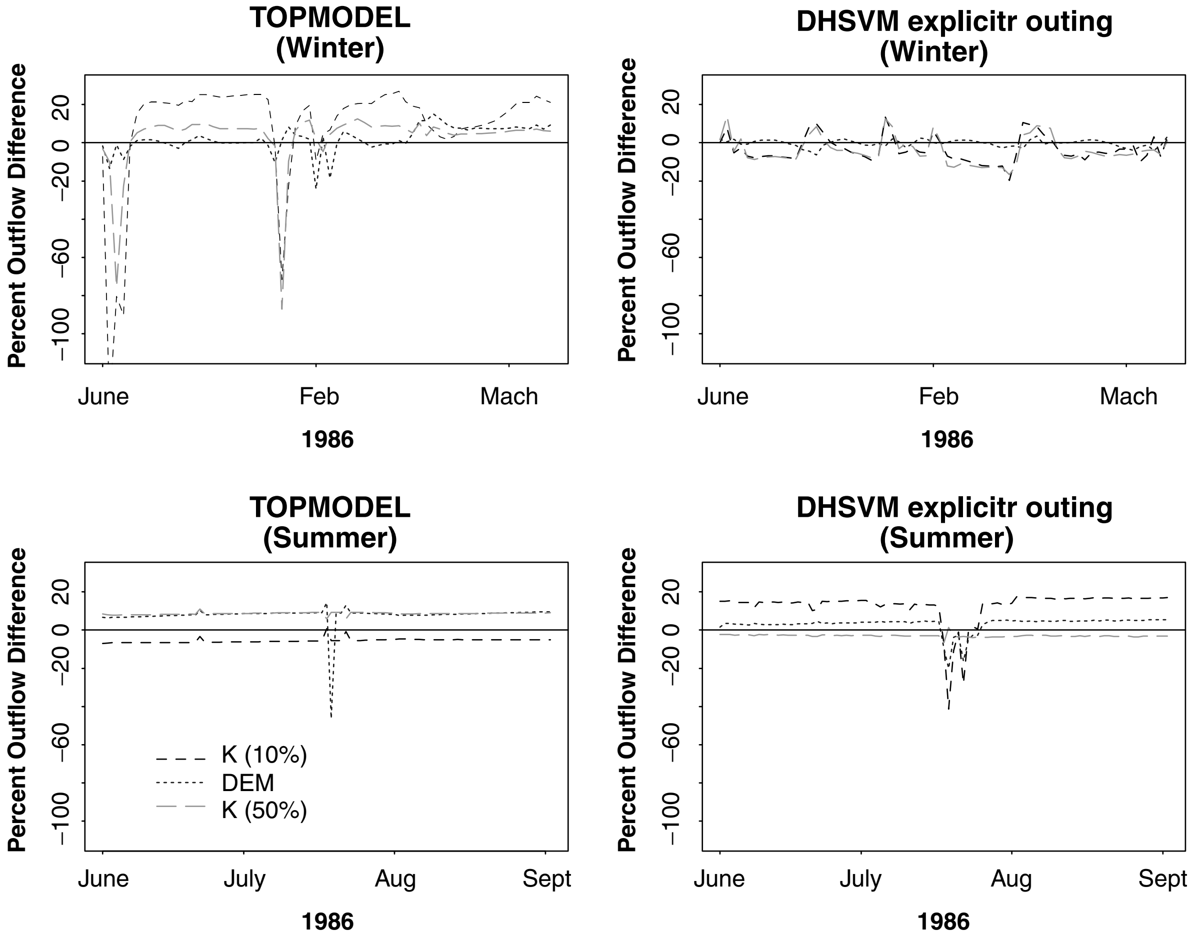


Figure 10. Sensitivity to simulated outflow to error (Gaussian noise) in input DEM and in the spatial pattern of soil hydraulic conductivity, K_{sat}—comparison between TOPMODEL and the explicit routing approach (PR). Random Gaussian noise ($\mu = 0$; $\sigma = 5$ m) is applied to the DEM. Two scenarios of Gaussian noise are applied to the K_{sat} image: low ($\mu = 0$; $\sigma = 8$ m/day) and high ($\mu = 0$; $\sigma = 40$ m/day) noise scenarios

incorporated into the use of coarser resolution information, thus providing a TOPMODEL parameterization that maintains the characteristics of finer scale variability.

This simplicity, which permits analytic solutions to the scaling issues with TOPMODEL, however, also limits the ability of the TOPMODEL approach to capture the local soil moisture pattern. This limitation presents the main drawback of the TOPMODEL or implicit routing approach. Modelling results show significant differences in the spatial and temporal pattern of catchment soil moisture obtained using TOPMODEL and using the explicit routing approach. The explicit routing approach showed an increased spatial variability in catchment soil moisture during summer dry periods. These results correspond with results from field studies such as Grayson *et al.* (1998), Western *et al.* (1999) and Woods *et al.* (1997), which indicate that the control of saturated subsurface throughflow becomes more local during dry periods. The explicit routing model is designed to capture these effects, whereas TOPMODEL, as shown by the more consistent pattern of soil moisture through time, is not able to adequately model the shift towards more local control of distributed soil moisture. Field testing is necessary to confirm this finding. As it is often not feasible to obtain distributed soil moisture measurements for the entire watershed, results from explicit

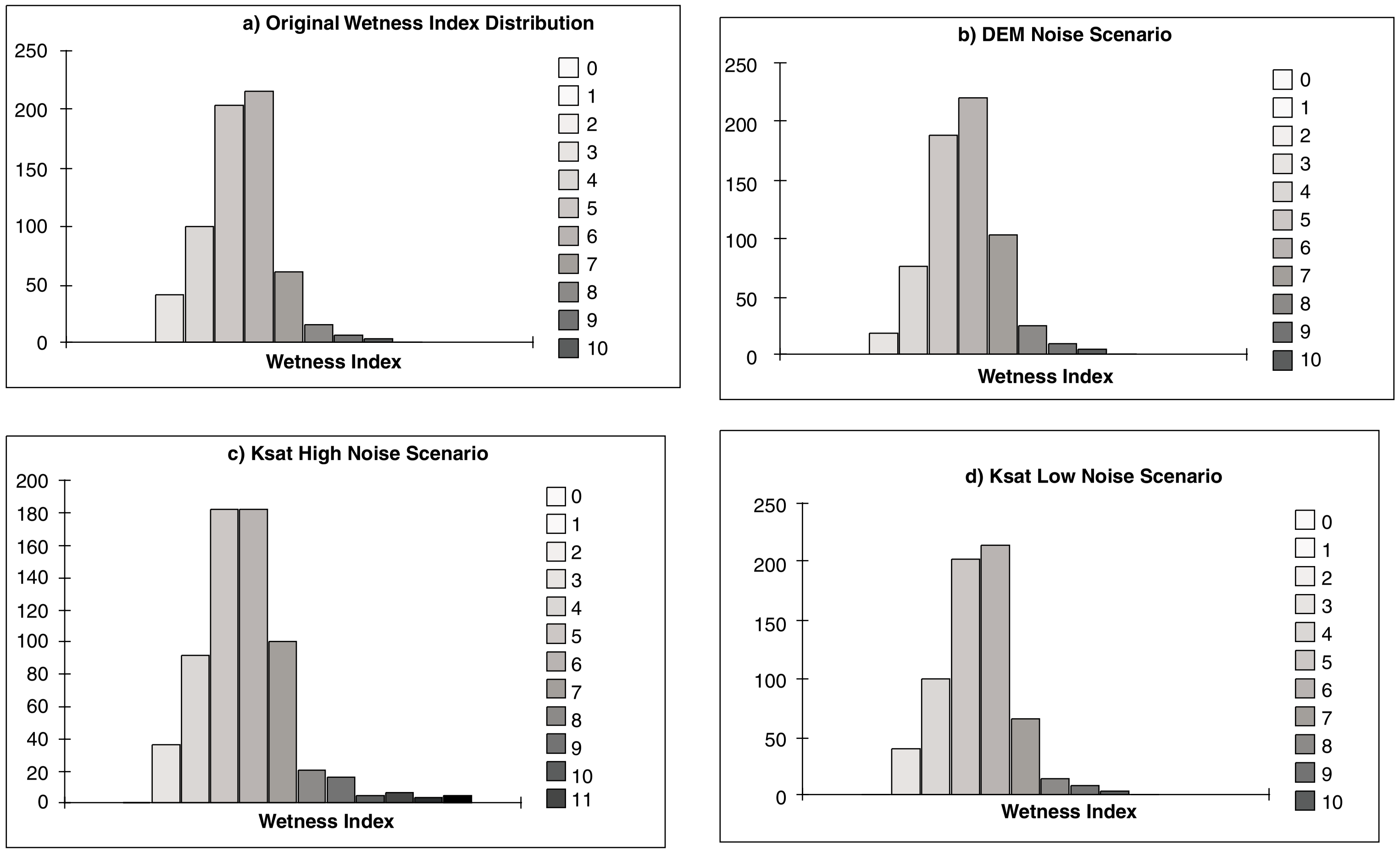


Figure 11. The effect of Gaussian noise in DEM and K_{sat} input information on the distribution of TOPMODEL wetness index. Random Gaussian noise ($\mu = 0$; $\sigma = 5$ m) is applied to the DEM. Two scenarios of Gaussian noise are applied to the K_{sat} image: low ($\mu = 0$; $\sigma = 8$ m/day) and high ($\mu = 0$; $\sigma = 40$ m/day) noise scenarios

routing simulations can be used to select particular sites for informative comparison. Sites should be chosen in both upslope areas that show, for explicit routing simulations, a large seasonal difference in soil moisture and in the areas near to the stream that remain wet into the summer dry season. Measurements from these two contrasting areas then can be used to assess how well each model is able to capture seasonal patterns in soil moisture distribution by comparing relative seasonal changes in soil moisture.

Soil moisture distribution may be important in assessing forest harvesting effects on ecosystem response, particularly productivity, in water-limited areas. The assessment of watershed contributions to stream chemistry is also sensitive to the spatial pattern of soil moisture and saturated areas. For these applications, where spatially distributed soil moisture is important, explicit routing may be the better approach, in spite of the computational costs. The incorporation of a dynamic wetness index distribution into TOPMODEL, as suggested by Barling *et al.* (1993) and Woods *et al.* (1997), may overcome some of these TOPMODEL limitations and provide another alternative. However, these approaches also require additional parameterization.

Results from this paper also highlight the problem of error in input topographic and soil information used for both modelling approaches. Modelling results suggest that TOPMODEL is more sensitive to random noise in both topographic and soil information, particularly during peak flow periods. This again suggests that the explicit routing approaches may be preferable, even in areas where limited data are available. Sensitivity to noise for explicit routing increases during low flow periods. This, however, is related to the more local control of soil moisture dynamics during this period, which is ignored by the TOPMODEL approach. Model responses to organized or spatially correlated noise were not tested.

The sensitivity of both distributed hydrological models to input noise also illustrates the inadequacies of using typically available input information without calibration. This is particularly true in the case of soil parameters, which often must be derived from secondary sources such as soil texture maps. These sensitivities may become important in the application of landscape models to areas without fine resolution information or in uncalibrated applications—a task for which these models are often designed. The low flow sensitivity to local areas observed with the explicit routing also suggests that during low flow periods these models will be particularly sensitive to higher resolution soil parameterization. In addition, in both approaches the dynamics of effective conductivity, which includes the effects of macropore flow and preferential flowpaths, may account for differences in peak, recession and low flow response. Incorporation of a temporally varying model of effective conductivity, as a function of soil moisture, could account for these effects.

Finally, this study found that altering the partitioning strategy used in the explicit routing approach produced relatively smaller changes to the resulting distributed soil moisture and runoff production. In comparison with TOPMODEL, aggregation approaches offer a viable method for increasing the computational efficiency of the explicit routing approach, at least at the small watershed ($1-100$ km^2) scale. The irregular shaped patches based on wetness interval indices, which incorporate hydrological information, did not show a significant improvement or degradation over the similar resolution grid-based approach. There may, however, be other arguments to support the use of the wetness interval strategy for partitioning the landscape because soil and vegetation characteristics also may be organized in this manner. Moore *et al.* (1993) and Band *et al.* (1993) discuss the advantages of incorporating these spatially organized processes into landscape representation. Further work will explore these issues in more detail.

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