To simulate the nutrient loading of Danish coastal waters, river discharge from unmonitored areas must be assessed. In an attempt to identify the most suitable method, for this purpose eight different versions of the three-parameter monthly water balance model “MWB-3” were tested on data from various Danish catchments for the period 1989-97. The model with the highest $R^2$ and the lowest correlation between the model parameters was chosen for subsequent establishment of regression equations between the model parameters and catchment and climate characteristics. The most important explanatory variables of the regressions are soil properties, potential evapotranspiration, groundwater table depth, percentage of wetland area and catchment slope. Mean $R^2$ was 0.82 for the calibration data subset (62 catchments) and 0.79 for the test data subset (22 catchments). Sensitivity tests indicate that the selected model version is more robust for application in catchments dominated by loamy soils than in catchments dominated by sandy soils. Though the MWB-3 model provides a good basis for determining the water balance of Danish catchments at the regional and national levels, modifications and extensions need to be considered for future studies.

Background and Objective of the Study

The European Water Framework Directive focuses on the protection of both inland and coastal waters and on the assessment of the impact of water management measures on runoff, nutrient loads, etc. Each country must ensure that methods are operationally available to estimate discharge at the national level (Council of the Euro-
pean Union 2000). One of the problems facing Denmark in this respect is that discharge and nutrient loading cannot be measured directly but need to be estimated for about 50% of the country due to tidal influences along much of the coastline (Müller-Wohlfeil et al. 2001a). The assessment of eutrophication in Danish coastal waters requires tools operating at least at a monthly time scale to cover seasonal dynamics in line with the monitoring frequency for nutrients in coastal and marine waters, i.e. 2–47 measurements per year (Danish Environmental Protection Agency 2000; Kaas and Markager 1998). In recent years, efforts have been made to describe the dynamics of nutrient loading of Danish coastal waters based on empirical models where riverine discharge has been identified as the most important parameter explaining the variation in nitrogen loading (Larsen 1996). Monthly water balance models are thus needed to provide input to the empirical nitrogen load models. Moreover, a previous study to simulate annual riverine discharge from unmonitored catchments for the whole of Denmark during the period 1989–97 revealed the necessity for monthly models to improve modelling of the variation in annual discharge in areas dominated by loamy soils (Müller-Wohlfeil et al. 2003).

Starting with the work of Thornthwaite (1948) and Thornthwaite and Mather (1955, 1957), monthly water balance models have been developed and are still being used and modified for various climatic and geohydrological conditions (Arnell 1992; Vandewiele et al. 1992; Makhlouf and Michel 1994; Johnson and Curtis 1994; Fernandez et al. 2000).

Monthly water balance models have been compared in a number of reviews (Alley 1984; Vandewiele et al. 1992; Vandewiele and Ni-Lar-Win 1998; Xu and Singh 1998). The general consensus is that 3–5 parameters should be sufficient to enable simulation of monthly river discharge in catchments located in humid regions.

From among the many models described in the literature, MWB-3 (Xu et al. 1996) was chosen to simulate monthly runoff in Denmark for a number of reasons. Firstly, calibration of MWB-3 only requires initial soil moisture and three parameters to be identified. Provided that all climatic input information and the observed specific discharge are available, the three parameters can be identified using the optimization procedure incorporated in the modelling tool. Secondly, MWB-3 is comparatively flexible as to representation of water balance components, thus enabling the user to operationally choose from among eight different model versions. Finally, different derivations of the model have been successfully applied to various catchments differing in climatic and geographical conditions (Vandewiele et al. 1992; Xu 1999; Ni-Lar-Win 1994). Five-parameter versions of the MWB model also exist enabling snow accumulation and thawing to be taken into account. However, preliminary test runs with the five-parameter models revealed that monthly snow accumulation and thawing are of minor importance for most of the catchments and periods selected. Additionally, some of the model parameters were identified as being non-significant, which was normally not the case with the three-parameter model versions.
The main objective of the present study was to assess the ability of MWB-3 to simulate monthly river discharge from unmonitored Danish catchments located in various parts of the country.

**Data and Methods**

**The Modelling Tool**

MWB-3 can be regarded as a flexible modelling tool rather than a unique model. The total water balance Eq. (1) defines how moisture storage ($sm_t$) at month $t$ can be calculated as the difference between the sum of soil moisture storage at month $t-1$ and precipitation ($p_t$) on the one hand, and the sum of actual evapotranspiration ($e_t$) and total runoff ($d_t$) on the other (Xu et al. 1996; Xu 1999). The units of all variables specified in this section are mm.

Water balance equation: 

$$sm_t = sm_{t-1} + p_t - e_t - d_t$$

(1)

The different components considered for the water balance equation are calculated as follows and users may choose between two different alternative equations for the calculation of actual evapotranspiration Eqs. ((2a) and (2b))

Actual Evapotranspiration: 

$$e_t = \min(\omega_t - \exp(-A_1 e_t) - A_2 sm_t, 0) \quad 0 \leq A_1 \leq 1$$

(2a)

Actual evapotranspiration: 

$$e_t = \min(\omega_t (1-\exp(-A_1 e_t)), 0) \quad 0 \leq A$$

(2b)

Total computed runoff: 

$$d_t = s_t + f_t$$

(3)

Slow-flow: 

$$s_t = A_2 (sm_{t-1})^{b_1} \quad 0 \leq A_2, \quad b_1 = 1 \text{ or } 2$$

(4)

Fast-flow: 

$$f_t = A_3 (sm_{t-1})^{b_2} \quad 0 \leq A_3, \quad b_2 = 1 \text{ or } 2$$

(5)

where $e_p_t$ is potential evapotranspiration during month $t$; $\omega_t = p_t + sm_{t-1}$ is the available water; $sm_{t-1} = \max(sm_{t-1}, 0)$ is the available storage with + indicating that this variable never becomes negative and is equal to 0 if $sm_{t-1}$ takes negative values; $n_t = p_t - e_p_t (1-e_p_t)$ is the active precipitation; $A_1$ [-] in (Eq.2a), [mm$^{-1}$] in (Eq.2b), $A_2$ ([month$^{-1}$]) and $A_3$ ([mm$^{-1}$]) are the free model parameters. Xu et al. (1996) define active precipitation as the monthly precipitation minus evapotranspiration, which contributes to the soil moisture storage.

Total runoff can be decomposed into fast-flow ($f$ in Eqs. (3) and (5)) and slow-flow ($s$ in Eqs. (3) and (4)). “Fast-flow” depends on soil moisture storage and active precipitation, while “slow-flow” only depends on soil moisture storage. For both fast-flow and slow-flow, the dependency on soil moisture storage may be assumed to be either linear or non-linear, i.e. either i) $b_1 = b_2 = 1$ or ii) $b_1 = b_2 = 2$ or iii) $b_2 = 1$ and $b_2 = 2$ or iv) $b_2 = 2$ and $b_2 = 1$ in Eqs. (4) and (5). Hence, the runoff components and evapotranspiration can each be described on the basis of two different equations.
Model users may thus choose between eight (2^3) different model versions and need to specify four different free parameters (A_1-A_3 and the initial moisture storage), each of which is related to actual evapotranspiration, fast-flow, slow-flow and the water balance equation, respectively (Table 1).

The input data required for running the model are precipitation and potential evapotranspiration. To calibrate the model, river discharge is needed in addition.

Input Data

Climatic Data – National monthly precipitation data are provided by the Danish Meteorological Institute (DMI) as gridded information (mesh size 10x10 km^2) together with tables suggesting corrections to the original measurements to account for the impact of wind-induced errors, out-splashing and wetting effects on the measurements (Danish Meteorological Institute 1998).

Potential evapotranspiration is also provided by the DMI as gridded information (EP_a; mm day^{-1}) with a mesh size of both 20x20 km^2 and 40x40 km^2. However, these high resolution data have not been available for the entire period 1989–97, thus necessitating the selection of 40x40 km^2 data as input information for the hydrological study. The values were calculated on the basis of a modified Penman-method (Penman 1956) using gridded information on mean daily temperature, relative humidity, wind speed and daily summed global radiation. Global radiation replaces the energy term (Mikkelsen and Olesen 1991).

The magnitude of the precipitation correction factors and the choice of the method for calculating potential evapotranspiration remain as subjects for discussion in Denmark. Recent investigations (Detlefsen and Plauborg 2001) indicate that potential evapotranspiration might be underestimated with the modified Penman equation of Mikkelsen and Olesen (1991).
Other Information on Catchment Properties Considered – Different types of digital soil information were considered for the study, one based on paper maps (scale 1:500,000) related to the topsoil down to depths of 30 cm (Danish Institute of Agricultural Sciences (DIAS) 1996), another representing subsoil conditions to a depth of approx. 1 m (Nielsen et al. 2000, paper map scale 1:200,000). Based on topsoil information for approx. 41,000 locations and additional subsoil information provided as a digital map (scale 1:500,000), Breuning Madsen et al. (1992) suggested a method used additionally in this study to calculate the effective field water capacity (mm) down to depths of 120 cm.

The only digitally available national maps on groundwater potentials (m) and groundwater table depths (m) relative to soil surface are based on data from groundwater table measurements performed during the last few decades. The data are provided as gridded information with a mesh size of 500mx500m² (R. Friborg, personal communication). The Geological Survey of Denmark and Greenland (GEUS) maintains a national database on groundwater abstraction based on records from individual abstractions. However, this is partly incomplete with respect to both geographic coordinates and abstraction data from different subregions.

Information on land use and land cover was extracted from the European CORINE database, adapted to Danish conditions (European Commission 1993).

Mean values of catchment slope and the topographic index (Beven and Kirkby 1979) were derived from a 50 x 50 m² mesh size digital elevation model available from the National Cadastre and Survey (vertical resolution 1 m, based on 5 m isolines). Drainage network density was derived from a digital database of Danish rivers based on a 1:25,000 scale paper map (Nielsen et al. 2000).

Selection of Catchments – The study was partly based on data previously used for the assessment of annual river discharge during the period 1989–99 from a total of 225 Danish catchments of up to 300 km² in size (Müller-Wohlfeil et al. 2003). For many of these catchments, the long-term difference between annual precipitation (corrected for wind-induced errors, out-splashing and wetting effects; Danish Meteorological Institute 1998) and annual potential evapotranspiration may be larger than the observed discharge (i.e. \( \overline{P} \text{ (mm)} - E\overline{P} \text{ (mm)} > \overline{Q} \text{ (mm)} \)). This may be due to:

- systematic errors in the measurements or subsequent data processing of precipitation, discharge or the inputs used to calculate potential evapotranspiration,
- possible problems with the method used to calculate potential evapotranspiration,
- subsurface water loss to coastal areas,
- export of water abstracted from groundwater aquifers and subsequently removed from the catchments

Due to its simplicity, the MWB-3 model – like many other simple models – requires closed water balances, which means in particular that river discharge may neither be smaller than precipitation minus evapotranspiration nor larger than precipitation.
Fig. 1. Location of the 84 catchments considered for model calibration (dark lines indicating catchment boundaries) and validation in Denmark. The boundaries of the catchments used for the model test are grey, while broken lines represents the coastline.

consequence, catchments that could not meet the requirement could not be used for the final identification of model parameters and hence had to be treated separately. Based on an evaluation of all climatic and river discharge input data, regionalization of model parameters was first restricted to those of the 225 catchments used for the annual study (Müller-Wohlfeil et al. 2003) in which the mean annual sum of potential evapotranspiration and observed discharge is greater than the corrected precipitation for the period 1989–97. This data set was supplemented with similar data from a number of catchments larger than 300 km². The restrictive selection of catchments for model calibration and validation means that the approach can only be expected to provide good results for catchments not revealing obvious water balance problems. In problem cases, for instance if the difference between precipitation and
River Discharge from Danish Catchments

evapotranspiration is larger than the observed discharge, modelling will result in discharge values larger than the ones observed. In Denmark, large areas of moraine deposits from the latest glacial period (Weichsel) located immediately east of the main water divide (Fig. 1) are known to receive deep groundwater from areas located west of the main water divide. Based on multivariate analyses, Müller-Wohlfeil et al. (2001c) showed that these catchments could be identified as an outlier cluster with respect to hydrological response. The average annual difference between precipitation minus potential evapotranspiration on the one hand and observed discharge on the other during this period (1989-1997) for the catchments belonging to this cluster was approximately -162 mm. This difference was taken as an approximate threshold value to exclude catchment areas potentially receiving additional deep groundwater from adjacent areas. Hence, catchments with a water balance difference of less than -150 mm were excluded from the present study. This reduced the total number of catchments fulfilling all of the above requirements to 84 partly nested catchments ranging in size from 0.7 km² to 2,602 km² (mean 161 km²). These catchments are located all over the country. However, since the region west of the main water divide was only represented by 2 catchments, it was decided to include both in the calibration (Fig. 1).

Automatic Parameter Estimation for Monitored Catchments

The model parameters for monitored areas were estimated separately for each catchment by ordinary least squares (OLS), which involves solving the minimisation problem:

$$\text{Minimum sum of squares (SSE)} = \min \sum_{i=1}^{n} (y_i - \hat{y}_i(x_i; A))^2$$

where $y_i$ and $\hat{y}_i$ are observed and computed discharge, respectively, and the differences between $y_i$ and $\hat{y}_i$ are called model errors or residuals $\varepsilon_i$, $x_i$ is a vector of inputs (such as rainfall and potential evaporation), and $A$ is a parameter vector about which inference is sought. According to Clarke (1973), the residuals should be mutually uncorrelated and have a zero mean and a constant variance $\sigma^2_i$ (i.e., $E(\varepsilon_i, \varepsilon_{i-k}) = 0$ for all $k \neq 0$; $E(\varepsilon_i^2) = \sigma^2_i$). Moreover, if approximate confidence intervals are to be given for the estimated model parameters, a further assumption must be made about the probability distribution of the residuals that the $\varepsilon_i$ are distributed normally.

The above assumptions need to be tested. A methodology and illustrations for testing the validity of the assumptions when applied to the MWB-3 model are discussed in detail by Xu (2001) and are beyond the scope of the present paper.

In this study, an automatic optimisation method was used and the minimization of SSE (Eq.(6)) was performed using the VA05A computer package (Hopper 1978; Vandewiele et al. 1992). Minimisation of SSE (Eq.(6)) with respect to the parameters $A_i$ results in estimates of $A_i$. Illustrations of this procedure applied can be found in Vandewiele et al. (1992).
Table 2 – Catchment and climatic variables included in the regression analysis. Asterisks indicate that the respective variable is considered as percentage of the total catchment area. The column titled “tested” specifies whether the specific variable has been included in the stepwise regression to identify the initial soil moisture $s_{mi}$ and model parameters $A_1, A_2$ and $A_3$.

<table>
<thead>
<tr>
<th>VARIABLE – explanation</th>
<th>Symbol</th>
<th>Tested</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total catchment area (km²)</td>
<td>Cat</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Urban areas *</td>
<td>$U_r$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Agricultural areas *</td>
<td>$Ag$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Forested and semi-natural area *</td>
<td>$Fo$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Wetland areas *</td>
<td>$We$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Water body areas *</td>
<td>$Wa$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Areas covered by organic soils *</td>
<td>$S_{org}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Areas covered by sandy soils *</td>
<td>$S_{sd}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Areas with sandy sub-soils *</td>
<td>$Sub_{sd}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Areas with clayey sub-soils *</td>
<td>$Sub_{clay}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Effective field water capacity (mm) of the soil 0-120 cm below soil surface</td>
<td>$EFWC$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Mean catchment slope (%)</td>
<td>$Slope$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Slope along the main watercourses (%)</td>
<td>$Catslope$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Mean topographic index (according to Beven and Kirkby, 1979)</td>
<td>$Lnatan\beta$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Mean catchment elevation (m.a.s.l)</td>
<td>$Alt$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Average depth of groundwater table (m)</td>
<td>$GWDav$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Maximum depth of groundwater table (m)</td>
<td>$GWDmax$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Parameter $A_3$</td>
<td>$A_3$</td>
<td>$A_{1-3}$</td>
</tr>
<tr>
<td>Mean annual precipitation during 1989-1997 (mm)</td>
<td>$P_{av_{89-97}}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Mean annual precipitation during the normal period 1961-1990 (mm)</td>
<td>$P_{av_{61-90}}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Maximum monthly precipitation during 1989-1997 (mm)</td>
<td>$P_{max_{m89-97}}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Mean annual potential evapotranspiration during 1989-1997 (mm)</td>
<td>$ETP_{av_{89-97}}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Sum of precipitation during the current and the preceding two months (mm)</td>
<td>$P_{0.3}$</td>
<td>$sm_{i}$</td>
</tr>
<tr>
<td>Sum of potential evapotranspiration during the current and the preceding two months (mm)</td>
<td>$ETP_{0.3}$</td>
<td>$sm_{i}$</td>
</tr>
<tr>
<td>Mean potential evapotranspiration during the normal period 1961-1990 (mm)</td>
<td>$ETP_{av_{89-97}}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Maximum monthly potential evapotranspiration during 1989-1997 (mm)</td>
<td>$ETP_{max_{m89-97}}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Ratio between the annual mean and the monthly maximum potential evapotranspiration during 1989-1997</td>
<td>$\frac{ETP_{av_{89-97}}}{ETP_{max_{m89-97}}}$</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>Season is a class variable, taking one of four levels (1,2,3,4)</td>
<td>Season</td>
<td>$A_{1-3, sm_{i}}$</td>
</tr>
<tr>
<td>If month = January, February or March, then season = 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If month = April, May or June, then season = 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If month = July, August or September, then season = 3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If month = October, November or December, then season = 4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Parameter Estimation for Unmonitored Catchments Based on Regression Equations

Estimation of runoff from the unmonitored part of Denmark as the main objective of the study necessitates a regionalization procedure to estimate the model parameters. In the present study, multiple regression was used to identify the model parameters based on 62 of the 84 catchments, a subset of 22 catchments being saved for testing the regression equations. The equations were identified using stepwise regression to fit the best model to a specified number of variables (SAS 2000). As part of the identification processes performed separately for all parameters, variables were added from the list (Table 2) until the increase of model fit, expressed by the coefficient of multiple determination \( R^2 \) (Eqs. 7a,b,c), became smaller than 1%.

\[
R^2 = 1 - \frac{SSE}{SST}, \quad \text{with } SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad \text{and } SST = \sum_{i=1}^{n} (y_i - \bar{y})^2
\]  

where \( SSE \) is the sum of squared errors, \( SST \) is the total sum of squares, \( y_i \) is the observed runoff for observation \( i \), \( \hat{y}_i \) is the estimated runoff for observation \( i \), and \( \bar{y} \) is the mean observed runoff. This method is identical to using the Nash/Sutcliffe (1970) efficiency criterion.

Results and Discussion

Automatic Calibration of all Model Versions and Selection of the Model for Regionalization

Prior to assessing whether and to what extent model parameter values can be related to physical properties of the catchments, which is a prerequisite if the model is to be applied to unmonitored catchments, a common model had to be selected based on a comparison of the eight different model versions. Due to resource limitations, it was necessary to base the comparison on a subset of 52 of the 84 catchments. The first comparison criterion used was the coefficient of multiple determination. With all model versions, the \( R^2 \) value was equal to or greater than 0.8 (Table 3). Model version 5 was marginally best with respect to the \( R^2 \) statistics.

Another selection criterion used was the possibility of interpreting parameter values in terms of their physical meaning and estimating the respective values from digital data on catchment properties.

Correlation coefficients between the three model parameters \( A_1, A_2 \) and \( A_3 \) were computed separately for each of the eight model versions based on optimised parameter values identified for each of the 52 catchments (Table 4). P-values were specified to assess the significance of the correlations and regressions identified. Assuming that the data are normally distributed, the ratio of the mean square for the regression model to the mean square for error is an “F-statistic”. In case of the regression models, the F-statistic tests the null hypothesis that none of the explana-
### Table 3 - $R^2$ statistics for the eight model versions based on 1989–97 data for 52 catchments.

Stddev: Standard deviation. 95% CL: 95% confidence limits. IQR: Interquartile range.

<table>
<thead>
<tr>
<th>Model version</th>
<th>Mean</th>
<th>Std dev</th>
<th>95% CL of mean</th>
<th>Median</th>
<th>IQR</th>
<th>95% CL of median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>0.841</td>
<td>0.0574</td>
<td>0.825 to 0.857</td>
<td>0.855</td>
<td>0.070</td>
<td>0.833 to 0.861</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.821</td>
<td>0.0629</td>
<td>0.803 to 0.838</td>
<td>0.832</td>
<td>0.056</td>
<td>0.811 to 0.846</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.825</td>
<td>0.1399</td>
<td>0.786 to 0.864</td>
<td>0.851</td>
<td>0.084</td>
<td>0.830 to 0.876</td>
</tr>
<tr>
<td>Model 4</td>
<td>0.800</td>
<td>0.1280</td>
<td>0.764 to 0.836</td>
<td>0.839</td>
<td>0.074</td>
<td>0.820 to 0.854</td>
</tr>
<tr>
<td>Model 5</td>
<td>0.847</td>
<td>0.0544</td>
<td>0.832 to 0.862</td>
<td>0.860</td>
<td>0.052</td>
<td>0.839 to 0.867</td>
</tr>
<tr>
<td>Model 6</td>
<td>0.830</td>
<td>0.0842</td>
<td>0.806 to 0.853</td>
<td>0.842</td>
<td>0.070</td>
<td>0.826 to 0.860</td>
</tr>
<tr>
<td>Model 7</td>
<td>0.846</td>
<td>0.0668</td>
<td>0.828 to 0.865</td>
<td>0.856</td>
<td>0.083</td>
<td>0.836 to 0.877</td>
</tr>
<tr>
<td>Model 8</td>
<td>0.829</td>
<td>0.1117</td>
<td>0.798 to 0.860</td>
<td>0.852</td>
<td>0.074</td>
<td>0.828 to 0.869</td>
</tr>
<tr>
<td>Average</td>
<td>0.830</td>
<td>0.1117</td>
<td>0.798 to 0.860</td>
<td>0.852</td>
<td>0.074</td>
<td>0.828 to 0.869</td>
</tr>
</tbody>
</table>

### Table 4 - Correlation coefficients between the model parameters $A_1$, $A_2$ and $A_3$ for each model version generated globally from the calibration results for a set of 52 catchments. The p-values specified in columns 4 to 6 are a measure for the significance of the correlations. Small p-values indicate that the model is significant in explaining the variation in the dependent variable, e.g. a p-value of 0.0001 indicates that a given correlation is significant at the 99.999% confidence level.

<table>
<thead>
<tr>
<th>Model version</th>
<th>$A_1$ vs $A_2$</th>
<th>$A_1$ vs $A_3$</th>
<th>$A_2$ vs $A_3$</th>
<th>$p_{A_1}$ vs $A_2$</th>
<th>$p_{A_1}$ vs $A_3$</th>
<th>$p_{A_2}$ vs $A_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>0.41</td>
<td>-0.70</td>
<td>-0.10</td>
<td>0.0034</td>
<td>&lt;.0001</td>
<td>0.513</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.36</td>
<td>-0.76</td>
<td>-0.25</td>
<td>0.0111</td>
<td>&lt;.0001</td>
<td>0.0809</td>
</tr>
<tr>
<td>Model 3</td>
<td>-0.72</td>
<td>-0.78</td>
<td>0.92</td>
<td>&lt;.0001</td>
<td>&lt;.0001</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Model 4</td>
<td>-0.71</td>
<td>-0.80</td>
<td>0.91</td>
<td>&lt;.0001</td>
<td>&lt;.0001</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Model 5</td>
<td>-0.14</td>
<td>0.92</td>
<td>0.04</td>
<td>0.3421</td>
<td>&lt;.0001</td>
<td>0.7909</td>
</tr>
<tr>
<td>Model 6</td>
<td>-0.20</td>
<td>0.90</td>
<td>-0.15</td>
<td>0.1545</td>
<td>&lt;.0001</td>
<td>0.2931</td>
</tr>
<tr>
<td>Model 7</td>
<td>0.84</td>
<td>0.92</td>
<td>0.92</td>
<td>&lt;.0001</td>
<td>&lt;.0001</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Model 8</td>
<td>0.84</td>
<td>0.82</td>
<td>0.81</td>
<td>&lt;.0001</td>
<td>&lt;.0001</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

### Table 5 - Optimised parameter values for model 5 based on calibration data on 62 catchments. The per cent coefficient of variation is defined as $CV_p=100(\text{stddev/mean})$. Note that the means, stddev, minimum and maximum values are scaled, i.e. multiplied by 1000.

<table>
<thead>
<tr>
<th>Variable [unit]</th>
<th>Mean</th>
<th>Stddev</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Skewness</th>
<th>CVp</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_1$ [mm$^{-1}$]</td>
<td>12.95</td>
<td>12.07</td>
<td>0.51</td>
<td>68.11</td>
<td>1.99</td>
<td>93.21</td>
</tr>
<tr>
<td>$A_2$ [month$^{-1}$]</td>
<td>35.82</td>
<td>18.42</td>
<td>6.32</td>
<td>95.19</td>
<td>0.96</td>
<td>51.42</td>
</tr>
<tr>
<td>$A_3$ [mm$^{-1}$]</td>
<td>1.60</td>
<td>1.04</td>
<td>0.01</td>
<td>3.89</td>
<td>0.15</td>
<td>65.02</td>
</tr>
</tbody>
</table>
River Discharge from Danish Catchments

tory variables have any effect. The p-value (probability value or observed significance level) is the probability of obtaining a statistic greater than the computed F-statistic when the null hypothesis is true. Small p-values indicate that the null hypothesis can be rejected.

When interpreting Table 4 one has to remember that evapotranspiration decreases with increasing $A_1$ for the first four model versions, but increases with increasing $A_1$ for model versions 5, 6, 7 and 8. A particularly strong correlation exists between $A_1$ and $A_3$, which are the factors regulating actual evapotranspiration and fast-flow, respectively. This may be explained by the fact that catchments dominated by a high percentage of fast-flow are more likely to be exposed to higher evapotranspiration enhanced by moist soil conditions. Loamy and organic soils or shallow groundwater tables may dominate many catchments of this type. The occurrence of loamy soils may be associated with the amplification of fast runoff due to lower permeability and the existence of tile drainage networks.

The correlation between the parameter $A_2$ and the other two parameters is generally lower (average 0.5), but still very high in those cases (model versions 3, 4, 7 and 8) where the actual soil moisture storage is considered to contribute non-linearly to slow-flow. When $A_2$ and $A_3$ are strongly correlated, the correlation of $A_2$ to soil properties is either very weak or doubtful since it cannot be assumed that both fast-flow and slow-flow runoff are strongly and positively correlated with percentage of area covered by loamy soils. These model versions (versions 3, 4, 7 and 8) thus had to be eliminated as suitable models. Generally, $A_2$ and $A_3$ are particularly strongly correlated in catchments located on sandy soils in Jutland, where the flow response is generally more delayed and less variable, and where differences between flow components may be more difficult to detect than on the loamy soil catchments of the Danish islands. Among the remaining model versions it was difficult to relate more than one parameter ($A_3$) to the digitally available catchment properties in cases where the evapotranspiration Eq. (2a) was used (model versions 1 and 2). The only difference between the remaining two model versions, i.e. 5 and 6, is the way soil water storage is considered for the calculation of fast-flow. It turned out to be easier to correlate $A_3$ to digital catchment properties when both fast-flow and slow-flow were based on linear storage (model version 5). It was also this model version that yielded the highest $R^2$. The concept of linear storage for simulation of subsurface and groundwater flow is not uncommon, not even for conceptual models operating at a daily time scale such as the Stanford watershed model (Crawford and Linsley 1966), NAM (Nielsen and Hansen 1973), HBV (Bergström 1995), PRMS (Leavesly and Stannard 1995) and the UBC watershed model (Quick 1995). Statistics of parameter values for the selected model 5 are presented in Table 5.

According to the assessment of approximately 3,750 observations of monthly river discharge from 46 catchments for the period 1992 to 1997, both the absolute and the root mean squared difference between observed and computed river discharge increase with flow. However, the correlation coefficient, expressed as $R^2$-
values, between river discharge and the differences between observed and computed river discharge is not higher than 0.09 and 0.24 for the absolute and the root mean squared differences, respectively, if the values are considered in mm, and the $R^2$-values are even smaller (approximately 0.04) if the differences are considered as percentages of observed river discharge.

With respect to disparities in observed versus computed runoff between years with different runoff regimes, it can be concluded that in years with high mean river discharge the differences in mm are normally higher than in years with lower mean river discharge. However, the medians of the percentage difference reveal no correlation with river discharge.

**Regression Equations Established for the Selected Model Version 5**

The establishment of the regression equations involved transformation of the response variables $A_1$ and $A_3$ following the suggestions of a maximum likelihood analysis performed to avoid non-linearity and a heteroscedastic relationship between the explanatory and the response variables. Any retransformation of the response variables, which is required after the linearised model has been fitted, needs to be performed in a bias-reducing manner (Miller 1984; Koch and Smillie 1987). Let $Y$ be the response variable, $\beta_0$ the intercept, $\beta_1$ a parameter of the regression model, $X$ a variable and $\varepsilon$ a random error. In cases where a square root transformation is most appropriate, i.e. $(Y)^{0.5} = \beta_0 + \beta_1 X + \varepsilon$, the low-bias estimator is equal to $\hat{E}(Y) = (\beta_0 + \beta_1 X)^2 + \varepsilon^2$, whereas the estimator for the logarithmic transformation of the response function, i.e. $\ln(Y) = \beta_0 + \beta_1 X + \varepsilon$, becomes $\hat{E}(Y) = \exp(\beta_0 + \beta_1 X + \exp(0.5\varepsilon^2))$.

The best regression equations found between the parameters of model 5 and different variables considered are:

$$A_1 = \exp(-16.281-(0.023 S_{sd})-(0.034 GWDAv)+(3.096\frac{ETP_{av,89-97}}{ETP_{av,89-97}})) \exp(0.141)$$

$R^2 = 0.80, \ n = 62$

$$A_3 = (0.0069-(0.0004 S_{dS})) + (1.96E-04 EFWC))^2 + 6048E-05$$

$R^2 = 0.75, \ n = 62$

$$A_2(\text{Jutland}) = 0.554 + (22.018 A_3) - (0.001 ETP_{av,89-97}) + (0.0051 We)$$

$R^2 = 0.84, \ n = 26$

$$A_2(\text{islands}) = 0.0114 + (5.57E-03 \ We) + (4.70E-04 Sub_{sd}) + (0.0124 slope) - (0.0013 GWDAv)$$

$R^2 = 0.65, \ n = 34$

$$s_{m} = 4.342352330 + \beta_{season} + P_{0.3} + ETP_{0.3} + (0.0151 S_{sd}) - (0.0157 S_{org})$$

$R^2 = 0.61, \ n= 3,456 \ monthly \ observations$
River Discharge from Danish Catchments

$sm_i$ is the initial soil water storage, which needs to be specified for the first time step when running the model. The value of parameter $\beta$ of the class variable season (Table 2) varies according to the month of the year (-0.029 for January to March (level =1), 0.227 for April to June (level =2), 0.049 for July to September (level =3), 0 for October to December (level =4)).

The p-values for all regression models were at least $< 0.01$, indicating strong statistical significance. Individual p-values for each variable considered for the regression equations established for the three parameters $A_1, A_2$ and $A_3$ are specified in Table 6.

Although the catchment areas considered for the model calibration vary between 0.7 and 2,600 km$^2$, no scale dependency has been detected. There was only a very small correlation coefficient with low significance between the catchment area and the model parameters. As soon as other important variables, such as for instance soil texture, were included in a regression model, catchment size became insignificant. Similarly, no correlation exists between the model fit ($R^2$) and catchment size. Hence, no scaling effects have to be considered.

Parameter $A_1$ is negatively correlated with the percentage of sandy soils and is hence positively correlated with the complementary soil type categories, loamy and organic soils. This is due to the fact that precipitation on areas covered by sandy soils is more likely to percolate to the groundwater compared to soils with finer texture and high effective field capacity. As potential evapotranspiration is positively correlated with $A_1$, it is considered twice for the calculation of actual evapotranspiration, both as monthly values and by its longer-term mean when applying the regression equation. This may provide a basis for reconsideration of the equation used to calculate actual evapotranspiration aimed at removing the free parameter $A_1$ and thereby decreasing the uncertainty. Moreover, like many other simple water balance approaches (e.g., Evans and Jakeman 1998; Moussavi et al. 1989; Xiong and Guo 1999) MWB-3 currently considers only one single subsurface storage component in order to keep the number of model parameters to be calibrated at a minimum, since a reduced number of parameters may increase the information content per parameter and potentially allow for a more accurate determination of the parameter and a more reliable correlation of the values obtained with catchment characteristics (Dooge 1977). This restriction is problematic in areas dominated by deep sandy soils, where actual evapotranspiration would be reduced considerably in very dry periods, when deep subsurface storages are not available for evapotranspiration.

Much of the variation in $A_3$, the parameter enhancing fast-flow, can be explained by soil conditions. For the same reason $A_3$ is positively correlated with a decreasing percentage of sandy topsoils due to the fact that the effective field capacity increases with an increasing percentage of loamy and organic topsoils. It is important to note that the explanatory variables are not correlated, but rather provide complementary information.

Estimation of parameter values was found to be more difficult for $A_2$, which
Table 6 – Parameter statistics for catchment variables, resulting from a cross-validation estimation of the regression equation used to estimate the model parameters $A_1$, $A_2$ and $A_3$ to be used with model 5. The upper and lower CIs are the 95% confidence intervals of the regression equations applied in the present study. CVp and RMS CVp are the percent coefficient of variation (see table 5) and the root mean squared value of the percent coefficient of variation (i.e. $\sqrt{CV_p^2}$), respectively. Note and all values printed using italic fonts are scaled, i.e. multiplied by 1000.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Max.</th>
<th>CI upper 95%</th>
<th>Min.</th>
<th>CI lower 95%</th>
<th>Stddev</th>
<th>CVp</th>
<th>RMS CVp</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_1$: $S_{sd}$</td>
<td>-23.40</td>
<td>-22.01</td>
<td>-19.10</td>
<td>-24.44</td>
<td>-27.60</td>
<td>0.32</td>
<td>-1.35</td>
<td>1.35</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$A_1$: $\frac{ETP_{av_{90-97}}}{ETP_{max_{90-97}}}$</td>
<td>3.0795</td>
<td>3.5809</td>
<td>4.7965</td>
<td>2.84489</td>
<td>1.3768</td>
<td>0.10122</td>
<td>3.29</td>
<td>3.29</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$A_1$: $GWD_{av}$</td>
<td>-33.50</td>
<td>-25.30</td>
<td>-9.60</td>
<td>-43.09</td>
<td>-57.20</td>
<td>2.00</td>
<td>5.87</td>
<td>5.87</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$A_2$: Islands: We</td>
<td>5.43</td>
<td>6.68</td>
<td>9.30</td>
<td>1.73</td>
<td>1.60</td>
<td>0.69</td>
<td>12.75</td>
<td>12.75</td>
<td>0.0065</td>
</tr>
<tr>
<td>$A_2$: Islands: $Sub_{sd}$</td>
<td>0.47</td>
<td>0.53</td>
<td>0.60</td>
<td>0.35</td>
<td>0.60</td>
<td>0.02</td>
<td>5.07</td>
<td>5.07</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$A_2$: Island: $GWD_{av}$</td>
<td>-1.29</td>
<td>-0.99</td>
<td>-0.40</td>
<td>-1.46</td>
<td>-0.40</td>
<td>0.07</td>
<td>5.60</td>
<td>5.60</td>
<td>0.0075</td>
</tr>
<tr>
<td>$A_2$: Islands: $Slope$</td>
<td>12.37</td>
<td>13.73</td>
<td>21.60</td>
<td>10.90</td>
<td>3.20</td>
<td>0.66</td>
<td>5.31</td>
<td>5.31</td>
<td>0.0100</td>
</tr>
<tr>
<td>$A_2$: Jutland: $ETP_{av_{90-97}}$</td>
<td>-1.00</td>
<td>-0.93</td>
<td>-0.60</td>
<td>-1.09</td>
<td>-1.40</td>
<td>0.03</td>
<td>3.28</td>
<td>3.28</td>
<td>0.0001</td>
</tr>
<tr>
<td>$A_2$: Jutland: $A_3$</td>
<td>22.01</td>
<td>23.24</td>
<td>26.25</td>
<td>21.15</td>
<td>17.79</td>
<td>0.39</td>
<td>1.78</td>
<td>1.78</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$A_2$: Jutland: We</td>
<td>5.07</td>
<td>5.39</td>
<td>8.00</td>
<td>4.75</td>
<td>2.20</td>
<td>0.16</td>
<td>3.06</td>
<td>3.06</td>
<td>0.0038</td>
</tr>
<tr>
<td>$A_3$: $EFWC$</td>
<td>0.20</td>
<td>0.22</td>
<td>0.10</td>
<td>0.17</td>
<td>0.30</td>
<td>0.01</td>
<td>2.90</td>
<td>2.90</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$A_3$: $S_{sd}$</td>
<td>-0.36</td>
<td>-0.34</td>
<td>-0.30</td>
<td>-0.37</td>
<td>-0.40</td>
<td>0.00</td>
<td>-1.08</td>
<td>1.08</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.51</td>
<td>4.10</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
required subdivision of the calibration data set into a mainland data set (i.e. Jutland) and a data set for the island part of Denmark (Islands). For Jutland, $A_2$ is positively correlated with $A_3$ and wetland areas, and negatively correlated with evapotranspiration. For the islands, $A_2$ can be parameterized without using information on any of the other parameters, $A_2$ increasing with percentage wetlands, sandy subsoils and average catchment slope, and decreasing with average depths of the groundwater table. Some of the relationships found for parameter $A_2$ could be assumed to apply also to the fast-flow parameter $A_3$, such as percentage of wetland areas. The occurrence of wetlands reflects long-term moist conditions. These may be associated with both local soil and topographic conditions but normally relate to lowlands and riparian areas. Müller-Wohlfeil et al. (2003) have shown that relief properties (slope) are positively correlated with flow. An explanation could be that the spatial resolution of precipitation information is relatively coarse (10x10 km²), while the digital elevation model has a mesh size of (50x50 m²). The latter may therefore provide additional information on orographically driven precipitation conditions not included in the precipitation grid.

**Influence of Initial Soil Moisture Storage**

Knowledge about the initial soil moisture ($s_{mi}$) is required as an initial input to the model. Test simulation runs were performed on catchment 130005 (see Fig. 1), which is located in mainland Denmark on sandy soils where groundwater runoff prevails. For a given situation, the initial soil moisture was varied between 100% and 10% (10% intervals) of optimised storage values identified in advance. It was found that after a two year running-in period, the runoff size had become almost independent of initial soil moisture. The effect of inaccurate specification of initial soil moisture conditions will be even less for catchments where total runoff is dominated by fast-flow. Thus, the model is robust enough to identify the virtual soil moisture storage if a running-in period of 2 years is provided as model input in advance. Optimized initial soil moisture conditions were therefore used throughout the whole study based on the assumption that it might always be possible to start running the model two years prior to the period of interest since climatic data are available for the two-year running-in period.

**Testing the Model on Unmonitored Catchments**

The regression equations, excepting the one for estimating initial soil moisture storage, were then applied to a subset of 22 geographically well-distributed catchments (Fig. 1). The overall results are presented in Table 7. The difference between the calibration data sets and the test data in terms of mean $R^2$ is small (0.82 compared to 0.79), but larger with respect to model residuals expressed as average error and average root mean square error (RMSE, see Table 7). These values are of the order of magnitude found previously with the MWB-3 model (Xu 1999; Vandewiele and Elias 1995). Given an uncertainty of 5–10% in observed annual runoff, this test
Fig. 2. Observed total river discharge (d-obs) versus simulated total river discharge (d-sim), simulated fast-flow runoff (f-sim) and simulated slow-flow (s-sim) for the catchments 550018 (a), 100006 (b) and 580023 (c).
River Discharge from Danish Catchments

Table 7 - Modelling results based on automatic calibration of 62 catchments compared to results for 22 test catchments based on the application of parameters derived from the regression equations. In all cases model 5 was applied. The average error (%) is defined as 
$$100 \frac{1}{n} \sum_{1}^{n} |\frac{Q_{\text{obs},t} - Q_{\text{sim},t}}{Q_{\text{obs},t}}|$$
and avg. RMSE (%) is defined as 
$$100 \sqrt{\frac{1}{n} \sum_{1}^{n} \left(\frac{Q_{\text{obs},t} - Q_{\text{sim},t}}{Q_{\text{obs},t}}\right)^2}$$
where $Q_{\text{obs}}$ and $Q_{\text{sim}}$ are monitored and simulated river discharge and $n$ is the number of observations.

<table>
<thead>
<tr>
<th>Data set</th>
<th>n</th>
<th>Mean R²</th>
<th>Max. R²</th>
<th>Min. R²</th>
<th>Average error (%)</th>
<th>Average RMSE (%)</th>
<th>Max. RMSE %</th>
<th>Min RMSE %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>62</td>
<td>0.82</td>
<td>0.94</td>
<td>0.45</td>
<td>3.77</td>
<td>5.24</td>
<td>22.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Test data</td>
<td>22</td>
<td>0.79</td>
<td>0.91</td>
<td>0.64</td>
<td>-6.18</td>
<td>10.72</td>
<td>20.88</td>
<td>3.24</td>
</tr>
</tbody>
</table>

suggests that the model is capable of estimating monthly runoff for unmonitored catchments within an acceptable margin of error.

Figs. 2a,b,c shows the difference between observed and computed river discharge during the years 1992-1997 for three different test catchments, one (100006, model fit $R^2=0.77$) located in the sandy parts of Northern-Jutland, the other two (550018, $R^2=0.90; 580023, R^2=0.70$) representing typical runoff patterns from island catchments where loamy soils prevail (Fig. 1).

Model Sensitivity and Uncertainties Involved

A number of model uncertainties exist that can be only partly quantified. The first source of uncertainty is related to the quality of input data. Methods to derive climatic input data, particularly potential evapotranspiration, need to be compared. Xu and Vandewiele (1995) found that the random errors in input data adversely affect model performance, and significantly so when the random errors in precipitation data exceed 15%. Systematic errors, which seem to be more likely in the case of the present study, significantly affect model parameter values and hence estimation of the other water balance terms. According to Vejen et al. (1999), the total error of the method used to correct measured precipitation does not exceed 8%. The observed discharge may also be subject to significant uncertainty. Potential error sources are related to i) uncertainties in discharge measurements (accidental errors, systematic observer errors and systematic instrument errors) and ii) data processing. For Danish conditions, Blicher (1991) found that the latter may vary between 3-4 and 10% on a daily basis.

A second source of uncertainty is whether the calibration period is representative and sufficiently long to enable reliable identification of parameter values. Xu and
Vandewiele (1995) found that a 10-year calibration period was necessary and sufficient for this type of monthly water balance, while extending the calibration sample length to 15 or 20 years did not yield any substantial improvement. The second part of the error arises from the statistical representatives of the sample data used for calibration. To reduce this uncertainty several calibration periods of sufficient length must be included. This is not possible in the present study, however, due to the limited availability of data.

A third source of uncertainty is the information used in the automatic procedure for optimizing the MWB-3 model. Currently, MWB-3 only uses observed discharge for parameter optimization. The precision of poorly determined parameters fitted to runoff data could be substantially improved by pooling the runoff data with other kinds of hydrological data, such as groundwater depth and soil moisture. This may enhance the possibility of determining better relationships between model parameters and catchment characteristics.

A fourth source of uncertainty is the identification of the free model parameters, particularly the low-flow parameter $A_2$, when using catchment information to establish regression equations enabling model application in unmonitored catchments. This imperfection may be related to model structure and/or the digitally available data sets on catchment properties. Moreover, it might be conceptually difficult to distinguish strictly between different runoff components. The treatment of parameter identification problems needs to be examined in future studies.

Another source of uncertainty is the fact that the establishment and validation of the parameter regression equations depend on the catchments available and selected for calibration, as well as on subsequent tests of both their spatial distribution and the range of catchment properties that they represent and cover. To assess this uncertainty for the present study, the robustness of the model equation was investigated with respect to the variation in parameter values, as well as the fit and error of the regression equations. The procedure applied for this purpose follows the cross-validation approach, i.e. each of the regression equations is estimated $n$ times with $n-1$ observations, starting by excluding the first observation, then the second while re-including the first, followed by exclusion of the third and re-inclusion of the second and so forth until the $n^{th}$ is reached. The results of this procedure are presented in Tables 6 and 8.

The per cent coefficient of variation ($CV_p$, with $CP_p = \frac{100 \times \text{stddev}}{\text{mean}}$) for the parameter estimates of all variables contributing to each of the three regression equations is generally low and only exceeds 6 in a single case (Table 6). Variation, and hence uncertainty, is generally higher for $A_2$, particularly for the island part of Denmark, having the equation with the lowest $R^2$ among all the multiple regressions (Table 6). A similar pattern exists with respect to the variation in $R^2$ expressed as $CV_p$, which never exceeded 2.24 (Table 8), while the maximum $CV_p$ for the root mean square error (RMSE) was approximately 4.15 (Table 8), in both cases for parameter $A_2$ for Jutland where the regression is based on the smallest number of catch-
Table 8 - Statistics of the regression model fit ($R^2$) and root mean square error values resulting from a cross-validation estimation when applying model 5. RMSE is the root mean squared error.

<table>
<thead>
<tr>
<th></th>
<th>R² A₂</th>
<th>RMSE A₂</th>
<th>R² A₂</th>
<th>RMSE A₂</th>
<th>R² A₁</th>
<th>RMSE A₁</th>
<th>R² A₃</th>
<th>RMSE A₃</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jutland</td>
<td>0.84</td>
<td>0.01</td>
<td>0.65</td>
<td>0.01</td>
<td>0.80</td>
<td>0.53</td>
<td>0.75</td>
<td>0.01</td>
</tr>
<tr>
<td>Islands</td>
<td>0.65</td>
<td>0.01</td>
<td>0.71</td>
<td>0.01</td>
<td>0.82</td>
<td>0.53</td>
<td>0.78</td>
<td>0.01</td>
</tr>
<tr>
<td>Mean</td>
<td>0.84</td>
<td>0.01</td>
<td>0.65</td>
<td>0.01</td>
<td>0.80</td>
<td>0.53</td>
<td>0.75</td>
<td>0.01</td>
</tr>
<tr>
<td>Median</td>
<td>0.90</td>
<td>0.01</td>
<td>0.71</td>
<td>0.01</td>
<td>0.82</td>
<td>0.53</td>
<td>0.78</td>
<td>0.01</td>
</tr>
<tr>
<td>Max</td>
<td>0.78</td>
<td>0.01</td>
<td>0.55</td>
<td>0.01</td>
<td>0.78</td>
<td>0.51</td>
<td>0.73</td>
<td>0.01</td>
</tr>
<tr>
<td>Min</td>
<td>0.02</td>
<td>0.00</td>
<td>0.02</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>SD</td>
<td>2.24</td>
<td>4.15</td>
<td>3.53</td>
<td>2.23</td>
<td>0.74</td>
<td>1.17</td>
<td>0.91</td>
<td>1.24</td>
</tr>
</tbody>
</table>

ments (Table 6). It can be concluded that the range of parameter values increases with decreasing model fit quality and increasing model error. Since the range of all catchment parameter values lies within the 95% confidence intervals of the regression equation finally used for the study, the dependency of the regression estimates on the catchment selection is regarded as a minor source of uncertainty under the conditions pertaining in the present study.

It is nevertheless important to bear in mind that the initial selection of 84 catchments considered for the regionalization study was based on criteria that resulted in some areas of Denmark being poorly represented (e.g. the areas west of the main water divide). Those badly represented regions need to be included in future studies after modification of the model, provided that improved national data sets on water management and hydrogeology become available.

The uncertainty related to the estimation of model parameters also involves the sensitivity of the model to mis-specification of the model parameter values ($A_1$, $A_2$ and $A_3$). This was tested for the two different catchments representing areas dominated by sandy soils and loamy soils, respectively (Figs. 3 and 4). Although the total runoff in both catchments is of the same magnitude, the sandy catchment (130005) is dominated by slow-flow, while total runoff in the loamy catchment (470063) is dominated by fast-flow. Starting from optimised parameter values, the value of each parameter was reduced stepwise by 10% at a time relative to the optimised value, i.e. from 100% down to 10%. In both cases, the most significant changes expressed by an increase in error and decrease in fit were observed for parameter $A_1$, particularly in the catchment dominated by sandy soils. Due to the dominance of fast-flow in the loamy catchment, parameter $A_2$ is of less importance for the model fit and error than in the sandy catchment. To some extent this is even true for parameter $A_3$. Thus, following a 50% reduction, the absolute error in total flow rose to approx. 8% and 10% for the sandy and the loamy catchment, respectively, while $R^2$ of the fit decreased even more, from 0.893 to 0.7 (i.e. 21.6%) in the sandy catchment, compared to a reduction from 0.933 to 0.816 (12.5%) in the loamy catchment. Note that due to the
Fig. 3. Sensitivity of model to change parameter values $A_1$, $A_2$, $A_3$, for catchment 470063. The test starts from values that are optimized and then reduced stepwise by 10% of the optimized value. All steps are shown for parameter $A_1$, whereas only the steps from 90 to 10% are shown for parameters $A_2$ and $A_3$. The runoff component values are expressed relative to the optimized value.
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Fig. 4. Sensitivity of model to change parameter values $A_1$, $A_2$, $A_3$, for catchment 130005. The test starts from values that are optimized and then reduced stepwise by 10% of the optimized value. All steps are shown for parameter $A_1$, whereas only the steps from 90 to 10% are shown for parameters $A_2$ and $A_3$. The runoff component values are expressed relative to the optimized value.

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absolute size of the optimised values for $A_3$, a 10% reduction for $A_3$ is 3.50E-05 in the sandy catchment compared to 1.70E-04 in the loamy catchment. The absolute size of each 10% step is thus about 5 times greater in the loamy catchment than in the sandy catchment. Figs. 3 and 4 also reveal that a change in only one parameter affects all runoff components, thus indicating that all flow components are linked through the subsurface storage.

The main conclusion is that due to the more direct runoff response in the loamy catchments, transformation filters introduced by the parameters are of less importance than in the sandy catchments. Under Danish conditions, the selected model version thus seems to be more robust for application in loamy catchments than in sandy soil catchments.

**Conclusions and Outlook**

MWB-3 was tested as a potential model for estimating runoff from Danish catchments ranging in size between 0.7 km$^2$ and 2,602 km$^2$. All eight model versions yielded good results with respect to total runoff and sub-division into flow-components when applying the automatic parameter calibration accompanying MWB-3. Model version 5 was subsequently selected for establishment of the regression equations between catchment properties and model parameters for estimating parameter values for unmonitored catchments. Of the 84 catchments meeting the study requirements, a subset of 62 catchments was used to calibrate the model, while the remaining subset of 22 catchments was used to test the regression equations established, while concomitantly ensuring that both data sets covered as many of the different regions of Denmark as possible. The establishment of these equations was performed independently for the whole data set for both the evapotranspiration and the fast-flow model parameters. To determine the slow-flow parameter, however, the calibration data set had to be subdivided and the fast-flow parameter included as an explanatory variable in one of the resulting equations. The regression equations were applied to derive parameter values for the subsequent runoff simulations performed on each of the 22 catchments. The mean relative error obtained for both model calibration and testing was similar in magnitude to that of previous studies performed with the model and was regarded as acceptable given the large uncertainty associated with the various input data (Xu 1999).

The MWB-3 model proved to be a suitable tool for simulating monthly water balances in Danish catchments apparently with seemingly closed water balances. Model performance, expressed by average values of the coefficient of multiple determination $R^2$, was 0.82 for the calibration data sets and 0.79 for the validation data sets. In contrast, areas in which the long-term water balances are not closed had to be omitted from the study from the start. In particular, the current model cannot be applied to areas located in the region west of the main water divide, to which the
model has been applied but no further independent tests have been performed. The present study revealed a number of issues to be addressed in future studies:

- Due to the difficulty of independently establishing a regression equation between the slow-flow parameter and catchment properties, the structure of the model should be investigated further. Different new versions of the flow equations will be tested aiming at identifying good and physically meaningful correlations between all free parameters and information on catchment properties.

- As long-term potential evapotranspiration is currently used as a variable for the evapotranspiration regression, the equation used for the calculation of the actual evapotranspiration should be modified and simplified.

- The current version of MWB-3 only considers one subsurface storage, which might not always be sufficient in areas with predominant groundwater runoff. Future studies will have to include the establishment and testing of different concepts with respect to subsurface storages and the subsequent calculation of actual evapotranspiration.

- Procedures will be implemented to enable Monte-Carlo simulation to identify the relationship between the model fit and error and between various combinations of parameter sets to assess the uniqueness of the parameter combinations identified.

- The reliability of the input information, such as climatic data and observed runoff, needs to be further investigated. Moreover, the databases on subsurface conditions affecting deep groundwater exchange and the effect of water management measures on water balances at the catchment scale must be improved. The Geological Survey of Denmark and Greenland is responsible for assessing groundwater resources in Denmark (Madsen et al. 1998). Data from these activities and those of the Danish counties may considerably improve our insight into subsurface fluxes at the regional and national level.

- Inclusion of features such as groundwater abstraction and subsurface flow across catchment boundaries necessitates modification of the model structure. This is a prerequisite for the successful application of the model to those areas that could not be included in the present study. For example, application of the current model version to catchments where the long-term difference between precipitation and evapotranspiration is larger than observed discharge would inevitably lead to overestimation of simulated discharge.

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