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Relationship between Topography, Land Use and Soil Moisture in Loess Hill Slopes

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Abstract

The relationship between topography, land use, and topsoil moisture storage was investigated for a small catchment with undulating deep loess hill slopes in the south of the Netherlands. For a period of 10 months, soil moisture profiles were measured weekly at 15 locations throughout the catchment. A Generalized Additive Model was employed to find relationships between various factors influencing soil moisture. The model defines a water balance as a sum of non-linear components. The water balance was applied to our data at various spatial (catchment, response unit, hillslope and plot), and temporal (monthly, weekly and daily) scales. Each of the water balance components was parameterized as a function of topographic, land use, weather and antecedent soil moisture variables. The model framework is hierarchical: it starts at the coarsest spatio-temporal resolution, the water balance components found here act as constraints when identifying models at finer resolutions. It turned out that the importance of land-use variables varied considerably with temporal resolution. At coarse resolutions land-use was unimportant, whereas at finer resolutions it became more relevant. Land use was equally important over all spatial resolutions (response unit and finer). Topography was mostly relevant at the plot scale. The water balance terms became increasingly non-linear at finer scales. Evapotranspiration depended mainly on reference evapotranspiration and crop cover. Drainage to deeper layers depended mainly on soil moisture and to a lesser extent on topography. Lateral transport was weakly dependent on topography. It appeared that autoregressive components became increasingly important at finer temporal resolutions.

Keywords: GAM, SWAP, Topography, Landuse, Soil moisture

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1. Introduction

Soil moisture storage plays an important role in hydrological modelling (Troch *et al*., 1993; Akinremi *et al*., 1995) as well as in modelling the interaction between the land and atmosphere (Wood *et al*., 1992; Acs, 1994; Chen and Hu, 2004). Spatial heterogeneity in terrain properties and spatio-temporal variation in vegetation and weather result in highly variable soil moisture content at various scales (Entekhabi and Eagleson, 1989; Wood *et al*., 1992; Troch *et al*., 1993). Due to this variability compared to e.g. discharge and ground water, it is relatively difficult to observe soil moisture adequately on a regular basis. Apart from detailed field experiments in relatively small areas (Teuling *et al*., 2006), in-situ soil moisture observations are rare. A notable exception is the regular gravimetric observation of soil moisture in the former Soviet Union that started at a few hundred agro-meteorological stations from 1930s (Robock, *et al*., 2000). Most of these data plus the soil moisture data from Illinois and Iowa states in USA have been gathered in the Global Soil Moisture Data Bank (Robock, *et al*., 2000). In spite of this difficulty with in-situ soil moisture monitoring, it is generally acknowledged that knowledge of the (profile average) soil moisture state is important for the initialization of current generation of land-atmosphere models (Jikang and Islam, 2002). Furthermore, it plays a key role in any catchment-scale hydrological modelling efforts since it largely controls surface flow, infiltration, interflow, deep seepage, capillary rise, root water uptake, evaporation, transpiration, soil moisture storage and redistribution (Abbaspour and Schulin, 1996).

Most field to catchment scale unsaturated zone models use the Richards equation to describe the movement of water through the catchment. The applicability of this solution is however often questioned, especially when describing the system at larger spatial and temporal scales and when only limited observational data is available for model calibration (Blöschl and Sivapalan, 1995). In the domain of dynamic modelling there are hardly any studies available that evaluate other model concepts. In contrast, using static models, there are quite a number of studies on the effect of topography (Reid, 1973; Burt and Butcher, 1985; Carve and Gascuel-odux, 1997; Famiglietti *et al*. 1998; Western *et al*. 1999; Moore *et al*. 1988; Qiu *et al*., 2001; Svetlitchnyi *et al*., 2003; Pellenq *et al*., 2003) and land use (Fu *et al*., 2000; Hawley *et al*., 1983; Qiu *et al*., 2001; Mahe *et al*., 2005) on soil moisture distribution.

In this study, we tried to gain insight in the most important factors influencing the soil moisture dynamics in a small catchment using dynamic models. The study catchment has an undulating landform, heterogeneous land use and contains deep, well drained soils with a high water retention capacity. Under these conditions it is unclear whether soil moisture patterns (both laterally and vertically) arise due to topography or land use effects. In the identification we took both topographic and land use factors into account. Our ultimate aim was to compare the structure of models at different scales, to answer the question what mechanisms were dominant at different scales. Identifying these dominant mechanisms makes it easier to build suitable conceptual models for soil moisture prediction and collection of relevant data more efficient.

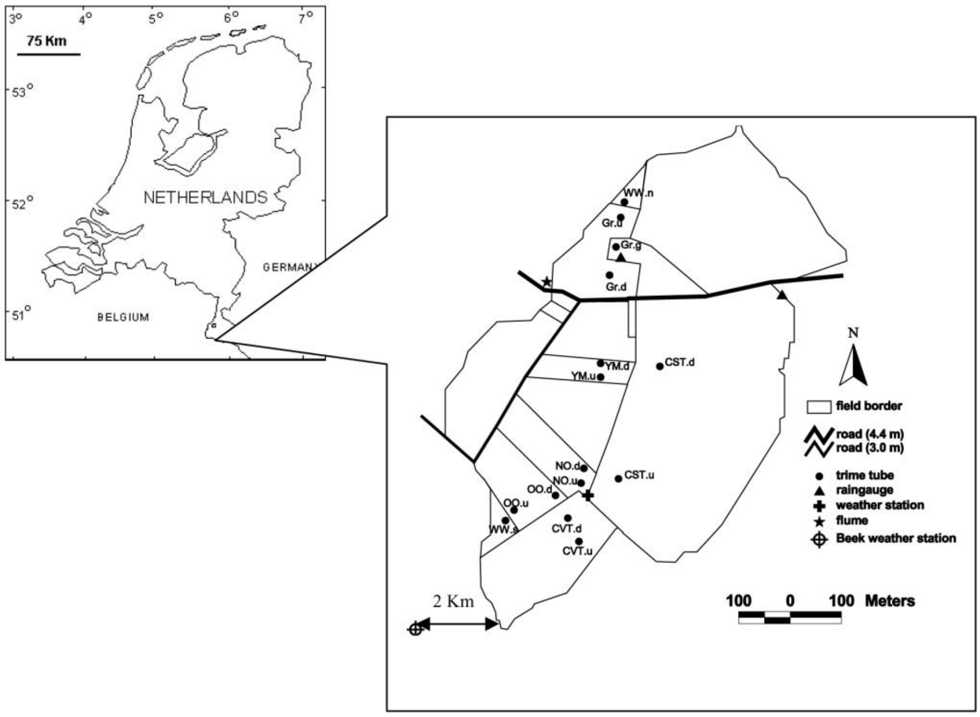

Figure 1. The study area and location of the measurements (for abbreviations, see Table 1). The observations at Gr.g were omitted from the analysis because this location was intermediate to Gr.u, Gr.d, but with a different management practice.

2. Description of the study area

The data used in this study originate from the Catsop catchment. The catchment is situated in the hilly loess region of South Limburg in the Netherlands (50º 95´N, 5º78´E; Fig. 1). It has an area of 0.42 km^2, and is almost entirely used for agricultural purposes. Within this small catchment four land use types were distinguished: Arable (79.5%), Orchard (7.9%), Grassland (11.8%), and Infrastructure (0.8%). Fig. 2 presents the land use pattern of the Catsop catchment during the winter season of 2003-2004. Arable land is cultivated mainly with winter wheat, spring barley, sugar beet, potato, and yellow mustard. Yellow mustard is a second crop, functioning as an erosion prevention measure. It is planted after harvesting the cereals at the end of the summer, and later in the season chopped into small pieces and spread on land surface as green manure and protection cover. Grasslands are utilized in two ways. Some fields are grazed by cows from April to October (less than 0.5 cows per ha) and the other fields are harvested by machinery (Fig. 2). During the last 5 years the area of orchards increased from nil to about 8%. The only available infrastructure within the catchment are a few tarred roads and one ditch near the outlet which runs parallel to the main road (Fig. 1).

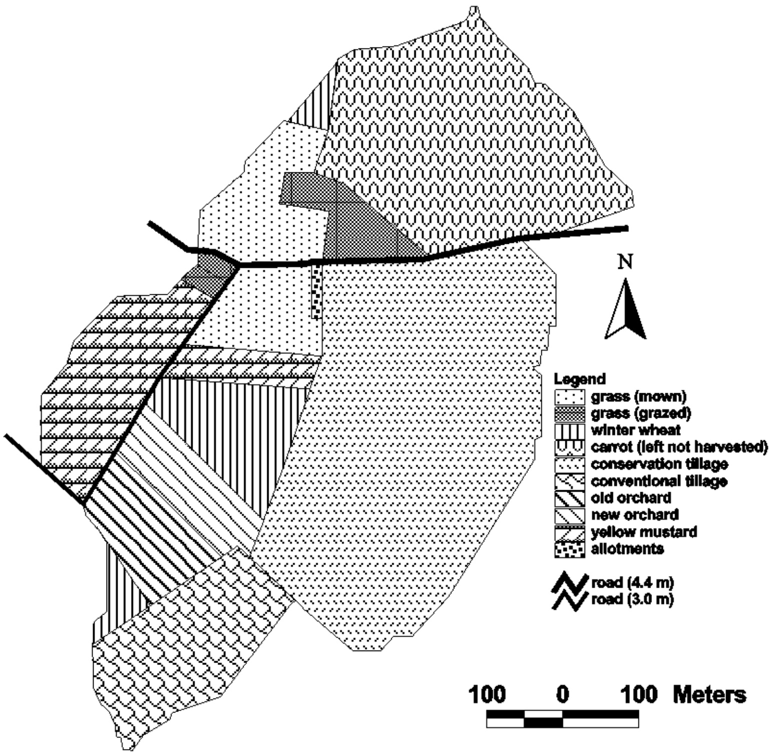

Figure 2. Land use in the Catsop catchment during the winter season of 2003-2004

Tab. 1 lists some of the properties at the observation locations. The climate is temperate humid, with a mean annual precipitation of ca. 740 mm. Precipitation occurs mainly as rainfall and is evenly distributed over the whole year. However, the rainfall pattern in winter and summer is different. Summer events are shorter and more intensive while winter events are on average longer and less intensive.

3. Data collection

Soil moisture was monitored in 15 tubes of 1 meter depth with a Time Domain Reflectometry system (*Trime-FM*) once every week for the period of November 2003-September 2004.

Table 1. General information of the observation locations (Fig. 1 for a map).

Land use	Observation location	Nr[1]	Slope	Upslope length[2]	Upslope area[3]	Topog. index[4]	Wetness coef [5]
Grass	Gr.u	44	9.2	54.1	0.06	8.73	0.87
	Gr.d	47	14.1	78.3	0.1	8.94	0.91
Conservational tillage	CST.u	21	8.7	122.4	0.15	9.73	0.97
	CST.d	16	4	160.7	0.61	11.62	1.01
Conventional tillage	CVT.u	19	7.0	84.1	0.1	9.59	1.17
	CVT.d	14	4.1	60.0	0.07	9.70	1.07
Wheat	WW.n	36	3.9	5.0	0.01	7.75	0.85
	WW.s	37	4.3	147.3	0.21	10.62	0.99
Yellow mustard	YM.u	21	5.0	340.0	1.88	12.83	1.14
	YM.d	21	4.8	360.0	1.9	12.88	1.20
Old orchard	OO.u	16	5.7	78.3	0.09	9.67	0.90
	OO.d	16	7.7	162.4	0.17	10.04	1.12
New orchard	NO.u	21	6.1	70.0	0.08	9.48	1.15
	NO.d	21	7.1	224.1	0.33	10.80	1.04

[1] Number of measurement times for each observation location
[2] Distance between divide and the observation point along hillslope in m
[3] Area of upstream catchment area at the observation point in ha
[4] $\ln(a/\tan\beta)$ topographic index (Beven and Kirkby, 1979)
[5] Wetness coefficient according to Svetlitchnyi *et al*. (2003)

The values for the top four layers are averaged to one mean root-zone soil moisture value, which is the value that is henceforth called *soil moisture* in this study. The values for the 80-100 cm layer were excluded because of the large observation errors in this layer. The locations of these tubes and other measurement equipment are shown in Fig. 1. The main topographic characteristics of each observation location are given in Tab. 1. For each land use type and management practice, at least two tubes were installed. Two tipping bucket rain gauges and one small standalone weather station were installed as well. All observed meteorological variables agreed well with the observations at the Beek weather station (50 55'N, 5 47'E), at a distance of less than 2 km from the study area. The reference evapotranspiration rate was calculated with the Penman-Monteith equation using daily meteorological data of the Beek station. Discharge was measured at the catchment outlet using a partial flume with a capacity of 950 l/s and a stilling well with a vertical float recorder. Discharge measurements were collected at 5 minute intervals during the period November 2003 - September 2004. Although the discharge observations may be relevant to questions about (multi-scale) unsaturated zone soil moisture modelling, these data were not used in this study (see the last part of the discussion and conclusions section).

4. Model framework

We identified water balance models at different scales. In space we distinguished catchment, response unit (arable, grass or orchard), hill slope (7 units) and plot (14 units) scales; temporally, we distinguished monthly, bi-weekly and weekly scales. At each scale, for each spatio-temporal unit the water balance of the root zone is described by the following equation

$$S_{j,k} = S_{j,k-1} + EP_{j,k} + c_{ju} LI_{j,k} - LO_{j,k} - ET_{j,k} - D_{j,k} \tag{1}$$

where all units are in mm. $S_{j,k}$ is soil moisture at spatial unit j and time instant k, EP is effective precipitation, LI is lateral inflow (from an upslope unit), LO is lateral outflow (to a downslope unit into the river channel), ET is evapotranspiration and D is drainage out of the root zone to deeper layers. c_{ju} is a factor to correct for the surface area upslope from j (which can be different from the area of unit j), hence $c_{ju}=area_{\mathrm{upslope}}/area_{\mathrm{j}}$. The LI component is only present at the plot scale. We indicate the spatial scale with the following letters: C for catchment, R for response unit, H for hill slope and P for plot; and the temporal scale is indicated with the letters M for monthly, B for bi-weakly, and W for weekly. Thus, evapotranspiration for the bi-weekly response unit scale, in the second unit and the fifth time period is indicated by $ET_{R2,B5}$.

The water balance model is hierarchical, meaning that the water balance components for spatio-temporal units at finer scales sum up to the value of the corresponding components at a coarser scale, for instance:

$$ET_{R2,M1} = \frac{\sum_{u=2}^{6} area_u ET_{Hu,M1}}{area_{R1}} = \frac{\sum_{u=2}^{6}\sum_{v=1}^{4} area_u ET_{Hu,Wv}}{area_{R1}} = \frac{\sum_{u=3}^{10}\sum_{v=1}^{4} area_u ET_{Pu,Wv}}{area_{R1}} \tag{2}$$

This equation states that the evapotranspiration for the second response unit in the first month (first term at left) equals the total evapotranspiration of the five hill slopes inside this response unit for that month (second term). It also equals evapotranspiration summed over the hill slopes and the four weeks in this month (third term), as well as the sum over plots 3 to 10 (which are located in hill slopes two to six, and response unit two), and the four weeks in this month (fourth term). The reason for using a hierarchical model is that it constrains the water balance model at finer resolutions, so that unique solutions are always obtained. Without such constraints it is (for our data and modelling technique) not possible to obtain stable models at weekly and plot scales. Note however, that constraints are applied only to the water balance fluxes (not to soil moisture storage).

Two additional constraints are applied to the GAM models: evapotranspiration is always equal to or smaller than the reference evapotranspiration, and no more than 5% of soil moisture can drain out of the soil profile in any time period.

We employed a Generalized Additive Model (GAM) to find relationships between the various factors influencing soil moisture. GAM is a non-parametric model that has been described in detail in Hastie and Tibshirani (1990). Since the early nineties the method has especially been applied in biological applications (e.g. Guisan *et al*., 2002). We will very briefly describe the technique here, starting with the definition of linear model as a sum of k variables with associated parameters β.

$$Y(i) = \beta_0 + \beta_1 X_1(i) + \ldots + \beta_k X_k(i) + e(i) \quad (3)$$

The error e is assumed to be normally distributed with mean zero. A variable X refers to any variable or composite variable that can be explicitly calculated (i.e. independent of Y), e.g. $X_3=X_1X_2$. Therefore the linear model can quite well describe all kinds of parametric nonlinear relations. In additive models the terms βX are replaced by (usually fairly simple) non-parametric functions of the X variables. The model in eq. 3 can be re-written as

$$Y(i) = \alpha + f_1(X_1(i)) + \ldots + f_k(X_k(i)) + e(i) \quad (4)$$

The functions $f_k(..)$ are usually assumed to be splines with a small number of knots, or the output from a loess smoother (Cleveland, 1979; Venables and Ripley, 2002). More complex functions can be used, but this may cause the model to over-fit the observed data and thus not generalize well to new data sets. Obviously, the choice of the function $f(..)$ (Both type and complexity) is critical. GAMs fit within the framework of the generalized linear model (GLM), which extends the linear model to errors with a non-normal distribution but is still limited to distributions of the exponential family (such as binomial, Poisson or gamma). For an explanation of GLMs McCullagh and Nelder (1989). Coming back to the water balance as given in eq. 1, in terms of a GAM it looks as follows.

$$
\begin{aligned}
&g(S_{j,k}) = S_{j,k-1} + EP_{j,k} + c_{ju} LI_{ju,k} - LO_{jd,k} - ET_{j,k} - D_{j,k} + e_{i,k} \\
&EP_{j,k} = f(P_k, S_{j,k-1}, T_j, L_{j,k}) \\
&LI_{j,k} = f(P_k, S_{j,k-1}, T_j, L_{j,k}, S_{ju,k-1}, T_{ju}, L_{ju,k}) \\
&LO_{j,k} = f(P_k, S_{j,k-1}, T_j, L_{j,k}, S_{jd,k-1}, T_{jd}, L_{ju,k}) \\
&ET_{j,k} = f(P_k, S_{j,k-1}, ETP_{j,k}, T_j, L_{j,k}) \\
&D_{j,k} = f(P_k, S_{j,k-1}, T_j) \\
&e_i \sim r(\mu_i)
\end{aligned}
\tag{5}
$$

The independent variable, $S_{j,k}$, may be transformed by the function g, depending on the error distribution that is chosen for r. For instance, if r is the normal distribution, g is the identity function; and if r follows a Poisson distribution g is the natural logarithm, if r follows a Gamma function, g is the inverse function (McCullagh and Nelder, 1989). In this study, we evaluate these three distributions for r: Normal, Poisson and Gamma.

All the independent variables in the non-parametric functions *f(..)* are observed variables. A list of observed variables is given for each water balance component, but only two of these may be chosen at maximum. Thus *f(..)* is a non-parametric function of one or two variables. The variable P stands for observed precipitation which is homogeneous over the entire catchment, therefore P does not contain a subscript j. The variable T refers to one of the terrain variables: soil type, slope (%), upslope length (m), upslope area (ha), the $\ln(a/\tan\beta)$ topographic index (Fig. 3; Beven and Kirkby, 1979), and the wetness coefficient (Fig. 3; Svetlitchnyi *et al*., 2003). The terrain variables only vary spatially. All these variables were calculated for 10 m pixels. At plot, hill slope and response unit scales the terrain variables were defined as averages of the values at the pixel scale. At the catchment scale terrain variables are not defined. The variable L refers to one of the land use variables: crop cover (none, sparsely, or full), and tillage (land is tilled or not tilled). The land use variables were calculated per plot. At higher aggregation levels the value of the dominant land use was taken. Land use variables were not defined at the catchment scale. The variable ETP refers to the Penman-Monteith reference evapotranspiration, calculated on the basis of the weather data. The subscript ju indicates a spatial unit located upslope from j, and jd a spatial unit downslope from j. The model as formulated by equation 5 is only valid for the plot scale. For the catchment, response unit and hillslope scales, LI is zero and LO is given by

$$LO_{j,k} = f(P_k, S_{j,k-1}, T_j, L_{j,k}) \tag{6}$$

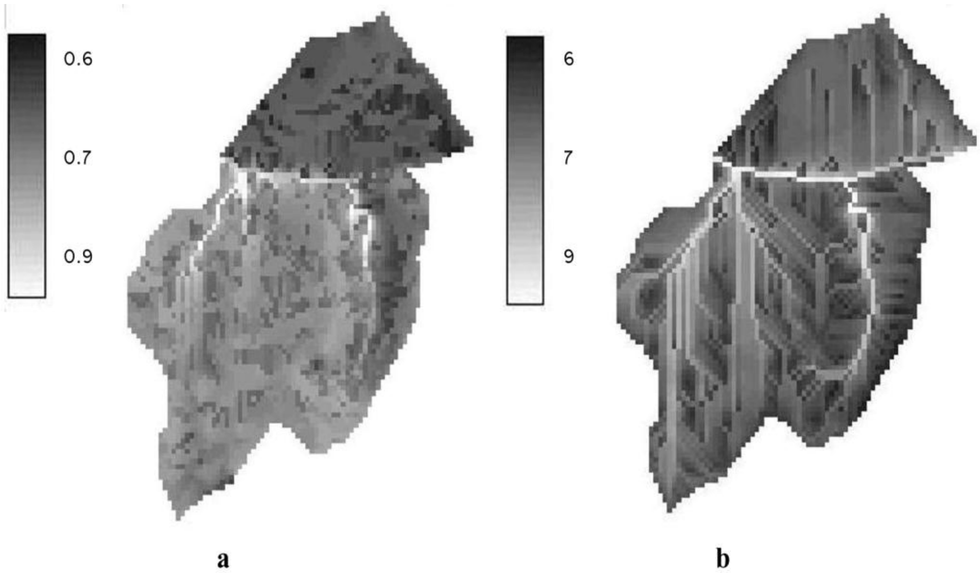

Figure 3. a) Wetness coefficient (Svetlitchnyi *et al*. 2003); and b) topographic index (Beven and Kirkby, 1979) for the Catsop catchment

Unfortunately, there is no unique metric available to measure non-linearity of one or two-dimensional functions. In this study, we measured the non-linearity of the water balance terms *f(..)* by fitting a linear line (or plane) through the response variables and comparing the fit through the data with this model, relative to the fit by the corresponding loess model (where fit is in both cases expressed in RMSE). Hence,

$$NI = 1 - \frac{RMSE_{loess}}{RMSE_{lin}} \tag{7}$$

where NI is a non-linearity index, $RMSE_{lin}$ is the RMSE of the linear model and $RMSE_{loess}$ is the RMSE of the loess model for the same water balance component. A high value of NI (close to 1) indicates a highly non-linear relation, whereas a low value indicates a linear relation.

5. Model fitting

We fitted the GAM models to our data using the R programming environment using the *gam* library (Hastie, 1991; Venables and Ripley, 2002). We applied the loess smoother with a span of 0.8 (i.e. considering 80% of the data within one window) and using a first order polynomial. The values at observation locations are assumed to be representative for the plot in which it is located; averages for plots are used for the accompanying hill slope (and so on). The used aggregation scheme is shown in Tab. 2. To choose the appropriate explanatory variables (only one or two per water balance component) from the list of allowed variables, we used a leave-one-out cross validation scheme. A model is fitted on all the data minus the data that applies to one spatio-temporal unit, and the value for this unit is predicted back. This is subsequently repeated while leaving out data for each spatio-temporal unit. The average error was calculated from the individual errors, using the root mean squared error (RMSE) statistic. The best-performing models were further tested by investigating all the non-parametric functions for the water balance components visually to see whether the shape can be explained qualitatively. Next, the model errors were tested for randomness (Lilliefors test), temporal autocorrelation (correlogram, all model scales), and spatial autocorrelation (correlogram, only models at the hill slope scale).

Table 2. Aggregation from plot to response unit. For WW (winter wheat), plots coincide with hill slopes, and for Gr (grass) the hill slope coincides with response unit.

Observation code	Plot code	Hillslope code	Response unit code
Gr.u	1	1	1
Gr.d	2	1	1
CST.u	3	2	2
CST.d	4	2	2
CVT.u	5	3	2
CVT.d	6	3	2
WW.n	7	4	2
WW.s	8	5	2
YM.u	9	6	2
YM.d	10	6	2
OO.u	11	7	3
OO.d	12	7	3
NO.u	13	8	3
NO.d	14	8	3

6. Model evaluation

The non-parametric water balance model was evaluated not only through cross validation and residual analysis but also by comparing its performance to that an AR (1) model as well as the conceptual water balance model, SWAP (Van Dam, 2000; Kroes and Van Dam, 2003). The AR (1) model has the following form.

$$S_{j,k} = a_j S_{j,k-1} + P_k \tag{8}$$

Where a_j is a model coefficient that is constant for the simulation period, but different per spatial unit. The parameterisation of SWAP and its calibration for the Catsop catchment has been explained in Sheikh and Van Loon (2006).

We used the first half of the available data for every observation location (all observations before 5 February) for calibration (SWAP and AR (1) model) and deriving the non-parametric functions *f(..)* (GAMs, eq. 5). The second part of the data (all data after 5 February) was used for validation. Model predictions and the observations of the validation data were compared using the RMSE statistic.

7. Results

7.1. Soil moisture variation and general results

The distribution of soil moisture per observation point is shown in Fig. 4. The figure shows that there are large differences between observation points, even when looking at seasonally aggregated values. Especially, the downslope locations (new orchard, grass and conservation tillage) are characterised by high soil moisture contents. Also, the differences between old orchard (upslope) and new orchard fit into this pattern (Fig. 1). Furthermore, it is interesting to note that with increasing average soil moisture, variation increases (see the width of the 75 and 95 percentiles in relation to the mean soil moisture content), while there is not a pronounced skewness in the distributions. Relations between soil moisture mean and variance have been investigated for other catchments as well (Fig. 2 in Teuling and Troch, 2005), but relationships seem to be case dependent.

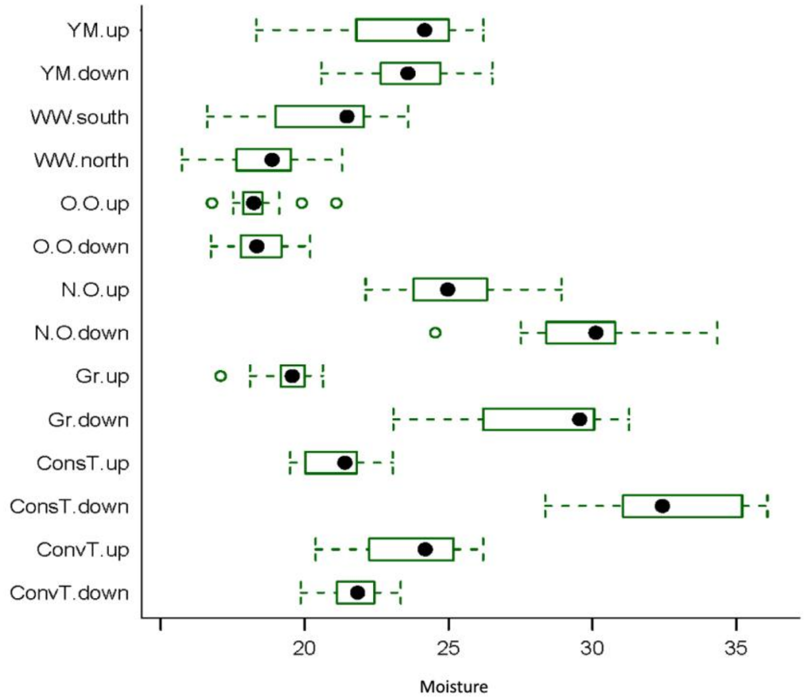

Figure 4. Box and whisker plot of soil moisture distribution per observation point

7.2. Explanatory variables at different scales

The modelling procedure did result in significant models (only variables significant at P<0.05 were included). A somewhat un-expected result was that all best performing models did contain non-parametric functions for the various water balance components that were not apparently wrong (on the basis of qualitative reasoning). In all but one case model errors were normally distributed (the one exception was a model at the catchment scale with weekly time steps, assuming a Poisson error), and only in two cases (models at the monthly time scale) the model errors had a temporal correlation. Spatially correlated model errors were not encountered. On the basis of this result it was decided to consider only the best performing models based on normal errors.

An example of model output is shown in Fig. 5. Here the predictions for the upslope and downslope grassland plots are shown at monthly, bi-weekly and weekly scales (along with precipitation and reference evapotranspiration). For the upslope grassland plot the model operating at the monthly scale is illustrated in detail in Fig. 6.

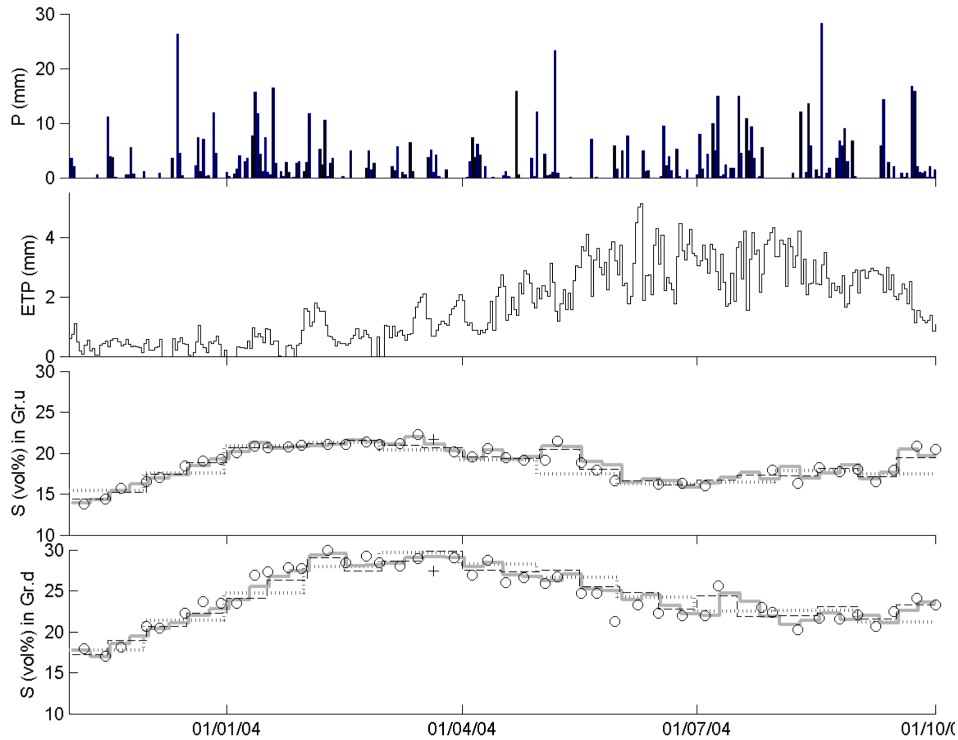

Figure 5. Example of prediction with GAM for the two grassland plots. The upper axis gives precipitation, the second gives reference evapotranspiration, the third axis from the top gives soil moisture of the upslope grassland plot (Gr.u), and the lowest axis gives soil moisture of the downslope grassland plot (Gr.d). The circles indicate observations that were used to derive the model, and the plus indicates the observation which is used for cross-validation. The solid line gives the weekly predictions, the dashed line the bi-weekly predictions and the dotted line the monthly predictions.

Fig. 6 shows how effective precipitation declines above a threshold precipitation of 15 mm/h, but only in the case of a tilled soil (for an untilled soil the relation between observed precipitation and effective precipitation is nearly linear). Next, lateral inflow is shown to be a function of both precipitation and the wetness coefficient. Outflow is a function of the wetness coefficient only. The reference evapotranspiration is the main determinant for evapotranspiration and upstream area is the main determinant for drainage. The relations shown in Fig. 6 relate to the lower five rows in Tab. 3 (2nd column). Tab. 3 shows, for all scales, the explanatory variables of the models with the smallest predictive error. Especially at the catchment and response unit scales, sometimes no significant relation was found for the drainage component (shown with a '-' in Tab. 3). With more detailed temporal scales, (bi-weekly and weekly), soil moisture becomes a suitable explanatory variable, whereas at monthly scales precipitation and evapotranspiration are more important. With finer spatial scale, the number of explanatory variables is increasing mainly with topographic variables (wetness coefficient, upslope area and topographic index). Especially for lateral outlfow as well as drainage there is a marked shift between the hill slope and plot scales.

Table 3. Selected explanatory variables for GAMs and model error for different spatio-temporal model scales. The model error is highlighted in bold. The explanatory variables are abbreviated as follows: S = soil moisture, ST = soil type, SL = slope, UL = upslope length, UA = upslope area, TI = topographic index, WC = wetness coefficient, CC = crop cover, TL = tillage, P = precipitation, E = Penman-Monteith reference evapotranspiration. The subscript *u* refers to the upslope unit.

Spatial scale	Temporal scale		
water balance component	month	two weeks	week
Catchment	0.014	0.012	0.012
EP	P	P	P
LO	S	S	S
ET	E	E, S	E, S
D	-	-	-
Response unit	0.015	0.011	0.007
EP	P	P, TL	P, TL
LO	P,CC	P	P
ET	E	E, S	E, S
D	-	-	S
Hillslope	0.013	0.006	0.007
EP	P, TL	P, S	P, S
LO	WC	P,WC	S, WC
ET	E, CC	E, CC	S, CC
D	P	S	S
Plot	0.016	0.012	0.006
EP	P, TL	P, S	P, S
LI	P, WC	S_u, TI_u	S_u, TI_u
LO	WC	UA	TI
ET	E	E, CC	E, S
D	UA	S, UA	S, TI

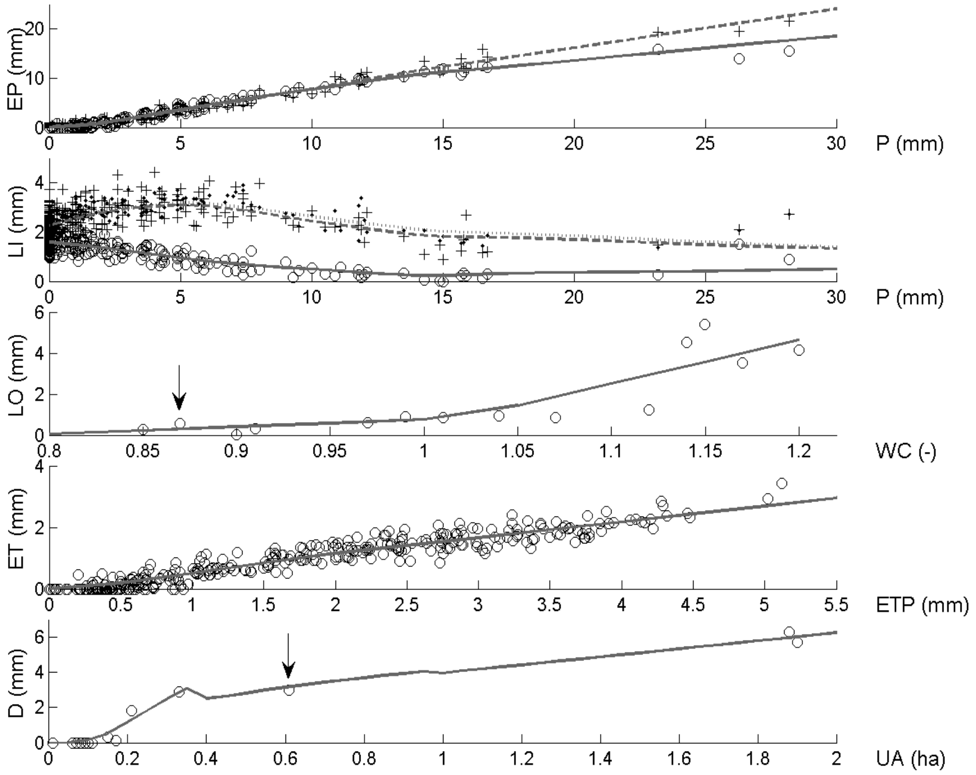

Figure 6. Example non-parametric functions of water balance components in the GAM for the upslope grassland plot, at the monthly time scale. The relations shown in this figure relate to the lower five rows in Tab. 3 (2nd column). In the upper axis effective precipitation is a function of observed precipitation and tillage (*EP=f(P,TI)*). The solid line refers to a tilled soil, and the dashed to an untilled soil. In the second axis from the top lateral inflow from upslope depends on both observed precipitation and the wetness coefficient (*LI=f(P,WC)*). This function is not shown fully in three dimensions, but rather with a two-dimensional graph with the relation *LI=f(P)* at three different values for WC: 0.86 (solid line), 1.0 (dashed line), and 1.2 (dotted line). For the grassland plot, the value of 0.86 is relevant. The two arrows (in the third and fifth axis) point at the WC and UA values for the grassland plot.

As stated in the section 4, non-linearity of the water balance terms was observed with an index relating a linear fit with the fit by the corresponding loess model for a water balance term (where fit is in both cases expressed in RMSE, eq. 7). The results of this analysis are shown in Fig. 7. It appears that the non-linearity increases with scale.

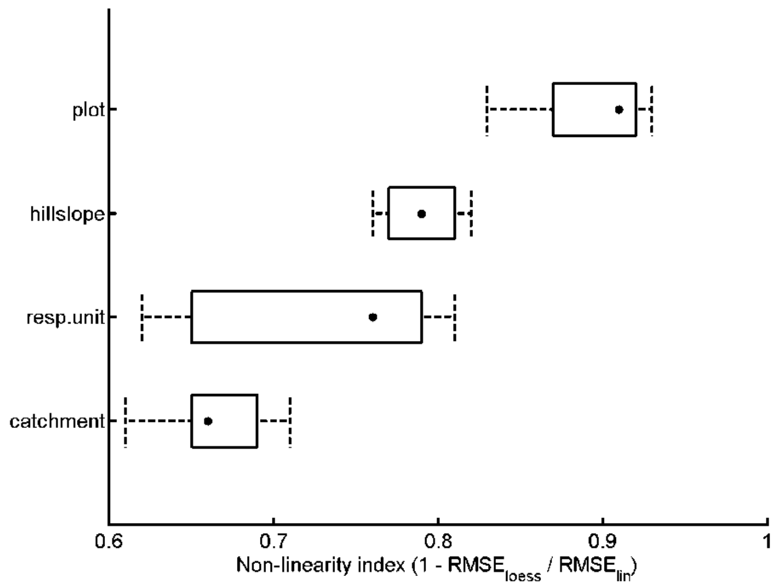

Figure 7. Non-linearity of the water balance terms, as a function of scale

7.3. Comparing the generalized additive water balance model with an AR(1) model and SWAP

At all scales we see that the RMSE for the GAMs is smaller than that of SWAP, which is in turn smaller than AR (1) (Tab. 4). While this pattern is quite consistent, the differences are not big. Note that RMSE for the GAM in Tab. 4 is not entirely comparable to that in Tab. 3. In Tab. 3 it is based on cross validation, and in Tab. 4 on a split data set.

At the response unit and hill slope scales the pattern of RMSE variation over units/hill slopes is also quite consistent (especially when comparing the GAMs with SWAP). Arguably, RMSE of predicted soil moisture is a very limited measure for a water balance model (see also the discussion in section 6.3.5). But also detailed visual checks on the output from the three models lead to the conclusion that results for soil moisture are not dramatically different. The only outstanding structural error is that the AR (1) model appears to systematically under-predict extreme wetness and over-predict dry periods (Fig. 8). For the partitioning between actual evaporation and drainage there are however considerable differences between the GAM models and SWAP. Fig. 9 illustrates these differences for the water balance over the entire study period. On average, the GAMs under-predict actual evapotranspiration by 13% and drainage by 4%, both in comparison to SWAP. In the GAMs these terms are compensated by a lateral outflow term, which is not present in SWAP.

Table 4. Comparison of prediction error (RMSE) of GAM, SWAP and AR (1) model, all applied to the same calibration/validation data.

Spatial scale	RMSE		
	GAM	SWAP	AR(1)
Catchment	0.011	0.012	0.012
Response unit			
Arable	0.006	0.006	0.008
Grass	0.009	0.011	0.010
Orchard	0.011	0.012	0.012
Hill slope			
grass	0.008	0.015	0.017
winter wheat (two slopes averaged)	0.010	0.017	0.017
conservation tillage	0.005	0.009	0.012
conventional tillage	0.006	0.007	0.009
yellow mustard	0.007	0.009	0.015
new orchard	0.009	0.011	0.014
old orchard	0.010	0.014	0.014

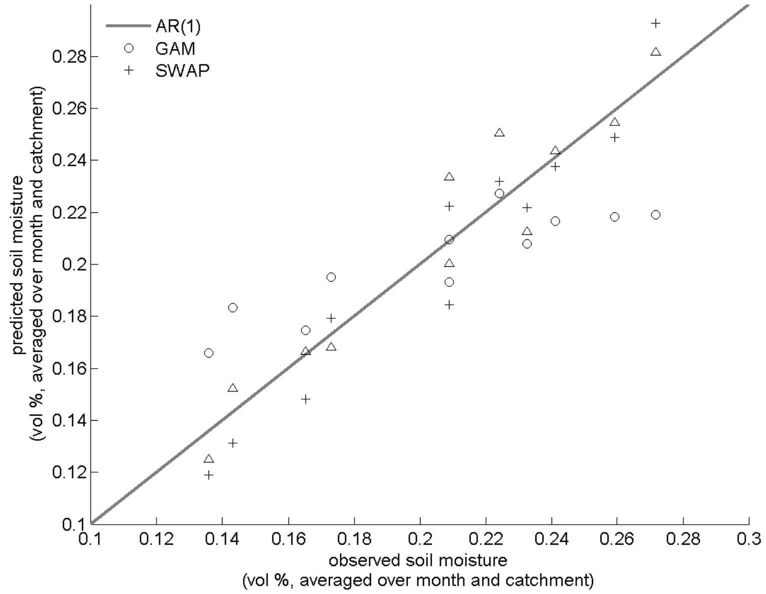

Figure 8. Model residuals for monthly averaged data. The GAM and SWAP predictions do not show a clear trend, but the AR model over-predicts at low soil moisture and over-predicts at high soil moisture values.

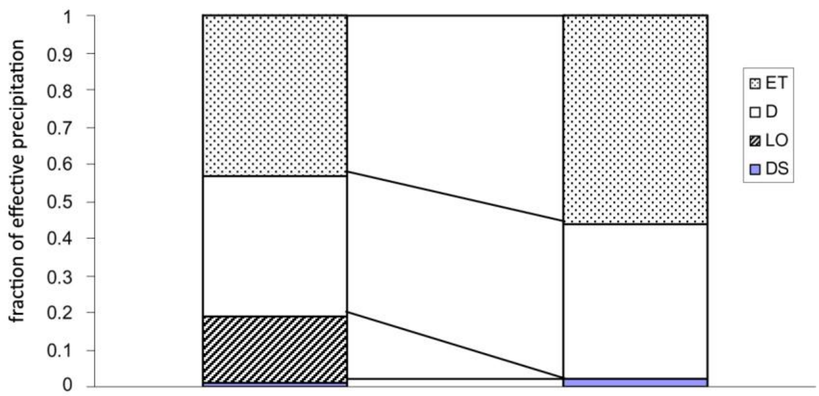

Figure 9. Visual display of the partitioning of the water balance terms, aggregated over the total study period, where DS means the difference in water storage, LO means lateral outflow, D means drainage and ET actual evapotranspiration; all terms integrated over the entire research period (eq. 5).

8. Discussion

The relation between soil moisture and topography (mainly slope gradient, aspect, relative elevation, and shape of slope profile) has been investigated frequently (Reid, 1973; Burt and Butcher, 1985; Carve and Gascuel-Odux, 1997; Famiglietti *et al*., 1998; Western *et al*. 1999; Moore *et al*. 1988; Svetlitchnyi *et al*., 2003; Pellenq *et al*., 2003). Also the effect of land use often has been studied (Fu *et al*., 2000; Hawley *et al*., 1983; Mahe *et al*., 2005). Findings in these studies differ due to locally different situations (e.g. climate, geology, human influence). We believe, on the basis of the results from this study, that different conclusions can also be reached when focussing at different spatial or temporal scales. When parameterising our water balance model at coarse temporal scales, we find that mainly rainfall and potential evapotranspiration are dominant factors, together with crop cover. At finer temporal scales soil moisture becomes more important (rendering precipitation less influential). Soil moisture acts as a non-linear filter on the rainfall input. Apparently, this process is too fast to be visible at a monthly scale, but at bi-weekly and weekly scales it is detectable (Tab. 3, columns two-four). Land use is influential at all scales (Tab. 3), but especially at response unit and hill slope scales. The sharp differences between the hill slope and plot scales are remarkable. At the hill slope scale, the wetness coefficient and crop cover are the most effective terrain and land use variables, whereas at the plot scale it is the upslope area and the topographic index (compare hill slope with plot in Tab. 3) that are important.

The shape of the response functions for the water balance components could be explained qualitatively. In addition, the residuals of the GAMs were not correlated over time (tested for all scales) and were also not spatially correlated (tested for the models at the plot scale). With finer scales, the non-linearity of the water balance components increased (Fig. 7). This is an aspect which has often been mentioned in the hydrologic literature. It is generally believed that most processes lead to highly non-linear responses at point scales, and that responses become more linear at coarser scales due to spatio-temporal averaging (Blöschl and Sivapalan, 1995). In spite of theoretical evidence for this property in hydrological systems, little direct empirical evidence of this property exists (especially at the intermediate scales of hill slope and response unit). Our results provide this evidence.

After meeting these minimal requirements for a useful model, the results from the GAM were compared with a (simpler) AR (1) model and a (more complex) physically based water balance model. This comparison measured by RMSE led to the conclusion that the GAM performed slightly better than both other models (Tab. 4). Apart from a structural difference between the AR (1) model and the other models, there appeared to be few differences for soil moisture. The AR (1) model appeared to structurally under-predict extreme wetness and over-predict dry periods, and the partitioning between the various loess terms appeared to be different between the GAMs and SWAP. In the GAMs a lateral outflow term was consistently present, whereas such a term is absent in the SWAP model (which models a 1D column). This led to lower estimates of both actual evapotranspiration and drainage by the GAMs in comparison to SWAP. The presence of a significant lateral outflow term together with the observation that topographic variables were important at the hill slope and plot scale led to the conclusion that lateral flow processes were important in Catsop. This result corresponds with the results by Michiels *et al*. (1989) but is in conflict with the conclusion from Ritsema *et al*. (1996) that lateral flow processes play a minor role in Catsop. Part of this difference is in the definition of the term lateral flow. Ritsema *et al*. (1996) consider only flow that is observed within the root zone of a hill slope (Jackson, 1992). In this study, lateral flow is all the water that leaves a spatial unit as discharge. Another explanation can be that Ritsema *et al*. (1996) collected (very detailed) data for a single slope in the catchment, whereas in this study various slopes were observed simultaneously.

This study addressed the issue of hydrological model identification at different scales. It is an old (and returning) subject of research (e.g. Klemes, 1983; Beven, 1995; Blöschl and Sivapalan, 1995). This study contributed with a new approach to identify dominant mechanics at different scales: a hierarchical generalized additive model. Generalized additive models are valuable research tools that are, in contrast to other non-parametric modelling techniques like neural networks (e.g. Jiang and Cotton, 2004) and self-organising maps (Schütze *et al*., 2005), hardly used for hydrologic applications. Yet, as this study demonstrated, the technique appeared to be quite useful, in particular for water balance models. GAMs can be calibrated fast, which allows the evaluation of many candidate models, and the response-curve of individual water balance components can be assessed visually and tested statistically (using all the techniques available for GLMs). With this study we emphasized not the results but the possibility of GAMs application for finding appropriate parameterisations at a given scale. The result can be used as a starting point for building conceptual models of the entire water balance, or only a single component. An example of analysing a single water balance component within an identified GAM model would be to replace one component with a given parametric function, and subsequently evaluating whether the resulting model would perform equally well (or better) as its nonparametric counterpart. An example of a suitable formulation of drainage to a deeper layer can e.g. be taken from eq. 14 of Laio *et al*. (2001) and an example of a parametric replacement for the evapotranspiration function can be found in eq. 3 of Teuling and Troch (2005). Young (1998) and Wilby *et al*. (2003) demonstrated that also other non-parametric techniques (viz. autoregressive TVP models and neural network models) can be used to evaluate hydrological model concepts.

For the Catsop catchment we can confirm that water balance models are scale dependent, meaning that when defining a model at a different spatio-temporal resolution, an entirely different process description is required. Of course this situation is partially due to our limited set of observations (with RS-observations scale dependency might have been less), but therewith not less valid in any practical situation. Although the idea of scale dependent models has been hypothesized a while ago by Beven (1995), surprisingly little empirical evidence to either confirm or reject this hypothesis has been reported until now. This is probably due to the fact that most models have a parametric basis, for which it is hard to specify a large number of different candidate models. On the other hand, most data-based models (such as neural networks or complex autoregressive models) are entirely geared towards prediction and do not provide a method to single out individual water balance components. In relation to soil moisture prediction, some work has been done to derive field-averaged values from point observations, using scaling theory (e.g. Warrick *et al*., 1977; Russo and Bresler, 1980; Rodriguez-Iturbe *et al*., 1995; Western and Blöschl, 1999). Scaling theories have only been applied to relatively homogeneous fields with limited relief and human influence, and within a limited spatio-temporal range.

9. Conclusion

While GAMs are in principle suitable for water balance modelling, as stated previously, several practical difficulties need attention. The first is the risk for over-parameterisation. GAMs always need (like any non-parametric model) a calibration-validation cycle to check whether the defined model can be generalised. In this study, this was implemented via a leave-one-out cross validation scheme. Next, GAMs are not always stable, hence one needs to check the stability of a solution through a sensitivity analysis, and apply some form of regularization (Hansen, 1998). A very straightforward regularization scheme was applied in this study, first deriving coarse-scale models and then using these to constrain the fine-scale models (i.e. a hierarchical modelling approach). Apart from being easy to apply, it is unclear to us whether a hierarchical modelling approach offers any advantages over other regularization schemes like Tikhonov regularization or TSVD (Hansen, 1998). A potential source of problems are artefacts that result from the limited information content of the observations, relative to the number of water balance components that are being specified. In our study, this results in the property that the same set of explanatory variables can only be used for one water balance component (Tab. 3). If a water balance component (e.g. Effective Precipitation) is identified as being influenced by observed precipitation, another component (e.g. Lateral Outflow) will not be identified as being influenced by precipitation alone. While from a statistical perspective this is exactly what one desires, from a physical viewpoint it makes no sense because it is well possible that two independent processes rely on the same explanatory variable. This situation can only be resolved by additional observations (on individual water balance components). An additional observation available for our study area is catchment discharge. With discharge it is possible to set the sum of lateral outflow (over all spatial units) equal to observed catchment discharge. If the model concept suits the system under study, this additional data should result in lower soil moisture prediction errors. A failure to achieve this does however not automatically lead to a rejection of the model. The question of how and under which conditions catchment discharge leads to enhanced soil moisture predictions is a subject of future studies.

The possibility of GAMs to evaluate range of model structures relatively easily also opens new possibilities to re-think the concept of information content of observations in relation to the model complexity (Jakeman *et al*., 1993). For non-parametric models like GAMs one can express model complexity in terms of the number of required explanatory variables (provided that the resulting model is tested in some cross-validation scheme). Through the observation of longer records or additional state variables, one can measure both changes in model performance and model complexity. The point at which the model performance does not increase anymore is the complexity that is warranted.

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